Abstracts S167

was no statistical difference in operative steps (U = 24.00, p = 0.73). Compared to the control group, the patient group exhibits stronger frontal-parietal and frontal-occipital regions (p < 0.01, FDR correction). And the patient group's network was accompanied by a lower clustering coefficient (t = -2.770, p = 0.010) as well as a longer characteristic path length (t = 2.766, p = 0.009) than the control group.

Conclusions: Based on behaviors and the network analysis conducted here, the cool executive function in schizophrenia is affected in a certain degree, especially the flexibility. To recover cognitive executive function is the crucial way to improve patients' cool executive function.

doi:10.1016/j.ijpsycho.2021.07.463

SleepZzNet: Sleep Stage Classification Using Single-Channel EEG Based on CNN and Transformer

Huiyu Chen^{a,*}, Zhigang Yin^b, Peng Zhang^b, Panfei Liu^b
^aUniversity of Chinese Academy of Sciences
^bChinese Academy of Sciences

*Presenter.

Background: Sleep stage classification is one of the most important methods to diagnose narcolepsy and sleep disorders. By analyzing the polysomnogram, which includes bioelectrical signals such as EEG and ECG, the whole night's sleep is divided into 30-second epochs, each belonging to five sleep stages: Wake, N1, N2, N3, and REM stages, according to the AASM guidelines. As deep learning has made breakthroughs in various fields in recent years, automatic sleep stages classification tasks are also undergoing a revolution from traditional methods to deep learning methods. Models combining convolutional neural networks and recurrent neural networks (e.g., LSTM) achieve state-of-the-art performance on many benchmark datasets.

Methods: This paper proposes an effective deep learning model called SleepZzNet for processing end-to-end single-channel EEG signals for automatic sleep stages classification. The major contributions of this paper are: First, we propose a convolutional neural network as a feature extractor for extracting time-invariant features within epochs. This CNN network is a one-dimensional convolutional neural network that combines the advantages of ResNet and SENet. Second, we introduce the Transformer to extract temporal features over long sleep periods. We concatenate features of multiple epochs output by CNN in the temporal dimension as input to Transformer. In addition, since the Transformer uses a parallel structure, it is necessary to encode the positional relationships of epochs in the input sequence. Besides, to solve the problem of unbalanced sleep stages data classes, we use Focal Loss as the loss function. It gives larger weights to the classes with fewer samples and focuses more on the difficult samples (e.g., N1 sleep stage) during training.

Results: We used Sleep-EDF as the benchmark dataset, with data recorded from 20 healthy subjects. Table 1 shows the performance of SleepZzNet compared with other models. We only selected methods that extract features from the raw EEG signal using deep learning models. Overall, we get an accuracy of 86.1% on the Sleep-EDF dataset and F1 scores on each class that achieves performance similar to that of state-of-the-art methods. In particular, performing the N1 classes has been improved.

Conclusions: In conclusion, we propose a new end-to-end automatic sleep stage classification deep learning model. The model takes a single-channel EEG signal as input and uses a changed ResNet-18 and SENet to

extract sleep-related features during time periods and then learns long-time sleep transition rules by Transformer. The results show the model achieves comparable performance to other state-of-the-art results on benchmark datasets.

doi:10.1016/j.ijpsycho.2021.07.464

Automatic Sleep Staging Using CNN-HMM Based on Raw Single-Channel EEG

Xiyu Ji^{a,*}, Rong Liu^a, Hongyu Liang^a, Honghui Li^a
^aDalian University of Technology
*Presenter

Background: To avoid class imbalance, the synthetic minority oversampling technique is first used to optimize the 39 whole-night Fpz-Cz EEG recordings in Sleep-EDF dataset to generate class-balance training set. Then, the CNN performs training with it to extract temporal, frequency and temporal-frequency features based on a 10-fold cross-validation. Afterwards, the original data is used to test end-to-end automatic staging of sleep EEG. Finally, the HMM is used to correct the staging results.

Methods: To avoid class imbalance, the synthetic minority oversampling technique is first used to optimize the 39 whole-night Fpz-Cz EEG recordings in Sleep-EDF dataset to generate class-balance training set. Then, the CNN performs training with it to extract temporal, frequency and temporal-frequency features based on a 10-fold cross-validation. Afterwards, the original data is used to test end-to-end automatic staging of sleep EEG. Finally, the HMM is used to correct the staging results.

Results: The results showed that our model achieved similar overall accuracy and macro F1-score (82.75%-75.62) compared with the state-of-the-art CNN-LSTM model (82.0%-76.9) on same data set. Moreover, the training time of our model was only one fifth of that of the CNN-LSTM model.

Conclusions: This demonstrates that proposed the CNN-HMM model not only avoids the artificial features selection, but also has good applicability. Specifically, the temporal transition rules of sleep EEGs are well taken into account with large, reduced training time.

doi:10.1016/j.ijpsycho.2021.07.465

Alterations in Functional Connectivity in the Locus Coeruleus-Norepinephrine System in Chronic Insomnia Disorder

Liang Gong^{a,*}, Jian Wang^a, Bei Zhang^a ^aChengdu Second People's Hospital *Presenter.

Background: Mental syndromes such as anxiety and depression are common comorbidities in patients with chronic insomnia disorder (CID). The locus coeruleus noradrenergic (LC-NE) system is considered to be crucial for the modulation of emotion and sleep/ wake cycle. LC-NE system is also a critical mediator of stress-induced anxiety. However, whether the LC-NE system contributes to the underlying mechanism linking insomnia and these comorbidities