SleepGNet: Automatic Sleep Staging Model Based on Graph Convolu-tional Network

Wenyuan Cui
Department of Electronic and Electrical Engineering
Southern University of Science and Technology
Shenzhen, China
11912304@mail.sustech.edu.cn

Weichen Qian
Department of Information Engineering
Nantong Industry & Trade Technician College
Nantong, China
447166221@qq.com

Xinrong Chen*
Academy for Engineering and Technology
Fudan University
Shanghai, China
chenxinrong@fudan.edu.cn

***Abstract*—Sleep has an indispensable role in human health. It serves as an essential function that help maintain healthy both mentally and physically. Many people nowadays do not conform to healthy sleep patterns. Furthermore, insufficient access to sleep education and treatment aids leads to people engaging in harmful sleep behaviors and requiring treatment for sleep disorders, which has caused a sleep crisis and is a public issue. Sleep stage classification is a great tool for helping solve these disorders and improve the sleep quality of humans. Yet, classifying all sleep stages accurately and automatically based on extracting features from multiple EEG epochs is a challenging task. In this work, a novel sleep staging model is proposed, which is named SleepGNet. The time frequency images derived from EEG epochs as input are transformed into sequential images through the parallel filter-bank layers. In order to achieve faster convergence during training procedure and more accurate classification results with fewer training times, Graph Convolutional Network (GCN) is used to dig the connections between every epochs more effectively. Experimental results on Sleep-EDF database indicate that SleepGNet outperforms the state-of-the-art sleep staging methods and the overall accuracy is about 86.6%.**

Keywords—Graph convolutional network, Sleep stage classification, Time frequency images, EEG

I. INTRODUCTION

Sleep has an indispensable role in human health. It serves as an essential function that help maintain healthy both mentally and physically. Nowadays, many people do not conform to healthy sleep patterns. Moreover, insufficient education and treatment aids in sleep has led to harmful sleep behaviors, which makes the sleep crisis and is a public health issue[1]. Sleep stage classification is a great tool for helping solve these disorders and improve the sleep quality of humans.

Polysomnogram (PSG) is a combination of several signals used for monitoring sleep such as electroencephalogram (EEG), electromyogram (EMG), electrooculogram (EOG) and electrocardiogram (ECG)[2]. This sleep cycle information can be divided into different stages based on the guidelines of the American Academy of Sleep Medicine (AASM)[3] or Rechtschaffen and Kales standards[4]. A complete sleep cycle can be divided into two categories, which are rapid eye movement (REM) stage and three non rapid eye movement stages, namely N1, N2, and N3 stages. However, PSG has various disadvantages like the inconvenience caused by plenty of sensors and the effect of the foreign sleep environment on the patients[5]. Therefore, it is demanding to implement household sleep health monitor using PSG, which will cause some problems in convenience and economy. Therefore, the single channel portable sleep monitor is now gradually becoming popular. It usually uses only one sensor to monitor the sleep signals through one certain signal like EEG, which makes it possible for the sleep monitor to be used in the own house of patients. Certain studies also mention some improvement in data-collecting device like the HARU sleep sensor, which is light and portable, but it has a comparable scoring accuracy with PSG devices[6]. Based on the extracted data, the efforts of human experts are often needed in order to analyze the EEG signals and acquire useful information. Since the household equipment will extract mass data which will take much effort of the human expert to be analyzed, it will be a more effective method to analyze these data via artificial intelligence.

In sleep research community two main strategies are used to implement automatic sleep staging, which are conventional machine learning (ML) methods and deep learning (DL) methods[7]. Certain approach uses instance-based algorithm like the Support Vector Machines (SVM). Other typical machine leaning method such as hierarchical decision tree is also used in some research. Yet some research argue that the performance of tradition-al machine learning approaches are close to state-of-art method[7]. These traditional machine learning methods need some handcraft features of the signals as prior knowledge and cannot be directly applied on raw EEG signals. However, deep learning based methods have the advantage of processing large amounts of data and the features from raw input data can be directly learned with little knowledge. Yet, it can still be applied on feature-based research and achieves good results. Using deep learning based methods is the current trend in automatic sleep staging. The reviews about deep learning based automatic sleep stage classifications are mainly focusing on the different performance caused by different models used in classifiers like CNN or RNN, etc. In this paper, the previous researches are reviewed based on the features they used.

The most common way of applied deep learning is to apply it directly on the raw EEG data, which means no feature is extracted in this category. Plenty of research recently have attempted this approach. CNN with 14 layers are used to apply directly on raw-EEG signals, in which the accuracy reaches 0.87 and Cohen kappa reaches 0.81[8]. This research also points out a deficiency which is also a typical deficiency in the latest research on non-feature-extraction automatic sleep stage classification: errors occur in stages that are contiguous in sleep cycles. While in this research, errors between all contiguous sleep cycles pairs exists, in recent study, only the classification of N1 stage

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remains a problem[6]. This work shows that it is difficult to recognize N1 since it is a transition stage from wakefulness to deep sleep. Therefore, there exists no clear distinction between stages. Some of the researcher attributes this problem to the disagreement between experienced manual scorers in the datasets[9]. Besides the single CNN model, numerous other models are also used in this non-feature-extraction approach. Time-Distributed CNN is used and achieve an overall accuracy of 0.85 [10]. And the model of CNN + LSTM is utilized and reach a high performance[11,12]. As can be noted, deep learning models can be directly applied to raw-EEG data and a high performance can be reached when classifying sleep stages. However, there is still a problem exists that the classification of the transition stage-N1 stage, is not so valid. The reason might be that the lack of the information about energy transition in different stage when doing raw-EEG analysis makes it hard to distinguish between the transition area in EEG signals.

The frequency domain of the raw-EEG signal is another approach in automatic sleep stage classification. By applying a short-term Fourier Transform on the raw-EEG signal, the frequency domain features which can be utilized for describing changes in EEG signals are able to be extracted. Research uses the frequency domain information in RNN and LSTM, achieving an early state-of-art performance. Using a long-term sequential modelling method on the STFT results, achieves a significant improvement on N1 compared to the E2E-ARNN baseline. There is a problem for frequency analysis approach that since a sequence of temporal signal is required in order to do frequency domain analysis, it will cost much time so that it is hard to be applied on real-time applications such as household sleep monitor. While the author of asserts that the performances are decent even processing with only one single epoch of temporal data. To conclude, frequency-domain based approach is able to improve the distinction in transient area and reach state-of-art performance.

This work is to get all target labels simultaneously. So a novel network applying GCN is introduced to automatic sleep staging.

II. Method

The proposed framework, SleepGNet, is shown in Fig. 1. Formally, EEG epochs with the length L, can be represented by $(S_{e1}, S_{e2}, ..., S_{eL})$. To get the output sequence $(y_1, y_2, ..., y_L)$, $p(y_1, y_2, ..., y_L \mid S_{e1}, S_{e2}, ..., S_{eL})$ need be maximized.

Firstly, the time-frequency image S is obtained by transforming the epoch. Then, the image S is preprocessed by parallel filter-bank layers. And then, an image X is formed by concatenating the all images, which is feature vectors. Moreover, the feature vector x is obtained by the bidirectional RNN based on attention. Next, the feature vectors $\overline{X} = (\overline{x}_1, \overline{x}_2, ..., \overline{x}_L)$ are modeled by bidirectional RNN and GCN, respectively. Finally, the output $O_G = (o_{G1}, o_{G2}, ..., o_{GL})$ from GCN is used to obtain the output $\hat{Y} = (\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_L)$.

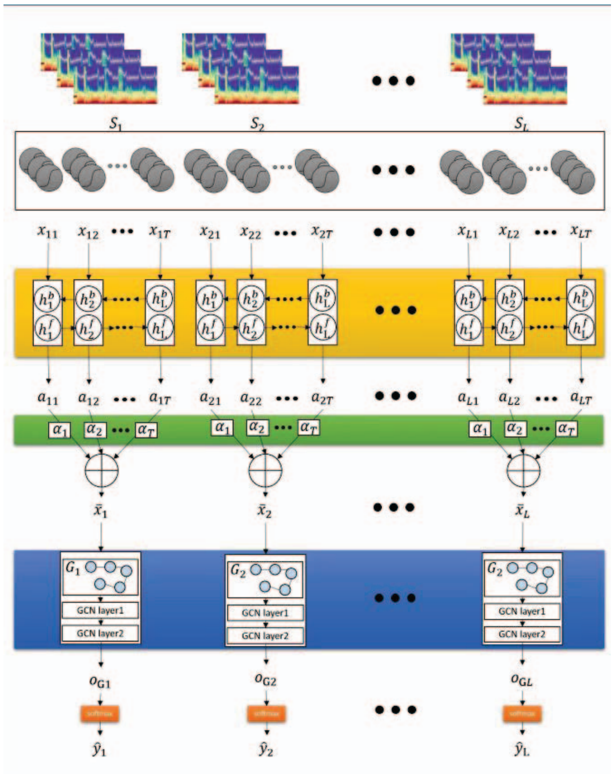


Fig. 1. The framework of SleepGNet

A. Time-Frequency Image Representation

For each 30-second EEG epoch, the time-frequency image are obtained by short-time Fourier transform (STFT). In the method, the window with two seconds size and half overlap are used. Next, to log the power spectra, logarithm scaling is applied. In this work, an image $S \in R^{F \times T}$ with the number of frequency bins $F = 129$ and the spectral columns $T = 29$ can be obtained.

B. Filter-bank Layers

A fully-connected layer is used in each Filter-bank Layer, in which M hidden units are adopted and $M < F$. The weight matrix of filter-bank is $W \in R^{F \times M}$. Then, the constraints are enforced for the filter-bank, which ensure the non-negative characteristics with band-limited and ordered frequency.

$$W_{fb} = f_+(W) \odot T \tag{1}$$

where f_+, the sigmoid function, denotes the function is non-negative, which makes the elements of W non-negative. The constant matrix $T \in R_+^{F \times M}$ is non-negative. The $\odot$ is element-wise multiplication operator.

By the filter-bank layer, the output image $X \in \mathbb{R}^{M \times T}$ is as follows.

$$X = W_{fb}^{\mathrm{T}} S \tag{2}$$

In frequency direction, the image channels of the output image $X \in R^{M \times T}$ are concatenated, which generates a $M \times T$ image.

C. Epoch-level Modeling

After the filter-bank layers, the feature vector at the time t is $X \equiv (x_1, x_2, \ldots, x_T)$, $x_t \in R^M$, $1 \le t \le T$. And the feature vector can be obtained by the bidirectional RNN based on attention.

In the RNN, the recurrent layers iterate over the feature vectors and the hidden state vectors $H^f = (h_1^f, h_2^f, \ldots, h_T^f)$ and $H^b = (h_1^b, h_2^b, \ldots, h_T^b)$ are computed.

$$h_t^f = \sigma(x_t, h_{t-1}^f) \tag{3}$$

$$h_t^b = \sigma(x_t, h_{t+1}^b) \text{ , } 1 \le t \le T \tag{4}$$

According to equation (3) and equation (4), σ , biRNN with less parameters can be used by Gated Recurrent Unit (GRU) cell. Therefore, the GRU cell is implemented as following:

$$r_t = sig\,\mathrm{mod}(W_{sr} s_t + W_{hr} h_{t-1} + b_r) \tag{5}$$

$$\upsilon_t = sig\,\mathrm{mod}(W_{sz} s_t + W_{hz} h_{t-1} + b_z) \tag{6}$$

$$\bar{h}_t = \tanh(W_{sh} s_t + W_{hh}(r_t \odot h_{t-1}) + b_h) \tag{7}$$

$$h_t = \upsilon_t \odot h_{t-1} + (1 - z_t) \odot \bar{h}_t \text{ ,} \tag{8}$$

where W is the weight matrices and b is the bias. Then r represents the reset gate vector, υ represents the update gate vector and $\bar{h}$ represents the hidden state vector for candidate. The output vectors is $A_o = (a_1, a_2, \ldots, a_T)$.

$$a_t = W_{ha}[h_t^b \oplus h_t^f] + b_a \tag{9}$$

And $\oplus$ is the vector concatenation.

The attention layer is adopted to combine the output vectors with different times. Here the attention weight α_t in the time t is computed.

$$\alpha_t = \frac{\exp(f_s(a_t))}{\sum_{i=1}^{T} \exp(f_s(a_i))} \tag{10}$$

where f is the scoring function.

$$f_s(a) = a^{\mathrm{T}} W_{att} \tag{11}$$

where W_{att} is the weight matrix. The attentional feature vector $\bar{x}$ is computed.

$$\bar{x} = \sum_{t=1}^{T} \alpha_i a_t \tag{12}$$

D. Sequence-level GCN Modeling

To obtain the output vectors O , GCN is used.

In GCN, the feature vectors $\overline{X_f} = (\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_L)$ is encoded and the output vector is $O_G = (o_{G1}, o_{G2}, \ldots, o_{GL})$.

Formally, GCN meets the following rule:

$$H^{(l+1)} = \varphi\left(\tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} H^{(l)} W^{(l)} \right) \tag{13}$$

where $\tilde{A} = A_{adj} + I_N$ is the adjacency matrix, which is from the undirected graph G, I_N is the identity matrix. Weight matrixes are $\tilde{D}_{ii} = \sum_j \tilde{A}_{ij}$ and $W^{(l)}$. Activation function is $\varphi(.)$. The activation matrix $H^{(l)} \in \mathbf{R}^{N \times D}$ is in the l^{th} layer, $H^{(0)} = \overline{X}$.

Here, a symmetric adjacency matrix A_{adj} is used to model the epoch-wise feature vectors. Then the two-layer GCN is adopted.

$$A_{adj} = \begin{pmatrix} a_{11} & \cdots & a_{1j} \\ \vdots & \ddots & \vdots \\ a_{i1} & \cdots & a_{ij} \end{pmatrix}^{T \times T} \text{ , } 1 \le i \le T \text{ , } 1 \le j \le T \tag{14}$$

where $a_{ij} = 1$, if $i = j+1$ or $i = j-1$, otherwise $a_{ij} = 0$.

In the pre-processing step, $\hat{A} = \tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}}$ is calculated. The output vectors o_{Gl} is computed.

$$o_{Gl} = \hat{A}\,\mathrm{Re}LU(\hat{A}\overline{x_l} W^{(0)}) W^{(1)} \text{ , } 1 \le l \le L \tag{15}$$

Where the weight matrix $W^{(0)} \in \mathbf{R}^{M \times T}$ is for hidden layer. $W^{(1)} \in \mathbf{R}^{T \times F}$ is the output weight matrix.

The output vector is $O_o = (o_1, o_2, \ldots, o_L)$, which is computed through $o_l = o_{Rl} + o_{Gl}$, $1 \le l \le L$. Here, $+$ is the addition between vectors.

E. Loss for Sequence

The classification is based on the sleep stage probabilities through softmax layer, which is $\hat{Y} = (\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_L)$. For the network, the input sequence is $(S_{e1}, S_{e2}, ..., S_{eL})$ and the ground-truth vector is

$(y_1, y_2, ..., y_L)$. The network parameters are solved by minimizing the loss function.

$$E(\theta) = -\frac{1}{L}\sum_{n=1}^{N}\sum_{l=1}^{L} y_l \log(y_l(\theta) + \frac{\lambda}{2}\|\theta\|_2^2 \qquad (16)$$

where θ is the parameter, λ is the hyper-parameter.

III. Evaluation

A. Datasets

To evaluate the models, the public sleep dataset, Sleep-EDF, is used in the experiment. There are 39 EEG recordings with 20 subjects, which are split into training set with 14 subjects, validation set with 4 subjects, and test set with 2 subjects.

B. The Parameters Settings

To implement the experiment, TensorFlow-gpu v1.13.1 is used. The parameters for SleepGNet are shown in Table I.

TABLE I. THE PARAMETERS OF SLEEPGNET USED FOR AUTOMATIC SLEEP STAGING.

Item	Value
Sequence length L	20
Number of filters M	32
hidden state vector	64
the attention weights	64
the symmetric adjacency matrix	128*128
The rate in dropout	0.25
The parameter of regularization	10^{-4}

C. Methods for Comparison

The mainstream methods, IITNet [11], Se-qSleepNet+ [12], SleepEEGNet [13], DeepSleepNet [14], Ti-nySleepNet [15], XsleepNet [6], Multitask CNN [7], 1-max CNN [8], Attentional RNN [9] were used for comparison.

D. Experimental Results

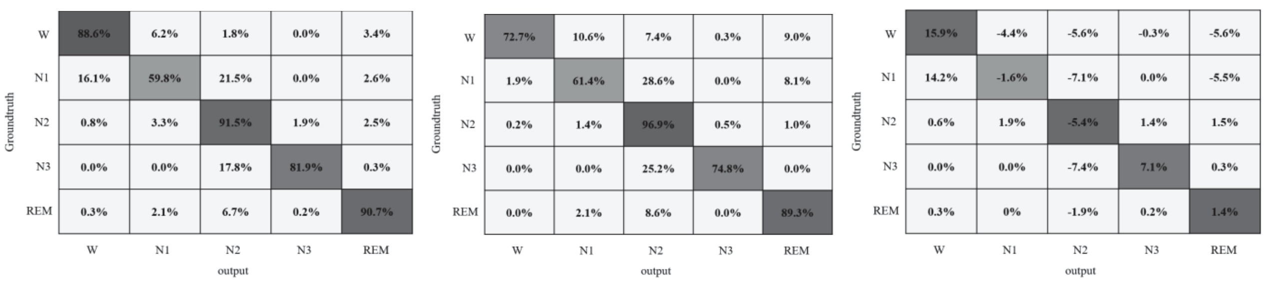
To quantify the comprehensive performance of the methods, overall accuracy (ACC), macro F1-score (MF1), Cohen's Kappa coefficient (κ) are used, which are shown in Table II.

TABLE II. THE PERFORMANCE COMPARISON RESULTS

Datasets	Methods	Manual	EEG Channels	Fs (Hz)	Epoch (sec)	Overall Metrics ACC	MF1	κ
Sleep-EDF-20 (±30 mins)	IITNet	R&K	Fpz-Cz	100	30	84.0	77.7	0.78
	SeqSleepNet+	R&K	Fpz-Cz	100	30	85.2	79.6	0.79
	SleepEEGNet	R&K	Fpz-Cz	100	30	84.3	79.7	0.79
	DeepSleepNet	R&K	Fpz-Cz	100	30	82.0	76.9	0.76
	TinySleepNet	R&K	Fpz-Cz	100	30	85.4	80.5	0.80
	XSleepNet1	R&K	Fpz-Cz	100	30	86.0	80.0	0.81
	Our method	R&K	Fpz-Cz	100	30	86.6	79.3	0.83

In the results, the proposed method completed the sleep stages with the ACC of 86.6%, which achieved the better performance than the state-of-the-art methods. Furthermore, the results displayed that the agreement of Cohen's Kappa coefficient between the proposed model with the sleep experts, in which (0.81-1) means the perfect performance. The confusion matrix of SleepGNet and the DeepSleepNet are shown in Fig. 2, in which SleepGNet outperforms in the classification of sleep stage REM, N3, and W.

Fig. 3 shows the output sleep map and posterior probability distribution for each sleep stage of the subjects in the sleepEDF dataset. Due to the absence of vertical mixing of colors, it demonstrates the stability of our model at different sleep stages. It can be seen that the output hypnosis map is very consistent with the corresponding ground truth. As a result, SleepGNet showed comprehensive and significant improvement in all sleep stages of both large and small databases. SleepGNet is trained independently of a large amount of data and is not easily overfitting.



(a) The confusion matrix of SleepGNet (b) the confusion matrix of DeepSleepNet (c) the difference between them

Fig. 2. The confusion matrix.

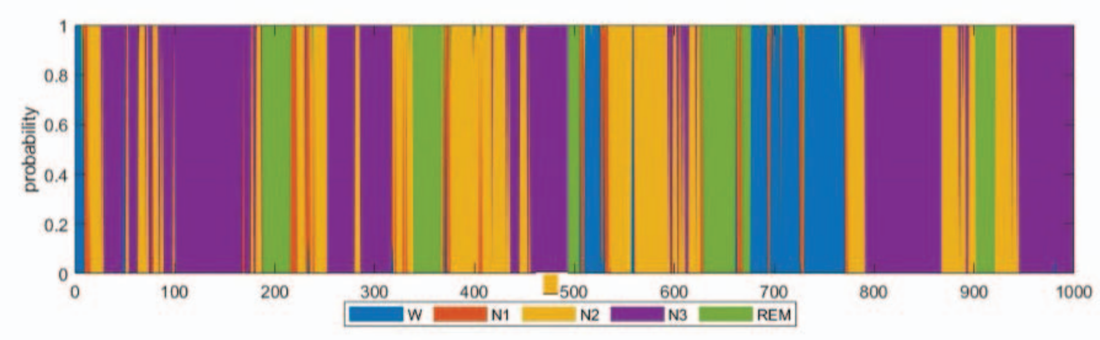


Fig. 3. Posteriori probability distribution of different sleep stages.

IV. Conclusion

A novel model based on deep learning for automatic sleep staging, is named SleepGnet, which has can replace manual sleep staging. In our model, to learn frequency-domain filters, a parallel filter-bank layer is utilized. Then, GCN makes the model faster convergence, which can be completed in fewer training times for more accurate classification results. Moreover, the attention-based recurrent layer place is used to model sequence features. The experimental results on the database show that the proposed method gets the best performance.

There are some limitations in SleepGnet. One side, the input, time-frequency image, may ignore some information compared to the raw signal, resulting in limited improvement in the accuracy of automatic sleep staging. The other side, all the epochs need to be accessed simultaneously, which will limit the application in some real-time situations.

In the future, SleepGnet will be improved to access multi-views input and the automatic sleep staging model will be developed for the big data sleep management system.

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