

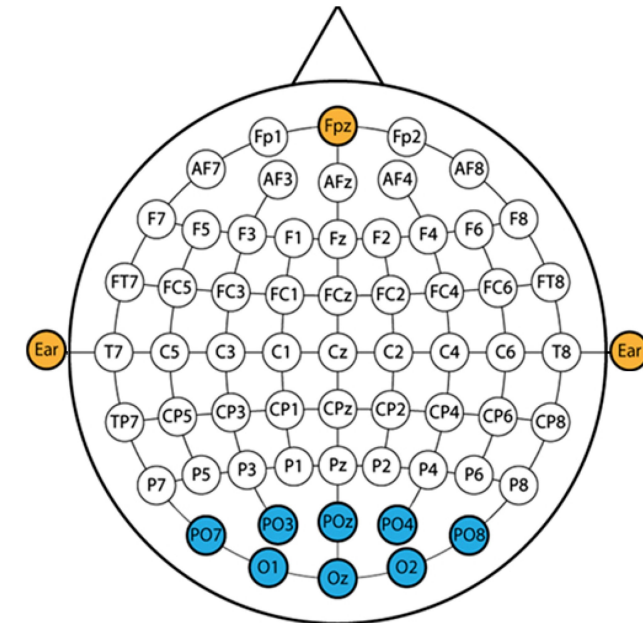
Introduction

Objective

Design a proof-of-concept system with BCI-integrated wheelchair technology for people with quadriplegia that will measure cognitive fatigue and compensate by refining BCI parameters to reduce classification errors of standard wheelchair movement commands.

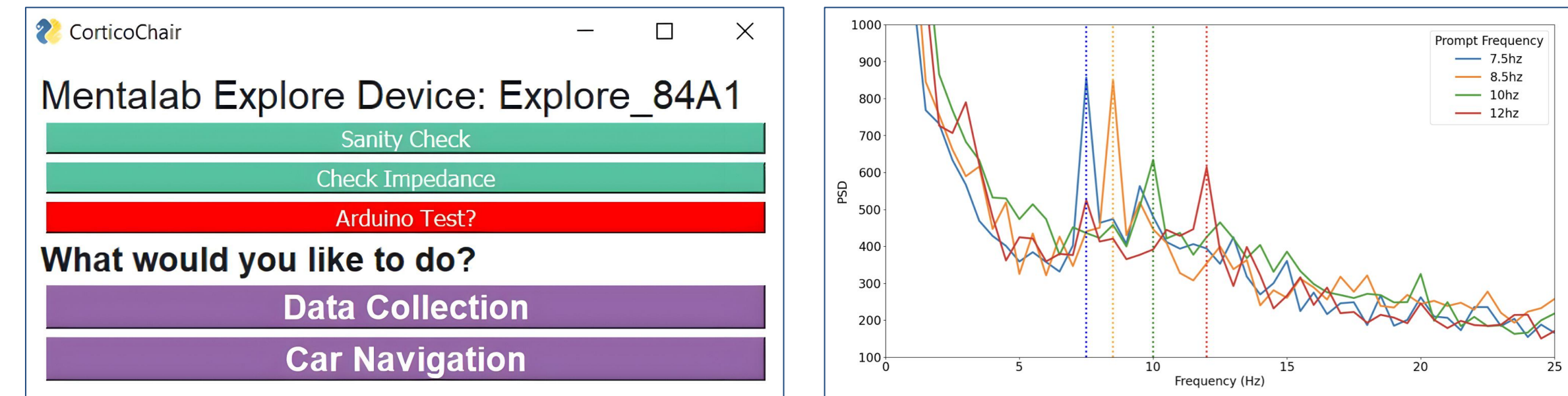
Background

- Brain-computer interfaces (**BCI**) allow humans to output commands to machines through the mapping of EEG readings [1]
- Individuals with quadriplegia** can use non-invasive BCIs to interface with assistive devices such as wheelchairs
- Steady-state visually evoked potential (**SSVEP**) is used to elicit reproducible neural activity by showing users visual stimuli flashing at specific frequencies [2]
- Cognitive fatigue** arises when users are exposed to SSVEP visual stimuli for long periods of time which negatively affects BCI performance as EEG signal-to-noise ratio decreases [2]

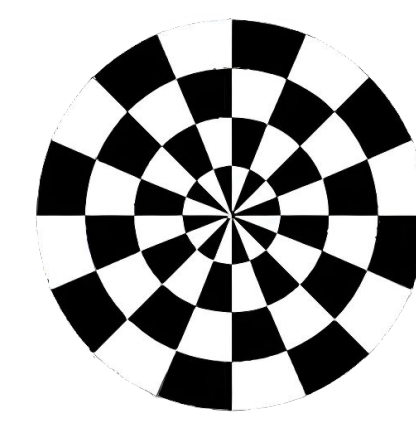


[3]

Setting Up SSVEP Experiments

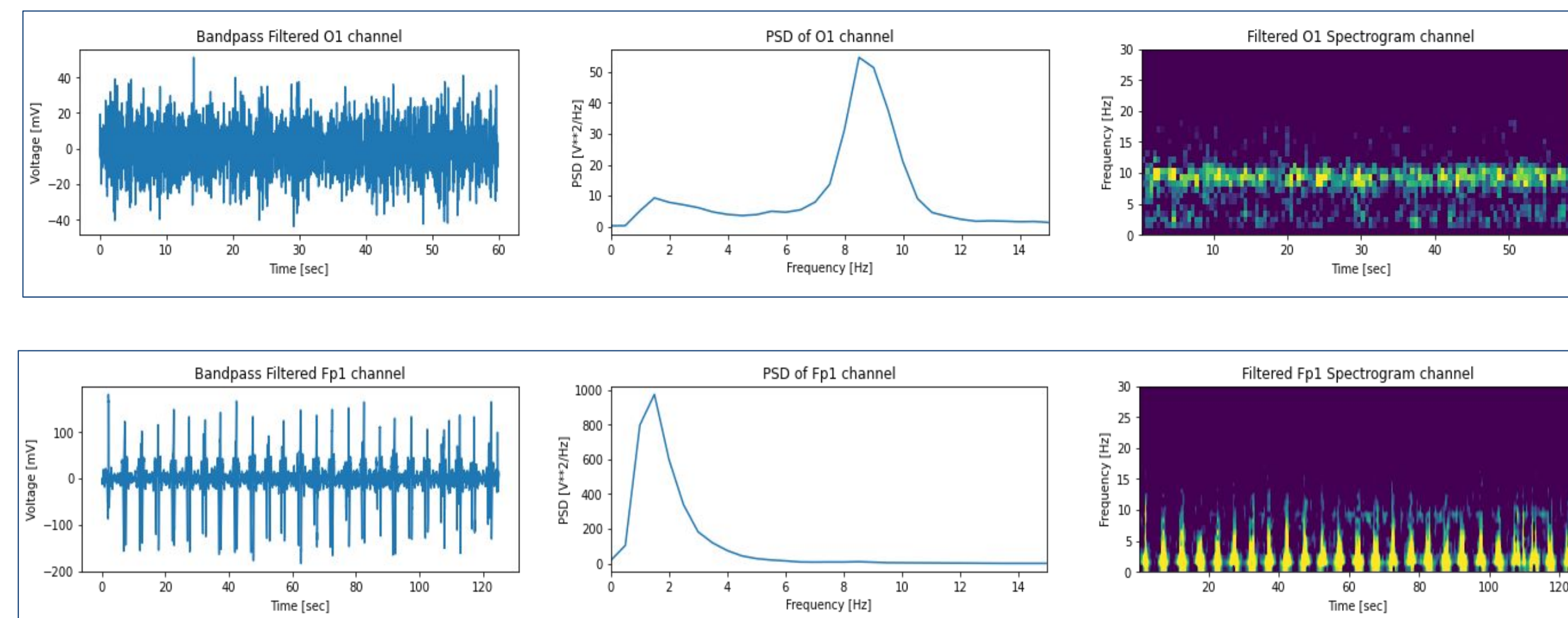


- The user is prompted to look at one of the four stimuli.
- The EEG response is recorded and a classification is made.
- The classification is compared with the ground-truth value.



Sanity Checking

- The presence of eye blinks and alpha waves when the eyes were closed were verified to check the quality of the EEG data.
- The increase in alpha wave power occurs when a user closes their eyes, and suggests that the EEG headset is identifying useful data rather than noise [4].



Methods

Canonical Correlation Analysis (CCA)

- Computes correlation coefficients between:
 - Each EEG sample from the occipital region
 - SSVEP input stimuli frequencies
- The frequency with the highest correlation score is chosen
- CCA is robust to noise and detects SSVEP signals better than its traditional counterparts [5]

Measuring Cognitive Fatigue

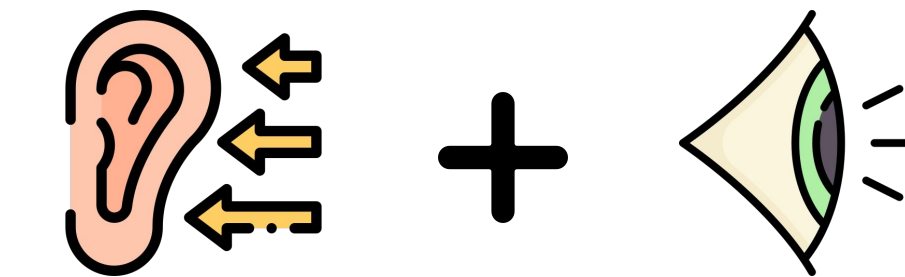
- Fatigue score is a ratio of frontal lobe band powers [6]

$$\frac{\alpha + \theta}{\beta}$$
- Measured values will be compared between non-fatigued and fatigued trials
- Likert-style** questionnaire will be used as a “ground-truth”



Dual n-back test

- Induce cognitive fatigue with high confidence and experimental ease [7]

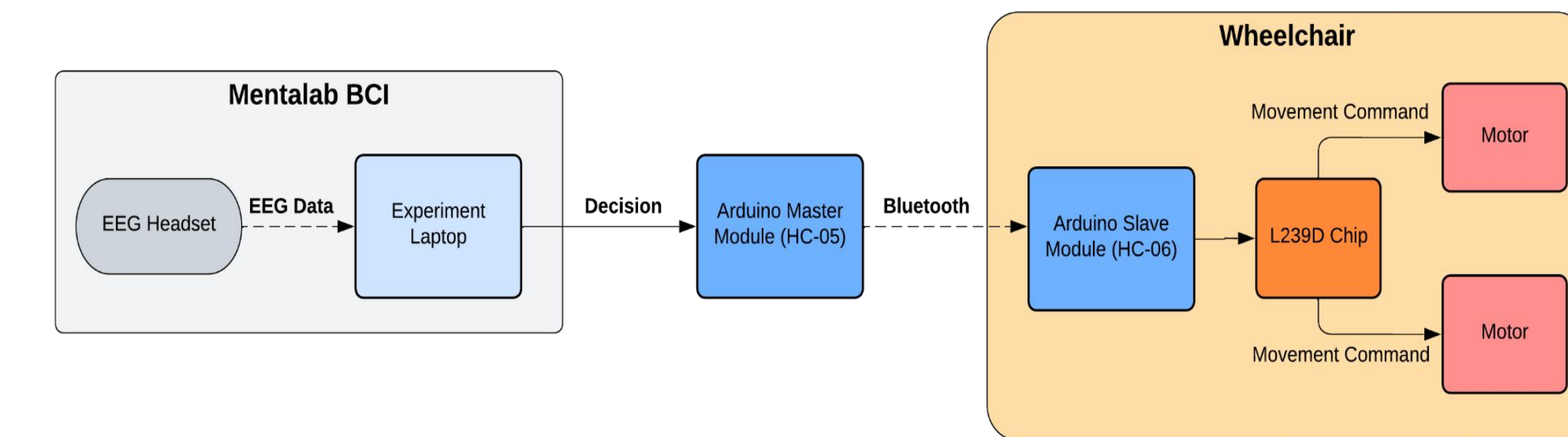


Convolutional Neural Network (CNN)

- Train on labelled samples of EEG:
 - Samples are processed through layers of convolutions, normalizations and non-linear activations
 - Layer parameters are automatically learned through the minimization of a global loss function
- Cognitive fatigue is used to weight the final layers
 - Fatigue scores for a trial are concatenated to linear layers at the end

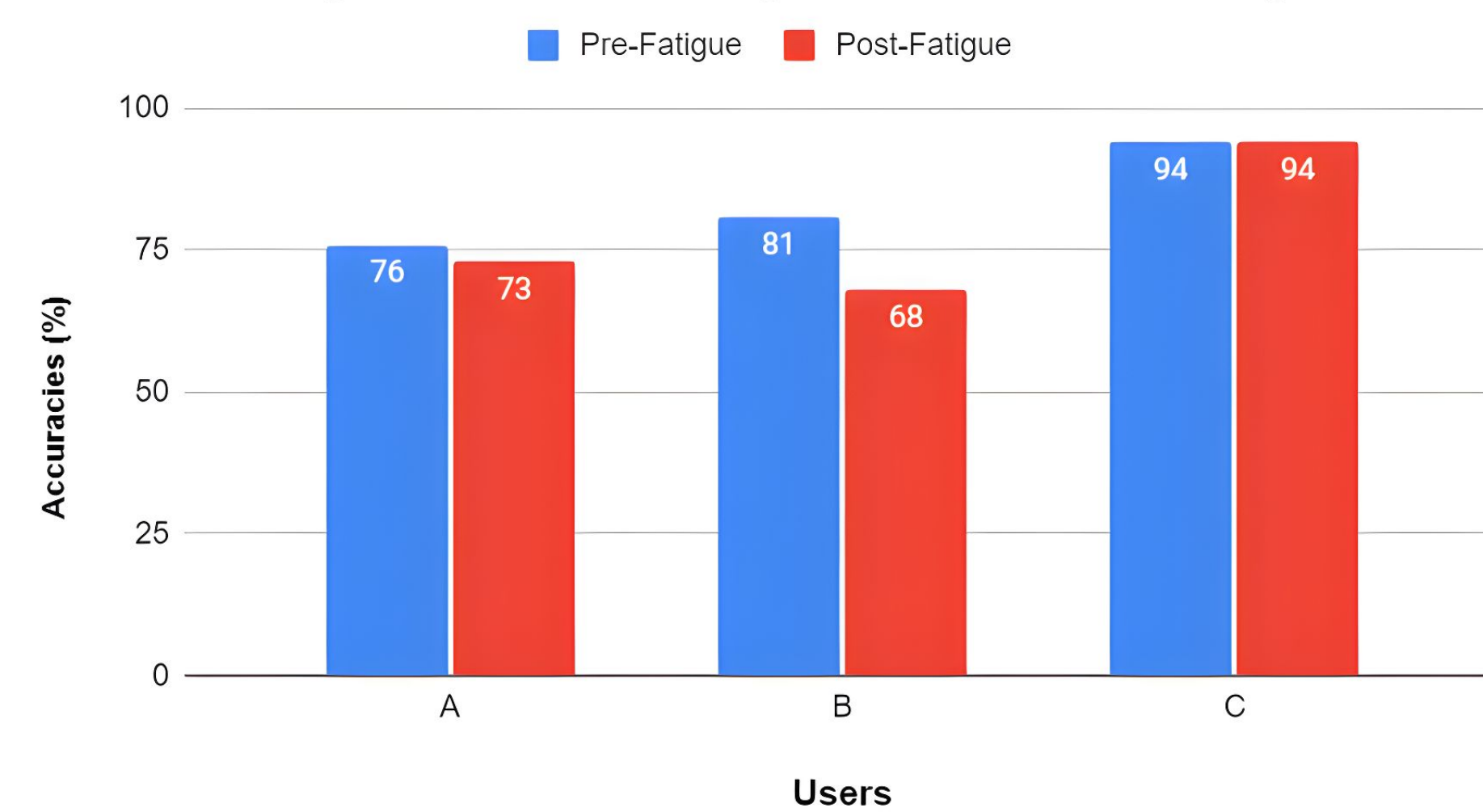
Physical Interface - Model Wheelchair

- A miniaturized motorized car was built to model a user's motorized wheelchair
- Depending on the signal and decision sent by the central module, one of four commands will be selected:
 - Stop
 - Turn left
 - Turn right
 - Move forward

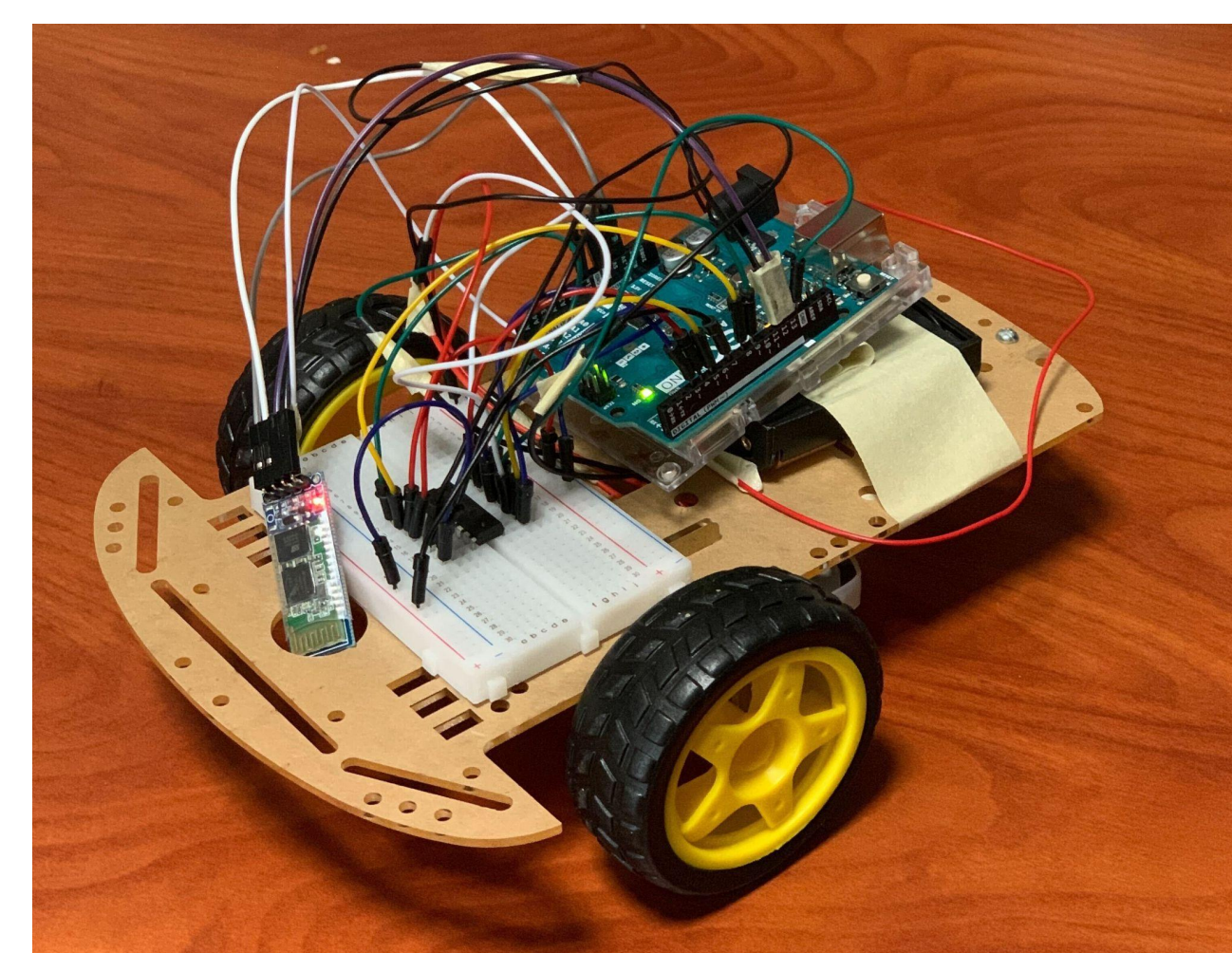
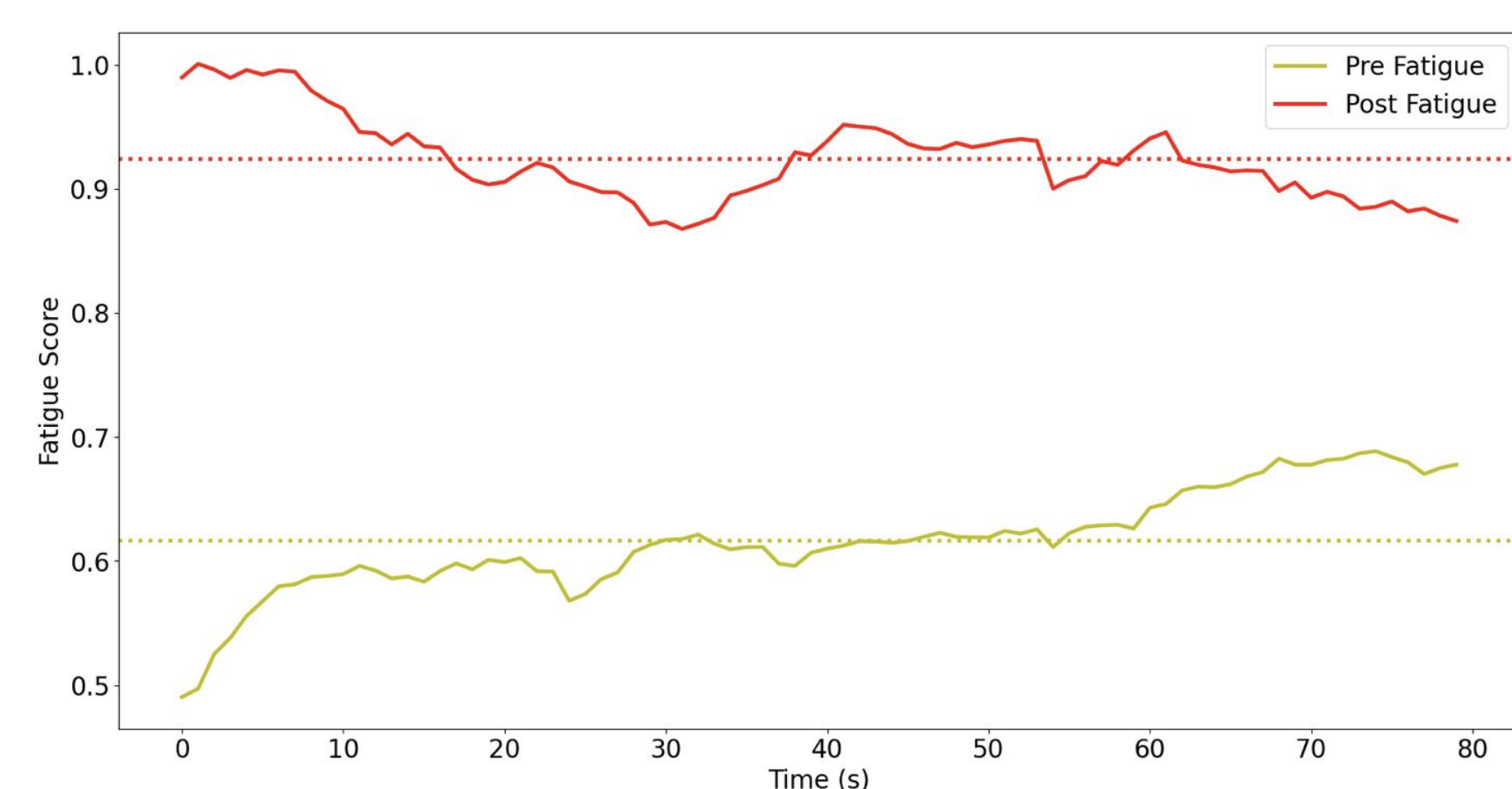
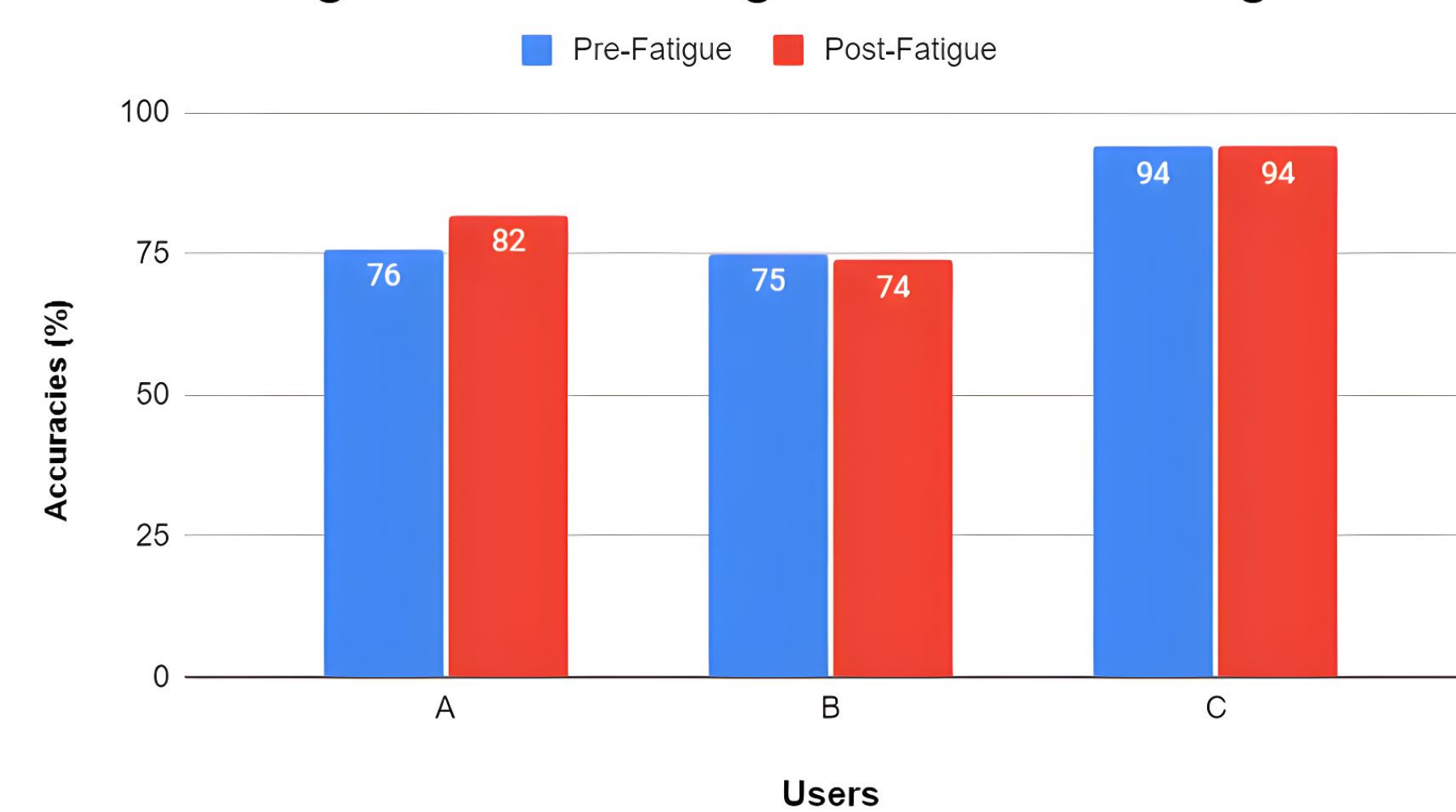


Results

Pre-Fatigue and Post-Fatigue Accuracies using CCA



Pre-Fatigue and Post-Fatigue Accuracies using CNN



Conclusion

Discussion

- Evaluated the CCA and CNN on three test users
 - Each user did a session before and after a cognitively-fatiguing activity
- CCA was found to have a drop in performance after the user undergoes the cognitively-fatiguing task
- CNN was found to have a similar or higher level of performance
 - User A has increased performance after fatigue
 - User B has a less significant decrease
 - User C has strong performance before and after

Future Direction

- Collect more data for training purposes and evaluation
 - Increase the variety of user characteristics when collecting data (e.g., age, gender, ethnicity, etc.)
- Investigate different ways of integrating cognitive fatigue as a parameter in the CNN model
 - Use Likert values instead of fatigue score
- Integrate CNN and decision motor outputs with programmable wheelchair
- Refine fatigue score algorithm to reduce noise

References and Affiliations

- P. Diez, "Introduction," in Smart wheelchairs and brain-computer interfaces: Mobile assistive technologies, *Elsevier Science & Technology Books*, 2018, pp. 1–17.
- H. A. Lamti, M. M. Ben Khelifa, A. M. Alimi, and P. Gorce, "Influence of mental fatigue on P300 and SSVEP during virtual wheelchair navigation," *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2014.
- S. E. Karabulut, M. M. Khorasani, and A. Pantanowitz, "Neurocartographer: CC-WGAN based SSVEP data generation to produce a model toward symmetrical behaviour to the human brain," *Symmetry*, vol. 14, no. 8, p. 1600, 2022.
- R. J. Barry, A. R. Clarke, S. J. Johnstone, C. A. Magee, J. A. Rushby, "EEG differences between eyes-closed and eyes-open resting conditions" *Clinical Neurophysiology*, Vol. 118, no. 12, pp. 2765-2773, 2007.
- W. Chen, S.-K. Chen, Y.-H. Liu, Y.-J. Chen, and C.-S. Chen, "An electric wheelchair manipulating system using SSVEP-based BCI system," *Biosensors*, vol. 12, no. 10, p. 772, 2022.
- F. Dehaes, A. Dupres, G. Di Flumeri, K. Verdiere, G. Borghini, F. Babiloni, and R. Roy, "Monitoring Pilot's cognitive fatigue with engagement features in simulated and actual flight conditions using a hybrid fNIRS-EEG passive BCI," *2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, 2018.
- A. Myrden and T. Chau, "Effects of user mental state on EEG-BCI Performance," *Frontiers in Human Neuroscience*, vol. 9, 2015.

Acknowledgements

We would like to acknowledge the NRE Lab and the counsel provided by Professor James Tung and Aravind Ravi throughout the term. We would like to thank Professor Maud Gorbet, Dr. Eric Kubica, and Dr. Calvin Young for their feedback on our project. Finally, we would like to thank WATOLINK for supplying the Mentalab Explore device and providing guidance with operating the equipment.