Estimating average response time for Stop-signal paradigm from Electroencephalography (EEG) signals

Thesis Advisor: Alexander Savostyanov

Presenter: Enes Kuzucu

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Novosibirsk State University



- 1. The Task
- 2. Data
- 3. Current Model

Introduction





- · Estimate a person's cognitive inhibitory ability using EEG data ,
- Make a classification based on their inhibitory response time for different age groups and genders

DATA





DATA



- 101 subjects and has been collected using a BCI 2000 EEG data collection system.
- During the task completion for each participant EEG was recorded with labels of all events.
- The EEG signals were recorded using 62 channels
- The EEG electrodes were placed according to the extended international 10–10 system
- Signal is 0.1–100 Hz analog bandpass filtered and digitized at 1000 Hz, referred to Cz with ground
- In addition, vertical electro-oculogram (VEOG) was recorded for detecting eye movement artifacts which allow us to eliminate these noise from main signal.
- Each subject experiment consisted of around 100 iterations.





Current Main Problems :

- Cognitive behavior and inhibitory response time changes with aging and tiredness of the subjects.
- In our data we have different age groups and different genders.
- We have only consist of 100 samples.
- Nature of EEG data which is extremely non-stationary
- EEG is very weak with cross-subject classification depended features.

MODEL:

- A hybrid model for EEG-based gender recognition
- A Long Short-Term Memory deep learning network for the prediction of epileptic
- Age and gender classification using brain-computer interface
- Classification of EEG with Recurrent Neural Networks
- Classification of Hand Movements from EEG using
- Convolution- and Attention-Based Neural Network
- EEG-based emotion recognition using deep learning network with principal component based covariate shift adaptation.
- EEG-based Intention Recognition from Spatio-Temporal Representations via
- $\cdot\,$ Feature selection in high dimensional EEG
- LSTM A Search Space Odyssey
- On the Usability of Electroencephalographic Signals
- Optimized Feature Subsets for Epileptic Seizure Prediction Studies
- WGAN Domain Adaptation for EEG-Based Emotion Recognition

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Main Ideas:

- \cdot Treating EEG as a sequential data
- Preserving Spatial Feature

MODEL

- LSTM has been widely utilized for learning and classifying time-series data including bio-signals
- LSTM has been used in other tasks requiring remembering and aggregation of feature embeddings, notably natural language processing
- Recent studies have successfully used LSTM architectures for EEG analysis given the time-dependant nature of these signals.
- Attention mechanism by focusing on certain timesteps of the signal
- Attention-based LSTM architecture can improve classification performance using EEG signals by focusing on essential task-relevant features from different time-steps

MODEL :Importantce of spatial features





EEG-based Intention Recognition from Spatio-Temporal Representations via Cascade and Parallel Convolutional Recurrent Neural Networks ,Dalin Zhang



Thank you very much

MODEL

Most existing works either only consider EEG as chain-likesequences neglecting complex dependencies between adjacent signals or performing simple temporal averaging over EEG sequences. In this paper, we introduce both cascade and parallel convolutional recurrent neural network models for precisely identifying human intended movements by effectively learning compositional spatio-temporal representations of raw EEG streams. The proposed models grasp the spatial correlations between physically neighbouring EEG signals by converting the chain-like EEG sequences into 2D mesh-like hierarchy. A LSTM based recurrent network is able to extract the subtle temporal dependencies of EEG data streams.

From the EEG electrode map, it is observed that each electrode is physically neighboring multiple electrodes which measures the EEG signals in a certain area of brain, while the elements of the chain-like 1D EEG data vectors are restricted to two neighborsFurthermore, different brain regions correspond to different brain activities. From this conceptualization, we convert the 1D EEG data vectors to 2D EEG

Results