Computer Methods and Programs in Biomedicine 187 (2020) 105253

Contents lists available at ScienceDirect

Computer Methods and Programs in Biomedicine

journal homepage: www.elsevier.com/locate/cmpb

Sleep staging algorithm based on multichannel data adding and multifeature screening

Wu Huang[a], Bing Guo[a,*], Yan Shen[b], Xiangdong Tang[c], Tao Zhang[d], Dan Li[d], Zhonghui Jiang[d]

[a] Sichuan University, Chengdu, SC, China
[b] Chengdu University of Information Technology, Chengdu, SC, China
[c] Sleep Medicine Center, West China Hospital, Sichuan University,Chengdu, SC, China
[d] Chengdu Techman Software Co.,Ltd, Chengdu, SC, China

ARTICLE INFO

Article history:
Received 2 April 2019
Revised 27 November 2019
Accepted 29 November 2019
Available online xxx

Keywords:
Feature screening
ReliefF
Signal adding
Sleep staging
SVM

ABSTRACT

Background: Sleep staging is an important basis of sleep research, which is closely related to both normal sleep physiology and sleep disorders. Many studies have reported various sleep staging algorithms of which the framework generally consists of three parts: signal preprocessing, feature extraction and classification. However, there are few studies on the superposition of signals and feature screening for sleep staging.

Objective: The objectives were to (1) Analyze the effective signal enhancement based on the superposition of homologous and heterogeneous signals, (2) Find a better way to use multichannel signals, (3) Study a systematic method of feature screening for sleep staging, and (4) Improve the performance of automatic sleep staging.

Methods: In this paper, a novel method of signal preprocessing and feature screening was proposed. In the signal preprocessing, multi-channel signal superposition was applied to improve the effective information contained in the original signal. In the feature screening, 62 features were initially selected including the time-domain features, frequency-domain features and nonlinear features, and a ReliefF algorithm was employed to select 14 features highly correlated to sleep stages from the former 62 features. Then, Pearson correlation coefficients were used to remove 2 redundant features from the 14 features to eventually obtain 12 features. Next, with the aforementioned signal preprocessing method, the 12 selected features and a support vector machine (SVM) classifier were used for sleep staging based on thirty recordings.

Results: Comparing the performance of sleep staging using different single-channel signals and different multi-channel superposition signals, we found that the best performance was obtained while using the superposition of two electroencephalogram (EEG) signals. The overall accuracies of sleep staging with 2–6 classes obtained by superposing the two EEG signals reach 98.28%, 95.50%, 94.28%, 93.08% and 92.34%, respectively, and the kappa coefficient of sleep staging with 6 classes reaches 84.07%.

Conclusions: Among the proposed sleep staging methods of using single-channel signal and multi-channel signal superposition, the best performance and consistency were obtained while using the superposition of two electroencephalogram (EEG) signals. The multichannel signal superposition method pointed out a valuable direction for improving the performance of automatic sleep staging in both theoretical research and engineering applications, and the proposed systematical feature screening method opened up a reasonable pathway for better selecting type and number of features for sleep staging.

1. Introduction

Knowledge of sleep stages has a long history. In 1929, Hans Berger [1] first recorded electroencephalogram (EEG) of the human body and found difference in EEG patterns between sleep-

* Corresponding author.
E-mail address: guobing@scu.edu.cn (B. Guo).

https://doi.org/10.1016/j.cmpb.2019.105253
0169-2607/

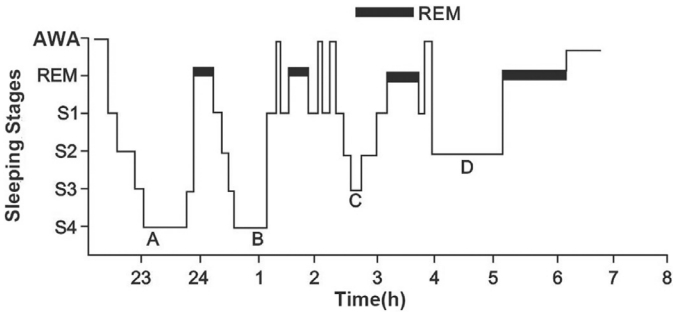


Fig. 1. Normal sleep staging structure.

ing and waking, and thus a new journey for human sleep research through EEG was initiated. In 1937, Loomis et al. [2] discovered the existence of EEG staging during sleep. After that, periodic changes of sleep depth were discovered by Dement and Kleitman [3], which laid the foundation for the most important sleep stages in sleep analysis. Furthermore, Alan Rechtschaffen and Anthony Kales [4] normalized the sleep staging rules and established a complete classification standard for sleep staging. According to the R & K sleep staging rules, the human usually has four or five basic repetitive sleep cycles throughout the night, and each sleep cycle commonly consists of six states: non-rapid eye movement (S1(N1), S2(N2), S3(N3), S4(N4)), rapid eye movement (REM), and waking (AWA). The sleep cycles were presented in Fig. 1.

Sleep stages are intrinsic nature to humans and sleep staging has important physiological significance. In recent decades, researchers found that sleep is closely related to some basic physiological activities of the human body, such as fatigue recovery, memory enhancement, immunity and endocrine [5–7].

Automatic sleep staging is a difficult problem. Agarwal et al. [8] pointed out that the subjective and inaccurate definition of sleep staging rules make it difficult to automatically classify sleep stages. According to the sleep staging rules of the American academy of sleep medicine (AASM) [9], effective interpretation of sleep staging needs to be based on EEG, electro-oculogram (EOG) and electromyogram (EMG) signals, among which EEG is the most important signal for sleep staging. An EEG signal has nonlinear and dynamic characteristics and varies in amplitude and frequency in different sleep stages. Therefore, it is not easy to accurately interpret and analyze an EEG signal.

Automatic sleep staging is of great significance. In spite of difficulties, automatic sleep staging is efficient and labor-saving, and can simultaneously eliminate the difference in subjective judgement. Therefore, many researchers were attracted to study in this field [10–46]. Flexer et al. [11] adopted the Gaussian observation hidden Markov model (GOHMM) for the three-state sleep staging using a single-channel EEG signal, and the average classification accuracy was approximately 80%. Kullback-leibler divergence (KL) was used by Zhovna et al. [12] for analyzing the sleep stages, and the classification accuracy reached 93.2%. Mendez et al. [14] used a time-varying autoregressive model to extract HRV features from a single-channel electrocardiogram (ECG) signal and used a hidden Markov chain for sleep stages classification. An artificial neural network (ANN) classification method was used by Tagluk et al. [16] to extract features from EEG, EOG and EMG signals for sleep staging, and the accuracy was approximately 74.7 ± 1.63%. Gunes et al. [17] extracted 129 features from a single-channel EEG signal, and applied the k-means clustering-based feature weighting (KMCFW) and the decision tree classification algorithms for sleep staging. In this work, the classification accuracy was improved to 82.15%. Wu et al. [19] adopted two modern adaptive signal processing technologies, the empirical intrinsic geometry and the synchro squeezing transform, to quantify the dynamic characteristics of respiratory (Resp) and the EEG signal, and its classification accuracy reaches 89.3%. Imtiaz et al. [23] extracted spectral edge frequency (SEF) features from the 8–16 Hz frequency band of a single-channel EEG signal for sleep staging. In this work, the sensitivity and specificity reached 83% and 89%, respectively. Subsequently, another study from this group [24] reported that sleep staging using a single-channel EEG signal can be achieved based on an ultralow power chip system, and the accuracy could reach 98.7%. Chen et al. [30] developed a sleep staging decision support algorithm with symbolic fusion (SF), and the overall classification accuracy reached 76%. Diykh et al. [32] extracted the similarity features of the time-domain and the structure diagram from a single-channel EEG signal, and the k-means algorithm was used for sleep staging. Finally, an average accuracy of 95.93% was achieved. Randomholm et al. [33] studied sleep staging using in-ear electrodes to record a single EEG signal. Chriskos et al. [34] processed single-channel EEG data using modern mathematical tools such as the synchronization likelihood ratio and graph theory metrics to achieve an accuracy of 89.07%. A random under sampling boosting technique (RUSBoost) was used by Hassan et al.[39] for automatic sleep mode recognition. In 2017, another study conducted by Hassan et al. [40] used decision support system to conduct sleep staging, and the accuracy of six-state sleep staging reached 92.43%. In recent years, deep learning algorithm has been gradually applied to sleep staging, and some progress has been made. Supratak et al. [41] extracted time-invariant features using Convolutional Neural Networks (CNN), and then used bidirectional Long Term Memory (BLSTM) to automatically learn the sleep staging conversion rules from the original data, and the accuracy reached 86.2%. Langkvist's et al. [42] used selective attention automatic encoder to express learning features, and the accuracy of sleep staging reached 77.7 ± 6.9%. Yuan et al. [43] used the Hybrid Self-Attentive Deep Learning Networks for sleep staging, and the accuracy was nearly 73%. Paishi et al. [44] used deep neural network to extract features from RR time series and EEG signals for sleep staging, and the classification accuracy of two-state sleep staging reached 85.51%. Sokolovsky et al. [45] used CNN deep learning neural network to automatically complete the feature discovery and classification of sleep stages, and the accuracy of sleep staging reached 81%. Mousavi et al. [46] used the sequence-to-sequence deep learning method to complete the sleep staging automatically and an accuracy of 84.26% is obtained.

There are still insufficient studies on automatic sleep staging. The above section presented many studies on classification methods for sleep staging. However, there are few studies on the superposition of signals and feature screening.

In this paper, the method of signal preprocessing and systematic features screening were studied to improve the performance of sleep staging. In terms of signal preprocessing, a multi-channel signal superposition method is used to reduce noise and improve the effective information contained in original signals, and simultaneously study the influence of signal type in different superimposed signals on the results of sleep staging. In terms of feature screening, we study systematic feature selection with an appropriate feature number for sleep staging.

This paper is divided into five parts. The first part introduces the research history, importance, related research work and author's innovation about sleep staging. The second part describes the materials and our proposed method, which includes original signal superposition and feature screening for sleep staging. The third part discusses the experimental results that show the performance of sleep staging based on signal superposition and feature screening. The fourth part presents the discussion, showing comparison between the proposed method and the latest method and pointing out the future work. The fifth part concludes this work

Table 1
Basic information of sleep data in Sleep-EDF Expanded original database.

Database	Data Classification	Number	Channel Signal	Lead	Sampling Rate
*Sleep-EDF Expanded	SCxxxxxx-PSG.edf	153	EEG	Fpz-Cz	100Hz
			EEG	Pz-Oz	100Hz
			EOG	horizontal	100Hz
			Resp	Oro-nasal	1Hz
			EMG	submental	1Hz
			Temp	rectal	1Hz
			Event	marker	1Hz
	STxxxxxx-PSG.edf	44	EEG	Fpz-Cz	100Hz
			EEG	Pz-Oz	100Hz
			EOG	horizontal	100Hz
			EMG	submental	100Hz
			Marker		10Hz

Table 2
Sizes of six sleep stages labeled by experts.

Classes/R&K Standard	Number of Epochs/30s
AWA	57329
N1	2633
N2	13589
N3	2026
N4	1677
REM	5302
Total	82556

and point out a new pathway for the study of automatic sleep staging algorithm.

2. Materials and methods

2.1. Materials

The recordings used for studying sleep staging have been obtained from the Sleep-EDF Expanded database of MIT-BIH [47]. The database contains 197 sleep recordings, and each recording contains EEG, EOG, EMG signals and event markers. The 153 SC* files (SC = Sleep Cassette) were obtained in a 1987–1991 study of age effects on sleep in healthy Caucasians aged 25–101, and the 44 ST* files (ST = Sleep Telemetry) were obtained in a 1994 study of temazepam effects on sleep in 22 Caucasian males and females, subjects had mild difficulty falling asleep. The information of recorded data is shown in Table 1.

In this study, 30 recordings were randomly selected from the healthy people's recordings for automatic sleep staging. All these original recordings were divided into 30 second epochs, which were labeled by experienced doctors according to R&K rules. This annotation serves as a reference standard of the automatic sleep staging. A total of 82,556 epochs labeled by these experts are contained in the 30 recordings, and the numbers of epochs belonging to each sleep stage is listed in Table 2.

In this paper, the experimental data set is divided into training set, verification set and test set according to the proportion of 7:2:1.

2.2. Methods

In this section, an algorithm based on multi-channel signal adding and multi-feature screening for sleep staging is proposed. The main idea is to make full use of the effective information in multi-channel original signals and systematically screen the dominant features of sleep stages to improve the performance of sleep staging. The flowchart of the algorithm is shown in Fig. 2.

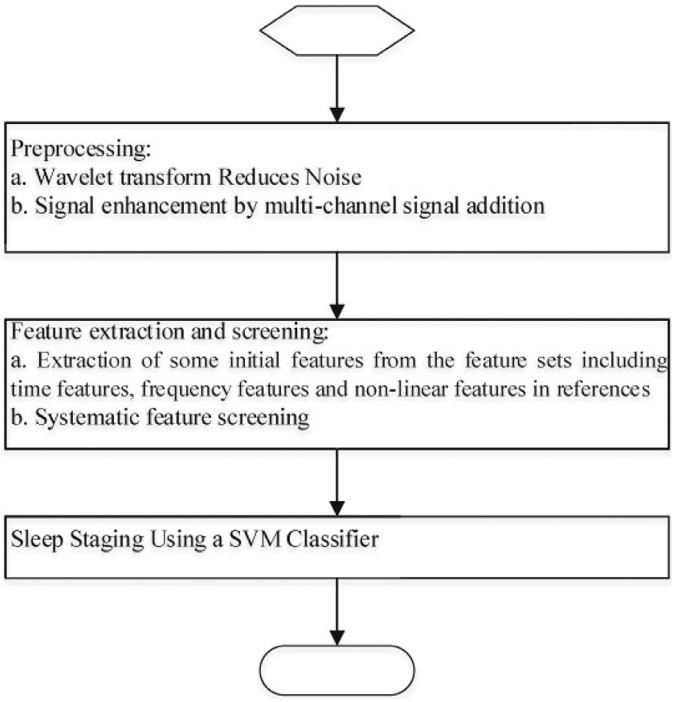


Fig. 2. The flowchart of sleep staging based on multi-channel signal adding and multi-feature screening.

In this flowchart, firstly, the white noises in the original signal are reduced and the effective sleep stage information in the multi-channel signal is enhanced by preprocessing. Then, some time-domain features, frequency-domain features and non-linear features are screened by a ReliefF algorithm and the Pearson correlation analysis. Finally, a support vector machine (SVM) classifier is applied for sleep staging.

2.2.1. Signal preprocessing

Wavelet transform-based filtering Wavelet transform-based filtering can be used to effectively reduce noise interference in the original signal. In clinical sleep staging, only the frequency spectrum of EEG signals between 0.5Hz and 30Hz is usually concerned. To reduce the noise that contributes to the frequency sub-bands less than 0.5Hz and more than 30Hz, Daubechies (db4) wavelet is used to decompose the original EEG signal in seven layers, and the wavelet coefficients in the frequency sub-bands less than 0.5Hz and more than 32Hz are set to zero. Subsequently, the decomposed signal is reconstructed by inverse transform using db4 wavelet. Here, the Mallat algorithm is used for fast wavelet decomposition.

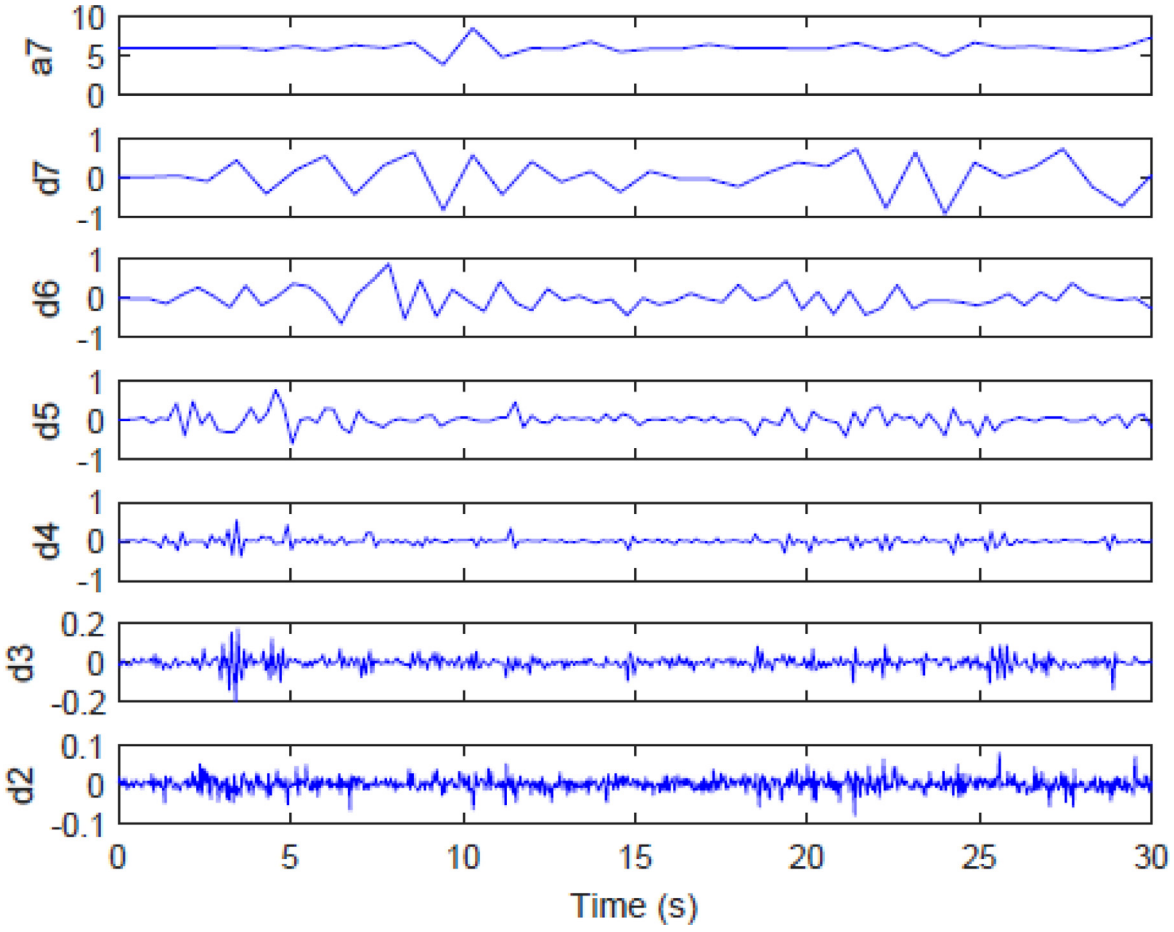


Fig. 3. Wavelet decomposition of the first data epoch from the SC4001E0-PSG.edf recording.

The Mallat wavelet decomposition algorithm is a common fast calculation algorithm using multiresolution analysis [48]. This algorithm contains the H and G wavelet decomposition filters, and the equations for wavelet decomposition are shown in Eqs. 1–3

$$A_0[x(n)] = x(n), \tag{1}$$

$$A_i[x(n)] = \sum_k H(2n-k)A_{i-1}[x(n)], \tag{2}$$

$$D_i[x(n)] = \sum_k G(2n-k)D_{i-1}[x(n)], \tag{3}$$

where $x(n)$ is the original signal and i is the decomposition level. H and G are the wavelet decomposition filters. A_i is the wavelet approximate coefficient at the i layer (low frequency), and D_i is the wavelet detail coefficients at the i layer (high frequency). At each scale of $2i$, the signal is decomposed into the wavelet approximate coefficients A_i, and the wavelet detailed coefficients D_i. For the i-level wavelet signal decomposition, the frequency ranges of node A_i and D_i are $0 \sim (f_s/2^{i+1})$ and $(f_s/2^{i+1}) \sim (f_s/2^i)$ respectively, where f_s is the sampling frequency. The effect of wavelet decomposition of an EEG signal is shown in Fig. 3.

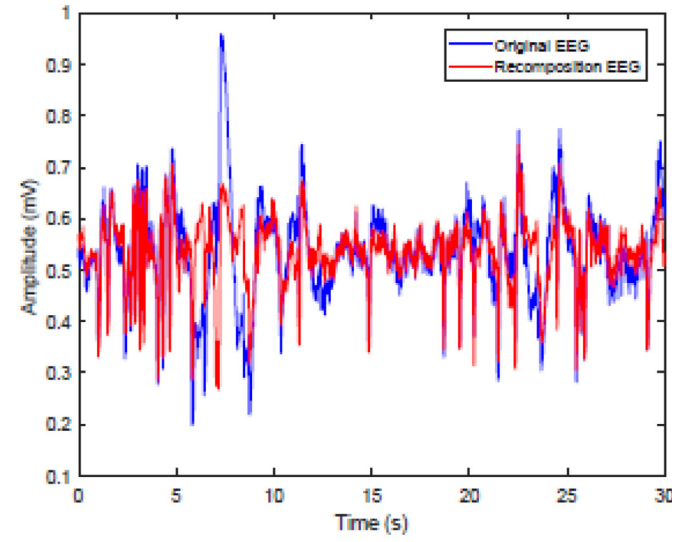
Fig. 4 (a) shows the comparison between the original EEG signal and the reconstructed EEG signal after wavelet filtering. Figure 4(b) gives the comparison of amplitude spectrum between the original signal and the reconstructed signal. As can be seen from Fig. 4, the high frequency part of the reconstructed signal above 32Hz is effectively weakened.

Original signal adding Difference of signals would impact the performance of automatic sleep staging. There are different studies focus on sleep staging using different signals, which mainly include EEG, EOG, EMG, ECG and Resp. signal [10–46]. See Table 3.

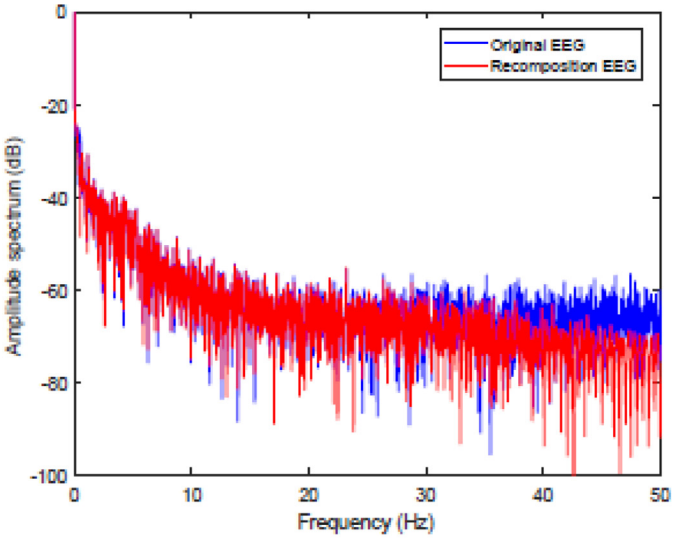
Table 3
Original signals used in different literature for sleep staging.

Order	Adding methods	Signal type	References
1	Single signal	EEG	[10,11,13,17,18,21,23,24][25] [28,33,34,36,37,39–41][46]
		Resp	[19]
		ECG	[14]
2	Multiple signals	EEG+EOG+EMG	[16,26,29,31,42,43]
		EEG+EMG	[27]
		EEG+ECG	[20,44]
		EEG+EOG	[45]
		ECG+Resp	[19,36]

In Table 3, EEG signal is the most frequently used signal, and most of the studies use an independent EEG signal but different EEG leads for sleep staging, including Fpz-Cz [12,37], Fp1-C3 [13], Fp1-A2 [23], F3-A2 [21], F4-A1 [21], C3-A2 [11,21,28,33], C4-A1 [17,18,21,25,36], Cz-A1 [23], Pz-Oz [33,39,40], O1-A2 [21,23], O2-A1[21]. These studies have found that different single EEG lead signals have different effects on sleep staging. Radha et al. [21] found that the prefrontal leaf lead (F3-A2) is more conducive to sleep staging. Diykh et al. [33] found that the use of a Pz-Oz lead in the apical and occipital regions would be better for sleep staging, which is supported by another research of Zhu et al. [22]. According to the AASM sleep staging criteria [9], central area C is considered better for determining sleep staging. Although the results



(a)



(b)

Fig. 4. Comparison of the original signal and the filtered signal (a) Comparison of the original EEG and reconstructed EEG waveforms (b) Comparison of the amplitude spectrum between the original EEG and the reconstructed EEG.

of these studies are different, they have concluded that EEG lead locations have an impact on performance of sleep staging.

How to choose and combine different signals for better sleep staging? In this paper, the adding of different channel signals is used to enhance the effective information in the original signals. Signal-adding techniques are often used to reduce white noise and enhance the effective information of signals in biological signal studies. For example, since the visual evoked potential (VEP) is very weak, the effective information of VEP directly recorded is easily overwhelmed by noise and cannot be distinguished. Therefore, to observe the VEP, the signal must be synchronously added multiple times (Fig. 5). As shown in Fig. 5(a), the effective information of the VEP without adding is not obvious. However, Fig. 5(b) shows that after 100 times adding the VEP data, the VEP characteristics become evident.

According to random signal theory, signal addition can effectively reduce white noise. This is because the white noise of different signals are random, and thus they are offset by each other after signal addition. Suppose that there is a pure random signal $x(n)$,with N observation samples. As $N \to \infty$, the sum of the observation samples tends to 0, as expressed in Eq. 4

$$\sum x(n) = 0 \quad n = 0, 1, 2, \ldots, N, N \to \infty. \tag{4}$$

Suppose there are M pure random signal sequences $x_m(n)$, As $M \to \infty$, the sum of each corresponding point of all signal sequences is 0, as expressed in Eq. 5

$$\sum x_m(n) = 0 \quad m = 0, 1, 2, \ldots, M, M \to \infty. \tag{5}$$

According to Eqs. 4 and 5, signal addition can weaken the white noise interference. In addition, the signal superposition can enhance synchronous effective information in signals. Thus, a method for adding original signals, which uses characteristics of different sleeping stages included in multichannel signals for sleep staging, is proposed in this paper. The Eq. (6) for signal addition can be expressed as

$$Ax(i) = \frac{1}{N}\sum_{k=1}^{N} x_k(i), \tag{6}$$

where N is the number of added signals. $Ax(i)$ is the average value of N different channel signals, and $x_k(i)$ are the original signals from different channels including the EEG, EOG and EMG signals. In principle, all three types of signals (EEG, EOG, and EMG) contain effective sleeping stage information, which enables the three types of signals to combine with each other for sleep staging.

Fig. 6 shows the waveform of a signal epoch with two added EEG signals. The added signal reduces the white noise in the original signal while retaining the original EEG signal characteristics.

Fig. 7 shows the superposition of different types of signals. Fig. 7(a) shows the addition of the EEG signal and the EOG signal. In Fig. 7(a), noise is weakened on the added signal, but the waveform characteristics of the EEG signal are retained. In addition, some waveform characteristics of the EOG are fused in the added signal. Fig. 7(b) shows the superposition of the EEG signal, EOG signal and EMG signal, which is similar to that showed in Fig. 7(a). Since the sampling rate of the EMG signal in the original data is too low (1 Hz), there exists a loss of information. This leads to little influence of the added EMG signal on the performance.

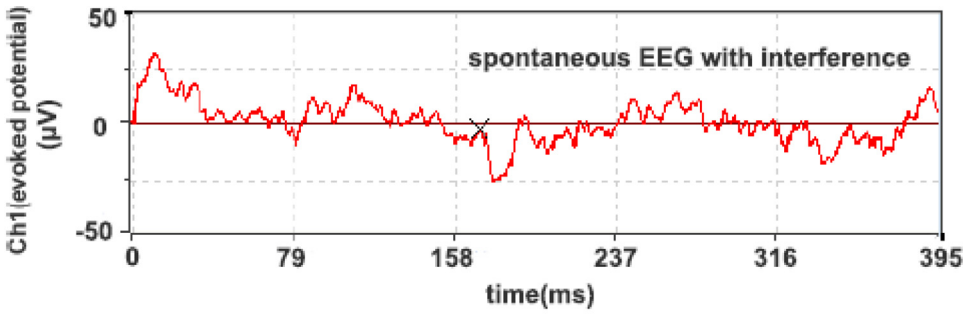
2.2.2. Feature extraction and screening

Feature extraction is important for sleep staging. There are a large number of sleep staging features in different studies, including the time-domain features., frequency-domain features and nonlinear features. The abilities of these features for sleep staging are different, and to improve the quality and efficiency of sleep staging, it is necessary to screen out irrelevant and redundant features. The flow chart for feature screening is shown in Fig. 8.

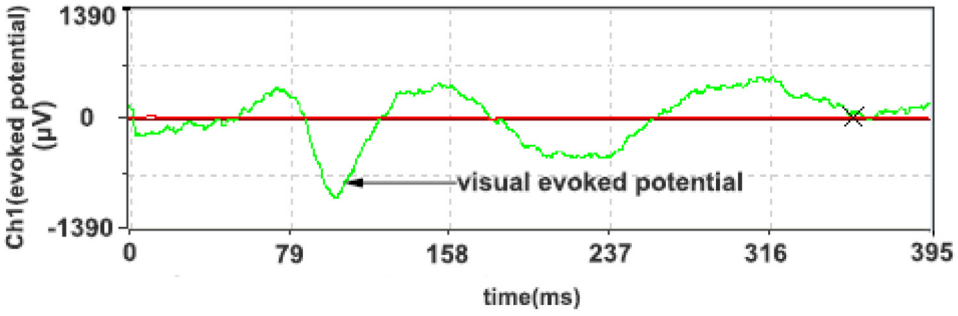
Extraction of initial features

The types and numbers of sleep stage features used in different literatures often vary greatly, ranging from using only non-linear features to using time-domain features, frequency-domain features and non-linear features; from using only a few features [25] to using hundreds of features [17], there are few systematic methods to choose the types and quantities of sleep stage features in literatures.

In order to systematically select the type and quantity of sleep staging features, 62 features related to sleep staging are preliminarily selected from the three types of feature domains mentioned in the literature, namely time-domain features, frequency-domain features and nonlinear features, as shown in Table 4.



(a)



(b)

Fig. 5. Comparison of the VEP before and after adding signals 100 times. (a) The EEG signal without adding. (b) The visual evoked potential with adding signals 100 times.

Table 4
Initial features extracted from signals according to the literature.

Order	Feature class	Features	References
1	Time Domain	Minimum, Maximum, Mean, Mode, Total Distance, Standard, Deviation, Variance, Coefficient of Variation, Skewness, Kurtosis, First Quartile, Second Quartile, Third Quartile	[2,14,21] [33,34,36] [39,40]
2	Frequency Domain	Spectral Edge Frequency (SEF), SEF50(8-16Hz), SEF95(8-16Hz),SEF95-SEF50(8-16Hz),SEF50(0.5-50Hz), SEF95(0.5-50Hz),SEF95-SEF50(0.5-50Hz), Relative Spectral Powers of δ, α, β, γ, σ, and θRhythms, Means of Absolute Values of Coefficients in D2 Wavelet (16-32HZ), D3 Wavelet (8-16HZ),D4 Wavelet (4-8HZ) and A4 Wavelet (2-4HZ), Coefficient Energy Mean in D2 Wavelet (16-32HZ), D3 Wavelet (8-16HZ),D4 Wavelet (4-8HZ) and A4 Wavelet (2-4HZ), Standard deviation of coefficient in D2 Wavelet (16-32HZ),D3 Wavelet (8-16HZ), D4 Wavelet (4-8HZ) and A4 Wavelet (2-4HZ), Mean of Absolute Value of Wavelet Coefficients in D2 /D1, D3/D2, D4/D3 and A4/D4, Relative Energy Ratio in δ/θ, δ/α, δ/β, δ/γ, θ/α, θ/σ, θ/β, θ/γ, α/σ, α/β, α/γ, δ/σ, σ/β, σ/γ and β/γ	[2,14,21] [33,34,36] [39,40] [10,21,23] [24,25,27] [31,49,50]
3	Nonlinear	Zero Crossing Rate, Sample Entropy, Permutation Entropy, Approximate Entropy, Spectral Entropy, Fractal Dimension	[10,11,13] [16,21,25] [36]

The 62 relevant features show the characteristics of sleep staging from different aspects. For example, entropy is used to indicate the signal complexity and becomes larger as the EEG signal becomes more complex. In the awake stage, the EEG signal is complex, and thus its entropy is high. In contrast, in the deep sleep stage, the EEG signal is simple, and thus its entropy is low.

Screening features with high quality using a ReliefF algorithm

The ReliefF algorithm is generally used to evaluate the relevance of features to labels [51]. Highly relevant features can commendably reflect the discrimination of samples from different classes and the similarity of samples from the same class. Quantitatively, the ReliefF algorithm outputs a weight to indicate the corresponding relevance of each input feature. The pseudo code of the ReliefF algorithm is showed in Algorithm 1.

In Algorithm 1, $W[A]$ is the weight vector corresponding to feature. The higher the weight, the better the corresponding feature. The number of iterations is denoted by m ; R_i is a sample randomly selected from the sample spaces I_1, I_2, $\cdots$, I_n, and C represents the sample classes. $Class(R_i)$ is the label of R_i. H is the set of k nearest samples (hits) sharing the same classes with R_i, and $M(C)$ is the set of k nearest samples (misses) having classes C that are different from that of R_i. The number of user-defined nearest neighbors is denoted by k. The sum of the distances between R_i and H is

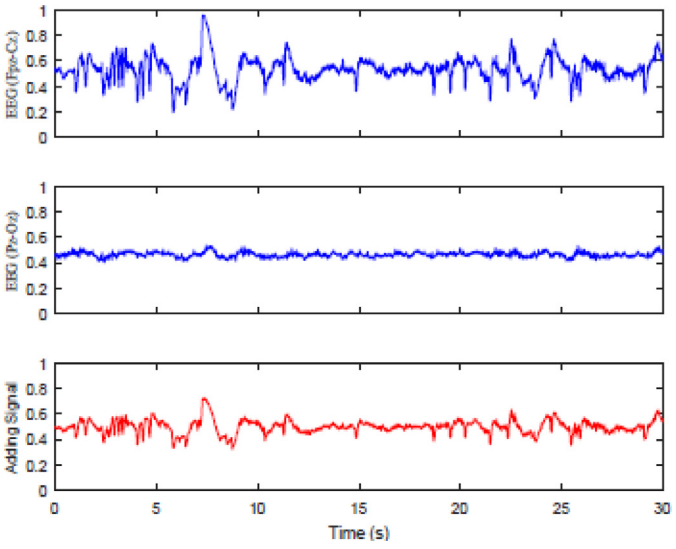


Fig. 6. Comparison of the single-channel signals (EEG (Fpz-Cz), EEG (Pz-Oz)) and their adding signals.

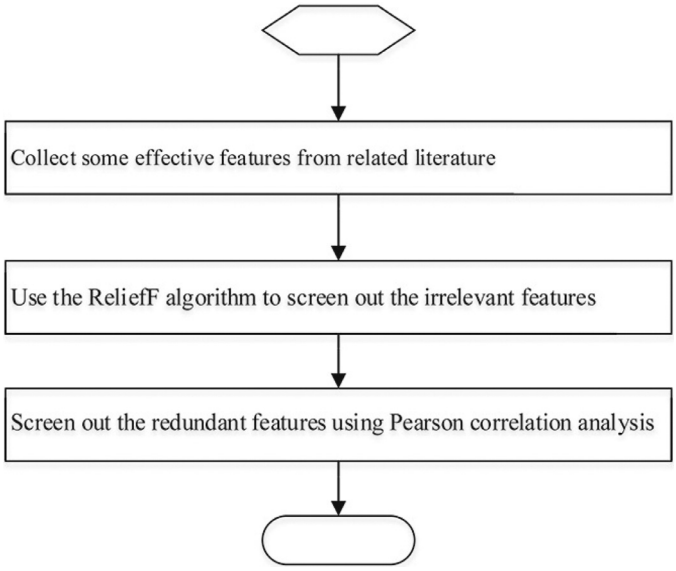


Fig. 8. The flow chart of feature screening for sleep staging.

Algorithm 1 Pseudo code of the ReliefF algorithm.

Input: a vector of attribute values and the label of each training sample
Output: the weight vector $W[A]$ estimating the quality of each feature contained in set A.
1:Set all weights $W[A]$: = 0.
2:**for** i:=1 **to** m **do begin**
3: randomly select an instance R_i.
4: find the k nearest hits H_j.
5: **for** each class $C \neq class(R_i)$ **do**
6: from class C find the k nearest misses $M_j(C)$.
7:**for** A = 1 **to** a **do**
8:$W[A] = W[A] - h1 + h2$.
9:**end**

denoted by $h1$, and the smaller $h1$, the better the algorithm performance. The sum of the distances between R_i and M is denoted by $h2$, and the larger $h2$, the better the algorithm performance. The equation for calculating $h1$ and $h2$ is shown in Eqs. 7–9

$$h1 = \sum_{j=1}^{k} \frac{diff(A, R_i, H_j)}{m \times k}, \tag{7}$$

$$h2 = \begin{array}{l} \sum_{C \neq class(R_i)} [\frac{P(C)}{1-P(class(R_i))} \times \\ \sum_{j=1}^{k} diff(A, R_i, M_j(C))]/(m \times k), \end{array} \tag{8}$$

$$diff(A, I_1, I_2) = \frac{|value(A, I_1) - value(A, I_2)|}{max(A) - min(A)}. \tag{9}$$

In Eqs. 7–9, $P(C)$ is the probability that a class C sample occupies the entire lost class sample, and $1 - P(class(R_i))$ is the sum of probabilities of non-R_i samples; $diff(A, I_1, I_2)$ is the difference function determined by the equation in Eq. 9 for calculating the distance between samples I_1 and I_2 based on feature vector A; $value(A, I)$ is the value of feature A under sample instance I.

The weights of 62 relevant features that are chosen based on other studies are calculated by a ReliefF algorithm, namely that the larger the ReliefF weight, the higher the correlation between the feature and sleep stages. Table 5 lists the first 30 features with

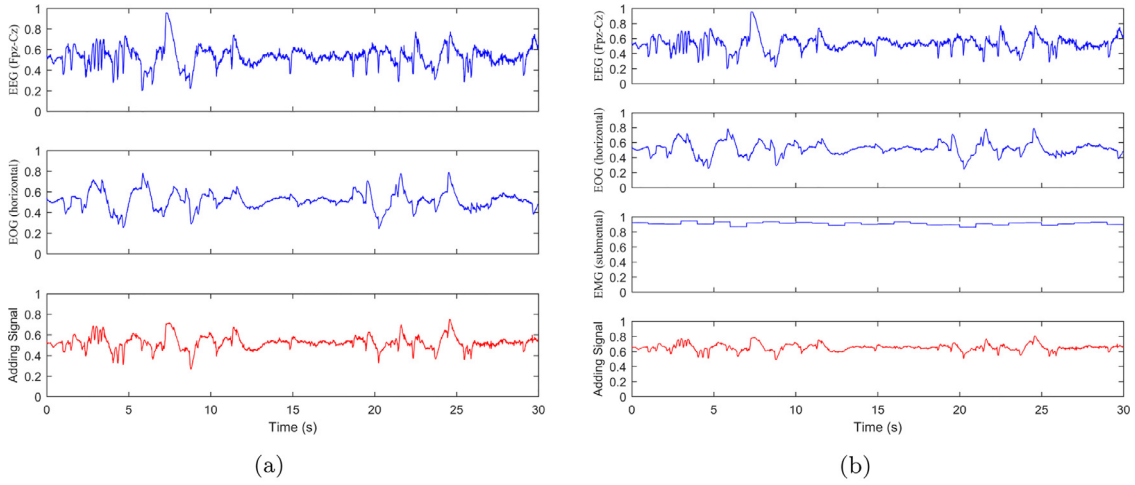


Fig. 7. Comparison of the single-channel signals (EEG (Fpz-Cz), EOG and EMG) and the multichannel adding signals. (a) EEG (Fpz-Cz) and EOG signals and their superposition signals. (b) EEG (Fpz-Cz), EOG, EMG signals and their superposition signals.

Table 5
The first 30 features with their ReliefF weights.

Order	Feature Name	ReliefF Weight
1	Permutation entropy	0.085516
2	Zero-crossing rate	0.080254
3	Fractal dimension	0.057646
4	Ratios of average absolute values of the wavelet coefficients between adjacent sub-bands: D3/D2	0.056529
5	SEF50 (8-16Hz)	0.055258
6	Minimum value	0.05264
7	Relative energy of δ rhythm	0.050256
8	Variation	0.048546
9	Standard deviation	0.048387
10	Mean	0.047813
11	SEF95 (8-16Hz)	0.045453
12	Range	0.044457
13	Third quartile	0.044344
14	Second quartile	0.04257
15	Relative energy of β rhythm	0.041595
16	SEF95-SEF50 (8-16Hz)	0.038316
17	Ratios of average absolute values of the wavelet coefficients between adjacent sub-bands:D4/D3	0.03777
18	First quartile	0.035883
19	Kurtosis	0.035539
20	Skewness	0.035482
21	Maximum value	0.035071
22	Relative energy of γ rhythm	0.03312
23	Relative energy of θ rhythm	0.030555
24	Ratios of average absolute values of the wavelet coefficients between adjacent sub-bands:A4 / D4	0.029529
25	Energy ratio β/γ	0.028282
26	Energy ratio θ/α	0.027354
27	Variance	0.024444
28	Energy ratio σ/γ	0.023688
29	Energy ratio θ/β	0.021878
30	Energy ratio θ/σ	0.021417

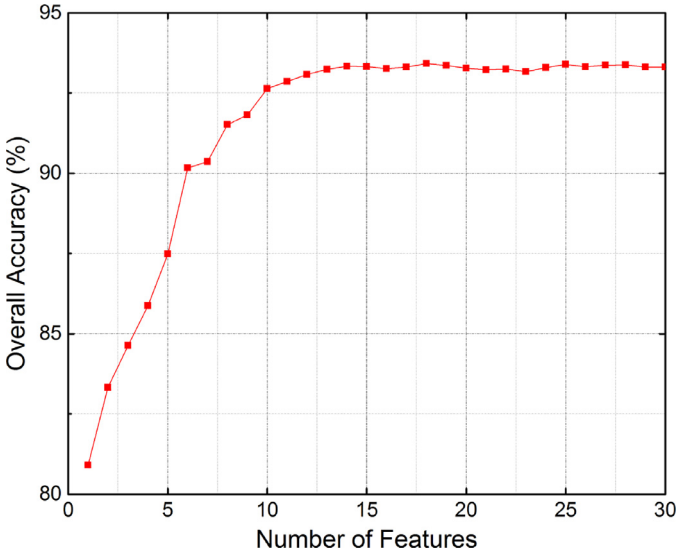


Fig. 9. Overall accuracy of sleep staging versus number of features selected by ReliefF.

their ReliefF weights. The ReliefF weights of the features after the 30th are very small, indicating that these features would have little positive impact on sleep staging.

There exists a certain relationship between the number of screened features and the performance of sleep staging. To investigate the relationship, we plot the overall accuracy of sleep staging versus the number of features from 1 to 30 screened by the ReliefF algorithm, as shown in Fig. 9. Fig. 9 show that different overall accuracy is obtained while using different number of screened features. In addition, when the number of classified features is more than 14, the overall accuracy of sleep staging tends to be stable, and adding the number of features has little influence on the accuracy of sleep staging. Therefore, the first 14 features obtained by the ReliefF algorithm are screened.

Elimination of redundant features using Pearson correlation coefficients

Although the above ReliefF algorithm can screen relevant features, it cannot screen redundant features. When there is a strong correlation between these features, redundancy is generated. Deleting redundant features is valuable for improving the efficiency of sleep staging.

In this paper, the correlation between features is calculated by the Pearson correlation coefficients. The formula for calculating the Pearson correlation coefficients is shown in Eq. 10

$$\rho(X,Y) = \frac{\mathrm{E}[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \times \sigma_Y}. \tag{10}$$

In Eq. (10), μ is the average value and σ is the standard deviation. E is the mathematical expectation. If a Pearson correlation coefficient of a feature pair whose absolute value is greater than or equal to the threshold 0.95, the feature pair is considered highly relevant, and the features whose ReliefF weights are relatively low can be removed.

The Pearson correlation coefficients between the 14 features are calculated by Eq. 10. The feature number in Table 6 is the same as the sorting result number in Table 5. Table 6 shows that only two Pearson correlation coefficients of the feature pairs (i) standard deviation and variation (ii) mean and second quartile are greater than or equal to the threshold 0.95. Therefore, two redundant features, the standard deviation and the second quartile whose ReliefF weights are relatively low, are removed from the 14 features.

Table 6
Pearson correlation coefficients between the first 14 features.

Order	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	1.00	0.67	0.37	-0.94	0.41	-0.36	-0.25	0.18	0.18	-0.03	0.62	0.31	0.03	0.00
2	0.67	1.00	0.79	-0.63	0.51	-0.07	-0.72	-0.12	-0.12	-0.01	0.41	0.03	-0.06	0.01
3	0.37	0.79	1.00	-0.28	0.36	0.21	-0.83	-0.34	-0.34	0.01	0.15	-0.26	-0.11	0.02
4	-0.94	-0.63	-0.28	1.00	-0.50	0.42	0.14	-0.26	-0.26	0.03	-0.76	-0.37	-0.06	0.01
5	0.41	0.51	0.36	-0.50	1.00	-0.15	-0.23	0.07	0.07	0.06	0.69	0.16	0.08	0.07
6	-0.36	-0.07	0.21	0.42	-0.15	1.00	-0.23	-0.85	-0.83	0.27	-0.33	-0.92	-0.10	0.25
7	-0.25	-0.72	-0.83	0.14	-0.23	-0.23	1.00	0.32	0.32	0.00	0.01	0.26	0.11	-0.01
8	0.18	-0.12	-0.34	-0.26	0.07	-0.85	0.32	1.00	**1.00**	-0.03	0.23	0.91	0.41	-0.01
9	0.18	-0.12	-0.34	-0.26	0.07	-0.83	0.32	1.00	1.00	0.03	0.23	0.91	0.46	0.05
10	-0.03	-0.01	0.01	0.03	0.06	0.27	0.00	-0.03	0.03	1.00	0.01	0.02	0.89	**1.00**
11	0.62	0.41	0.15	-0.76	0.69	-0.33	0.01	0.23	0.23	0.01	1.00	0.32	0.10	0.03
12	0.31	0.03	-0.26	-0.37	0.16	-0.92	0.26	0.91	0.91	0.02	0.32	1.00	0.40	0.05
13	0.03	-0.06	-0.11	-0.06	0.08	-0.10	0.11	0.41	0.46	0.89	0.10	0.40	1.00	0.90
14	0.00	0.01	0.02	0.01	0.07	0.25	-0.01	-0.01	0.05	1.00	0.03	0.05	0.90	1.00

2.2.3. SVM for sleep staging

In this paper, a support vector machine (SVM) classifier is used to classify sleep stages. An SVM can be transformed into a quadratic optimization problem. Therefore, the global optimal solution can be theoretically obtained. In addition, the objective function of an SVM is optimized according to the principle of structural risk minimization; thus, an SVM has comparatively good generalization ability.

In this paper, SVM is used to construct an one-vs-one multiclass classifier to classify six sleep states [52,53]. The equations with the used SVM are expresses as Eqs. 11 to 13. Eq. 11 expresses the maximum objective function of SVM

$$\begin{aligned} \max_{\alpha} \quad & \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j \kappa(x_i, x_j) \\ \text{s.t.} \quad & C \geq \alpha_i \geq 0, i = 1, 2, \ldots, n \\ & \sum_{i=1}^{n} \alpha_i y_i = 0. \end{aligned} \tag{11}$$

In Eq. 11, x_i and x_j refer to the eigenvalues of the ith and the jth samples, respectively, y_i and y_j are labels for the ith and the jth samples, respectively. α_i and α_j are the parameters to be optimized, and C is the penalty coefficient. n is the number of training samples. The kernel function $\kappa(x_i, x_j)$ is chosen as a radial kernel function, which can be expressed as

$$\kappa(x_i, x_j) = \exp\left(-\frac{||x_i - x_j||^2}{2\sigma^2}\right) \tag{12}$$

where σ^2 is the nuclear parameter, which can control the width of the radial kernel function. The classification decision function can be expressed as

$$f(x) = sign\left[\sum_{i=1}^{n} \alpha_i^* y_i \kappa(x, x_i) + b^*\right] \tag{13}$$

$$b^* = y_j - \sum_{i=1}^{n} \alpha_i^* y_i \kappa(x_i, x_j) \tag{14}$$

where α_i^* is the optimal solution of α^i.

In order to improve the classification performance of SVM, the training set and verification set are used in the training process to optimize the hyper-parameters (C, σ^2) of SVM by the cross-validation.

3. Results

3.1. Performance of sleep staging using a single selected feature

To verify the effectiveness of these selected features for sleep staging, we independently investigate each selected feature. Concretely, the performance of sleep staging will be investigated based on a single feature using the same 30 subjects and a fixed SVM classifier.We first plot the boxplots of each selected feature on six sleep stages, as shown in Fig. 10.

As shown in Fig. 10(a), the difference among the sleep stages is significant when the Permutation entropy feature is used, indicating that this feature has a good ability to classify sleep stages. In contrast, Figs. 10 (i)–(l) show that the features whose ReliefF weights are low is not as well as the features with high weights. Table 7 lists the overall accuracies and Kappa coefficients of the final 12 selected features, where the Kappa coefficient is used to measure the consistency of the classification.

As shown in Table 7, although the 12 selected features are all effective features, the overall accuracy and Kappa coefficient of sleep staging using a single feature are relatively low, which are not more than 80.76% and 56%, respectively. This is because a single feature could discriminate a part of sleep stages, such as N1, N2, N3 and N4, but hard to discriminate the rest of the sleep stages, such as REM and N4, which may result in a poor overall performance. Although using a single feature may suffer this difficulty, but their can complement each other while using them together for sleep staging. Therefore, to improve the overall performance, it is necessary to use multi-features for sleep staging.

3.2. Performance of sleep staging based on the proposed signal adding methods

In this section, we compare the performance of sleep staging using the single EEG, EMG, and EOG signals and different multichannel superposition signals. The 10-fold cross-validation is used to predict the labels of test samples, and the average of ten predicted results is used as the final results. The performances of the six-state sleep staging using different single signals and multichannel superposition signals are shown in Table 8 and Fig. 11. In Table 8, MSen, MSpe, MF1 and MAUC denote the macro averages of sensitivity, specificity, F1-score and AUC of the six sleep stages, respectively.

As shown in Table 8 and Fig. 11, when using different single-channel signals for sleep staging, it is clear that the best classification performance is achieved by using the EEG signals, followed by that using the EOG signal. When using the EMG signal, the classification performance achieved is the worst, which may be due to the information loss caused by the low 1Hz sampling rate of the EMG signal in the original sleep data. When using different multichannel superposition signals for sleep staging, using the EEG1+EEG2 signal achieves the highest overall accuracy 92.34% and the highest Kappa coefficient 84.07%. When the EEG signal is added to the EOG and EMG heterogeneous signals, the classification accuracy is not significantly improved, and the Kappa coefficient is reduced, indicating that the classification performance becomes worse. It is

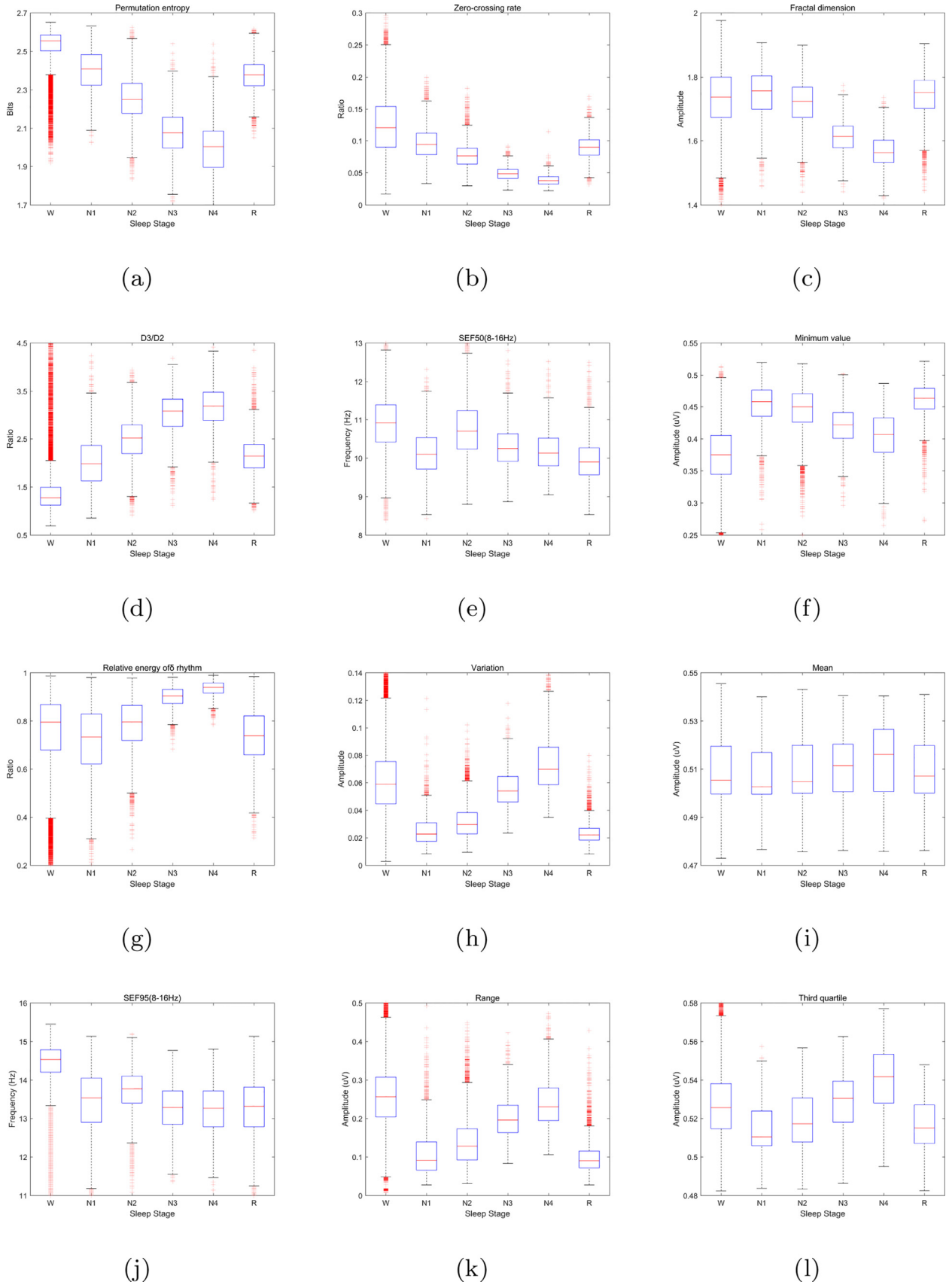


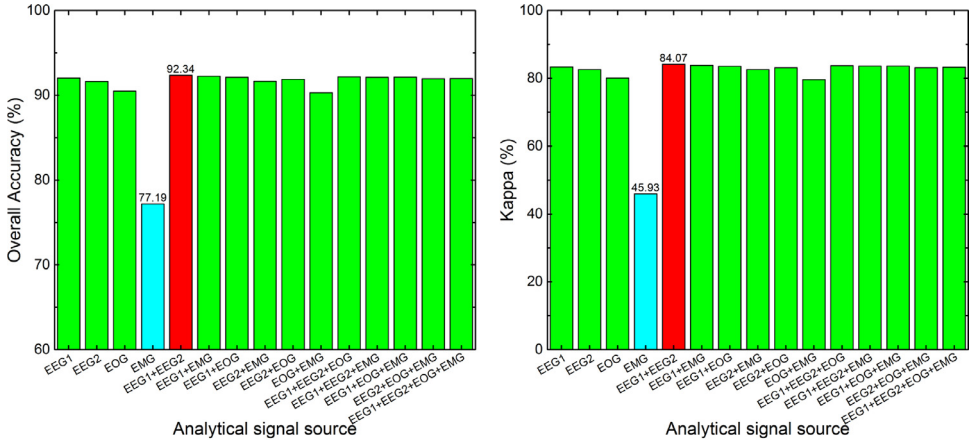
Fig. 10. Samples of each selected feature distributed on the six sleep stages. The selected feature include (a) Permutation entropy, (b)Zero-crossing rate (c) Fractal dimension (8-16Hz), (d) D3/D2, (e) SEF50 (8-16Hz), (f) Minimum value, (g) Relative energy of δ rhythm, (h) Variation, (i) Mean, (j) SEF95 (8-16Hz), (k) Range and (l) Third quartile.

Table 7
Overall accuracies and Kappa coefficients of sleep staging using single selected features.

Order	Feature Name	Overall Accuracy(%)	Kappa Coefficient(%)
1	Permutation entropy	80.76	56.00
2	Zero-crossing rate	70.37	8.21
3	Fractal dimension	68.68	0
4	Ratios of average absolute values of the wavelet coefficients between adjacent sub-bands:D3/D2	79.63	54.68
5	SEF50 (8-16Hz)	65.91	0
6	Minimum value	74.71	38.81
7	Relative energy of δ rhythm	69.73	0
8	Variation	72.77	32.88
9	Mean	68.46	0
10	SEF95 (8-16Hz)	72.90	34.75
11	Range	74.39	37.56
12	Third quartile	68.70	0

Table 8
The performance of six-state sleep staging based on different single-channel signals and multichannel superposition signals.

No.	Analytical Signal	Overall Accuracy(%)	Kappa(%)	MSen(%)	MSpe(%)	MF1(%)	MAUC
1	EEG1(Fpz-Cz)	92.04	83.32	71.38	97.91	72.77	0.96
2	EEG2 (Pz-Oz)	91.63	82.54	68.94	97.95	70.10	0.97
3	EOG	90.48	80.08	67.17	97.53	68.84	0.96
4	EMG	77.19	45.93	28.74	91.47	28.85	0.73
5	EEG1+EEG2	92.34	84.07	72.48	98.21	73.58	0.97
6	EEG1+EMG	92.24	83.82	72.68	98.05	73.93	0.97
7	EEG1+EOG	92.10	83.52	72.50	98.01	73.80	0.97
8	EEG2+EMG	91.65	82.59	68.89	97.98	70.01	0.96
9	EEG2+EOG	91.88	83.07	70.32	98.05	71.67	0.97
10	EOG+EMG	90.28	79.58	65.21	97.43	67.20	0.95
11	EEG1+EEG2+EOG	92.17	83.70	71.54	98.15	72.83	0.97
12	EEG1+EEG2+EMG	92.09	83.56	71.51	98.16	72.52	0.97
13	EEG1+EOG+EMG	92.12	83.56	72.19	98.00	73.56	0.97
14	EEG2+EOG+EMG	91.94	83.08	68.37	97.94	70.54	0.95
15	EEG1+EEG2+EOG+EMG	91.96	83.25	70.76	98.07	72.01	0.97



(a) (b)

Fig. 11. The overall accuracies and Kappa coefficients of six-state sleep staging are compared between different single-channel signals and multichannel superposition signals. (a) Overall Accuracy comparison; (b) Kappa coefficient comparison.

probably because there exists difference of phases between these heterogeneous signals that results in the weakening of the effective information when they are superposed, thereby reducing the overall classification performance.

Fig. 12 compares overall accuracies of sleep staging with different numbers of classes based on different single-channel signals and multichannel superposition signals. As can be seen from Fig. 12, the curves of overall accuracies with different numbers of classes present the same trend for all the signals. In addition, by comparing the overall accuracies using different single-channel signals and multichannel superposition signals for sleep staging, we found that using the EEG1+ EEG2 signal achieves the best performance of sleep staging from 2 calsses to 6 classes.Tables 9–13 present the confusion matrix obtained when the EEG1+EEG2 signal is used for 2–6 states sleep staging.

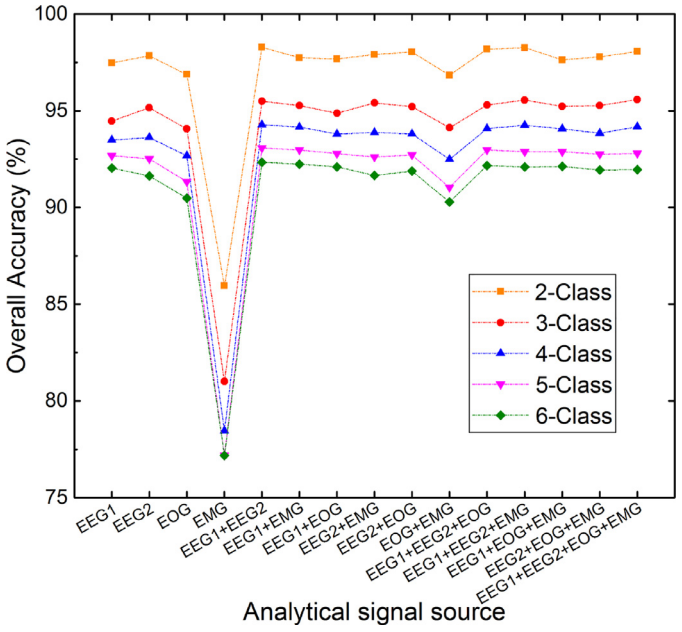


Fig. 12. The overall accuracies of 2–6 classes sleep staging are compared between different single-channel signals and multichannel superposition signals.

Table 9
Confusion matrix of EEG1+EEG2 for 2-state sleep staging.

True/Predicted	AWA	N1-N4,REM	Sen(%)
AWA	56783	546	99.05
N1-N4,REM	875	24352	96.53

Table 10
Confusion matrix of EEG1+EEG2 for 3-state sleep staging.

True/Predicted	AWA	N1-N4	REM	Sen(%)
AWA	56783	404	142	99.05
N1-N4	675	18047	1203	90.57
REM	200	1092	4010	75.63

Table 11
Confusion matrix of EEG1+EEG2 for 4-state sleep staging.

True/Predicted	AWA	N1-N2	N3-N4	REM	Sen(%)
AWA	56783	395	9	142	99.05
N1-N2	616	13972	433	1201	86.13
N3-N4	59	573	3069	2	82.88
REM	200	1088	4	4010	75.63

Table 12
Confusion matrix of EEG1+EEG2 for 5-state sleep staging.

True/Predicted	AWA	N1	N2	N3-N4	REM	Sen(%)
AWA	56783	264	131	9	142	99.05
N1	433	981	638	3	578	37.26
N2	183	357	11996	430	623	88.28
N3-N4	59	3	570	3069	2	82.88
REM	200	367	721	4	4010	75.63

Table 13
Confusion matrix of EEG1+EEG2 for 6-state sleep staging.

True/Predicted	AWA	N1	N2	N3	N4	REM	Sen(%)
AWA	56783	264	131	9	0	142	99.05
N1	433	981	638	3	0	578	37.26
N2	183	357	11996	399	31	623	88.28
N3	29	3	536	1173	284	1	57.90
N4	30	0	34	325	1287	1	76.74
REM	200	367	721	3	1	4010	75.63

3.3. Hypnogram

Hypnogram is a graphical representation of the final outcome of sleep staging. Fig. 13 shows the hypnograms of four subjects from the Sleep-EDF Expanded database of MIT-BIH, in which the results obtained by using the proposed algorithm (red curve) and those annotated by these experts (blue curve) are compared. The black small circles on the red curves represent the samples that are correctly predicted by the proposed algorithm, and the green solid circles on the red curves represent the samples that are wrongly predicted.

As can be seen from Fig. 13, the hypnogram annotated by experts in each sleep data contains 3–5 complete sleep cycles. Except for the sleep data in Fig. 13(b) that only contains few N4 stage, the first two sleep cycles in the rest of sleep data contain more N4 stage and few deep sleep stages contained in the subsequent sleep cycle(s), which is consistent with the normal hypnogram. The hypnograms plotted by the proposed algorithm are almost consistent with the expert annotation, except for less samples that are predicted as the wrong sleep stages. Figs. 13(a)to –(d) show that no samples are wrongly predicted as N1 stage, and very few samples are wrongly predicted as N4 stage.

Generally, the above results show that the best performance of sleep staging can be obtained by adding two EEG signals. Compared with using a single-channel EEG signal for sleep staging, using multi-channel EEG signals can achieve better performance of sleep staging and backup each other between signals, but this method may reduce computational efficiency and cause inconvenience, especially in portable sleep staging devices. In contrast, using single-channel EEG signals to classify sleep stages would be more convenient.

4. Discussion

There are many studies on sleep staging which usually focus on the classification methods [10–46]. Some studies adopted the traditional time-frequency analysis method for sleep staging [17–38], and some other studies adopted the deep learning neural network for sleep staging [41–46,54–56]. Table 14 compares the classification accuracies obtained by the proposed method and some methods of sleep staging in the last 5 years. As can be seen from Table 14, the overall accuracies of 2–6 state sleep staging obtained by using the proposed method are next to and very close to those by Hassan et al. [35]. However, it should be noticed that the metrics used in these methods are not exactly the same. For example, we used the overall accuracy as the metric to assess the performance of sleep staging, but Diykh et al. [33] and Hassan team [40] used the average value of accuracies of all classes as the metric.

The study on the enhancement of the original data itself plays an important role in the improvement of sleep staging. This paper attempts to improve the overall accuracy of sleep staging from the very beginning by using the original signal adding method. Thus study found that adding the homogeneous signals such as EEG+EEG, could improve the performance of sleep staging compared with that using a single-channel signal. However, adding the heterogeneous signals, such as EEG+EOG or EEG+EOG+EMG, did not improve the performance of sleep staging. This may be due to the loss of effective information of added signals caused by the phase differences of heterogeneous signals. Currently, we can only study two EEG signals that are provided in the Sleep-EDF Expanded database. But in the future, we may be able to study the signal enhancement by adding different leads of EEG signals if more EEG data are provided. In addition, because the class imbalance exists in the sleep data, how to balance them in preprocessing is also a valuable research topic.

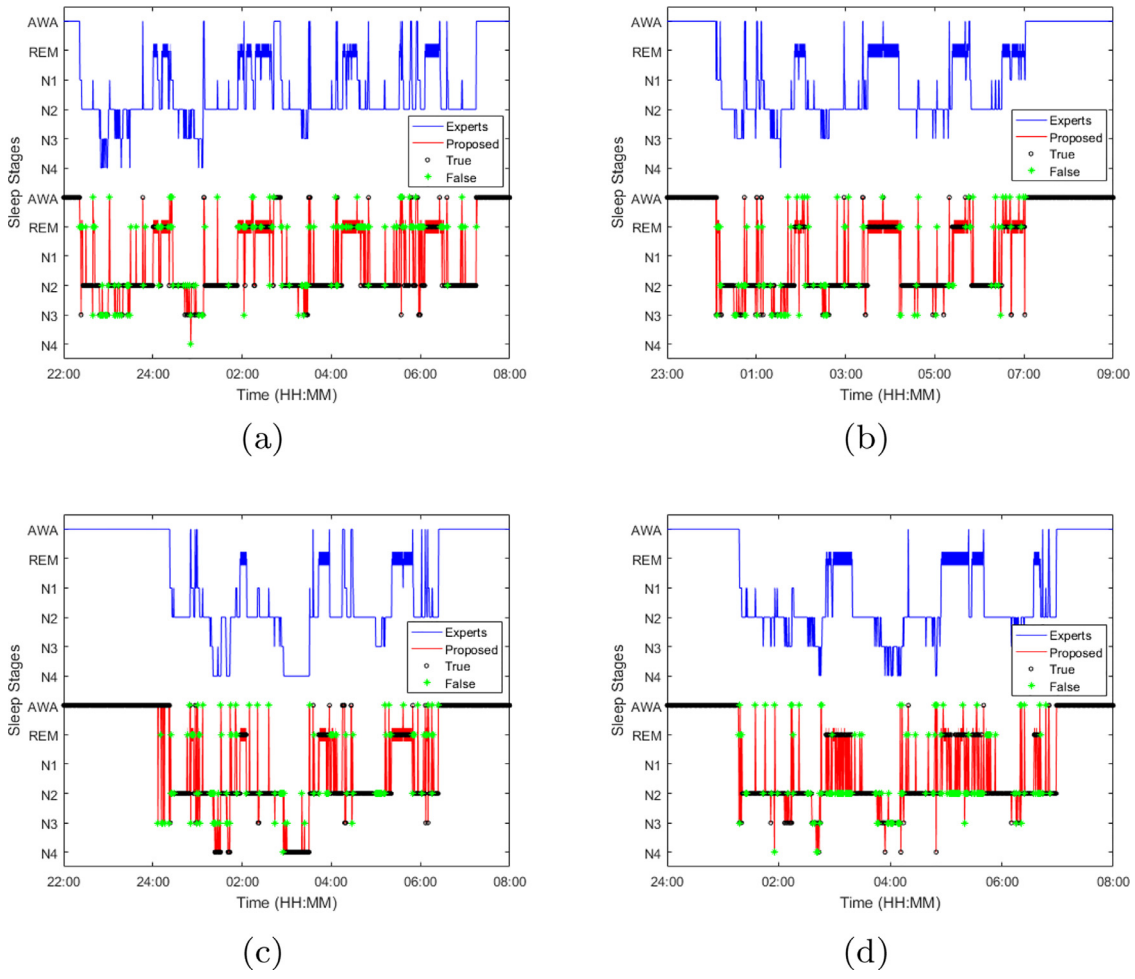


Fig. 13. Comparison of hypnograms ploted by the proposed algorithm and marked by experts. (a) Data SC4012E0-PSG (b) Data SC4061E0-PSG (c) Data SC4112E0-PSG (d) SC4031E0-PSG.

Table 14
Comparison of accuracy (%) between the proposed method and the latest methods.

Methods	Channels	2 Classes	3 Classes	4 Classes	5 Classes	6 Classes
Liu et al. [30]	EEGs	–	–	–	80.47	–
Chen et al. [31]	EEGs, EOGs, EMG	–	–	–	76.00	–
Diykh et al. [33]	EEG	–	–	–	–	95.93
Stochholm et al. [34]	EEG	94.64	–	–	82	–
Hassan et al. [35]	EEG	97.73	93.55	91.2	90.11	88.62
Chriskos et al. [36]	EEGs	–	–	89.07	–	–
Sertbas et al. [37]	EEG	–	–	–	86.66	–
Beattie et al. [38]	3D accelerometer, PPG	–	–	69	–	–
Hassan et al. [39]	EEG	98.15	94.23	92.66	83.49	88.07
Hassan et al. [40]	EEG	99.75	96.55	94.36	93.69	92.43
Supratak et al. [41]	EEG	–	–	–	82.00	–
Langkvist et al. [42]	EEGs, EOGs, EMG	–	–	–	77.70	–
Yuan et al. [43]	EEGs, EOGs, EMG, et al.	–	–	–	73.28	–
Tripathy et al. [44]	EEG, ECG	85.51	–	–	73.70	–
Sokolovsky et al. [45]	EEGs, EOG	–	–	–	81.00	–
Mousavi et al. [46]	EEG	–	–	–	84.26	–
Michielli et al. [54]	EEG	–	–	90.8	86.74	–
Sors et al. [55]	EEG	–	–	–	87	–
Yildirim et al. [56]	EEG + EOG	98.06	94.64	92.36	91.22	91.00
Proposed Method	EEG1+ EEG2	98.28	95.50	94.28	93.08	92.34

Feature selection is another important and worthwhile factor that affects the performance of sleep staging. In this paper, 62 relevant features were studied, among which the features for sleep staging were screened by using a ReliefF algorithm and the Pearson correlation coefficient. In this study, we found that different features extracted from the original data have different influence on sleep staging. Due to the complexity of EEG signals, the extracted features and the classification methods used are related to the original data, which is why it is difficult to unify the features and classification methods. Therefore, finding more generalized features for sleep staging based on different original data is another direction that needs to be studied. In addition, how to

screen the optimal features with an appropriate feature number to improve the performance of sleep staging is another direction that need to be studied in the future. Finally, how to construct new and effective features for sleep staging, such as the features based on graph theory, is also a direction that needs to be studied.

5. Conclusion

In this paper, we proposed a multi-channel signal adding method for sleep staging. The results showed that a good performance was obtained while using the proposed method, and in six-state sleep staging, the highest overall classification accuracy of 92.34% was obtained based on the superposition of two EEG signals. Using the multi-channel signal superposition method for sleep staging has the theoretical and engineering significance. Theoretically, the adding signals can reduce the white noise interference and enhance the effective information in signals. In engineering, superposition signals can be backed up each other automatically, which lays a foundation for automatic sleep staging analysis. In addition, a ReliefF algorithm was used to systematically screen the extracted features for sleep staging. The results showed that, when the number of features was selected to a certain threshold, increasing the number of features has limited improvement on the overall accuracy. Therefore, selecting appropriate types and number of effective features could improve the accuracy and efficiency of algorithms for sleep staging.

Conflict of interest statement

The authors declare that they have NO affiliations with or involvement in any organization or entity with any financial or non-financial interest in the subject matter or materials discussed in this manuscript.

Acknowledgments

This work was supported in part by the State Key Program of National Natural Science Foundation of China under grant no.61332001; The National Natural Science Foundation of China under grant no. 61772352, 61472050; the Science and Technology Planning Project of Sichuan Province under grant no. 2019YFG0400, 2018GZDZX0031, 2018GZDZX0004, 2017GZDZX0003, 2018JY0182, 19ZDYF1286.

References

[1] H. Berger, Uber das elektroenkelphalogramm des mensen, Arch Pyschiatr Nervenkr 87 (1929). 527-70
[2] A.L. Loomis, N. Harvey, G.A. Hobart, Cerebral states during sleep, as studied by human brain potentials, J. Exp. Psychol 21 (2) (1937). 127–44
[3] W. Dement, N. Kleitman, Cyclic variations in EEG during sleep and their relation to eye movements' body motility and dreaming, Electroencephalogr. Clin. Neurophysiol. 9 (4) (1957) 673–690.
[4] A. Rechtschaffen, A. Kales, A manual of standardized terminology: Techniques and scoring system for sleep stages of human subjects,los angeles, Brain Information Service/Brain Research Institute, UCLA, 1968.
[5] L. Besedovsky, H.V.V. Ngo, S. Dimitrov, et al., Auditory closed-loop stimulation of EEG slow oscillations strengthens sleep and signs of its immune-supportive function, Nat. Commun. 8 (1) (2017) 1984.
[6] S. Diekelmann, J. Born, The memory function of sleep, Nat. Rev. Neurosci. 11 (2) (2010) 114–126.
[7] L. Xie, H. Kang, Q. Xu, et al., Sleep drives metabolite clearance from the adult brain, Science 342 (6165) (2013) 373–377.
[8] R. Agarwal, J. Gotman, Computer-assisted sleep staging, IEEE T. Bio-med. Eng. 48 (12) (2001) 1412.
[9] C. Iber, S. Ancoli-Israel, A. Chesson, et al., AASM manual for the scoring of sleep and associated events:, 2015. http://www.aasmnet.org/scoringmanual/, Accessed.
[10] J. Fell, J. Rijschke, K. Mann, et al., Discrimination of sleep stages: a comparison between spectral and nonlinear EEG measures, Electroencephalogr. Clin. Neurophysiol. 98 (5) (1996) 401–410.
[11] A. Flexer, G. Gruber, G. Dorffner, A reliable probabilistic sleep stager based on a single EEG signal, Artif. Intell. Med. 33 (3) (2005) 199–207.
[12] I. Zhovna, I.D. Shallom, Automatic detection and classification of sleep stages by multichannel EEG signal modeling, in: 2008 30th Annual International IEEE EMBS Conference,August, volume 20–24, 2008, pp. 2665–2668.
[13] A. Piryatinska, G. Terdik, W. Woyczynski, et al., Automated detection of neonate EEG sleep stages, Comput. Meth. Prog. Bio. 95 (1) (2009) 31–46.
[14] M.O. Mendez, M. Matteucci, S. Cerutti, et al., Sleep staging classification based on HRV: time-variant analysis, Int. Conf. IEEE Eng.Med. Biol. Soc. (2009) 9–12.
[15] G. Fang, C. Zhang, Y. Xia, et al., The effect of different EEG derivations on sleep staging in rats: the frontal midline-parietal bipolar electrode for sleep scoring, Physiol. Meas. 30 (7) (2009) 589–601.
[16] M.E. Tagluk, N. Sezgin, M. Akin, Estimation of sleep stages by an artificial neural network employing EEG, EMG and EOG, J. Med. Syst. 34 (4) (2010) 717–725.
[17] S. Gunes, K. Polat, S. Yonsunkaya, Efficient sleep stage recongnition system based on EEG signal using k-means clustering based feature weighting, Expert Syst Appl 37 (12) (2010) 7922–7928.
[18] B. Koley, D. Dey, An ensemble system for automatic sleep stage classification using single channel EEG signal, Comput. Biol. Med. 42 (12) (2012) 1186–1195.
[19] H. Wu, R. Talmon, Y.L. Lo, Assess sleep stage by modern signal processing techniques, IEEE T. Bio-med. Eng. 62 (4) (2015) 1159–1168.
[20] J.R. Yeh, C.K. Peng, M.T. Lo, et al., Investigating the interaction between heart rate variability and sleep EEG using nonlinear algorithms, J. Neurosci. Meth. 219 (2) (2013) 233–239.
[21] M. Radha, G. Garcia-Molina, M. Poel, et al., Comparison of feature and classifier algorithms for online automatic sleep staging based on a single EEG signal, Eng. Med. Biol. Soc. 1 (2014) 1876–1880.
[22] G. Zhu, Y. Li, P.P. Wen, Analysis and classification of sleep stages based on difference visibility graphs from a single-channel EEG signal, IEEE J. Biomed. Health 18 (6) (2014) 1813–1821.
[23] S.A. Imtiaz, E.R. Villegas, A low computational cost algorithm for REM sleep detection using single channel EEG, Ann. Biomed. Eng. 42 (11) (2014) 2344–2359.
[24] S.A. Imtiaz, Z. Jiang, E. Rodriguez-Villegas, An ultralow power system on chip for automatic sleep staging, IEEE J. Solid-st. Circ. 52 (3) (2017) 822–833.
[25] Z. Liu, H. Zhang, H. Zhao, et al., Study on sleep staging based on EEG signals, Chinese J. Biom. Eng. 34 (6) (2015) 693–700.
[26] T. Lajnef, S. Chaibi, P. Ruby, Learning machines and sleeping brains: automatic sleep stage classification using decision tree multi-class support vector machines, J. Neurosci. Meth. 250 (2015) 94–105.
[27] S.F. Liang, C.E. Kuo, F.Z. Shaw, et al., Combination of expert knowledge and a genetic fuzzy inference system for automatic sleep staging, IEEE T. Bio-med. Eng. 63 (10) (2015) 1–11.
[28] M. Younes, M. Ostrowski, M. Soiferman, et al., Odds ratio product of sleep EEG as a continuous measure of sleep state, Sleep 38 (4) (2015) 641–654.
[29] S. Xiao, B. Wang, J. Zhang, et al., An improved k-means clustering algorithm for sleep stages classification, Soc. Instrum. Control Eng.Jpn. 7 (2015) 1222–1227.
[30] X. Liu, J. Shi, Y. Tu, et al., Joint collaborative representation based sleep stage classification with multi-channel EEG signals, Eng. Med. Biol. Soc. (2015).
[31] C. Chen, X. Liu, A. Ugon, Symbolic fusion: a novel decision support algorithm for sleep staging application, Mobihealth (2015).
[32] C. Chen, A. Ugon, X. Zhang, et al., Personalized sleep staging system using evolutionary algorithm and symbolic fusion, Eng. Med. Biol. Soc. (2016) 2266–2269.
[33] M. Diykh, Y. Li, P. Wen, EEG sleep stages classification based on time domain features and structural graph similarity, IEEE Trans. Neural Syst. Rehabil. Eng. 24 (11) (2016) 1159–1168.
[34] A. Stochholm, K. Mikkelsen, P. Kidmose, Automatic sleep stage classification using ear-EEG, Eng. Med. Biol. Soc. (2016).
[35] A.R. Hassan, M.I.H. Bhuiyan, Automatic sleep scoring using statistical features in the EMD domain and ensemble methods, Biocybern. Biomed. Eng. 36 (1) (2016) 248–255.
[36] P. Chriskos, D.S. Kaitalidou, G. Karakasis, et al., Automatic sleep stage classification applying machine learning algorithms on EEG recordings, in: 2017 IEEE 30th International Symposium on Computer-Based Medical Systems, 2017, pp. 435–439.
[37] N. Sertbas, Y. Yaslan, An ensemble multi kernel framework for sleep stage classification, Int. Conf. Comput. Sci.Eng. (2017) 348–353.
[38] Z. Beattie, Y. Oyang, A. Statan, et al., Estimation of sleep stages in a healthy adult population from optical plethysmography and accelerometer signals, Physiol. Meas. 38 (11) (2017) 1968–1979.
[39] A.R. Hassan, M.I.H. Bhuiyan, Automated identification of sleep states from EEG signals by means of ensemble empirical mode decomposition and random under sampling boosting, Comput. Meth. Prog. Bio. 140 (2017) 201–210.
[40] A.R. Hassan, A. Subasi, A decision support system for automated identification of sleep stages from single-channel EEG signals, Knowl.-Based Syst. 128 (2017) 115–124.
[41] A. Supratak, H. Dong, C. Wu, et al., Deepsleepnet: a model for automatic sleep stage scoring based on raw single-channel EEG, IEEE Trans. Neural Syst. Rehabil. Eng. (2017). 1-1
[42] M. Langkvist, A. Loutfi, A deep learning approach with an attention mechanism for automatic sleep stage classification, 2018. arXiv:1805.05036.
[43] Y. Yuan, K. Jia, F. Ma, et al., Multivariate sleep stage classification using hybrid self-attentive deep learning networks, in: IEEE International Conference on Bioinformatics and Biomedicine (BIBM), 2018.
[44] R.K. Tripathy, A.U. Rajendra, Use of features from RR-time series and EEG signals for automated classification of sleep stages in deep neural network framework, Biocybernetics and Biomedical Engineering, 2018.

[45] M. Sokolovsky, F. Guerrero, S. Paisarnsrisomsuk, et al., Deep learning for automated feature discovery and classification of sleep stages, in: IEEE/ACM Transactions on Computational Biology and Bioinformatics, 2019, pp. 1–11.
[46] S. Mousavi, F. Afghah, U.R. Acharya, SleepEEGNet: Automated sleep stage scoring with sequence to sequence deep learning approach, 2019. arXiv:1903.02108.
[47] A.L. Goldberger, L.A. Amaral, L. Glass, et al., Physiobank, physiotoolkit, and physionet: components of a new research resource for complex physiologic signals, Circulation 101 (23) (2000) 215–220.
[48] X. Wang, T. Lv, Q. Yu, et al., A sleep staging method using multi-parameters, DEStech Transactions on Computer Science and Engineering, 2018.
[49] B. Sen, M. Peker, A. Cavusoglu, et al., A comparative study on classification of sleep stage based on EEG signals using feature selection and classification algorithms, J. Med. Syst. 38 (2014) 18–687.
[50] A. Krakovska, K. Mezeiova, Automatic sleep scoring: a search for an optimal combination of measures, Artif. Intell. Med. 53 (2011) 25–33.
[51] M. Robnik-Sikonja, I. Kononenko, Theoretical and empirical analysis of ReliefF and RReliefF, Mach. Learn. 53 (1–2) (2003) 23–69.
[52] C. Cortes, V. Vapnik, Support-vector networks,machine learning, 20(3)(1995) 273–297.
[53] D. Meyer, F.H.T. Wien, Support vector machines, R News 1 (3) (2001) 23–26.
[54] N. Michielli, U.R. Acharya, F. Molinari, Cascaded LSTM recurrent neural network for automated sleep stage classification using single-channel EEG signals, Comput. Biol. Med. 106 (2019) 71–81.
[55] A. Sors, S. Bonnet, S. Mirek, et al., A convolutional neural network for sleep stage scoring from raw single-channel EEG, Biomed. Signal Proces. 42 (2018) 107–114.
[56] O. Yildirim, U.B. Baloglu, U.R. Acharya, A deep learning model for automated sleep stages classification using PSG signals, Int. J. Environ. Res. Public Health 16 (4) (2019) 599.