Brain Computer Interface (BCI)

Advisor: Dr. Reinkensmeyer

Team Members: Reyson Sioson, Bryce Lindsey, Rebecca Kan, Trisha Mendoza

UCI Samueli School of Engineering

Background and Project Goal

Background:
- People with complete or severe loss of motor functions can still generate specific brain signals through motor imagery
- BCI's can analyze these signals and assign an output for various applications

Goal:
- Decode three active motor imagery states and one passive state to control a video game
- Allow future development of systems that utilize mind-based inputs

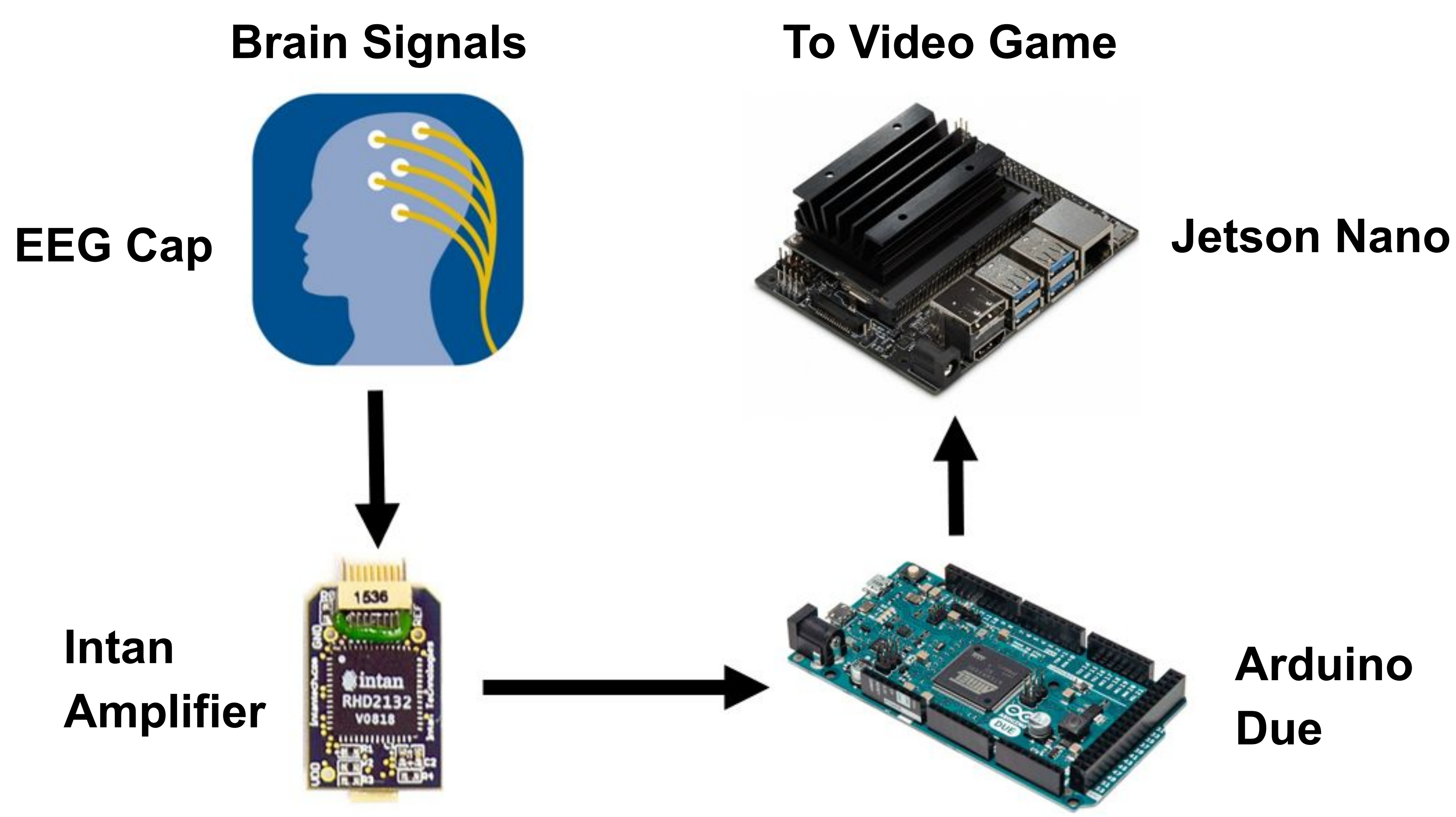
Requirements

- Signals generated by eye and physical movements as well as visually evoked potentials (SSVEPs, P300) should not be used to decode outputs
- BCI must decode an idle state and three active states generated by motor imagery
- Electrodes can not be invasive and must be comfortable to wear for long periods of time
- Artifacts (blinks, noise, muscle signals, etc.) must be filtered out

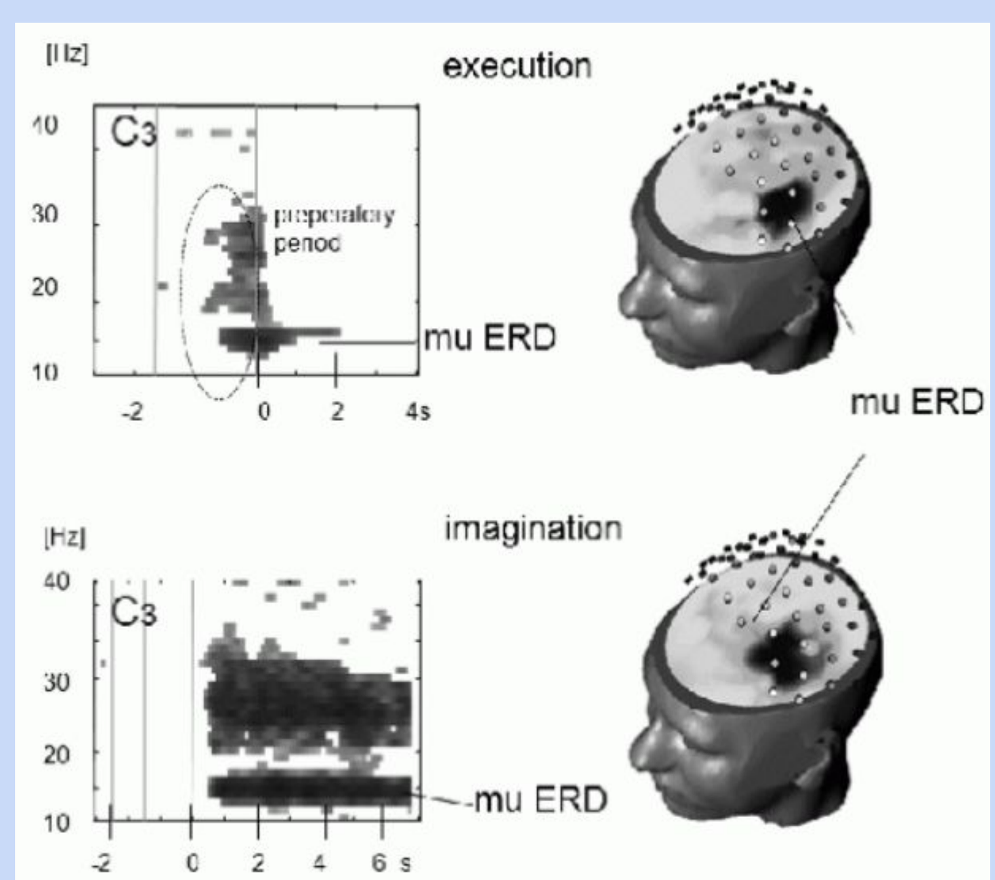
Hardware

- **EEG Cap:** Non-invasive method of acquiring brain signals via electrodes
- **Intan Amplifier:** microchip that amplifies and converts EEG signals into digital data
- **Arduino:** microcontroller that samples data from the intan amplifier
- **Jetson Nano:** Linux PC used to operate decoding model
  - Preprocessing: Artifacts are filtered and Fourier Transform is applied to segmented data
  - Pattern Recognition: Machine learning algorithm recognizes motor imagery patterns
  - Output: Communicates control signals to video game

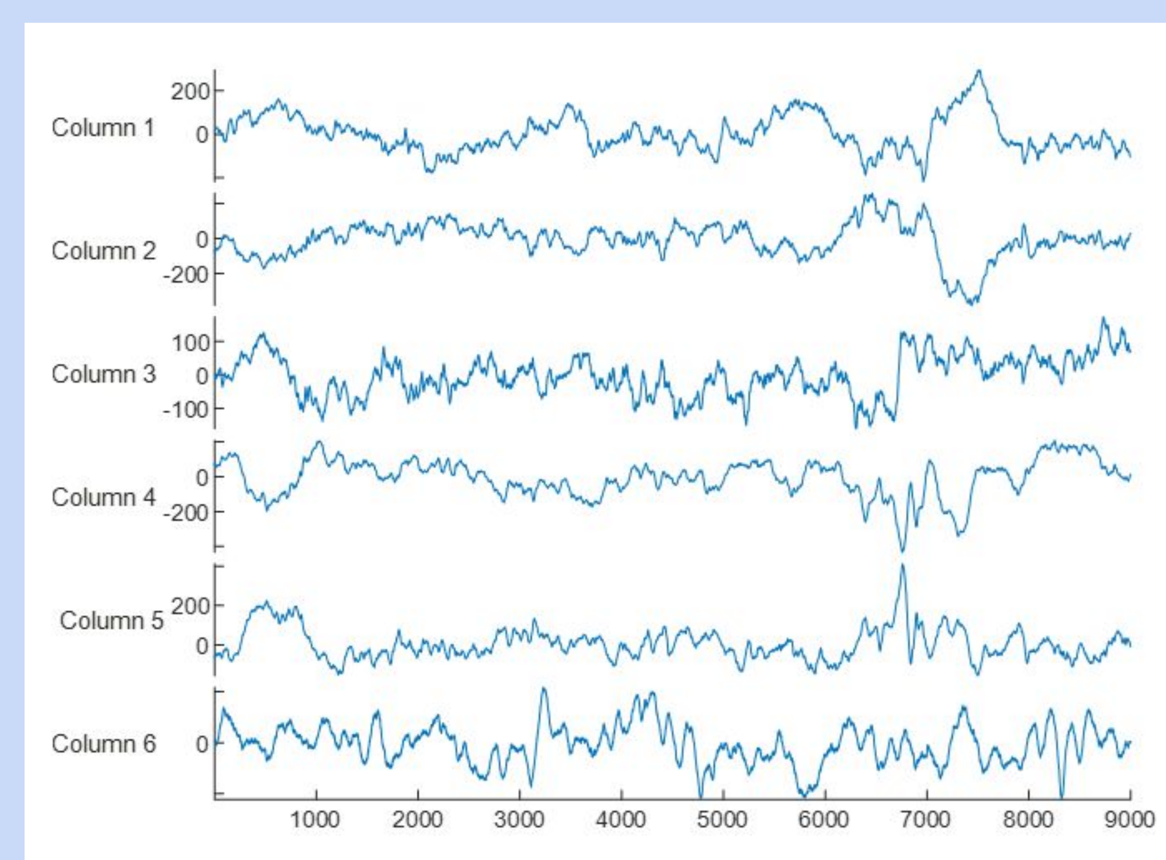
Brain Computer Interface System



Electrophysiology & EEG Data



ERD/ERS time-frequency maps **(left side)** and topographical maps of mu ERD **(right side)** of a subject during execution **(upper panel)** versus imagination of a right hand movement **(lower panel)**.



An example of raw EEG data for 6 different channels. Prior to plotting, the data is referenced. In this case, a common average is being used.

Current Status

- Testing Open BCI's capabilities with signal acquisition, while learning how to properly adjust the cap and reduce impedances
  - Selected cap for final BCI system
- Training model created to see if distinct patterns can be determined between left and right hand movement through motor imagery
- Communication between all hardware components
- Researching deep learning algorithms that will be tested once data is acquired

Next Steps

- Test the hardware capabilities and improve design to diminish possible noise and artifact generation
- Study motor imagery responses to understand which commands create distinct responses
  - Create training models in order to study four different commands
- Configure preprocessing parameters (filters, fast Fourier transform, sampling size, etc.)
- Gather data to train machine learning algorithm to decode distinct motor imagery events

References

- "A Beginner's Guide to Brain-Computer Interface and Convolutional Neural Networks", Medium, 2019.
- P. Bashivan, I. Rish, M. Yeasin and N. Codella, "Learning Representations from EEG with Deep Recurrent-Convolutional Neural Networks", arXiv.org, 2019.
- "Brain-Computer Interface (BCI) Race", Cybathlon.ethz.ch, 2019.
- J. Ng, M. Hausknecht, S. Vijayanarasimhan, O. Vinyals, R. Monga and G. Toderici, "Beyond Short Snippets: Deep Networks for Video Classification", arXiv.org, 2019.
- Tabar, Y. and Halici, U. (2019). A novel deep learning approach for classification of EEG motor imagery signals.
- Pfurtscheller, G. and H. Lopes Da Silva, F. "EEG Event-Related Desynchronization (ERD) and Event-Related Synchronization (ERS)", Neupsy Key
- Zhang, X. et al. (2016) "A Survey on Deep Learning based Brain Computer Interface: Recent Advancs and New Frontiers"