MSc in Computational Cognitive Neuroscience

braincontrol human technology

Goldsmiths UNIVERSITY OF LONDON

Addressing BCI Illiteracy with Imagined Speech and Visual Imagery EEG-based Brain Computer Interfaces

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Background

EEG-based BCI systems allow users the ability to communicate through controlling a computer with their thoughts.[3] Currently there are many combinations of mental paradigms that are classified by Machine learning (ML) or Deep Learning (DL) methods. Visual Imagery is one paradigm, referring to imagining perceptual experiences in one's mind. Liquidweb, a collaborator in this project, previously found success in utilising VI BCIs. However, certain novice users could not perform the specific paradigm, known as BCI illiteracy.

Recent research, to address BCI illiteracy proposed an intuitive paradigm, combining VI with Imagined Speech (IS)[3]. IS is defined as first-person imagery of speaking in one's mind[3]. The research found that most individual subjects significantly performed better in one paradigm over the other. It has also been shown that those who showed higher visual imagery capabilities performed better in Motor Imagery paradigm[5].

For classification, a one-dimensional Convolutional Neural Network (1D-CNN) has shown previous success over ML in the ability to extract features from cross channels and capture information transfer between different brain regions[4].

Aims

This study aims to take a comprehensive user-centric approach to reduce BCI illiteracy and optimise decoding performance. By including questionnaires to assess visual imagery capabilities[5] and control for dyslexia[7], utilising intuitive paradigms VI and IS and utilising a 1D-CNN[4] for optimal classification.

Hypotheses

- VI – observe alpha and beta modulations changes.
- IS – observe gamma oscillations in the temporal/dominant speech and language areas.
- Higher VVIQ scores will perform better on the VI paradigm, higher Dyslexia scores will perform poorer on the IS paradigm.

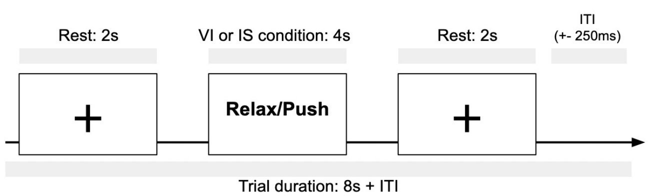

Figure 1. Diagrammatic representation of the data collection protocol.

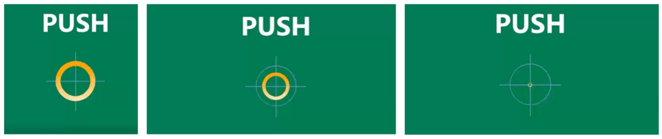

Figure 2. Screenshots of the Visual Imagery instruction video.

Design & Methods

- Within-subjects comparison: Aiming to collect 15 participants, 200 trials in total with 100 in the VI condition and 100 IS condition, with randomized 'Push' and 'Relax', counterbalanced between 4 paradigm blocks (2 of each).
- Participants will complete the Vividness of Visual Imagery[5] and Dyslexia[7] questionnaires.
- Instruction videos for each paradigm (Figure 2) will be shown to the participants before the experiment.
- PsychoPy will display the VI and IS paradigms shown in Figure 1.
- EEG data will be collected with 64 channel BioSemi Active (512 Hz).

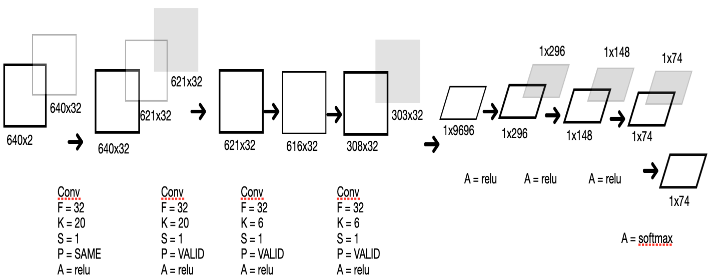

Figure 3. Diagrammatic representation of 1D-CNN architecture. Layers 1-10 (from left).

Data Processing and Deep Learning Architecture

Data preprocessing:

- The pre-processing pipeline will be programmed using MNE-Python.

Data Analysis:

- The Non-parametric Cluster-Based Permutation analyses will be performed using FieldTrip, which is a toolbox in MATLAB[6].
- The time frequency decomposition of the EEG data will take account of the space, time, and frequency.

Offline Data Classification:

- The 1D-CNN[4] model will be implemented with PyTorch.
- 1D-CNN – assessing optimal classification performance through experimenting with different activation functions, learning rate and training epochs.

Potential Results

- Non-parametric Cluster-Based Permutation will find significant difference between the two paradigms VI vs IS.
- 1D-CNN will achieve high accuracy in classification performance and transfer learning for subject-specific accuracy.

- 3. Lee, S. H., Lee, M., & Lee, S. W. (2020). Neural Decoding of Imagined Speech and Visual Imagery as Intuitive Paradigms for BCI Communication. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 28(12).
- 4. Mattioli, F., Porcaro, C., & Baldassarre, G. (2021). A 1D CNN for high accuracy classification and transfer learning in motor imagery EEG-based brain-computer interface. Journal of Neural Engineering, 18(6).
- 5. Leeuwis, N., Paas, A., & Alimardani, M. (2021). Vividness of Visual Imagery and Personality Impact Motor-Imagery Brain Computer Interfaces. Frontiers in Human Neuroscience, 15.
- 6. *(1999, July 21). Cluster-based permutation tests on time-frequency data. www.Fieldtriptoolbox.org. Retrieved January 30, 2023, from https://www.fieldtriptoolbox.org/tutorial/cluster_permutation_freq/*
- 7. *Everatt, John & Smythe, Ian & Ocampo, Dina Joana & Veii, Kazuvire. (2002). Dyslexia Assessment of the Biscriptal Reader. Topics in Language Disorders. 22. 32-45.*