Towards a Gamified Therapeutic Brain-Computer Interface for Children with Gait Impairment

by
Krishna Sarvani Desabhotla

A thesis submitted to the Department of Biomedical Engineering,
Cullen College of Engineering
in partial fulfillment of the requirements for the degree of

Bachelor of Science
in Biomedical Engineering

Chair of Committee: Dr. Jose Luis Contreras-Vidal

Committee Member: Dr. Yingchun Zhang

Committee Member: Dr. Stuart Long

University of Houston
May 2022

ACKNOWLEDGMENTS

I would like to thank Dr. Contreras-Vidal for his guidance and support of my work and curiosity. I am grateful to my graduate student mentors, Alexander G. Steele and K. Michelle Patrick-Krueger, for their advice and encouragement. Thank you to my committee members, Dr. Zhang and Dr. Long for their support of my thesis. I would like to offer my gratitude to the Office of Undergraduate Research for their support of my research endeavors through the Summer Undergraduate Research Fellowship and the Provost Undergraduate Research Fellowship programs. Finally, this research is supported in part by the NSF IUCRC BRAIN award # 1650536, Mission Connect - a TIRR Foundation, and the UH Technology Gap Fund.

ABSTRACT

Central nervous system (CNS) disorders cause over 1 billion people to live with a life-altering handicap. Some CNS disorders, such as cerebral palsy and spina bifida, affect one-four per 1000 and one per 2758 children respectively, according to the Centers for Disease Control. These pediatric CNS disorders leave patients with many years of living with partial or complete motor impairment. Brain-computer interfaces (BCIs) have been researched as tools for rehabilitation for adults with disabilities due to neurological disease, brain injury or amputation; however, research on the design of BCI systems for children has not received the same level of attention by the scientific community. This is unfortunate as the developing brain is very plastic, thus, children may be the best candidates for BCIs for neurorehabilitation.

The primary aim of this project was to adapt a system, developed in the Laboratory for Non-Invasive Brain-Machine Interface Systems at the University of Houston, that can be used for BCI system development for children. Such a system will provide real-time data capture from two types of sensors (scalp electroencephalography or EEG, and joint angle data from the lower limbs) during treadmill walking while providing real-time visual feedback of the child's gait pattern via a digital avatar. To achieve this aim, a system was created in the MATLAB programming environment that initializes, acquires and synchronizes EEG and joint angles, and then, filters and sends joint angles to control the digital avatar and in parallel, stores time-locked unprocessed EEG and joint angle data for offline processing - the first step in designing a BCI system.

Applications of the system include, but are not limited to, investigating the neural representations for motor control in children, and extracting neural and kinematic features for diagnostic purposes and for the design of closed-loop BCI systems for children.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1 Introduction

1.1 Pediatric Neuromotor Disorders

Central nervous system (CNS) disorders are responsible for causing over 1 billion people worldwide to live with some type of life-altering handicap [5]. Some CNS disorders cause degradation of the motor system, such as Parkinson's disease, and begin during an individual's middle or late years of life. Other disorders, such as cerebral palsy and spina bifida begin before, during, or closely after childbirth, resulting in many more years of living with partial or complete motor impairment. Cerebral palsy and spina bifida affect one-four per 1000 and one per 2758 children respectively, leaving many of those affected with limited or no walking ability [6, 7].

There are no cures for diseases such as cerebral palsy, but research suggests that early therapeutic interventions could improve the quality of life for children suffering from these disorders [8]. Early neuromotor interventions can take the most advantage of the developing brain's plasticity and mitigate adverse effects to muscle and bone development that may accrue from disuse [9, 10]. Consequently, aiming to improve living conditions for children with mobility-limiting disorders is a necessary goal for rehabilitation research.

Traditional therapies to improve motor capabilities for children with cerebral palsy include occupational and physical therapy, home visits and the use of assistive technology devices. Newer interventions are incorporating the use of robotics and neural engineering into rehabilitation [11, 12]. Interventions could include the use of robotic assistive devices, brain-computer interfaces, as well as combinations of the two.

1.2 Brain-Computer Interfaces

A brain-computer interface (BCI) is defined as a system that acquires brain signals to command interactions between the brain and its internal or external environments [13]. In the external environment, BCIs can be used to control computer cursors, keyboards, robotic devices, and even virtual prostheses [14, 15, 16]. In the internal environment, BCIs can be effective in helping individuals modulate their neuronal oscillations; this is currently explored as a potential therapy for attention deficit hyperactivity disorder (ADHD) [17].

BCI components include the signal acquisition system, processing and translation (decoding) algorithms, and the end effector device or computer program [1]. Some brain-computer interfaces include feedback for the user, these are characterized as closed-loop BCIs. An overview of a brain-computer interface is shown in Fig 1.

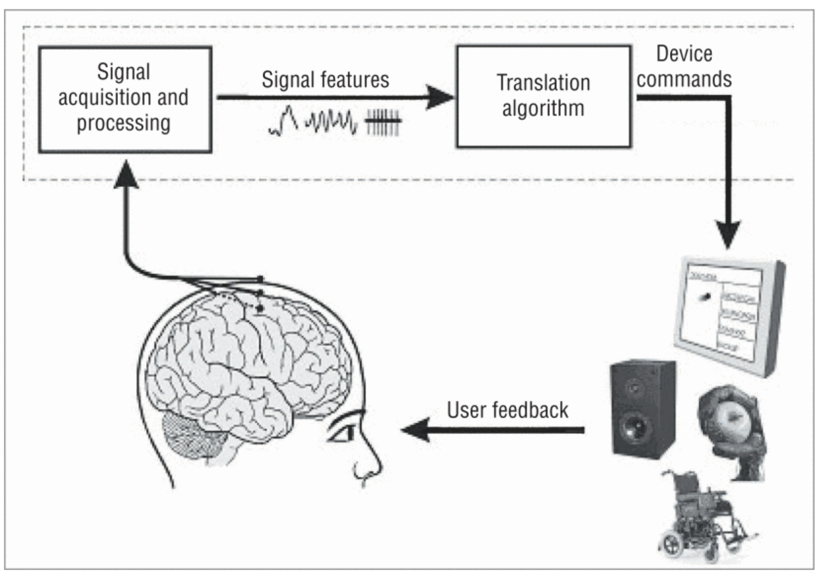

Figure 1: BCI overview. Brain signals are recorded and processed through a neural decoding algorithm that executes device commands based on specific patterns of neural activity, and provides feedback for the user [1].

Brain-computer interfaces provide opportunities for mobility-impaired populations to interact with the world without having to engage the peripheral nervous system or musculature which may be weak or damaged [16]. BCIs provide an avenue for enhancing independence in individuals that are heavily dependent on caregivers and family members, and research shows that improvements in self efficacy can lead to better rehabilitation outcomes [18].

Studies on the use of brain-computer interfaces for motor rehabilitation have shown improved outcomes [19]. Although mobility-impaired individuals of all age groups could benefit from BCI-based neurorehabilitation, research has mostly focused on applications for adults. The use of BCIs in pediatric populations, especially for motor rehabilitation, has not been widely studied.

1.2.1 Brain Signal Acquisition

Brain-computer interfaces can be characterized as invasive and noninvasive, and this distinction is dependent on how the brain signal is acquired.

Any recording method that requires implantation is invasive or semi-invasive, such as electrocorticography (ECoG), where electrodes are placed on the surface of the brain to record electrical activity [20]. Invasive signals have high signal-to-noise ratios and location specificity compared to noninvasive signals, as they are located closer to the electrical activity that the neurons generate. Recording methods that do not require implantation are noninvasive, such as electroencephalography (EEG) where electrodes are placed on the scalp [21].

1.2.2 Processing and Translation

There are various methods for processing the acquired brain signal and executing commands based on those signals. Typically, processing techniques involve filtering the raw data to remove noise and the extraction of features that are used to drive commands. The extraction of important features from the raw data can be accomplished by decoders.

The nature of the extracted features depends on the experimental and command protocols. For a speller BCI, where brain signals are used to spell words on a computer, an experimental protocol may involve the use of visual evoked potentials (VEPs), whereby various stimuli are flashed at different frequencies, and the user is asked to focus on a specific target stimulus. Based on the brain signals acquired, researchers can predict the target based on the frequency of the VEPs [22]. For a BCI to control a robotic arm, the brain signal may be recorded from the user's motor cortex as the user imagines moving an arm [23].

1.2.3 Feedback

Closed loop BCIs provide the brain with feedback; Fig 1 shows an example of a closed-loop BCI wherein commands from the cortex are translated into device commands, and information about command execution is given to the user as feedback [1]. Feedback is typically sensory, and can include visual and tactile representations of the executed command, and auditory tones that indicate success/failure.

Feedback is also the basis of neuromodulation, whereby individuals receive feedback on their neural oscillations, and are asked to perform specific tasks that will affect those oscillations [17]. Feedback can be especially important in creating experimental protocols for pediatric BCIs as the use of feedback lends itself to the gamification of the experimental experience, which can aid in keeping the attention of a young subject [24].

1.3 Pediatric Brain-Computer Interfaces

To establish neurorehabilitative options for children with motor disorders, it is essential to understand sensorimotor development determine whether children's developing neural circuitry can control BCIs, thereby producing adequate decoder accuracy for practical use. King et al. suggest that improvements in sensorimotor behavior during the course of childhood could be attributed to the development of static and dynamic state estimation, and it is important to determine whether these improvements in state estimation translate into an improved ability to control a noninvasive BCI [25].

Recently, researchers conducted a pilot study testing sensorimotor (SMR) modulations during an imagined hand motion task and exploring whether typically developing children from the ages of 12-17 could control noninvasive BCIs for various P300 tasks [26]. They achieved an accuracy of 61% for the SMR task which is comparable to findings in similar studies conducted with adults [26, 27]. Although this study explores older children's ability to control BCIs, it is not clear whether this finding will be replicable in younger children, or for the lower limbs of the body, a necessary component for using BCIs in gait rehabilitation.

Of interest is exploring whether pediatric lower limb joint angles during walking can be predicted from EEG data while providing the subject with visual feedback. Using existing experimental paradigms for adults to explore noninvasive BCIs for gait rehabilitation can provide a standard for assessing decoder capability and BCI performance when testing with children of different ages. He et al. conducted experiments in which lower limb joint angles and EEG data were collected from adults, and a decoder was trained to predict the joint angles from the EEG data [27]. Subjects received visual feedback during the trial through the form of a walking avatar where the joints were controlled by the subject's recorded and predicted joint angles [27]. Performing a similar experiment with children and assessing decoder accuracy would inform how effectively children of this age range can use noninvasive BCIs, and would expand the discussion concerning whether BCIs are a viable rehabilitation option for children with movement disorders and to determine whether there are certain neurological benchmarks that children must meet before they can effectively use an EEG-based BCI.

1.4 Research Aims and Objectives

The objective of this thesis was to build a system that performs the following functions:

1. collect time-locked EEG and lower limb joint angle data for offline analysis during trials where a child is walking on a treadmill

2. provide the subject with visual feedback using an avatar whose gait is controlled by the joint angles of the user

This is a system that collects data for offline analysis and in parallel provides visual feedback of gait. The deliverable of this thesis is a system that can be used to collect multi-modal brain-body imaging data that will contribute to the understanding of pediatric neuromotor development based on EEG and lower limb kinematic data, and ultimately, to the design of BCI systems for children.

2 Current State of Research of BCI Systems

Literature on the use of pediatric closed-loop brain-computer interfaces is limited, and this systematic review of the literature attempts to address the following questions: what types of BCIs and brain signals are being used to explore the implementation of pediatric closed-loop BCIs? Which tasks are used to train the BCIs? What kinds of de-noising techniques and decoders are being used? What levels of accuracies can be achieved from these systems?

2.1 Methods

2.1.1 Search Methods for Study Identification

PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) is a systematic review and meta-analysis protocol [28], which was used to identify studies for this review. The search was conducted on March 16, 2022 with the PubMed database using the following search criteria: ('Pediatric' OR 'Children') AND ('Brain Computer Interface' OR 'Brain Machine Interface' OR 'Human Robotic Interface' OR 'Human Robot Interface' OR 'BCI' OR 'BMI'). Studies that were not within the inclusion criteria were excluded and the remaining studies were screened to find studies using brain-computer interfaces with feedback where at least some of the subjects were children (< 18 yrs old). Some of the studies excluded were literature reviews and meta-analyses, and their citations were searched for studies that matched the inclusion criteria. An overview of this process is shown in Fig 2.

The following criteria were used to determine whether to exclude search results:

- Experimental studies only - Literature reviews and meta-analyses were excluded.

- Brain signals only - Studies that incorporated the use of signals from other parts of the body, such as muscle activation recorded by electromyography (EMG) were excluded.

- Subjects - Studies containing at least one pediatric subject were included.

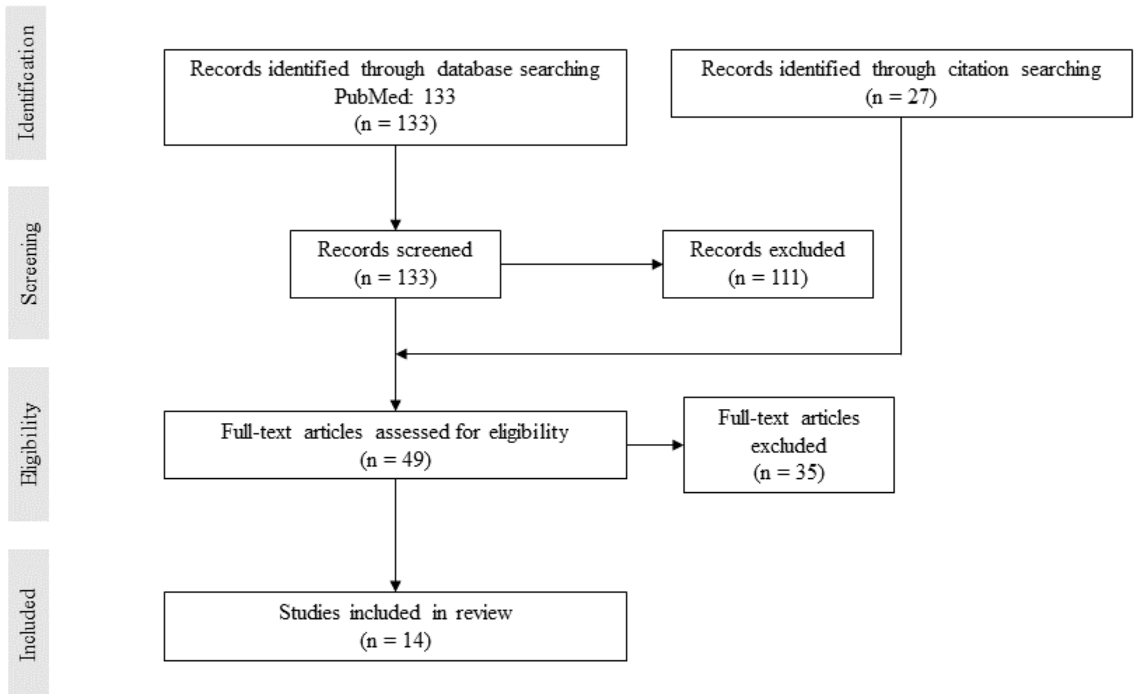

Figure 2: PRISMA study selection diagram. The stages of study selection include identification, screening, eligibility, and included studies. This process led to a total of 14 included studies.

2.1.2 Data Extraction

The following categories of data were collected and presented in Table 1.

- Brain-computer interface type
- Signal type: signal use for feature extraction
- Task information: task executed during BCI training and online trials
- Results: mean accuracy or other reported performance metric

- Number of channels used
- De-noising technique
- Decoder used for classification

2.2 Results

2.2.1 What kinds of brain-computer interfaces and brain signals were used?

Except for a study using electrocorticography (ECoG) involving pediatric subjects with intractable epilepsy [29], all of the studies used electroencephalography (EEG)-based BCIs. This is expected, since many of the studies involved healthy pediatric populations as well as populations with ADHD - a disorder where treatment does not involve surgery.

There were three main signals used for feature extraction from the BCIs:

- Event related potentials (ERPs)
- Visual evoked potentials (VEPs)
- Attention measurements from the Neurosky MindWave headset [30]
- Frequency-band power

Event related potentials (ERPs) are characteristic waveforms or potentials that can be evoked by specific events. In the analyzed studies, the ERPs include P300, P100, N200, and slow cortical potentials. In an oddball paradigm, where there are some target and many non-target stimuli, the P300, P100, and N200 peaks can be used to differentiate between target/non-target stimulation [31]. The amplitude of the peaks is dependent on user-engagement; thus, P300 is a convenient signal to analyze for applications associated with attention-training for children with attention deficit hyperactive disorder (ADHD). Slow cortical potentials are indications of negative shifts in the cortical cell network, which reduces the activation threshold [32]. A dearth of slow cortical potentials is implicated in attention deficits, as children with attention issues were shown to have less slow cortical potential activity [33].

Visual evoked potentials are apparent in brain signals when stimuli are flashed at various frequencies, and the user is asked to focus on a target. These VEPs can be evoked through continuous flashing at certain frequencies in the case of steady-state visual evoked potentials (SSVEPs), or through the perception of movement in movement-visual evoked potentials (mVEPs). SSVEPs are commonly used for target selection; however, the continuous flickering can lead to eyestrain [34], so Beveridge et al. focused on the use of mVEPs to control car position in a video-game [35].

The Neurosky MindWave device is a commercially available EEG system that provides the user with EEG recordings as well as metrics (0-100) for attention and meditation states [30]. The attention metric was used to control the efficiency with which avatars moved in attention-training games [29, 36, 17, 37].

The frequency band-based BCIs are more heterogeneous and can involve different tasks. Breshears et al. used the γ band (36-90 Hz) for the ECoG-based BCI, as increases in the γ band over the sensorimotor area are associated with motor imagery [38]. Huang et al. [39] focused on the use of α (8-13 Hz), β (13-30 Hz), and θ (4-8 Hz) wave amplitudes from the O1 and O2 electrodes to calculate an engagement metric as

$$Engagement = \frac{\beta}{\alpha + \theta}. \tag{1}$$

since an increase in β band power and simultaneous decrease in α and θ band power is associated with an increase in user engagement.

2.2.2 Which tasks were used to train BCIs?

Most studies which focused on training for ADHD incorporated the use of games including Connect4, Tetris, Pac-Man, a racing game, etc [36, 40, 41, 35, 42, 43, 29]. When developing BCIs for children, it is important to take their reduced attention span into consideration when designing the tasks or virtual environments, especially since features in the EEG and ECoG signals are more distinct as the user pays attention. Thus, the gamification of BCIs for ADHD therapy can enhance attention in a population that suffers from attention deficits. Two studies created BCIs for children with ADHD to enhance reading capabilities and to encourage users to engage with stories, and Huang et al. created a contextual training session to bring the subject's attention back if they were losing focus [39, 44].

In some studies, target selection was used for command execution, such as spelling [45]. In Beraldo et al., a robot was steered through selection direction and orientation commands such as "go forward", "turn left" etc. through a P300-based BCI [46]. Furthermore, in Breshears et al. γ band activity is used to control a robotic arm [29].

One study did not provide an explicit task to the subjects; rather, by providing them with feedback on the shift in their slow-cortical potentials, Strehl et al. asked the subjects to try different strategies to regulate their SCPs and adjust their strategy according to the feedback [17]. This approach, called neurofeedback, is interesting since it is less stimulating than the other studies; however, it showed significant improvement [17].

2.2.3 What levels of accuracies were achieved by these systems?

Studies reported two main metrics: mean decoder accuracy and/or qualitative measures of performance. The main qualitative measure of performance the ADHD

Rating Scale (ADHD-RS), which is a measurement of the behavioral symptoms associated with ADHD [47]. Another qualitative measure was a comparison of quiz and recall scores before and after the training. In studies that created and tested therapies for ADHD where the attention metric was the signal, significant changes to the ADHD-RS were indicators of the potential success of the therapy. Those studies all reported significant improvements in behavior and the ADHD-RS scale.

One study reported that slow cortical potential training was effective since SCP amplitude changed over time. Another study reported that adults had greater accuracies than children, except at higher frequencies for an SSVEP trial [45]. For target selection-based BCIs, the more non-targets for every-target, the better the decoder accuracy is. Fouillen et al. created a P300 template for use in a P300 game, and found that the template accuracy was lower than the accuracy from individual data [41].

Quantitative metrics were used in studies where a decoder was executing commands based on features from the brain signals. The mean accuracy achieved was 76.5% [46, 36, 48, 40, 37, 35, 29]. The accuracies are variable for the same signal type because of different tasks, thus, the only conclusion which can be generalized is that the decoder accuracies for children are comparable to accuracies achieved by adults from non-invasive closed-loop BCIs [27].

2.2.4 What De-noising Techniques and Decoders Were Used?

De-noising techniques are generally used to help with decoding since the artifacts and noise in unprocessed EEG signals can impede feature extraction. Many studies used bandpass or lowpass filters for de-noising with the upper cutoff frequency around 30 Hz (the upper limit of the β frequency). One study used a lowpass filter with a cutoff frequency of 552.96 Hz to account for the flashing frequencies used in an SSVEP task [45]. Some studies also used common average referencing and other baseline correction methods.

Some studies used linear decoders such as Bayesian and Fisher linear discriminant analysis [46, 35, 41, 36]. Other studies used machine learning and neural network classifiers [43, 42, 40, 48]. Another set of studies used frequency band power for classification [29, 39, 17]. Finally, the studies using the MindWave device used the 'attention' metric provided from the device, so no classification was described [49, 44].

2.3 Discussion

As part of this literature review, 14 papers were included in the analysis, and the studies had a total of 428 pediatric subjects. The information collected in this review includes BCI type, signal type, task, results, de-noising technique, and decoder used for classification. The EEG-based BCIs are the most common of the studies analyzed due to their non-invasive nature. Of the signals used for EEG-based BCIs, SSVEPs and P300 tasks have the potential to cause the user fatigue and can be time-consuming; however, the pediatric decoder accuracies were generally comparable to studies in adults. The use of mVEPs was suggested as a potential signal to use for BCI control that might not fatigue the subject [35]. Another signal type that does not involve user fatigue is using specific frequency bands for feature extraction during a task. The most common de-noising technique was bandpass filtering the signals to remove noise. Of the studies analyzed, linear decoders were used most often; however, some studies also used machine learning and neural network-based classification. This is probably due to the low computational power required for linear decoders, making their implementation for online-BCIs simpler. However, there are advancements in machine learning and neural network decoders that are enabling online implementation. Overall, for developing pediatric BCIs and choosing the signal, de-noising, and decoder type, the accuracy expected, user fatigue, and available computational power should be considered.

=

Table 1: Information extracted from each study including BCI type, signal type, task performed, reported results, number of channels used, de-noising techniques, and decoder types

BCI	Signal	Task	Results	Channels	De-noising	Decoder	References
EEG	P300	steering robot with forward, stop/go back, turn left, turn right commands (4 choices)	mean accuracy: 81.67%	16	1-24 Hz BPF CAR	Bayesian Linear Discriminant Analysis	[46]
EEG	P300	P300-based tetris: choice of 4 pieces and 4 orientations (16 choices)	100% (5th repetition)	12	0.1-30 Hz BPF 50 Hz Notch	Naive Bayes Classifier	[36]
EEG	P300	P300-based tetris: choice of 4 orientations and then 4 positions (4 choices x2)	62.5% (6th repetition)	12	0.1-30 Hz BPF 50 Hz Notch	Naive Bayes Classifier	[36]
EEG	P300, MI (mu, beta)	P300-based tetris: choice of 4 orientations; MI-based tetris: horizontal position	Users reached required position within 30s on most trials	12	0.1-30 Hz BPF 50 Hz Notch	Naive Bayes Classifier (P300) Fisher Linear Discriminant (MI)	[36]
EEG	P300	Choose number and focus on target	mean accuracy: 68.9%	3	Baseline Correction	Subsampling, DWT, Multi-layer Perceptron	[48]
EEG	P300	Anispell, T-Search	mean accuracy: 70.67%	4	0.5-30 Hz BPF Moving Average RLS	SVM	[40]

Table 1: Continued

EEG	P100, N200, P300	4 games: Connect 4, Connecticut4, IceMemory, Armageddon	Lower accuracy when playing with template compared to self-accuracy	16	1-20 Hz BPF	Linear Mixed Effect Model	[41]
EEG	SSVEP	Target selection	79% accuracy	6	1-30 Hz BPF	Canonical Correction Analysis	[37]
EEG	SSVEP	Spell by focusing on LED associated with desired command	Low Freq: adults>>children Med Freq: adults>youngest children High Freq: no significant difference	8	0.1 Hz HPF 552.96 Hz LPF	Bremen BCI Signal Processing Algorithm - Spatial Filter	[45]
EEG	mVEP	Control position of car in racing game through 5 different stimuli	68% average accuracy	12	10 Hz LPF	Linear Discriminant Analysis	[35]
EEG	Slow Cortical Potentials	SCP negativity/ positivity shift	Amplitudes for negativity trials changed significantly over time	3	40 Hz LPF	SCP Amplitude Calculation	[17]
EEG	Attention level (0-100%)	Harvest Challenge game	Enhanced sustained attention during gameplay	1	0.5-35 Hz BPF	θ/β ratio	[49]
EEG	Attention level (0-100%)	Engaging with stories	Improvements in attention span and decreases in hyperactivity behavior over time	1	-	MindWave Attention Metric	[44]

Table 1: Continued

EEG	Attention	Cogoland, increased focus meant increased efficiency of avatar in game	Significant reduction in ADHD-RS inattention scores	2	-	4-30 Hz Machine Learning Analysis	[42]
EEG	Attention	Cogoland, increased focus meant increased efficiency of avatar in game	improvement on ADHD-RS scale	4	-	4-30 Hz Machine Learning Analysis	[43]
EEG	β, α, θ waves	Maintain engagement while reading, enhanced by contextual training session	Recall score increased by 40.9% and quiz score increased by 26.8%	14	ICA	Frequency-Based Engagement Calculation	[39]
ECoG	γ band	Imagined hand opening/closing and phoneme tasks to control either Space Invaders, Pac-Man and/or Raiden X, or controlling robotic hand	mean accuracy: 81%	48-64	0-250 Hz BPF	Frequency-Based Decoding	[29]

3 Methods

The goal of this thesis was to adapt a system developed in the Laboratory for Non-invasive Brain-Machine Interface Systems at the University of Houston, that can be used for BCI system development for children by providing real-time data capture from EEG and joint angle sensors during treadmill walking while providing real-time visual feedback of the child's gait pattern via a digital avatar. To achieve this, a system was in MATLAB that initializes, acquires and synchronizes EEG and joint angles, and then, filters and sends joint angles to control the digital avatar and in parallel stores time-locked unprocessed EEG and joint angle data for offline processing.

During the trial, the subject would be walking at a slow, comfortable pace (1 mph) on a treadmill and facing a TV screen showing an avatar that is driven by goniometer sensors placed on the hip, knee, and ankle joints of the participants, thus, modeling their walking pattern. The EEG and joint angle data would be stored for offline analysis.

An online version of this system was built first by our group eight years ago and was used in experiments with healthy adults and adult stroke patients [27, 50, 51, 52, 53, 54, 55]. The avatar was built in Unity 3D, the system was built in C++, and the interface between the avatar and the system was written in C# . The avatar built for this system, shown in Fig 3, is representative of an adult.

Since many computer environment specifications, including operating systems, have changed since the C++ system was built, the decision was made to create a system for data collection in MATLAB that can interface with an avatar for visual feedback.

Figure 3: Virtual avatar mid-step.

3.1 Participant

Data collection was conducted with a pediatric subject (female, aged 12) with no history of neurological disease or lower limb pathology. The subject and her parents provided assent and informed consent respectively, for the subject's participation in the experiment. All experimental protocols and informed consent/assent were approved by the Institutional Review Board (IRB) at the University of Houston. All experiments were performed in accordance with the 45 Code of Federal Regulations (CFR) part 46 ("The Common Rule"), specifically addressing the protection of human study subjects as promulgated by the U.S. Department of Health and Human Services (DHHS).

3.2 System Specifications

3.2.1 Equipment Specifications

The two main sets of equipment for running this system are the EEG and goniometer hardware. To build and test the system, 64-channel EEG and six-channel joint angle data from six goniometers were used. EEG (ActiCap system, Brain Products GmbH, Germany) was sampled at 100Hz and transmitted to BrainVision Recorder, a recording software application from Brain Vision [56]. The EEG cap was set to use the extended 10-20 system with four channels (sensors originally at FT9, FT10, TP9, and TP10) used for electrooculography (EOG) recordings of eye movements and eye blinks. TP9 was placed above the left eye, TP10 was placed below the left eye, FT9 was placed to the left of the eye, and FT10 was placed to the right of the right eye. The EEG montage is shown in diagram of this setup is shown in Fig 10.

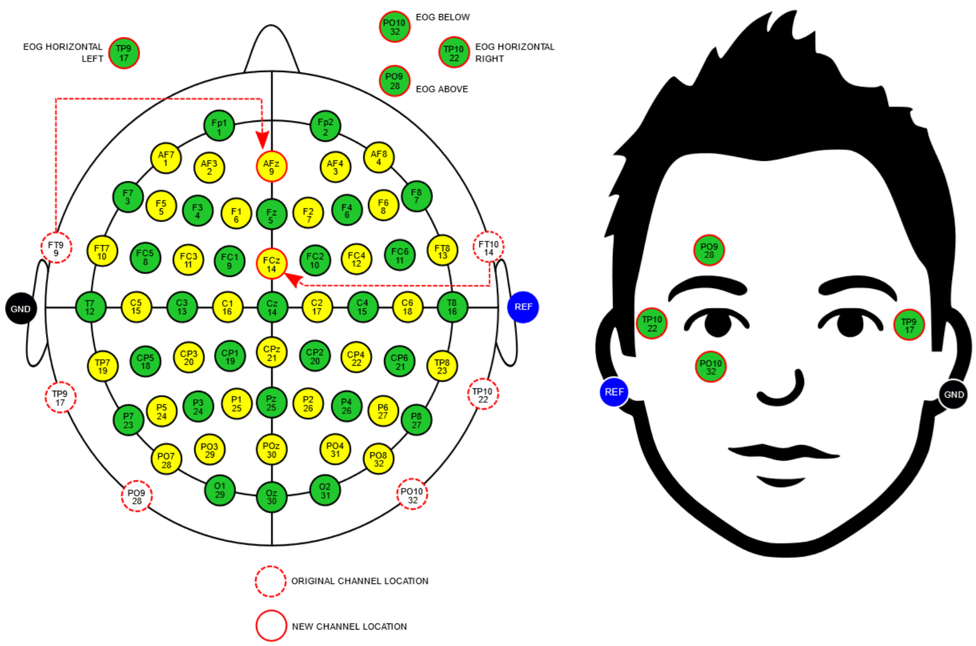

Figure 4: 60-channel EEG montage and 4 channel EOG montage outlining changes to 10-20 system.

The six goniometers (SG150 & SG110/A Gonio electrodes, Biometrics Ltd, UK), shown in Fig 5, were sampled at 1000Hz and transmitted to the Biometrics Analysis Application, a recording software application from Biometrics.

Figure 5: (A) Sagittal and (B) frontal view of the goniometers (Biometrics Ltd, UK) placed on the subject's hip, knee, and ankle joints. The joint centers were found through palpitation, and held in place through tape.

3.2.2 Software Specifications

For this system, a computer running Windows 11 OS and MATLAB 2021b (MathWorks, Natick, MA) were used. BrainVision Recorder (version 1.24.0101) and the Biometrics Analysis Application (version 10) are the applications used to interface with the EEG and goniometer hardware respectively. To bring the EEG and joint angle data to MATLAB, the Remote Data Access (RDA) and OnLine Interface (OLI) protocols were used. Version 2 (2013) of the RDA protocol and version 1 (2018) of the OLI protocol were used respectively [3, 2].

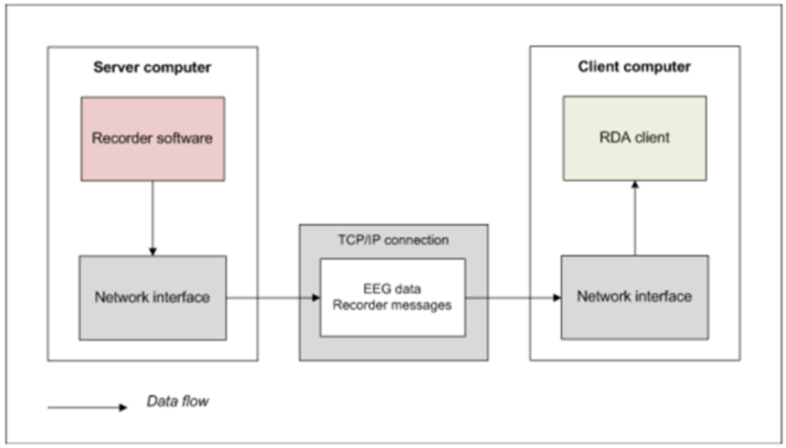

Figure 6: The Remote Data Access protocol utilizes the TCP/IP connection to send data between the BrainVision Recorder application and MATLAB, the RDA client [2].

The RDA protocol for BrainVision sets MATLAB as a client and allows MATLAB to access data from BrainVision Recorder through the Transmission Control Protocol/Internet Protocol (TCP/IP) toolbox (version 2.0.6) in MATLAB as shown in Fig 6 [57]. BrainVision Recorder sends MATLAB data packets every 20ms, and the amount of data sent depends on the sampling rate of the EEG. For a 100Hz sampling rate, 2 samples for each of the 64 channels are sent to MATLAB every 20ms.

The OnLine Interface utilizes a Dynamic Link Library (DLL) file to create a shared memory block between the Biometrics Analysis Application and MATLAB [3]. A representation of this relationship is shown in Fig 7.

3.3 System Components

The main components of the system are the processes used for raw data storage in parallel with avatar control for visual feedback. An overview of this system is shown in Fig 8.

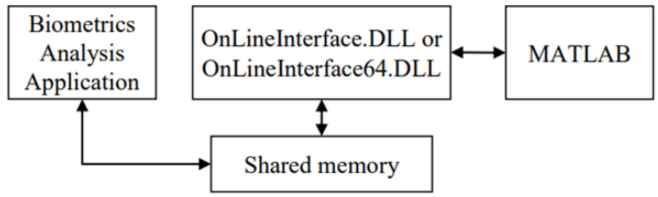

Figure 7: The OnLineInterface.dll creates a shared memory block between the Biometrics Analysis Application and MATLAB [3].

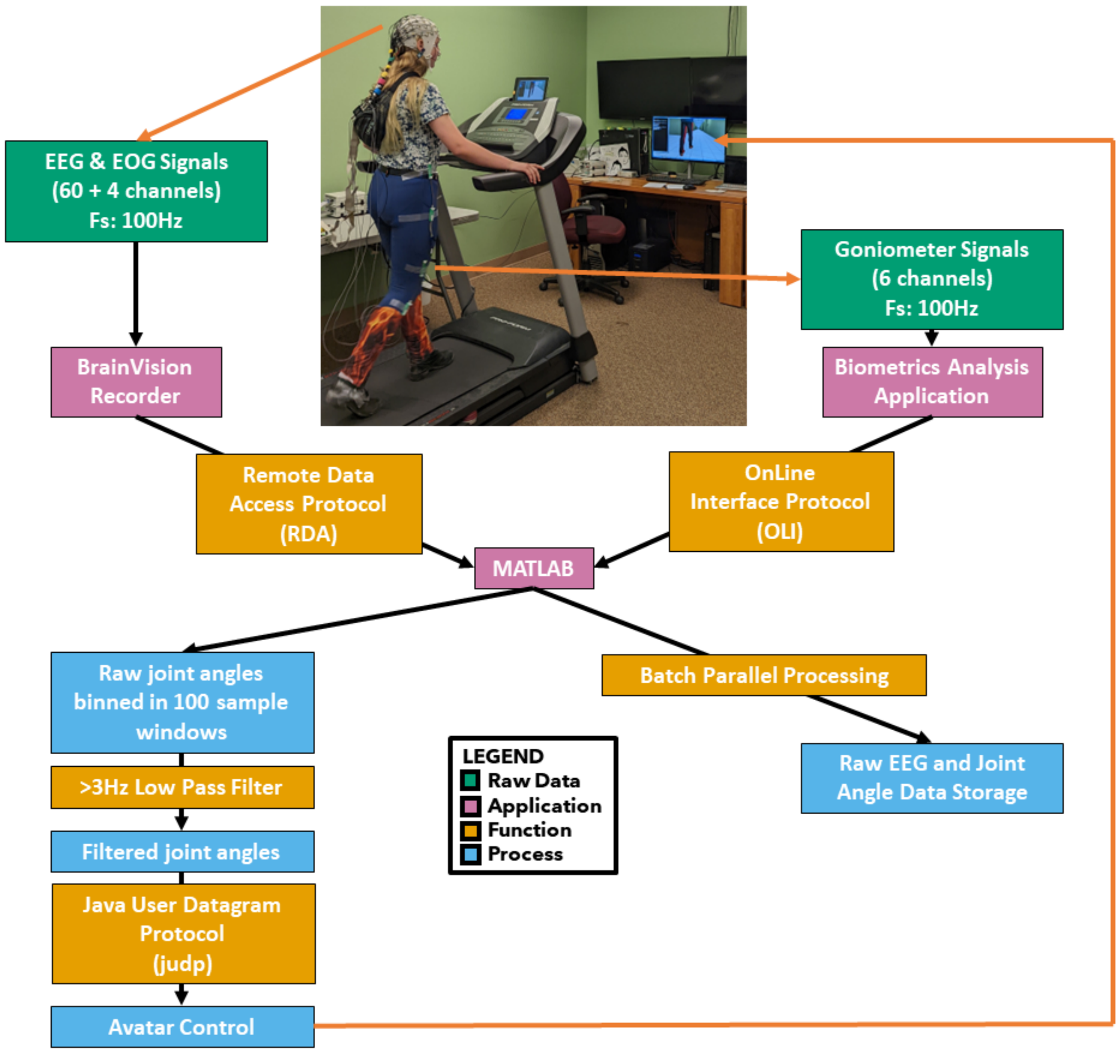

Figure 8: Flowchart of avatar system. Raw EEG and joint angles are sent to MATLAB from BrainVision Recorder and Biometrics Analysis Application respectively. In parallel, filtered joint angle data control the virtual avatar.

3.3.1 Visual Feedback Component

For the visual feedback component, raw joint angle data was stored in 100-sample windows to filter. Due to the slow walking speed, previous work shows that 0-3Hz covers the most power for the joint angle signals [58, 50]. Thus, a 3 Hz low pass filter was applied to the 100-sample bins, and this data was sent to the avatar using the 'judp' function. The 'judp' function uses MATLAB to call Java code to send/receive User Datagram Protocol (UDP) packets [59]. The avatar is an executable Unity 3D game, which can receive joint angle inputs through UDP packets. The avatar midstep is shown in Fig 3.

3.3.2 Data Storage Component

For the data storage component, MATLAB stored raw EEG and goniometer data as they enter the system as shown in Fig 8. Whenever MATLAB received data from BrainVision Recorder through the RDA protocol, the OLI protocol was executed to retrieve joint angle data from the Biometrics Analysis Application. The OLI protocol was executed within the RDA protocol, and raw EEG and goniometer data were stored through the same script. Once a new data packet arrives into the system, it is concatenated to the existing data array. This script was executed through MATLAB's 'batch' function (Parallel Processing Toolbox); it is used to run scripts or functions in parallel using a separate cluster worker [60]. The data storage component was executed in parallel with the visual feedback component. The data stored through this script would be used for offline analysis.

3.4 System Validation

To validate the system, the system components were tested separately before testing the system as a whole with a child. The data storage component was run for 25 minutes to check whether there would be any buffer overflow from concatenating incoming data with stored data; however, this was not an issue. The resulting data variables were of the size 64x149976 (EEG) and 6x149976 (joint angle). Both signals were sampled at 100Hz, so this was a 24.996 min run. This validation step is shown in Fig 9.

The visual feedback component was tested with each of the six goniometers to check that the filter was removing the power line and background noise, and that the goniometers were controlling the joints of the avatar. This was done by moving each goniometer individually and observing that the movement of the avatar joint followed the movement of the goniometer. Erratic movement would indicate incomplete noise removal; thus, it was also determined whether the avatar was moving smoothly. The avatar midstep is shown in Fig 3.

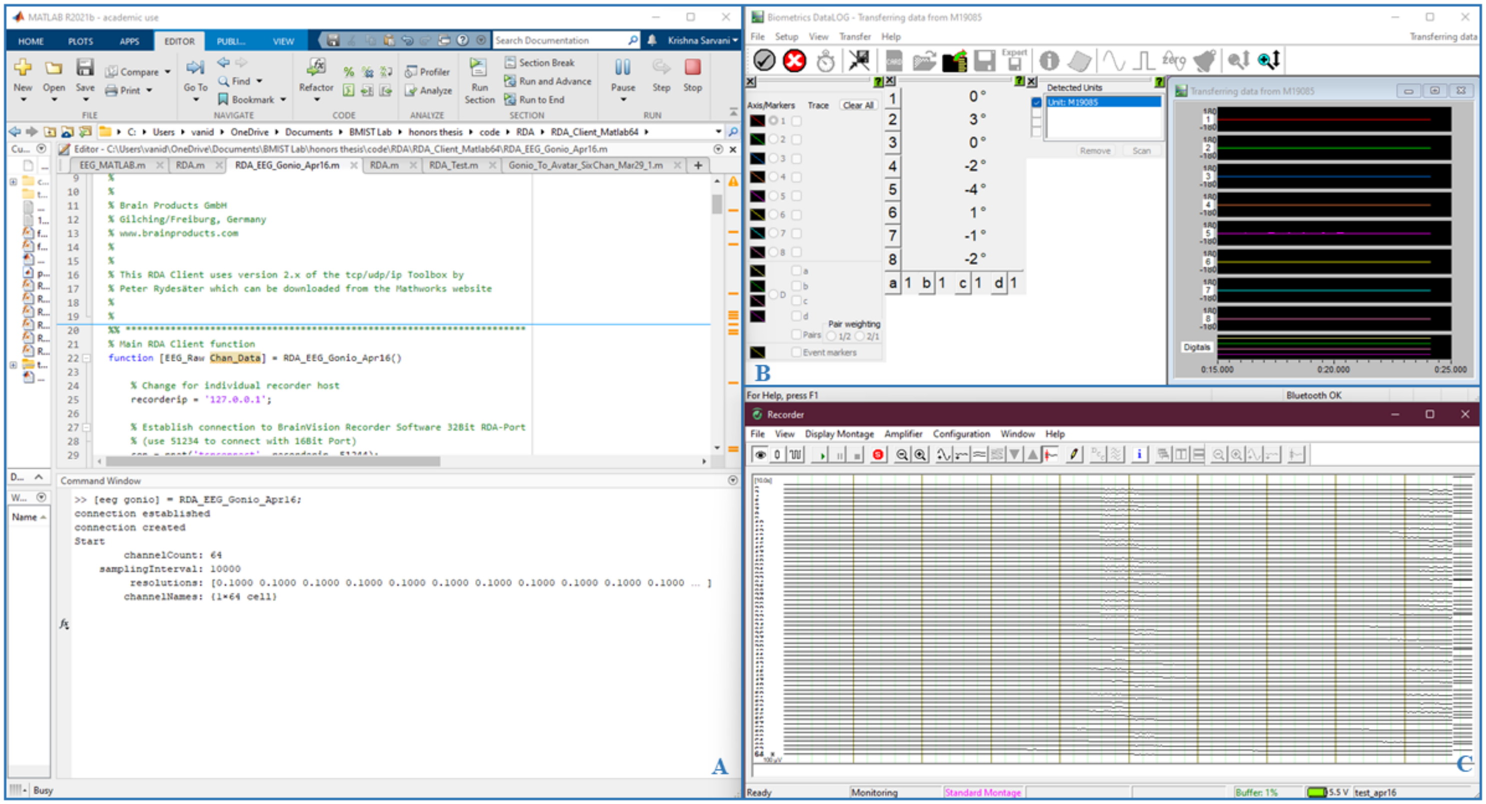

Figure 9: Data storage protocol of system. (A) MATLAB script and command window. (B) Biometrics Analysis Application window displaying joint angles. (C) BrainVision Recorder application window displaying EEG data by channel.

.

3.5 Data Collection with a Pediatric Subject

The subject (female, aged 12) was fitted with 60-channel EEG, four-channel EOG, and six goniometers on the hips, knees, and ankles. Channel impedances were recorded before and after the data collection, impedances were maintained below 60 kΩ. Customized 3D printed applicators were used to place the goniometers on the subject, which were attached with double-sided medical tape and held in place with surgical tape. The goniometers were placed such that the center of the goniometer spring was at the center of the joint, which was found via palpitation.

Prior to starting the trial, the goniometer measurements were zeroed when the subject stood upright. During the trial, the subject walked on a treadmill for 10 min at a slow pace (1 mph) while watching the avatar follow her gait pattern.

4 Results

To validate the system, one child (female, 12 years old) was recruited and participated in the study after providing assent (the parent provided informed consent). After setting up the EEG and placing the goniometers on the child and explaining the task to child, the system captured 10 min of raw EEG (60 channels), EOG (4 channels), and joint angle (6 channels) data, sampled at 100Hz. A 20s window of the raw EEG and EOG data is shown in Fig 10.

The raw joint angle data was (1) scaled according to the calibration protocol and (2) low-passed filtered with a 5^{th}-order butterworth filter with a cutoff frequency of 3Hz. A representation of the joint angles for each joint through the course of a gait cycle is shown in Fig 11. The gait trajectory follows the range for joint angles as described by Campbell et al. [4]. The ranges for the joints are: hip (-15 to 30°), knee (-20 to 70°), and ankle (-10 to 10°).

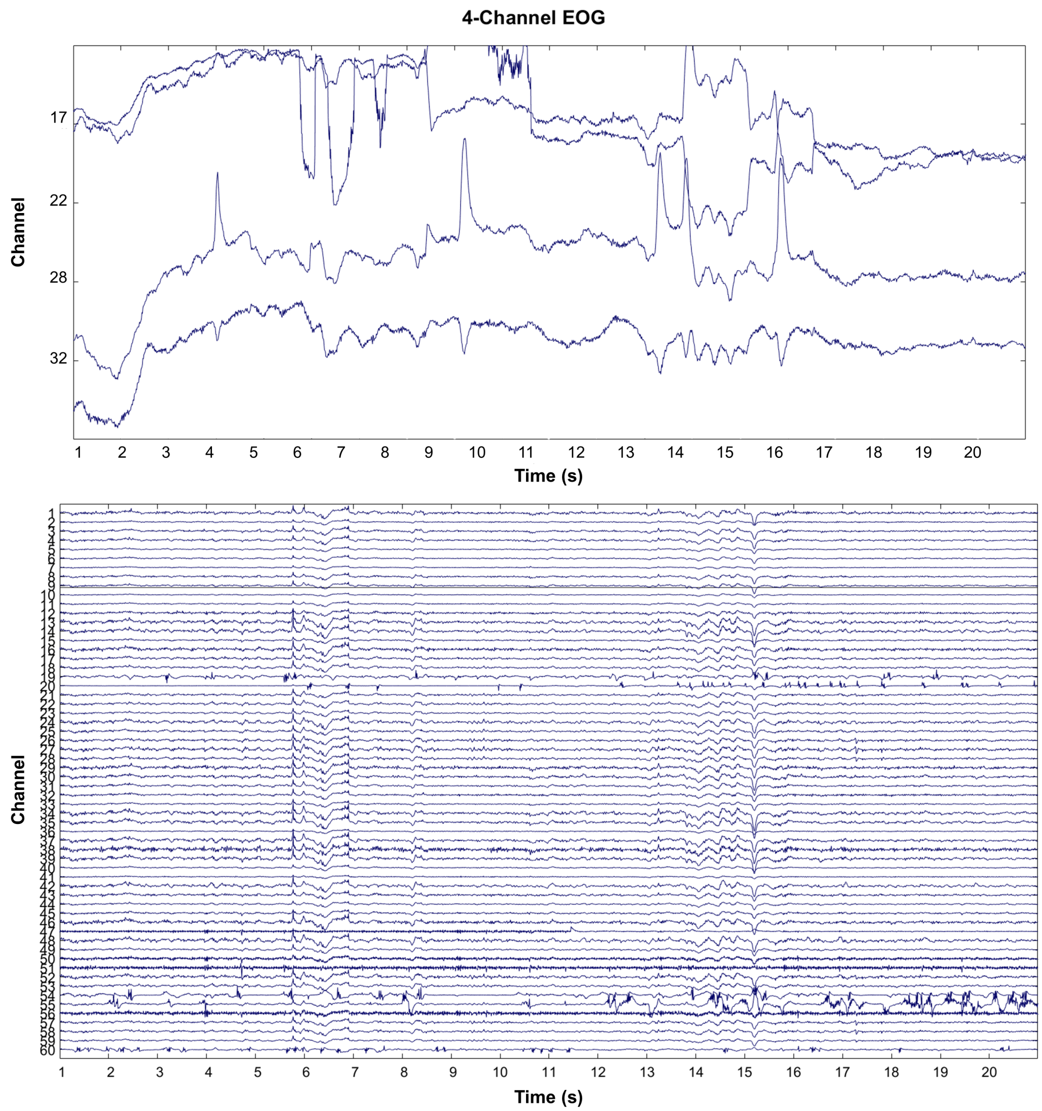

Figure 10: Unprocessed EOG (A) and EEG (B) data collected from subject. Data shown in a 20s window. Placement of EEG and EOG channels are shown in Fig 4.

5 Discussion and Conclusion

The objective of this thesis was to adapt a system that can be used for BCI system development for children that would provide real-time data capture from scalp electroencephalography (EEG) and joint angle sensors during treadmill walking while providing real-time visual feedback of the subject's gait pattern via a digital avatar.

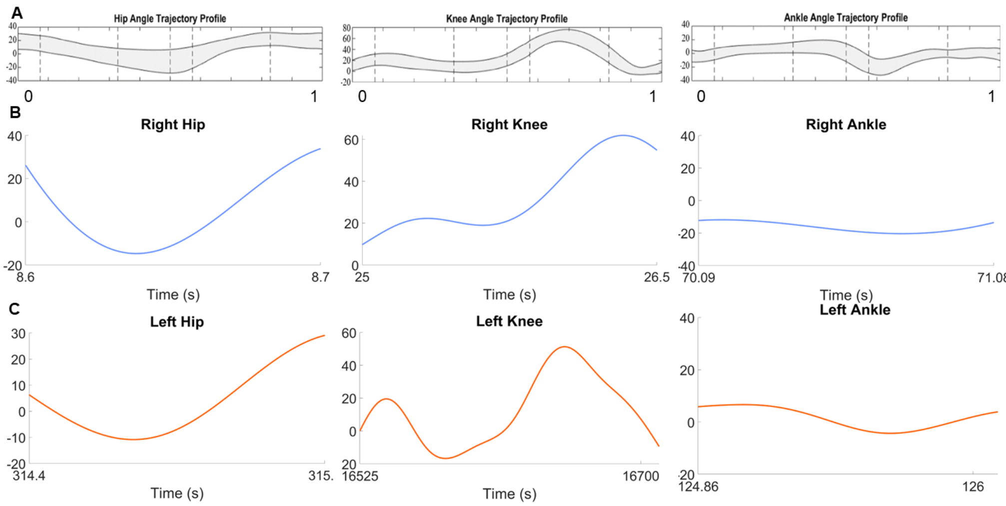

Figure 11: Gait trajectory profiles. Representation of one gait cycle (A) from Campbell et al. [4]. Right (B) and left (C) leg gait trajectories of subject from present study for hip, knee and ankle joints for 1 gait cycle.

For this goal, a system was created in the MATLAB programming environment that initializes, acquires and synchronizes EEG and joint angles, and then, filters and sends joint angles to control the digital avatar and in parallel store time-locked unprocessed EEG and joint angle data for offline processing.

5.1 Challenges

There were certain challenges that needed to be overcome in the development of the system described in this thesis. When using the original system (built in C++) described in He et al. [27], there were some issues with software versioning. Since the system was built almost eight years ago, many of the toolboxes and software application versions that were used as part of the program were transitioned out of use. This made recreating the programming environment necessary to successfully run the program was challenging. Thus, the decision was made to transition to a MATLAB-based version of the system since MATLAB toolboxes generally retain backwards and forwards compatibility between MATLAB versions.

Once the decision was made to build the system in MATLAB, the main challenge was the inter-operability between the various applications. Interfacing options such as the Remote Data Access Protocol (RDA) and OnLineInterface Protocol (OLI) exist for BrainVision Recorder and the Biometrics Analysis Application respectively; however, integrating them in an effective way proved to be a challenge since their internal mechanisms are different. The RDA protocol sends packets of data from BrainVision Recorder every 20ms, whereas the OLI protocol requires MATLAB to retrieve joint angle data by accessing the shared memory between the Biometrics Analysis Application and MATLAB.

There were also some challenges in learning how to properly use the EEG and goniometer hardware. It took many trials with lab members to learn how to efficiently set up the EEG system and how to check that all of the hardware components are functional. In addition, it was noted that the previous palpitation methods to determine the center of joints may be uncomfortable for the pediatric subject, so the suggestion of a prosthetist/orthotist was used for locating joint centers to place the goniometers.

Furthermore, the joint angles enter the MATLAB system with signs that are dependent on calibration; however, the signs associated with the original C++ system differ from the signs required for the MATLAB system. When conducting the trial with the pediatric subject, it was noted that the knee joints pf the digital avatar were moving in the opposite direction to the child's gait. This issue was fixed after the trial by testing the signs for the joint angles that send to the avatar.

5.2 Limitations of the System

There are multiple limitations to the system, including the sample size, sampling rate, and lack of decoder calibration post-trial. The validation of the system only involved a trial with a single subject and for one 10 min session only. The validation was in collecting and storing the data; however, this data was not analyzed for feature extraction or decoder calibration after the conclusion of the trial. Feature extraction and decoder calibration could use one of the methods described in Section 2, such as the use of support vector machine learning.

The sampling rate used for this system was 100Hz. This was due to hardware limitations that only allowed the collection of 200,000 samples for each of the EEG, EOG, and joint angle sensors. As a result, a sampling rate of 1000Hz (as is conventionally used for EEG data collection) would have only allowed for the collection of 3.5 min of data. Thus, the decision was made to use a sampling rate of 100Hz, which is usually used for closed-loop BCIs.

A closed-loop BCI was not implemented in this system, since it was used for data collection. Closed-loop BCI implementation would involve training a decoder after a data collection trial, and in a subsequent trial using the decoder to predict the joint angles from the EEG data in real-time and using those predicted angles to control the digital avatar.

5.3 Future Work

Future work would involve using this system to collect data from a larger sample size of typically developing children. Another aspect of improvement would include building a pediatric virtual avatar in a more engaging environment to keep the attention of the young subjects, and to interface this system with the pediatric avatar. This system would also be used for data collection with the pediatric population to determine the neural representations of motor control in children and use those features to design closed-loop BCI systems for rehabilitation.

References

[1] D. J. McFarland and J. R. Wolpaw, "Brain-computer interface operation of robotic and prosthetic devices," *Computer*, vol. 41, no. 10, pp. 52–56, 2008.

[2] BrainVision Recorder, "RDA client for matlab."

[3] Biometrics Ltd, "Using MATLAB with DataLITE, DataLOG and DataLINK."

[4] S. M. Campbell, C. P. Diduch, and J. W. Sensinger, "Autonomous assistance-as-needed control of a lower limb exoskeleton with guaranteed stability," *IEEE Access*, vol. 8, pp. 51 168–51 178, 2020.

[5] V. L. Feigin, E. Nichols, T. Alam, M. S. Bannick, E. Beghi, N. Blake, W. J. Culpepper, E. R. Dorsey, A. Elbaz, R. G. Ellenbogen, J. L. Fisher, C. Fitzmaurice, G. Guissani, L. Gelnnie, S. L. James, C. Owens Johnson, N. J. Kassebaum, G. Logroscino, B. Marin, W. C. Mountjoy-Venning, N. Minh, R. Ofori-Asenso, A. P. Patel, M. Piccininno, G. A. Roth, T. J. Steiner, L. J. Stovner, C. E. I. Szoeke, A. Theadom, S. E. Vollset, M. Taylor Wallin, C. Wright, J. Raymond Zunt, N. Abbasi, A. Foad Abd-Allah, Abdelalim, I. Abdollahpour, V. Aboyans, H. Niguse Abraha, D. Acharya, A. A. Adamu, O. M. Adebayo, A. Moshood Adeoye, J. C. Adsuar, M. Afarideh, S. Agrawal, A. Ahmadi, M. Beshir Ahmed, A. N. Aichour, I. Aichour, M. Taki Eddine Aichour, R. Olusola Akinyemi, N. Akseer, A. Al-Eyadhy, R. Al-Shahi salman, F. Alahdab, K. Addis Alene, S. Mohamed Aljunid, K. Altirkawi, N. Alvis-Guzman, N. Hamed Anber, C. Abelardo T Antonio, J. Arabloo, O. Aremu, J. Ärnlöv, H. Asayesh, R. Jawad Asghar, H. Tasew Atalay, A. Awasthi, B. Paulina Ayala Quintanilla, T. B. Ayuk, A. Badawi, M. Banach, J. Adel Mattar Banoub, M. A. Barboza, S. L. Barker-Collo, T. Winfried Bärnighausen, B. T. Baune, N. Bedi, M. Behzadifar, M. Behzadifar, Y. Béjot, B. Begashaw Bekele, A. Bekele Belachew,

D. A. Bennett, I. M. Bensenor, A. Berhane, M. Beuran, K. Bhattacharyya, Z. A. Bhutta, B. Biadgo, A. Bijani, N. Bililign, M. Shahdaat Bin Sayeed, C. Kynrint Blazes, C. Brayne, Z. A. Butt, I. R. Campos-Nonato, C. Cantu-Brito, M. Car, R. Cárdenas, J. J. Carrero, F. Carvalho, C. A. Castañeda-Orjuela, F. Castro, F. Catalá-López, E. Cerin, Y. Chaiah, J.-C. Chang, I. Chatziralli, P. Pei-Chia Chiang, H. Christensen, D. J. Christopher, C. Cooper, P. Angelo Cortesi, V. M. Costa, M. H. Criqui, C. Stephen Crowe, A. Antonio Moura Damasceno, A. Daryani, V. De la Cruz-Góngora, F. Pio De La Hoz, D. De Leo, M. Girma Degefa, G. Teklemariam Demoz, K. Deribe, S. D. Dharmaratne, D. Diaz, M. Tadese Dinberu, S. Djalalinia, D. Teye Doku, M. Dubey, E. Dubljanin, E. Ejeta Duken, D. Edvardsson, Z. El-Khatib, M. Endres, A. Yesuf Endries, S. Eskandarieh, A. Esteghamati, S. Esteghamati, F. Farhadi, A. Faro, F. Farzadfar, M. Hosein Farzaei, B. Fatima, S.-M. Fereshtehnejad, E. Fernandes, G. Tolu Feyissa, I. Filip, F. Fischer, T. Fukumoto, M. Ganji, F. Gbetoho Gankpe, M. A. Garcia-Gordillo, A. Kahsu Gebre, T. Gebrehiwo Gebremichael, B. K. Gelaw, J. M. Geleijnse, D. Geremew, K. Embaye Gezae, M. Ghasemi-Kasman, M. Y. Gidey, P. Singh Gill, T. K. Gill, E. V. Gnedovskaya, A. C. Goulart, A. Grada, G. Grosso, Y. Guo, R. Gupta, R. Gupta, J. A. Haagsma, T. B. Hagos, A. Haj-Mirzaian, A. Haj-Mirzaian, R. R. Hamadeh, S. Hamidi, G. J. Hankey, Y. Hao, J. Maria Haro, H. Hassankhani, H. Yimam Hassen, R. Havmoeller, S. I. Hay, M. I. Hegazy, B. Heidari, A. Henok, F. Heydarpour, C. Linh Hoang, M. K. Hole, E. Homaie Rad, S. Mostafa Hosseini, G. Hu, E. U. Igumbor, O. Stephen Ilesanmi, S. Sina Naghibi Irvani, S. Mohammed Shariful Islam, M. Jakovljevic, M. Javanbakht, R. Prakash Jha, Y. B. Jobanputra, J. B. Jonas, J. Jerzy Jóźwiak, M. Jürisson, A. Kahsay, R. Kalani, Y. Kalkonde, T. Abegaz Kamil, T. Kanchan, M. Karami, A. Karch, N. Karimi,

A. Kasaeian, T. Dessale Kassa, Z. Yohannes Kassa, A. Kaul, A. Teshome Kefale, P. Njenga Keiyoro, Y. Saleh Khader, M. Abdullatif Khafaie, I. A. Khalil, E. Ahmad Khan, Y.-H. Khang, H. Khazaie, A. A. Kiadaliri, D. N. Kiirithio, A. S. Kim, D. Kim, Y.-E. Kim, Y. Jin Kim, A. Kisa, Y. Kokubo, A. Koyanagi, R. V. Krishnamurthi, B. Kuate Defo, B. Kucuk Bicer, M. Kumar, B. Lacey, A. Lafranconi, V. C. Lansingh, A. Latifi, C. Tesema Leshargie, S. Li, Y. Liao, S. Linn, W. David Lo, J. Christian F Lopez, S. Lorkowski, P. A. Lotufo, R. M. Lucas, R. Lunevicius, M. T. Mackay, N. Bahadur Mahotra, M. Majdan, R. Majdzadeh, A. Majeed, R. Malekzadeh, D. Carvalho Malta, N. Manafi, M. Ali Mansournia, L. Giovanni Mantovani, W. März, T. Phosa Mashamba-Thompson, B. Ballard Massenburg, K. K V Mate, C. McAlinden, J. J. McGrath, V. Mehta, T. Meier, H. Gebre Meles, A. Melese, P. T. N. Memiah, Z. A. Memish, W. Mendoza, D. Tadese Mengistu, G. Mengistu, A. Meretoja, T. J. Meretoja, T. Mestrovic, B. Miazgowski, T. Miazgowski, T. R. Miller, G. Mini, E. M. Mirrakhimov, B. Moazen, B. Mohajer, N. Mohammad Gholi Mezerji, M. Mohammadi, M. Mohammadi-Khanaposhtani, R. Mohammadibakhsh, M. Mohammadnia-Afrouzi, S. Mohammed, F. Mohebi, A. H. Mokdad, L. Monasta, S. Mondello, Y. Moodley, M. Moosazadeh, G. Moradi, M. Moradi-Lakeh, M. Moradinazar, P. Moraga, I. Moreno Velásquez, S. Douglas Morrison, S. Meysam Mousavi, O. Sada Muhammed, W. Muruet, K. Imran Musa, G. Mustafa, M. Naderi, G. Nagel, A. Naheed, G. Naik, F. Najafi, V. Nangia, I. Negoi, R. Irina Negoi, C. Richard, J. Newton, J. W. Ngunjiri, C. Tat Nguyen, L. Hoang Nguyen, D. Nur Anggraini Ningrum, Y. Legesse Nirayo, M. R. Nixon, B. Norrving, J. Jacques Noubiap, M. Nourollahpour Shiadeh, P. S. Nyasulu, F. Akpojene Ogbo, I.-H. Oh, A. T. Olagunju, T. O. Olagunju, P. R. Olivares, O. E. Onwujekwe, E. Oren, M. Ojo Owolabi, M. P A, A. H. Pakpour, W.-H. Pan, S. Panda-Jonas, J. Durai Pandian, S. Kishor Patel, D. M.

Pereira, M. Petzold, J. David Pillay, M. A. Piradov, G. V. Polanczyk, S. Polinder, M. J. Postma, R. Poulton, H. Poustchi, S. Prakash, V. Prakash, M. Qorbani, A. Radfar, A. Rafay, A. Rafiei, F. Rahim, V. Rahimi-Movaghar, M. Rahman, M. Hifz Ur Rahman, M. Aziz Rahman, R. U. Ram, A. Ranta, D. Laith Rawaf, S. Rawaf, N. Reinig, C. Reis, A. M. N. Renzaho, S. Resnikoff, S. Rezaeian, M. Sadegh Rezai, C. Miguel Rios González, N. L. S. Roberts, L. Roever, L. Ronfani, E. Merdassa Roro, G. Roshandel, A. Rostami, P. Sabbagh, R. L. Sacco, P. S. Sachdev, B. Saddik, R. Safari, Hosein Safari-Faramani, S. Safi, S. Safiri, R. Sagar, R. Sahathevan, A. Sahebkar, M. Ali Sahraian, P. Salamati, S. Salehi Zahabi, Y. Salimi, A. M. Samy, J. Sanabria, I. S. Santos, N. Santric Milicevic, Milena M Sarrafzadegan, B. Sartorius, S. Sarvi, B. Sathian, M. Satpathy, A. R. Sawant, M. Sawhney, I. J. C. Schneider, D. C. Schöttker, Ben Schwebel, S. Seedat, S. G. Sepanlou, H. Shabaninejad, A. Shafieesabet, M. Ali Shaikh, R. A. Shakir, M. Shams-Beyranvand, M. Shamsizadeh, M. Sharif, M. Sharif-Alhoseini, J. She, A. Sheikh, K. N. Sheth, M. Shigematsu, R. Shiri, R. Shirkoohi, I. Shiue, S. Siabani, T. J. Siddiqi, I. Dora Sigfusdottir, R. Sigurvinsdottir, D. H. Silberberg, J. P. Silva, D. G. Alves Silveira, J. A. Singh, D. N. Sinha, E. Skiadaresi, M. Smith, B. Hasan Sobaih, S. Sobhani, M. Soofi, I. N. Soyiri, L. A. Sposato, D. J. Stein, M. B. Stein, M. A. Stokes, M. Babale Sufiyan, B. L. Sykes, P. Sylaja, R. Tabarés-Seisdedos, B. J. Te Ao, A. Tehrani-Banihashemi, M.-H. Temsah, O. Temsah, J. Singh Thakur, A. G. Thrift, R. Topor-Madry, M. Tortajada-Girbés, M. R. Tovani-Palone, K. Xuan Tran, Bach Bao Tran, T. Clement Truelsen, A. Gebremeskel Tsadik, L. Tudor Car, K. Nnanna Ukwaja, I. Ullah, M. Shariq Usman, l. A. Uthman, P. R. Valdez, T. Juhani Vasankari, R. Vasanthan, Y. Veisani, N. Venketasubramanian, F. S. Violante, V. Vlassov, K. Vosoughi, G. T. Vu, I. S. Vujcic, F. S. Wagnew, Y. Waheed, Y.-P. Wang, E. Weiderpass, J. Weiss, H. A. Whiteford, T. Wijeratne, A. S. Winkler, C. Shey Wiysonge, C. D. A. Wolfe,

G. Xu, A. Yadollahpour, T. Yamada, Y. Yano, M. Yaseri, H. Yatsuya, E. M. Yimer, P. Yip, E. Yisma, N. Yonemoto, M. Yousefifard, C. Yu, Z. Zaidi, S. B. Zaman, M. Zamani, H. Zandian, Z. Zare, Y. Zhang, S. Zodpey, M. Naghavi, C. J. L. Murray, and T. Vos, "Global, regional, and national burden of neurological disorders, 1990–2016: a systematic analysis for the global burden of disease study 2016," *The Lancet Neurology*, vol. 18, no. 5, pp. 459–480, 2019.

[6] "Cerebral Palsy - CDC," Dec 2020.

[7] "Spina bifida - CDC," Sep 2020.

[8] E. Fosch-Villaronga, A. Čartolovni, and R. L. Pierce, "Promoting inclusiveness in exoskeleton robotics: addressing challenges for pediatric access," *Paladyn, Journal of Behavioral Robotics*, vol. 11, no. 1, pp. 327–339, 2020.

[9] V. L. Rose and C. J. Arellano, "Simple models highlight differences in the walking biomechanics of young children and adults," *Journal of Experimental Biology*, vol. 224, no. 22, p. jeb243040, 2021.

[10] I. Novak, C. Morgan, L. Adde, J. Blackman, R. N. Boyd, J. Brunstrom-Hernandez, G. Cioni, D. Damiano, J. Darrah, A.-C. Eliasson, L. S. de Vries, C. Einspieler, M. Fahey, D. Fehlings, D. M. Ferriero, L. Fetters, S. Fiori, H. Forssberg, A. M. Gordon, S. Greaves, A. Guzzetta, M. Hadders-Algra, R. Harbourne, A. Kakooa-Mwesige, P. Karlsson, L. Krumlinde-Sundholm, B. Latal, A. Loughran-Fowlds, N. Maitre, S. McIntrye, G. Noritz, L. Pennington, D. M. Romeo, R. Shepher, A. J. Spittle, M. Thornton, J. Valentine, K. Walker, R. White, and N. Badawi, "Early, accurate diagnosis and early intervention in cerebral palsy: advances in diagnosis and treatment," *JAMA Pediatrics*, vol. 171, no. 9, pp. 897–907, 2017.

[11] D. Eguren, M. Cestari, T. P. Luu, A. Kilicarslan, A. Steele, and J. L. Contreras-Vidal, "Design of a customizable, modular pediatric exoskeleton for rehabilitation and mobility," in *2019 IEEE International Conference on Systems, Man and Cybernetics (SMC)*. IEEE, 2019, pp. 2411–2416.

[12] T.-W. Kim and B.-H. Lee, "Clinical usefulness of brain-computer interface-controlled functional electrical stimulation for improving brain activity in children with spastic cerebral palsy: a pilot randomized controlled trial," *Journal of Physical Therapy Science*, vol. 28, no. 9, pp. 2491–2494, 2016.

[13] J. J. Daly and J. E. Huggins, "Brain-computer interface: current and emerging rehabilitation applications," *Archives of Physical Medicine and Rehabilitation*, vol. 96, no. 3, pp. S1–S7, 2015.

[14] J. R. Wolpaw, D. J. McFarland, G. W. Neat, and C. A. Forneris, "An eeg-based brain-computer interface for cursor control," *Electroencephalography and Clinical Neurophysiology*, vol. 78, no. 3, pp. 252–259, 1991.

[15] D. J. Krusienski and J. J. Shih, "Control of a visual keyboard using an electrocorticographic brain–computer interface," *Neurorehabilitation and Neural Repair*, vol. 25, no. 4, pp. 323–331, 2011.

[16] A. Kilicarslan, S. Prasad, R. G. Grossman, and J. L. Contreras-Vidal, "High accuracy decoding of user intentions using eeg to control a lower-body exoskeleton," in *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2013, pp. 5606–5609.

[17] U. Strehl, U. Leins, G. Goth, C. Klinger, T. Hinterberger, and N. Birbaumer, "Self-regulation of slow cortical potentials: a new treatment for children with attention-deficit/hyperactivity disorder," *Pediatrics*, vol. 118, no. 5, pp. e1530–e1540, 2006.

[18] M. Torrisi, M. C. De Cola, A. Buda, L. Carioti, M. V. Scaltrito, P. Bramanti, A. Manuli, R. De Luca, and R. S. Calabrò, "Self-efficacy, poststroke depression, and rehabilitation outcomes: is there a correlation?" *Journal of Stroke and Cerebrovascular Diseases*, vol. 27, no. 11, pp. 3208–3211, 2018.

[19] N. A. Bhagat, N. Yozbatiran, J. L. Sullivan, R. Paranjape, C. Losey, Z. Hernandez, Z. Keser, R. Grossman, G. E. Francisco, M. K. O'Malley *et al.*, "Neural activity modulations and motor recovery following brain-exoskeleton interface mediated stroke rehabilitation," *NeuroImage: Clinical*, vol. 28, p. 102502, 2020.

[20] E. C. Leuthardt, G. Schalk, J. R. Wolpaw, J. G. Ojemann, and D. W. Moran, "A brain–computer interface using electrocorticographic signals in humans," *Journal of Neural Engineering*, vol. 1, no. 2, p. 63, 2004.

[21] J. R. Wolpaw and D. J. McFarland, "Multichannel eeg-based brain-computer communication," *Electroencephalography and Clinical Neurophysiology*, vol. 90, no. 6, pp. 444–449, 1994.

[22] C. S. Herrmann, "Human eeg responses to 1–100 hz flicker: resonance phenomena in visual cortex and their potential correlation to cognitive phenomena," *Experimental Brain Research*, vol. 137, no. 3, pp. 346–353, 2001.

[23] G. Onose, C. Grozea, A. Anghelescu, C. Daia, C. J. Sinescu, A. V. Ciurea, T. Spircu, A. Mirea, I. Andone, C. Spânu, A Popescu, A.-S. Mihaescu, S. Fazli, M. Danoczy, and P. F, "On the feasibility of using motor imagery eeg-based brain–computer interface in chronic tetraplegics for assistive robotic arm control: a clinical test and long-term post-trial follow-up," *Spinal Cord*, vol. 50, no. 8, pp. 599–608, 2012.

[24] G. Beraldo, A. Suppiej, C. Forest, L. Tonin, and E. Menegatti, "Brain-computer interface for children: state-of-the-art and challenges," in *2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*. IEEE, 2020, pp. 24–29.

[25] B. R. King, M. A. Oliveira, J. L. Contreras-Vidal, and J. E. Clark, "Development of state estimation explains improvements in sensorimotor performance across childhood," *Journal of Neurophysiology*, vol. 107, no. 11, pp. 3040–3049, 2012.

[26] D. Kelly, E. Zewdie, and A. Kirton, "Pediatric brain-computer interface competency: A pilot study." in *GBCIC*, 2019.

[27] Y. He, T. P. Luu, K. Nathan, S. Nakagome, and J. L. Contreras-Vidal, "A mobile brain-body imaging dataset recorded during treadmill walking with a brain-computer interface," *Scientific Data*, vol. 5, no. 1, pp. 1–10, 2018.

[28] M. J. Page, J. E. McKenzie, P. M. Bossuyt, I. Boutron, T. C. Hoffmann, C. D. Mulrow, L. Shamseer, J. M. Tetzlaff, E. A. Akl, S. E. Brennan, R. Chou, J. Glanville, J. M. Grimshaw, A. Hróbjartsson, M. M. Lalu, T. Li, E. W. Loder, E. Mayo-Wilson, S. McDonald, L. A. McGuinness, L. A. Stewart, J. Thomas, A. C. Tricco, V. A. Welch, P. Whiting, and D. Moher, "The prisma 2020 statement: An updated guideline for reporting systematic reviews," *International Journal of Surgery*, vol. 88, p. 105906, 2021.

[29] J. D. Breshears, C. M. Gaona, J. L. Roland, M. Sharma, N. R. Anderson, D. T. Bundy, Z. V. Freudenburg, M. D. Smyth, J. Zempel, D. D. Limbrick, W. D. Smart, and E. C. Leuthardt, "Decoding motor signals from the pediatric cortex: implications for brain-computer interfaces in children," *Pediatrics*, vol. 128, no. 1, pp. e160–e168, 2011.

[30] W. Sałabun, "Processing and spectral analysis of the raw eeg signal from the mindwave," *Przeglad Elektrotechniczny*, vol. 90, no. 2, pp. 169–174, 2014.

[31] T. W. Picton, "The p300 wave of the human event-related potential," *Journal of Clinical Neurophysiology*, vol. 9, no. 4, pp. 456–479, 1992.

[32] N. Birbaumer, T. Elbert, A. G. Canavan, and B. Rockstroh, "Slow potentials of the cerebral cortex and behavior." *Physiological Reviews*, vol. 70, no. 1, pp. 1–41, 1990.

[33] B. Rockstroh, T. Elbert, W. Lutzenberger, and N. Birbaumer, "Biofeedback: Evaluation and therapy in children with attentional dysfunctions," in *Brain and Behavior in Child Psychiatry.* Springer, 1990, pp. 345–357.

[34] L. G. Faber, N. M. Maurits, and M. M. Lorist, "Mental fatigue affects visual selective attention," *PloS one*, vol. 7, no. 10, p. e48073, 2012.

[35] R. Beveridge, S. Wilson, M. Callaghan, and D. Coyle, "Neurogaming with motion-onset visual evoked potentials (mveps): adults versus teenagers," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 4, pp. 572–581, 2019.

[36] G. Pires, M. Torres, N. Casaleiro, U. Nunes, and M. Castelo-Branco, "Playing tetris with non-invasive bci," in *2011 IEEE 1st International Conference on Serious Games and Applications for Health (SEGAH).* IEEE, 2011, pp. 1–6.

[37] J. J. Norton, J. Mullins, B. E. Alitz, and T. Bretl, "The performance of 9–11-year-old children using an ssvep-based bci for target selection," *Journal of Neural Engineering*, vol. 15, no. 5, p. 056012, 2018.

[38] J. Ginter Jr, K. Blinowska, M. Kamiński, P. Durka, G. Pfurtscheller, and C. Neuper, "Propagation of eeg activity in the beta and gamma band during movement

imagery in humans," *Methods of Information in Medicine*, vol. 44, no. 01, pp. 106–113, 2005.

[39] J. Huang, C. Yu, Y. Wang, Y. Zhao, S. Liu, C. Mo, J. Liu, L. Zhang, and Y. Shi, "Focus: enhancing children's engagement in reading by using contextual bci training sessions," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2014, pp. 1905–1908.

[40] D. A. Rohani, H. B. Sorensen, and S. Puthusserypady, "Brain-computer interface using p300 and virtual reality: a gaming approach for treating adhd," in *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE, 2014, pp. 3606–3609.

[41] M. Fouillen, E. Maby, M. Partyka, V. Herbillon, and J. Mattout, "Performance, transfer learning and underlying physiology in children playing p300 bci games." in *GBCIC*, 2019.

[42] X. Qian, B. R. Y. Loo, F. X. Castellanos, S. Liu, H. L. Koh, X. W. W. Poh, R. Krishnan, D. Fung, M. W. Chee, C. Guan, T.-S. Lee, C. G. Lim, and J. Zhou, "Brain-computer-interface-based intervention re-normalizes brain functional network topology in children with attention deficit/hyperactivity disorder," *Translational Psychiatry*, vol. 8, no. 1, pp. 1–11, 2018.

[43] C. G. Lim, T. S. Lee, C. Guan, D. S. S. Fung, Y. Zhao, S. S. W. Teng, H. Zhang, and K. R. R. Krishnan, "A brain-computer interface based attention training program for treating attention deficit hyperactivity disorder," *PloS One*, vol. 7, no. 10, p. e46692, 2012.

[44] K. Park, T. Kihl, S. Park, M.-J. Kim, and J. Chang, "Fairy tale directed game-based training system for children with adhd using bci and motion sensing technologies," *Behaviour & Information Technology*, vol. 38, no. 6, pp. 564–577, 2019.

[45] J. Ehlers, D. Valbuena, A. Stiller, and A. Gräser, "Age-specific mechanisms in an ssvep-based bci scenario: evidences from spontaneous rhythms and neuronal oscillators," *Computational Intelligence and Neuroscience*, vol. 2012, 2012.

[46] G. Beraldo, S. Tortora, and E. Menegatti, "Towards a brain-robot interface for children," in *2019 IEEE International Conference on Systems, Man and Cybernetics (SMC)*. IEEE, 2019, pp. 2799–2805.

[47] D. Pappas, "Adhd rating scale-iv: Checklists, norms, and clinical interpretation," *Journal of Psychoeducational Assessment*, vol. 24, no. 2, pp. 172–178, 2006.

[48] L. Vareka, T. Prokop, J. Stebeták, and R. Moucek, "Guess the number-applying a simple brain-computer interface to school-age children." in *BIOSIGNALS*, 2016, pp. 263–270.

[49] D. Z. Blandón, J. E. Muñoz, D. S. Lopez, and O. H. Gallo, "Influence of a bci neurofeedback videogame in children with adhd. quantifying the brain activity through an eeg signal processing dedicated toolbox," in *2016 IEEE 11th Colombian Computing Conference (CCC)*. IEEE, 2016, pp. 1–8.

[50] T. P. Luu, Y. He, S. Brown, S. Nakagome, and J. L. Contreras-Vidal, "A closed-loop brain computer interface to a virtual reality avatar: Gait adaptation to visual kinematic perturbations," in *2015 International Conference on Virtual Rehabilitation (ICVR)*. IEEE, 2015, pp. 30–37.

[51] T. Luu, Y. He, S. Brown, S. Nakagome, and J. Contreras-Vidal, "Gait adaptation to visual kinematic perturbations using a real-time closed-loop brain–computer

interface to a virtual reality avatar," *Journal of Neural Engineering*, vol. 13, no. 3, p. 036006, 2016.

[52] T. P. Luu, Y. He, S. Nakagame, J. Gorges, K. Nathan, and J. L. Contreras-Vidal, "Unscented kalman filter for neural decoding of human treadmill walking from non-invasive electroencephalography," in *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2016, pp. 1548–1551.

[53] T. P. Luu, Y. He, S. Nakagome, and J. L. Contreras-Vidal, "Eeg-based brain-computer interface to a virtual walking avatar engages cortical adaptation," in *2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*. IEEE, 2017, pp. 3054–3057.

[54] T. P. Luu, Y. He, S. Nakagome, K. Nathan, S. Brown, J. Gorges, and J. L. Contreras-Vidal, "Multi-trial gait adaptation of healthy individuals during visual kinematic perturbations," *Frontiers in Human Neuroscience*, vol. 11, p. 320, 2017.

[55] T. P. Luu, S. Nakagome, Y. He, and J. L. Contreras-Vidal, "Real-time eeg-based brain-computer interface to a virtual avatar enhances cortical involvement in human treadmill walking," *Scientific Reports*, vol. 7, no. 1, pp. 1–12, 2017.

[56] "Brainvision Recorder," Mar 2021.

[57] P. Rydesater, "TCP/UDP/IP toolbox 2.0.6," 2022.

[58] E. K. Antonsson and R. W. Mann, "The frequency content of gait," *Journal of Biomechanics*, vol. 18, no. 1, pp. 39–47, 1985.

[59] K. Bartlett, "A simple UDP communications application - MATLAB," 2022.

[60] "Batch - MATLAB."