MSc in Computational Cognitive Neuroscience

LIQUIDWEB Innovative Human-machine Interfaces

Goldsmiths UNIVERSITY OF LONDON

Optimal classification of EEG-based visual imagery by Brain Computer Interface (BCI) systems

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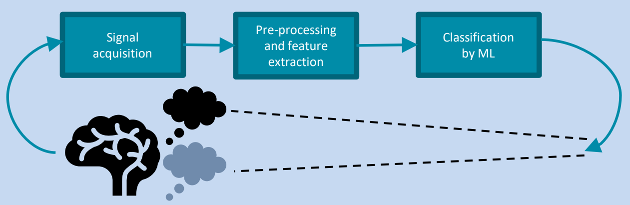
Context

BCI technologies are systems allowing for communication between a subject and an external device (i.e. a computer) without the need of engaging one's peripheral nervous system.

This is possible thanks to the acquisition of a subject's brain activity (e.g. via EEG) which is then fed into a machine learning (ML) classifier that learns to discriminate the patient's intentions based solely on their brain signal.

One of the frameworks for such communication is embedded in the context of visual imagery during which a subject visualizes an object or an action.

This, in turn, produces a unique pattern of brain activity that can be learnt by ML algorithms.



Data analysis methods

Different Artifact-rejection/repair Approaches

ICA | Signal amplitude | "Autoreject" | Visual inspection

Different Feature Extraction Approaches

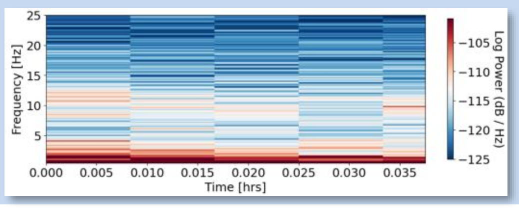
PSD | CSP | PCA | LFDA

Classification Accuracy & other metrics

Traditional ML (SVM, LDA) | Deep Learning (CNN, RNN, hybrid)

Inferential Statistics

Additionally, the possibility of feeding raw EEG and spectrogram images data will be explored



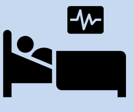
Objectives

1. Find artifact-rejection and feature extraction techniques best suited for the EEG data signal treatment by traditional ML and deep learning (DL) approaches

2. Compare the accuracy of ML and DL approaches to classifying VI EEG data

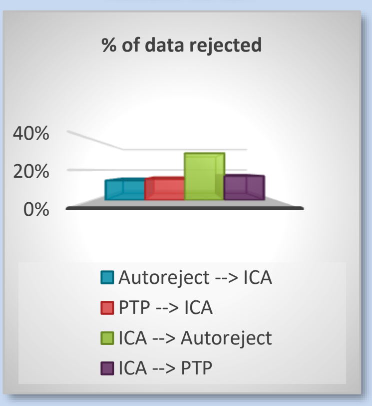
Rationale

Augment the communication of Locked In Syndrome patients with the outside world by improving the efficacy of BCI systems



(Expected) Results

Results so far:



Hypotheses:

Best feature-extraction techniques are PSD, CSP, DWT[3]

DL models will achieve greater accuracy than traditional ML models[4]

Convolutional networks can classify raw EEG data and spectrograms with satisfactory accuracy[5]

Experimental design

Brain activity EEG recording of one participant engaging in 30 trials of:

60s Resting State → 10s Push VI → 10s Relax VI → 10s Push VI → 10s Relax VI → 10s Push VI → 10s Relax VI → 10s Push VI → 10s Relax VI → 10s Push VI → 10s Relax VI

resulting in 150 x 10 second long time-series instances of Push and Relax VI each

Limitations

Sample size per instance too small for DL

Data of just one participant

Low resolution EEG headset

?

[1]Goldsmiths, University of London
[2]LiquidWeb s.r.l.

[3]Hong, K.-S., Khan, M. J., & Hong, M. J. (2018). Feature Extraction and Classification Methods for Hybrid fNIRSEEG Brain-Computer Interfaces. *Frontiers in Human Neuroscience*, 12.
[4]Castro, A. J. F., Cruzit, J. N. P., Guzman, J. J. C. D., Pajarillo, J. J. T., Rilloraza, A. M. M., Nieles, J. P. M., & Prado, S. V. (2020). Development of a Deep Learning-Based Brain-Computer Interface for Visual Imagery Recognition. *16th IEEE International Colloquium on Signal Processing Its Applications (CSPA)*
[5]Craik, A., He, Y., & Contreras-Vidal, J. L. (2019). Deep learning for electroencephalogram (EEG) classification tasks: A review. *Journal of Neural Engineering*, 16(3)