

Confused Student Classification Using EEG brainwave

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1 Motivation

Emotion recognition is a difficult problem with various applications. For example, detecting when a student is confused by course presentation materials may help improve Massive Open Online Course materials [2]. For this project, we propose using a newer method to classify confusion in students on a particularly challenging data-set with EEG data for classification. We hope to get better or at least comparable results to previous state-of-the-art methods.

2 Dataset

Confused Student EEG brainwave data. This dataset is collected from 10 students while they were watching video clips from MOOC. Some videos were extracted assuming not to confuse the students and another set of videos were collected to confuse the college students. There were 10 video clips of each category. The students wore a single-channel wireless MindSet EEG device to record the EEG signal from students' brains. After the session students rated their confusion level on a scale of 1-7 which were later normalized to 0-1 where 0 means not confused and 1 means confused. Every video is 2 minutes long but the first and last 30 seconds are chopped off. EEG signal is recorded for 1 minute with a sampling frequency of 0.5 seconds. Each of 10 students watched 10 videos. So, the dataset consists of $(60/0.5) \times 10 \times 10 = 12,000$ sample points. The dataset consists of raw EEG signals and its sub bands like delta, theta, alpha, beta and gamma. There are two types of levels which are predefined and user-defined.

Dataset Link: [Confused student EEG brainwave dataset](#)

3 Possible methods

2 Autoencoders, one on a sample of confusion, and another on a sample of non-confusion, to generate loss values on remaining data points, which will be used to predict class.

Combination of Autoencoder for feature extraction with LSTM [5], potentially utilizing the work of removing confounding factors as in Wang et al. [3]

Combination of Autoencoder with RNN

Autoencoders with Bidirectional LSTM RNN [1]

Deep CNN with autoencoders [4]

4 Possible results

We plan to experiment with different methods utilizing autoencoders and other methods and compare the accuracy of the models to each other and to the current state-of-the-art [3]. We hope to get results comparable to or better than the state-of-the-art done by Wang et. al. [3].

References

- [1] Zhaoheng Ni, Ahmet Cem Yuksel, Xiuyan Ni, Michael I Mandel, and Lei Xie. Confused or not confused? disentangling brain activity from eeg data using bidirectional lstm recurrent neural networks. In *Proceedings of the 8th ACM International Conference on Bioinformatics, Computational Biology, and Health Informatics*, pages 241–246, 2017.
- [2] Haohan Wang, Yiwei Li, Xiaobo Hu, Yucong Yang, Zhu Meng, and Kai-min Chang. Using eeg to improve massive open online courses feedback interaction. In *AIED Workshops*, 2013.
- [3] Haohan Wang, Zhenglin Wu, and Eric P Xing. Removing confounding factors associated weights in deep neural networks improves the prediction accuracy for healthcare applications. In *PSB*, pages 54–65. World Scientific, 2019.
- [4] Tingxi Wen and Zhongnan Zhang. Deep convolution neural network and autoencoders-based unsupervised feature learning of eeg signals. *IEEE Access*, 6:25399–25410, 2018.
- [5] Xiaofen Xing, Zhenqi Li, Tianyuan Xu, Lin Shu, Bin Hu, and Xiangmin Xu. Sae+lstm: A new framework for emotion recognition from multi-channel eeg. *Frontiers in neurorobotics*, 13:37, 2019.