BRAINBRAILLE: TOWARDS PASSIVE TRAINING IN BRAIN COMPUTER INTERFACES USING FNIRS

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BRAINBRAILLE: TOWARDS PASSIVE TRAINING IN BRAIN COMPUTER INTERFACES USING FNIRS

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CHAPTER 1

ABSTRACT

Amyotrophic Lateral Sclerosis (ALS) is a debilitating movement disability that causes patients to gradually lose their ability to voluntarily control their muscles. In some cases, patients who are "locked-in" are unable to move any muscles, leaving them with no means of communicating with caregivers. Brain-computer interfaces (BCIs) attempt to create a means of communication directly through brain activity, removing the need for movement. BrainBraille is a novel interaction method for BCIs, enabling complex text-based communication using attempted movements with a six-region pseudo-binary encoding. In this dissertation, I explore a wearable BCI using functional near-infrared scanning (fNIRS) to make BrainBraille mobile. In an early study, I show that transitional gestures based on executed movements of two hands can be classified in two participants with up to 93% accuracy. I explore how transitional gestures can benefit BrainBraille by expanding the vocabulary and enabling faster responses. Finally, I evaluate future paths for integrating passive haptic training into BrainBraille to reduce the physical exertion needed to learn a BCI for ALS patients.

CHAPTER 2
INTRODUCTION

People with motor disabilities like Amyotrophic Lateral Sclerosis (ALS) face numerous challenges in daily life due to a loss of voluntary muscle control. ALS has an incidence rate of 6 per 100,000 and is one of the most common neuromotor diseases in adults [1]. ALS patients often have difficulty communicating with their caregivers and many different systems have been proposed and implemented to assist with the gap in communication. Most of these systems depend on allowing movement through the muscles they can still control, but these need to be heavily customized to the patient. Moreover, they cannot be used by patients who have locked-in syndrome, who are unable to move any muscles [2].

To circumvent this issue, brain-computer interfaces (BCIs) allow communication with computers directly through brain activity, bypassing the peripheral nervous system [3]. For people with motor disabilities like ALS, BCIs can allow them to communicate directly with people around them, improving their quality of life and easing their interactions by letting them have more control over the way they are treated by caretakers [4]. While some BCIs rely on invasive, surgical approaches, many non-invasive BCI systems have been proposed to reduce the risk and cost of using a new interface.

The most common method for non-invasive brain-computer interfaces is electroencephalography (EEG), which measures electrical potentials in the brain. However, EEG data is noisy and has limited information transfer rates [5]. In contrast, functional near-infrared scanning (fNIRS) is a promising new method using near-infrared light to detect hemoglobin concentrations in the brain and allows for greater resolution in signals obtained from the brain [6].

Through BrainBraille, I demonstrate a novel, wearable brain-computer interface using fNIRS to measure attempted movements from activity in the motor cortex. While there have been past brain-computer interfaces using fNIRS on the motor cortex to allow direct brain communication, these have been very limited in their communication capabilities, such as only allowing “yes” or “no” answers. BrainBraille aims to provide far more versatility in communication, hoping to enable brain-computer communication in complete sentences. My system also contributes a faster and more intuitive method of communication than past brain-computer interface paradigms.

The most unique contribution of my work comes from its communication modality: The original BrainBraille setup maps six parts of the body onto a Braille character in a pseudo-binary configuration, and an alphabetic letter is obtained from the movement. Over time, these letters are combined to form a complete grammatical language through attempted or executed muscle contractions, thereby giving users with motor impairments a much more versatile means for communication. In my study, I focus on movement transitions in two parts instead, providing a window into the viability of six-region BrainBraille, and creating a potentially faster transition-based configuration. Whereas past modes like the P300 Speller (described in Section 3.1) have required two choices to be made for each letter, ours has the potential of reducing it to one and allowing direct transitions from one letter to the next. The language structure further enhances the system by enabling increased accuracy with time series modeling tools such as time-series Support Vector Machines (SVMs) with Tslearn [7] or Hidden Markov Models using the Kaldi toolkit and Georgia Tech Gesture Toolkit [8, 9]. Using this approach, I demonstrate a cross-validation accuracy of 93% on one participant and 70% on the other.

Moreover, whereas Zhao et al. [10] focus on fMRI to demonstrate the viability of the BrainBraille communication modality, the use of fNIRS in my system expands it to be portable and wearable. Portability is valuable for BCIs as most patients have some means of assisted movement and need to maintain communication while mobile. Unlike fMRI, where the patient has to be brought to the interface, fNIRS brings the interface to the patient. It is significantly costly and physically exhausting to use a system like fMRI for a brain-computer interface due to the difficulty of running fMRI sessions and preparing patients for the sessions.

My project also aims to pave the way for using passive haptic learning (PHL) with a BCI to enable the learning of gestures at the periphery of attention. Passive haptic learning is an approach to passively stimulate areas with vibrations when they are performing other tasks to assist their learning process [11]. In the past, passive haptic learning has been demonstrated to help with learning typing skills [11] and rehabilitation [12] for people with spinal cord injuries. PHL would enable faster learning of the BrainBraille system, forming a feedback system whereby the user can learn much faster than possible with past brain-computer interfaces.

Combined together, these components demonstrate a promising new approach to allow patients with motor disabilities to communicate faster, more intuitively and learn to use their new interface faster. Further, thanks to the Braille modality, the system is language-independent and can easily provide function even for non-English speakers. These improvements bring patients closer to having a more versatile and usable communication system without extensive, costly customization.

CHAPTER 3

RELATED WORK

3.1 Brain Computer Interfaces

Many different BCI systems have been developed over the past decades, but the most well-known of these is the P300 Speller [13], out of which several improvements [14] and variations [15] have been made. The P300 Speller utilizes a visual 2D grid containing letters, where the user first chooses a row and then a column. By repeating the process, they can form phrases to communicate. Researchers have augmented the P300 Speller with other simultaneous actions or attempted different electrode placements with mixed success. Since then, different invasive [14] and non-invasive [16] methods have been tried to achieve better usability, communication rates and accuracy.

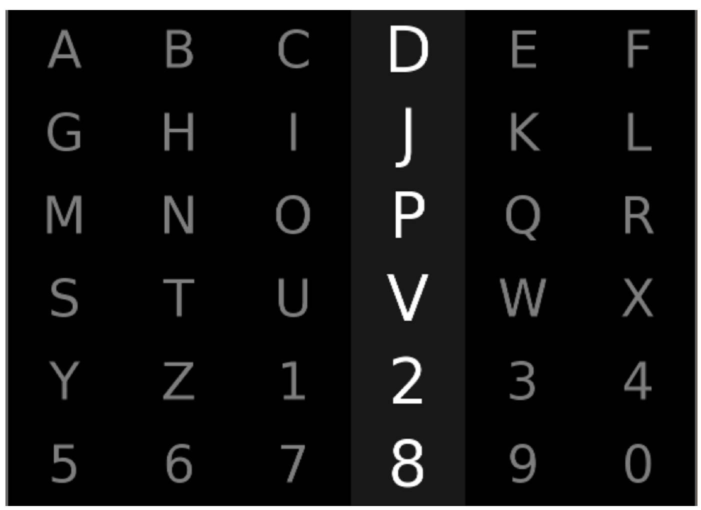

Figure 3.1: An example visual grid used by the P300 speller.

The most common method for non-invasive brain-computer interfaces is electroencephalography (EEG). EEG sensors are often cheap and easy to develop, but also come with shortcomings such as a vulnerability to motion artifacts. Past non-invasive BCIs using EEG signals have been able to achieve up to 21 characters per minute using visual evoked potentials [5]. Unfortunately, visual evoked potentials require intense visual attention from the user, making the systems difficult to learn and use.

3.2 Functional Near-Infrared Spectroscopy

Functional near-infrared spectroscopy (fNIRS) is a non-invasive neuroimaging approach using near-infrared light to detect changes to hemoglobin concentration in the brain [6]. fNIRS has recently gained attention in the neuroimaging field as a more portable alternative to an older method, functional magnetic resonance imaging (fMRI) [17]. Both fNIRS and fMRI rely on measuring the hemodynamic response, unlike methods such as EEG which measure electrophysiological activity.

Advances in fMRI-based brain computer interfaces can often be translated to fNIRS, due to similar hemodynamic properties in both neuroimaging methods. The blood-oxygen-level-dependent (BOLD) signal measured by fMRI correlates directly with the oxygenated hemoglobin levels measured by fNIRS [18]. While fMRI has been studied for much longer, hardware constraints pose difficulties that make a wearable BCI using fMRI nearly impossible. Therefore, the portability of fNIRS-based BCIs allow for a much more usable interface.

3.3 Modalities of BCI Interaction

In addition to different types of hardware and neuroimaging methods, brain computer interfaces make use of different forms of sensorimotor activity. The primarily modalities in brain-computer interfaces for communication are visual [19], audio [20] and movement [2]. These are often paired with cues and stimuli in the corresponding modality to standardize communication. For example, the P300 Speller described in section 2.1 functions by constantly showing the user a visual stimuli during usage. Sometimes, an alternative modality is more useful: Movement-based BCIs can be paired with tactile stimulation [21], or even have no stimulation at all [22].

Interaction modalities based on the movement of a subject can further be divided into three: Imagined movement, attempted movement and executed movement. Imagined movement is movement that the users make entirely in their head [23]. Attempted movement is when the user tries to move a part of their body while executed movement is when the attempted movement successfully moves a part of the body. There is little distinction between attempted and executed movement in healthy users, but the difference becomes critical for people with movement disabilities. Executed movement includes visual feedback, feedback from the muscle and intermediary motor control areas [24].

My work primarily focuses on attempted movement, as this approach has the greatest potential in assistive interfaces for users with movement disabilities. Executed movement is often limited to a few muscles in ALS patients, and entirely impossible in those with locked-in syndrome [2]. Meanwhile, imagined movement has often been the subject of scrutiny due to its low accuracy compared to attempted movement [25].

Past work investigating attempted movement in BCIs has typically used different hand motions such as visually cued selection tasks [21], tapping [25] and American Sign Language gestures [26]. Attempted movement is also currently the most efficient modality of BCI communication. Using attempted handwriting, a paralyzed subject with an invasive BCI was able to achieve up to 90 characters per minute, the highest information transfer rate so far [22]. Compared to such methods, full-body attempted movement allows easier recognition thanks to the distribution of body regions across the motor cortex.

3.4 Passive Learning

Passive learning is the phenomenon of acquiring knowledge through stimuli at the periphery of attention [27]. Passive haptic learning (PHL) uses vibrotactile stimulation in different regions of the body to help users learn patterned, rhythmic motions without any effort. Early work on PHL focused on learning how to play the piano, demonstrating that passive haptic learning does not require attention and can effectively reinforce learned movements in users [28]. PHL has been used to train users in a variety of communication modalities, such as typing in Braille [11] and morse code [29]. The success of these training approaches, especially in Braille, demonstrated the possibility that BrainBraille could be reinforced passively to teach how to use the brain-computer interface. More recently, passive haptic learning has been demonstrated to help with rehabilitation as well, demonstrating alternative potential uses for people with motor disabilities [12].

CHAPTER 4
METHODS

4.1 Data Collection

The fNIRS data for my research was collected using a NIRx NIRSport device. The NIRSport is a wearable multi-channel fNIRS system which uses a flexible headcap that stretches around the user's head. The hardware consists of 39 optodes, divided into 16 infrared light sources and 23 detectors. There are also 8 additional short-distance detectors to detect and control for blood flow in the scalp. The custom montage I made for these optodes and short-distance detectors focused on the intersection of the frontal and parietal lobe, where many of the motor regions relevant to my work can be found. While most of the optodes were above the typical location of the primary motor cortex, extra care has to be taken in placing optodes with hemodynamic signals as cerebral blood flow can homogenize hemodynamics across different brain areas. I highlight the brain regions on the right hemisphere of the diagram below, in particular including the regions of the primary motor cortex (M1) relevant to hand movements according to literature [30].

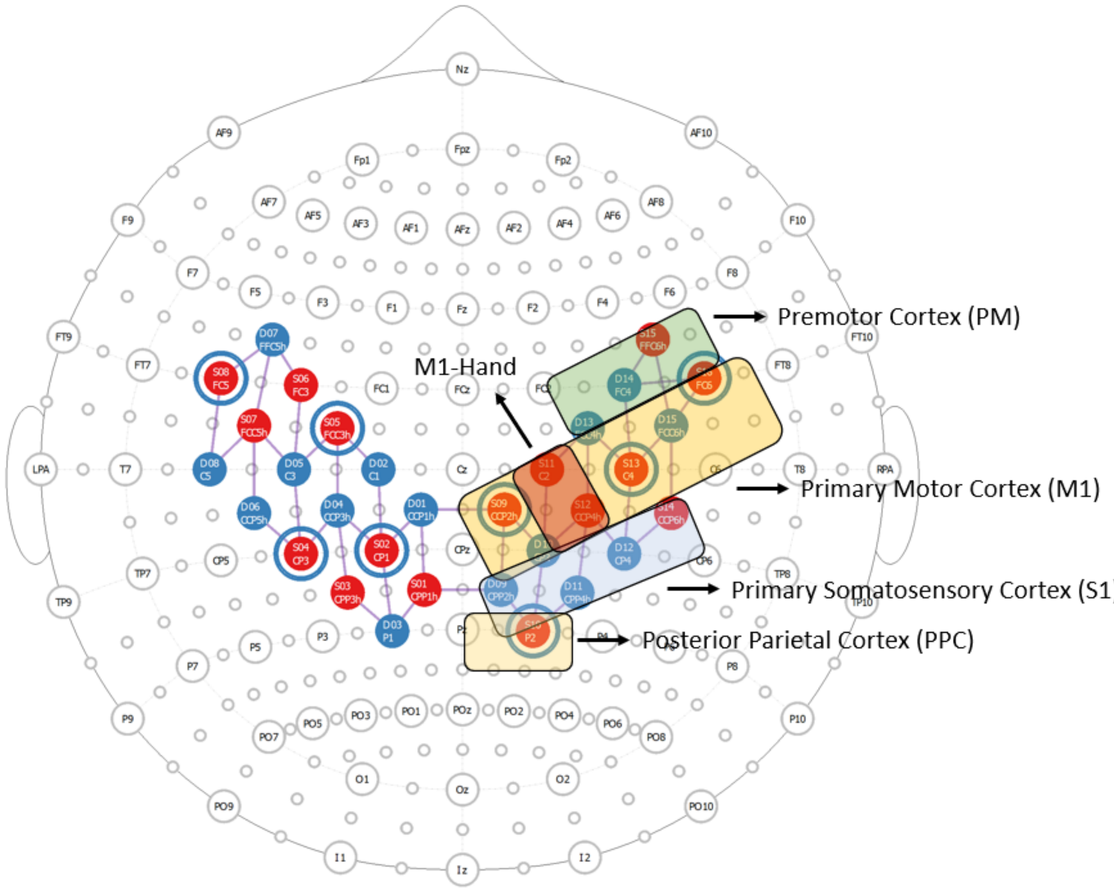

Figure 4.1: The arrangement of different channels on a model of the scalp. Sources are colored red while detectors are colored blue. Short channels highlighted with blue rings, arranged around different sources. Right hemisphere shows brain regions below optodes.

The data collection was performed in a confined, controlled environment to avoid any noise in the data. To ensure that the signal wouldn't be affected by irrelevant sensorimotor activity, the participant was put into a dark room with electromagnetic shielding and no sound. The participant was instructed to lie down after putting on the NIRSport. Lying down on a comfortable surface is a necessary step for avoiding noise from passive motor activity while sitting or standing. The study used a visual cue to prompt the participant on what activity to perform, which may have caused some noise, particularly in optodes close to the posterior parietal cortex (PPC).

4.2 Study Design

In order to evaluate whether fNIRS was feasible for reliably classifying movement in different parts of the body, I performed a study based on transitions in activity between two body regions: flexion of the fingers on both hands. Examining both hands was a good prototype for a more expansive study in the future, as the left and right hand typically provide notably distinct signals that are lateralized to one hemisphere of the brain.

The study consisted of two participants, P1 and P2. P1 is healthy, right-handed, 25 years old and male while P2 is healthy, left-handed, 21 years old and non-binary. For my current studies, healthy users were preferred as ALS patients can be difficult to access and performing tasks in a lab environment may come with great difficulties. A limited number of participants was used for this study due to COVID limitations. The fNIRS headcap on a participant is shown below.

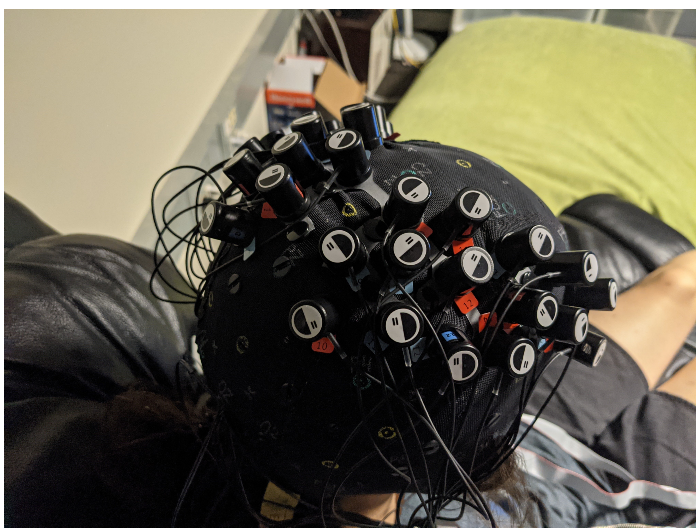

Figure 4.2: The NIRSport fNIRS headset on a study participant.

Data was collected from each participant over a 15-minute duration with 30 trials during which the participant either flexed first their right hand, and then their left hand or first their left hand and then their right hand. Each hand was flexed for 6 seconds, followed by a 15-second rest during which neither was flexed. The left-to-right and right-to-left trials were distributed in a random order and prompted by visual cues on a computer screen.

4.3 Hemodynamic Signal Processing

Hemodynamic signals reflect complicated blood flow dynamics across the entirety of the brain, and the signals must be pre-processed before they are sent to a classifier model. The signals are initially collected as a XDF file from the NIRSport, including the oxygenated and deoxygenated fNIRS time series as well as metadata about the channels with their locations.

The most relevant channels from the time series were identified using a Generalized Linear Model (GLM). The GLM was fitted to a designed regressor approximating what a hemodynamic response should ideally look like based on the participants' heart rate and the timing of the left and right hand gestures. The derivative and dispersion derivative were calculated for both the regressors and the time series from the data. After fitting the GLM, the weights given by the GLM for each channel were used to determine the t-scores for discriminating left hand, right hand and their differential. Channels for oxygenated hemoglobin (HbO) and deoxygenated hemoglobin (HbR) were identified separately by searching for positive t-scores with oxygenated hemoglobin and negative t-scores with deoxygenated hemoglobin. Channels that showed a strongly positive or strongly negative response to both left and right hands were excluded as they didn't have any discriminative power. These were used to select the channels to be used in the time-series support vector machine (SVM), with channels that were below a 70% quantile threshold discarded.

After channel selection, I applied a 0.09Hz third-order low-pass Butterworth filter to remove hemodynamic noise due to the heart rate (1Hz), breathing rate (0.3Hz) and Mayer waves (0.1Hz), which are oscillations in arterial blood pressure due to baroreceptors. The 0.09Hz number was determined based on past literature in fNIRS signal processing, which showed that it's the most common frequency to apply the filter at [31], in particular because it can filter out Mayer waves. The figure below shows how the filter was used to clean the signal.

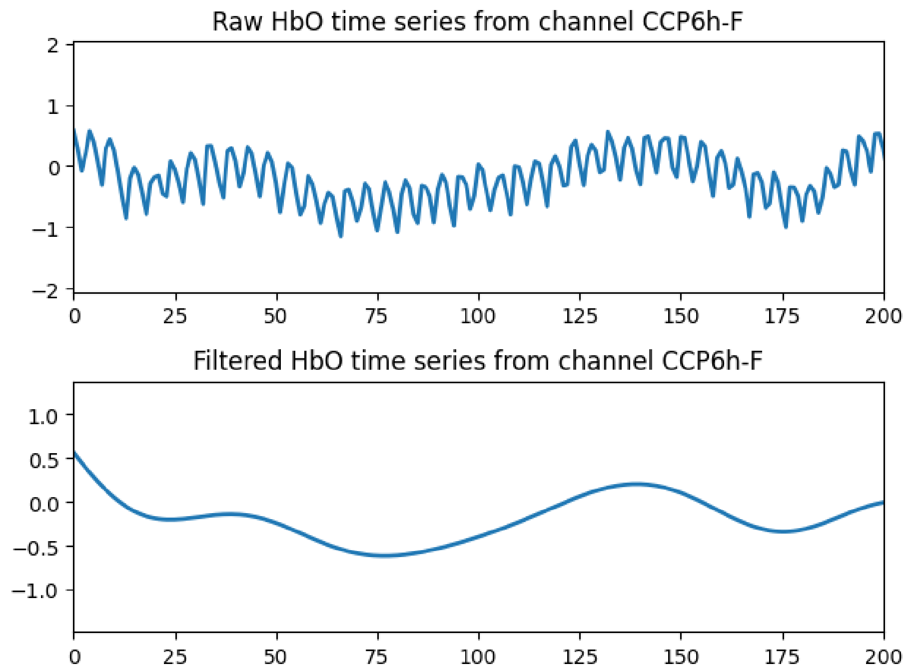

Figure 4.3: Signal from a channel determined to be useful during channel selection, before and after low-pass filtering.

4.4 Classification

For classification, I segmented each gesture epoch by selecting the 120 samples after each event starting a left to right or right to left sequence. 120 samples is equivalent to 24 seconds given the 5Hz rate of the NIRSport headset, which included six seconds of left hand tension, six seconds of right hand tension and twelve seconds of rest. However, due to the time delay of hemodynamic signals, some of the effects of the hand tension were only visible up to three seconds after the participant first started tensing their hand. Within the extracted epochs, I only included the channels from the previous selection, testing oxygenated and deoxygenated responses independently as well as together.

Afterwards, I used independent component analysis (ICA) to reduce the dimensionality of the data. Then, I used a time-series support vector machine (SVM) from the Tslearn package for binary classification between the two hands. The parameters for these algorithms were tuned using a cross-validated grid search approach. A separate test set beyond cross-validation was not created due to the small size of the dataset. Then, the final results were determined using a 5-fold stratified cross-validation with the final, tuned model for each participant.

CHAPTER 5

RESULTS

Based on the GLM described in the Methods section, I identified which channels were the most relevant to the discrimination of the left and right hand signals. The weights given by the GLM for both participants are shown in the figure below. After calculating the t-scores for each of these channels, I identified the most relevant channels by thresholding scores above the 70% quantile. Oxygenated (HbO) and deoxygenated (HbR) channels that had the largest difference between the left and right hand were selected from among these channels. The selected channels for both P1 and P2 are shown in the table below, reported according to the international 10-5 EEG placement system. Selecting different channels for each participant was necessary for accurate and meaningful results as there is significant individual variance in localized areas of activity, cerebral blood flow and headset fit.

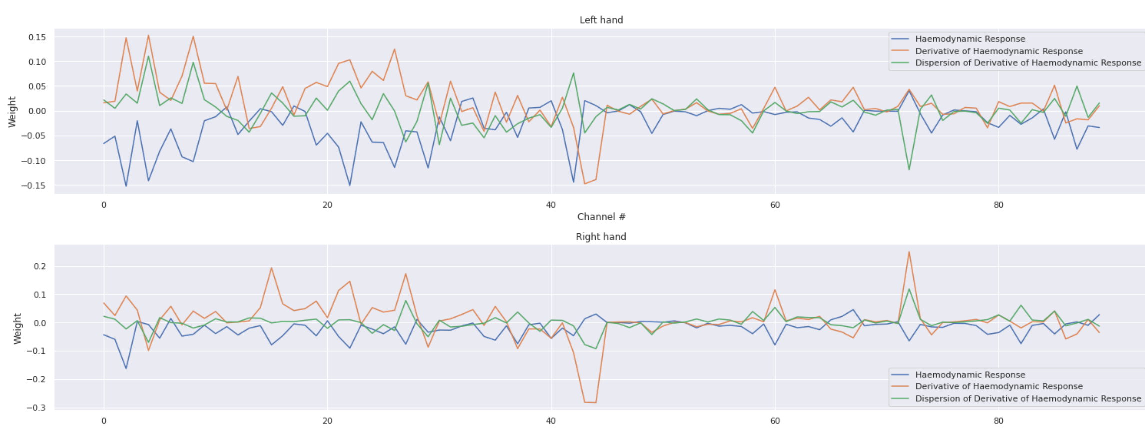

Figure 5.1: P1 above and P2 below. The weight given to the hemodynamic response, its derivative and dispersion derivative for each fNIRS channel in left and right hand by the GLM.

Based on their locations, these channels are primarily in the lateral portions of the channel arrangement and in the frontal lobe. The locations are close to where the motor responses in M1 should be based on past literature, although some of the channels selected

Participant	Left > Right, Oxygenated	Left > Right, Deoxygenated	Right > Left, Oxygenated	Right > Left, Deoxygenated
P1	CP1-CCP, CP1-C1, CP1-P1, CP1-CCP, CPP3h-C, CP3-CCP, CCP4h-C	CPP1h-C, CP1-P1, CPP3h-P, CPP3h-C, FCC3h-C, FC3-FFC, FCC5h-F, CCP2h-C, CCP4h-F, C4-CP4, C4-FC4, CCP6h-F, FFC6h-F	P2-CP2, C2-FCC, C4-CP4, CCP6h-F, FFC6h-F	C4-FCC, CCP6h-C, FC6-FCC
P2	FCC3h-C, FC3-C3, FCC5h-C, CCP4h-C, C4-FCC, CCP6h-C, CCP6h-F	CP1-C1, FCC5h-C, FC5-FFC, FC5-C5, P2-CPP, FFC6h-F, FC6-FCC	CP1-CCP, CP1-C1, CP1-CCP, CPP3h-P, FCC5h-C, P2-CPP2h, P2-CPP4h, CCP4h-C, FC6-FC4, FC6-FCC	CPP1h-C, FC3-C3, P2-CP2, CCP6h-C, FFC6h-F

Table 5.1: Selected oxygenated (HbO) and deoxygenated (HbR) channels for P1 and P2 in the 10-5 system. The Left > Right and Right > Left channels were combined during classification.

Participant	HbO + HbR	HbO	HbR
P1	87%	80%	**93%**
P2	70%	70%	**70%**

Table 5.2: 5-fold cross validation accuracy for P1 and P2 using different sets of selected channels with ICA and SVM.

were more lateral than expected, suggesting they may be coming from the sensory cortex in the parietal lobe or from different motor regions than the hand. Another explanation could be that this effect was caused by the fit of the headset on the participant's head, particularly due to hair getting in the way of the fabric headcap.

The pre-processed time series data from the selected channels was then used in the classification section of the pipeline. The grid search optimization found that a SVM with a sigmoid kernel and ICA with 10 components got the best results. The best accuracy for P1 and P2 were 93% and 70% respectively, determined using five-fold cross validation across all 30 samples. Notably, the best accuracy was observed when only using deoxygenated (HbR) channels for classification. Results were also attempted using different selections of channels between oxygenated, deoxygenated and their combination, which are shown in the table above.

CHAPTER 6
DISCUSSION

6.1 Limitations

The current study was performed with a small number of participants due to COVID-19 constraints as well as the time-consuming procedure for collecting fNIRS data. The current study was intended to demonstrate the possibility of a motor activity-based wearable fNIRS interface and did not attempt generalizability. I anticipate that an exclusion criteria would be necessary when more participants are included in future work. Neither a user-adaptive or user-independent model was attempted due to the limited participants as well as the difficulty of constructing these models for neural activity.

The delayed nature of hemodynamic responses necessitated longer durations for recording each trial, in particular with long rest sessions. Otherwise, signals from different movements would merge to make a very noisy dataset. However, this also reduced the total trials per participant to 30, and the 5-fold split used for testing meant the results were only based on a few trials for each fold with no separate held-out test set. The duration constraint also greatly limited the information transfer rate of the interface. A possible solution could be to combine it with EEG sensors, taking advantage of the reliability of hemodynamic responses and performing early classification on it while using EEG to get more instantaneous responses due to attempted movement. Combining fNIRS with EEG would increase the robustness to artifacts in each signal, as some artifacts exclusively affect blood flow or electrophysiology and not the other.

All users in the present study were healthy and any attempted movement would also result in executed movement. Testing on healthy participants brings three limitations that impede the results from translating to brain-computer interfaces for ALS patients. Firstly, executed movement often results in motion artifacts that impede the data, by altering blood flow in the case of hemodynamic signals and by shifting skin across the body. Secondly, executed movement results in sensory feedback based on the motion, meaning some of the detected activity may have been in the sensory cortex rather than the motor cortex. Thirdly, there are notable differences in the brain structure of ALS patients due to their conditions and both neural activity and blood flow would be altered as a result. It would be critical to test the system with ALS patients in the future, but significant work is needed before the interface is ready for being used with patients due to the strenuous nature of using BCIs with attempted movements.

6.2 Future Work

Future work will aim to both increase the number of participants and eventually, work with the target demographic of ALS patients. The former will increase the generalizability of BrainBraille and make the results more reliable while the latter will bring it closer to being a tool that can be used by patients themselves. However, doing both at the same time is unlikely due to the difficulty of finding groups of patients for such a study.

The current classification was performed using a time-series support vector machine for convenience. In the future, these results could be improved by using Hidden Markov Models (HMMs) or Recurrent Neural Networks (RNNs). Both models have shown promise and could enhance accuracy in the future. Alternatively, Zhao et al.'s approach of combining Viterbi decoding [10] with a support vector machine could be promising when using the system with a language-based format instead of the current two-hand experiment. Early classification models could also be beneficial to respond to the delayed hemodynamic response quickly, increasing the information transfer rate of the future interface. With early classification, it would be critical to find a balance between accuracy and speed, especially considering the application to ALS populations may already necessitate delays between attempted movements due to their exhaustion.

I also hope to further investigate transitional gestures. Transitional gestures make use of the transitional states when a user is switching between actions to obtain more information from behavior. The current study's approach with the left-to-right and right-to-left movement was based on this idea. In future gesture-based brain-computer interfaces, transitional gestures can allow more information to be encoded within the communication and for communication to happen with greater speed. The six-region setup of BrainBraille as used by Zhao et al. only allows up to 64 different characters, obtained when the user makes the motion in all body parts concurrently. However, transitional states between six regions can allow up to 180 different characters when the concurrency requirement is relaxed thanks to the different possible permutations. It can also make communication faster, as the user can simply switch between different regions over time, instead of activating a region for some time and keeping it active to be recognized. Switching between regions would be particularly useful for ALS patients who are easily strained after movement tasks due to their muscular dysfunction.

Finally, future work will attempt to use passive haptic learning to allow the system to be learned passively. The addition of PHL would significantly enhance the usability and learnability of the brain-computer interface, giving an advantage to brain-computer interfaces using movement over visual alternatives. Passive learning would significantly reduce the time required to introduce a patient to the interface and particularly reduce the amount of physical exertion needed. PHL could also allow customization based on the functioning muscles of ALS patients who are not locked-in, assisting them with retaining muscle control and enhancing their communication capabilities.

CHAPTER 7
CONCLUSION

In this dissertation, I explored an attempted movement-based alternative gestural brain-computer interface called BrainBraille. BrainBraille can allow ALS patients who have very limited or no control over their muscles to communicate at the phrase level with much higher text entry rates than past non-invasive brain computer interfaces. BrainBraille would allow ALS patients to communicate in complex sentences rather than simple commands, giving them more flexibility over their interactions. BrainBraille has various other improvements over past brain-computer interfaces that makes it more user-friendly. Compared to the common visual modalities in other non-invasive brain-computer interfaces, BrainBraille does not demand the user's continuous visual attention.

In an early study, I expanded recent work on BrainBraille with fMRI to enable its use in a wearable, mobile setting using fNIRS. I designed a machine learning model that can classify between attempted movement in the two hands with up to 93% accuracy even with limited samples using a support vector machine. My work pointed a promising direction towards wearable usage of BrainBraille as using fNIRS would allow BrainBraille to function better when a user is in motion, and make it more comfortable than EEG-based sensing approaches which may require abrasive gel to acquire a reliable signal.

BrainBraille has great room for expansion and demonstrates the potential of gesture-based brain-computer interface modalities using attempted movement. In the future, using transitional gestures with the six-region pseudo-binary encoding can allow for a much wider range of characters to be communicated at higher information transfer rates than the present version of BrainBraille. Moreover, the potential of passive haptic learning could make it the first brain-computer interface to be learned without conscious effort from its user.

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