MSc in Computational Cognitive Neuroscience

Goldsmiths UNIVERSITY OF LONDON

Using Machine Learning to classify hand-gestures

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BrainControl
Mind power for assistive technologies

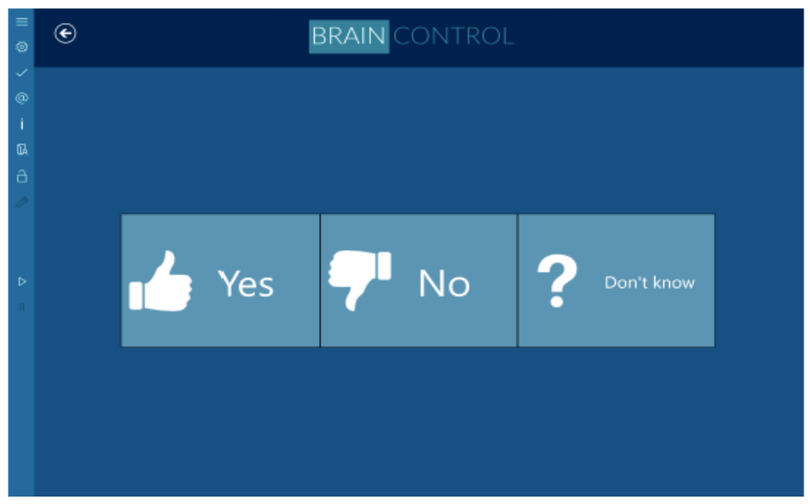
Background and Objectives

- **Brain-Computer Interfaces (BCIs)**

BCIs pair neural feedback with advanced machine learning (ML) techniques to enable patients and healthy individuals to control external apparatus and augment communication.

- **BCI at LiquidWeb: BrainControl**

Thinking of a movement (push) generates neural signals similar to actual motor cortex activity. This phenomenon is known as **motor imagery.** For paralysed patients, motor imagery signals and ML algorithms are used to build models that can correctly classify movements. In the case of partial paralysis, patients can perform simple gestures holding an accelerometer, which are translated into commands for an user-interface system (right) (Fedele, Gioia, & Giannini, 2016)



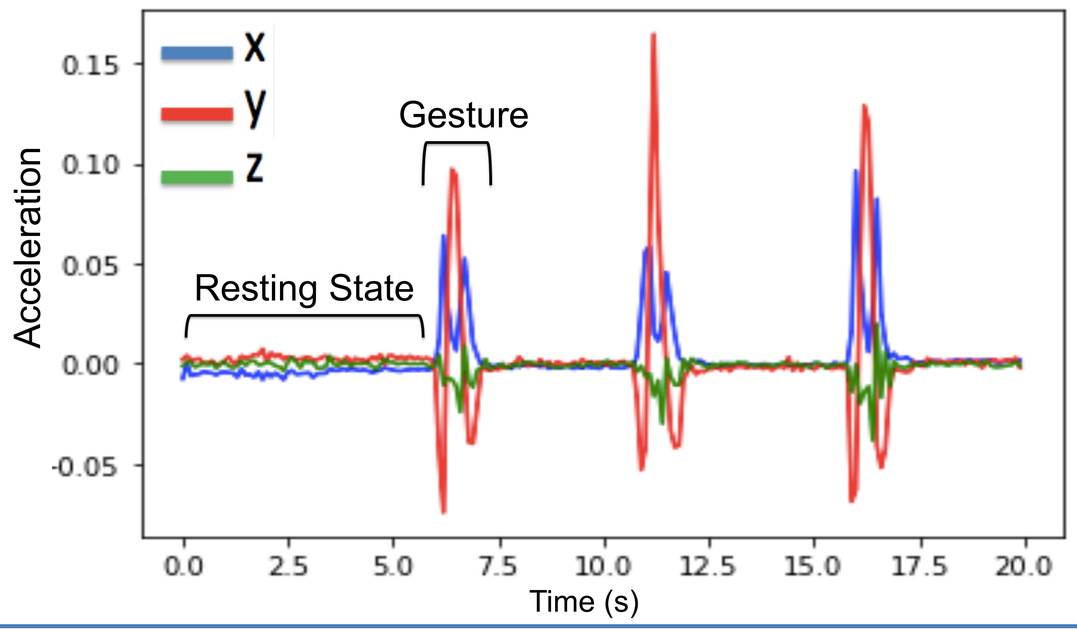
- **Aim and Objectives**

Using data that simulates patients' residual movements, this research project aims at improving **gesture recognition** via different **segmentation** algorithms, **feature engineering** methods and **ML architectures.**

Methods: Segmentation and feature extraction

- **Data**

Data was recorded using a three-dimensional (x, y, z) accelerometer (**up, left and right gestures).** Gestures lasted for 1 second, interleaved by 4 seconds of resting period. The final recording is a time-series with positive and negative accelerations across the axes. The figure shows the first 20 seconds recordings for the left-gesture dataset.



- **Offline Segmentation**

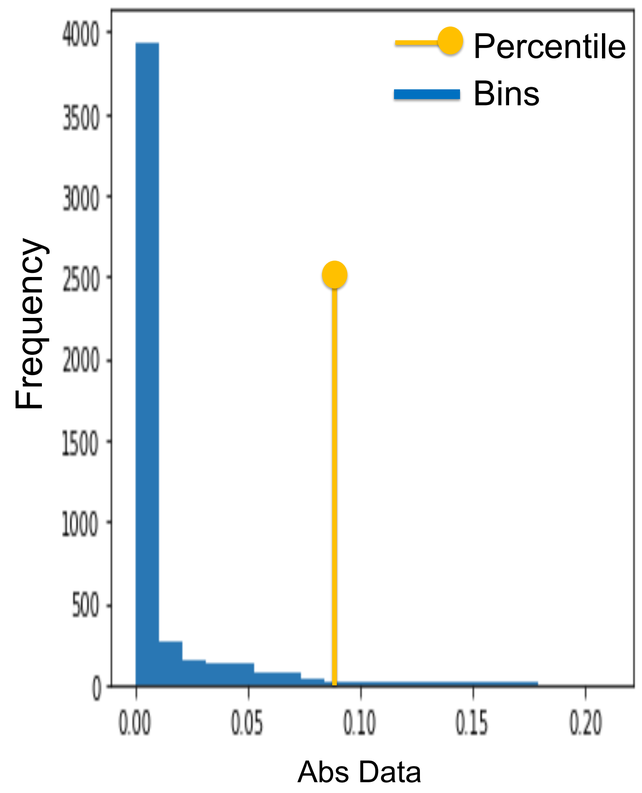
extracting only gestures, excluding resting periods.

Unique Percentile Approach

Combining data visualisation and exploratory analyses, **threshold values** were empirically derived.

Looking at the frequency distribution of the data in absolute terms, **unique percentile** values were selected, above which only gestures are found.

This approach was decided as a shift from a resting period to a gesture generated an average percentile change of ~90 percent.

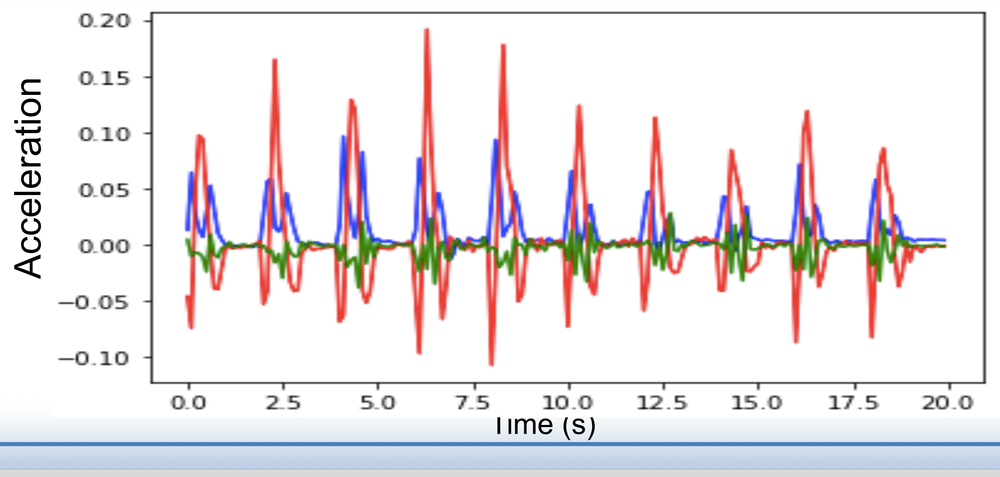


- **Gesture Extraction**

The figure on the right shows the successful segmentation output for the left-gesture dataset.

- **Feature extraction**

For each axis and for each gesture, the **maximum, minimum** and **the area** were extracted as features. This resulted in a 228-by-9 array, where 9 are the feature dimensions, and 228 the total number of gestures.



Results and Next Steps

- **Support Vector Machine (SVM)**

A multi-class (one-vs-all) SVM classifier was fitted on the data to test the accuracy when classifying unseen **left, right, up** gestures.

The data was split into **training** and **test sets.** Using 5-fold cross-validation, SVM resulted in **95 % accuracy** on average.

- **What is next?**

1. Online segmentation

What other statistical properties are needed to extract gestures succesfully during online performance?

2. Features and ML / Deep Learning

Are there any other features to achieve better accuracy? Also, are there any other classification algorithms or deep learning architectures that can be used?

Reference

Fedele, P., Gioia, M., Giannini, F., & Rufa, A. (2016). Results of a 3 Year Study of a BCI-Based Communicator for Patients with Severe Disabilities. *International Conference On Advances In Computer-Human Interactions*.