Cedalion:

Exploration of Brain Computer Interface for Individuals with Cerebral Palsy

UC HCI Lab

next lives here



Team - HCI group



Madhav Lolla PhD student



Shivchander Sudalairaj MS student



Professor Anca Ralescu



Anam Hashmi MEng student



Sreekar Puchala PhD student

Cerebral Palsy and BCI

- Cerebral Palsy (CP), which occurs in about 2 out of 1000 births, is a group of disorders that affect movement and posture
- Currently, there are no known direct treatments to CP
- Recently, BCI has been used to enable communication & control in people who are completely immobile (locked-in syndrome)
- This approach has limited success in people with CP since individuals with CP suffer from unpredictable spasms, which makes most of the EEG signals noisy and unusable
- The main motivation of the project is to propose an approach to apply EEG-BCI integrated robotic systems in helping people with Cerebral Palsy

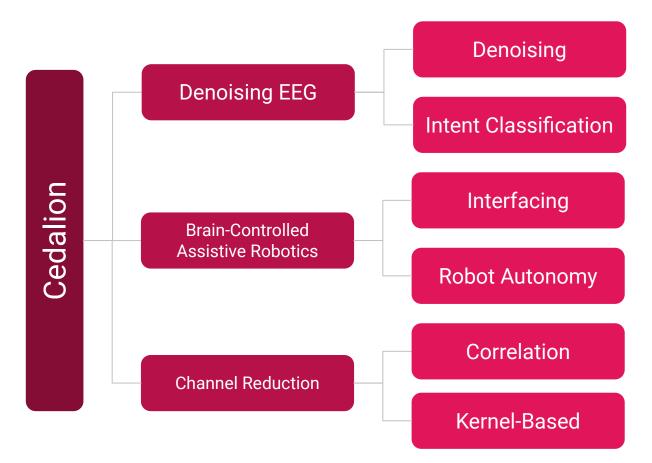
Goals

- Explore a platform for EEG-based BCI for CP by using a two-pronged approach:
 - New techniques to isolate and analyze signals of interest, i.e., to identify the useful signal out of its noisy background
 - A BCI model from a healthy subject transferred and adapted to the CP subject
 - The healthy subject does not suffer from CP
 - Similar in gender, age, cultural background, educational level, and intellectual abilities

Objectives

- Identifying and exploring venues to improve the baseline quality of life of people with cerebral palsy
- Designing and developing solutions to help people suffering from cerebral palsy to perform menial tasks, such as the every day routine, with comfort and ease
 - For instance, making the robot grab a cup of water

Project Overview



Technologies and Frameworks







Droidlet hello robot

Unicorn EEG Headset

- Unicorn Hybrid EEG Electrodes for dry or wet recordings
- EEG data acquisition and processing
- High Signal-to-Noise Ratio with 24 Bit and 250 Hz
- High-end brain-computer interface (BCI) applications
- Correct positions of EEG electrodes for real brain wave recordings
- Customizable and programmable software tools





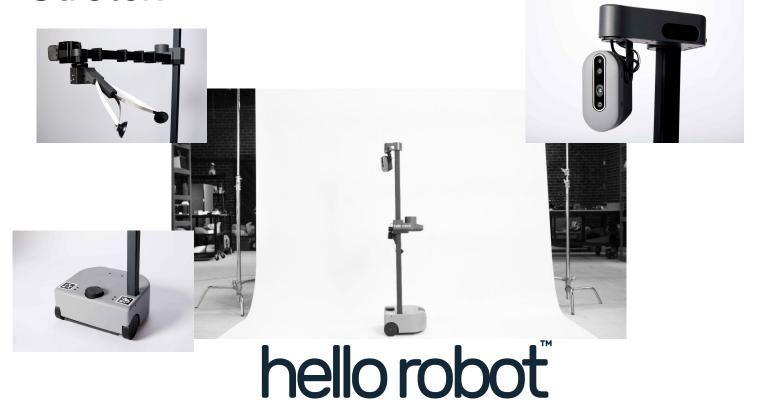
Stretch

Venture researching in mobile manipulators to help enhance the lives of older adults, people with disabilities, and caregivers

hello robot



Stretch



Technologies and Frameworks







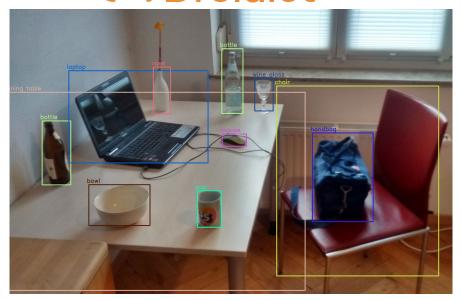
Droidlet is an early research project for Al researchers to explore ideas around grounded dialogue, interactive learning and human-computer interfaces.

Droidlet

Perception: Process information form the world, store in memory

Memory: Nexus of information from environment and all other systems

V Droidlet



Computer Vision

- Object Detection: Identify Objects of interest from the real world and measure the distance from the robot
- Scene Recognition: Identify and recognize the room in which the robot is present/looking at
- Obstacle Avoidance: Avoiding objects during navigation to prevent collision





Droidlet

Dashboard:

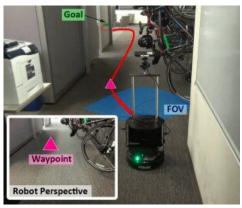
Communication Interface

NLU: Natural language parser and intent classification

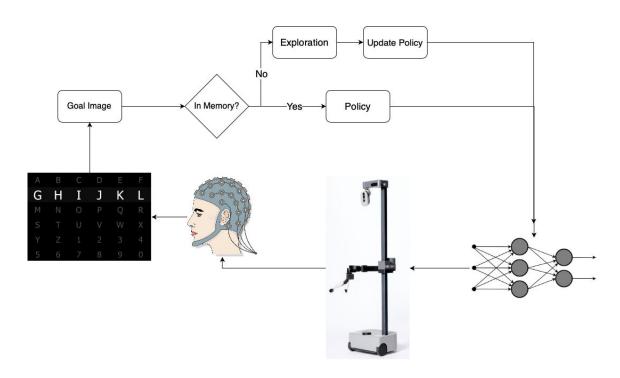
Navigational Framework

V Droidlet

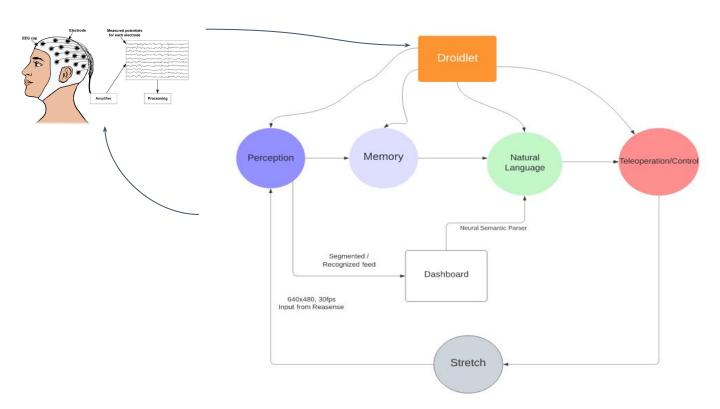




P300 Speller-controlled Workflow



Assistive Robotics Workflow



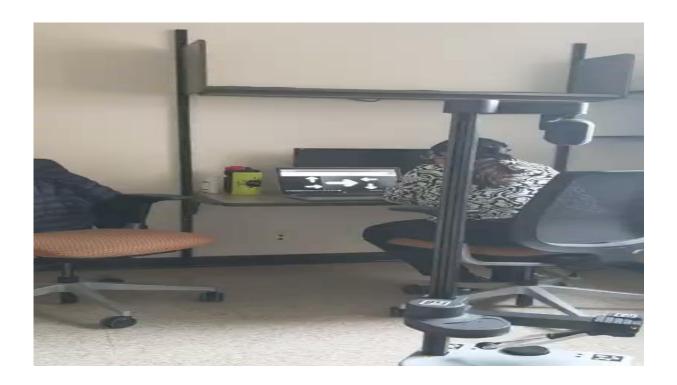
P300 Speller



P300 Speller

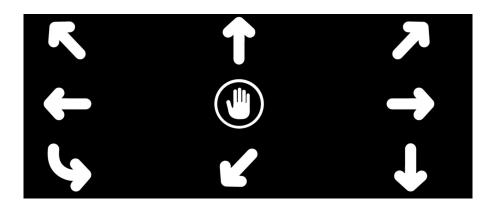


P300 Speller



Unicorn Speller and P300 Paradigm

- P300 (P3) wave is an event-related potential (ERP) component elicited in the process of decision making
- Concentrate on specific characters on the speller board in order to select them mentally
- The characters of Unicorn Speller boards are customizable and can be sent via the Unicorn Speller network output to external applications or devices



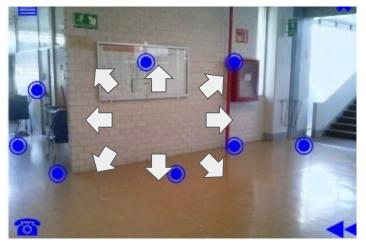
Scenario Based p300 speller:

- Scene (current) represented as base image
- Stimulus points encoded:
 - Objects on map
 - Arbitrary regions (markers)
- Stimulus generated via flashing stimulus--points



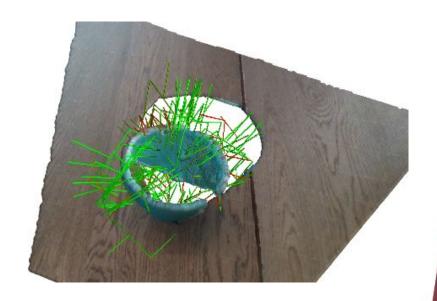
Navigation:

- Evoked onto Base image by Navigation core stack
- 9 grid directional joystick
- Path planner moves/pans towards stimulus node after it is selected.
- Joystick can be called by stimulus-capab
 -le icon



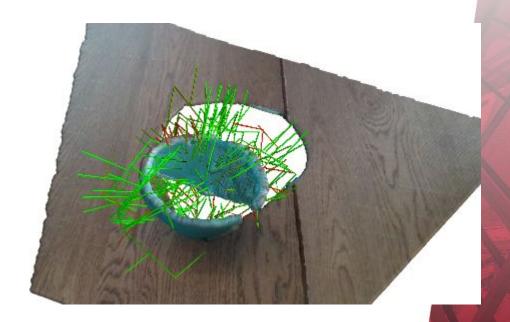
GraspNet 1-billion:

- benchmark that contains
 190 cluttered and complex scenes.
- Captured from Kinect Azure and RealSense D435.
- 88 objects and over1.1 billion grasp poses.



GraspNet 1-billion:

- Each image is 6D pose Image.
- Grasp poses indications are third-person.





Effects of Cerebral Palsy on EEG

- Unpredictable body movements (spasms) are observed from our CP subject
- The frequent spasms cause significant physical interference to the electrodes that are used for detecting EEG signals
- The physical interference directly adds considerable noise to the EEG signals observed from CP subjects
- The noisy EEG signals are characteristically different from the signals observed from healthy individuals, making it hard to apply the same models that were developed for the healthy subjects to CP subjects

Objectives

- Explore the EEG signals obtained from CP subjects with those from a healthy subject with similar physical and intellectual abilities
- Compare pairwise, between a CP subject and a healthy subject, the EEG signals associated with visual and motor imaging tasks
- Develop a novel deep learning approach with transfer learning to obtain a model feasible for CP subjects, adapted from a model for the healthy subject.

Dataset - PhysioNet EEG Motor Imagery

- Dataset contains one or two minute EEG recordings from 109 healthy subjects
- Subjects performed different motor/imagery tasks while 64-channel EEG were recorded
- Each subject performed 14 experimental runs pertaining to one of the tasks:
 - Rest
 - Open and close left or right fist
 - Imagine opening and closing left or right fist
 - Open and close both fists or both feet
 - Imagine opening and closing both fists or both feet

Data Preprocessing

- Selected only the 8 channels available with Unicorn: ['Fz', 'C3', 'Cz', 'C4', 'Pz', 'PO7', 'Oz', 'PO8']
- Selected only the tasks which involved Rest, Imagined motion of Left and Right Hands
- Apply Bandpass Filter using Finite Impulse Response Window

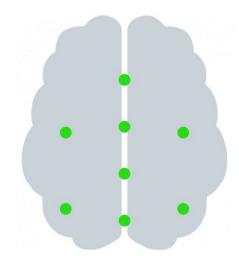
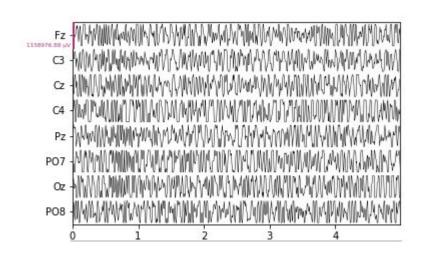


Fig: Positions of electrodes

Solution

- Developed a deep learning model based on autoencoder architecture
- Trained with noisy signals as input and associated denoised signal and intent as output
- Trained by minimizing loss between the noisy signal and the respective clean signal using gradient descent techniques

Gaussian Normal Noise (Timesteps)



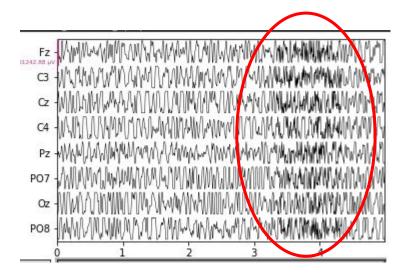


Fig: Gaussian noise added to a random time slice of the signal across all channels

Gaussian Normal Noise (Channels)

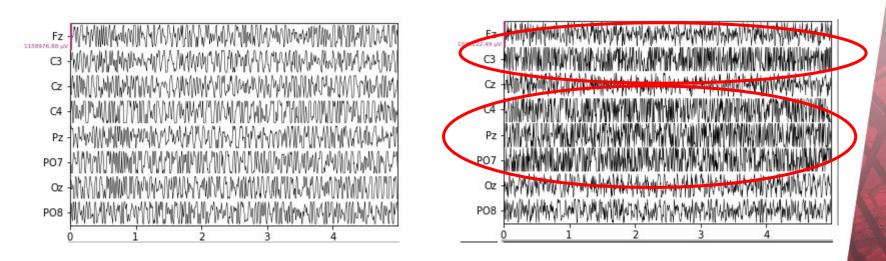
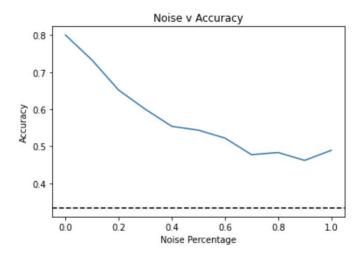
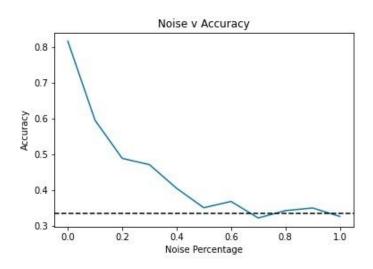


Fig: Gaussian noise added to random channels of the signal across the entire timestep

Results



Noise across Timesteps



Noise across Channels



Objectives

- Optimal channel selection for reducing dimensionality of EEG data.
- Develop a Machine/Deep Learning based approach to classify Motor Imagery Signals.
- Mapping the classified signals to control external devices.

Motivation of the Study

- It is a common practice to increase the number of channels to improve the spatial resolution of the EEG signals.
- Leads to an increase in the dimension of EEG data thereby failing the model to generalize and overfit.

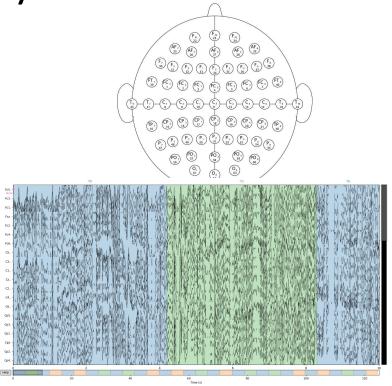
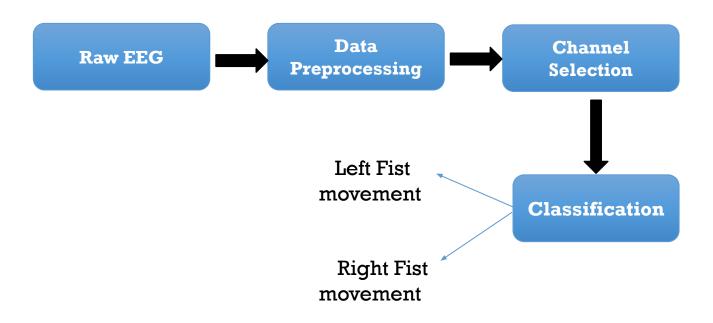


Fig. 2. EEG electrode placement and EEG signal activity.

Solution



Data Preprocessing

- Motor Imagery signals are reported to lie in the frequency band of 7 to 30 Hz.
- An FIR one-pass zero-phase non-causal band-pass filter was designed.
- Selected tasks include movement of the left fist and movement of the right fist.

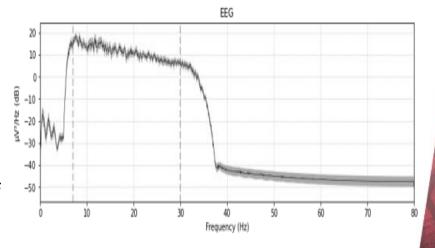
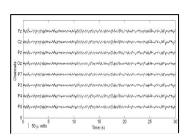


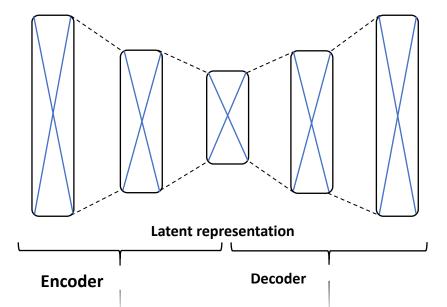
Fig. 3. Showing PSD of the band-pass filtered EEG signal.

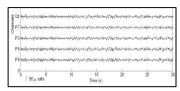
Channel Selection: Auto Encoder

- ☐ Optimal channel selection for improving accuracy and reducing dimensionality of data.
 - o 64 EEG channels were reduced to 32 and 16 channels using Auto Encoder.



Input EEG signal





Output EEG signal with reduced number of channels

Classification Results

Table showing average accuracies for different number of EEG channel selection using an Auto Encoder.

Classification Model	64 Channels	32 Channels	16 Channels
KNN	77.97%	73.33%	63.19%
SVM	77.97%	74.97%	65.75%
Random Forest	66.84%	64.72%	60.25%
LSTM	78%		78%

