DEEP LEARNING –BASED FORECASTING OF EEG TIME SERIES FOR BRAIN-STATE-DEPENDENT TMS

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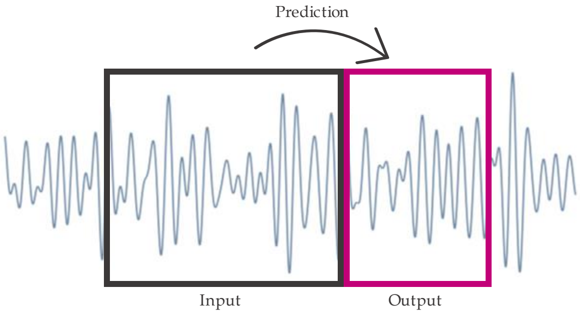

FIGURE 1. Our model predicts the upcoming signal in one EEG channel based on preceding signal in the same channel.

1 BACKGROUND

- Coupling TMS with real-time EEG can improve its efficacy [1]
- However, algorithmic decision making requires time
  - Thus, a forecast method for the EEG signal is needed
- So far, only an autoregressive model has been used for this [1]
- To improve on this, we propose a deep learning model for predicting resting state EEG signal in C3-channel

2 METHODS

MODEL

- The model is a close adaptation of the Wavenet-model [3]
- The main ingredients are causal convolution operations that enable causal analysis of the time series

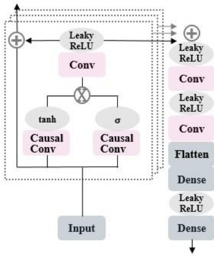

FIGURE 2. The model architecture.

DATA

- Resting state eyes open data from healthy subjects (N=72)*
- Band-pass filtered to 8-12 Hz

EXPERIMENTS

- All predictions are for upcoming 150 ms based on the previous 1500 ms
- For each model ...
  - … the train and test data sets were chosen at random from the pool of subjects
  - … test data was from 10 subjects

Experiment 1

- 50 models were trained, each with data from 60 subjects

Experiment 2

- 50 models x 20, 30, 40, 50 & 60 subjects
- The amount of data per subject was decreased proportionately as the amount of subjects was increased

3 RESULTS & CONCLUSIONS

EXPERIMENT 1

- Predictions on the test sets of the 50 models achieved a mean absolute error of 0.24 μV

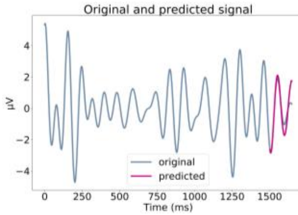

FIGURE 3. An example prediction made by one of the models.

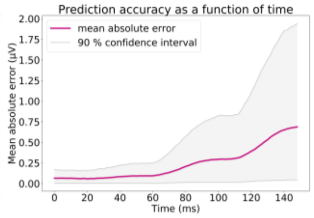

FIGURE 4. Mean prediction accuracy of the 50 models.

EXPERIMENT 2

- Medians of errors of the different models range from 0.42 to 0.44 μV
- Here, the models trained on 60 subjects (with data limited to 1/3) achieved a mean absolute error of 0.56 μV (cf. Experiment 1)
- These findings suggest that the generalisability of the model doesn't depend on the amount of subjects used but rather on just having more data

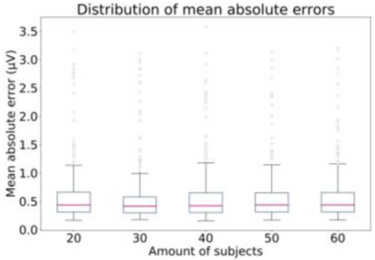

FIGURE 5. Distribution of the errors for each condition. Each score represents the mean error of predictions of one model on one of its test subjects.

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*Data sets were retrieved from PRED+CT (http://predict.cs.unm.edu/), accession number d003 [2]