MODULE 3-P2: Brain-computer interfaces for sensorimotor recovery after stroke

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1 Introduction

- Past studies conducted have demonstrated the applicability of EEG-based neurofeedback training (NFT) to stroke rehabilitation in a specialized HMI system called brain-computer interface (BCI) [1, 2].
- In this project we aim to work towards the next breakthrough in EEG-BCI-based motor recovery for stroke by developing effective deep learning (DL)-based techniques that will potentially advance the technology and science behind BCI-based stroke rehabilitation.
- In particular, we propose to extend the conventional BCI-based protocols for stroke therapy towards greater functional recovery of upper extremities. This will include building a high performance deep learning decoder that can decode fine motor activity from EEG signals.
- **Aims**:

1. To build a BCI-based stroke rehabilitation paradigm for distal upper extremities
2. To build a high performance deep learning model that can detect and decode fine motor activity from EEG in real time

2 BCI for distal upper limbs

- These are the main components of a BCI. Similar concepts are used for the on-going research for distal upper extremities.

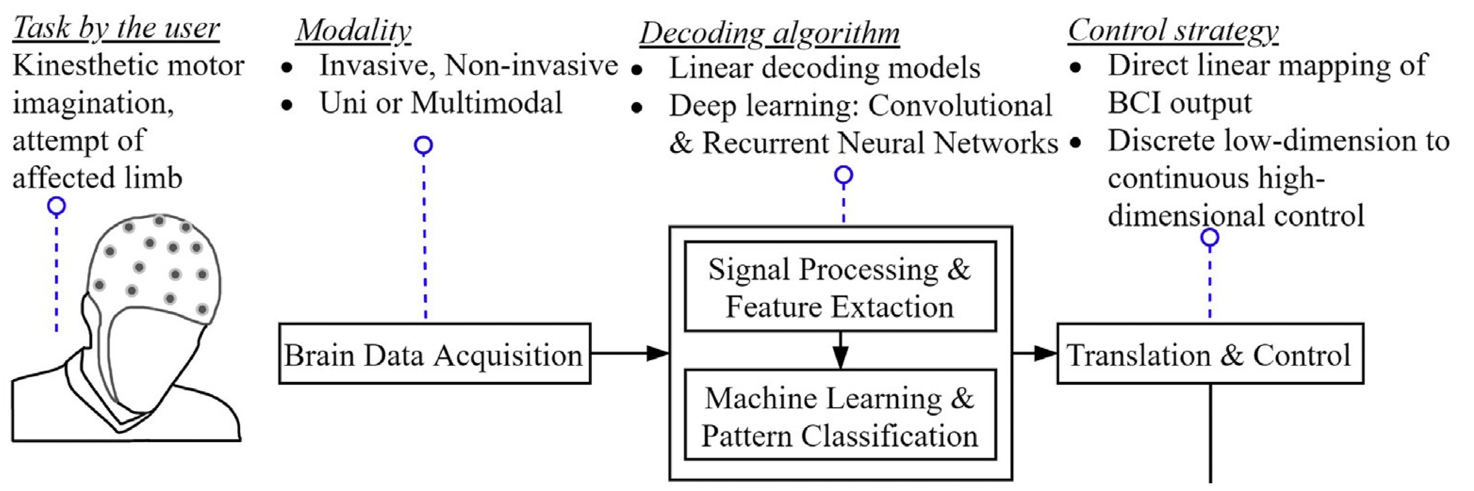

Figure 1: The key components of a BCI [3]. The brain data acquired is sent to relevant blocks of signal processing and feature extraction to enhance the quality of and extract the features of interest from the raw brain signals. These are then used with ML/DL models to predict the motor activity that the user wishes to accomplish. This decoded information is then translated to control commands to actuate an external device.

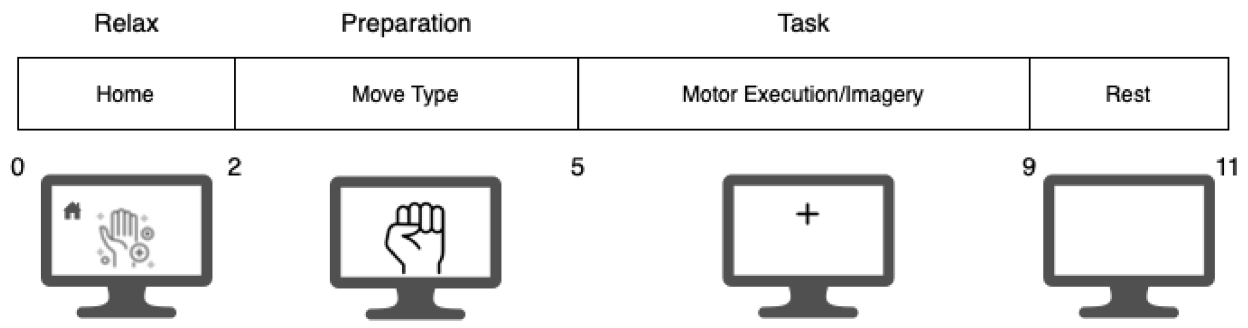

Figure 2: Experimental Protocol, Trial-based motor activity. A single motor action is performed every trial. For this experiment, three types of motor actions were considered: hand opening, hand closing (grasping) and pinching. The trial began with the home period, asking the participant to reset his/her hand in the home position. The next screen informed the participant about the type of action to be performed. As the screen was replaced with the fixation cross, the person then performed the activity, after which the trial ended.

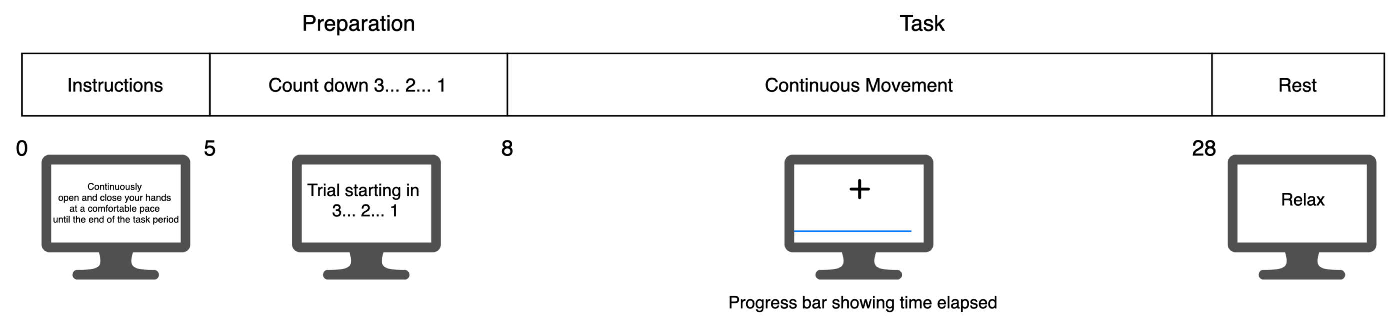

Figure 3: Experimental Protocol, Continuous motor activity. In this design, the participant was asked to make hand movements continuously for a duration of 20s. Hence, we refer to each set of such tasks as blocks, rather than trials. Each block began with instructions on performing continuous hand opening and hand closing movements. Next, a countdown helped the participant prepare for the task to begin. During the continuous movement task, the screen showed a fixation cross along with a progress bar, showing the elapsed time. The participant was tasked to perform the repeated hand movements till the end of the task period.

- For an initial exploratory analysis, we considered two types of tasks: (A) trial-based single motor activity and (B) continuous, repeated motor activity.
- Figure 2 shows the experiment protocol used for collecting data for (A) trial-based single motor activity. Here, we considered three types of motor actions: hand opening, hand closing and pinching. We also considered both, motor execution and motor imagery. A total of 30 trials consisted of one run of tasks. In each run, the participant was instructed whether to perform motor execution or motor imagery. A total of 10 such runs were collected for each participant.
- Figure 3 shows the experiment protocol used for collecting data for (B) continuous and repeated motor activity. In this set of tasks, the participant only performed repeated motor execution of hand opening and hand closing in a self-paced manner. A total of 50 blocks were collected for each participant.
- Data from more participants is being collected for both types of protocols which help to build a high performance deep learning model. Insights into the decoding performance of each type of task will help to further refine the design of the treatment paradigm to be used in the clinic with stroke patients.
- Figure 4 shows the preliminary classification results. More accurate deep learning models will be investigated in future to further enhance performance.

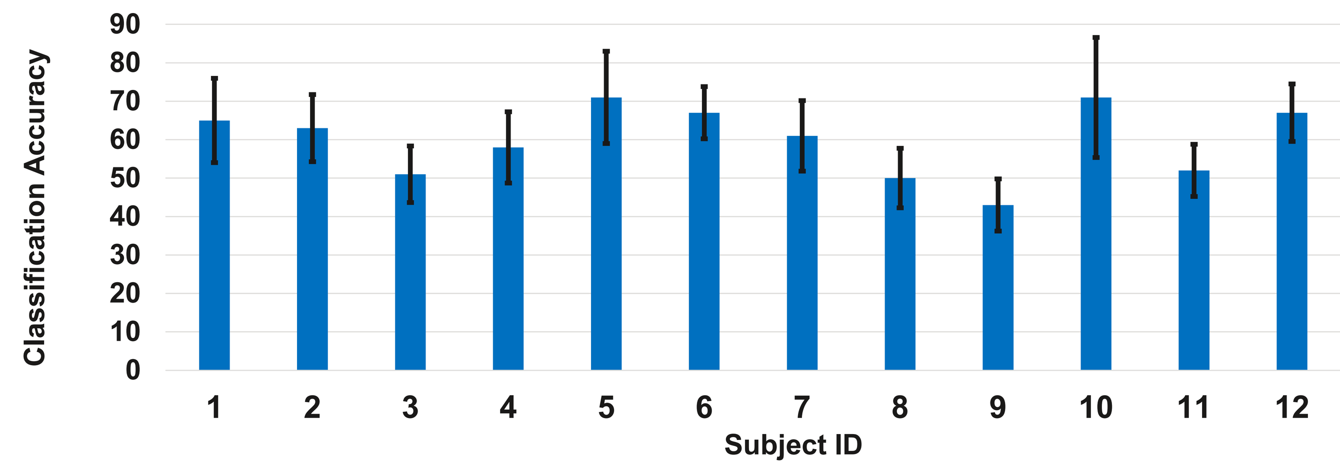

Figure 4: Classification accuracy of 12 subjects performing hand opening and hand closing gestures. These 12 subjects performed trial-based hand movements, as described in the experimental protocol in Figure 2. EEGNet [5] was used as the deep learning model to perform subject-specific binary classification using the participants' EEG data. A total of 59 EEG channels were used for recording whole brain EEG data.

4 Future work

- Based on the preliminary analysis, we are currently developing a high performance deep learning model to achieve satisfactory decoding performance for both types of protocols. The performance of each type of protocol will help to determine the final design of the BCI-based treatment used for stroke rehabilitation.

References:

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