CS 532 Intelligent Computing

Project Phase 1 (21100187, 21000130)

Project Selection and Domain Understanding

Mental Attention State Classification for the Human Brain using EEG-based BCI data

Introduction

Specific frequency bands have been detected at the frontal and centroparietal lobes of the brain have been found to be linked to the human mental attention state [1]. An experiment has shown that the delta, theta and beta activities have been found to increase more in a mental focused state at the frontal lobe than an unfocused one [2]. By using electroencephalography (EEG) based BCI intrinsic or passive activity data self-generated by specified individuals under simulation or obtained live [3], we aim to detect and classify the current mental attention state of an individual into several categories of states, the most prominent being - *focused*, *unfocused* (may also be described as lost-in-thought or mind-wandering) and *drowsy* (or sleep). The classification of an individual's mental attention state has various applications such as monitoring control tasks where high focus and concentration levels have to be maintained ranging, such as the detection of driver fatigue or classroom student attention [4]. However, there are several problems with the recognition of a BCI user's cognitive state that dynamically varies and affects classification performance along with the lack of interpretability and availability of BCI obtained datasets. A complete EEG data processing and classification pipeline will be designed and developed including a neural network based classifier as well as a hybrid neuro-genetic fuzzy system (HNGFS) for this task.

Related Works.

A prominent study in the area used 5 different models for performing 2 different tasks: detecting stress and no-stress states; and classifying stress levels into high and low stress [5]. These models were Linear Discriminate Analysis (LDA), *K*-Nearest Neighbor (KNN), Linear and Cubic Support Vector Machine (SVM) Classifiers, and Random Forest Classifiers. Of these, Cubic SVMs and KNNs performed better than all other metrics in most of the experiments. Another research study targets classification of human mental attention states into focused, unfocused and sleep classes with machine learning methods such as SVM and kNN as well as ANFIS [6]. It establishes a data processing pipeline for 25 hours of EEG-based passive BCI data obtained from

5 different participants. SVM yields the best classification results, achieving a high accuracy (96.7% best, 91.72% avg) after a comparative analysis. One study even showed how LDA, KNN, SVM, Naive Bayes, and Decision Trees could be used together (ensembled bucket of models) to improve classification accuracy of different emotional states [7]. The same paper discussed how dimensionality reduction techniques like Sequential Feature Selection (SFS) could be used to significantly improve classification accuracy by simplifying the feature space.

Recent studies have also achieved optimal performance utilizing deep learning based classifiers on this domain and its associated applications. One such research work dives into a crucial application of identifying mental attention states for drivers specifically to detect and prevent the adverse consequences of driver fatigue, a major cause of traffic accidents [8]. For this purpose, it trains deep convolutional neural network based classifiers along with residual learning on 15 channels of EEG signals and physiological signal data obtained from users operating driving simulation software. The study develops and presents two resultant mental state classifiers EEG-Conv suited for inter-subject mental variability and EEG-Conv-R which integrates residual learning for faster training convergence, delivering better performance than prior LSTM, HMM and SVM-based classifiers. Another paper designs and employs an end-to-end CNN based framework using transfer learning for inter-subject classification of continuous attention and diverted attention from EEG BCI data results which are also evaluated against a neurophysiological assessment test [9]. Furthermore, the study also presents an experiment to investigate the effects of movement intent on detection of attention diversion and its corresponding BCI performance. Finally, to counter the adverse impact on BCI performance and restore it, the study presents a GAN model for EEG data augmentation under attention diverse, achieving interpretable results and a more generalizable pipeline.

References:

[1] Groppe, D. M., Bickel, S., Keller, C. J., Jain, S. K., Hwang, S. T., Harden, C., & Mehta, A. D. 2013. Dominant frequencies of resting human brain activity as measured by the electrocorticogram. NeuroImage, 79, 223–233. https://doi.org/10.1016/j.neuroimage.2013.04.044

[2] Ko, Li-Wei, Chikara, Rupesh K., Lee, Yi-Chieh, Lin, Wen-Chieh. 2020. Exploration of User's Mental State Changes during Performing Brain–Computer Interface. Sensors 20, no. 11: 3169. https://doi.org/10.3390/s20113169

[3] EEG data for Mental Attention State Detection. 2021. Retrieved 15 March 2021, from https://www.kaggle.com/inancigdem/eeg-data-for-mental-attention-state-detection.

[4] Gong, Yan & Xu, Samuel. 2019. Mental State Detection in Classroom Based on EEG Brain Signals. Natural Science. 11. 315-322. 10.4236/ns.2019.1111034.

[5] Attallah, Omneya. 2020. An Effective Mental Stress State Detection and Evaluation System Using Minimum Number of Frontal Brain Electrodes. Diagnostics (Basel, Switzerland) vol. 10,5 292. doi:10.3390/diagnostics10050292

[6] Çiğdem İnan Acı, Murat Kaya, Yuriy Mishchenko. 2019. Distinguishing mental attention states of humans via an EEG-based passive BCI using machine learning methods, Expert Systems with Applications, Volume 134, Pages 153-166, ISSN 0957-4174, https://doi.org/10.1016/j.eswa.2019.05.057.

[7] Bozhkov, Lachezar & Georgieva, Petia & Trifonov, Roumen. (2014). Brain Neural Data Analysis Using Machine Learning Feature Selection and Classification Methods. Communications in Computer and Information Science. 459. 123-132. 10.1007/978-3-319-11071-4_12.

[8] Zeng, H., Yang, C., Dai, G., Qin, F., Zhang, J., Kong, W. 2018. EEG classification of driver mental states by deep learning. *Cognitive neurodynamics*, *12*(6), 597–606. https://doi.org/10.1007/s11571-018-9496-y

[9] Fahimi F, Zhang Z, Goh WB, Lee TS, Ang KK, Guan C. 2019. Inter-subject transfer learning with an end-to-end deep convolutional neural network for EEG-based BCI. J Neural Eng. doi: 10.1088/1741-2552/aaf3f6. Epub 2018 Nov 26. PMID: 30524056.