MSc in Computational Cognitive Neuroscience

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Using Visual Imagery-Generated EEG Signals to Control External Devices via a Brain-Computer Interface

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Background

A Brain-Computer Interface (BCI) allows users to control a device with just the power of thought[1]. Locked-In Syndrome (LIS) patients typically suffer from complete paralysis but retain conscious awareness. It is easy to see how someone suffering from LIS could benefit from BCI technology.

Motor Imagery involves imagining movements of body parts, which activates similar areas of the brain compared to actually moving the body part. Visual imagery[2] differs from this as the patient would imagine, for example, a box being pushed away from them.

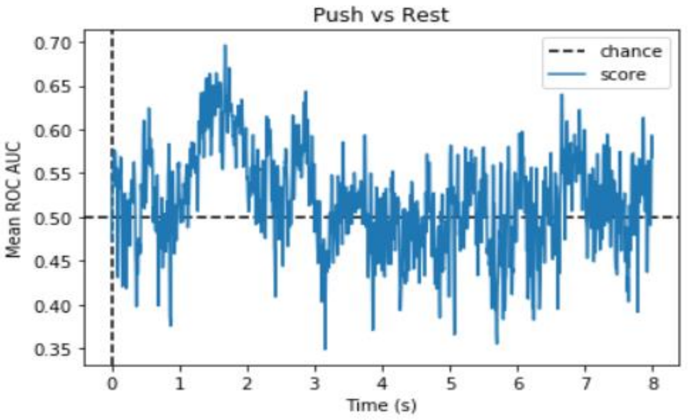
Our aim is to use visual imagery only to distinguish between the user imagining a push versus just being at rest. We do this by taking 300 samples of push and rest EEG signals across 14 channels and then using machine learning to classify the data into the two categories.

Simple classifier

MNE again has a built in function for doing binary classification. The plot on the right shows how good this classifier is at each time point in an 8 seconds period (256Hz). As we can see, the period around 1.5-2 seconds offers the best ability to classify the epochs correctly, however it only gets us to 65% AUC.

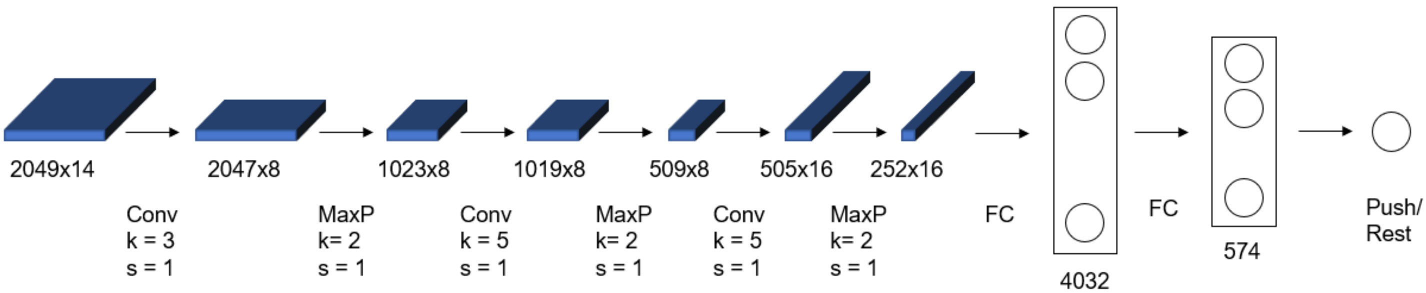
Preprocessing

The first step once the data had been collected was to preprocess the data. This was achieved by setting thresholds on the mean, standard deviation, min and max of the 14 EEG channels combined. This removed 17 epochs of data, leaving us with 283 epochs. We then do something called equalising the data, which means removing a few more epochs so that the split of push and rest is 50% each. Luckily, MNE has a built in function for this, reducing epochs to 278.



Evolutionary process

We start with 30 1-dimensional convolutional neural networks (CNNs) with randomly chosen hyperparameters. We train these on a training set using 5-fold cross validation and pick the 5 'fittest' models. These 5 best performers each seed 10 new CNNs with hyperparameters randomly perturbed. Again we train using 5-fold cross validation. The 5 best are picked and we repeat the process. Finally, after 130 CNNs have been trained, we pick the best performing CNN and test on the holdout test set.



The winning architecture

- 3 convolutional layers and 1 dense layer
- Dropout after each max pooling and dense layer
- Mixture of relu and tanh activation functions
- RMS Prop optimisation with learning rate = 4.6x10-4

Results

- 5-fold cross validation for hyperparameter optimisation
- 90 epochs (32%) hold out test set
- Area Under Curve (AUC) assessed
- This 1-D CNN hit 79% AUC

[1] Christoph Gugar et al, "Complete Locked-In and Locked-In Patients: Command Following Assessment and Communication with Vibro-Tactile P300 and Motor Imagery Brain-Computer Interface Tools", Frontiers in Neuroscience, May 2017.

[2] Nataliya Kosmyna et al, "Attending to Visual Sttimuli versus Performing Visual Imagery as a Control Strategy for EEG-based Brain-Computer Interfaces", Nature, Sep 2018.

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