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Special Focus on Brain Machine Interfaces and Applications

Hybrid spiking neural network for sleep electroencephalogram signals

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Abstract Sleep staging is important for assessing sleep quality. So far, many scholars have tried to achieve automatic sleep staging by using neural networks. However, most researchers only perform sleep staging based on artificial neural networks and their variant models, which can not fully mine and model the bio-electrical signals. In this paper, we propose a new hybrid spiking neural network (HSNN) model for automatic sleep staging. Specifically, we use a spiking neural network to classify sleep EEG signals. In addition, we adopt a hybrid macro/micro back propagation algorithm, aiming to overcome the limitations of existing error back propagation methods for spiking neural network. In order to verify the effectiveness of HSNN, we evaluate it on the public sleep dataset ISRUC-SLEEP (Institute of Systems and Robotics, University of Coimbra-Sleep). The results show that the proposed method achieves satisfactory performance on ISRUC-SLEEP.

Keywords spiking neural network, electroencephalogram signals, sleep staging

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1 Introduction

Sleep disorders have severe influences on human health and life. Sleep staging is a crucial way to evaluate sleep quality and diagnose sleep disorders. The American Academy of Sleep Medicine (AASM) categorizes sleep into several stages, including awake (W), non-rapid eye movement (NREM), and REM (R). NREM is further divided into three stages: N1 (transitional sleep), N2 (light sleep), and N3 (deep sleep). The sleep cycle consists of alternating stages of REM and non-REM. To be specific, a sleep cycle, which occurs three or four times throughout one night [1], usually consists of N1-N2-N3-N2-R.

Polysomnography (PSG) refers to physiological signals detected during sleep, including electroencephalogram (EEG) and electrooculogram (EOG). Different sleep cycles can be distinguished by observing the amplitude and frequency of the PSG signals. Staging sleep by visual observations of PSG signals from experts is a time-consuming task, usually taking several hours to classify the PSG signals overnight. Moreover, due to the influence of subjective factors, the classification results of different experts may vary greatly. Therefore, establishing an effective automatic sleep staging model which is independent of subjective interpretations of different experts can effectively save time and offer objective sleep assessments.

In order to construct the automatic sleep staging model, artificial neural network (ANN) [2] and ANN variants such as convolutional neural network (CNN) and long short-term memory (LSTM) [3, 4] are gradually applied to sleep staging. Although traditional neural networks are inspired by the brain, their structure, information transmission methods, and learning rules are fundamentally different from those of the biological brain. One of the most important differences is the way information travels between neurons. Therefore, these models cannot fully model brain data, which poses a challenge to achieving high-precision sleep staging.

To solve the above challenges, we propose a hybrid spiking neural network (HSNN) model for sleep staging, which is a brain-like model. Specifically, in order to model the transmission of information

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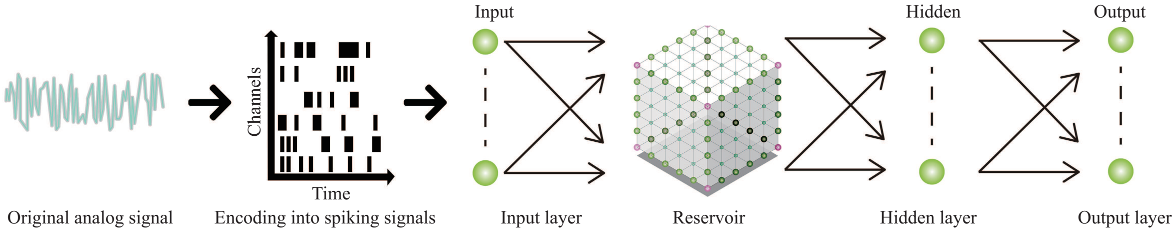

Figure 1 (Color online) HSNN for sleep staging. The HSNN is constructed as the input layer, reservoir, hidden layer, and output layer based on the LIF neurons. The arrows between different layers indicate the synaptic connections between neurons. The different layers are fully connected.

between neurons, we adopt the spiking neural network (SNN) to build the model, which is most similar to the biological neural network. SNN has high brain-like properties and can catch up with traditional neural networks in terms of performance, which is our motivation for choosing it for research. First, EEG signals are encoded as spiking signals. The spiking signals are input into the three-dimensional structure reservoir, which can capture rich biological neuron dynamics and has the potential to simulate complex information processing in the brain. At the same time, in order to deal with the difficulty of back propagation calculation due to the complex differential equations and the non-differentiable spiking events encountered during training, we use the hybrid macro/micro level back propagation (HM2-BP) algorithm as a training method. Finally, we perform experimental verification on the sleep dataset. The proposed model achieves the best performance.

2 Related work

There has been a considerable amount of work in the field of sleep staging [3–13]. Based on popular deep learning models, such as CNN and recurrent neural networks (RNN), more models have been come up in this aspect. For example, fast discriminative complex valued CNN [14] is used to capture the information hidden in the sleep EEG signals and distinguish sleep stages. Based on multivariable multimodal physiological signals, a new CNN model [3] improves the accuracy of sleep staging by obtaining the transition rules between sleep stages. There are other studies, such as extracting functional connectivity indexes from EEG and generating multidimensional images as the input stages of sleep on CNN models [15]. SeqSleepNet [16] is a hierarchical recurrent neural network and converts the task into a sequence-to-sequence classification problem. At the same time, some researchers attempted to implement new neural networks, with the combination of CNN and RNN, to the sleep stage classification. DeepSleepNet [4] is a deep learning model utilizing CNN to obtain time-invariant features and bidirectional LSTM memory to study transition rules. Besides, with the development of attention mechanisms, deep bidirectional RNN [17] is also used in the single-guide signal sleep stage classification. Recently, the graph neural network (GNN) has been used in sleep staging. The GNN model [10] takes graphics as input and then learns how to infer and predict how objects and their relationships evolve over time. It will not be easily disturbed by noise, showing a powerful performance. Although these studies have achieved good results, they still ignore some problems. They are not sufficiently brain-like, in terms of modeling do not consider the distance relationship of brain neurons in space, which directly leads to expensive calculations and higher power consumption. The SNN with a high brain-like degree has been developed for several years, gradually reached similar accuracy, and has lower cost, which has great development potential.

3 Methodology

We establish a sleep staging model based on the leaky integrate and fire (LIF) neurons [18] as shown in Figure 1. First of all, we encode the raw EEG signals into spiking signals. Secondly, to model the information hidden in the spiking signals, we input the spiking signals into a reservoir with a three-dimensional structure. Finally, we further improve the learning ability of our model based on the fully connected hidden layer and output the prediction results.

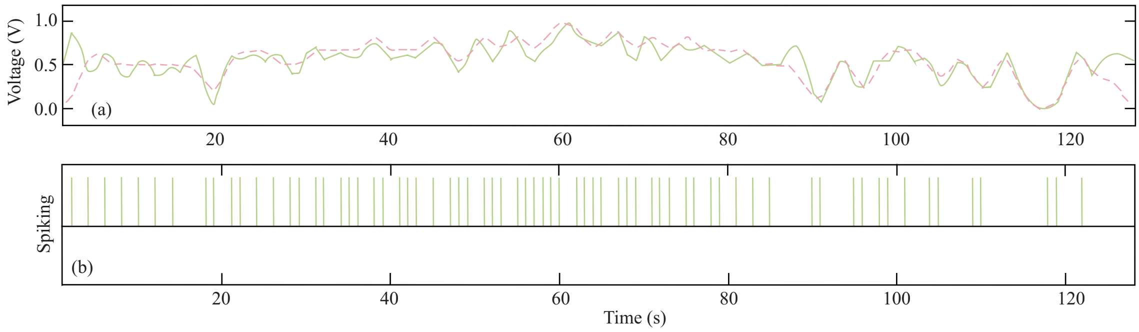

Figure 2 (Color online) EEG signal encoding experiment result. (a) The green curve is the original EEG signal, the pink dotted curve is the restored EEG signal, which the spike train is decoded into; (b) the green curves are encoded from the original EEG signal by BSA.

3.1 EEG encoding

The human brain is composed of billions of neurons, and information is transmitted between neurons in the form of electrical spikes, constituting the thinking activity of the human brain. In order to cater to the brain-like nature of HSNN, we need to convert EEG signals into spike signals. As a typical way, Ben's spike algorithm (BSA) [19] is used to encode EEG data in this paper. BSA is a fast and stable encoder. In addition, since it is based on an FIR filter, the encoded spike sequence can be reversely converted into its original waveform. In this way, it is viable to check the extent to which the coded spike sequence simulates the original wave.

In order to test the effect of the BSA algorithm on the encoding of the dataset in this paper, the BSA algorithm has been applied to encode and decode some channels in the data. Figure 2 has demonstrated the encoding and decoding results from a small segment of a channel in sleep EEG data through the BSA algorithm. In Figure 2(a), the green curve is the original EEG signal. It is encoded into the spike train in Figure 2(b) by the BSA algorithm. The pink dotted curve is the restored EEG signal, which the spike train is decoded into. The MSE of the original signal and the decoded restored signal is 0.016. Some other experiments have been conducted as well. For instance, the same filter has been used to encode and decode the fragments of each channel in the same sample. The data of each sample is less different from the original sequence after decoding. This indicates that the BSA algorithm can effectively retain the characteristic information of the original sequence in different EEG channels. Therefore, in this study, the parameters of the same BSA algorithm can be applied to encode all samples in the dataset, and the encoded spike train can retain the feature information of the original EEG data.

3.2 LIF neurons

Because LIF [18] neurons are more complex and closer to biology, they have been widely used in many SNN studies. HSNN is constructed based on LIF neurons. When neurons in the brain are in resting potential, the inside and outside of the neuron cell membrane maintain a -70 mV potential, which can be changed by stimulation of other neurons. When the potential of the neuron cell membrane reaches the threshold, the neuron emits spiking signals along its axon. This connection between neurons is called a synapse. When spiking signals are transmitted to postsynaptic neurons, the potentials of postsynaptic neurons will be affected. This process takes a certain amount of time. The effect of the spiking signals on the cell potential is temporary, and the cell will gradually recover its resting potential. After the presynaptic neuron emits a spiking signal, it will enter a refractory period, during which the influence of the stimulation on the neuron is reduced or ignored. Inspired by biological neurons, many types of biological neuron models have been derived. The LIF neurons were used in this paper. In this neuron, after the neuron receives the input current, the cell membrane potential will increase. When the cell membrane rises to the activation threshold, it sends a spike, a process is called integral ignition. At the same time, in order to imitate a real neuron, after a spiking signal is emitted, or when there is no input, the cell membrane potential returns to the resting potential. Its dynamic process can be described by the following differential equation:

$$I(t) - \frac{V_m}{R_m} = C_m \frac{\mathrm{d}V_m(t)}{\mathrm{d}t}, \tag{1}$$

where C_m represents the capacitance of the cell membrane, V_m represents the electrical potential of the cell membrane, and $I(t)$ represents the input current.

We describe the integrate-and-fire process of the LIF neurons as follows: reaching the threshold, emitting spiking signal, resetting to resting potential, refractory period, where the refractory period refers to a period of time (milliseconds) after the input current is large enough to activate the threshold and emits the spiking signal, during which the spiking signal cannot be activated even if an infinite current is an input. When the membrane potential reaches or exceeds the threshold, the membrane potential at this time will be reset to the resting potential and maintained during the refractory period, then the next cycle will start again.

Based on the above analysis of the integrate-and-fire process of the LIF neurons, the input current of LIF neurons can be divided into two parts:

$$I(t) = I_C + I_R, \tag{2}$$

where I_C is the current that other connected neurons emit spikes and I_R is the current existing in the neuron. Due to the memory effect of the neuron, the current inside the neuron will not be cleared directly when there is no input current. By Ohm's law, $I(t)$ can be represented as

$$I(t) = \frac{u(t)}{R} + C\frac{\mathrm{d}u}{\mathrm{d}t}. \tag{3}$$

Based on $T_m = RC$, Eq. (3) can be rewritten as

$$T_m\frac{\mathrm{d}u}{\mathrm{d}t} = -u(t) + RI(t), \tag{4}$$

where u means the electrical potential of the cell membrane, T_m is a time constant for the cell membrane. According to the equation, if there is enough time, the membrane potential will decay exponentially to the resting potential without input. The time constant is the characteristic time of decay. For a neuron, it is in the range of 10 ms, which is long enough for the duration of a 1 ms spiking. The LIF neuron is a simple and highly computational spike neuron, so it can be applied to large networks and is widely used by researchers. The LIF neurons were also used in this paper to build an SNN.

3.3 HSNN architecture

The HSNN is constructed as the input layer, reservoir, hidden layer, and output layer based on the LIF neurons.

Input layer. The number of neurons in the input layer is consistent with the number of channels in the sample, and every signal in each channel is one-to-one corresponded to a neuron.

Reservoir. The reservoir mainly simulates the connection of neurons in the brain. In the reservoir, neurons are arranged in a three-dimensional space, all neurons are connected according to a certain probability, which is shown as

$$P(i,j) = C \cdot \exp\left(-\frac{D(i,j)}{\lambda^2}\right), \tag{5}$$

where $P(i,j)$ represents the probability that two neurons are connected, $D(i,j)$ represents the distance between two neurons, C and λ are control variables. When the Euclidean distance between neurons is closer, the probability of their connection is greater; when the distance is farther, the probability of connection is smaller. The connection weights in the reservoir can be fixed or can be trained. The reservoir can map the input time series to a high-dimensional state, making it easier to find hidden features of the data, which makes the model very suitable for processing time series signals.

Hidden layer. The number of neurons in the hidden layer can be determined by demand. The hidden layer is fully connected with the reservoir and output layer. The weight update strategy was inspired by the HM2-BP algorithm.

Output layer. The number of neurons in the output layer is consistent with the number of classification tasks, and each output neuron corresponds to a period.

The input layer is sparsely connected to the reservoir, with the connection weight fixed. There are some sparse connections in the reservoir and the connection weights are also fixed. With the reservoir fully connected to the hidden layer, the connection weight is a trainable parameter. Lateral inhibition is added between neurons in the output layer, which means, if connected, any pair of neurons in the output layer will have a weight of -1.

To sum up, in the HSNN model, the input layer is responsible for receiving the spiking sequences encoded by EEG, then the reservoir maps the input sequences to high-dimensional states. Afterward, the hidden layer learns the features of data, and finally, the output layer outputs the results. The parameters to be trained are connection weights between the reservoir and the hidden layer as well as those between the hidden layer and the output layer.

3.4 Optimization algorithm

SNN can process temporal and spatial data as well as operate on hardware with extremely low power consumption. However, due to complicated differential equations and non-differentiable impulsive events encountered in training, SNN has not yet achieved the same performance as traditional deep artificial neural networks, which is a long-term challenge. Although researchers have proposed many BP algorithms for SNN, the existing SNN back propagation algorithms have many shortcomings. SNN is limited in terms of scalability, lack of proper handling of spiking discontinuities, and mismatch between the rate coded loss function and computed gradient. SpikeProp [20] algorithm is the first attempt to train the SNN based on discrete spikes. It specifically deduces the value of the loss function for the spiking time. However, SpikeProp limits a neuron to emit only one pulse, which is quite different from the real neuron. Some existing back propagation algorithms either have poor learning scalability [20], or are lack proper treatments to the discontinuity of the spike [21], by regarding it as noise or smoothening the discrete spike to calculate the gradient.

HSNN is presented by utilizing the HM2-BP [22] algorithm for training multi-layer SNN. At the micro level, the proposed spike-train level post-synaptic potential (S-PSP) [23] can accurately capture the time effect. Frequency coding errors are defined at the macro level and calculated and backpropagated at the macro and micro levels. Different from the existing back propagation methods, HM2-BP directly calculates the frequency-coded loss function. The accuracy of HM2-BP on MNIST and N-MNIST data sets reaches 99.49% and 98.88% [22], respectively, which exceeds the best performance of the existing SNN back propagation algorithm.

Frequency coding is commonly used in SNN to define the loss of each training sample in the output layer. As shown in Eq. (6), $\boldsymbol{o}$ and $\boldsymbol{y}$ are respectively the actual number and predicted number of spikes fired by neurons in the output layer.

$$E = \frac{1}{2}\|\boldsymbol{o} - \boldsymbol{y}\|_2^2, \tag{6}$$

$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial a_i} \times \frac{\partial a_i}{\partial w_{ij}}. \tag{7}$$

HM2-BP has disassembled (6) into two parts to calculate the gradient, as shown in (7), where a_i represents the membrane potential after integrated inputs of the postsynaptic neuron, and w_{ij} is the connection weight of the i-th neuron and the j-th neuron. In this way, error back propagation is separated into two parts: (1) $\frac{\partial E}{\partial a_i}$, back propagation through the spike frequency (macro level), and (2) $\frac{\partial a_i}{\partial w_{ij}}$, back propagation through the spike train (micro level). Normally, there is a certain connection between the actual label o_i and the membrane potential a_i of the post-synaptic neuron integrated input, which is represented as

$$o_i = g(a_i) = \left\lfloor \frac{a_i}{\nu} \right\rfloor. \tag{8}$$

Then Eq. (6) can be rewritten as

$$E = \frac{1}{2}\|\boldsymbol{o} - \boldsymbol{y}\|_2^2 = \frac{1}{2}\|g(\boldsymbol{a}) - \boldsymbol{y}\|_2^2. \tag{9}$$

HM2-BP algorithm accurately calculates the S-PSP of each pair of synaptic spiking sequences to explain that the given synaptic spiking sequence affects the post-synaptic time contribution of discharge, which is denoted by $e_{i|j}(t_i^{(f)})$.

For the i-th neurons in the m-th layer, according to the above equation, the macro-level back propagation and micro-level back propagation are calculated respectively. macro-level back propagation is given by

$$\delta_i^m = \frac{\partial E}{\partial a_i^m} = \left(o_i^m - y_i^m\right) g'\left(a_i^m\right) = \frac{o_i^m - y_i^m}{\nu}. \tag{10}$$

At the macro level, the S-PSP integrates the impact of the spike train on the number of spiking signals emitted by each neuron, thereby backpropagating the frequency-coded loss.

At the micro level, because the membrane potential a_i of postsynaptic neurons integrates input is composed of the time contribution of all presynaptic neurons to postsynaptic neurons and the weight between neurons. Hence, a_i can be represented as

$$a_i = \sum_j w_{ij} e_{i|j}. \tag{11}$$

Finally, micro-level back propagation is given by

$$\frac{\partial a_i^m}{\partial w_{ij}} = e_{i|j}^m + \frac{e_{i|j}^m}{\nu} \sum_{l=1}^{r^{m-1}} w_{il} \frac{\partial e_{i|l}^m}{\partial o_i^m}, \tag{12}$$

where (8) and (11) are combined to get the result of (12). The S-PSP of each pair of pre-synaptic/post-synaptic spiking sequences has been accurately calculated by HM2-BP to explain the contribution of a given pre-synaptic spiking sequence to the time of post-synaptic neuron discharge according to the exact peak time.

4 Results and discussion

4.1 Dataset and preprocessing

To verify the effectiveness of the HSNN, we evaluate it on the ISRUC-SLEEP dataset [24]. The ISRUC-SLEEP dataset consists of PSG data collected from eight hours of sleep throughout the night. Each segment was classified by two sleep specialists at the Sleep Medicine Centre of the Hospital of Coimbra University (CHUC) according to the AASM sleep staging criteria. Sleep specialists divided the data into five groups: W, N1, N2, N3, and R. This dataset consists of three subsets, among which subgroup 3 was used in this study. The EEG dataset in this paper contains 6 channels, namely C3-A2, C4-A1, F3-A2, F4-A1, O1-A2, and O2-A1. Since each channel collects each unit time of the sleep data 200 times per second (200 Hz) within the period of 30 s long in the data, the dataset with 6 channels can produce 36000 signal points.

To remove power frequency noise and background myoelectric noise from EEG signals, the original EEG signals were processed with a 50 Hz notch filter and a fourth-order band-pass Butterworth filter. In addition, down sampling was also performed on the data, which reduced the EEG frequency to one-third of its original level. Afterward, there were 2000 signal points on each channel. According to the experimental results of BSA [19], the BSA algorithm can transform the original EEG analog signals into spike sequences and effectively retain the feature information. EEG signals processed by filtering and down sampling are encoded by BSA to obtain the 6-channel spike train of the input SNN, and the sleep staging correlation experiment based on HSNN is carried out.

4.2 Baseline methods

We compare the HSNN with the following baselines:

- MMCNN [3]. A temporal sleep stage classification CNN uses multivariate and multimodal time series.
- CNN-GRU [25]. A CNN-GRU deep learning model for classifying sleep stages. Involving CNN and gated recurrent units (GRU), to automatically extract the most appropriate features and sequence trends of PSG signals, without utilizing hand crafted features for scoring sleep stages.
- LSTM [26]. A novel cascaded RNN architecture based on LSTM blocks is proposed for the automated scoring of sleep stages using EEG signals derived from a single-channel.
- HNN [27]. A multi-domain hybrid neural networks (HNN) model combines the deep neural network (DNN) as state-of-the-art classifiers for automatic sleep staging using pediatric EEG signals.
- DeepSleepNet [4]. A model utilizes CNN to extract time-invariant features, and bidirectional-LSTM to learn transition rules among sleep stages automatically from EEG epochs.

Table 1 The value of hyperparameters in HSNN

Hyperparameter	Value
Input neurons number	6
Reservoir neurons number	135
Hidden neurons number	4096
Output neurons number	5
Weight limit	8
Voltage threshold	20
Refractory period	2

4.3 Experiment settings

Since we use EEG data of 6 channels in this paper, each neuron in the input layer receives EEG data of one channel over a period of time. Thus, there are 6 neurons in the input layer. There are also 135 spike neurons in the reservoir, each with a three-dimensional structure of $3 \times 3 \times 15$. There are 4096 neurons in the hidden layer. There are 5 neurons in the output layer, corresponding with 5 categories classified by sleep stages. Each neuron in the input layer was randomly connected to 32 neurons in the reservoir, and the connection weight is fixed at 8 or -8 to simulate excitatory and inhibitory transmitters in biological neurons respectively. The probability connection between every two neurons in the reservoir is as shown in (4), which means, the closer the neurons are in space, the greater the probability of connection becomes. The connection weight is fixed at 1 or -1, and the excitatory and inhibitory transmitters in biological neurons are simulated respectively. Fully connected between the reservoir and the hidden layer, as well as between the hidden layer and the output layer, the connection weight is a trainable parameter. The output layer has lateral inhibition. The HSNN parameters are as shown in Table 1. In addition, a 6-channel spike train is obtained, after the EEG data in the original dataset has been filtered and spiking encoded. In order to keep the balance of samples, the down-sampling method was adopted. After the removal of data, the ratio of the training set to the test set was maintained at 4:1. The six-channel spike train has been input into the HSNN for the experiment.

4.4 Evaluation metrics

Accuracy (ACC) and macro average F1-score (MF1) are used to evaluate the classification effect of the model.

$$\mathrm{Acc} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FN} + \mathrm{TN} + \mathrm{FP}}, \tag{13}$$

where TP, TN, FP, and FN correspond respectively to the true positive, true negative, false positive, and false negative counts of the considered class. F1-score is the harmonic average of precision and recall and MF1 is the average of all the F1-score in the same subject. The F1-score is represented as

$$\text{F1-score} = 2 \cdot \frac{\mathrm{PR} \cdot \mathrm{RE}}{\mathrm{PR} + \mathrm{RE}}, \tag{14}$$

where PR means precision rate and RE means recall rate. PR among all the cases judged to be positive, how many are really positive. RE measures the ability to correctly call cases from a class defined by a fixed correct label.

4.5 Experimental result and analysis

In order to evaluate the performance of the HSNN, we have compared and analyzed our HSNN model with the popular traditional models. Figure 3 shows that the proposed model achieves the best performance with an average ACC of 0.76 and an average MF1 of 0.75. The traditional MMCNN is suboptimal, with an average ACC of 0.65 and an average MF1 of 0.63.

The detailed results of HSNN sleep staging for different subjects are shown in Figure 4. The average ACC and average MF1 of the ten subjects are 0.76 and 0.75, respectively. In each subject, the highest ACC is 0.81 for subject 5, the highest MF1 value is 0.79 for subject 4 and subject 7. Figure 4 presents the model that has the best recognition effect in N1 stage and N2 stage, and the F1-score in these two stages is higher than those in other states. On the contrary, the F1-score of this model in the REM stage

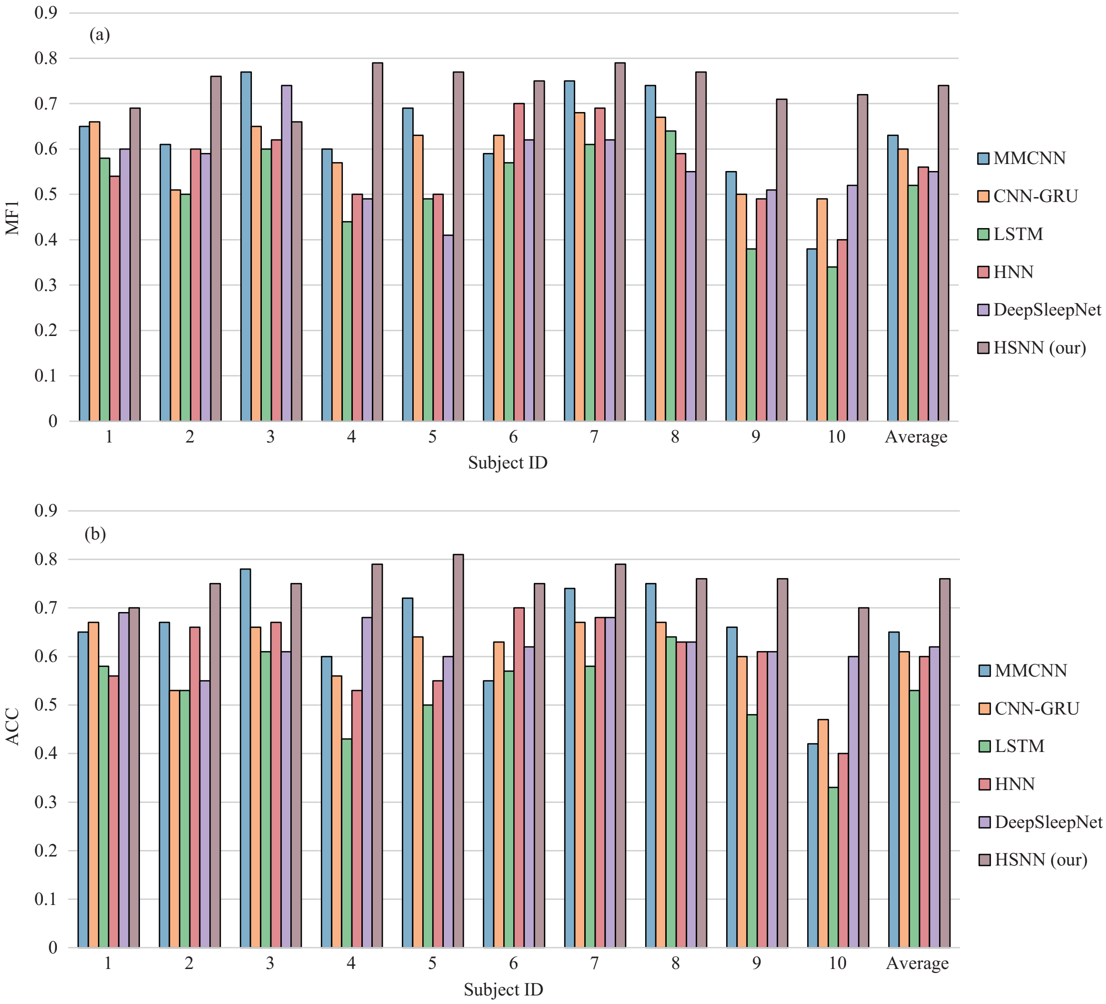

Figure 3 (Color online) Comparison results of our model and traditional models. (a) MF1; (b) ACC.

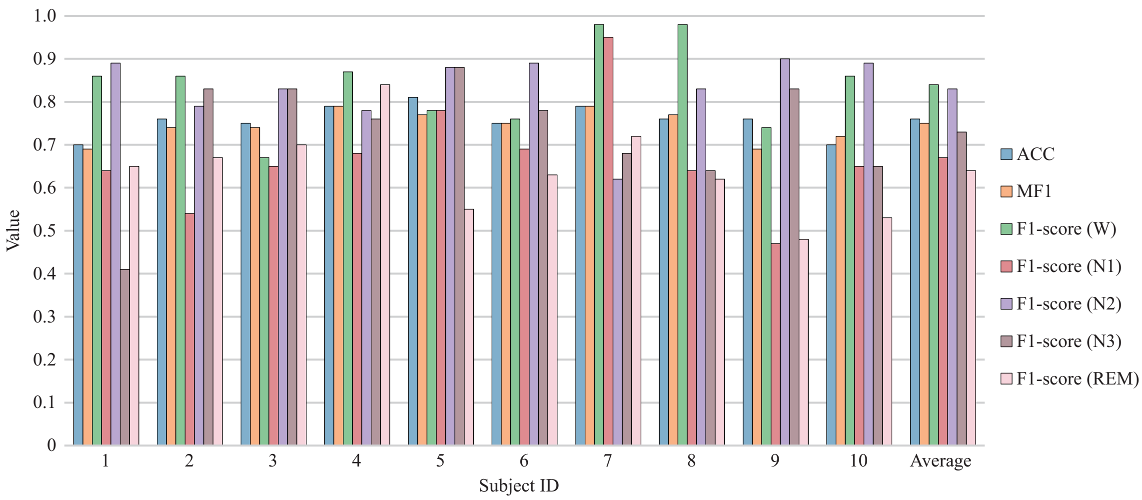

Figure 4 (Color online) Detailed results of our model on different subjects.

is low. This stage is also easy to confuse during manual interpretation. Generally speaking, the HSNN based on the HM2-BP algorithm achieves a more reliable classification result.

In order to explore the influence of different components of our HSNN on the classification performance, different network structures are set up for ablation experiments in this paper. The experimental results

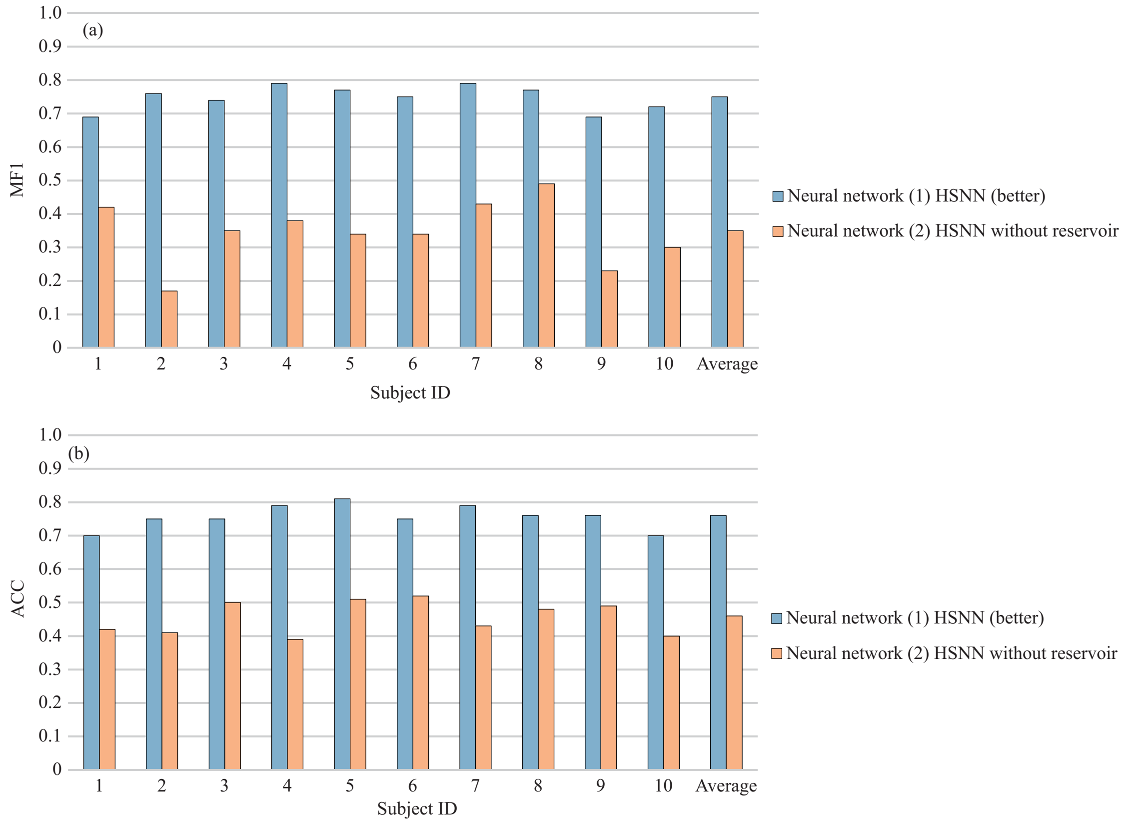

Figure 5 (Color online) Ablation experiment of the proposed model. (a) MF1; (b) ACC.

are shown in Figure 5. The neural network (1) in the figure is the HSNN model used in this paper. The neural network (2) is based on the neural network (1) to remove the reservoir module, which means the network contains 6 neurons in the input layer, 4096 neurons in the hidden layer, and 5 neurons in the output layer. In the case of the neural network (2), it has removed the reservoir module in the network. Then the average classification accuracy decreases from 0.76 to 0.46, and the average MF1 decreases significantly from 0.75 to 0.35. This demonstrates that the reservoir can map the data to the high-dimensional state, which has a good effect on the model classification results.

5 Conclusion

Sleep is an indispensable physiological activity for human beings. The state and quality of sleep reflect the health status of human beings. It is an important method to study sleep according to EEG signals. Studying sleep stages can help assess sleep quality, diagnose and treat sleep disorders. Automatic sleep staging methods can save the energy cost of human beings and obtain objective sleep staging reports, which is of great significance in clinical and research fields. SNN, with the focus of research on constructing a new generation of artificial intelligence by mimicking the human brain, has the ability to learn spatio-temporal data. Although it is still in its early stage of development, it shows the potential of strong learning ability. In this paper, an HSNN model is constructed based on the HM2-BP algorithm and a series of classification experiments are conducted in combination with sleep EEG data. In order to analyze the performance of the sleep staging model in this paper, the classification results are compared with those of the traditional neural networks. Experimental results show that the HSNN performs better in sleep staging than traditional neural networks.

Since the SNN uses sparse spikes for communication, it is considered to be an energy-efficient model. Many spike neuron models are described by differential equations, so analog circuits or digital circuits can be used to directly express SNN, and the network state can be continuously updated during the training process. However, it is undeniable that the current article only focuses on the research of multivariate EEG signals, but the research on univariate EEG signals contributes to the development of wearable devices. Therefore, the scope of future work may include trying to use univariate EEG data and trying to use SNN on hardware to take advantage of its low energy consumption.

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