Measuring Sleep Quality from EEG with Machine Learning Approaches

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***Abstract*—This study aims at measuring last-night sleep quality from electroencephalography (EEG). We design a sleep experiment to collect waking EEG signals from eight subjects under three different sleep conditions: 8 hours sleep, 6 hours sleep, and 4 hours sleep. We utilize three machine learning approaches, *k*-Nearest Neighbor (*k*NN), support vector machine (SVM), and discriminative graph regularized extreme learning machine (GELM), to classify extracted EEG features of power spectral density (PSD). The accuracies of these three classifiers without feature selection are 36.68%, 48.28%, 62.16%, respectively. By using minimal-redundancy-maximal-relevance (MRMR) algorithm and the brain topography, the classification accuracy of GELM with 9 features is improved largely and increased to 83.57% in average. To investigate critical frequency bands for measuring sleep quality, we examine the features of each band and observe their energy changing. The experimental results indicate that Gamma band is more relevant to measuring sleep quality.**

I. Introduction

Sleep is of great importance to humans. Enough sleep is not only the basis of health and energy, but also the guarantee of productivity. An objective and reliable measurement of sleep quality is one of the most valuable research topics in the field of transportation, medicine, health care, neuroscience, and food industry. The sleep quality is especially important to the railway driver because it affects drivers' attention, judgment and execution. Nowadays, pressures and sleep disorders are prevalent among the drivers, which becomes a potential threat to safe driving. In order to measure the sleep quality of drivers in advance and get rid of "risky" drivers, the railway company is seeking an objective and reliable measurement of sleep quality. With quick development of wearable EEG signal acquiring devices, EEG-based sleep quality measurement is considered as a feasible choice. The current sleep quality measuring approaches could be divided into two categories: subjective sleep quality measurement and objective sleep quality measurement [1].

The subjective sleep quality measuring method is to judge the sleep quality by self-evaluation via sleep diaries, questionnaires, interviews, and indexes. The popular subjective sleep quality measuring methods include Pittsburgh Sleep Quality Index [2], Epworth Sleep Scale [3], and Sleep Diaries [4]. However, we have no way of knowing whether the respondents are honest, conscientious, responsible for self assessment and related records and in many cases they may provide false information or fill in the questionnaire not seriously. Secondly, the subjective evaluation method is more troublesome, time-consuming and laborious, which requires participants to seriously think about, a detailed answer, record relevant information in time, in the meantime, experiment personnel also need a manual investigation and analysis of the information in order to give a sleep quality evaluation and judgment of the subject. Finally, the subjective evaluation method requires subjects have a certain cultural level, enough introspection and self-discipline. Many participants may not clearly understand the subjective evaluation method on the provided requirements and problems or they can't do accurate understanding and judgment on their own, thus failing to actively provide accurate and reliable information. Hence, as described above, subjective sleep quality measurements do not meet our needs.

The objective sleep quality measuring method is to judge the sleep quality based on physiological signals. The conventional objective sleep quality measuring approaches include polysomnography [5] and actigraphy. For this kind of method, subjects need to wear equipment like a band during the sleep. The limitation of this method is that users should wear the equipment for a long time, so this approach can not meet the requirements of us to quickly check the quality of sleeping of high-speed rail drivers. Therefore, we hope to develop a fast and easy method. Since recent research shows that EEG signals can reflect the fatigue state accurately [6][7] , we focus on EEG-based sleep quality measuring in this paper.

So far no common acknowledgements about the precise definition of the sleep quality have been acquired by the researchers over the world, because it is a rather vague and subjective notion in itself. Besides, for different individuals, there are different standards, since sleep quality is both correlated to the objective factors such as the total sleep time, sleep onset latency, sleep disruptive events, and sleep efficiency [1], and to the subjective factors including the mood, stress and anxiety. Moreover, different people may set different standards for the sleep quality. Even if the sleep time is long enough and

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the sleep environment is satisfactorily quiet and comfortable, some people could still feel dissatisfied with their sleep quality, while others may find themselves full of energy even if their sleep time is not thought to be long enough. Some people may evaluate their sleep quality based on the current waking state, whereas other may do it according to their sleep process. How people evaluate their sleep quality may be also affected by their mood and the surroundings.

The length of sleep is directly related to the sleep quality for the majority of the normal people. In most cases, lack of adequate sleep time leads to poorer sleep quality, while sufficient sleep time may ensure a good sleep. Therefore, in this study, we take the total sleep time as the substitute to measure the sleep quality. Based on the researches and surveys conducted by the experts in National Sleep Foundation (NSF), generally speaking, 8-hour sleep presents a high sleep quality, particularly for young adults. That means whether the sleep time is more or less than 8 hours results in the reduction of the sleep quality. And the sleep time no more than 4 hours or no less than 12 hours means an awful sleep in terms of its quality [8]. Based on the findings of NSF, we hypothesize in this study that a sleep of about 8 hours means a favorable sleep quality; a sleep of 6 hours corresponds to the a normal sleep quality; a sleep of 4 hours represents a poor sleep quality.

To investigate the underlying mechanisms of sleep quality, sleep deprivation experiment is the common method. Sleep deprivation means not having enough sleep. It can be chronic sleep deprivation or acute sleep deprivation. It can also be total sleep deprivation and partial sleep deprivation. Here, we adopt the acute partial sleep deprivation experiment.

II. Related work

Li *et al.* [9] tried to study the influence of lack of sleep on the event-related potentials of the event under the stimulation. In both cases of sufficient sleeping and lack of sleep, audio stimulation was given to subjects, and then the parallel factor analysis method was used to analyze the event-related potentials of the subjects in both cases. They found that compared with the sufficient sleeping, event-related potentials activities of the subjects are near to the forehead, and Gamma frequency band had delay and attenuation in the case of lack of sleep.

Jin *et al.* [10] observed the influence of lack of sleep on the connection between the brain regions. After the functional cluster analysis was conducted on the electroencephalogram (EEG) in both cases of sufficient sleeping and lack of sleep by the subjects, they found the functional cluster of subjects was changed in the case of lack of sleep.

Na *et al.* [11] attempt to investigate the influence of lack of sleep on the connection between cerebral hemisphere. After the mutual information analysis was conducted on EEG in both cases of sufficient sleeping and lack of sleep, they found the connection between the hemispheres was weakened in the case of lack of sleep.

Sánchez *et al.* [12] discussed whether the influence of lack of sleep of the same period on EEG of women was the same as the influence on EEG of men, and they found that compared with men, the influence of lack of sleep of the same period on women was more peaceful, but women needed more sleep to recover from lack of sleep.

Tassi *et al.* [13] tried to observe the influence of lack of sleep on EEG, and they found that compared with the case of sufficient sleeping, Theta wave of subjects in the EEG increased in the case of lack of sleep.

Lorenzo *et al.* [14] investigated the influence of lack of sleep on the EEG of men, and they found that compared with sufficient sleeping, Theta wave of EEG of male subjects increased, the Alpha wave decreased, and the Beta wave in the central brain regions increased.

Jeong *et al.* [15] studied the influence of lack of sleep on the dimension complexity of EEG, and they found that compared with sufficient sleeping, the dimension complexity of EEG of the subjects was reduced in the case of lack of sleep. They speculated that the information processing function of brain decreases under the condition of lack of sleep.

As described above, the existing work analyzed the differences and changes in some aspects of the treated EEG mainly based on the two different sleep qualities: sufficient sleep and lack of sleep. However, there is no research on the feasibility of sleep quality classification with machine learning approaches. On the contrary, we analyze the differences of EEG based on three kinds of sleep qualities: good sleep, normal sleep and poor sleep in this paper, and study sleep quality measuring method using machine learning approaches.

III. Methods

A. Frequency Bands and Sleep Cycle

EEG signals can be divided into five different frequency bands: Delta, Theta, Alpha, Beta and Gamma band.

(1) Delta band (frequency 1-4Hz): When adults are in deep sleep, the delta wave will appear.

(2) Theta band (frequency 4-8Hz): When adults are sleepy and drowsy, the theta wave will appear. The slow wave including the delta wave and the theta wave is associated with the inhibited state of brain.

(3) Alpha band (frequency 8-13Hz): When adults are awake and calm or close their eyes, the alpha wave will appear. It is associated with the calm state of brain.

(4) Beta band (frequency 13-30Hz): When adults are focused, nervous, alert, or anxious, the beta wave will appear. It is associated with the excited state of brain.

(5) Gamma band (frequency 30-50Hz): When adults are executing complicated tasks which need parallel processing, the gamma wave will appear. It is supposed to be linked with the cognitive function [16].

Sleep is a naturally recurring state of mind. Its characteristics are lowered reaction to external stimuli and temporary consciousness loss. Sleep is controlled by the internal circadian clock. There is a sleep cycle in humans' sleep, which lasts about ninety minutes. Most people will experience four to six sleep cycles in one night's sleep. The sleep cycle can be divided into rapid eye movement (REM) stage and non-rapid eye movement (NREM) stage. The non-rapid eye movement stage can be further divided into three stages: N1, N2, and N3 [17].

(1) NREM stage 1: This stage consists of 5% to 10% of the total sleep time. In this stage, humans are in the transition between awake and asleep. The EEG changes from alpha wave (8-13Hz) into theta wave (4-7Hz). This stage may be associated with sudden twitches and hypnic jerks.

(2) NREM stage 2: This stage consists of 45% to 55% of the total sleep time. In this stage, humans are already asleep. The theta wave is prevalent in the EEG and sleep spindles as well as K-complexes can be observed.

(3) NREM stage 3: This stage consists of 15% to 25% of the total sleep time. In this stage, humans are in deep sleep. The delta wave is prevalent in the EEG. It is the most restful stage of the sleep. Parasomnias such as night terrors and sleep walking might occur.

(4) REM stage: This stage consists of 20% to 25% of the total sleep time. The physiological signals such as EEG are quite similar to that of a waking state. However, sleeper in this stage is harder to be aroused than at any other stage. The sleeper will experience vivid dreams, which helps to synthesize memory segments. This stage is associated with the study ability.

B. Preprocessing

First of all, the raw EEG are preprocessed in the following manner:

1) Down-sampling: The original sampling frequency of EEG is 1000Hz, and the amount of data is too big to deal with. Therefore, down-sampling is adopted, and the original EEG frequency is reduced to 200Hz, which facilitates the subsequent processing.

2) Dealing with the bad EEG electrodes: During the experiments, there exist several bad electrodes occasionally, and the corresponding EEG signals cannot be collected correctly. However, if the data of bad electrodes are simply removed, the follow-up data processing will be inconsistent. Therefore, a neighbor interpolation method is adopted to process failure EEG electrodes, replacing the error noise signal of bad EEG electrodes with the average of the neighbor EEG electrodes.

3) Removing EEG artifact: In this work, a 1-50 Hz band-pass filter [18] is adopted to filter out noise. In the experimental design of this study, subjects are required to sit quietly with eyes closed during the whole course to avoid the appearance of EOG and EMG to a large extent.

C. Feature extraction

After the preprocessing of EEG signals, the features of EEG are extracted. The most commonly used feature is PSD, which essentially reflects the energy change of EEG. Taking the five different frequency bands of EEG into account, the effect of sleep quality on EEG may be mainly reflected in one or several frequency bands. After the short-time Fourier transform, PSD, the commonly used EEG feature in five frequency bands was extracted. Because the total number of EEG electrodes is 62, there are 310 PSD features in all, which are concatenated together to form a 310-dimensional feature vector.

In this paper, Hanning window-based discrete short-time Fourier transform (STFT) algorithm is adopted to extract the PSD, a time-frequency feature of EEG. The PSD feature represents the signal power within the unit frequency band.

Suppose the EEG sequence recorded by an electrode is *x*[n]={ x_1,x_2,...x_n }, then the short-time Fourier transform of the EEG sequence is:

$$STFT\{x[n]\}(m,\omega_k) \equiv X\left(m,\omega_k\right) = \sum_{n=1}^{N} x[n]w[n{-}m]e^{-j\omega_k n}$$

where $\omega_k = \frac{2\pi k}{N}$ represents the angular frequency, and $k = 0, 1, ...N-1$. $w[n]$ represents a window function. The window function used in this study is Hanning window as follows:

$$w(n) = \begin{cases} 0.5\left[1 - cos\left(\frac{2\pi n}{M-1}\right)\right] & 1 \le n < M \\ 0 & o.w. \end{cases}$$

When the EEG is divided into different EEG frequency bands (Delta: 1∼3Hz; Theta: 4∼7Hz; Alpha: 8∼13Hz; Beta: 14∼30Hz; Gamma: 31∼50Hz), the Fourier transform of each band is calculated, and then the energy spectrum of each band is calculated by:

$$E\left(\omega_k\right) = X\left(m,\omega_k\right) X^*\left(m,\omega_k\right)$$

where, $X^*\left(m,\omega_k\right)$ is a conjugate function of $X\left(m,\omega_k\right)$. Then, PSD is defined as:

$$PSD(w_k) = \frac{1}{N}E(w_k), k = 0, 1...N-1$$

D. Feature smoothing

The extracted PSD features have a more severe jitter. Although the effect of sleep quality on EEG is intuitively regarded to be stable and continuous, it is necessary to smooth the EEG features with severe jitter.

Previous researches have found that, the feature smoothing methods, such as moving average (MA) and linear dynamical system (LDS) [19], help to improve the performance of classifiers during emotion classification, and the LDS method performs more stable than the MA method [20][21] . Therefore, we apply the LDS method to smooth EEG features, making attempt to remove noises effectively and get more reliable data.

E. Classification

After obtaining the processed features of EEG, the next step is to analyze the influence of sleep quality on the features. Our strategy is to study whether we can train a classifier which can accurately distinguish different sleep qualities with EEG features. We utilize three approaches of machine learning: *k*-Nearest Neighbor (*k*NN), support vector machine (SVM), discriminative graph regularized extreme learning machine (GELM) [22]. The parameter *k* in *k*NN is set to be 1, the kernel function of SVM is linear kernel. For each subject, we choose 900 samples (300 for good sleep quality, 300 for medium sleep quality, 300 for poor sleep quality) as the testing data, the 6300 samples from the other 7 subjects as the training data, where the number of features of PSD are 310 dimensional, containing all the combinations of 62 different electrodes and 5 frequency bands.

F. Feature selection

There are actually 310 features for one sample on total five bands. However, our training set only has 6300 samples for training, which implies that the 310 dimensions are too high for us. Therefore, we evaluate and compare five feature selection methods: Joint Mutual Information (JMI) [23], Conditional Infomax Feature Extraction (CIFE) [24], Mutual Information Features Selecting (MIFS) [25], Mutual Information Maximisation (MIM) [26], and Minimal-redundancy Maximal-relevance (MRMR) [27]. They are used to select effective features, reduce the feature dimension, and enhance the recognition accuracy.

IV. Experiments

A. Purpose

The purpose of our experiment is to collect waking EEG under different conditions of sleep quality and then analyze the data to find the influences that sleep quality leaves on the EEG. The differences among EEG under different conditions can be used to train models to realize the EEG-based sleep quality measurement. The experiment consists of two parts: sleep deprivation experiment and EEG collection experiment. The subjects are required to take part in both experiments three times.

B. Subjects

Eight subjects, six of which are male and two are female, participate in the experiment. They are all at the age of 21 to 23. They had a regular sleep and stayed in good health before the experiment. None of them have any history of mental disease or drug use. Besides, they didn't have any contact with hypnotic, caffeine or alcohol at the previous week before they come to the experiment. Anything that contains what will affect sleep was prohibited.

C. Sleep deprivation experiment

In the sleep deprivation experiment, subjects were required to sleep at home at night for four, six, and eight hours, respectively, and then they participated in the EEG collection experiment in the following days.

D. EEG collection experiment

The EEG collection experiment took thirty minutes. During the whole process of EEG collection, the subjects were required to keep their eyes closed and stay awake. While subjects were also required to sit still on the chair, EEG signals were recorded with ESI NeuroScan System at a sampling rate of 1000 Hz from 62-channel electrode cap according to the international 10-20 system, simultaneously. The experimenter watched the EEG and subjects from outside the laboratory. There was no stimuli, no task and no interruption during the experiment. Fig. 1 shows the actual scene of the experiment.

Fig. 1. The actual scene of our experiment.

V. Results and discussions

A. Classification

We chose 900 samples of one subject as testing data, and 6300 samples from the other 7 subjects as training data. The accuracies of three classifiers with 310 dimensions of PSD features are shown in Table I .

From the results in Table I, we can see that, for total 310 features on all bands, the classification accuracy of GELM is 62.16% in average, which is much higher than those of *k*NN and SVM. We also compare the average accuracies of each frequency bands. Table II represents the experimental results. From Table II, we find that all the results of GELMs are higher than those of SVMs and kNN.

One of the primary problems is whether there exist some key frequency bands for the EEG-based sleep quality evaluation. These frequency bands contain key discriminative information for different sleep quality. The variance of sleep quality has a significant influence on these frequency bands. In terms of this, we are able to obtain a higher classification accuracy with the EEG features from these key frequency bands. We extracted 62-dimension PSD features from EEG on Delta, Theta, Alpha, Beta and Gamma frequency bands, and compared them with the 310-dimension features of total frequency band. The results of the classification are shown in Table II.

The average recognition accuracy of Gamma frequency band is higher than all other frequency bands, which shows that the Gamma frequency band is associated with the quality of sleep much more closely. In contrast, the Theta and Delta frequency band perform poorly. The average recognition accuracy of the Gamma frequency band reaches 66.70%, which is higher than the accuracy of all the other frequency bands. These results indicate that there exist critical frequency bands for the EEG-based sleep quality evaluation, and the features of these key frequency bands can effectively improve the classification performance.

TABLE I
CLASSIFICATION ACCURACIES(%) OF KNN ,SVM AND GELM CLASSIFIERS USING 310 TOTAL FEATURES TO TRAIN AND TEST

Algorithms	Subject1	Subject2	Subject3	Subject4	Subject5	Subject6	Subject7	Subject8	Average(±sd)
*k*NN	37.00	43.00	34.67	65.11	39.56	4.11	16.78	53.22	36.68±19.24
SVM	44.22	61.56	50.89	81.44	42.11	35.22	33.00	37.78	48.28±16.26
GELM	44.56	61.11	56.44	89.44	54.33	83.00	47.67	60.78	**62.16±16.01**

TABLE II
CLASSIFICATION ACCURACIES(%) OF DIFFERENT FREQUENCY BANDS USING SVM AND GELM

Frequency Band	Algorithm	Subject1	Subject2	Subject3	Subject4	Subject5	Subject6	Subject7	Subject8	Average(±sd)
Delta	SVM	36.00	33.00	33.33	48.56	49.56	61.78	65.00	38.22	45.68±12.64
	GELM	51.89	44.78	67.78	71.11	62.56	61.67	58.44	63.11	60.17±8.48
Theta	SVM	28.22	47.44	33.33	64.56	32.89	54.44	37.78	25.22	40.49±13.74
	GELM	53.56	18.00	38.44	42.44	52.11	50.33	59.11	56.67	46.33±13.37
Alpha	SVM	39.33	62.33	57.67	51.89	66.67	45.00	37.67	38.11	49.83±11.49
	GELM	72.22	64.89	55.89	50.89	68.00	73.44	44.44	49.89	59.96±11.10
Beta	SVM	64.56	66.33	38.67	64.44	64.22	44.56	33.67	46.56	52.88±13.42
	GELM	62.67	66.67	47.56	66.22	61.33	70.56	55.11	69.89	62.50±7.84
Gamma	SVM	62.00	63.78	33.33	66.67	66.11	69.11	33.33	58.00	**56.54 ±14.70**
	GELM	65.11	62.22	55.67	66.67	72.78	100.00	39.89	71.22	**66.70±17.02**
Total	SVM	44.22	61.56	50.89	81.44	42.11	35.22	33.00	37.78	48.28±16.26
	GELM	44.56	61.11	56.44	89.44	54.33	83.00	47.67	60.78	62.16±16.01

We further present the percentage of frequency band energy accounting for the total power of all frequency bands. The experimental the results are shown in Table III. The absolute power of Alpha frequency band and the proportion of Alpha frequency band accounting for the total power of all frequency bands are higher than those of the other frequency bands, it is because we recorded EEG data under the conditions that participants closed their eyes, sit quietly and stayed awake without any external stimuli and interference. When people keep themselves aware, quiet or eyes-closed, Alpha wave will be dominant, and its amplitude appears from small to large. It is generally believed that Alpha wave is the main performance of the electrical activity when the cerebral cortex is in awake and quite states. Moreover, with the increase of sleep quality, the energy change of Gamma frequency band tends to be the most obvious changing, and the percentage of Gamma frequency band accounting for the total power of all frequency bands is increasing. These results indicate that the Gamma frequency band contains the most relevant information for sleep quality evaluation among different frequency bands, which is consistent with the previous experimental results of classification accuracies.

B. Feature selection

The number of dimensions of PSD features is 310 from the total five frequency bands, which may contain some redundant information, since there exist some critical frequency bands for EEG-based sleep quality evaluation. Therefore, we adopt different feature selection methods to extract the optimal subset of features. Fig. 2 depicts the performance of five different feature selection methods to select 10 and 20 features.

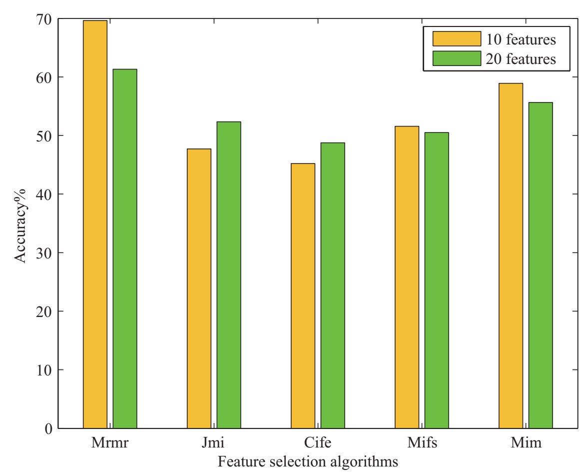

Fig. 2. Performance comparison of five different feature selection algorithms.

TABLE III
ENERGY CHANGE(%) OF EACH FREQUENCY BAND ACCOUNTING FOR THE TOTAL ENERGY OF ALL FREQUENCY BANDS UNDER THE DIFFERENT SLEEP QUALITY

Sleep Hours	Delta	Theta	Alpha	Beta	**Gamma**
4	14.6	20.6	40.1	18.3	**6.4**
6	10.8	18.8	39.1	21.7	**9.6**
8	10.6	19.1	35.2	22.9	**12.3**

From the results, we can find that the minimal-redundancy-maximal-relevance (MRMR) algorithm achieves the highest

TABLE IV
CLASSIFICATION ACCURACIES(%) OF DIFFERENT FEATURES SELECTED BY MRMR AND USING KNN, SVM AND GELM

Feature dimension	Algorithm	Subject1	Subject2	Subject3	Subject4	Subject5	Subject6	Subject7	Subject8	Average(±sd)
6	*k*NN	66.11	46.22	44.56	31.56	77.22	49.00	45.65	48.78	51.13±14.11
	SVM	67.56	68.44	64.44	68.67	92.56	91.11	54.22	57.00	70.50±14.20
	GELM	87.89	62.22	64.78	67.89	72.00	97.78	58.67	60.11	71.41±14.13
8	*k*NN	60.22	48.44	68.67	33.56	96.89	55.89	53.78	65.22	60.33±18.32
	SVM	63.89	71.22	90.11	73.56	70.11	91.22	62.22	58.22	72.57±12.26
	GELM	94.11	75.33	74.89	53.56	87.22	85.78	58.89	59.11	73.61±15.06
10	*k*NN	42.22	68.67	67.67	41.33	85.56	60.56	50.11	63.89	60.00±14.95
	SVM	40.00	69.44	91.78	76.89	73.78	82.78	61.00	61.33	69.63±15.83
	GELM	50.33	71.22	88.44	68.89	97.56	92.44	56.67	58.56	73.01±17.84
12	***k*NN**	49.78	67.67	67.56	35.11	71.78	83.11	51.11	69.22	**61.92±15.34**
	SVM	52.00	72.88	91.56	74.78	73.00	97.00	67.11	66.00	**74.29±14.31**
	GELM	60.44	70.89	96.89	68.89	80.56	98.22	60.67	70.78	**75.91±14.79**
14	*k*NN	51.44	69.67	75.22	28.33	53.22	67.89	37.44	71.56	56.85±17.21
	SVM	43.11	72.00	65.11	76.11	64.44	99.67	49.44	61.22	66.39±17.29
	GELM	52.11	69.67	85.78	68.67	61.11	100.00	49.78	65.44	69.07±16.79
16	*k*NN	43.33	81.89	75.33	29.44	53.78	69.56	42.11	72.67	58.51±18.97
	SVM	44.22	68.44	66.44	78.33	61.67	95.22	49.78	59.89	65.50±16.05
	GELM	53.22	77.00	79.44	76.11	56.67	95.11	51.00	60.67	68.65±15.58
18	*k*NN	43.00	79.00	67.22	26.11	55.00	61.00	39.33	67.11	54.72±17.45
	SVM	45.56	61.78	60.22	77.56	57.33	95.11	51.33	55.11	63.00±15.98
	GELM	51.00	64.89	84.56	68.00	55.67	97.33	47.44	53.44	65.29±17.57
20	*k*NN	43.33	71.33	60.44	31.78	63.89	57.33	36.44	66.22	53.84±14.71
	SVM	46.44	57.67	66.33	80.78	58.89	82.44	49.22	48.78	61.32±14.11
	GELM	51.33	66.22	81.44	69.11	62.44	78.33	49.67	86.56	68.14±13.53

TABLE V
CLASSIFICATION ACCURACIES(%) OF 9 FEATURES SELECTED BY MRMR AND BRAIN TOPOGRAPHY AND CLASSIFIED BY SVM AND GELM

Algorithm	Subject1	Subject2	Subject3	Subject4	Subject5	Subject6	Subject7	Subject8	Average(±sd)
SVM	63.44	96.89	71.56	89.44	84.78	97.78	63.33	78.11	80.67±13.82
GELM	67.56	88.67	65.00	91.89	98.00	95.33	67.89	94.22	83.57±14.15

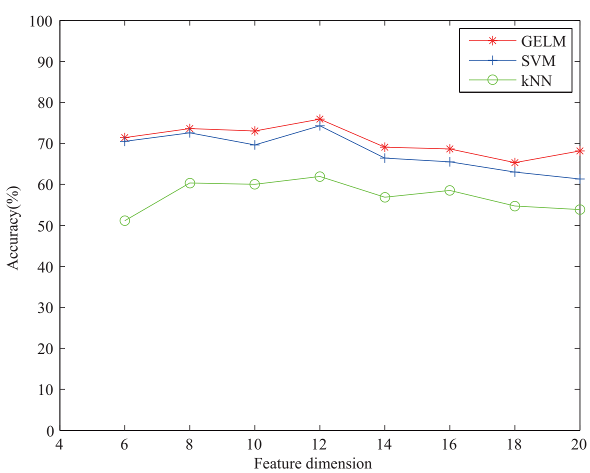

Fig. 3. The accuracies of KNN, SVM and GELM with different features selected by MRMR algorithm.

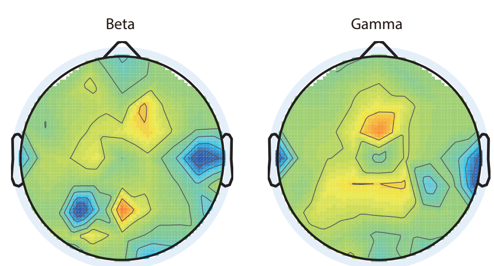

Fig. 4. The change of average energy distribution in Beta and Gamma bands.

accuracy. These results indicate that MRMR can achieve the best performance among those five methods for EEG-based sleep quality evaluation.

We further investigate how the performance varies with the numbers of feature dimensions from 6 to 20 using MRMR algorithm. The experimental results are depicted in Fig. 3. The details are shown in Table IV. From Fig. 3 and Table IV, we can see that GELM is more suitable for sleep quality

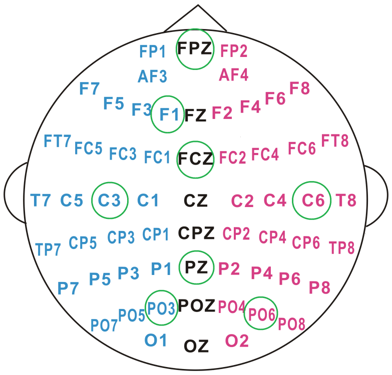

Fig. 5. Nine electrodes selected by MRMR and brain topographic map energy analysis.

measuring than the others and the best dimension of EEG features is twelve for all the three machine learning methods. The 12 features are the electrodes: F8 in Alpha band; C6, F5, F8 and PO3 in Beta band; C3 and PO6 in Gamma band; F1, F6 and FC1 in delta band; FCZ and C3 in theta band.

Moreover, the changes of the average energy distribution show the key electrodes: when the energy changes significantly under different conditions, the electrodes distinguish different sleep quality more effectively. We calculate the difference of average energy distribution in each frequency band for every electrode under 4 hours-sleep and 6 hours-sleep, and multiply it by the difference of 6 hours-sleep and 8 hours-sleep. This inner product can be seen as the energy changes approximatively. By plotting the brain topography with the inner product (Fig. 4), we find that the electrode PZ in Beta band and the electrode FCZ in Gamma band show remarkable changes with different sleep time. Based on the above 12 features selected by MRMR, we further try to enhance the performance by adding high energy-changed electrodes and removing low energy-changed electrodes. The final 9 features (Fig. 5) are the electrodes: PZ, C6, and PO3 in Beta band; C3, PO6, FCZ, and FPZ in Gamma band; F1 in delta band; and FCZ in theta band. Table V shows that GELM achieves the accuracy of 83.57% in average.

VI. Conclusion and Future Work

In this paper, we have designed a sleep experiment, and have collected EEG of eight subjects under the conditions of good, normal and poor sleep qualities, respectively. We have compared the performance of three machine learning algorithms (*k*NN, SVM and GELM) for classification of sleep quality, and found that GELM is superior to others. From the experimental results, we have found that Gamma band is the key frequency band for sleep quality evaluation. We have compared five feature selection algorithms. The experimental results indicate that MRMR is the most suitable algorithm and its recognition rate reaches 83.57% through the brain topographic map energy analysis.

As future work, we will carry our further study on this research from the following three aspects: 1) to design more complex types of experiments with tasks; 2) to investigate whether there is a gender difference on the influence of sleep quality on EEG; 3) to examine whether there exists stable EEG patterns over time for sleep quality measuring.

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References

[1] A. D. Krystal and J. D. Edinger, "Measuring sleep quality," *Sleep Medicine*, vol. 9, pp. S10–S17, 2008.

[2] D. J. Buysse, C. F. Reynolds, T. H. Monk, S. R. Berman, and D. J. Kupfer, "The pittsburgh sleep quality index: a new instrument for psychiatric practice and research," *Psychiatry Research*, vol. 28, no. 2, pp. 193–213, 1989.

[3] M. W. Johns *et al.*, "A new method for measuring daytime sleepiness: the epworth sleepiness scale," *Sleep*, vol. 14, no. 6, pp. 540–545, 1991.

[4] T. H. Monk, C. F. REYNOLDS, D. J. Kupfer, D. J. Buysse, P. A. Coble, A. J. Hayes, M. A. Machen, S. R. Petrie, and A. M. Ritenour, "The pittsburgh sleep diary," *Journal of Sleep Research*, vol. 3, no. 2, pp. 111–120, 1994.

[5] Y.-K. Teng, L.-C. Chiang, K.-H. Lue, S.-W. Chang, L. Wang, S.-P. Lee, H. Ting, and S.-D. Lee, "Poor sleep quality measured by polysomnography in non-obese asthmatic children with or without moderate to severe obstructive sleep apnea," *Sleep Medicine*, vol. 15, no. 9, pp. 1062–1067, 2014.

[6] L.-C. Shi and B.-L. Lu, "EEG-based vigilance estimation using extreme learning machines," *Neurocomputing*, vol. 102, pp. 135–143, 2013.

[7] Y.-Q. Zhang, W.-L. Zheng, and B.-L. Lu, "Transfer components between subjects for EEG-based driving fatigue detection," in *Neural Information Processing*. Springer, 2015, pp. 61–68.

[8] M. Hirshkowitz, K. Whiton, S. M. Albert, C. Alessi, O. Bruni, L. DonCarlos, N. Hazen, J. Herman, E. S. Katz, L. Kheirandish-Gozal *et al.*, "National sleep foundations sleep time duration recommendations: methodology and results summary," *Sleep Health*, vol. 1, no. 1, pp. 40–43, 2015.

[9] N. Li, Y. Wang, M. Wang, and H. Liu, "Effects of sleep deprivation on gamma oscillation of waking human EEG," *Progress in Natural Science*, vol. 18, no. 12, pp. 1533–1537, 2008.

[10] S.-H. Jin, S. H. Na, S. Y. Kim, and D.-J. Kim, "Effects of total sleep-deprivation on waking human EEG: functional cluster analysis," *Clinical Neurophysiology*, vol. 115, no. 12, pp. 2825–2833, 2004.

[11] S. H. Na, S.-H. Jin, and S. Y. Kim, "The effects of total sleep deprivation on brain functional organization: mutual information analysis of waking human EEG," *International Journal of Psychophysiology*, vol. 62, no. 2, pp. 238–242, 2006.

[12] A. I. Sánchez, Y. del Rı, Y. Villanueva, E. Pérez-Garci *et al.*, "Effect of 38 h of total sleep deprivation on the waking EEG in women: sex differences," *International Journal of Psychophysiology*, vol. 50, no. 3, pp. 213–224, 2003.

[13] P. Tassi, A. Bonnefond, O. Engasser, A. Hoeft, R. Eschenlauer, and A. Muzet, "EEG spectral power and cognitive performance during sleep inertia: the effect of normal sleep duration and partial sleep deprivation," *Physiology & Behavior*, vol. 87, no. 1, pp. 177–184, 2006.

[14] I. Lorenzo, J. Ramos, C. Arce, M. Guevara, and M. Corsi-Cabrera, "Effect of total sleep deprivation on reaction time and waking EEG activity in man," *Sleep*, vol. 18, pp. 346–346, 1995.

[15] M. Dai-Jin Kim, "Effect of total sleep deprivation on the dimensional complexity of the waking EEG," *Sleep*, vol. 24, no. 2, p. 197, 2001.

[16] K. Mann, P. Bäcker, and J. Röschke, "Dynamical properties of the sleep EEG in different frequency bands," *International Journal of Neuroscience*, vol. 73, no. 3-4, pp. 161–169, 1993.

[17] Y. Niiyama, R. Fujiwara, N. Satoh, and Y. Hishikawa, "Endogenous components of event-related potential appearing during nrem stage 1 and rem sleep in man," *International Journal of Psychophysiology*, vol. 17, no. 2, pp. 165–174, 1994.

[18] M. J. T. Smith and R. M. Mersereau, "Introduction to digital signal processing: A computer laboratory textbook," p. 120, 1991.

[19] L.-C. Shi and B.-L. Lu, "Off-line and on-line vigilance estimation based on linear dynamical system and manifold learning," in *32nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE, 2010, pp. 6587–6590.

[20] X.-W. Wang, D. Nie, and B.-L. Lu, "Emotional state classification from EEG data using machine learning approach," *Neurocomputing*, vol. 129, pp. 94–106, 2014.

[21] R.-N. Duan, J.-Y. Zhu, and B.-L. Lu, "Differential entropy feature for EEG-based emotion classification," in *2013 6th International IEEE/EMBS Conference on Neural Engineering*. IEEE, 2013, pp. 81–84.

[22] Y. Peng, S. Wang, X. Long, and B.-L. Lu, "Discriminative graph regularized extreme learning machine and its application to face recognition," *Neurocomputing*, vol. 149, pp. 340–353, 2015.

[23] H. Yang and J. Moody, "Feature selection based on joint mutual information," in *Proceedings of International ICSC Symposium on Advances in Intelligent Data Analysis*. Citeseer, 1999, pp. 22–25.

[24] D. Lin and X. Tang, "Conditional infomax learning: an integrated framework for feature extraction and fusion," in *ECCV 2006*. Springer, 2006, pp. 68–82.

[25] R. Battiti, "Using mutual information for selecting features in supervised neural net learning," *IEEE Transactions on Neural Networks*, vol. 5, no. 4, pp. 537–550, 1994.

[26] D. D. Lewis, "Feature selection and feature extraction for text categorization," in *Proceedings of the Workshop on Speech and Natural Language*. Association for Computational Linguistics, 1992, pp. 212–217.

[27] H. Peng, F. Long, and C. Ding, "Feature selection based on mutual information criteria of max-dependency, max-relevance, and min-redundancy," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 27, no. 8, pp. 1226–1238, 2005.