EEG-Based Motor Imagery Decoding with Deep Learning

1. Introduction

People affected by some pathologies, such as paralysis or neuromuscular disorders, face significant challenges in interacting with their environment and carrying out daily activities. Despite the inability to move their muscles, individuals with these pathologies can often still engage in mental processes related to movement. The concept of EEG-Based Motor Imagery Decoding aims to capture and analyze the brain activity of such individuals, leveraging machine learning methods to interpret the intended movements they are thinking about. These imagined movements can include actions like "*right hand up*," "*right hand down*," "*left hand up*," "*left hand down*," and more.

While ongoing research in this field is promising, with active investigations into effective solutions, the development of practical and reliable applications for real-life conditions remains a work in progress. Despite the challenges, the potential of EEG-Based Motor Imagery Decoding to offer a means of communication and control for individuals with limited physical abilities holds significant promise for improving their quality of life.

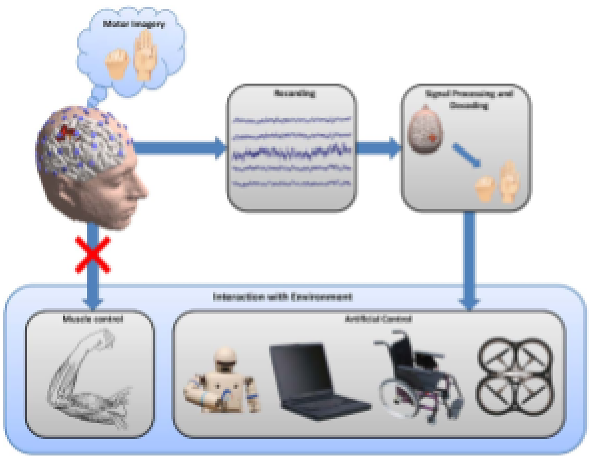

Fig.1 EEG-Based Motor Imagery Decoding

Fig. 1 illustrates the process of EEG-based Motor Imagery decoding. The methodology involves capturing brain activity using multiple sensors placed on the subject's head. These sensors are designed to record the electrical activities originating from various regions of the brain. Each sensor generates a time series representing the electrical signals corresponding to different time instants during the recording. The collected EEG signals, forming a multi-channel input, are then fed into a machine learning model. This model jointly processes these signals and makes predictions regarding the specific movement that the patient is thinking about during the recording. Many machine learning can be used to approach this problem. These days, there is a growing interest in the use of deep neural networks, which recently showed to outperform other machine learning methods. Examples of popular models used to solve this task are EEGNET, ShallowConvNET, and EEGConformer, with EEGNET providing state-of-the-art results most of the time.

The objective of this project is to develop various neural networks designed for decoding Motor Imagery from EEG data and to evaluate their performance.

2. Methodology

The main focus for the students is on implementing neural networks for decoding motor imagery. All students will utilize the same dataset (BNCI2014001) and library (SpeechBrain-MOBB), both of which are detailed below.

2.1 Datasets

To train and test the implemented models, students will utilize the widely used BNCI2014001 dataset for Motor Imagery. This dataset comprises EEG data from 9 subjects, involving the mental simulation (without execution) of four distinct motor imagery tasks: imagining movement of the left hand (class 1), right hand (class 2), both feet (class 3), and tongue (class 4). Each subject participated in two sessions on different days, with each session consisting of 6 runs separated by short breaks. A single run encompasses 48 trials (12 for each of the four classes), resulting in a total of 288 trials per session.

2.2 Library

Students will use a recently-released library for EEG processing, which is called SpeechBrain-MOABB. This library is designed to simplify the development and evaluation of neural networks for multiple EEG tasks, including motor imagery.

SpeechBrain-MOABB efficiently handles various aspects related to the EEG pipeline, including data loading, preprocessing, data augmentation, batching, training/evaluation loops on different subjects, multiple seed evaluations, hyperparameter tuning, and more. Consequently, students can primarily concentrate on designing their neural networks.

SpeechBrain-MOABB also includes an experimental protocol for ensuring a fair assessment of EEG models. This protocol includes multi-seed evaluation and standardized hyperparameter tuning. Students have to use this protocol to enable a fair comparison of models with the state-of-the-art. Moreover, SpeechBrain-MOABB already offers baselines for well-known models such as EEGNET, ShallowConvnet, and EEGConformer. Students are encouraged to utilize these baselines as templates, modifying only the necessary components required for implementing and integrating their models.

2.3 Work Plan

Students have their freedom and flexibility to organize the steps necessary for completing this project according to their preferences. However, a suggested work plan for this project is outlined below

1. Familiarizing with SpeechBrain-MOABB:

- Explore the comprehensive README.md file in the SpeechBrain-MOABB repository for details about the toolkit and EEG processing.
- Utilize the provided tutorials to gain a better understanding of how the library operates.

- Attend the optional seminar associated with the course, focusing on EEG processing with SpeechBrain-MOABB, for valuable insights.
- Run an initial experiment by replicating results achieved with EEGNET for the designated task. Ensure smooth functioning of the environment and compare results with the expected outcomes.

2. Literature Review:

- In parallel to step 1, conduct a literature review on deep learning models, with a specific focus on recent models proposed for EEG processing.
- Examine details of standard models such as EEGNET, ShallowConvNet, and EEG Conformer.
- Explore recent literature to gain insights into models that can be implemented.

3. First Model Implementation:

- Implement a basic model to familiarize yourself with plugging custom models into EEG pipelines.
- Use the existing EEGNET recipe as a starting point and learn how to integrate new models. Ensure that the input and output from your model align with the expected format for the rest of the pipelines.

4. Implement and Test Different Models:

- Develop and test various complex models, including those not previously applied in this context.
- We encourage creativity and intuition of the students to explore ideas and attempt the implementation of new models. This phase forms the core of the project, and a higher number of original models will enhance the project evaluation.

5. Write the Report:

- Submit a project report in the form of a Google Colab notebook (refer to project guidelines). Utilize the notebook format for convenient inclusion of code, text, tables, and images. You need to provide runnable code for replicating main results, explanations of implemented models, result tables, critical result analyses, discussions, and other relevant content.

3. Evaluation

The project is graded on a scale of up to 30 points. Within the scope of this project, it is crucial to introduce novel neural network architectures that have not been previously employed in this context. Students are required to implement these new models, ensuring accuracy, and effectively evaluating their performance.

To assess these models, students must use the experimental protocol for model evaluation and hyperparameter tuning embedded in SpeechBrain-MOABB. Models capable of surpassing EEGNET not only can achieve a top grade but may also be considered for potential follow-up publications. To enhance your grade, it is encouraged to explore a variety of original models.

Refer to the project guidelines for comprehensive details on the project evaluation process.

4. Tips

- Time Management: Undertaking a project of this nature demands careful time management. It is advisable to initiate the project at the earliest opportunity. Avoid starting the project in the final weeks leading up to the submission deadline. Experimentation may require significant time for convergence, debugging can be challenging, and accurate model implementation may take time.

- Computational Resources: Although the dataset used is small, the hyperparameter tuning and multi-seed evaluation process can be computationally intensive. We suggest starting the initial development stage with basic computational resources, such as Google Colab. Once the models are implemented, consider utilizing more advanced resources like Google Colab Pro or Gradient for the full experimental protocol with hyperparameter tuning. Special computational requirements can be met through GPUs provided by Compute Canada, subject to approval from the professor.

- Small Models: Note that models commonly used for EEG processing are smaller compared to those used in speech processing, NLP, and computer vision. Due to limited data in EEG, models with thousands or hundreds of thousands of parameters are employed, unlike the models with millions or billions of parameters used in other domains. If using a model inherited from these domains, downsizing is necessary.

- Individual Work: This is an individual project. Collaboration is not allowed. Violations will result in lower grades and will be reported. Each student must independently implement different models with distinct code implementations. Avoid sharing details about the models you are exploring with other students. While students can seek advice from their lab instructor, the work itself must be done independently