A Features Fusion Method for Sleep Stage Classification Using EEG and EMG

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Abstract. To achieve accurate sleep stage classification and improve its generalization ability, we presented a features fusion method to classify sleep stage using Electroencephalogram (EEG) and Electromyography (EMG). We regarded EEG and EMG samples from MIT-BIH Polysomnographic database as analysis objects. First of all, we used the Discrete Wavelet Transform (DWT) to filter noise of signals and extract energy ratio of α, β, θ and δ wave from EEG and the high frequency component from EMG, and used Sample Entropy (SampEn) algorithm to extract nonlinear characteristics of EEG. Then, we compared the accuracy difference of sleep stage classification method between using EEG and using EEG and EMG features fusion by inputting these features to Support Vector Machine (SVM) classifier to train and test. Finally, we used cross-validation method to train and test different samples to verify its generalization ability. The experiment of testing accuracy showed a satisfactory result with accuracy of 91.86%, and the average accuracy raised 4.94% compared to the sleep stage classification method using EEG. The cross-validation results indicated that this method has better generalization ability.

Keywords: EEG · EMG · Energy feature · Sample entropy · Features fusion · Support vector machine classifier · Sleep stage classification

1 Introduction

In this rapid developing society, life pressure is becoming more and more intense thus many people have appeared symptoms of sleep disorder which has huge impacts on people health. Currently, sleep disorder has been identified as a common and harmful disease [1]. Disease related to sleep is diagnosed and treated based on assessment of sleep quality. An objective and effective way of achieving sleep quality assessment is sleep staging through human physiological signals.

The classical sleep staging method is that many characteristic parameters from EEG (Electroencephalogram, EEG) were extracted by using different analytical methods and then classifier can be used to classify sleep stages. Liu [2] used the nonlinear analysis of symbolic dynamics, spectrum analysis and detrended fluctuation analysis to reach the mean of sleep staging accuracy of 92.87%, however, the generalization ability of algorithm is still need to be improved since it only trained and validated separately each sample. Xie [3] improved the generalization ability of model by adopting discrete

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wavelet transform combined nonlinear SVM, but the accuracy rate (81.56%) still could not meet the requirement.

In order to improve the accuracy of sleep staging, several experts paid attention to sleep staging study by using other body physiological signals, such as ECG, EOG, and EMG and so on. Some studies combined EEG and EOG to classify sleep stages [4], and others do sleep classification using EOG and EMG [5], which could perform better performance.

In this study, we proposing a sleep staging method using EEG and EMG features fusion in order to increase its generalization ability and accuracy. Since EEG and EMG have different characteristics wave in various sleep stages, we can extract the time-frequency domain features by calculating energy feature ratio. Besides, we adopted sample entropy algorithm which is suitable for nonlinear analysis of biological signals to extract nonlinear features of EEG because of the EEG signal's non-stationary. We inputted these features into support vector machine classifier to obtain a sleep staging method with higher accuracy and broader generalization.

2 Materials and Method

2.1 Data Source

This article used two signals included EEG and EMG from the MIT-BIH database polysomnography [6] that recorded several physiological signals of 16 test subjects during sleep. This study chose four samples included slp41, slp45 and slp48 as subjects because they had integral sleep stages. And the sampling frequency is 250 Hz. In order to test the accuracy and generalization ability of method, the result was compared to the sleep stage results that recorded by an experienced doctor after every 30 s.

2.2 Method

The flow diagram of this method was shown in Fig. 5. Firstly, the high-frequency noise from raw signals was filtered by using wavelet decomposition. Secondly, the energy ratio of α, β, θ and δ waves and sample entropy from EEG were extracted as the first part of the feature parameters. Thirdly, the energy ratio of high-frequency from EMG was extracted by using wavelet decomposition as the second part of the feature parameters. Finally, the first part of the feature parameters were inputted SVM classification to train and test compared to two parts of the feature parameters.

(1) **Data Preprocess**

EEG and EMG usually contain some unknown frequency components, especially ECG and muscle and eye movements will largely have an effect on EEG. Therefore, wavelet decomposition was used to filter these noises in order to improve the measurement accuracy in this study.

Discrete Wavelet Transform (DWT) is so automatically adapt to analysis time-frequency signal that makes it particularly suitable for non-stationary signals. Generally speaking, the appropriate decomposition level was selected according to the characteristics of signals in practice. For example, the signal was decomposed into i layer, and the frequency range of nodes included A_i and D_i is respectively $0 \sim \frac{fs}{2^{i+1}}$ and $\frac{fs}{2^{i+1}} \sim \frac{fs}{2^i}$, where fs is the sampling frequency.

Generally, researchers are interested in the frequency range of EEG between 0.5 Hz and 35 Hz [7], and the high-frequency components of representing EMG muscle movement are more concentrated in the 30 to 125 Hz [8] in clinical medicine. The signals' sampling frequency is 250 Hz in the database, therefore, the raw signals of EEG and EMG were respectively decomposed into 7 and 3 layer by using "db4" Wavelet. Then a heuristic threshold method was used to filter. The effect was shown in Fig. 1 after data of EEG and EMG from object slp48 for 10 s was filtered.

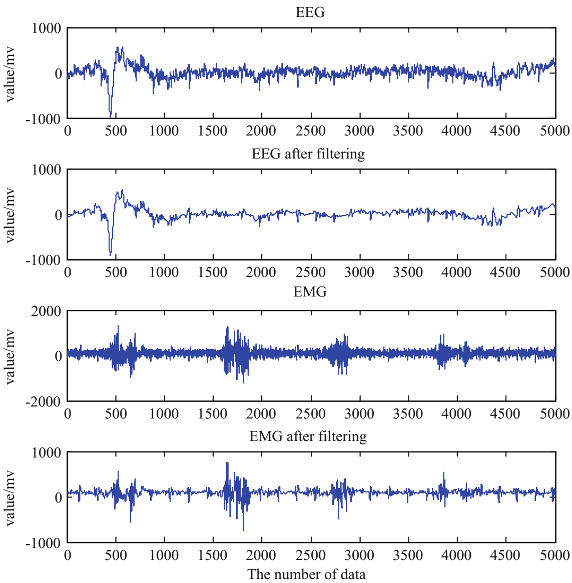

Fig. 1. Effect diagram of EEG and EMG denoise

(2) Feature Extraction

According to the 2007 American Academy of Sleep Medicine (AASM) developed, sleep can be divided into five stages: the Wake phase (W phase), Non-Rapid Eye Movement 1 phase (N1 phase), Non-Rapid Eye Movement 2 phase (N2 phase), Non-Rapid Eye Movement 3 phase (N3 phase) and Rapid Eye Movement phase (REM phase) [9]. It is the crucial step of achieving accurate sleep staging to extract features represented the various sleep stages. Some features of each sleep stage were shown in Table 1.

In order to analysis features, we need to choose some data of sleep subjects' five stages. For example, slp45 sample was chose as analysis object, whose sleep time was 380 min and the length of each data for 30 s was 7500 point. We chose data what each of the stages from EEG and EMG for 25 min.

(a) *Energy Feature*

According to the corresponding relationship of Table 1 between sleep stages and characteristic waves of EEG and EMG, EEG was decomposed into 7 layer by using "db4" Wavelet. Based on the relationship of wavelet decomposition nodes and frequency, D3 represents β wave, D4 represents α wave, D5 represents θ wave and D6 + D7 represents δ wave. The energy ratios of four waves on total energy (0–30 Hz) are calculated. Then EMG was decomposed into 3 layer by using "db4" Wavelet, D1 + D2 represents muscle movement frequency (30–125 Hz), and the energy ratio of that on total energy (0–125 Hz) was calculated. The energy ratio was calculated as in Eqs. (1) and (2):

$$\eta_i = \frac{\sum_{k=1}^{n} |D_i(k)|^2}{E_s} \tag{1}$$

$$E_S = \sum_{k=1}^{N} |D_i(k)|^2 \tag{2}$$

Where, η_i represents energy ratio of the i-th layer frequency band on the total energy. $D_i(k)$ represents the k-th wavelet coefficient of the i-th layer. n represents the data number of i-th layer. E_s represents total energy. N represents the data number of total layers.

The results were shown in Fig. 2, which energy ratio of α, β, θ, δ waves and EMG high-frequency components for each sleep stage were calculated. And the average values of feature energy ratio in different sleep stages were shown in Fig. 3.

We can make conclusion from Figs. 2 and 3: energy ratio of α wave was the most obvious in Wake phase, which began to decrease with the depth of sleep, however, it began to increase when reached REM phase; energy ratio of β wave was smaller than that of α wave, which is similar to α wave in each sleep phase; energy ratio of θ wave was less than other waves in the whole sleep process, but it increased obviously in REM phase; energy ratio of δ wave accounted for a larger proportion in the whole sleep process and achieved maximum in the N3 phase; energy ratio of EMG high frequency components was largest in the Wake phase, followed by N3 phase, and almost had little in the REM phase. These features met the characteristics listed in Table 1, which shown that the method based on discrete wavelet transform to extract feature energy ratio of EEG and EMG can achieve sleep stages classification (Fig. 3).

(b) *Sample Entropy*

Sample Entropy (SampEn) is a measurement method of measuring sequence complexity, which calculation is faster and more accurate.

Sample entropy can be represented with SampEn (m, r, N), where, m is the embedding dimension, which is usually 1 or 2, but we will select 2 in the practical application; r is similar tolerance, He [10], who believed that the result is better when r = 0.2SD (SD standard deviation of the original data); N represents the data length, He [10] proved that the experiment result is ideal when N = 1000. The Sample Entropy of EEG was shown in Fig. 4.

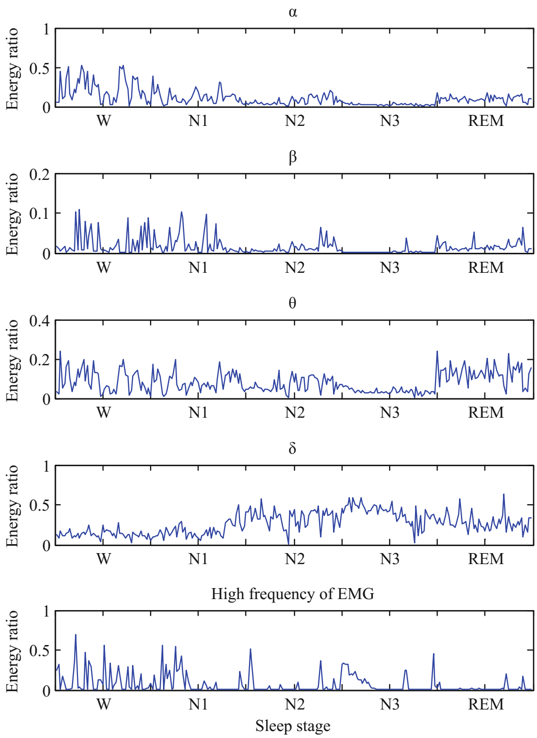

Fig. 2. Energy ratio of four rhythm waves and EMG high frequency components in each sleep stage

Table 1. Features of each sleep stage

Sleep stages	Features
W	α(8–13 Hz), β(13–30 Hz), highest EMG
N1	θ(4–8 Hz), higher EMG
N2	Sleep spindles(12–14 Hz), EMG is weaker than N1
N3	δ(1–4 Hz), lower EMG
REM	α(8–13 Hz), β(13–30 Hz), EMG disappeared

From Fig. 4 we can see that Sample Entropy of EEG was the largest. Because EEG complexity was high due to strong brain activity in Wake phase. Brain activity weakened with the depth of sleep, Sample Entropy of EEG correspondingly decreased. However, EEG activity increased with the brain began to dream in the REM phase. It caused that complexity of EEG increased, so Sample Entropy started to increase. These obvious difference features suggested that Sample Entropy can further show sleep information.

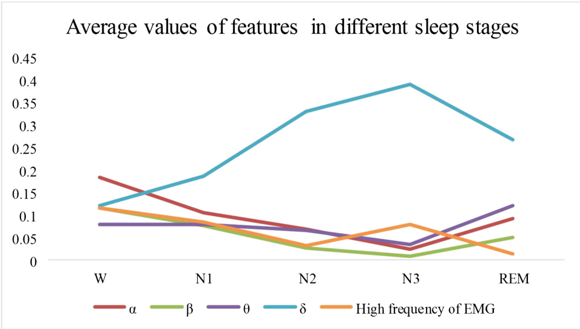

Fig. 3. Average value of different feature parameters in each sleep stage

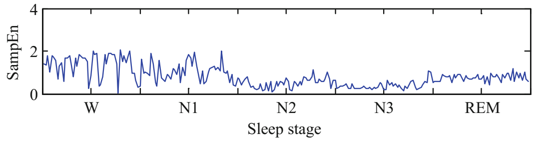

Fig. 4. EEG sample entropy in each sleep stage

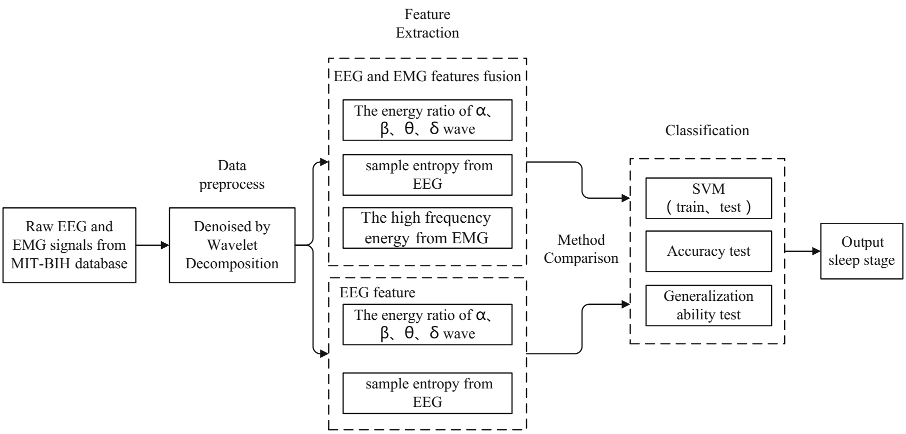

Fig. 5. Flow diagram of sleep staging based on EEG and EMG features fusion

(3) Support Vector Machine (SVM) Classifier

SVM can solve many problems such as small sample, nonlinear, high dimension and so on, which is becoming the preferred method of pattern recognition [11]. For nonlinear problems, its basic idea is that function is transformed into linear problem by $x \to \phi(x)$ mapping into a high-dimensional space in which the optimal classification hyperplane is built. This mapping is achieved by kernel function $K(x_i, x_j) = \phi(x_i) \cdot \phi(x_j)$ [12] to take the optimal classification function, as in:

$$y = sgn\{\sum_{i=1}^{m} \alpha_i y_i K(x_i, x) + b\} \tag{3}$$

This paper selected RBF kernel function, as in:

$$K(x_i, x) = exp(-\gamma * \|x - x_i\|^2) \tag{4}$$

Three steps that this paper utilized SVM to classify were as follows.

Step 1: Six feature parameters of slp41, slp45 and slp48 sample overnight sleep data where slp41 totals 780 groups, slp45 totals 755 groups and slp48 totals 760 groups were extracted.

Step 2: Mixing feature parameters of slp41, slp45 and slp48 samples, we could obtain a total of 2295 groups' sample features, where 70% was used to establish sleep SVM classification model as training samples.

Step 3: The remaining was used to test the accuracy of the classification as testing samples.

3 Results

In order to verify the advantages of this method, we designed an experiment what compared the accuracy between sleep stages classification using EEG and sleep stages classification using EEG and EMG features fusion. Classification results of the two methods were shown in Table 2. The average increase rate of the sleep staging accuracy was shown in Table 3.

Table 2. Comparison of automatic sleep staging results between with EMG and without EMG

Sleep stage	Training samples (70% of slp45 and slp48)			Testing samples (30% of slp45 and slp48)		
	Number	Accuracy (%)		Number	Accuracy (%)	
		No EMG	Add EMG		No EMG	Add EMG
W	392	96.43	100	168	88.10	96.42
N1	368	95.38	99.73	157	84.08	90.45
N2	622	95.18	95.34	267	85.39	88.76
N3	83	96.39	100	35	87.50	91.43
REM	142	95.77	100	61	85.25	96.72
Total	1607	95.64	98.13	688	85.47	91.86

To further verify the generalization capability of the method, this experiment utilized cross-validation to train and test different samples. Firstly, we chose the one of slp41, slp45 and slp48 samples as the training set to build model, and then the remaining two samples were used to test by the model. The generalization capability testing results were shown in Table 4.

4 Discussions

Table 2 shown that the classification result of sleep staging method using EEG and EMG features fusion is better, and the overall accuracy rate can reach 91.86%, which is better than many sleep staging methods mentioned in most articles.

Through Tables 2 and 3 we can see that the accuracy of every sleep stage has increased, especially REM phase is the highest and W phase follows after adding EMG. However, the increase rate of N2 and N3 phase is lower after adding EMG. Therefore, it is a focus of future research directions for us to improve the accuracy of sleep staging. Overall, the average increase rate of sleep staging accuracy is 4.94% after adding EMG. It indicates that adding EMG can effectively improve the accuracy of sleep staging.

Table 3. Average increase rate for each sleep stage accuracy

Sleep stage	W	N1	N2	N3	R	Average
The average increase rate (%)	5.95	5.36	1.77	3.77	7.85	4.94

By testing generalization ability in Table 4, we can see that the effect of cross-validation between different samples was ideal and the average accuracy rate reached 82.68%. It indicates that this sleep staging method based on EEG and EMG features fusion has certain generalization ability compared to the previous algorithm. There are some factors will affect the model accuracy such as artificial calibration errors, the continuous of various sleep stages.

Table 4. Test results of generalization ability of the staging sleep based on EEG and ECG features fusion

Training samples	Testing samples			
	slp41	slp45	slp48	The average accuracy
slp41	——	82.01%	86.43%	84.22%
slp45	81.41%	——	84.45%	82.93%
slp48	82.69%	79.10%	——	80.90%
The average accuracy	——	——	——	82.68%

5 Conclusion

In this study, a features fusion method for sleep stage classification using EEG and EMG was proposed. Through contrastive experiment, we conclude that working with EMG can significantly improve sleep staging accuracy. Cross-validation results show that the method has a certain generalization. The experiment results have high reliability, and the method can complete accurately sleep staging, which provide an effective basis for assessing the quality of sleep, which has great prospects in future clinical application. The results also provide many other interesting resources in classifying sleep stages by using multi-parameter to obtain more accurate results.

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