Transfer Learning for Generalized Movement Prediction in Brain-Computer Interfaces

Motivation

Brain Computer Interface (BCI) research has led to significant progress in a multitude of applications, including letting paralyzed patients control robotic arms [1], improving sleep quality [2], and mitigating the effects of major depressive disorders [3]. However, current state-of-the-art BCIs typically fail to generalize well enough for everyday use due to two key factors. First, ***current BCIs rely on models fine tuned to training data from every individual*** [4]; this makes it difficult to implement BCIs before substantial training data is collected for each person. Second, ***most existing BCI research is confined to the laboratory***, where movements are constrained to the research task and thus do not accurately represent the diversity of neural signals. Some research has trained BCIs in naturalistic settings [5, 6] -- settings that give subjects freedom to move at will -- but more translational work must be done to take advances from the lab to the real world.

One possible solution to these issues is to leverage approaches from transfer learning to naturalistic brain data. *Transfer learning* (TL) trains a model on one domain and task, then transfers that model to a new domain with little or no new training [7]. TL could reduce the amount of training data required for a new subject by leveraging knowledge from previous subjects. Thus, **this proposal seeks to combine deep learning with transfer learning to develop a generalized BCI that can predict and detect arm movements from neural signals in naturalistic settings, with minimal to no training on new human subjects.**

TL has received increasing attention in the machine learning (ML) community and has great potential to advance ML research. In particular, it could lower the need for large labeled training data and open up ML to new applications where training data is scarce or expensive to obtain, like BCIs, medical imaging [8], and robotics [9]. TL could also help develop less hyper-specialized models since its models are engineered to be flexible and could even improve system robustness. **This project will help to develop new techniques in transfer learning that could benefit the ML community as a whole**, while also **answering important questions in neuroscience.**

Aim 1: Develop a generalized BCI decoder to predict arm movements from neural and video data collected from multiple human subjects. I plan to train a deep neural network on ECoG (electrocorticography, where electrodes are implanted under the skull on the surface of the brain) data and simultaneously recorded video data from 12 subjects who underwent epilepsy monitoring for a week in the hospital [4]. This dataset provides naturalistic data that is sufficiently large for training. My current lab has previously used this data to decode and predicted an individual's wrist movements using the video data as ground truth [5, 10]. However, these decoders were trained for use on single individuals. To expand prediction to more than one subject, I plan to aggregate the ECoG data from all subjects and train a new network on the aggregated data.

Since electrode locations are defined by surgical needs, one roadblock to aggregating this data is that not all ECoG arrays represent the same brain areas. To resolve this issue, I will map the ECoG data to registered brain areas using recent techniques in ECoG anatomical mapping [11]. This process maps individual electrodes to different brain areas, such as the motor cortex, so that the neural network will know what the signals from each electrode represent. Once all subjects ECoG arrays are mapped to a "common map," the neural network can be trained on aggregate ECoG data for all subjects. A proof-of-concept for transfer learning in the network is to train on 60% of the subjects' data and test accuracy for predicting up and down arm movements on the remaining data.

Aim 2: Test the generalized BCI decoder on new subjects in real-time in the hospital setting. After development of the generalized decoder framework in Aim 1, the next step will be to test its effectiveness on differing amounts of training data (none, 1 hour and 1 day's worth) for a new human subject. The predicted variable will be the same (predicting up and down arm movement), but the subject's particular neural signals and ECoG electrode locations will be new to the BCI. The BCI will take each new subject's electrode locations as input, so neural signals can be mapped to anatomical areas of the brain. The subject will use the BCI to control the up-down movement of a cursor on a computer with their neural motor signals [12]. The subject will receive instructions to direct the cursor either up or down within a certain timeframe (e.g. 5 seconds), which will determine the accuracy of the BCI. I will compare BCI accuracies for the different amounts of training data, to see how training impacts performance.

Intellectual Merit

This project will contribute new knowledge to both transfer learning and neuroscience. Exploring transfer learning in the context of BCIs will provide insights into transfer learning techniques, such as methods to aggregate data across domains, and how much new training data to include from the new domain. Also, I will develop a method to aggregate ECoG data across multiple subjects, independent of electrode placement, which could help other ECoG researchers smoothly compare data between subjects. Lastly, the project will advance BCI research by developing a generalized BCI that can work quickly for new subjects in naturalistic settings. I have the appropriate skills, knowledge, and resources available to make this project successful. The required ECoG dataset is accessible through my lab and gaining access to new subjects is highly feasible. Further, I am co-advised by a biology professor and a computer science professor, representing the mixture of disciplinary expertise required for this project. I also represent this mixture, as I have valuable experience analyzing large brain datasets [13,14], and I have a B.S. in computer science.

Broader Impacts

For many people who could use BCIs to better interact with the world, a BCI for their day-to-day would greatly impact their quality of life. Many BCIs are still confined to the laboratory, providing a barrier to home use for people such as amputees or paraplegics. **This project seeks to mitigate this barrier by developing a BCI that can handle naturalistic/real-life settings and also remove the barrier of significant training time.** However, BCIs can also present significant ethical and social concerns, such as data privacy and user agency. Staying true to my interests in social justice and ethics, I will continue to consider the ethical impacts that this research may have on the participants by leveraging resources from the research concentration in neuroethics at the UW Center for Neurotechnology. I will also continue research mentorships with younger students, high schoolers, and undergraduates to encourage bright young minds to engage in research with positive social impacts.

[1] Grigorescu *Robotica* 2012 | [2] Chen *ICIEA*, 2018 | [3] Delaloye *Dialogues Clin Neurosci* 2014.
[4] Benabid *The Lancet Neurology* 2019 | [5] Wang *Frontiers in Human Neuroscience* 2016. | [6] Wang *AAAI* 2018
[7] Tan *Artificial Neural Networks and ML - ICANN* 2018 | [8] Chang *IEEE Trans. Pattern Anal. Mach. Intell* 2018
[9] Delhaisse *2017 International Joint Conference on Neural Networks (IJCNN)* 2017
[10] Singh *2019 Conference on Cognitive Computational Neuroscience* 2019 | [11] Stolk *Nature Protocols* 2018
[12] Wolpaw *Proc Natl Acad Sci U S A* 2004 | [13] Steine-Hanson *Procedia Computer Science* 2018
[14] Stocco *bioRxiv* 2019