Human Brain Age Prediction based on EEG Signals

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Introduction

From childhood to adult, the functionality of the human brain undergoes progressive changes. EEG records the electrical activity of brain cells in real time, which is a planar map that records the correlation between potential and time. For people of different ages, the EEG is most likely to contain features that characterize the level of brain maturation. It has been shown that the difference between a person's true age and brain maturation level is relatively stable over time, and this difference, which we call the BrainAge Index (BAI), can be used as a bio-marker for neurological disorders, reflecting the extent to which the brain deviates from normal developmental levels. In this course project, the team members found a resting EEG dataset in the OpenNeuro database containing 111 healthy individuals resting with eyes closed for 4 min. Based on this dataset we built a deep learning model for BA prediction, which contains four layers and can better extract the spatiotemporal features of EEG. We used K-Fold Cross Validation for training and obtained a mean error of 8.7 years between BA and true age.

Dataset

This EEG dataset contains resting-state EEG extracted from the experimental paradigm used in the Stimulus-Selective Response Modulation (SRM) project at the Dept. of Psychology, University of Oslo, Norway.
The data is recorded with a BioSemi ActiveTwo system, using 64 electrodes following the positional scheme of the extended 10-20 system (10-10). Each datafile comprises four minutes of uninterrupted EEG acquired while the subjects were resting with their eyes closed. The dataset includes EEG from 111 healthy control subjects (the "t1" session), of which a number underwent an additional EEG recording at a later date (the "t2" session). In this project, we selected all EEGs from the "t1" time period and pre-processed them.

Methods

Data preprocessing

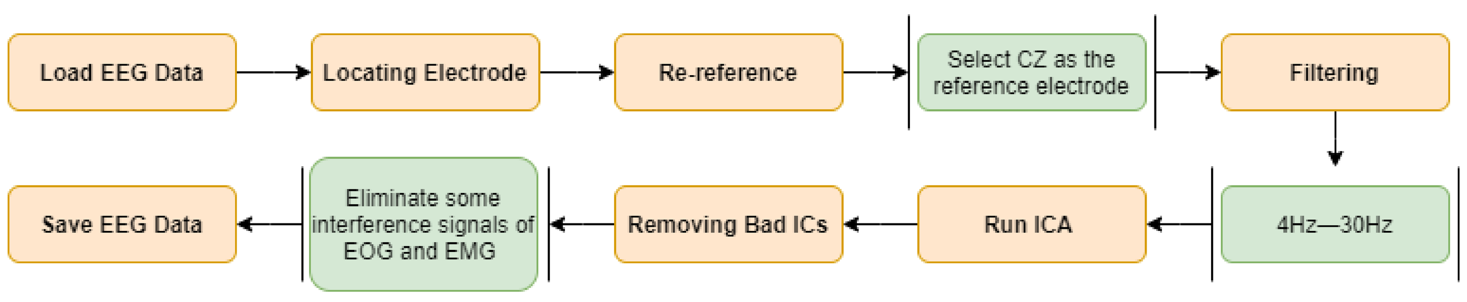

Figure 1: Data preprocessing flow chart

1. Loading EEG Data: Import the raw data;
2. Channel Locations: Information about the locations of the recording electrodes is required to plot EEG scalp maps and to estimate source positions for data components;
3. Re-reference: Select CZ as the reference electrode.
4. Filter the Data (FIR Filter): EEG data was band-pass filtered between 4 and 30Hz.
5. Blind Source Separation: Independent Component Analysis(ICA)

Model - BAPM

Brain Age Prediction Model (BAPM) (Figure 2) is a model composed of four layers, namely:

1. **StCNN (Short-term temporal convolutional layer)**: a 1-dimensional convolutional layer which aggregates groups of timestamps along the time dimension. It aims to extracts short-term patterns from the preprocessed EEG signals. Meanwhile, the layer effectively reduces the data size during the training process.
2. **Spatial Attention Layer**: This layer includes a multi-head GaAN (Gated Attention Network) module which aggregates information among the channels (electrodes) using a pre-calculated graph (using Pearson Correlation Coefficient).
3. **Temporal Layer**: This layer is simply a GRU to run through all the reduced "timestamps" and aggregate the temporal features. The output will be a fully aggregated spatial-temporal embedding feature tensor.
4. **Transfer Layer**: This layer uses two fully-connected sub-layers (and ReLU as the activation function) to first aggregate the information along the channel dimension, then aggregate the features along the feature dimension. The final output will be the prediction age value.

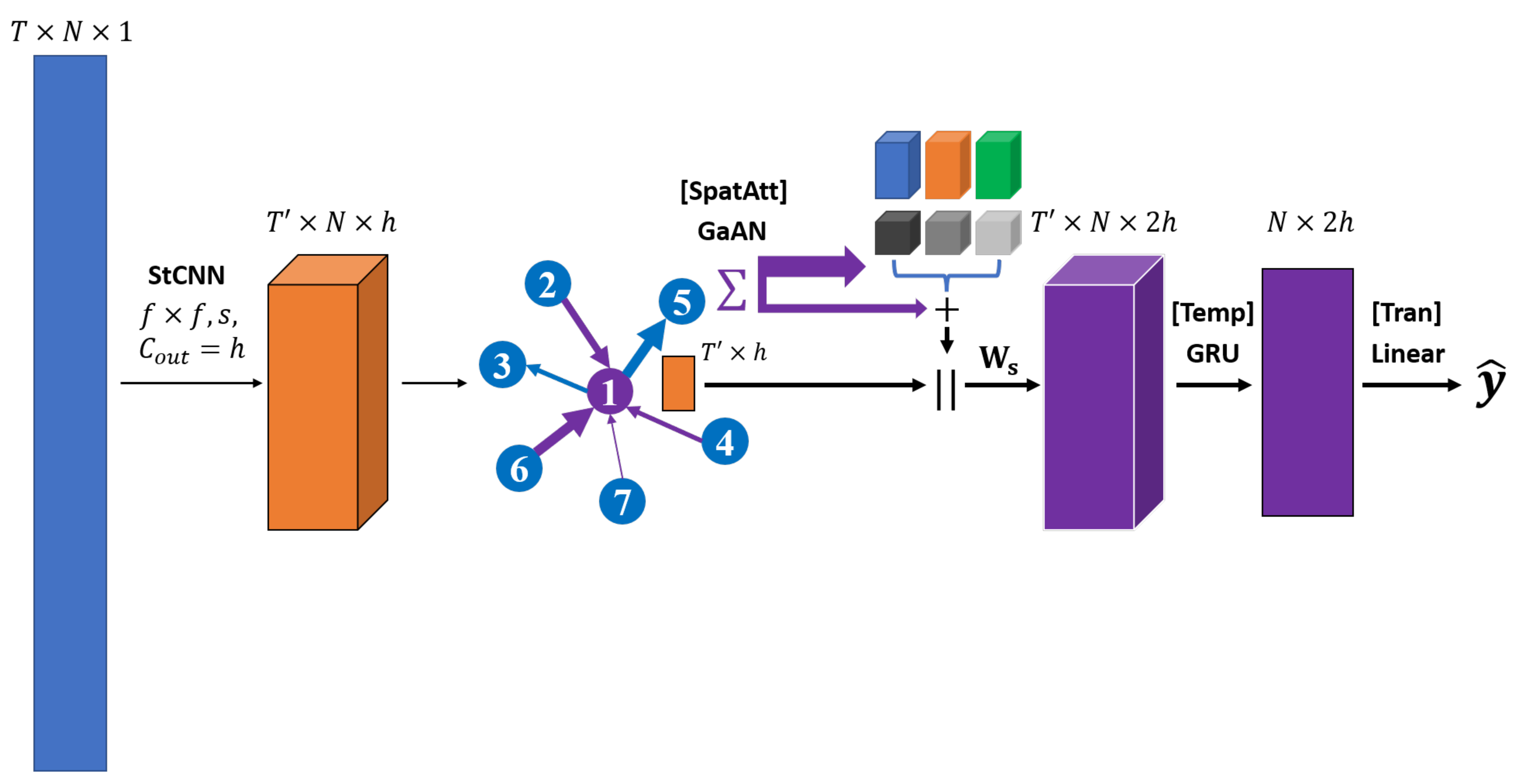

Figure 2: Model structure of BAPM

Experiment

Settings

For metrics, we use MAE (Mean Absolute Error), RMSE (Rooted Mean Squared Error) and MAPE (Mean Absolute Percentage Error) to evaluate the model performance.
The preprocessed EEG data contains 245760 timestamps ($240s$). The frequency is $1024Hz$ and the number of electrodes is 63. The data includes 111 subjects, 11 of which are removed. The data of each subject is further split uniformly into multiple samples. For the train-validation-test split, we first shuffle the samples and select the last 20% as the test data. Then the rest of the data is split $4:1$ for the training and validation set. We perform K-Fold Cross Validation on our model with settings as s16-stf4.
The implementation uses PyTorch and DGL and the experiments are run on *Tesla P100-PCIE-16GB*. The batch size, total training epochs, learning rate, hidden dimension, number of attention heads are specified as 5, 100, 0.01, 5 and 3 respectively. The selected optimizer is Adam and the loss function is SmoothL1Loss which is more resistant to noises than MSELoss. For StCNN, several stride values are tested.

We use two comparison models, namely FeedForward (simple fully-connections) and GRUNet (simply use GRU to extract temporal features). We also propose three variant models from BAPM, namely BAPM-CG (use a customized graph to perform graph convolution), BAPM-1 (StCNN + TranLayer) and BAPM-2 (StCNN + SpatAttLayer + TranLayer). BAPM-1 and BAPM-2 are used for ablation experiment on BAPM (StCNN + SpatAttLayer + TempLayer + TranLayer).
For more details, refer to `https://github.com/WingsUpete/EEG2Age`.

Results

The training loss curve of BAPM on the dataset with s16-stf4 settings is shown in Figure 3). The training loss rapidly descends in the first 5 epochs. Then, it steadily goes down until about 60 epochs. Afterwards, the model seems to converge and fluctuate around 7.5.

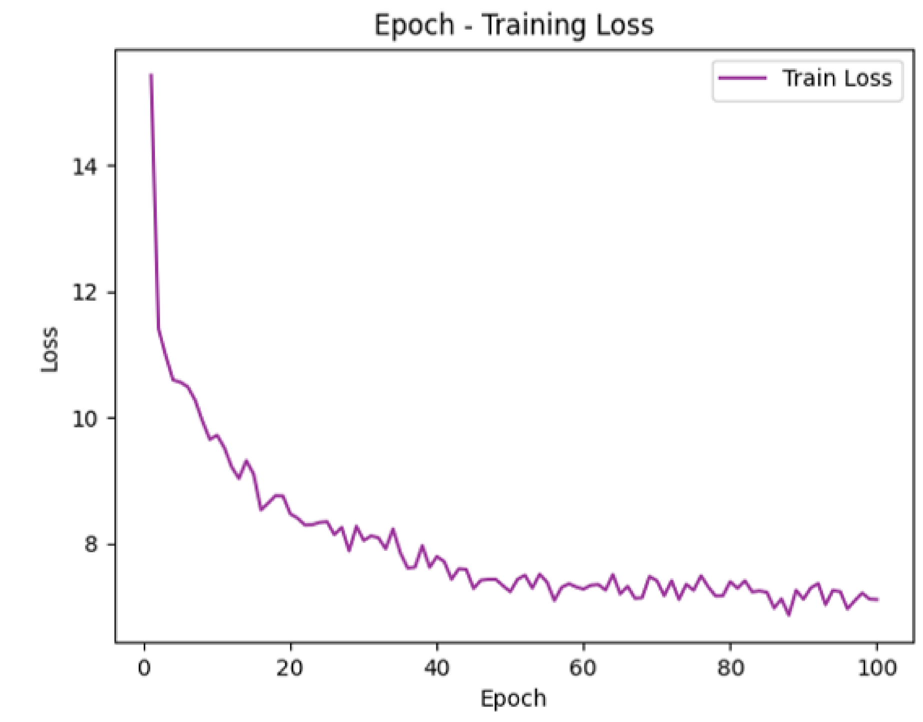

Figure 3: Training loss curve of BAPM on the dataset with s16-stf4 settings.

The results are shown in Figure 4.

Model	SRM Resting-state EEG s16-stf4		
	MAE	RMSE	MAPE
FeedForward	37.1000	39.5578	1.0000
GRUNet	11.5837	14.0128	0.3384
BAPM	**8.0607**	**10.8924**	0.2423
BAPM-CG	8.5720	11.2067	0.2730
BAPM-1	11.4550	14.3746	0.3191
BAPM-2	11.1898	14.0586	0.3140

Model	SRM Resting-state EEG TTpS (sec)				
	s8	s12	s16	s24	s32
FeedForward	-	-	0.0101	-	-
GRUNet	-	-	0.0701	-	-
BAPM	0.0388	0.0283	0.0230	0.0195	0.0166
BAPM-CG	-	-	0.0223	-	-
BAPM-1	-	-	0.0110	-	-
BAPM-2	-	-	0.0218	-	-

Stride Factor	SRM Resting-state EEG s16		
	MAE	RMSE	MAPE
1 (1s)	9.8407	12.7894	0.2935
2 (0.5s)	8.4396	11.0257	0.2547
4 (0.25s)	8.0199	**10.7034**	**0.2428**
8 (0.125s)	**7.9656**	11.4174	0.2464

Metrics	SRM Resting-state EEG BAPM (stf4)				
	s8	s12	s16	s24	s32
MAE	8.6207	8.2052	**8.0607**	8.3351	8.8679
RMSE	10.9219	11.3111	**10.8924**	11.1475	11.9708
MAPE	0.2610	0.2374	0.2423	**0.2347**	0.2594

Figure 4: Upper Left: results on SRM Resting-state EEG data for the models. Upper right: TTpS (Training time per sample, unit: second) for the models. Bottom Left: results for BAPM, with a sample split of 16 (s16) and different stride factor settings. Bottom right: results for BAPM, with a stride of 4 (stf4) and different sample split settings.

It can be discovered that:

- BAPM performs the best on all three metrics.
- The training time is not significantly longer than a simple feed-forward neural network, since StCNN largely reduces the dimension.
- BAPM-CG performs slightly worse than BAPM, indicating that our customized graph design may be inadequate to show the true relationships among the electrodes.
- The results of BAPM-1 and BAPM-2 prove the importance of performing both spatial and temporal feature extractions. When we gradually add back the modules, the results improve step by step. The performance largely increases as soon as both spatial and temporal feature extraction layers are recovered.
- The results vary as the number of samples split from one subject increases. For MAE and RMSE, a sample split of 16 gives the best results while for MAPE, a sample split of 24 gives the best results.
- The results are best when the stride factor is 4 (MAE is not much worse than that of s8). Theoretically, there should also be a stride factor value between 1 and 1024 which provides the best results. However, our $16GB$ GPU has been overloaded when the value is over 8.

A K-Fold Cross Validation process has proven that our model performs relatively stably with an average MAE = 8.7286, RMSE = 11.3910, MAPE = 0.2759.

Conclusion

With limited time, we designed a model - BAPM to predict the age of human beings according to the EEG signals. Our model managed to outperform two baseline models on all three metrics efficiently. Nevertheless, there is still plenty space for improvement and more data is required to test the performance of the model.

Prospect

There have been many research reports on BA in recent years, such as EEG-based BA metrics can be used as a marker for dementia patients, predicting the brain maturation level of adolescents, and also illuminating the link between BA and lifespan. More and more reports demonstrated that BA can be used as a biomarker for neuroscientific diseases, especially for the early prevention, control and treatment of chronic neurodegenerative diseases with high significance.
In this course project, we completed BA predictions from resting-state EEG data only, which is not far from the results of current cutting-edge articles in the field. After this class, the sample size can be increased and the parameters can be optimized in order to achieve better standards.Meanwhile, the accuracy of BA as a disease indicator can also be evaluated by using publicly available patient data sets for various diseases.

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