Joint sleep staging model based on pressure-sensitive sleep signal

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Abstract. Sleep quality is an important indicator of human health, and sleep staging is a prerequisite for assessing sleep quality. In this paper, the CNN-BILSTM sleep staging model is proposed based on the pressure-sensing sleep signal collected by the smart mattress. The CNN network is used as the feature extraction part for the problem of the traditional sleep staging model in the pressure-sensing sleep stage [2]. This part can automatically extract the pressure sense. The staging characteristics of the sleep signal, combined with the BiLSTM model for sleep staging. In the experiment, the sleep data of 11 different experimenters based on smart mattress collection were used to identify the three sleep stages, in order to verify the superiority of the sleep stage of the model [3]. Two kinds of contrast experiments were used, one was compared with a single CNN stage, the BiLSTM model was compared, and the other was compared with the traditional feature extraction based sleep stage model. The experimental results show that the model has an accuracy of more than 80%. Better than traditional sleep staging and single deep learning sleep staging program.

1. Introduction

In the 1960s, the California Institute of EEG based on polysomnography (PSG) collected EEG signals (EEG) combined with EOG (EMG) released the standard for sleep staging[3], divided sleep into awake, rapid eye rotation Period (REM), non-rapid eye rotation period (NREM), in which NREM stage is divided into sleep stage I (S1), sleep stage II (S3), sleep stage III (S3), and stage IV (S4), except in addition, REM, S1, and S2 are also considered to be shallow sleep periods, while S3 and S4 are considered to be deep sleep periods[16]. So far, the sleep staging results of polysomnography have become the gold standard for sleep staging.

So far, many methods of sleep staging have been proposed based on EEG and ECG signals [11]. In summary, the main idea is to use EEG or ECG to extract some statistical features or features related to sleep stages, such as heart rate variability [4]. There are two biggest drawbacks: one is the need to collect electrical signals based on high-precision equipment, and the other is the need for interdisciplinary professionals to extract real sleep characteristics [5], otherwise the extracted features for sleep staging will not achieve the desired results.

In recent years, with the development of computer technology, a large number of non-contact monitoring devices based on pressure sensors have emerged. How to use this type of data for sleep staging has become a hot topic in current research [6][19][20] [twenty one]. Such non-contact devices cannot achieve the signal quality of the PSG level, so the sleep staging research based on this data generally increases the hardware acquisition frequency, and then uses the traditional feature
engineering method for sleep staging. The shortcomings of this approach are obvious and cannot be extended to market conditions.

In this paper, a sleep learning staging algorithm based on low-sampling frequency pressure sensing signals is proposed. This kind of data cannot accurately extract accurate sleep features by using feature engineering methods. The proposed algorithm avoids the defects of manual extraction features and uses convolutional nerves. The network performs sleep staging feature extraction, and then uses long and short memory neural network for sleep staging.[8] The final experiment shows that the algorithm is significantly improved compared to the existing algorithms.

2. Prerequisites

2.1. Sample production algorithm
This article uses the smart mattress to collect the head signal and chest signal collected by the pressure sensor for sleep staging research, the sampling frequency is 50Hz, and use PSG synchronous recording sleep to carry out label making, with PSG sleep staging as the gold standard To make a sample label, the PSG sleep staging step is 30s, which is a sleep state every 30s. Due to the fact that the deep sleep state and the awake state frequency are much lower than the shallow sleep state in the actual scene, direct sample production may result in an unbalanced sample state, which may result in the model not being able to learn enough classification features[9]. In order to solve this problem, this paper uses the sliding window method to make samples in the awake and deep sleep state. The sample production algorithm solves the problem of uneven data distribution to some extent.

Table 1: CreateSample (T, W, S)

| Input: Head pressure signal T, chest pressure signal W, PSG sleep stage S |
|---|
| For each sample of S: |
| If Sample status is awake state: |
| Sliding window size is 30s |
| If Sample status is Light sleep state: |
| Sliding window size is 15s |
| If Sample status is deep sleep state: |
| Sliding window size is 10s |
| Output: Data Set D |

The algorithm performs sliding window processing in awake, light sleep, and deep sleep state, and expands the sample in these three states[11], which solves the sample imbalance problem to some extent.

2.2. Support Vector Machine
Support vector machine (SVM) as a classic machine learning classification model has a wide range of applications in classification tasks. The traditional support vector machine is especially suitable for the solution of the two classification problem. With the deep research, the current support vector machine is also slowly applied. In the field of multi-classification problems. The core idea of multi-classification is to decompose the problem into multiple two-class problems. The idea of support vector machine is to map sample data to high-dimensional space, and find a hyperplane in high-dimensional space to divide the sample data into two categories. If the sample is inseparable in a low latitude space, the sample is mapped to a high dimensional feature space for linear separability. Under normal circumstances, the effect of SVM classification is affected by its kernel function. The effects of different kernel functions are very different. In the experimental process, the classic RBF kernel function is used to verify the effect of the classifier.

2.3. Hidden Markov Model
Hidden Markov Model (HMM) is a probabilistic model for time series[13]. It is a model for generating observable state sequences from an unobservable state sequence [12]. The basic structure
of the model can be shown in Figure 1, and $x$ is observable. State, $y$ represents the hidden state, and in the sleep staging model, $x$ is the true sleep staging, and $y$ is a detectable sleep signal or a feature based on sleep signal extraction. So far, HMM has been used in sleep staging studies based on HRV signals [15]. The superiority of this model is that the current sleep state is greatly affected by the previous state, which is consistent with the law of sleep changes.

![Figure 1. Hidden Markov structure](image)

### 2.4. Convolutional neural networks

The convolutional neural network is a feedforward neural network [9]. The common structure is shown in Figure 2. It consists of several convolutional layers, pooled layers and fully connected layers. The function of the convolutional layer is to input the data. Feature extraction obtains several local features, while the pooling layer selects and filters the local features, then combines the local features with the global features through the fully connected layer, and finally outputs the classification label results through the activation function [8].

![Figure 2. CNN](image)

Convolutional neural networks have a certain degree of application in image processing, speech, and NLP fields [16], especially in image processing technology and are quite mature, and are still in the beginning stage in signal processing.

### 2.5. Long-term memory neural network

Cyclic neural network (RNN) is a kind of neural network for processing serialized data. The difference between CNN and network structure makes it solve the problem of information transmission to a certain extent. Therefore, it has unique advantages in processing sequence data. However, ordinary RNN There are certain flaws - when the time interval becomes larger, the RNN loses the ability to learn the previous information [16]. In order to solve the problem of information loss, a variant LSTM model based on RNN is proposed.
Figure 3. RNN structure

The Long-Length Memory Neural Network (LSTM) is a special structure of RNN. The internal structure is shown in Figure 3: where $c_{t-1}$ represents the memory state at time $t-1$, and $x_t$ represents the input at time $t$, $h_{t-1}$ indicates the hidden state at time $t-1$, which contains three kinds of door structures: input gate, forgetting gate and output gate [17]. The long-term memory neural network stores useful information in the memory unit. The function of the forgetting gate is to forget the useless information. In the current research, when the memory unit forgets part of the useless information through the forgetting gate, it will supplement from the current input. A part of the information, the action is completed by the input gate, and finally the output is generated in combination with the memory unit information and the current input [18]. The specific update formula for each gate is as follows:

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + V_i c_{t-1} + b_i) \quad (1)$$
$$a_t = (W_a x_t + U_a h_{t-1} + V_a c_{t-1} + b_a) \quad (2)$$
$$c_t = a_t \odot c_{t-1} + i_t \odot \tanh(W_c x_t + U_c h_{t-1} + b_c) \quad (3)$$
$$o_t = \sigma(w_o x_t + U_o c_t + b_o) \quad (4)$$
$$h_t = o_t \odot \tanh(c_t) \quad (5)$$

$\sigma$ Represents sigmoid operation, $\odot$ Point multiplication, $W_i, U_i, V_i, b_i$ represent coefficient matrix and bias term.

2.6 Pressure sensing signal sleep staging model

At present, the existing sleep staging algorithm is basically based on EEG or ECG signals. This kind of signal is generally collected by professional equipment and has high precision. In recent years, the development of computer software and hardware technology has emerged, and many smart wearable monitoring devices have emerged. This kind of equipment is still in the development stage of sleep staging [21]. In order to make up for the defect of using feature engineering method to extract features in traditional methods, this paper proposes a feature extraction algorithm based on deep learning, combined with long and short memory neural network for sleep. Classification of stages [22]. The specific algorithm structure is shown in Figure 4.
Figure 4. Fusion staging model

The structure first uses 4 layers of CNN convolution for feature extraction, and uses BN and Dropout operations to prevent over-fitting before the activation function of each layer. The local feature is transformed into global features by using the fully-connected layer. The sleep signal is beneficial to the time series characteristics of sleep staging, and then joins the two-layer two-way long-term memory neural network for training. The softmax is used to divide sleep into three states: awake, shallow sleep and deep sleep.

3. Experiment

3.1. Dataset

The data used in the experiments in this paper are 11 pairs of normal people aged 26-55 years. Under normal sleep, the mattress and polysomnography simultaneously collect sleep signals [19]. The signals collected by the mattress include two types: brain pressure sensor and chest. The signal collected by the pressure sensor. The PSG staging standard is used as a gold standard for the production of sample labels. The mattress sampling rate is 50Hz, the mattress data is divided into 30s (1500 data points in the brain, 1500 data points in the chest), and then the sleep staging of PSG is used as the sample label, which divides sleep into awake, shallow sleep, Deep sleep in three states. The number of samples in it is as follows:

| status | awake | light | deep | total |
|--------|-------|-------|------|-------|
| train  | 5092  | 4384  | 3492 | 12968 |
| test   | 2184  | 1895  | 1280 | 5559  |

3.2. Evaluation

When measuring the effect of the algorithm, the accuracy rate (ACC), recall rate (Recall) and F1 are used to evaluate. The specific formula is as follows:

\[
ACC = \frac{TP + TN}{TP + FP + TN + FN}
\]  
\[
Recall = \frac{TP}{TP + FN}
\]  
\[
PR = \frac{TP}{TP + FP}
\]  
\[
F1 = \frac{2*PR*RE}{PR + RE}
\]

Where TP is the number of positive classes that are determined to be positive, TN is the number of negative classes that are judged to be negative, FP is the number of positive classes that are determined to be negative, and FN is the number of negative classes that are determined to be positive.
ACC is a measure of the correct proportion of the model and is generally used to measure the effect of the classification model. RE is the Recall of Equation 7.

3.3. Classifying
In this paper, the four-layer CNN and the two-layer BILSTM fusion model are used for feature extraction. Finally, the softmax classifier is used to divide the sleep state into awake, light sleep, and deep sleep. CNN is mainly used to extract timing-independent features, and BILSTM extracts timing-related features in the sequence and finally uses the classifier for sleep staging.

4. Experiments and Results

4.1. Parametric experiment
This paper compares the accuracy of different models on the pressure-sensing sleep signal to verify the effect of the integrated model. In order to find the optimal CNN staging model, the experimental phase, adjust the CNN structure, training batches, etc. to see the impact on the results, the effect is as shown in four:

![Graph showing Convolution kernel accuracy](image1)

Figure 5. Convolution kernel accuracy

Experiments used 2 to 6 layers of convolution to check the accuracy of the CNN model. It can be seen that the accuracy of the 4-layer convolution decreases, indicating that the generalization ability of the model begins to decline. Therefore, we use the 4-layer CNN for sleep staging.

4.2. Batch influences

![Graph showing Batch Impact on accuracy](image2)

Figure 6. Batch Impact on accuracy
Figure 6 shows the change of accuracy, recall rate and F1_Score under different training batches. It can be seen that the overall effect of the model is best when the training batch is 256 times. Therefore, the structural parameters of the CNN model in the experiment are four. Layer convolution layer, training batch is 256.

4.3. Model comparison
In the second half of the CNN_BiLSTM model, we adjusted the model in the same way. The results show that the two-layer BILSTM model has the highest accuracy. To verify the effect of the CNN_BiLSTM model, the results are as follows:

Table 3: comparison

| Model       | acc  | recall | F1   |
|-------------|------|--------|------|
| CNN         | 77.3%| 68.3%  | 78.5%|
| BILSTM      | 56.5%| 53.7%  | 50.2%|
| CNN_BILSTM  | 86.1%| 85.4%  | 83.3%|
| CNN_SVM     | 81.7%| 72.2%  | 71.6%|

It can be seen that the CNN_BILSTM model has a 9% improvement in the classification of pressure-sensitive sleep signals. It is proved that the CNN_BILSTM network has a better improvement than a single neural network sleep staging. Compared with the CNN_SVM combination model, the accuracy rate is improved by nearly 5%.

4.4. Compared with traditional models
In order to verify the superiority of CNN_BILSTM in the traditional sleep staging model, the heart rate variability (HRV) characteristics were extracted based on the pressure sensitive signal, and the BILSTM model was compared with the traditional HMM model for sleep staging based on HRV. The results are shown in Table 4.

Table 4: compare Result

| Model    | acc  | recall | F1   |
|----------|------|--------|------|
| HMM      | 49.3%| 44.8%  | 45.1%|
| CNN_BILSTM | 56.7%| 53.6%  | 55.2%|

The above results show that the HRV extracted based on the pressure sensitive signal performs sleep staging, and CNN_BILSTM still has a certain degree of improvement compared with the traditional sleep staging method. However, the accuracy rate is not based on the original sleep signal for high sleep staging, which is because the signal collected by the low sampling frequency device cannot achieve better extraction results with the existing manual feature extraction algorithm. In this scenario, the use of deep learning for automatic feature learning has a good effect.

4.5. Experimental result
The classification results of the mixed sleep staging model for each sleep state are shown in Table 5:

Table 5: The classification results of the mixed sleep staging model for each sleep state

| True classes | Predicted classes | ACC (%) |
|--------------|-------------------|---------|
|              | W     | L      | D      |         |
| W            | 2083   | 93     | 4      | 95      |
| L            | 53     | 1534   | 308    | 81      |
| D            | 68     | 269    | 943    | 73      |

5. Result
It can be seen that CNN_BILSTM has a higher classification accuracy rate for awake and sleep in the BCG sleep signal staging, and the classification accuracy rate in the shallow sleep state is also as high as 81%, and the overall effect is ideal.

6. Conclusion
This paper proposes the CNN_BILSTM model, which uses the original pressure sensor signal to classify the three sleep stages. The model uses CNN and BiLSTM for feature extraction, and then uses SoftMax classifier for sleep staging. The results show that the model is effective for sleep staging on the pressure sensitive signal. It provides a feasible solution for the study of sleep staging of pressure sensitive signals based on low sampling rate in the future.

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