ML Project 2 - Report

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***Abstract*—**

I. Introduction

Machine Learning (ML) is has become a central tool in neuroscience, with applications in neural engineering (e.g. Brain-Computer Interfaces, BCIs), diagnostics and fundamental research. For instance, Jalilifard et al. [1] demonstrated the efficacy of Support Vector Machine (SVM) classifiers in basic emotions recognition, while Bose et al. [2] used Random Forest classifiers to automate seizure detection in epileptic patients with high accuracy. Indeed, all major ML methods have been applied to neural signals classification[3].

In this work, we examine the applications of such ML techniques in three classification problems using sEEG signals: i) distinguishing between the execution and observation of a movement; ii) differentiating between grasping a small versus a large object; iii) differentiating between observing the grasp of a small versus a large object.

Section II outlines the data acquisition process and its relevance to our classification tasks. In Section III, we describe the preprocessing of the sEEG signals and the extraction of relevant features. Sections IV and V present the models applied to our classification problems and their performance. In Section VI, we explore the idea of using only Deep Learning (DL) to directly extract features from the EEG signal. Finally, we discuss our results in Section VII and conclude in Section VIII.

II. Data acquisition and problem specification

The dataset comprises signals recorded from four participants, each implanted with sEEG electrodes in distinct brain regions. During multiple experimental sessions, participants were instructed to either observe or execute specific motor tasks. These tasks involved two types of movements: a palmar grasp (force-based movement) and a pinch grasp (precision-based movement). Each session included multiple trials structured as follows: in an execution trial, the trial begins with a start cue. One second later, a light cue signals the type of object (small or large) to be targeted. This light remains illuminated for 0.5 seconds before turning off. After an additional 1.5 seconds, a ”go” signal prompts the participant to lift their hand from the resting position, grasp the indicated object, return it to its original location, and place their hand back in the resting position. Observation trials followed an identical structure, except that participants passively observed the experimenter performing the actions. A light cue indicated the participant’s role (execution or observation) in each trial.

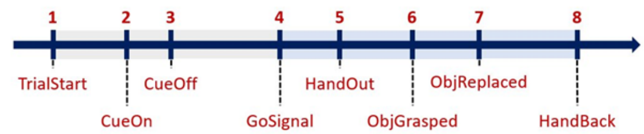

Figure 1. Timing of the trials

III. Data analysis

A. Channel responsiveness

Which regions have the most responsive channels, are they the same for execution & obervation?

- Across participant: same region? same nb of responsive channels?
- Are the channels responsive for obs also responsive for ex? Vice-versa?
- Do we find the expected regions? Link to mvt execution / observation?

For channels where we have response for both ex & obs, are the responses congruent (similar pattern) or incongruent (different)?

- Amplitude, shape of response $\rightarrow$ difference?
- Response pattern at the same timing?
- Similar frequency characteristics?
- Correlation? High correlation suggests congruence
- Are the results obtained similar for both movements?

IV. Action recognition

Do it for each participants

A. Models

SVM:
Random forest:
MLP:

B. Results

C. Discussion

Which freq. bands are important? Is it the same across subjects?

V. Object recognition

Do it for each participants

A. *Models*

SVM:

Random forest:

MLP:

B. *Results*

C. *Discussion*

Which freq. bands are important? Is it the same across subjects?

VI. Pure deep learning approach

Can a 1D conv. network learn relevant features for classification? Create and test model on trials themselves

VII. Discussion

VIII. Conclusion

IX. Ethical risks

X. Appendix

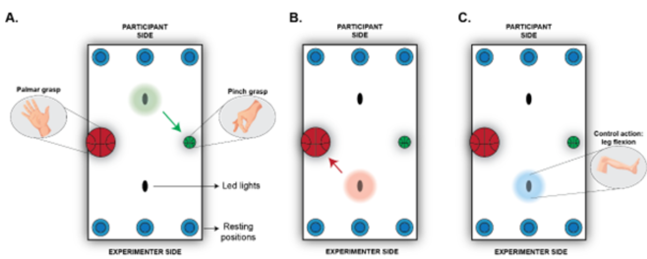

Figure 2. Experimental setup

Acknowledgements

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References

[1] A. Jalilifard, E. B. Pizzolato, and M. K. Islam, "Emotion classification using single-channel scalp-eeg recording," in *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2016, pp. 845–849.

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[3] M.-P. Hosseini, A. Hosseini, and K. Ahi, "A review on machine learning for eeg signal processing in bioengineering," *IEEE Reviews in Biomedical Engineering*, vol. 14, pp. 204–218, 2021.