A brain-computer interface inside your earphones

Green-light assessment

Epilepsy classification

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DELFT UNIVERSITY OF TECHNOLOGY

FACULTY OF ELECTRICAL ENGINEERING, MATHEMATICS AND COMPUTER SCIENCE

ELECTRICAL ENGINEERING PROGRAMME

1.1 Targets and deliverables

The overarching goal of the Signal Processing Subgroup is to automatically detect upcoming or ongoing seizure attacks in EEG signals recorded from inside the ear. Ideally, to study whether it is feasible to detect seizure attacks from in-ear recordings, we would need access to pre-existing data or gather epileptic people to record signals ourselves. However, since no in-ear based EEG data-set is available and limited time to conduct our Bachelor End Project, we decided to use a data-set containing EEG-scalp recordings from epileptic people and use the electrodes placed around the ear [1]. This will be a good indication whether in-ear based EEG for detecting seizures is realistic or not. Our work, will consist of three stages as shown in Figure 1.1. The deadline for our thesis is the 9th of June. By that date we aim to strive for a sensitivity of 90 % or in other words, we would like to have a high true positive (TP) rate and low false negative (FN) rate.

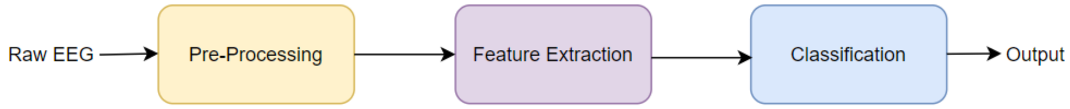

Figure 1.1: Seizure Detection Pipeline

1.2 Currently achieved level

Right now we have managed to create a basic complete signal processing pipeline that can take raw scalp EEG data and create a machine learning model. This model can be used to classify epileptic seizures with an accuracy of about 40%. The advantage of having a complete pipeline is that the steps taken can easily be changed later on with more advanced methods. The current pipeline does not select the electrodes around the ear, instead only using a single channel.
For pre-processing a bandpass filter is used with cutoff frequencies at 0.5 and 40 Hz, after which the filtered data is then separated into epochs of three seconds. The features used in our classifier are a combination of statistical time and frequency domain information of each epoch. The frequency domain parameters are extracted from each sub-frequency band signals created from the original EEG epochs.
These parameters represent the mean frequency, the spectral entropy (SE), the Renyi entropy (RE), the absolute and relative spectral powers of each frequency sub-bands, the power ratios between each relative spectral powers, the absolute and relative energy of each frequency sub-bands and finally the ratio between these relative energies. The extracted features previously mentioned were all obtained from the power spectral density (PSD) of each epoch computed via Welch's method [2].
In the time domain, we extracted the mean, the maximum and minimum value, the energy, the variance and the skewness of each epoch.
For the machine learning part, a type of random forest algorithm native to MATLAB called 'TreeBagger' is used. This model combines the results of multiple decision trees, which reduces the effects of overfitting and allows for more general classification.

1.3 Future studies

To complete the project multiple methods will be compared, we have set out the following improvements and additions to achieve this goal. As the pipeline is complete, it is much easier to compare these methods and thus achieve a higher sensitivity.
For prepossessing, further cleaning of the data can be done by use of Artefact Subspace Reconstruction (ASR), this method removes artefacts with high variance such as those generated by motor activity [3, 4].
To improve classification more useful features will be extracted, this includes implementing the wavelet transform. Eventually we will also select the most useful features from all the extracted ones through

methods like PCA or ICA.
Currently the classification is only done between a seizure happening and not happening, this will be further built on by adding a third class. This third class will consist of a short moment before the seizure happens, this way we wish to look at the feasibility of determining an upcoming seizure.
Furthermore extra classification methods will be implemented, this is so we can compare the performance between methods and determine a "best" one. Methods we are aiming to implement are Support Vector machines (SVM), but also deep learning methods such as Convolutional Neural Network (CNN), and Temporal Fusion Transformer (TFT) [5] potentially.

Bibliography

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