Machine Learning Engineer Nanodegree

Capstone Proposal

Omar Magdy
November 19th, 2019

Proposal

Domain Background

According to the World Health Organization (WHO), 1.25 million deaths result from road accidents every year. Consequently, lots of technologies have been developed in order to reduce the accidents to save people's lives. This project aims at developing a Brain-Computer Interface (BCI) that enables the prediction of the driver's behavior based on Electroencephalography (EEG) brain activity of car drivers. The project capitalizes on the extensive research that has been carried out on using spectral analysis of electroencephalogram (EEG) activity to estimate different physiological and psychological states.

Problem Statement

The main objective of this project will be to use machine learning techniques to classify driver's mental states.

When given processed EEG brain activity signal form the headset worn by the person during driving, fed as a stream of electrical voltage readings sampled from the brain for a record of a few seconds duration. This record is then passed by some signal processing operations in frequency domain to extract the underlying features, which is one of the most widely used method to analyze EEG data, is to decompose the signal into functionally distinct frequency bands, such as delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (30–100 Hz). We want to be able to detect the current mental state of the driver based on these frequency bands values. Using bands as the features to train the ML model to classify the brain concentration level, whether the person is: (focused, de-focused or drowsy).

Datasets and Inputs

For this project we will use "EEG data for Mental Attention State Detection" open source dataset on kaggle. This is a collection of 34 experiments for monitoring of attention state in human individuals using passive EEG BCI.

Each Matlab file contains the object of the data acquired from EMOTIV device during one experiment. The raw data is contained in o.data, which is array of size {number-of-samples}x25, thus o.data(:,i) comprises one data channel. The sampling frequency is 128 Hz. The list of data channels and their numerical ids is given below per EMOTIV documentation;

1-'ED_COUNTER' 2-'ED_INTERPOLATED' 3-'ED_RAW_CQ' 4-'ED_AF3' 5-'ED_F7' 6-'ED_F3' 7-'ED_FC5' 8-'ED_T7' 9-'ED_P7' 10-'ED_O1' 11-'ED_O2' 12-'ED_P8' 13-'ED_T8' 14-'ED_FC6' 15-'ED_F4' 16-'ED_F8' 17-'ED_AF4' 18-

'ED_GYROX' 19-'ED_GYROY' 20-'ED_TIMESTAMP' 21-'ED_ES_TIMESTAMP' 22-'ED_FUNC_ID' 23-'ED_FUNC_VALUE' 24-'ED_MARKER' 25'ED_SYNC_SIGNAL'

The EEG data is in the channels 4:17.

The experiments were conducted between 6 p.m and 7 p.m. The details of the experiments are given below:

Participants controlled a simulated passenger train over a primarily featureless route for a duration of 35 to 55 minutes. Specifically, during the first 10 minutes of each experiment, the participants were engaged in focused control of the simulated train, paying close attention to the simulator's controls, and following the developments on the screen in detail. During the second 10 minutes of the experiments, the participants stopped following the simulator and became de-focused. The participants did not provide any control inputs during that time and stopped paying attention to the developments on the computer screen; however, they were not allowed to close their eyes or drowse. Finally, during the third 10 minutes of the experiments, the participants were allowed to relax freely, close their eyes and doze off, as desired.

Solution Statement

The developed system will relate the brain activity of the driver before starting to drive the car with the driving pattern. Spectral signatures that correspond to different mental states will be extracted from the recorded EEG. Such signatures will be used to train different machine learning algorithms that will be subsequently used to decode the driver's EEG activity to infer his/her driving behavior. Implemented algorithms will be first examined on benchmark data of mental states available online. The algorithms will be then examined on data that will be recorded during the project. These algorithms will be then tailored to operate within the AUTOSAR framework. Based on the detected mental state, recommendations to the driver will be given. In addition, signals will be sent to different car components to limit the driver's capabilities in case of predicting a risky driving behavior.

Benchmark Model

For benchmark model, we will use the algorithms outlined in the review "Techniques for Mental-state Recognition in Brain–Computer Interfaces" (Fabien Lotte), which presents an introductory overview and a tutorial of signal-processing techniques that can be used to recognize mental states from electroencephalographic (EEG) signals in brain–computer interfaces. More particularly, this chapter presents how to extract relevant and robust spectral, spatial, and temporal information from noisy EEG signals (e.g., band-power features, spatial filters such as common spatial patterns or xDAWN, etc.), as well as a few classification algorithms (e.g., linear discriminant analysis or support vector machine) used to classify this information into a class of mental state. It also briefly touches on alternative, but currently less used approaches.

Evaluation Metrics

The evaluation metrics for this problem is simply the "Accuracy Score" for performance analysis during training and "F1-Score" for final evaluation on testing data.

Project Design

Data Preprocessing

First identify the different mental states in our dataset and what preprocessing needs to be done to make it uniform.

- Signal Pre-processing: Recorded EEG signals will be filtered to eliminate possible noise. Frequency-domain representation of the filtered signals will then be obtained.
- Label the data according to the experiment description attached with the open source dataset on kaggle.
- *Feature scaling using log transformation for distributions of continuous EEG data features.*
- *Detect and remove the outliers using IQR score.*
- *Data normalization to get equal contribution from all features*

Data Splitting

Split the data into a training set and testing set with an 80-20 split.

Feature Extraction

Use PCA for dimensionality reduction of data after vector concatenation of frequency bands value over all the headset channels, to fit the relatively small size of data (i.e number of entries) for each record.

Model training and performance evaluation

Train the algorithms proposed in the (Fabien Lotte) review: LDA and SVM, to decide the more suitable one for the data. Hence tune the hyperparameters of the chosen classifier using "Grid Search" and "Cross Validation" split of training data with performance evaluation using "Accuracy Score" to get the best estimator.

Final testing evaluation

Use "F1-Score" for final evaluation against testing data, using "micro" averaging for the multi-class detection, to get the final score of the trained model.

References

[1] Fabien Lotte. A Tutorial on EEG Signal Processing Techniques for Mental State Recognition in Brain-Computer Interfaces. Eduardo Reck Miranda; Julien Castet. Guide to Brain-Computer Music Interfacing, Springer, 2014. hal-01055103: https://hal.inria.fr/hal-01055103/document

[2] Compute the average bandpower of an EEG signal: https://raphaelvallat.com/bandpower.html?fbclid=IwAR1PI49_NWqdT4AXF9Ffe-keLmglCr7CKEAXY96PPbm2wRovsybVCpO2EV4