Design and Implementation of Machine Learning-based Assisted Sleep System

Jianhao Yang [1, a, *], Yike Xu [1, b], Shaocong Guo [2, c], Huawei Zhang [2, d], Shiyuan Liu [2, e], and Fanfan Zheng [3, f]

[1]School of Information Engineering, Electronic Information Engineering, Wuhan University of Technology, Wuhan City, Hubei Province, 430000;

[2]School of Information Engineering, Wuhan University of Technology, Wuhan City, Hubei Province, 430000;

[3]School of Safety Science and Emergency Management, Department of Public Safety and Emergency Management, Wuhan University of Technology, Wuhan City, Hubei Province, 430000, China

[a]264281@whut.edu.cn, [b]264269@whut.edu.cn, [c]shihuang@whut.edu.cn, [d]myzhww@whut.edu.cn, [e]1446671198@whut.edu.cn, [f]258059@whut.edu.cn

Keywords: Signal and information processing; EEG signal; Wavelet transform; Convolutional neural network; Assisted sleep; Sleep staging

Abstract: With the acceleration of the rhythm of life in today's society, people's life pressure is increasing day by day, and the quality of sleep is also getting lower and lower. In order to help people improve sleep quality effectively, an assistant sleep system based on machine learning is designed. The system consists of three parts: wearing terminal, cloud platform and APP. The wearing terminal collects EEG signal and assists the sleep of the users; the cloud platform runs the EEG processing algorithm based on wavelet transform and the sleep staging algorithm based on convolutional neural network to get the real-time sleep state; APP performs user feature information input, wake-up time setting and sleep status checking. This design combines signal processing algorithm and machine learning to realize an intelligent and effective assistant sleep system. The experimental results show that the system has high accuracy for sleep staging of users.

1. Introduction

In today's society, people's life pressure is increasing day by day, while the quality of sleep is getting lower and lower, which has seriously endangered people's physical and mental health [1]. Therefore, people's demand for intelligent sleep aids is increasing day by day. At present, there are many kinds of EEG-based sleep aids on the market, but they have the following shortcomings: (1) Most of the products are unidirectional, open-loop, non-feedback regulated hypnotic systems, and the hypnotic effect is not good. (2) Some products need professionals to control the instrument on the spot, and the degree of intellectualization is low. (3) The hypnotic method of the product is not professional, and the direct interference wake-up will greatly reduce the sleep quality of users. Based on the above situation, in order to help people effectively improve the quality of sleep, this paper proposes an assistant sleep system based on machine learning. Firstly, this paper describes the overall design of the system, and describes the functions and implementation of each part from the wearing terminal, cloud platform and user APP respectively. Then it describes the core algorithms, including the EEG processing algorithm based on wavelet transform and the sleep staging algorithm based on convolutional neural network. Secondly, it explains the overall working process of the system. Then, it uses Sleep-EDF database to improve the system. The experimental test and result analysis are carried out. Finally, the conclusion is drawn and the full text is summarized.

2. System Overall Design

As shown in Figure 1, machine learning-based assisted sleep system consists of three parts: wearing terminal, cloud platform and user APP. The wearing terminal mainly collects the user's signal and assists sleep; the cloud platform mainly stores and runs the algorithm; the user's APP can input the user's characteristic information, set the wake-up time and view the user's sleep status.

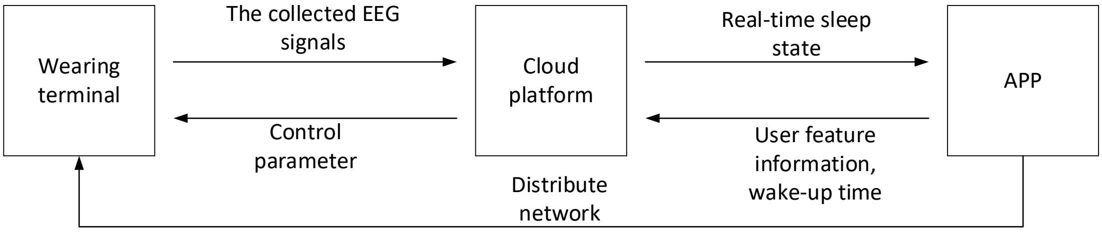

Fig. 1 System Overall Design Diagram

2.1 Design of Wearing Terminal.

The wearing terminal takes the processor STM32 as its core, including the EEG acquisition part and the sleep assistant part, and contacts users directly in the form of eye mask.

2.1.1 Design of Brain Wave Acquisition Part

In this system, three dry electrodes attached to the user's forehead are used to collect EEG signals. Because of the weak intensity of the collected signals, ADS1299 is used as ADC for pretreatment. ADC collects EEG data and sends it to cloud platform through ESP-8266, which is small in size, for algorithm analysis.

2.1.2 Design of Assisted Sleep Part

The assistant sleep of this system includes sound hypnosis [3] and sound-light awakening [4]. STM32 controls other modules according to the sleep period data sent by cloud platform through Wi-Fi. STM32 uses VS1053 to decode audio during sound hypnosis. The external osseous conduction oscillator plays white noise to the user, making it from awake state to shallow sleep state, and then playing pink noise to deep sleep state. When the acousto-optic wake-up is performed, the white noise is first played to make the user enter a shallow sleep state, and then the STM32 outputs PWM wave. Through the driving circuit, the lamp band emits warm light and its brightness gradually increases, thus completing the simulation of natural light and making the user gradually awake.

2.2 Cloud Platform Design.

The function of cloud platform is mainly to analyze the algorithm. The algorithms running on cloud platform mainly include EEG processing algorithm and sleep staging algorithm. After extracting the characteristics of EEG, sleep staging algorithm combines user information, environmental factors and historical data to output real-time sleep period accurately, and real-time sleep period will be used as feedback command to regulate the working state of auxiliary sleep part.

2.3 User APP Design.

App is an interactive interface between the system and users. It can realize the functions of input of user's characteristic information, setting of wake-up time and displaying of sleep results. The APP will upload the user's feature information to the cloud platform as the input of the algorithm, and also can get the sleep status from the cloud platform.

3. EEG Signal Processing and Sleep Staging

The core algorithms of this system include EEG processing algorithm based on wavelet transform and sleep staging algorithm based on convolutional neural network. The former is mainly used to extract the energy proportion of each rhythm wave of EEG, while the latter is mainly used to accurately staging sleep.

3.1 EEG Processing Algorithms Based on Wavelet Transform.

Referring to R&K standard [7], this paper divides human sleep into six stages: wake, REM and four non-REM stages, in which NREM can be divided into light sleep (including NREM1, NREM2) and deep sleep (SWS, including NREM3 and NREM4). It is known that the difference between different sleep periods is reflected in the difference of four characteristic waves contained in EEG signals. Wavelet transform method can decompose EEG signals according to different frequencies. Therefore, wavelet transform method can be used to extract the characteristic waves of EEG signals and calculate the relative energy as the characteristic quantities of each sleep period. This process is shown in Figure 2.

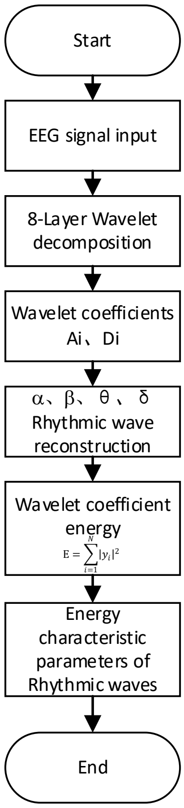

Fig 2 Brainwave processing algorithm flow chart

3.1.1 Feature Wave Extraction of EEG Signal

Discrete Wavelet Transform (DWT) is chosen in this paper. When using DWT, the accuracy of EEG feature extraction will be affected by the selection of wavelet function and transform scale. Liu Xuefeng et al. used different wavelet functions and scales to study EEG signals. When using wavelet transform with DB4 and scale 8, the amplitude-frequency characteristics of each rhythm wave are the most obvious. The energy distribution of known wavelet coefficients is different and can be used as feature information. According to the wavelet coefficients of the DWT decomposition with the db4 wavelet function and the scale of 8 and the corresponding frequency range, the paper selects the wavelet coefficients D3 (band: 6.25-12.5 Hz), D2 (band: 12.5-25 Hz), D4+D6 (band: 3.906-7.813 Hz) and D5+D6 (band: 2.344-4.688 Hz) as α,β,$\theta$and δ rhythm waves.

3.1.2 Energy Feature Extraction of EEG Signals

In different sleep periods, the energy of EEG signal and rhythm wave energy are different. As we know from the above, the DWT algorithm can extract four kinds of rhythm wave, so the ratio of the energy of each rhythm wave to the total energy of four rhythms can be used as the characteristic parameter to distinguish sleep period.

In the analysis of this paper, λ stands for rhythmic wave; $E_\lambda(t)$ represents the energy of each characteristic wave, i.e. E_α , E_β , E_θ , E_δ ; $n=4$,represents four kinds of rhythmic waves; E_{sum} represents the total energy of the four characteristic waves; $f_\lambda(t)$ stands for reconstructed signal. $i=0,1,\cdots,m$,it indicates that there are m sampling points for EEG signal and x_i represents the corresponding amplitude of $f_\lambda(t)$ sampling point.

The band energy value of $f_\lambda(t)$ -wavelet analysis can be expressed as

$$E_\lambda = \int | f_\lambda(t) |^2 dt = \sum_{i=1}^{m} | x_i |^2$$

Therefore, the relative energy of each rhythmic wave is expressed as:

$$A_\lambda = \frac{E_\lambda}{E_{sum}} = \frac{E_\lambda}{\sum_{1}^{n} E_\lambda}$$

3.2 Sleep Staging Algorithm based on Convolutional Neural Network.

Age, sex, physique and external environment are important factors affecting the threshold of each sleep period [9]. Therefore, in order to improve the accuracy of sleep staging, this paper uses convolutional neural network for machine learning.

When constructing sleep staging model, the user's personal characteristic information and pre-processed EEG signals are taken as input vectors of the neural network, and the staging result, which means the probability of sample distribution over 5 sleep stages (WAKE,N1,N2,SWS,REM), is taken as the output vector. Then, the neural network is trained with enough samples. In this process, the actual output value and the expected output value are compared when their error is smaller than the value we set, the group of weights W_{ij} and threshold is the correct internal representation of the neural network after self-adaptive learning. There are two processes involved:

(1) Forward process: the input network is continuously transmitted through each unit until the output of the neural network is obtained by the output unit;

(2) Reverse process: Comparing the actual output value with the expected output value to get the error between them, and then returning the error to the input layer step by step through the output layer, and continuously adjusting the connection weight and bias weight until the error between the actual output value and the expected output value is less than the pre-determined value. In this paper, a sleep staging model of DWT-CNN is constructed by combining the time-frequency matrix of DWT and convolutional neural network. As shown in Figure 3, the model consists of input layer (DWT time spectrum matrix), convolution layer 1 (Cov1), convolution layer 2 (Cov2), pooling layer 1 (Pool1), convolution layer 3 (Cov3), full connection layer 1 (FC1), full connection layer 2 (FC2) and output layer (probability of sample distribution in each sleep period).

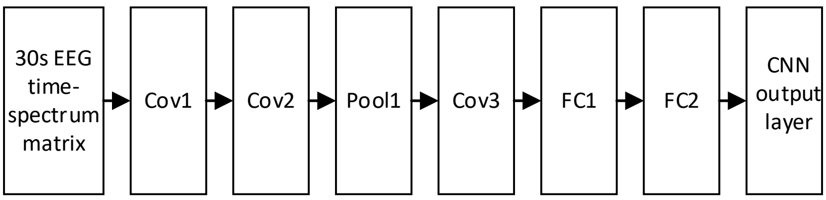

Fig. 3 Sleep staging model

The training of convolution neural network uses Adam Optimizer optimizer based on tensorflow. The learning rate is initially set to 10^{-4} . The parameters of convolution neural network are optimized by cross-entropy loss function. The cross-entropy loss function is as follows:

$$C(w,b) = -\frac{1}{n}\sum_x \sum_j \left[y_j ln a_j^L + (1-y_j) ln(1-a_j^L) \right]$$

Among them, w, b represent the current weights and biases of neural networks; x represents the input sample; j denotes neurons in the output layer; y represents our expected output value; a^L represents the actual output value.

4. System Workflow

As shown in Figure 4, the working process of the system is as follows: Firstly, STM32 with terminal is connected to cloud platform through ESP8266, and then APP uploads user feature information and wake-up time to set up before work. At work, the EEG acquisition part collects the user's EEG data and uploads it to the cloud platform. The cloud platform extracts the energy proportion of each rhythm wave as the characteristic quantity through the EEG processing algorithm based on wavelet transform. The characteristic quantity combines with the user's personal information, environment and historical data, and uses the sleep staging algorithm based on convolutional neural network to accurately judge the user's real-time sleep period. Then the auxiliary sleep part of the wearing terminal adopts different sleep aids or wake-up methods to adjust the sleep adaptively according to the different sleep periods. At the same time, the user can also view the sleep information on APP.

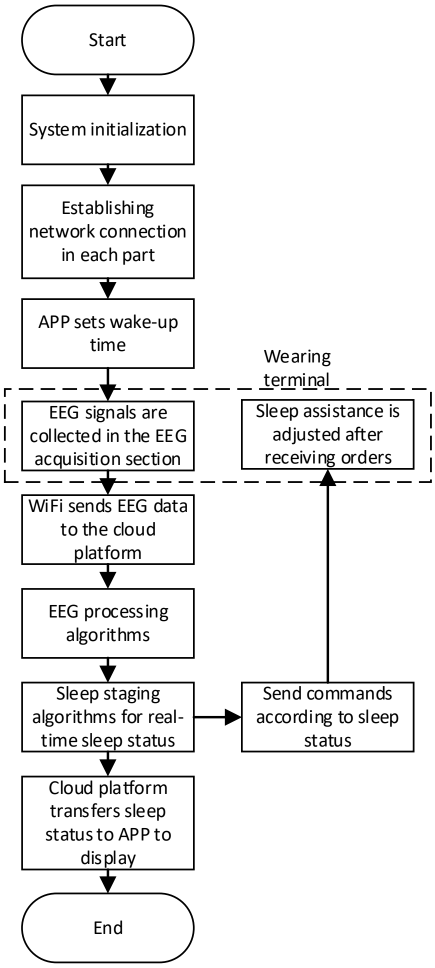

fig4 System flow chart

5. Results and Analysis

5.1 System Prototype Design

Maya software is used to build the model of the system, and the prototype design of the system as shown in Fig. 5 can be obtained. In Fig. 5, from left to right are the front, side and back of the prototype of the system.

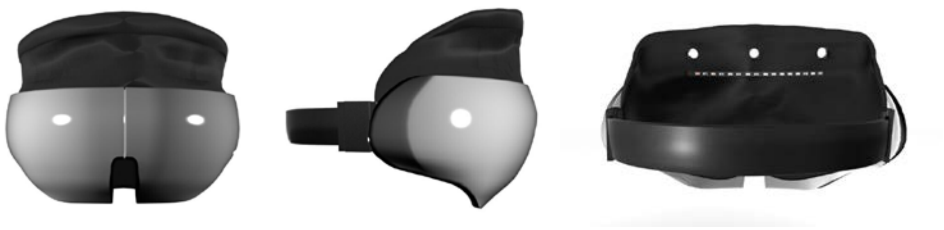

Fig. 5 System prototype design

5.2 Experimental Results and Analysis

In this paper, 25 groups of polysomnograms from Sleep-EDF database in MIT-BIH physiological information database [10] were used as training test data, including 25 sleep databases and 25 corresponding sleep label libraries. The latter is an artificially calibrated sleep stage, which can be used to verify the accuracy of this test.

5.2.1 Rhythm Wave Extraction Results

A 30 s data fragment (3000 data) is randomly selected and the rhythm wave of EEG signal is extracted by using the DWT algorithm. As shown in Figure 6, the rhythm wave waveforms are extracted. The power spectrum corresponding to each rhythm wave is shown in Figure 7. It can be seen that the frequency distribution of each rhythm wave is the same as the theoretical frequency band range specified in this paper, which verifies that the DWT algorithm can effectively extract the rhythm wave of EEG during sleep.

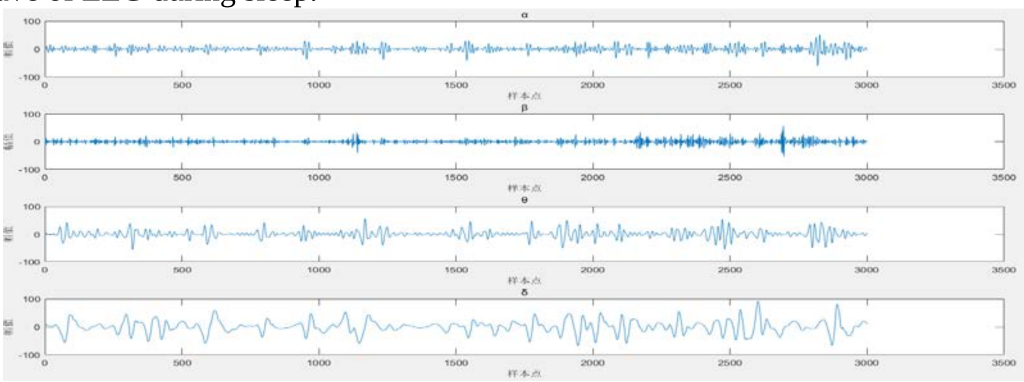

Fig.6 Images of each rhythm wave

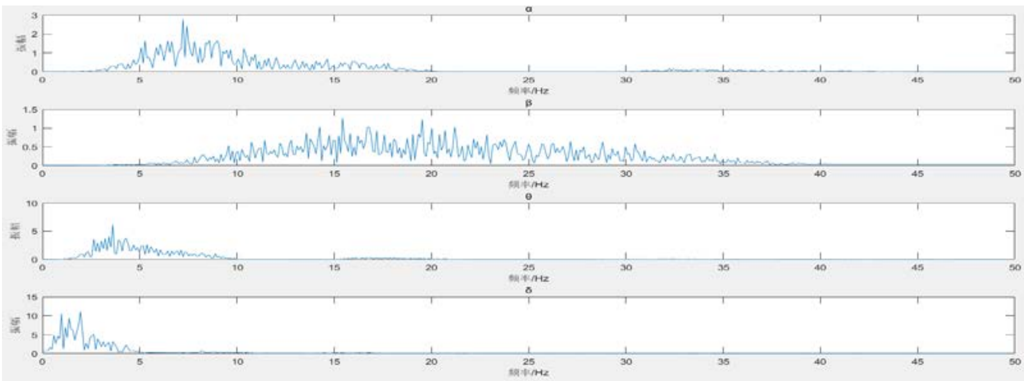

Fig 7 Power spectra of each rhythm wave

5.2.2 Sleep staging results

80% of the sample data were input into the sleep staging model of the system for training. After adjusting the parameters continuously, the remaining 20% of the sample data were input into the model for testing. After testing, the classification effect of sleep stages in this model can be obtained as shown in Table 1.

Table 1 Sleep Staging Effect Table

Input sample type	Total sample size	Classification results					Indicators of various categories		
		W	N1	N2	SWS	REM	PR	RE	F1
W	7927	6765	635	228	81	218	88.2	85.3	86.7
N1	2804	325	1308	641	29	501	41.2	46.6	43.7
N2	17799	362	690	14449	1554	744	89.5	81.1	85.1
SWS	5703	30	8	375	5286	4	75.8	92.6	83.4
REM	7717	185	533	434	20	6545	81.6	84.8	83.2
ACC = 81.9%; MF1 = 76.4%;									

As shown in Table 1, the global classification accuracy of the model is 81.9%, and the macro average F1 value is 76.4%. Among all sleep stages, the best classification effect is W class, whose F1 value is 86.7%. In addition, N2 class, SWS class and REM class have better classification effect, their F1 value is more than 83%. But among all types, the worst classification effect is N1 class, whose F1 value is only 43.7%. In a word, this model has good resolution for most sleep stages.

6. Conclusion

Machine-based Learning Assisted sleep system is mainly composed of three parts: wearing terminal, cloud platform and user APP. Through the EEG processing algorithm based on wavelet transform and the sleep staging algorithm based on convolutional neural network, the system can better determine the sleep period of users, thus adopting different sleep aids or wake-up means to adjust the sleep of users adaptively. Experiments show that the system has high accuracy for sleep staging of users. However, in the case of more complex user information and external conditions, the system can not accurately sleep staging, so we hope to design more complex and comprehensive algorithms to improve the system in the future.

References

[1] Corey Wakeling. Sleeplessness in Sleep[J]. Performance Research, 2016, 21(1).

[2] Chen ying. Development of sound sleep instrument based on eeg signal recognition [D]. Shaanxi University of science and technology, 2017.

[3] Nakamura, S.,Nakano, T., Mochizuki, N., et al. Proposal of sleep-promoting robot using vibratory pressure and sound stimulation[P]. IECON 2012 - 38th Annual Conference on IEEE Industrial Electronics Society,2012.

[4] Li Huhan. Human infrared sense-type sound and light wake-up clock [P]. Anhui: CN205028046U, 2016-02-10.

[5] Koley, B.L.,Dey, D.. Detection of characteristic waves of sleep EEG by continuous wavelet transform [P]. Computing and Communication Systems (NCCCS), 2012 National Conference on, 2012.

[6] Zhang Xiuli, xia bin. Study on sleep stages based on cnn-lstm network [J]. Microcomputer & application, 2017, 36(17): 88-91.

[7] Ma Lijun. Interpretation of the 2014 edition of AASM international classification of sleep disorders [J]. Chinese journal of practical diagnosis and treatment, 2017, 31(03): 209-212.

[8] Liu Xuefeng. Research on sleep feature extraction and staging based on eeg signal [D]. Zhengzhou University, 2018, 22-28.

[9] Parkes Katharine R. Age and work environment characteristics in relation to sleep: Additive, interactive and curvilinear effects.[J]. Applied ergonomics, 2016, 54.

[10] Ritu Singh, Rajesh Mehta,Navin Rajpal. Efficient wavelet families for ECG classification using neural classifiers [J]. Procedia Computer Science, 2018, 132.