Online Environmental Control of Multiple Devices using Transcranial Doppler (TCD) Ultrasonography

by

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A thesis submitted in conformity with the requirements for the degree of Master of Health Science
Graduate Department of the Institute of Biomaterials and Biomedical Engineering
University of Toronto

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Abstract

Individuals with severe impairments may use brain-computer interface (BCI) technologies in order to interact with their external environment. One non-invasive brain-monitoring technology which may be suitable for this purpose is transcranial Doppler ultrasound (TCD). Previous research has shown that TCD is useful in detecting changes in cerebral blood flow velocities after the performance of cognitive tasks which are often lateralized towards a specific hemisphere of the brain. However, to date, TCD has not been used in a BCI system. This thesis first explores TCD in an offline study, showing that on average, accuracies of 80.0% are attainable with user-specific training data and 74.6% with user-independent training data. Furthermore, consecutive sequential lateralizations do not decrease classification accuracies. In a subsequent online experiment, a TCD-BCI system yielded an average accuracy of 61.4%, but revealed key findings about the effects of user motivation and error streaks in an online system.
In the name of Allah, the Most Beneficent, the Most Merciful. As always, I begin with thanking God for the countless blessings He has given to me and my family.

I would also like to thank my dear mother for always being there for me, my father for his wisdom and guidance, my brothers Ilyas and Ibrahim for their companionship through the journey of life, and the rest of my family for their love and encouragement.

I would like to thank my supervisor Dr. Tom Chau for his continuous support and advice throughout this project, and my committee members Dr. Tony Easty and Dr. Patty Rigby for the feedback and direction they contributed. Thanks to the members of the PRISM Lab, particularly Pierre Duez and Ka Lun Tam for their software and hardware expertise.

To my friends and fellow graduate students Ajmal Khan and Ahmed Faress, I thank you for the good times we’ve shared during the last two years. And to my dear friend Zishan Zubair, thank you for accompanying me on our never-ending quest for knowledge.

Finally, I am grateful for the financial support from Hilda and William Courtney Clayton, Holland Bloorview Research Institute, Natural Sciences and Engineering Research Council of Canada, the Ontario Government, and the University of Toronto.
# Table of Contents

Acknowledgments.......................................................................................................................... iii  
Table of Contents........................................................................................................................ iv  
List of Tables ................................................................................................................................ vii  
List of Figures .............................................................................................................................. viii  
List of Abbreviations ..................................................................................................................... ix  
Chapter 1 ......................................................................................................................................... 1  
1 Introduction................................................................................................................................ 1  
  1.1 Rationale ............................................................................................................................. 1  
  1.2 Research Objectives and Hypothesis .................................................................................. 2  
    1.2.1 Objective 1: Preparation for an Online TCD-BCI System ..................................... 2  
    1.2.2 Objective 2: Implementation of an Online TCD-BCI System ................................ 2  
  1.3 Background ......................................................................................................................... 3  
    1.3.1 Physiology ............................................................................................................... 3  
    1.3.2 Doppler Ultrasound ................................................................................................. 4  
    1.3.3 Applications ............................................................................................................ 6  
    1.3.4 TCD as an Access Pathway .................................................................................... 6  
    1.3.5 TCD Raw Data and Laterality Data ........................................................................ 7  
  1.4 Thesis Layout ...................................................................................................................... 8  
Chapter 2 ......................................................................................................................................... 9  
2 Towards a hemodynamic BCI using transcranial Doppler (TCD) without user-specific training data ......................................................................................................................... 9  
  2.1 Abstract ............................................................................................................................. 9  
  2.2 Introduction ....................................................................................................................... 10  
  2.3 Methods ............................................................................................................................ 11  
    2.3.1 Participants ............................................................................................................... 11
Table of Contents

2.3.2 Instrumentation Setup ........................................................................................... 11
2.3.3 Mental Tasks ......................................................................................................... 12
2.3.4 Experimental Protocol .......................................................................................... 14
2.3.5 Analysis with User-Specific Training Data .......................................................... 15
2.3.6 Analysis without User-Specific Training Data ..................................................... 17
2.4 Results and Discussion ............................................................................................. 17
  2.4.1 Classification Accuracies ...................................................................................... 17
  2.4.2 Discussion ............................................................................................................. 18
  2.4.3 Limitations ............................................................................................................ 20
2.5 Conclusion ................................................................................................................ 21

Chapter 3 ....................................................................................................................................... 22
3 Online Control of Multiple Devices Using Transcranial Doppler (TCD) without User-
  Specific Training Data ............................................................................................................. 22
  3.1 Abstract ............................................................................................................................. 22
  3.2 Introduction ....................................................................................................................... 22
  3.3 Methods ............................................................................................................................. 24
    3.3.1 Participants ............................................................................................................ 24
    3.3.2 Instrumentation Setup ........................................................................................... 24
    3.3.3 Mental Tasks .......................................................................................................... 25
    3.3.4 Experimental Protocol .......................................................................................... 26
    3.3.5 Online Classification without User-Specific Training Data .................................. 27
    3.3.6 Offline Classification with User-Specific Training Data ....................................... 28
  3.4 Results and Discussion ................................................................................................. 29
    3.4.1 Online vs. Offline .................................................................................................. 29
    3.4.2 Dynamic Rest Period ............................................................................................ 30
    3.4.3 Error Streaks ......................................................................................................... 32
List of Tables

Table 1: Advantages and disadvantages of TCD as an access pathway........................................... 7

Table 2: Mean classification accuracies and standard deviations (std) for different activation
categories (L=left activation; R=right activation)........................................................................ 18
List of Figures

Figure 1: Process of converting intent into a functional activity .................................................... 3
Figure 2: Arteries in the Circle of Willis .......................................................................................... 4
Figure 3: The “ultrasonic window” where the TCD signal can be recorded ................................... 5
Figure 4: The raw data measured from the left probe and right probe ........................................... 8
Figure 5: Block diagram depicting experimental setup in Phase 1 .................................................. 12
Figure 6: Visual display cues given to participants for each task .................................................. 13
Figure 7: The sequence of mental activations used in the experimental protocol ............................. 15
Figure 8: Overall accuracy and standard deviation bars for all participants .................................. 18
Figure 9: Block diagram depicting experimental setup in Phase 2 ................................................. 25
Figure 10: Visual cues given to participants for each task ............................................................ 26
Figure 11: The sequence of mental activations used in the experimental protocol ........................... 27
Figure 12: Overall accuracy for each participant’s online and offline results ................................. 29
Figure 13: Online and offline accuracies in Phase 2 ................................................................. 31
Figure 14: The average accuracy and standard error of mean (SEM) of tasks following a particular duration of rest .............................................................................................................. 31
Figure 15: The effect of error streaks on the participant’s overall accuracy .................................. 32
Figure 16: The number of left and right device activations for each participant ............................ 33
Figure 17: Device bias based on asymmetrical CBFV magnitude .................................................. 34
Figure 18: The average accuracy of all 10 tasks during each of the 5 slide sets ............................. 36
Figure 19: The average accuracy of all 5 slide sets for each of the 10 tasks ................................. 36
# List of Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>ACA</td>
<td>Anterior Cerebral Artery</td>
</tr>
<tr>
<td>ALS</td>
<td>Amyotrophic Lateral Sclerosis</td>
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<tr>
<td>BCI</td>
<td>Brain-computer Interface</td>
</tr>
<tr>
<td>BMUS</td>
<td>British Medical Ultrasound Society</td>
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<tr>
<td>CBFV</td>
<td>Cerebral Blood Flow Velocity</td>
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<tr>
<td>EEG</td>
<td>Electroencephalography</td>
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<tr>
<td>fMRI</td>
<td>Functional Magnetic Resonance Imaging</td>
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<td>ICA</td>
<td>Internal Carotid Artery</td>
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<td>LDA</td>
<td>Linear Discriminant Analysis</td>
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<tr>
<td>MCA</td>
<td>Middle Cerebral Artery</td>
</tr>
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<td>MMG</td>
<td>Mechanomyography</td>
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<tr>
<td>NIRS</td>
<td>Near-infrared Spectroscopy</td>
</tr>
<tr>
<td>PCA</td>
<td>Posterior Cerebral Artery</td>
</tr>
<tr>
<td>PET</td>
<td>Positron Emission Tomography</td>
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<tr>
<td>TCD</td>
<td>Transcranial Doppler Ultrasonography</td>
</tr>
</tbody>
</table>
1 Introduction

1.1 Rationale

Individuals with critical disabilities may require access technologies in order to communicate and interact with their environment. Examples of such technologies include mechanomyographic (MMG) signals to measure small vibrations [1], infrared cameras to detect opening of the mouth [2], and computer vision to extract tongue protrusions in spastic cerebral palsy patients [3]. These access pathways have all been used to design functional access solutions.

Individuals with severe and multiple physical impairments but capable cognition are often unable to communicate. For example, amyotrophic lateral sclerosis (ALS) and anterior brainstem stroke are neuropathological conditions which disrupt neuromuscular channels, causing motor and communication impairments. Severe cases may result in locked-in syndrome [4, 5]. Such individuals are conscious and aware, but they are paralyzed and no longer have control over their external environment; the motion-based technologies mentioned above do not provide them with a pathway for communication. Over half a million individuals across the world are in a locked-in state [6]. Some of them are able to maintain control of their eyelids (classic locked-in syndrome [7]), whereas those with total locked-in syndrome have an absolute loss of movement [8]. This impairment has serious social and emotional impacts on both the locked-in patient and his/her family [9]. A brain-computer interface (BCI) can potentially allow these individuals to communicate again. This research investigates a non-invasive hemodynamic BCI that exploits changes in cerebral blood flow velocity (CBFV) using transcranial Doppler ultrasound (TCD). A TCD-BCI system can potentially increase the independence and the comfort of individuals with complex disabilities, giving them a sense of control of their surroundings [10].
1.2 Research Objectives and Hypothesis

The overall objective of this project is to allow online control of two external binary devices using TCD. This can be divided into the two specific objectives described below.

1.2.1 Objective 1: Preparation for an Online TCD-BCI System

In order to optimize use of TCD as a BCI for environmental control, there were a few issues which needed to be explored.

1) Determine the effect of multiple sequential lateralizations on the participant’s accuracy
2) Reduce activation and rest times (from previous studies [11]) to increase data transmission rates of the BCI system
3) Minimize the number of classification features to decrease processing time
4) Explore the possibility of classification without user-specific training data in order to decrease time needed for participant training

It was hypothesized that sequential lateralizations would not significantly reduce classification accuracy, that activation durations, rest durations, and the number of features can be minimized, and that a user-independent classifier would yield accuracies comparable to those of user-specific classifiers.

1.2.2 Objective 2: Implementation of an Online TCD-BCI System

The implementation of an online TCD-BCI system would be the first of its kind, providing insight into its viability and potential for improvement.

1) Develop an algorithm to classify the TCD data in real-time and control two devices with user-independent training data
2) Record data and accuracy during data collection session
3) Analyze the data to justify the measured accuracy and synthesize recommendations for improvement in future studies

It was hypothesized that the online accuracies will be lower than the equivalent offline accuracies, but in excess of chance.
1.3 Background

The vision of an access pathway which is used to translate functional intent into functional activity was described by Tai, Blain, and Chau, shown in Figure 1 [12]. This translation occurs via the access pathway, signal processing, and user interface. For this project, the access technology used was transcranial Doppler (TCD), and the user interface was environmental control.

![Figure 1: Process of converting intent into a functional activity [12]](image)

The following sections will provide a brief background on the physiological theory behind the TCD technology, the concept of Doppler ultrasound, and several applications of TCD.

1.3.1 Physiology

Blood flows to the brain through the internal carotid arteries and the vertebral arteries, connected by a circular formation of small arteries known as the Circle of Willis. The Circle of Willis supplies the brain with blood and ensures that the brain receives blood even if one of the arteries is blocked [13]. The carotid artery splits into the anterior cerebral artery (ACA), middle cerebral artery (MCA), anterior choroidal artery, and posterior communicating artery on each side of the brain. The ACA’s on either side of the brain are connected by the anterior communicating artery. The vertebral arteries combine to form the basilar artery, which splits into the left and right posterior cerebral arteries (PCA). These arteries form the Circle of Willis as illustrated in Figure 2 [14].
The majority of the brain is supplied by the ACA, PCA, or MCA. The ACA supplies the frontal pole, the MCA supplies the lateral areas of both hemispheres, and the PCA supplies the back of the brain [15].

Through the well-known mechanism called neurovascular coupling, changes in brain activity cause changes in cerebral blood flow velocity in the cerebral arteries [16]. This occurs due to an increase in neuronal activity which causes increased glucose and oxygen consumption, resulting in vasodilation of the microvessels which are linked to neurons through astrocytes. This consequently increases blood flow in the larger arteries, including the MCA, without affecting the diameters and blood flow volume in these larger vessels [17]. Cognitive activation can thus by detected by monitoring changes in blood flow velocity in the MCA, ACA, or PCA. However, the middle cerebral arteries are ideal for measuring changes in cerebral blood flow velocity because they perfuse about 80% of the brain [18, 19].

1.3.2 Doppler Ultrasound

Ultrasound waves are sound waves at a frequency greater than the limits of human hearing. Sound waves transmit through a series of compressions and rarefactions of the particles within a
medium. Medical sonography uses ultrasound to produce images of internal structures in the body through the partial reflection of ultrasound as it passes through tissue to be detected outside the body [20].

The frequency shift of sounds when there is a non-zero velocity between the source and the observer of the sound wave is known as the Doppler Effect. This concept is the basis of Doppler ultrasound, which can image moving structures within the body. Thus, Doppler ultrasonography is suitable for measuring cerebral blood flow velocities [21].

In practice, the absolute magnitudes of the Doppler ultrasound flow velocities are not measured due to the difficulty in determining the angle at which the skull is insonated. Instead, the relative changes in blood flow are examined [22].

The application of pulse-wave Doppler ultrasonography to the measurement of cerebral blood flow velocities is known as transcranial Doppler ultrasound (TCD). Although Doppler ultrasound measures blood flow volume, it can be considered equivalent to blood flow velocity due to the limited diameter change of the major cerebral arteries [22-24]. This technique was first applied by Rune and Aaslid in 1982 [25]. TCD can be obtained by placing the ultrasound probe at the temples, anterior to the ear, where the skull is thin enough for successful insonation of the ACA, MCA, and PCA (refer to Figure 3) [25].

Figure 3: The “ultrasonic window” where the TCD signal can be recorded, located over the temporal region where the skull is thin [26]
1.3.3 Applications

There are several medical applications of TCD, including the assessment of cerebral perfusion pressure, vasospasm diagnosis and management, traumatic brain injury assessment, diagnosis of brain death, detection of stenosis and occlusion, detection of cerebral microemboli, and screening children for neurovascular diseases [26-31]. Furthermore, Deppe et al present a review on the numerous other applications of TCD, including studies on vision, motor activation, epileptic discharges, migraines, transcranial magnetic stimulation, electroconvulsive therapy, acupuncture, music, visuospatial tasks, attention, habituation, memory, language and language recovery, genetics, behaviour, and other cognitive tasks [22].

There has also been significant research in the area of functional transcranial Doppler ultrasound, which is the application of TCD to measure cerebral blood flow velocity (CBFV) changes during mental activations. This includes cognitive, sensory, and motor tasks. Cerebral lateralization, or the localization of mental activities primarily in one hemisphere of the brain, is a major aspect of TCD research [32-40]. From these studies, it has been established that language tasks are primarily oriented in the left hemisphere and visuospatial tasks in the right hemisphere [19, 41]. For example, a simple word generation task can produce left lateralization between the hemispheres. This correlation was validated by showing a strong relationship between TCD signals, fMRI [42], and EEG [43].

Furthermore, TCD has been used to show that higher CBFV increases correlate to better performance in attention and vigilance tasks [38, 40], further solidifying the link between CBFV and cognitive activity. However, there has been little research on the use of TCD as a BCI, and particularly on control of one’s external environment.

1.3.4 TCD as an Access Pathway

TCD has several advantages (see Table 1), including its low cost relative to other imaging modalities, such as fMRI. The equipment is simple and minimal, and there is no requirement for a specialized environment. In fact, the system can be portable for bedside patient monitoring. TCD does not expose the subject to ionizing radiation or drugs [26]. However, there are guidelines which must be adhered to in order to make TCD safe for long-term monitoring.
One of the major advantages of this technology is its excellent temporal resolution, allowing continuous measurement of CBFV and an almost immediate response to cognitive activations [44]. However, there has been no research effort to quantify the temporal characteristics of event-related CBFV response using TCD.

The disadvantages of using TCD as an access pathway include the time it takes to prepare the user for measurements, including the application of the probe and the process of locating the MCA. In fact, the insonation window where the probes are placed may not be sufficiently large enough to make measurements, especially for the elderly and for some women [45]. Finally, the use of TCD as a BCI is non-intuitive for the user and would require training time, since it requires left and right activations through specific mental tasks.

There has been an abundance of research on the benefits and the accuracy of TCD as a means of measuring CBFV. However, to date, there are no studies which implement a TCD-BCI system.

<table>
<thead>
<tr>
<th>Advantages</th>
<th>Disadvantages</th>
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<tr>
<td>Relatively inexpensive (compared to fMRI)</td>
<td>Relatively long setup time</td>
</tr>
<tr>
<td>Simple and minimal equipment</td>
<td>Difficult to find a signal</td>
</tr>
<tr>
<td>No requirement for a specialized environment</td>
<td>Training requirement for BCI applications</td>
</tr>
<tr>
<td>No use of ionizing radiation or drugs</td>
<td>Low spatial resolution</td>
</tr>
<tr>
<td>Excellent temporal resolution, immediate response to cerebral activations</td>
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1.3.5 TCD Raw Data and Laterality Data

An example of the raw signal measured from the left and right TCD can be found in Figure 4 below. Furthermore, the laterality index can be calculated (more information in Chapter 2) to extract the relative change between left and right CBFV.
Figure 4: The raw data measured from the left probe (left) and right probe (right). The region before the red vertical line is the baseline period, red to black is the right lateralized task, black to green is the rest task, and green to black is the left lateralized task. The rightmost graph is the laterality index, where it is clear that laterality dips below 1 for right lateralized tasks and above 1 for left tasks.

1.4 Thesis Layout

This thesis is organized as a compilation of two papers, the first of which has been submitted and reviewed by the Journal of Neural Engineering, and the second is soon be submitted to the Journal of NeuroEngineering and Rehabilitation. These papers together address the objectives presented in section 1.2. Some portions of the two papers overlap because each stands independently.

Chapter 2 presents the findings on the offline TCD study as a precursor to an online system. Chapter 3 provides an in-depth analysis of the online system, outlining several potential directions for improvement. Finally, Chapter 4 summarizes the key contributions of this project.
Chapter 2

2 Towards a hemodynamic BCI using transcranial Doppler (TCD) without user-specific training data

Given that this thesis is assembled as a compilation of manuscripts, certain sections contain information already presented in Chapter 1. The reader is referred to sections 2.3 - 2.5 for unique material presented in this chapter.

2.1 Abstract

This paper investigates the use of transcranial Doppler (TCD), which was recently introduced as a new brain-computer interface (BCI) modality that detects task-induced hemispheric lateralization. To date, TCD has been used for classification between two mental activities and rest in single trial context with long inter-trial time periods. The objective of this research is to prepare for an online TCD-BCI system by reducing the time needed for each activation and refine the classification procedure, to determine whether classification accuracy is dependent on the sequence of lateralizations, and to explore the feasibility of a user-independent classifier. These questions are important when considering a practical BCI where users are likely to generate highly variable lateralization sequences in actual usage. In this paper, linear discriminant analysis and a set of four time-domain features were used to classify left vs. right activations utilizing user-specific training data, resulting in an overall accuracy of 80.0 ± 9.6%. Alternately, classification using user-independent data was also explored, resulting in accuracies of 74.6 ± 12.6% and 74.3 ± 10.7% using participant 9 and participant 18, respectively. This method of classification bypasses user-specific training, potentially improving the efficiency of the BCI system. These results indicate that TCD is a reliable modality for use in hemodynamic BCI research, and classification without user-specific training data in an online system will be further explored in future studies.
2.2 Introduction

Individuals with severe and multiple physical impairments but capable cognition are often unable to communicate, and typical motion-based technologies do not provide them with a pathway for communication [12]. A brain-computer interface (BCI) can potentially allow these individuals to communicate by translating mental activity directly into control signals, as has been demonstrated in previous research [10, 12].

Although there are several modalities which have been used in the design of BCI systems, this paper explores a recently proposed hemodynamic-based BCI [11]. Specifically, a non-invasive BCI that exploits changes in cerebral blood flow velocity (CBFV) using functional transcranial Doppler ultrasound (TCD). In particular, TCD is capable of monitoring the major arteries of the circle of Willis, including the middle cerebral artery (MCA), anterior cerebral artery (ACA), and posterior cerebral artery (PCA) [46]. The middle cerebral arteries are ideal for CBFV measurement because they perfuse about 80% of the brain and so they are strongly influenced by cognitive activities [18, 19]. TCD is a medical imaging technology, introduced in 1982 by Aaslid [25]. Since then, it has successfully been used in several clinical applications including the assessment of cerebral perfusion pressure, vasospasm diagnosis and management, traumatic brain injury assessment, screening for sickle cell disease, and in neurocritical care [26-31, 47]. The measure of cerebral lateralization using TCD while performing mental tasks has also been thoroughly researched, demonstrating the ability to detect task-induced hemispheric lateralizations [18, 19, 24, 34, 48].

TCD is advantageous because it is lightweight, portable, impervious to electrical artifacts [49], and relatively inexpensive [26]. Furthermore, TCD has excellent temporal resolution, making it possible to detect increased CBFV from cognitive activations within 5-10 seconds, limited only by the time it takes for a physiological change in blood flow to occur [43, 44].

The physiological coupling between cerebral blood flow and oxidative metabolism results in large changes in blood flow in order to support small changes in O₂ metabolic rate [50]. This supports the use of a hemodynamic BCI controlled through mental activity. Word generation tasks have been shown to preferentially increase CBFV in the left hemisphere [19, 34], whereas visuospatial tasks such as perceptual speed and mental rotation have been shown to favour CBFV increase in the right hemisphere [19, 41, 51, 52].
In the single TCD-based BCI study to date, TCD has been used to classify between activation and rest in single trial context with long inter-trial periods [11]. In the aforementioned study, participants performed a word generation, mental rotation, and baseline tasks (guided by onscreen prompts) for 45 seconds each, and 160 features were extracted from this data to classify left vs. right activations using Linear Discriminant Analysis (LDA). It is unknown whether classification accuracy is dependent on the sequence of lateralizations (e.g. successive left, successive right, or alternating activations), nor whether the admissible duration of lateralizations and baseline periods can be reduced to less than 45s. This paper builds on the inaugural TCD-BCI research, thus specifically investigates the shortening of the activation and baseline durations (thereby increasing data transmission rate), reduction in the number of features used in classification, and classification without user-specific training data. All of these are significant considerations in designing a practical BCI where users are likely to generate highly variable lateralizations sequences and where information transfer rates are important to users.

2.3 Methods

2.3.1 Participants

Eighteen able-bodied participants were recruited for this study, but three were excluded due to instrumentation issues during data collection. Thus, the data for 15 participants were analyzed (6 males, 9 females). Although there were more females than males recruited, the targeted patterns of hemispheric hemodynamic activations have been shown to be identical in males and females [52]. At the time of the study, participants were between 22 and 34 (average 27.2) years of age. All participants considered themselves to be right-handed, and had no history of neurological, cardiovascular, or respiratory disorders. All participants provided written informed consent. This study was approved by the research ethics boards of both Holland Bloorview Kids Rehabilitation Hospital and the University of Toronto.

2.3.2 Instrumentation Setup

Figure 5 depicts the instrumentation used in this study. The MultiDop X-4 TCD (Compumedics Germany) and accompanying headgear with fixed 2 MHz ultrasonic transducers were used to bilaterally acquire and visualize in real-time the Doppler spectra of blood flowing through each participant’s left and right middle cerebral arteries. The sampling frequency of the recorded data
was 100Hz. Aquasound ultrasound gel was applied between the probe and the skin to maximize the transmitted signal. The left and right MCAs were located according to the insonation procedure highlighted by Alexandrov et al [53]. This setup takes 15–45 minutes based on the participant’s physiology. Briefly, the arteries were located by adjusting the position of the probes until an insonation window was detected, then adjusting the angle to locate and optimize the signal of the MCAs. The probes were placed on the temporal acoustic windows, located on the temple (in line with the eyes) in most individuals. Depths of insonation ranged from 47mm – 63mm. All 15 participants had cerebral blood flow velocities within the expected limits [54].

The thermal cranial index (TIC) did not exceed 1.5, ensuring the participants were safe from skin damage due to heating of the probes. Furthermore, the probes were powered off every 15 minutes to provide the participants with a 5 minute break and allow the probes to cool down. This protocol complies with ultrasound safety guidelines [55].

![Figure 5: Block diagram depicting experimental setup](image)

### 2.3.3 Mental Tasks

Participants engaged in three different mental tasks. Each task was visually cued (see Figure 6) by a computer screen. Participants were instructed not to vocalize their thoughts during the experiment to avoid an increase of blood flow due to speech.

1) A verbal fluency task (i.e., thinking of words starting with a given letter) was used to elicit left-lateralized CBFV. Participants were cued with either a single letter or a consonant
blend, and instructed to not think of proper nouns. No letter cues were repeated within the protocol described below.

Figure 6: Visual display cues given to participants for each task
   a) The word generation task,   b) Baseline restoration task
   c) Figure-matching task,      d) Correct solution to figure-matching task.

2) A figure-matching task (i.e., overlaying two differently oriented geometric shapes via mental rotation) was invoked for right-lateralized CBFV. Participants were asked to determine, as quickly as possible, which of 4 smaller figures on the right was identical to a larger figure on the left. The figures were selected from a database such that each presentation of figures contained seemingly similar structures [56]. Before the figure-matching task ended, the correct figure was circled on-screen for 0.7 seconds.

3) To restore baseline CBFV, participants performed a baseline task, where they counted by ones at a self-selected pace. This task is known to be effective in reducing CBFVs in both hemispheres [57].
2.3.4 Experimental Protocol

Participants were seated comfortably before the TCD monitor in a quiet data collection room within a university-affiliated teaching hospital. Prior to donning the TCD headgear, participants were introduced to the aforementioned mental tasks.

The protocol contained five sequences of ten mental activities (five left- and five right-lateralized tasks) as shown in the timing diagrams of Figure 7. To establish a baseline signal, the first 45 seconds of each set was the baseline task. In between mental tasks, there was a 20 second counting task to restore baseline CBFV. The entire protocol contained a total of 25 left and 25 right tasks. Each of these 50 tasks was performed for 18 seconds. The total duration of each data collection session was approximately 35 minutes. However, with 2-3 minutes between each sequence to provide the participants a rest break and an additional 5 minutes after sequence B and sequence D to allow the probes to cool down, the study lasted approximately 50 minutes. The sequence of left and right activities varied per set in order to ascertain potential task sequence effects on CBFV. Participants did not receive any feedback during the study, and all analysis was performed offline.

To keep the participants continuously active during the figure-matching task, two consecutive mental rotation problems were presented for each right lateralization block (two 9 second activities per 18 second block), based on the average time needed for similar tasks in previous studies [52]. After completing the experiment, participants filled out a questionnaire which solicited their task preference, perceived tiredness via a Borg scale, and a subjective evaluation of their performance.
Figure 7: The sequence of mental activations used in the experimental protocol. Each sequence begins with a 45s baseline period, contains 5 left and 5 right activations, and has 20s baseline periods between activations.

2.3.5 Analysis with User-Specific Training Data

The left and right CBFV envelopes were exported from the TCD device for analysis. The data from the two probes were pre-filtered with a moving average spanning 1001 points, a window size of 10 seconds which was empirically determined based on the required smoothness of the data. The laterality index, $\Delta V(t)$, for a given sequence was calculated as the ratio of the instantaneous CBFV envelopes on the left and right sides, namely, $V_L(t)$ and $V_R(t)$,

$$\Delta V(t) = \frac{V_L(t)/V_L^0}{V_R(t)/V_R^0}, \ 0 \leq t \leq 380$$

where $V_L^0$ and $V_R^0$ denote the final point in the respective 45s baseline period of the filtered sequence. The values obtained for $V_L(t)/V_L^0$ and $V_R(t)/V_R^0$ typically ranged from 0.80 to 1.20, and the overall laterality index ranged from 0.93 – 1.09. The laterality data were then segmented into left and right activation windows according to the timing diagram in Figure 7, where an activation window is the 18 seconds of either left or right lateralization. Four features were
extracted from each window of laterality data, namely, the difference between the start value and the end value of the laterality index, the sum of the maximum and minimum laterality, the mean laterality, and the end laterality.

The number of features was intentionally minimized in order to maintain the classification speed needed for an online system. All four features were based on the entire activation window, rather than segments thereof. Subtracting the initial value in each activation window from the calculated features reduced feature value dependence on resting CBFV values and emphasized the CBFV changes during the task. However, one of the four features, the end value, was used to pinpoint the extent of lateralization without eliminating the influence of CBFV during baseline periods.

From these four features, two were selected using the Fisher criterion [58]. The Fisher criterion, \( J \), shown below, measures the difference between the laterality index values for left and right activations,

\[
J = \frac{|m_1 - m_2|^2}{s_1^2 - s_2^2}
\]

where \( m_1 \) and \( s_1 \) represent the mean and standard deviation of a feature over all left activations and \( m_2 \) and \( s_2 \) over all right activations. The values for \( J \) varied from 1.5 - 4.5. To avoid selecting two highly correlated features, the correlation between the feature with the highest Fisher ranking and each of the other features was calculated [11]. The feature with the highest Fisher ranking and the feature (amongst the second and third Fisher-ranked) which had the least correlation with the first feature were selected for classification.

Linear discriminant analysis (LDA) was used to classify left versus right activations. With only two features selected for classification, 50 trials from each participant were more than sufficient for training the classifier [59, 60]. A unique classifier was constructed for each participant, using exclusively his or her own data. Classification accuracy (percentage correct) was estimated via one thousand runs of five-fold cross-validation using the two selected features for each participant.
In order to determine whether or not successive activations degrade the quality of the CBFV signals, we dissected the test set into different categories of activation. Specifically, we estimated the accuracy of classifying the first left activation in a sequence, the first right activation, two successive left activations, a left after a right activation, two successive right activations, and a right after a left activation.

2.3.6 Analysis without User-Specific Training Data

We also explored the possibility of exclusively using the data from a single participant, herein referred to as the ‘training participant’, as the training set for all other participants. If this scheme were successful, the time-consuming collection of calibration data from each participant would not be necessary prior to individual use of TCD as a BCI.

For a given training participant, all the available data were used to train an LDA classifier to classify word generation versus figure-matching tasks in the feature space defined by the two user-specific features (identified by the procedure outlined in section 2.3.5). The same two features were derived from the data from all other participants and the corresponding feature vectors were then classified using the training participant’s LDA. This analysis was repeated with each participant serving as the training participant in turn, resulting in 15x14 accuracy values. The two training participants which yielded the highest average accuracies were further explored and each individual activation window was analyzed without user-specific training data.

2.4 Results and Discussion

2.4.1 Classification Accuracies

With user-specific classifiers, activations were classified as left or right-lateralized with an overall accuracy of 80.0 ± 9.6%. The chance threshold in this study is 63.33%, as determined by the method of Müller-Putz et al [61]. Using Participant 9 to train a single classifier, the overall accuracy in classifying the remaining participants was 74.6 ± 12.6%. Similarly, using Participant 18 as the training participant resulted in an overall accuracy of 74.3 ± 10.7%. For all three cases, individual activations were categorized to determine the feasibility of consecutive activations (see Table 2). The number of data samples in each category ranges from 28 to 168. Figure 8
displays classification accuracies for user-specific, Participant 9-trained and Participant 18-trained classifiers, respectively.

Table 2: Mean classification accuracies and standard deviations (std) for different activation categories (L=left activation; R=right activation)

<table>
<thead>
<tr>
<th>Activation category</th>
<th>User-specific classifier</th>
<th>Participant 9-trained classifier</th>
<th>Participant 18-trained classifier</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>std</td>
<td>Mean</td>
</tr>
<tr>
<td>Overall (n=14)</td>
<td>80.0</td>
<td>9.6</td>
<td>74.6</td>
</tr>
<tr>
<td>First L (n=3*14)</td>
<td>80.7</td>
<td>6.7</td>
<td>83.3</td>
</tr>
<tr>
<td>L After L (n=10*14)</td>
<td>83.0</td>
<td>8.7</td>
<td>89.3</td>
</tr>
<tr>
<td>L After R (n=12*14)</td>
<td>81.2</td>
<td>14.4</td>
<td>62.5</td>
</tr>
<tr>
<td>First R (n=2*14)</td>
<td>87.2</td>
<td>13.0</td>
<td>60.7</td>
</tr>
<tr>
<td>R After L (n=13*14)</td>
<td>78.4</td>
<td>14.9</td>
<td>78.0</td>
</tr>
<tr>
<td>R After R (n=10*14)</td>
<td>75.9</td>
<td>9.9</td>
<td>75.0</td>
</tr>
</tbody>
</table>

Figure 8: Overall accuracy and standard deviation bars for all participants utilizing user-specific classifiers, P9 trained classifier, and P18 trained classifier.

2.4.2 Discussion

This study explored the potential use of TCD as a BCI in two respects. The first aspect was the ability to accurately classify successive lateralization sequences while reducing the duration of
both activations and baseline periods. The second was the possibility of classification without user-specific training data.

The breakdown of categories, highlighted in the user-specific training data columns of Table 2, demonstrates that left vs. right activations over multiple activations does not significantly degrade classification accuracy. Physiologically, increased blood flows are accomplished through an increase in capillary blood flow velocity rather than capillary recruitment. Previous studies have shown that the CBFV response to mental activation is delayed by 2-3s, followed by a ramp of 6-10s up to a plateau, and then a similarly timed return to baseline post-activation [24, 50]. Thus, with a baseline duration of 20s, CBFV in both hemispheres settles to baseline even if the laterality index has not yet completely stabilized. Consecutive activations will not diminish accuracies as long as sufficient time is provided between activations. In this paper, the activation duration was reduced from 45s to 18s, and the baseline duration from 45s to 20s, while maintaining high classification accuracies [11]. This time may perhaps be further reduced in future studies. In fact, the ideal setup would depart from a system-paced paradigm by triggering subsequent activations after the CBFV returns to within a threshold of baseline in order to adaptively minimize the duration of counting tasks.

Classification accuracies obtained with and without user-specific training data did not differ significantly (p=0.1635; paired t-test). This suggests that cerebral blood flow velocity reacts similarly for all TCD users during the selected mental activities. Furthermore, this finding implies that in an online system, users with ideal, well-defined activations could be used to calibrate the system, allowing “plug-and-play” access for other users.

This result suggests that the laterality response to a particular task is similar across participants with respect to the features selected in our study. Previous studies have identified that the cerebral blood flow in the MCA is activated for word generation and figure-matching tasks in all participants [24, 62], and that the response correlates directly with the regional cerebral blood flow (rCBF) as measured by dynamic single photon emission computed tomography (DPSECT) and $^{133}$Xenon inhalation [63]. Thus, it is common amongst individuals for cerebral blood flow velocities to increase and decrease in a similar fashion during mental activations. In addition, the laterality index signal for a specific set of tasks (with identical durations of time) is similar
amongst all individuals. Therefore a set of training data from one user can be used to classify another user’s activations without user-specific training data.

To further enhance accuracies without user-specific training, a collection of representative training sets from a small number of individuals may be used to classify other users (rather than the data of a single participant) to better represent minor inter-subject differences. Finally, accuracies may be further improved in the future through training and/or real-time feedback [64-66].

2.4.3 Limitations

In general, the tasks were designed to induce similar lateralization among iterations while providing enough variation to keep the user engaged. However, the word generation task produced results that varied according to the letter(s) chosen for the task. Similarly, the figure-matching tasks also varied slightly based on the complexity of the figures and the degree of resemblance between the incorrect and the matching figures. That is, some figure-matching tasks were more difficult than others due to increased similarity among the five figures on the slide (of which only two were in fact identical).

One major factor in determining the accuracy of classification is the participant’s CBFV during the baseline task. If the participant could not clear his or her mind during this task, the signal would not return to baseline, resulting in inaccurate classification during the subsequent activations. In an online system, we propose to end the baseline task (within reasonable limits) once the user’s signal returns to within a range of the baseline level. This will not only improve the accuracy of left and right classifications, but will minimize the protocol duration, especially if users can quickly return their CBFVs to baseline.

The figure-matching task is not ideal for a BCI system because it requires visual cues and cannot be completed autonomously like the word generation task. Further research into a right lateralized task which can be performed without visualization is needed.

One concern with TCD systems is its susceptibility to motion artifact. Head and jaw movement can cause the probes to shift, distorting the signal. This is especially true when the probes are positioned at a sharp angle with respect to the surface of the skin (not flush against the face),
making them more sensitive to head and body movement. Finding an insonation window where the ultrasound probes are in a stable position would improve their robustness to motion artifact.

When used practically on the target population, the probes may need to be toggled on and off periodically to prevent heating and skin damage. Further research needs to be conducted to investigate the combination of TCD with other access technologies, which may also result in an overall improvement in accuracy.

2.5 Conclusion

This research significantly advances progress towards a TCD-based BCI system. Not only does it confirm previous research with regards to the high accuracies achievable using TCD, it does so by minimizing the duration of activations and baseline periods. The abbreviated duration reduces workload on the users and increases the overall data transmission rate. Furthermore, this research demonstrates classification of TCD lateralization data using only two features, thereby increasing the speed of the overall system. Our results also show that consecutive activations in varying sequences do not degrade the signal, a necessary requirement in designing a feasible BCI. Finally, our findings support the potential of classification without user-specific training data.
Chapter 3

3 Online Control of Multiple Devices Using Transcranial Doppler (TCD) without User-Specific Training Data

Given that this thesis is assembled as a compilation of manuscripts, certain sections contain information already presented in Chapter 1 and Chapter 2. The reader is referred to sections 3.3.4 - 3.5 for unique material presented in this chapter.

3.1 Abstract

Transcranial Doppler ultrasonography (TCD) has been previously shown to produce high accuracies when used in offline brain-computer interface (BCI) applications to classify between two mental tasks. However, there have been no investigations of an online TCD-BCI system. This paper implements such a system, allowing users to control two devices (a lamp and electromechanical toy), one with a word generation task and the other through mental rotation. Classification of mental task is achieved using linear discriminant analysis and a set of four time-domain features utilizing user-independent training data. In addition, a dynamic rest period (5-30s) is used between mental tasks. The overall accuracy of controlling the correct device in the online study was 61.43 ± 6.99%. There are several factors for the low accuracy, such as the influence of error streaks, participant motivation, and bias towards a particular device. The analysis of the recorded data revealed key findings such as the impact of dynamic rest durations and the optimum rest duration. The results of this paper are the first step towards an online TCD-BCI system, providing several recommendations and improvements for future studies.

3.2 Introduction

Individuals with severe neuromuscular disorders (e.g. muscular dystrophy, multiple sclerosis) often have difficulty interacting with their surroundings, and typical motion-based technologies do not provide them with a pathway for communication [12]. The use of brain-computer
interfaces (BCIs) to re-establish this connection can potentially allow these individuals to operate devices around them using mental activities as control signals [10, 12]. In particular, we are interested in hemodynamic BCIs, which have been shown using near-infrared spectroscopy (NIRS) to be effective in both offline [67-69] and online situations [70-72]. Furthermore, transcranial Doppler ultrasonography (TCD) has demonstrated high accuracies in offline studies [11, 73], but to date, has not yet been implemented in an online system.

TCD is a non-invasive ultrasound technology that exploits changes in cerebral blood flow velocity (CBFV). It is capable of monitoring the arteries within the circle of Willis [46], of which the middle cerebral arteries (MCAs) are the most relevant for a BCI system. The left and right MCAs perfuse about 80% of the brain and are therefore most reflective of the user’s cognitive efforts [18, 19]. TCD was first introduced as a medical imaging technology in 1982 [25], and has been widely applied clinically, for example, in the detection of increased intracranial pressure in neurocritical care [26], evaluation of subarachnoid haemorrhage [27], detection of microembolism [74] and monitoring cerebral circulation during cardiopulmonary bypass [29].

There is also growing interest in the use of TCD as a functional brain imaging tool [75]. The effect of cerebral lateralization while performing specific mental tasks has been well-documented and TCD has proven to be a reliable technology in detecting these hemispheric lateralizations [18, 19, 24, 34, 48]. TCD is capable of detecting changes in CBFV within 5-10 seconds, a limit determined by the physiological change in blood flow [43, 44]. The coupling between cerebral blood flow and oxidative metabolism is outlined in Buxton et al. [50]. The left hemisphere is preferentially lateralized during verbal fluency tasks [19, 34] and visuospatial tasks are preferentially right-lateralized [19, 41, 51, 52].

In previous offline studies, Myrden and Chau [11] discriminated between a single mental task and a rest state in 9 participants with accuracies in excess of 80%. Similarly, in another offline investigation, Aleem and Chau [73] demonstrated the potential for TCD-based classification of two mental states without user-specific training data, achieving accuracies of 74.3 ± 10.7%. In addition, that study recommended maintaining a dynamic rest period between mental activities. This paper builds on these findings and implements an online TCD-BCI system.
3.3 Methods

3.3.1 Participants

Fifteen able-bodied participants were recruited for this study. One was excluded due to instrumentation issues during data collection. Thus, data were collected from a total of 14 participants (5 males, 9 females) between the ages of 22 and 35 (average 28.2). The participants were all right-handed and had no history of neurological, respiratory, or cardiovascular disorders. The participants all provided written informed consent, and this study was approved by the research ethics boards of both Holland Bloorview Kids Rehabilitation Hospital and the University of Toronto.

3.3.2 Instrumentation Setup

The MultiDop X-4 TCD (Compumedics Germany) and accompanying bilateral headgear with fixed 2 MHz ultrasonic transducers were used to acquire the Doppler spectra of blood flowing through the left and right middle cerebral arteries. The system setup is illustrated in Figure 9. The data were recorded at a sampling frequency of 100Hz. Ultrasound gel was applied on the participants’ temple region and the left and right MCAs were located using the headgear ultrasound probes according to the insonation procedure highlighted by Alexandrov et al. [53]. All 14 participants had CBFVs within the expected limits, and at MCA depths ranging from 47-63mm [54].

Participants were given 5 minute breaks every 15 minutes, during which the probes were allowed to cool. Throughout the recording sessions, the thermal cranial index (TIC) of the probes did not exceed 1.5 to avoid participant discomfort or skin damage, as outlined in the British Medical Ultrasound Society safety guidelines [55].
3.3.3 Mental Tasks

Participants engaged in three mental tasks: word generation for left lateralization, figure-matching for right lateralization, and counting by ones to return to baseline (see Figure 10). The word generation task displayed either a single letter or a two-letter consonant blend (e.g. ‘Th’). When this visual cue (e.g., Figure 10a) was presented, participants thought of as many words as possible starting with the letter or constant blend. During the figure-matching task, participants were shown a larger figure on the left and four similar-looking figures on the right, of which only one was identical to the larger figure. These figures were selected from a database of three-dimensional images of various rotations [56]. When the cue (e.g., Figure 10c) was presented, participants attempted to find the matching figure by mentally rotating the candidates on the right. The matching figure was circled for 0.7s immediately before the rest task was cued (e.g., Figure 10d). The rest task punctuating each cognitive activity was visually cued (Figure 10b). Participants silently counted by ones at a self-selected pace, which is an effective method for returning the CBFV in each hemisphere to baseline levels [57]. All tasks were completed without vocalization of thoughts to avoid an increase of blood flow due to speech.
3.3.4 Experimental Protocol

Data collection occurred in the quiet testing rooms of Holland Bloorview Kids Rehabilitation Hospital. Upon arrival, participants were seated comfortably and given a brief refresher regarding the aforementioned mental tasks, to which they all had prior exposure. Before beginning the main protocol, participants went through a practice set of four activations to familiarize themselves with the online control of each device.

The protocol consisted of five sequences of ten mental activities, as shown in the timing diagram in Figure 11. The entire protocol contained a total of 25 left and 25 right tasks. The order of the ten activities in each specific slide set was randomized. For the first 45 seconds of each slide set, participants performed the rest task in order to establish a baseline signal. Each of the 50 mental activities lasted 18 seconds, but each figure-matching task consisted of two consecutive mental rotation problems to keep participants continuously active. This 9 second duration for each figure-matching problem was selected on the basis of average task completion times reported in literature [52].
In between mental tasks, there was a dynamic rest period ranging from 5 seconds to 30 seconds based on the length of time it required to restore CBFV to within 2.5% of baseline. If the rest period went beyond 30s without the CBFV returning to within 2.5% of the baseline values, the last second of the resting data was then averaged to produce new baseline values (i.e., baseline resetting). Factoring in the time for the rest tasks, the total duration of each data collection session was approximately 35 minutes. Participants completed a questionnaire soliciting a subjective evaluation of their own performance and rated their tiredness on a Borg scale.

Figure 11: The sequence of mental activations used in the experimental protocol. Each slide set began with a 45s baseline period, and contained a random sequence of activations. In total, there were 25 left and 25 right activations, 18s each, with 5-30s rest durations.

### 3.3.5 Online Classification without User-Specific Training Data

The CBFV data collected during mental activation was processed immediately following the conclusion of the activation period. The analysis was optimized through a computationally efficient classification scheme using a small number of features, resulting in a near real-time response. Data from the two probes were pre-filtered and the laterality index, $\Delta V(t)$, was
calculated as the ratio of the instantaneous CBFV envelopes on the left and right sides, namely, $V_L(t)$ and $V_R(t)$,

$$\Delta V(t) = \left( \frac{V_L(t)/V_L^0}{V_R(t)/V_R^0} \right)$$

where $V_L^0$ and $V_R^0$ initially denote the final point in the 45s baseline period of that particular sequence.

When used as training sets for other participants, data from participants 9 and 18 yielded the highest offline accuracy in an earlier study [73]. Thus, to explore the possibility of online classification without user-specific training data, we chose data from either participant 9 or 18 to train each participant’s individual classifier, whichever previously yielded the higher offline accuracy, as reported in [73]. Participants 9 and 18 used their own respective data for training.

Four features were extracted from the training data, of which the two most discriminatory and least correlated features were chosen based on the Fisher criterion. These two features were calculated from the participant’s online laterality data, and linear discriminant analysis (LDA) was used to classify left versus right activations. One of the devices changed state according to the classifier output. Left lateralized activations (word generation) toggled the state of the lamp. Right lateralized activations (figure-matching) turned the mechanical toy on for 5 seconds. The participants were informed about the task-device association before the study.

### 3.3.6 Offline Classification with User-Specific Training Data

The raw CBFV data were also analyzed offline using the same user-specific training data analysis outlined in [73]. This offline analysis allowed us to investigate the effect of having a dynamic rest period, the influence of error streaks on the participant’s overall accuracy, device bias due to naturally occurring discrepancies between left and right CBFV amplitudes, and the impact of motivation on the participant’s accuracies throughout the session. A unique linear discriminant analysis (LDA) classifier was developed for each participant. Training data for each classifier were derived from each participant’s previously recorded online study.
3.4 Results and Discussion

3.4.1 Online vs. Offline

The results of the online study are summarized in Figure 12, which shows the accuracy of device activations for each participant. The average accuracy across all participants was 61.43 ± 6.99%. The chance threshold in this study is 63.33%, as determined by the method of Müller-Putz et al. [61]. These accuracies are not acceptable for a BCI system. Nonetheless, we thoroughly analyze the collected data to determine the reasons for low classification accuracies and potential improvements for future studies.

In order to determine whether or not the TCD signal features are stationary (rendering the training data from 6 months earlier inadequate), we replicated the offline procedure detailed in [73]. Doing so yielded an average classification accuracy of 69.16 ± 12.21%, which is significantly greater than the chance threshold. The online and the offline analysis both used the same data, the same features, and the same classifier (LDA). However, the offline analysis used 1000 runs of 5-fold cross validation and user-specific training data from the online recordings rather than the training data from a previously recorded session.

![Figure 12: Overall accuracy for each participant’s online and offline results, compared to the level of chance. The level of chance is 63.33%, as indicated by the horizontal line.](image)
3.4.2 Dynamic Rest Period

The effectiveness of the dynamic rest period was analyzed offline by using the recorded online data and maintaining the initial baseline (after the 45s rest period) throughout the duration of the slide set. This online simulation resulted in an average classification accuracy of $60.71 \pm 7.00\%$, indicating that baseline resetting did not enhance discrimination ability. Figure 13 compares classification of online, offline, and online simulation without baseline resetting.

One possible explanation for the dynamic rest baseline reset being unsuccessful in improving accuracies is fatigue. As participants were further into a particular slide set, there was a higher likelihood that they focused less on clearing their thoughts during rest periods. However, during the first 45s baseline period of each slide set, the participants were more likely to be focusing on the counting task, leading to a more accurate baseline value. This baseline value was relatively stable for the 7-8 minute slide set provided the participant concentrates during rest periods, and so replacing that value with one which is a result of incomplete concentration did not improve results.

Consequently, rest minimization provided another useful result. The overall average rest duration for all the participants was $14.19 \pm 2.37$ seconds. However, the duration of rests ranged from 5 to 30 seconds. Classification accuracies were categorized based on the duration of rest prior to the task. Figure 14 illustrates the average accuracy of the activation following rests of varying durations. Each rest duration was based on a different number of samples. The maximum accuracy (85.7%) occurred after 24s of rest, followed by 77.8% accuracy for tasks after a 15s rest period. The preferred rest duration is 15 seconds because 24s rests may be too lengthy for participants to maintain in a real TCD-BCI system.
Figure 13: Online and offline accuracies. Average accuracy for the online study was 61.43 ± 6.99%. The offline analysis with user-specific training data resulted in a slightly improved accuracy of 69.16 ± 12.21%. The offline simulation of the online study, without resetting the initial baseline CBFVs (after an extended rest period) was not significantly different from the online results, 60.71 ± 7.00%.

Figure 14: The average accuracy and standard error of mean (SEM) of tasks following a particular duration of rest. The two highest accuracies occurred after 24s and 15s rest periods, as shown by the cross-hatched bars. Each bar is based on a different number of samples.
3.4.3 Error Streaks

Another potential cause for low accuracies in an online environment is the influence of error streaks on the participant’s temperament. An error streak is defined as consecutive tasks which were classified incorrectly. Therefore an error streak of 3 is three errors in a row within a single slide set. Figure 15 shows a decreasing accuracy trend as the maximum streak length increases. The decrease in overall accuracy for increasing maximum error streaks suggests a detrimental psychological effect due to errors. A greater maximum error streak increases the likelihood of multiple subsequent errors (which are not necessarily consecutive), lowering the overall classification accuracy. The impact of errors on participant motivation is something which is difficult to overcome in an online system, but will become less of an issue as classification improves.

![Graph showing the effect of error streaks on accuracy](image)

**Figure 15:** The effect of error streaks on the participant’s overall accuracy, showing the negative impact on the temperament of participants with a higher maximum error streak.

3.4.4 Device Bias

During the data collection, it was evident that most participants were biased towards one device or the other. As shown in the timing diagram in Figure 11, there were a total of 25 left and 25 right activations in the protocol. However, as shown in Figure 16, the number of activations for each device varies per participant. Across all participants, the left device was activated an average of 26.1 times and the right device 23.9 times.
Figure 16: The number of left and right device activations for each participant. The horizontal line is at 25 activations, which is the number of left and right tasks in the study.

To analyze the cause of this device bias, the left and right CBFV magnitudes were compared against the device bias (see Figure 17). From this plot, we can see that device bias is attributed in part to the inherent asymmetry in CBFV magnitude (i.e., a left CBFV which is larger than right CBFV makes it is easier to toggle the device activated by left lateralizations). Device bias occurred mostly in situations where one of the participant’s CBFVs tended to be significantly higher than the other even in the absence of intentional mental activity. This bias could be minimized by adjusting the probes to locate an area where the left and right MCA are more closely matched in terms of CBFV. In parallel, the laterality index algorithm might be modified to accommodate naturally occurring asymmetries in blood flow velocities.
Figure 17: Device bias based on asymmetrical CBFV magnitude. The first quadrant (dotted) shows that participants whose left probe was measuring a faster CBFV tended to activate Device 1 more often. Similarly, the third quadrant (striped) shows the opposite for participants whose right CBFV was faster.

The laterality equation normalizes the measured left and right CBFV values with their respective baseline values. This makes sense when the left and right CBFV magnitudes are similar because the increase or decrease in CBFV will be comparable on each side for a mental task that does not favour any particular hemisphere. The current calculation also make sense if the CBFVs differ from each other but are significantly slower than the individual’s maximum possible CBFV; the side with the higher CBFV will increase more during unlateralized mental activities due to its higher flow. However, when the CBFVs are not matched perfectly and one side is close to the maximum velocity, the algorithm fails. This saturation occurred for some participants where the CBFV had limited room to increase with cognitive activity due to the high velocities during baseline. Future algorithms could check the magnitude of the baseline CBFV and normalize it accordingly. In this case, a smaller CBFV increase on the side with a high baseline value should be equivalent to a larger change on the side with the lower CBFV baseline when calculating laterality.
3.4.5 Slide Set and Task Trends

To further understand the interaction of participant fatigue and motivation in the study, the average classification accuracies for the five slide sets as well as for each of the ten tasks were plotted. Figure 18 shows a clear dip in accuracy during the third slide set, and Figure 19 shows a cyclic down-up trend across the ten tasks, with increasing accuracy near the end of the slide set.

The third slide set yielded the poorest results while classification accuracies improved over the next two slide sets. This relates to the psychology of motivation, and the “goal-gradient” effect, which states that motivation to reach a goal increases as distance towards that goal decreases [76]. Slide set 3 was not particularly challenging compared to the other slide sets. However, the motivational state of the user would have been very different in the third slide set compared to the fifth. The outcomes of goal pursuit have a greater impact on the individual as they approach the goal’s end state [77]. Thus, participants might have been more concerned about their performance as they approached the end of the study, resulting in improved accuracy in toggling the correct device. The decrease in motivation between the first and the third slide set may be a result of excessive effort by the participants during the first and second slide set, resulting in reduced effort in the third [76]. However, by the fourth slide set, participants were within reach of their end-goal and may have intensified their activation efforts.

When the goal pursuit consists of multiple tasks, a cyclical down-and-up motivation pattern results as the user’s resources are iteratively depleted and replenished. This is evident in Figure 19, where there are two drops in accuracy during the ten tasks. The influences of motivation are intrinsic within human studies, but can be reduced with a sufficient period of time between trials to replenish resources [76].
Figure 18: The average accuracy of all 10 tasks during each of the 5 slide sets. The dip in slide set 3 reflects the “goal-gradient” psychological effect of motivation.

Figure 19: The average accuracy of all 5 slide sets for each of the 10 tasks. The cyclic down-up pattern and the rise in accuracy near the goal-end is evident.
3.4.6 Limitations

The figure-matching task requires visual cues, making it non-ideal for BCI systems since right lateralizations cannot be triggered autonomously. Presently, there are no known tasks which provide reliable right-sided lateralizations without visual cues.

Many of the participants were able to return their CBFVs to within the baseline threshold after five seconds of rest. Although the CBFV had physiologically returned to a resting state, five seconds may not be enough time to rest between periods of concentrated mental activity. In future studies, we propose using a minimum dynamic rest period of ten seconds or a static rest of fifteen seconds to optimize classification accuracy (see Figure 14).

During the study, we had limited time to locate the insonation windows and MCAs of each participant. This occasionally resulted in unbalanced left and right CBFV magnitudes, causing bias towards a specific device. The placement of the probes flush against the skin overlying the temporal bone (to prevent slipping) and establishing the same physiological depth of insonation and sampling volume on either side of the head is essential.

When used practically on locked-in patients, the caretaker must ensure that the headgear is modified to accommodate the patient lying in bed. Furthermore, the probes must be toggled on and off periodically to prevent burning of the patient’s skin. Finally, the system may be simplified to make use of only one mental activity, resulting in a system-paced paradigm (reduced speed due to scanning across list of devices).

3.5 Conclusion

This is the first TCD-based BCI system for environmental control to date. Its intention was to facilitate control of two devices, a lamp and a mechanical toy, respectively, with left and right lateralized mental activities. Although the classification accuracies were below the level of chance, there were a number of key findings. Baseline resetting of rest durations was less useful than initially anticipated. However, dynamic rests allowed for the investigation of a range of rest durations and the accuracy of subsequent activations, revealing high accuracies for activations following 24s and 15s rests. Possible reasons for low accuracies were the psychological impact of error streaks, fluctuating motivation associated with using an online system, and device bias due to asymmetrical left and right CBFV magnitudes at rest.
Chapter 4

4 Conclusion

4.1 List of Key Contributions

This project has contributed the following to the field of hemodynamic brain-computer interfaces using transcranial Doppler ultrasonography:

1. Confirmed the high classification accuracies of TCD after multiple sequential lateralizations in an offline setting even after streamlining the protocol and algorithm by:
   a. Reducing activation durations to 18s
   b. Reducing rest durations to 20s
   c. Minimizing the number of features calculated

2. Explored the potential of classification without user-specific training data in both an offline and an online study, demonstrating that classification accuracies are not significantly reduced. This can save user and caregiver time and effort by eliminating training data collection sessions, ultimately leading to an “out-of-the-box” BCI solution.

3. Implemented the first online TCD-BCI system, allowing users to toggle two devices using mental activations. This system has not yet reached acceptable accuracies, but there are several informative findings.
   a. The optimum rest periods are 15s and 24s, and baseline resetting is not a useful strategy after a long dynamic rest duration
   b. The presence of error streaks may degrade subsequent performance and user motivation may fluctuate
   c. The algorithm for calculating laterality index can be refined to take into account very high and asymmetrical left and right CBFVs (to avoid device bias)
4.2 Future Directions

This is the first study involving an online TCD-BCI system. The upcoming studies should improve on the current algorithm for calculating laterality index and classification, perhaps exploring the mathematical integration of the raw TCD data rather than feature extraction methods. The online study should then be repeated with a new set of participants, half of which should be classified with pre-collection training data and the other half classified with user-independent training data. This will allow further exploration of user-independent classification.

The rests should be static and 15 seconds long. It would be preferable to utilize a different type of right-lateralized task which requires little to no visual concentration from the participants. The influence of generating specific English letters and combinations of letters on cerebral blood flow velocity may also be explored to better understand the word generation task.

Furthermore, a three-class system which does not produce any control signals during rest would be more realistic. The three-class BCI can then be modified so that left activations toggle through a number of devices, right activations select a device to control, and rest periods make no changes.

In addition, TCD may be combined with other access pathways so that the limitations of TCD can be accounted with another technology, further improving accuracy and reliability.

Finally, once the online TCD-BCI system is further developed and is able to achieve higher accuracies, future studies should begin to test this system on the target population.
References


Appendices

A. Phase 1 Participant Questionnaire

1) Circle the statement which best describes your experience during word generation:
   a) I generated many words
   b) I tried to generate words but I just couldn’t think of very many
   c) I lost focus and couldn’t concentrate on word generation

2) Circle the statement which best describes your experience during counting:
   a) I always counted between tasks
   b) I tried counting but my mind ended up wandering
   c) I lost track of counting between some tasks, but just restarted the count

3) Answer the following about your experience during identical figures:
   A. How often did you find (or think you found) the identical figure?

   Never  Sometimes  Always
   1     2     3     4     5     6     7     8     9

   B. When you found (or thought you found) the identical figure, what did you usually do?
      a. Just waited until the time ran out
      b. Checked the other figures to make sure I got the right answer

4) Which task did you find the most tedious?
   a) Word generation
   b) Identical figures
   c) Counting

5) Which task did you find the most enjoyable?
   a) Word generation
   b) Identical figures
   c) Counting
6) How tired were you as a result of this session?

<table>
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<tr>
<th>Points</th>
<th>Tiredness</th>
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<tbody>
<tr>
<td>10</td>
<td>Very, very tired (almost max)</td>
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<tr>
<td>9</td>
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<td>Very tired</td>
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<td>Tired</td>
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<td>Somewhat tired</td>
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<td>Moderately tired</td>
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<td>3</td>
<td>Slightly tired</td>
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<td>2</td>
<td>Very rested/energetic</td>
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<td>1</td>
<td>Maximum energy</td>
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<tr>
<td>0.5</td>
<td>Very, very rested/energetic</td>
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B. Phase 2 Participant Questionnaire

1) Circle the statement which best describes your experience during word generation:
   a) I generated many words
   b) I tried to generate words but I just couldn’t think of very many
   c) I lost focus and couldn’t concentrate on word generation

2) Circle the statement which best describes your experience during counting:
   a) I always counted between tasks
   b) I tried counting but my mind ended up wandering
   c) I lost track of counting between some tasks, but just restarted the count

3) Answer the following about your experience during identical figures:
   A. How often did you find (or think you found) the identical figure?

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   B. When you found (or thought you found) the identical figure, what did you usually do?
      a. Just waited until the time ran out
      b. Checked the other figures to make sure I got the right answer
4) Which device did you have the most difficulty toggling (circle one)?
   a) Lamp
   b) Penguin Toy

5) How helpful/motivating did you find the feedback?

   Not Helpful                Very Helpful
   1          2          3          4          5

6) How tired were you as a result of this session?

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