NuroMotus: An Intelligent Exoskeleton System to Improve Cerebral Palsy Patient Mobility Using Brain Computer Interface

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ABSTRACT

Cerebral palsy (CP) is a neurological disorder affecting approximately 18 million individuals worldwide, severely compromising their mobility due to muscle spasticity and stiffness. While exoskeletons hold promise in restoring mobility to CP patients, their current application remains confined to clinical settings, primarily due to two significant challenges. Firstly, exoskeletons typically offer fixed assistance, limiting their adaptability to various essential movements, such as sitting or ascending stairs. Secondly, they introduce a competing dynamic with the patient's natural muscle functions. To address these challenges, this research project, NeuroMotus, leverages brain-computer interface to predict patient movements and deliver exoskeleton assistance based on angular data of leg joints. The system relies on decoding the intent signals generated by CP patients, which are captured directly from the brain's surface to anticipate forthcoming movements. It employs a customized procedure to isolate and train the NeuroMotus system by segmenting the 2-second period preceding voluntary movement, known as intent or bereitschaftspotential (BP). To gather the BP data, I designed an advanced and tailored EEG head cap equipped with five strategically positioned electrodes across the motor cortex.

The NeuroMotus algorithm that is trained on brain signals related to five crucial daily movements demonstrated an impressive 87% accuracy in predicting these movements. It optimizes exoskeletons in real-time by detecting movement intentions, calculating necessary leg joint angular rotations, and sending instructions to a virtual exoskeleton. This iterative process aims to enhance the mobility range of exoskeletons for individuals with cerebral palsy, promoting a seamless interaction between patients and their assistive devices. NeuroMotus represents a pioneering approach to improving the lives of CP patients by expanding their mobility and functionality in real-world scenarios. Integrating cutting-edge technology and neuroscience principles, this research has the potential to significantly enhance the quality of life for individuals living with cerebral palsy.

KEYWORDS

Cerebral Palsy, Bereitschaftspotential, Motor Cortex, Brain Computer Interface

INTRODUCTION

Cerebral palsy is a group of movement based disorders that primarily appears in childhood [1]. It is caused by abnormal brain development or brain damage in which parts of the brain that work on the body's mobility, posture, and balance underperform. The core of the problem is that a child with CP's brain that controls the basic motor functions of a child sends mixed and delayed signals affecting the way a child moves. About 3.6/1000 children develop some type of cerebral palsy in early childhood, making cerebral palsy the most common disorder among children. A child with CP can face numerous symptoms including weak muscles, muscle tension, and tremors. Spastic cerebral palsy, accounting for the majority of cases, is caused by damage to the brains motor cortex and pyramidal tracts which relays signals to the muscles [2]. That specifically causes the muscles of a child to experience a problem known as hypertension. Some of the common symptoms of spastic cerebral palsy include abnormal walking, involuntary movements, contractures, and stiffness.

Exoskeletons

In terms of rehabilitation exoskeletons have shown significant promise in restoring a CP patient's lost mobility [3, 16]. Exoskeletons are wearable devices that provide external support to the body and can assist with movement. For individuals with cerebral palsy, exoskeletons have the potential to offer several benefits: improved mobility, increased independence, and improved quality of life. Exoskeletons designed for individuals with mobility impairments such as cerebral palsy usually include knee and ankle actuators. These actuators are triggered on a stance and swing basis. During the stance phase, when the foot is in contact with the ground, the actuators provide support and stability to the leg. In the swing phase, when the foot is off the ground, the actuators provide assistance in lifting the leg to take the next step. This functionality is essential for individuals with cerebral palsy who have difficulty walking due to muscle weakness, poor coordination, or spasticity. By providing external support and assistance, exoskeletons can help improve their mobility, gait pattern, and quality of life.

Two significant challenges hinder the widespread use of CP exoskeletons in real-world scenarios. Firstly, existing CP exoskeletons provide assistance for a limited amount of movements in clinical settings - typically simply forward traditional walking. This leads to exoskeletons employing a one-size-fits-all approach, where their dynamics, such as torque and flexion, are designed based on basic straight-line walking movements. Consequently, when individuals with Cerebral Palsy wish to engage in different activities like climbing stairs, sitting down, or jumping, the current exoskeletons prove ineffective. As a result, their utilization remains restricted to clinical environments and has yet to extend into everyday life. Secondly, a competing relationship between the exoskeleton and the patient poses another obstacle. While voluntary movement originates from the human brain, the current technology of exoskeletons has not reached a level of responsiveness that can match the brain's capabilities. This lack of synchronization between the brain and the exoskeleton creates a sense of resistance for the user. Studies indicate that individuals wearing exoskeletons while performing tasks that require cognitive engagement experience heightened brain activity and find themselves in a competition with the exoskeletons, rather than experiencing a seamless integration [20]. Addressing these challenges is crucial for advancing the practical application of CP exoskeletons and enhancing their usability in real-world settings.

Challenges with Existing Solutions

The challenges highlighted on exoskeletons have been widely recognized and acknowledged by experts in the field. In order to overcome these challenges, researchers have delved into the exploration of movement prediction techniques to enhance the optimization of exoskeletons for a wider range of movements and promote their utilization in real-world environments (Table 1). However, the methods developed so far have encountered notable obstacles when it comes to their applicability within the cerebral palsy (CP) community.

Existing Technology	Challenge	Solution Visual
Steady State Visual Evoked Potentials (SSVEP), a cutting-edge technique that leverages visual cues, such as flashing lights, to elicit potentials highly correlated with specific movements of individual users. [12]	This solution operates asynchronously with the human body. Additionally, to trigger a desired movement, the patient must focus on the visual cue for a prolonged period of 2-3 seconds, severely limiting the practicality of exoskeletons in real-world settings.	 Figure 1: Visual evoked Exoskeleton[12]

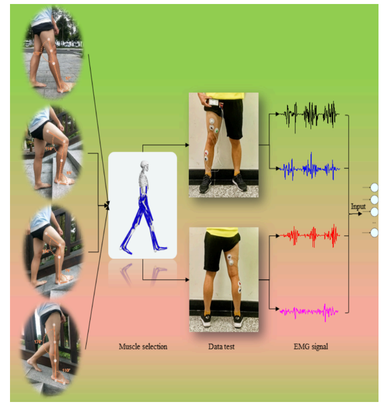
Surface electromyography (sEMG), involves reading electrical signals from muscles to estimate human intent. sEMG captures anticipatory information preceding limb movements, allowing for better coordination between humans and exoskeletons compared to reactive control methods. [13]	However, although this method proves effective for individuals without cerebral palsy, it unfortunately cannot be utilized by those with CP due to the reliance on electromyography data obtained from muscles and CP patients exhibit spasticity of muscles that causes erroneous EMG data	 Figure 2: EMG based Exoskeleton [13]

Table 1: Existing solutions to improve exoskeletons

SCIENTIFIC THEORY

Considering the limitations of current methodologies, it is imperative to adopt a novel approach to movement prediction in order to optimize exoskeletons for individuals with cerebral palsy. To address this, one potential avenue is the exploration of Brain-Computer Interface (BCI) [4]. This approach seeks to establish a direct connection between the user's brain activity and the control of the exoskeleton, enabling more precise and intuitive movement prediction and control. By harnessing the power of the brain's electrical signals and developing advanced algorithms, it is possible to overcome the challenges faced by existing methods and pave the way for improved exoskeleton optimization in the CP community.

Movement Intent

Electroencephalogram (EEG) signals are recordings of the electrical activity generated by the brain and can offer valuable insights into human functions. Various types of EEG signals exist, each with a unique frequency range and associated brain activity, including alpha waves (8-12 Hz), which are associated with relaxation; beta waves (12-30 Hz), which are linked to mental activity; gamma waves (30-100 Hz), which are involved in cognitive processes; theta waves (4-8 Hz), which are present during sleep and daydreaming; delta waves (< 4 Hz), which are associated with deep sleep; mu rhythms (7-14 Hz), which are associated with motor processes;

and P300 (0.5-4 Hz), which is involved in cognitive processing [7]. Mu rhythms are generated by motor movements, from the motor cortex of the brain and can be used to isolate movement related data.

Bereitschaftspotential (BP)

Mu rhythms are encompassed by MRCP or movement related cortical potentials which refers to the voltage of brain activity during human based motor tasks [4]. The EEG data of the 2 second period before movement starts is known as bereitschaftspotential (BP) or intent

1. Early BP: slow downset of voltage around 1.5 seconds before performing an action
2. Late BP: Fast downset of voltage 0.5 seconds before voluntary action

Intent signal detection is becoming a key technique to enable exoskeletons for the physically disabled [8]. Despite the motor limitations of Cerebral Palsy patients, most of the time the brain activity with respect to intent remains intact. Studies have determined that the intent signals of most Cerebral Palsy Patients are comparable to that of non-CP patients [6, 11]. Therefore through the use of BCI it is possible to predict patient movements using BP data and optimize exoskeletons for different movements.

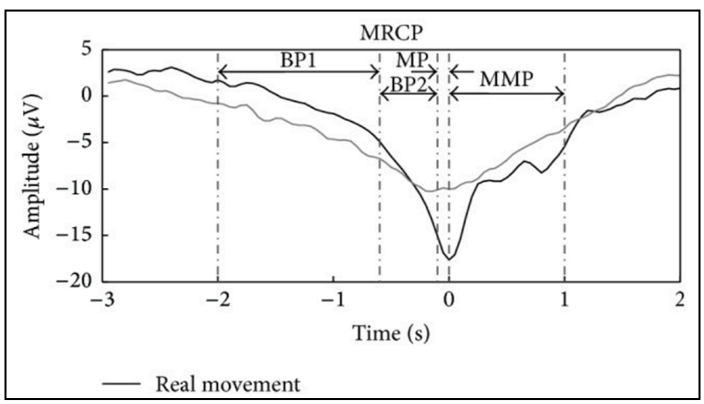


Figure 3: Bereitschaftspotential (BP) Downset of voltage before movement begins [4]

Problem and hypothesis

As discussed earlier, to solve the movement challenges of CP patients we want exoskeletons to work in harmony with the patient and also be able to execute different movement patterns. The hypothesis for this project was that I can isolate intent data for various movements and be able to detect those in real-time to enable smart exoskeletons.

METHODS

The purpose of the project was to develop a system for collecting signals from the Brain and detest movement intent from those signals. The testing and development of the systems was done on the primary investigator (myself). While I don't suffer from Cerebral Palsy, there is well documented and published research that brain signals remain intact for patients with Cerebral Palsy [6, 11]. Thus, the brain signals from a non-CP patient can be used as proxy to develop a system for CP patients

I broke down the project in multiple steps to incrementally develop the solution and test the hypothesis. There were 3 main phases of the project

- Phase1: Single leg raise. In this phase I controlled the variables to a single leg raise and isolated the Brain signals to identify movement intent. During this phase I could run multiple controlled tests and optimize the algorithm for predicting intent
- Phase2: This was the main phase of the project where I tested the hypothesis that BCI can be used for predicting multiple movements. A specialized cap (NeuroMotus) was developed in this phase to isolate mu signals from the motor cortex. This phase generated results that are reported in this paper
- Phase3: I took the project even further. And used the methods developed in phase2 of the project to implement a prototype real-time system to utilize BCI, detect intent, and then execute a simple robotic leg on the intended motion. This was developed as a demonstration of a working system. Details of this phase are included in Appendix A

In this section I will explain in detail the methodology for Phase1 and Phase2 of the project.

Phase 1: Prediction system for single Leg Raise

The purpose of phase 1 was to test whether the intent based method of movement prediction was applicable for a single movement. The subject sat comfortably in a chair and flexed the right leg forward repeatedly on cue. This controlled and isolated leg movement was used to calibrate the equipment and develop and optimize the algorithm for the project.

Signal Capture

The OpenBCI head cap is a clinically accepted solution for capturing high-quality EEG data. Designed with eight EEG electrode channels, this head cap maximizes input signals from the brain to provide accurate and reliable measurements. The Cyton board is designed to capture

Figure 4: OpenBCI setup for signal capture

high-quality EEG data with a range of customizable settings, making it an ideal tool for research and clinical applications. The OpenBCI headcap and cyton board was used to collect data in phase1 of the project.

Experimental Procedure

The timing and experimental procedure for the leg raise test can be seen below. It was designed to capture the EEG signals that occur during the 2 second period of intent. Each dataset captured started with a 3 second rest period. Then a cue was given to the subject. The subject is expected to voluntarily perform the movement after a variable time. I don't want the subject to move right on cue, since that could cause some of the brain's visual signals to be detected rather than mu signals. Thus a variable time wait was able to remove any interference from visual signals. The timing of the actual movement is detected by capturing an EMG signal from the thigh of the subject. After the movement the subject rests again for several seconds. This ensures that brain signals return to baseline.

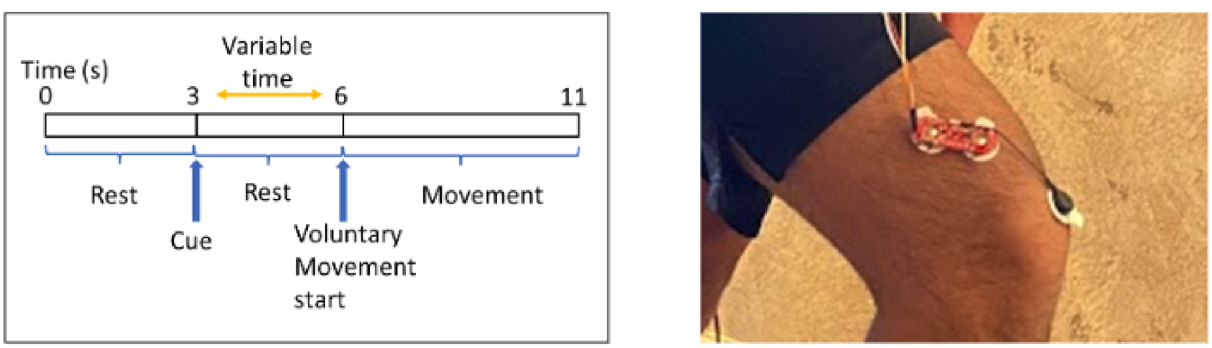


Figure 5: Experimental flow to capture data and EMG signals to detect movement

Data Collection

The procedure has specific timing requirements and events that need to be labeled based on triggers . To ensure synchronization of testing and data collection I used open-source PsychoPy time synchronous software

[18]. Using PsychoPy I was able to label the data appropriately to isolate intent data. The leg raise experiment is conducted for 50 trials and for 10 iterations (days).

Data Processing

EMG data was used to label the data identifying when voluntary movement began. Using this information, the 2 second time period of intent prior to movement was isolated. To ensure intent data was being captured a band pass filter was applied to isolate the 7-14 Hz frequencies of intent. The isolated BP/Intent data shows a distinct drop in voltage, indicating movement intent.

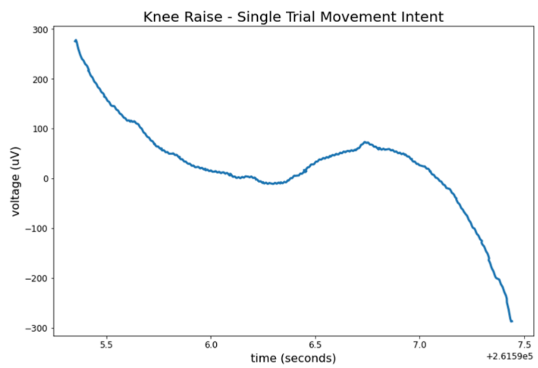


Figure 6: BP/Intent data for Leg Raise

Algorithm Development

Three different algorithms CNN, LSTM, and GRU were executed on the dataset.

CNN (Convolutional Neural Network) is a type of artificial neural network architecture used in deep learning, particularly in image and video processing applications. CNNs are designed to automatically learn and extract features from images by using convolutional layers that apply filters to input images. These filters detect patterns and edges in the image, and the output of the convolutional layers is passed through pooling layers that downsample the output to reduce the dimensionality of the feature map. The final output of the CNN is passed through one or more fully connected layers that perform classification or regression tasks.

LSTM (Long Short-Term Memory) is a type of artificial neural network architecture used in deep learning that is a variant of Recurrent Neural Networks (RNNs). LSTMs are designed to solve the problem of vanishing gradients that occur in traditional RNNs, making them well-suited for processing sequential data, such as speech, text, and video. They are widely used in various applications, including natural language processing, speech recognition, time series prediction, and image captioning, among others. The key feature of

LSTMs is their ability to selectively remember and forget previous inputs, making them particularly effective in capturing long-term dependencies in sequential data.

GRU (Gated Recurrent Unit) is a type of artificial neural network architecture used in deep learning that is similar to LSTM. GRUs are designed to address the problem of vanishing gradients in traditional RNNs and are well-suited for processing sequential data, such as speech, text, and video. GRUs use gating mechanisms to control the flow of information in the network, making them more computationally efficient than LSTMs while still being able to capture long-term dependencies in the data. They are widely used in various applications, including natural language processing, speech recognition, and image captioning, among others. The key feature of GRUs is their ability to selectively update and reset the hidden state, allowing them to remember important information and forget irrelevant information in the input sequence.

The results of the different algorithm on the single leg raise dataset are shown in Fig. 7. The CNN algorithm, after optimizations, performed the best with 94% AUC.

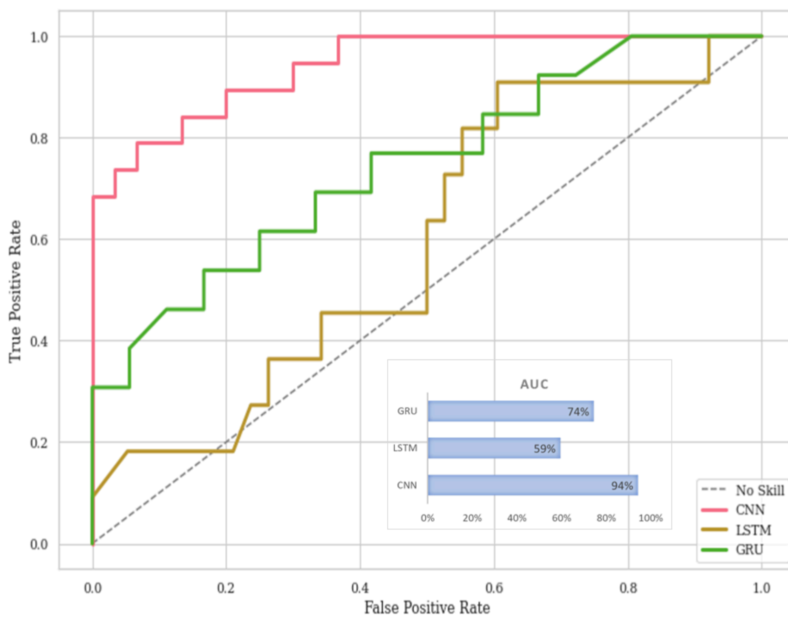


Figure 7: ROC and AUC curves for Leg Raise experiment

NueroMotus Final CNN Algorithm

A CNN2D model was used with 4 convolution layers, each following a pooling layer, dropout layer, and batch normalization layer to avoid overfitting. Each convolutional layer included padding (5, 0) to maintain the output size as well as a stride of (1, 1). It convoluted across time, with each filter having a depth of 5, one for each channel of the EEG data. At the end of the CNN, it only had one affine layer followed by a softmax classifier. Lastly, adam optimizer is used with training over 50 epochs.

Phase 2: Predicting multiple movements

The goal for phase 2 of the project was to test the fundamental hypothesis that multiple movement intent signals can be detected by the system. To do this five movement patterns were selected

- Stand up from a chair
- Sid down on a chair
- Step up on stairs
- Step down from stairs
- Walk step

These movement patterns were selected based on the activities of daily living (ADLs) that are essential for individuals to perform without assistance [17]. The goal is to enable these movements for better life of CP patients. During the initial testing a lot of interference was observed in the reading. This was because of the different brain signals that were picked up by the OpenBCI cap. To remedy that I had to isolate the signals from the motor cortex. Furthermore to generate the best data in reading signals from the brain a different kind of dry electrode was used. Using these ideas the NeuroMotus cap was developed and used for phase 2 testing

Optimum Electrode pattern

To get the best results I want to pick the signals from the motor cortex and reduce the noise from other brain signals. Initial testing revealed that using 8 electrodes was introducing too much noise in the systems. Based on literature I identified 4 different patterns of electrode placements to evaluate. These patterns were based on the 10-10 system and only 5 electrodes were used. To complete the evaluation the single leg raise (phase 1) experiment was conducted. The results as shown in Fig. 8, the pattern 1 - with electrodes right on top of the motor cortex is the best placement pattern. This pattern also makes sense based on studies. A lot of studies have been done on motor imagery. That is where a patient imagines a movement.

But, we are trying to understand when a patient is actually moving their limb and not just imagining it. The part of the brain that deals with motor intent is the motor cortex while motor imagery is done by the prefrontal cortex [15].

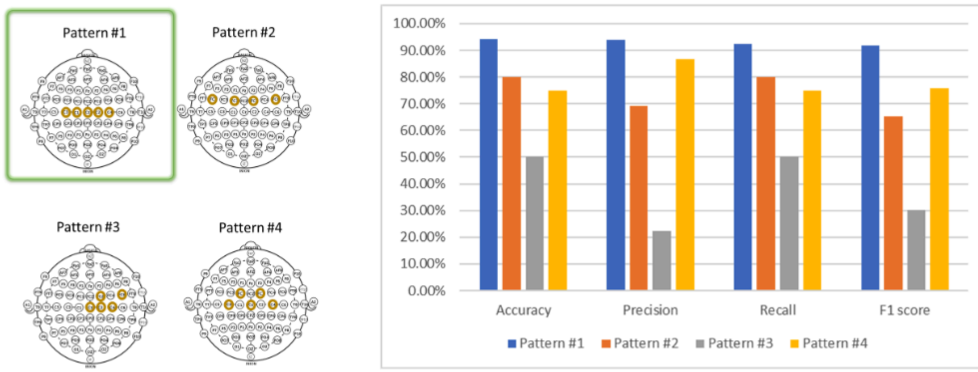


Figure 8: Different electrode patterns tests and comparative results

Developing the NeuroMotus Cap

The NeuroMotus cap was a custom design for the subject. The subject's head was measured using a tape measure. The Fig. 9 shows the measurement of Nasion-to-Inion and Preauricular left and right points. The 10-10 EEG electrode placement was used in the cap. For exact electrode placement, dry electrodes were glued onto a stretch band. The band was then sewn onto the cap. The dry portable electrodes were placed at CZ, C1, C3, C2, C4 from the 10-10 EEG electrode system. Final product was connected to the Cyton board. Ear clip electrode was used for reference ground and a strap was placed around the chin to ensure that the cap doesn’t move around. The cap was tested using the OpenBCI setup. Impedance check was done on all electrodes to ensure proper connectivity before data was collected.

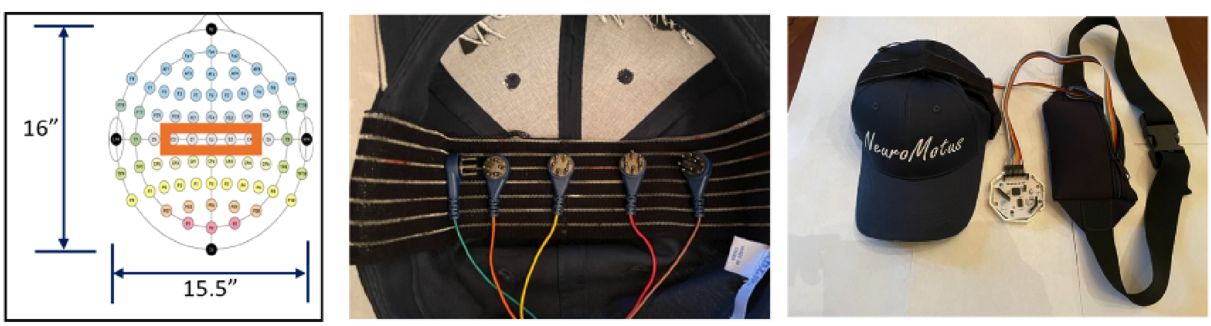


Figure 9: Neuromotus Cap development

Experiment Design

This phase follows a similar testing procedure to phase 1 of the project as shown in Fig. 5. But, the movement performed by the subject is different. For sit and stand movement a standard desk chair is used. Stairs in the home lab are used to perform step up and step down movements. Walk step is performed on a flat surface. Table 2 shows isolated BP graphs for each movement pattern.

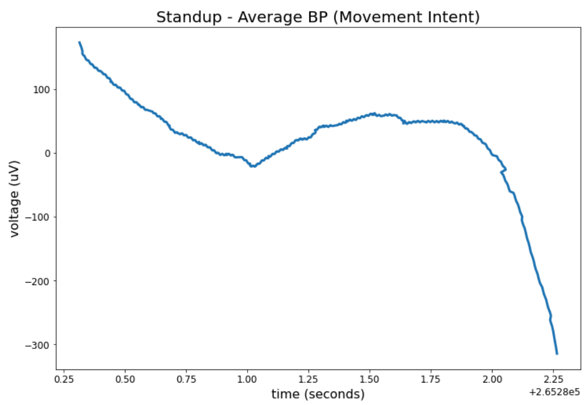
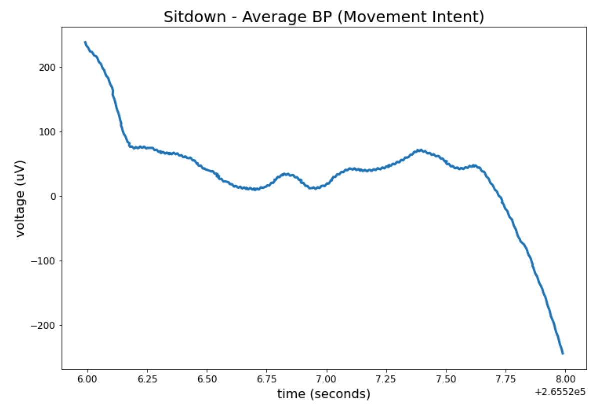
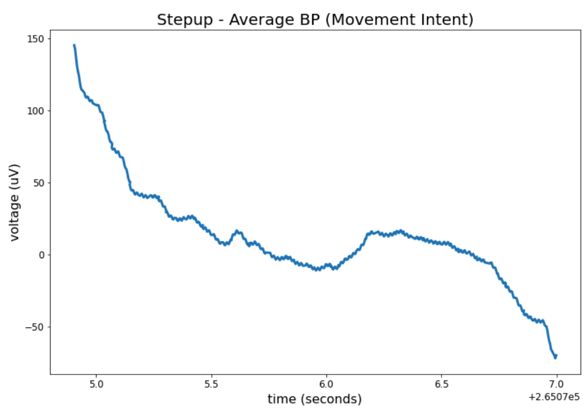
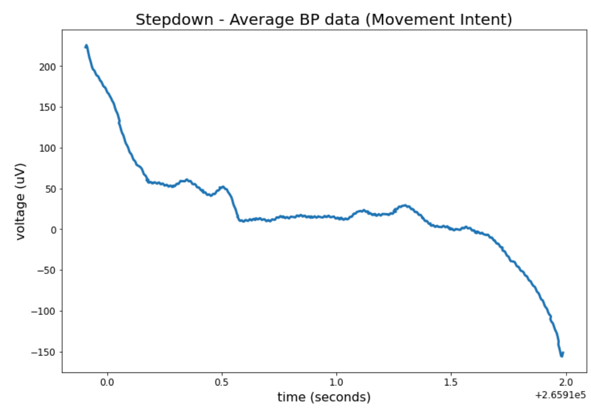
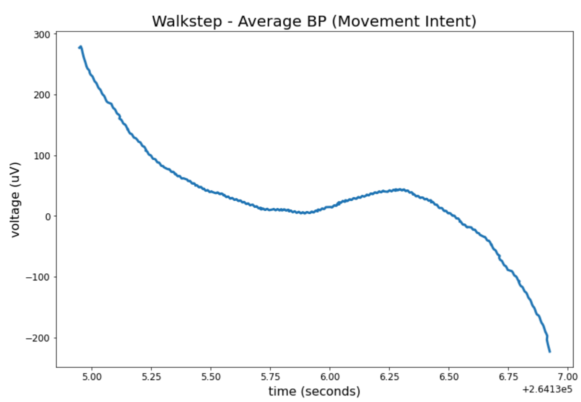
Standup	Sitdown
	
Step up	**Step down**
	
Walk step	
	

Table 2: BP/Intent graph for different movement patterns

RESULTS

The results of NeuroMotus' solution show that it is indeed possible to use peripheral EEG data, to isolate the bereitschafts potential readings and use such reading to enable exoskeletons to be more adept to real life scenarios. The metrics that measure the success of this experiment are both quantitative and qualitative. The quantitative results come from the convolutional neural networks numeral metrics on the ability to predict patient movement. The qualitative results derive from the mock exoskeleton's ability to access real time data and execute the intended movement in unison with the patient.

Quantitative Results

As mentioned previously, the CNN's metrics represent the quantitative results of this experiment as they represent how well the algorithm performed at predicting patient movements using the EEG data. The movements that were experimented on within this project include a regular walk step forward, standing up, sitting down, stepping up stairs, and stepping down stairs. For each one of these unique movements a modified CNN was trained using a 80/10/10 split for training, validation, and testing. The results below visualize the success of the system in a confusion matrix.

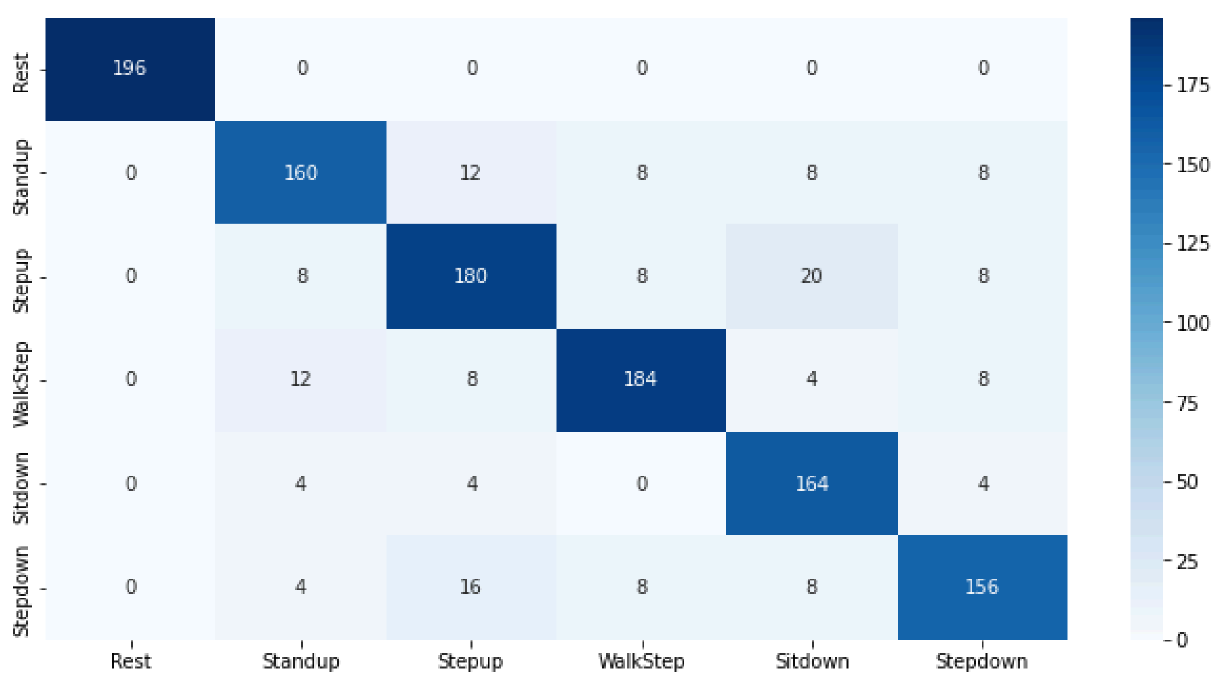


Figure 11: Confusion Matrix for different movement tests

The confusion matrix indicates the results of the testing portion of the data. As can be seen within the matrix the algorithm performed with both a high accuracy and precision; however, the matrix also highlights the false positive and false negative results within the experiment. Another way to interpret the results of the algorithm's ability to predict patient movements using preliminary BP data is a ROC curve.

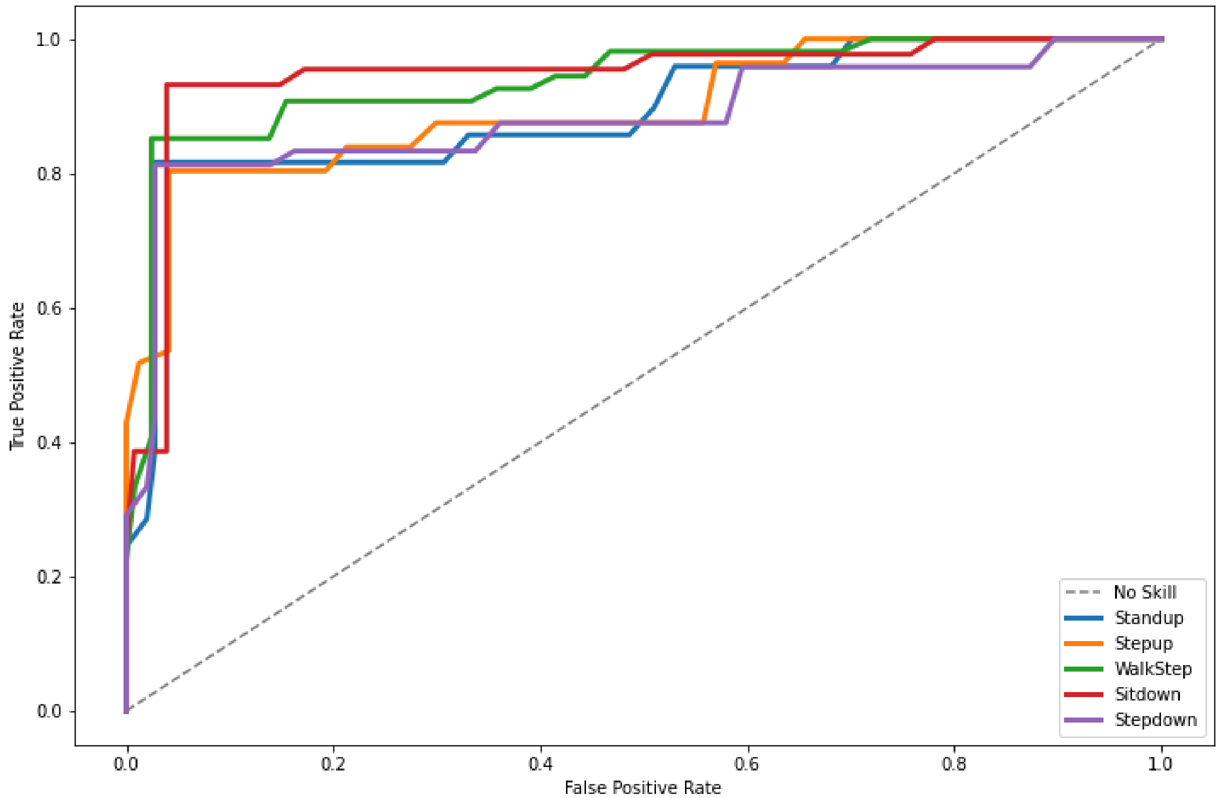


Figure 12: ROC curve for different movement experiments

The ROC curve above tracks the true positive rate vs. the false positive rate. The closer the lines are to achieving a 1.0 true positive rate the better the algorithm is performing at predicting movements. The graphical representation of the results indicates a similar message to the confusion matrix, which is that the algorithm performs with a high accuracy across all movements; however, it has minimal false positive results. Finally, below a table is listed that show the individual metric parameters for every movement pattern such as accuracy, precision, etc.

	Precision	Recall	F1-score	support
Rest	1.00	1.00	1.00	196
Standup	0.85	0.82	0.83	196
Stepup	0.82	0.80	0.81	224
Walkstep	0.88	0.85	0.87	216
Sitdown	0.80	0.93	0.86	176
Stepdown	0.85	0.81	0.83	192
Accuracy			**0.87**	1200
Macro Avg.	0.87	0.87	0.87	1200

Table 3: Model performance for different movement patterns

The composite average of the accuracy in predicting all the different movements comes to 87%. The table above also gives a number of other metrics that indicate the algorithm was able to achieve a considerably successful outcome. The results taken all together suggest that using anticipatory EEG information from electrodes located on the surface of the brain can be used to predict 5 unique patient movements with a substantial accuracy.

Qualitative Results

In addition to the high accuracy and quantitative results described above another important aspect of this project comes with respect to the qualitative results of the system. The purpose of this system is to enable a scenario where exoskeletons can predict patient movements and work in unison with patients to facilitate certain motions. So, the qualitative portion of this project comes with looking at the system work all together and observing if it is working with or against the patient. To test this qualitative aspect of the project a real time system was designed with a mock exoskeleton. The real time system works by gathering the EEG data, predicting the patient's upcoming movement, and moving an exoskeleton to the correct location concurrently with the patient. The results are determined by observing if it is able to accomplish the necessary steps to enable the concurrent motions. A detailed explanation of real-time implementation of the NeuroMotus projects is presented in Appendix A. As seen Fig. 18 the system does work in harmony with the subject for different movement patterns. This demonstrates the applicability of the NeuroMotus solution in real-life.

DISCUSSION

The NeuroMotus project signifies a profound shift in exoskeleton use for Cerebral Palsy patients. Through a sophisticated closed-loop system boasting an 87% accuracy rate, this project forecasts five essential daily movements. Additionally, it employs joint angle visualization software to precisely calculate assistive torque input times for each movement. This marks a groundbreaking advance in assistive technology, significantly expanding the applicability of exoskeletons for CP patients. The NeuroMotus project's primary accomplishment is its high-precision closed-loop system, with an 87% accuracy rate, predicting six crucial CP patient movements. This precision reduces fall and accident risks, vital for CP patients' safety. Furthermore, the software calculates torque input times accurately, ensuring optimal support during diverse movements, enhancing user comfort, and mitigating muscle fatigue.

This project also broadens CP exoskeleton mobility by incorporating five new movements, significantly enhancing patient independence. Establishing a practical method for real-world CP exoskeleton implementation is pivotal. This framework enables seamless integration into rehabilitation and daily routines, prioritizing accessibility and usability. The creation of a harmonious brain-exoskeleton relationship offers potential neuroplasticity benefits, potentially reducing long-term reliance on assistive devices.

Future Work

To maximize impact, future efforts should focus on:

- Integration with Biomotum's Spark Exoskeleton: Collaborating with Biomotum to integrate NeuroMotus into the Spark exoskeleton could extend its reach.
- Improving Algorithm Accuracy: Ongoing optimization of the prediction algorithm is crucial for enhanced safety and user experience.
- Clinical Trials: Rigorous trials with CP patients will provide essential insights, user feedback, and performance data, vital for fine-tuning the system.
- Broadening Applicability: Exploring possibilities to apply NeuroMotus beyond CP patients to other mobility impairments can widen its impact.

In conclusion, the NeuroMotus project revolutionizes exoskeleton use for CP patients with its high accuracy, expanded mobility, real-world applicability, and potential neuroplasticity benefits. Future work aims to build on these achievements, improving the lives of CP patients and potentially benefiting a broader user base.

APPENDIX A: Real-Time Implementation

In phase 3 of the project, I developed a real-time implementation of the project. The goal of this phase was to show a mock exoskeleton perform various movements based on intent data collected from the Neuromotus cap. The following figure shows the experimental setup and the mock exoskeleton

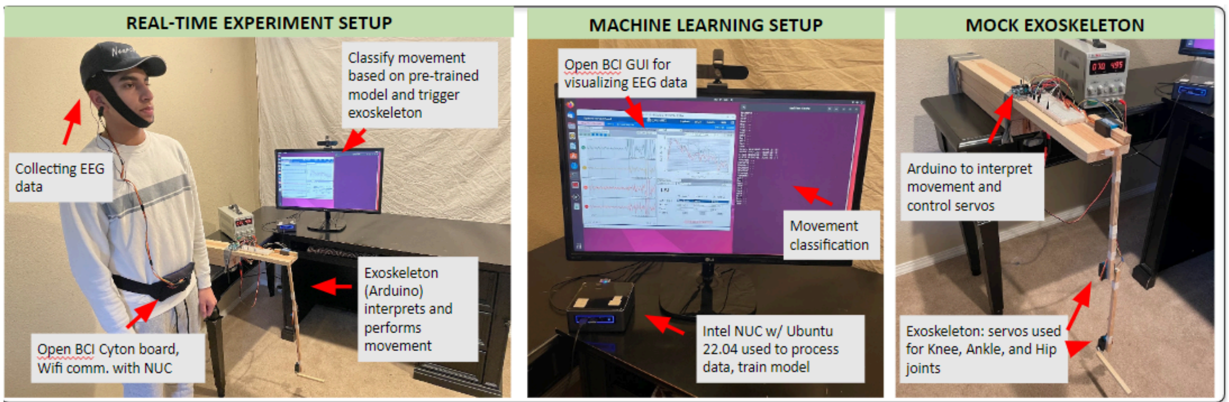


Figure 14: Experiment setup for Real-time testing

Real Time Intent Classification

For real-time classification the EEG time-series data is pre-processed and batched into 1.5-second increments at the outset. Following this, the data undergoes processing and band-pass filters are applied before being saved to a file. To classify the data in real-time, the file is read every 100ms, and the best pre-trained classifier is utilized. The resulting output is displayed on the screen displayed on screen identifying the movement intent detected and performed by the exoskeleton

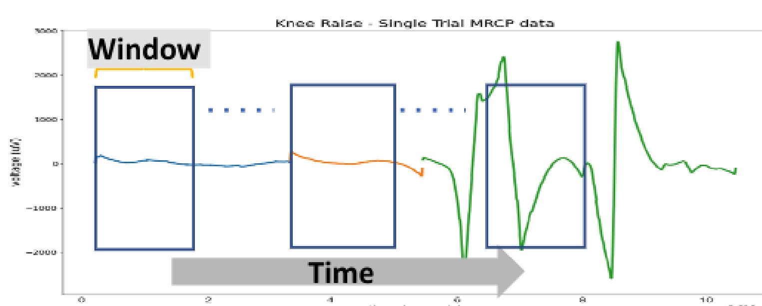


Figure 15: Methodology for real-time classification

Joint-angle Inputs For Exoskeletons

Current exoskeleton's function using input torque. Torque is rotational force that is defined by the cross product of force and radius. This means that joint angles play a crucial factor in determining the input torques for exoskeletons. In this project I used angle visualization software, Media pipe [19] and generated time-series joint angle inputs for exoskeletons. The following figure shows the visualization software detecting joint angles. The chart show the inputs provided to the exoskeleton to perform the movement

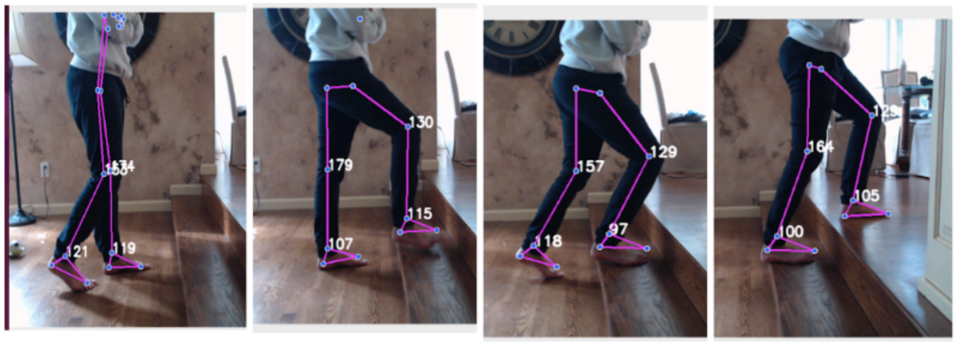


Figure 16: Angle visualization of one movement (step-up)

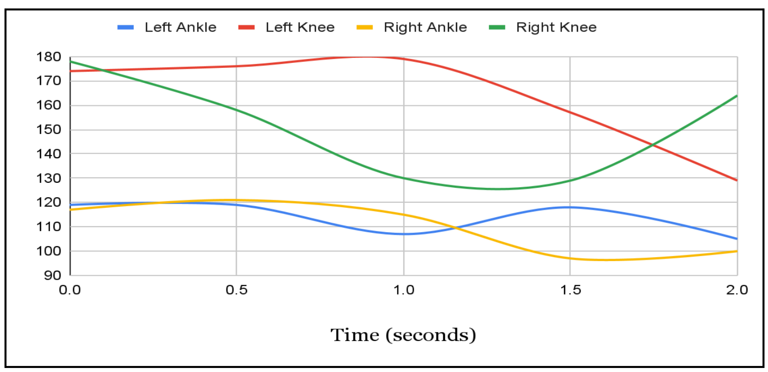


Figure 17: Angle input to exoskeletons to performance a movement (step-up)

Real-time implementation procedure

The following flow charts show the procedure to collect data and save into a file and how pre-trained mode is executed to move exoskeleton

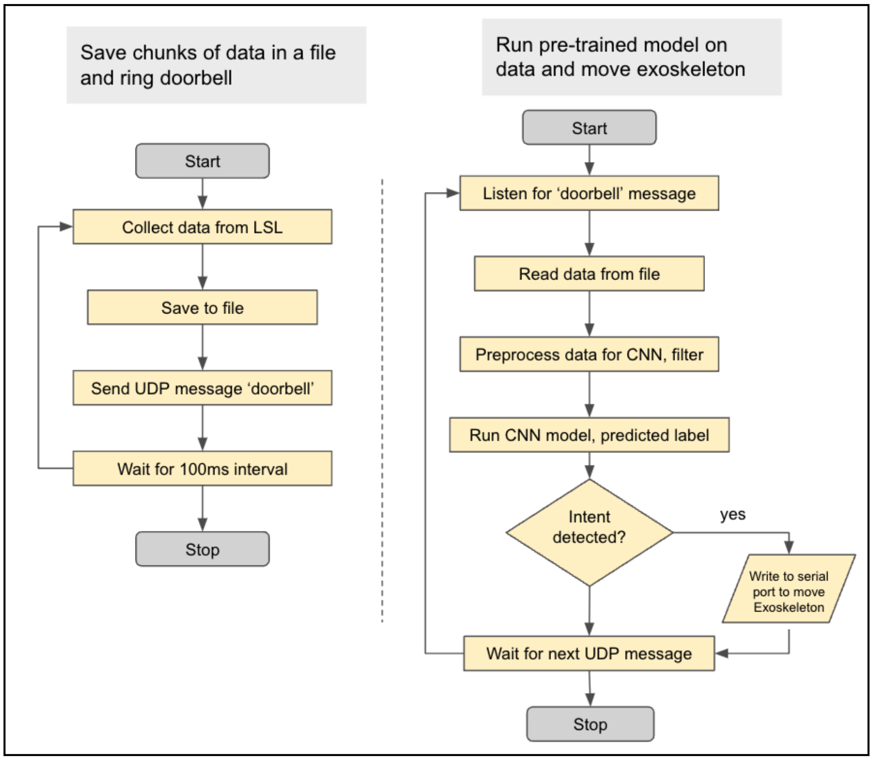


Figure 18: Real-time implementation flow charts

NeuroMotus: End-To -End Working Implementation

The following picture shows the entire implementation of Neuromotus solution along with pictures of end-state of each movement

Figure 19: Neuromotus end-to-end implementation

APPENDIX B - Product Cost

The total cost of the prototype Neuromotus system was $1172. Currently, the system uses off the shelf parts. Going forward the costs can be significantly reduced by custom parts. For example the Cyton board is the most expensive part of the system and it has many more channels than required for Neuromotus. Optimizations for other parts of the system and volume production can lower costs significantly.

Item	Cost
Open BCI Cyton biosensing board	$999.00
EEG Snap Electrodes	$29.99
Earclip Electrode	$32.99
Snap electrode cables	$59.99
Cap with logo	$20.00
Velcro strip	$10.00
Manufacturing	$20.00
Total	$1172

Table 4: Neuromotus - Product Cost breakdown

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