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Automatic sleep-stage classification for children using single-channel EEG

Liqiang Zhu[1], **Lizhi Peng**[1,*], **Yuan Zhang**[2], **Anton Kos**[3]

[1] *School of Information Science and Engineering, University of Jinan, Jinan, China*
[2] *College of Electronic and Information Engineering, Southwest University, Chongqing, China*
[3] *University of Ljubljana, Faculty of Electrical Engineering, Ljubljana, Slovenia*
**Corresponding author e-mail: plz@ujn.edu.cn*

Abstract. Nearly one-third of children suffer from sleep disorders. Although many researches have been conducted on the automatic sleep-stage classification for adults, the sleep stages of children have different characteristics. Therefore, there is an urgent need for sleep-stage classification specifically for children. The paper proposes a deep-learning model for the children automatic sleep-stage classification based on raw single-channel EEG. In the model, we utilize 1D convolutional neural networks (1D-CNN) to extract time-invariant features, and gated recurrent unit (GRU) to learn transition rules among sleep stages automatically from 30 s EEG epochs. Our method is tested on a dataset for children from 2 to 12 years of age. We use six different single-channel EEGs (F3-M2, F4-M1, C3-M2, C4-M1, O1-M2, O2- M1) to train the model separately, where the F4-M1 channel achieves the best results. Experimental results show that our method yields an overall classification accuracy of 83.36% and macro F1-score of 80.98%. This result indicates that our method has a great potential and lays the foundation for further research on the children sleep-stage classification.

Keywords: sleep-stage classification; EEG; deep learning; 1D-CNN; GRU

Uporaba enokanalnega EEG za samodejno razvrščanje stopenj spanja pri otrocih

Skoraj tretjina otrok trpi zaradi motenj spanja. Čeprav so bile izvedene številne raziskave o samodejnem razvrščanju stopenj spanja za odrasle, imajo stopnje spanja otrok različne značilnosti. Zato je nujno treba razvrstiti stopnje spanja posebej za otroke. Prispevek predlaga model globokega učenja za samodejno razvrščanje stopenj spanja pri otrocih, ki temelji na surovem enokanalnem signalu EEG. V modelu uporabljamo 1D konvolucijske nevronske mreže (1D-CNN) za pridobivanje časovno nespremenljivih funkcij in zaprto ponavljajočo se enoto (gated recurrent unit - GRU) za samodejno učenje pravil prehoda med stopnjami spanja iz 30 sekundnih EEG obdobij. Naša metoda je preizkušena na naboru podatkov pri otrocih, starih od 2 do 12 let. Za učenje našega modela ločeno uporabljamo šest različnih enokanalnih signalov EEG: F3-M2, F4-M1, C3-M2, C4-M1, O1-M2, O2-M1; pri čemer je kanal F4-M1 dosegel najboljše rezultate. Eksperimentalni rezultati kažejo, da naša metoda daje skupno natančnost razvrščanja 83,36% in makro oceno F1 80,98%. Ta rezultat kaže, da ima naša metoda velik potencial in postavlja temelje za nadaljnje raziskave na področju razvrščanja otrokovega spanca.

1 INTRODUCTION

With the improvement of modern medicine, the incidence of infectious and nutritional diseases that seriously affected the children's health in the past has dropped significantly. However, nearly one-third of the children suffer from sleep disorders [1]. Sleep disorders affect the children's physical and intellectual development, and can cause their psychological and behavioral problems, especially cognitive functions. Therefore, an adequate high-quality sleep plays a vital role in promoting the children's growth and development and physical and mental health. Polysomnography (PSG), as a standard diagnosing sleep-related disease, detects various physiological parameters during sleep. Sleep-stage scoring divides the physiological parameters in the PSG into 30-second continuous epochs according to the time axis and divide these epochs into different sleep stages according to the American Academy of Sleep Medicine (AASM) and R&K rules [2] [3]. The hypnogram obtained from the results of the sleep-stage scoring can intuitively reflect the sleep of subjects throughout the night and is used to evaluate the sleep quality and sleep-related problems [4]. Therefore, the sleep-stage classification is a key research topic to improve the sleep quality of children.

The age may be the most critical factor in differentiating the sleep pattern between the children and adults, due to the EEG variation reflected by PSG monitoring [5]. The AASM rules also include the sleep-stage scoring methods for children. However, the technicians need to spend a lot of time and effort on sleep

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stage scoring. In addition, the quality of the sleep-stage scoring depends on the experience and fatigue of technicians, and the agreement between the technicians is usually less than 90% [6]. Therefore, it is necessary to develop an automatic sleep-stage classification algorithm for children.

In the past few decades, some sleep-stage scoring methods based on machine learning have been proposed. Agarwal et al. [7] apply Maximum Overlap Wavelet Transform and Shift Invariant Transform to extract features in the time and frequency domain, and the Support Vector Machine (SVM) for the sleep-stage classification. Estrada et al. [8] propose three different schemes to extract characteristics of the EEG signals: relative spectral band energy, harmonic parameters and Itakura distance. See et al. [9] apply the sample entropy and the power spectrum of the harmonic parameters of the infinite impulse response filter and wavelet transform to extract features from the EEG data obtained from the Physionet database, and SVM for the sleep-stage classification. Hassan et al. [10] use a Tunable-Q factor Wavelet Transform to decompose EEG signals to extract various spectral features, and adaptive boosting for the sleep-stage classification. Alickovic et al. [11] use a multi-scale principal component analysis to denoise the Pz-Oz channel EEG signal, and use the discrete wavelet transform (DWT) to extract the most informative feature. The extracted features are the input into the integrated classifier.

In recent years, deep-learning algorithms have also been applied to the sleep-stage classification. Hsu et al. [12] extract energy features from the Fpz-Cz channel EEG signal, and propose a recursive neural classifier based on energy features for sleep staging. Zhang et al. [13] combine complex-valued anti-propagation and Fisher criterion, and propose a new model called fast discriminative complex-valued convolutional neural network to learn discriminative features and overcome the negative effects of unbalanced data sets. Supratak et al. [14] propose DeepSleepNet based on the original single-channel EEG, which uses CNNs to extract time-invariant features and bidirectional memory to automatically learn the transition rules between sleep stages from the EEG cycle. Sors et al. [15] use a 14-layer CNN to perform supervised learning of a 5-stage sleep-stage classification based on a single-channel EEG. Fraiwan et al. [16] research the application of long short-term memory learning system in the automatic sleep-stage scoring. Zhang et al. [17] develop a new unsupervised competitive CNN, which overcomes the difficulty of obtaining labeled data. Zhang et al. [18] propose a novel hybrid manifold-deep CNN with a hyperbolic attention for sleep staging.

The machine learning methods manually extract corresponding features based on the characteristics of EEG, leading to a poor generalization. Although the accuracy of the deep-learning methods is generally not as good as machine learning they can independently learn the EEG features and have a better generalization. In addition, the existing automatic sleep-stage classification methods are for adults by default. However, children and adults have different EEG characteristics, therefore these methods are not necessarily suitable for children.

In the paper, we propose an automatic sleep-stage classification method for children. Our contributions can be summarized as follows:

- We update the Alexnet to design our 1D-CNN architecture for the sleep-stage classification of children based on a labeled single-channel EEG.
- We introduce batch normalization and GRU to improve our model and use real clinical EEG signals to verify the effectiveness of our method.
- We verify the effect of different EEG channels for the children's automatic sleep-stage classification and lay the foundation for further research.

The paper is structured as follows. Section 2 introduces our sleep dataset, data processing and automatic sleep-stage classification of the proposed method. Section 3 describes our experiment and provides our analysis results. Section 4 draws conclusions of our work and presents plans for our future research.

2 DATA AND METHODS

2.1 Sleep Dataset of Children

The experimental raw dataset is collected from the Beijing Children's Hospital, China. It contains 26 PSG recordings of children from 2 to 12 years of age (8 females and 18 males). Among them, 15 have an obstructive sleep apnea and 11 are healthy. According to the sleep time of each child, the collected multi-channel physiological signal is 8 to 11 hours long from the evening to the next morning. The PSG recordings of the 26 children contain six EEG channels: F3-M2, F4-M1, C3-M2, C4-M1, O1-M2, O2-M1. The sampling frequency of the EEG signal is 256 Hz. For the PSG recordings, every 30 s time interval corresponds to a label, representing one of the five sleep stages (e.g., W, REM, N1, N2 and N3). The labels are provided by sleep experts according to the AASM sleep-scoring rules. Table 1 shows different distribution sleep stages in our sleep dataset.

Table 1. Proportion of the sleep-stage labels in sleep dataset of children (%).

W	N1	N2	N3	REM
12.17	10.07	42.86	17.94	16.96

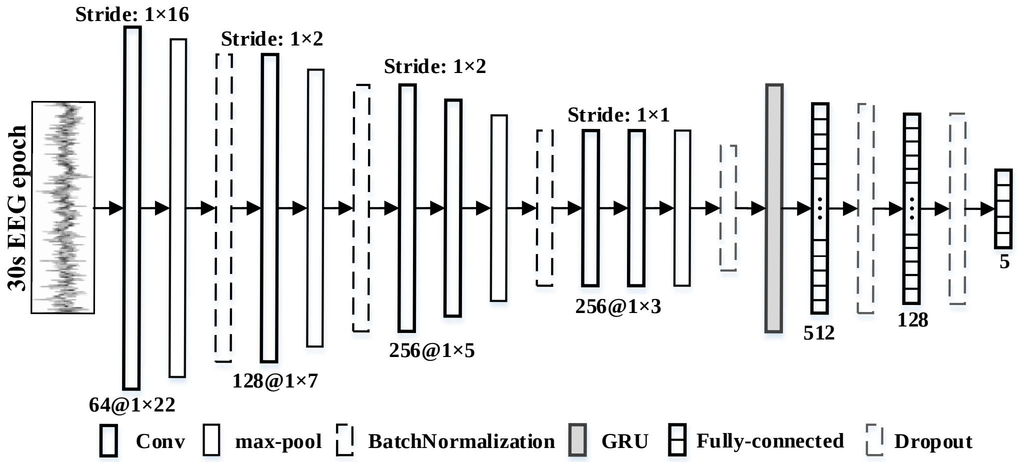

Figure 1. Architecture of our automatic sleep stage classification for children.

2.2 Data Processing

A F4-M1channel EEG signal is used to study the automatic sleep-stage classification taking 30s EEG epochs as the input. In order to extract 30s EEG epochs from a single-channel EEG signal, two steps in the data processing are follow:

- Dividing the continuous raw single-channel EEG into a sequence of 30s epochs and assigning a label to each epoch according to the annotation file. In this way, each 30s epoch can be used as an example of the sleep-stage classification. The EEG recordings of each child can be divided into 900 to 1300 30s epochs according to the length of sleep.
- Normalizing the 30s EEG epochs such that each one has a zero mean and unit variance. There are noises in real clinical EEG signals due to various reasons. Normalization operation can effectively reduce the impact of these noises.

2.3 Model

The architecture of our model is shown in Figure 1. We firstly use a 1D-CNN which can be trained to extract time-invariant features from each epoch. Then, we apply GRU which can be trained to encode the temporal information such as stage transition rules from an epoch in the extracted features. The last part is composed of fully-connected layers and a softmax layer that provides the sleep-stage classification result of 30s EEG epochs.

We update the Alexnet to design our 1D-CNN architecture. The input data of our model is a 30s EEG epoch. As this is a 1×7680 one-dimensional time sequence, we apply a 1D convolutional kernel to replace the 2D convolutional kernel. We add the batch normalization layers to the 1D-CNN and adjust the network structure according to our data characteristics. The 1D convolution operation is defined as:

$$y_i^l = \sigma g_{p^l}\left(\sum_{n=1}^{d} \omega_n^l \cdot y_{n+1}^{l-1} + b^l\right), i \in (1, N-d+1) \quad (1)$$

y_i^l is the i-th feature map of the output feature map set on layer l. ω_n^l and b^l are the weight vector and bias unit of the convolution kernel of layer l, respectively. d is the size of the convolution kernel. N is the length of input feature vector y_i^{l-1}. g_{p^l} is a p^l-strided subsampling operator, and σ is the activation function of convolutional layer l.

a 1×22 kernel with a stride of 1×16 is applied to the first convolutional layer. It is applied to replace the traditional filtering methods. It can be trained to reduce the data dimensions and retain useful information. A 1×7 kernel with a stride of 1×2 is applied to the second convolutional layer. A 1×5 kernel with a stride of 1×2 is applied to the third and the fourth convolutional layer. A 1×3 kernel with a stride of 1×1 is applied to the fifth and the sixth convolutional layer. In this way, the 1D-CNN part can be divided into four blocks. After each block, there is a 1×3 max-pooling layer with a step of 1×2. We apply a batch normalization layer after each of the first three max-pooling layers to reduce the internal covariate shift, accelerate the training process, and improve the model training accuracy and generalization ability. The principle of the batch normalization is as follows:

$$\hat{x}_i = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \varepsilon}} \quad (2)$$

$$y_i = \gamma \hat{x}_i + \beta \quad (3)$$

Expression (2) is used to normalize the training data of the batch. B represents a small batch that contains m examples. μ_B and σ_B^2 represent the mean and variance of B, respectively, and ε is used to avoid the tiny positive number used when the divisor is zero.

Expression (3) is used to perform a scale transformation and shift: multiply $\hat{x}_i$ by γ to adjust the value, plus β to increase the shift to get y_i, where γ is the scale factor and β is the translation factor. γ and β are learned by the network during training. They solve the problem that normalized $\hat{x}_i$ is basically limited to a normal distribution, which reduces the expressive ability of the network.

After the last max pooling layer, a GRU layer is applied to learn the temporal information. There are two fully-connected layers with 512 and 128 neurons after the GRU layer, respectively. Finally, the softmax layer outputs the results of the sleep-stage classification. All convolutional layers and fully connected layers use Relu ($f(x) = \max(0, x)$) as the activation function.

2.4 Optimization

We apply a multi-class cross-entropy as the cost function and perform a mini-batch training for stochastic optimization of the weights and biases. The expression of the mini-batch cost L is:

$$L(w, B) = -\sum_i^m y_i log p_i(w) \quad (4)$$

w represents the set of all learnable parameters, m is the number of examples of the mini-batch, B represents the training examples of the mini-batch, y_i is the one-hot encoded target classes, and p_i is the probability distribution of the sample prediction output by the softmax layer.

With the softmax activation function, minimizing the cross-entropy corresponds to maximizing the log-likelihood of the model-predicted class being equal to the true class. Classically, the backpropagation algorithm is applied to get the gradient. For optimization, we use the Adam optimizer with parameters (lr = 1×10^{-5}, β_1= 0.9, β_2 = 0.999).

In order to avoid overfitting, we apply dropout and L2 regularization. The expression of the cross- entropy loss function with the L2 regularization term is:

$$L_{L2} = L + \lambda\|\omega\|^2 \quad (5)$$

L is the basic cross-entropy loss function. $\lambda\|\omega\|^2$ is the L2 regularization term. λ and ω are the penalty factor and network parameter, respectively. We set $\lambda = 10^{-3}$.

3 EXPERIMENTS

3.1 Implementation Details

From the 26 children, we randomly select five children as the test set, and use a ten-fold cross-validation to train our model. The performance of the model is evaluated according to the following test criteria: confusion matrix, accuracy and F1 score.

Our experimental models are implemented using the Keras in the Tensorflow framework under the Python environment. Our experiments are conducted with a desktop PC equipped with Intel Intel i7-8700K CPU, 64 GB RAM and a NVIDIA GeForce GTX 1080Ti GPU.

3.2 Experimental results

To apply our model to portable wearable devices, an appropriate sensor channel is employed to collect the EEG recordings. Therefore, we use six different single-channel EEGs to train our model separately. Table 2 shows the performance of the model trained. Four of the six channels (F3-M2, F4-M1, C3-M2, and C4-M1) achieve an acceptable result with an accuracy above 80%. The F4-M1 channel achieves the best result, with the accuracy of 83.36% and the F1 score of 80.98%. However, the performance of the other two channels is not sufficiently satisfactory. The O1-M2 channel accuracy is 73.04%, and the O2-M1 channel EEG accuracy is 75.03%. Therefore, the F4-M1 channel is our first choice, and the F3-M2, C3-M2 and C4-M13 channels can be considered as substitutes and as references in our future research of automatic sleep staging for children.

Table 2. The performance of the model trained with different single-channel EEGs.

EEG channel	Accuracy	F1-score
F3-M2	80.13	76.70
F4-M1	**83.36**	**80.98**
C3-M2	80.38	75.12
C4-M1	81.90	78.78
O1-M2	75.03	72.05
O2-M1	73.04	70.49

The performance of our model is compared to 1D-CNN to verify the effect of GRU(Table 3). It indicates that 1D-CNN can be used for the sleep-stage classification of children, however the result is not very satisfactory. The 1D-CNN accuracy is 78.08% and the F1-score is 74.26%. Based on 1D-CNN, GRU is applied to learn the temporal information. The performance of the model is improved accordingly. The model overall classification accuracy is 83.36% and the macro F1-score is 80.98%.

Table 3. The 1D-CNN and model performance.

Model	Accuracy	F1-score
1D-CNN	78.08	74.26
1D-CNN_GRU	83.36	80.98

Table 4 details the performance of the model trained with the F4-M1 channel. The left part shows the confusion matrix and the right part shows the precision, recall, and F1score of the sleep stages (e.g., W, REM, N1, N2 and N3). A further analysis is given in Section 3.3.

Table 4. The performance of the model trained with the F4-M1 channel EEG.

	W	N1	N2	N3	REM	Pre	Rec	F1
W	93.4	3.0	0.3	0.1	3.2	90.3	93.4	91.8
N1	2.1	54.4	0.8	0.0	42.7	39.5	54.4	45.8
N2	2.2	18.2	75.2	0.3	4.1	98.7	75.2	85.4
N3	0.2	0.1	1.6	98.0	0.1	99.4	98.0	98.7
R	0.2	1.3	0.1	0.0	98.4	72.1	98.4	83.2

3.3 *Discussion*

We combine 1D-CNN and GRU to set-up our deep-learning model for an automatic sleep-stage classification for children. The model itself automatically learns the appropriate features. The experimental results show that using a single-channel EEG and deep learning for the sleep-stage classification without any feature-extraction stage provides an acceptable performance. The model training is end-to-end needing no expert knowledge for feature selection or signal preprocessing. This enabled training the model can be trained to learn the features that are most suitable for the sleep-stage classification of children. Training a deep learning model takes a lot of time and hardware equipment of an adequate performance, but once the model training is completed, the prediction is relatively cheap and can be carried out on PCs or portable wearable devices.

As seen from the confusion matrix of Table 4, the classification performance of stage W, stage N3 and stage REM is satisfactory. Some of the stage N2 epochs are mistakenly classified as stage N1. As stage N1 and stage N2 are contiguous in the sleep cycle, therefore stage N2 may contain similar patterns to stage N1. Stage N2 accounts for a large proportion of the sleep recordings (see Table 1), therefore the accuracy of stage N2 has a greater impact on the overall accuracy. A large number of stageN1 is mistakenly classified as stage REM. Stage N1 is a transitional stage in sleep, and the EEG features of stage N1 are not obvious. It is also difficult for sleep experts to classify stage N1 accurately. Therefore, the focus of our further work will be on how to improve the classification accuracy of the stage N1 and stage N2. The performance of such a supervised sleep-stage classification for children is inherently limited by the size of the available dataset and the quality of the available annotations.

4 Conclusion

To realize an automatic sleep-stage classification for children, we propose a sleep-staging deep learning model based on labeled single-channel EEG signals. We design 1D-CNN to extract time-invariant features and apply CRU to learn the temporal information. The end-to-end learning model requires no specific field feature extraction steps and overcoming the limitations of the manual feature extraction and improves the accuracy of the sleep-stage classification for children.

In the future work, our focus will be on collecting more PSG recordings for children with reliable annotations. We will conduct more experiments based on a larger amount of data to further improve our model. We will also take on effort to improve the performance of the automatic sleep-stage classification for children using multi-channel EEG signals.

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Liqiang Zhu received his BSc degree in 2019 from the College of Computer and Communication Engineering, Zhengzhou University of Light Industry, China. He is a master student majoring in computer technology at the Shandong Provincial Key Laboratory of Network Based Intelligent Computing, University of Jinan. His current research interests include biomedical image/signal processing and deep learning.

Lizhi Peng received his B.Eng. degree from the Xi'an Jiaotong University, M.Eng. degree from the University of Jinan and Ph.D. degree from Harbin Institute of Technology, in 1998, 2006 and 2015, respectively. In 2017, he was a visitor scholar of the Department of Computer Science of University of Otago, New Zealand. Currently, he is a Professor of the School of Information Science and Engineering, University of Jinan, Jinan, China. His current research interests include machine learning, evolutionary computing, computer network, and parallel computing.

Yuan Zhang is currently a Professor with the Collage of Electronics and Information Engineering, Southwest University, China. his research interests include wearable sensing for smart health, machine learning for auxiliary diagnosis and biomedical big data analysis. As the first author or corresponding author he has published over 60 peer-reviewed papers in international journals and conference proceedings, a book chapter, and is a holder of nine patents. He is a member of IEEE EMBS for Wearable Biomedical Sensors and Systems Technical Committee. He is an associate editor for the IEEE Reviews in Biomedical Engineering and IEEE Access. He has been a Leading Guest Editor for six special issue of the IEEE, Elsevier, Springer and InderScience publication. He is a senior member of IEEE and ACM.

Anton Kos received his Ph.D. degree in electrical engineering from the University of Ljubljana, Slovenia, in 2006. He is an associate professor at the Faculty of Electrical Engineering, University of Ljubljana. He is a member of the Laboratory of Information Technologies at the Department of Communication and Information Technologies. His teaching and research work includes communication networks and protocols, quality of service, dataflow computing and applications, usage of inertial sensors in biofeedback systems and applications, signal processing, and information systems. He is the (co)author of a scientific monography, over fifty papers published in international engineering journals, more than eighty papers presented at international conferences, and is a holder of two patents. His professional work encompasses co-organizing international VIPSI conferences, serving as a program committee member at several international conferences, and serving as an associate, topic, and guest editor for several international scientific journals. He is a senior member of IEEE, the Union of Electrical Engineering of Slovenia, and SICOM. Since 2018 he has been an IEEE Slovenia ComSoc chapter chair.