A Sleep Staging Method Using Multi-parameters

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Abstract. Sleep staging is an important basis for the diagnosis of sleep disorders and other related diseases. An auto sleep staging method based on multi-parameter features fusion was proposed. First, using the Discrete Wavelet Transform (DWT) to filter the raw signals, obtain 8 features of sleep staging. Then the parameters of features were inputted to Support Vector Machine (SVM) for training and classification. Finally, using the cross-validation to model different samples for verifying the generalization ability. The results show that the accuracy of the method reach 93.08%, which is 9.39% higher than based EEG, and reached 85.25% with cross-validation, that indicated a better generalization ability.

Introduction

Currently, sleep disorders have been identified as a public risk disorder[1]. Sleep staging is an important gist of diagnose to study sleep disorders and related diseases. At present, many sleep staging methods have been proposed, these methods mainly extracted features of EEG by time domain and frequency domain, the nonlinear dynamic[2], and classified by using Artificial Neural Networks (ANN) or Support Vector Machine (SVM). However, with the increasing requirement for the accuracy of staging, the sleep staging method using EEG alone can no longer meet human needs, the researchers begin to explore the changing rules of sleep processes with other physiological signals[3].

This study aimed at the current sleep staging algorithm in the low accuracy, generalization ability and other shortcomings. A sleep staging algorithm based on multi-parameters features fusion was proposed. By extracting the features of EEG, EMG, ECG, Resp in the database of MIT–BIH, training and testing the parameters by using the SVM classifier. Then the three sleep staging methods of basing sleep EEG, sleep EEG and ECG, sleep multi-parameters were compared, in order to obtain the sleep staging method with more accurate and generalization ability.

Data Preprocessing

The MIT-BIH multi-channel sleep database was selected in this paper[4]. The sleep EEG, EMG, ECG, and Resp signals in this database were used as the original signals. A total of 16 subjects were recorded in this database, and the sample frequency of the data was 250Hz. In the 16 test objects, only slp32, slp41, slp45, slp48 testing individual contains the complete EEG, ECG, EMG (from jaw), Resp signal and sleep phase is complete. So selected samples of slp32, slp41, slp45, slp48 as experimental objects. All data was divided into sections per 30 seconds, and sleep staging is determined by experts according to the R&K standard, which is used to test the accuracy of the algorithm.

In this paper, the original EEG signals were decomposed to 7 layers by using db3 wavelet. The EMG signals were decomposed to 3 layers by using sym3 wavelet. The ECG signals were decomposed to 6 layers by using db4 wavelet. The heuristic threshold method was used to deal with the noise of EEG, EMG, ECG signals. The median filter was used to deal with the noise of the Resp signal. Intercepted a piece of data (5000 pieces of data) of the test object slp45, and the effect of denoising was shown in figure 1.
Feature Extraction and Classification Algorithm

Feature Extraction Algorithm

In this paper, a total of eight features were extracted from four physiological parameter signals, and the description of each signal feature was shown in Table 1.

| Signals  | EEG         | EMG         | ECG         | RESP        |
|----------|-------------|-------------|-------------|-------------|
| Feature type | Frequency domain | Nonlinear feature | Frequency domain | Nonlinear feature | Time Domain |
| Feature description | Energy ratio $\eta_\alpha$, $\eta_\beta$, $\eta_\theta$, $\eta_\delta$ | Sample entropy $SampEn_s$ | High frequency component energy ratio $\eta_h$ | Sample entropy $SampEn_s$ | Mean $Mean_s$ |

Mallat Decomposition Algorithm

Mallat decomposition algorithm is a fast algorithm for calculating wavelet transform. The algorithm, also known as tower algorithm, is decomposed by decomposition filters $H$ and $G$.

Decomposition algorithm$^5$:

$$
A_i[x(n)] = x(n)
$$

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

$$
D_i[x(n)] = \sum_{k} G(2n-k)D_{i-1}[x(n)]
$$

In the equation, $x(n)$ is the original signal and $i$ is decomposition layers, $H$ and $G$ is the wavelet decomposition filter, $A_i$ is the approximate wavelet coefficient (low frequency)in the i-th layer, $D_i$ is the detailed wavelet coefficients (high frequency) in the i-th layer.

Characteristic Energy Ratio

The characteristic energy ratio is the ratio between the energy of the wavelet coefficient from the required layers and the energy of the wavelet coefficient from the total layers after decomposition.

Frequency range of alpha, beta, theta and delta waves is respectively 8~13 Hz, 13~30 Hz, 4~7 Hz, 1~4 Hz. In this paper, we used “db3” wavelet base to decompose the EEG signals into 7-layer wavelet, where the third layer (D3) represented the beta waves, the fourth layer (D4) represented alpha waves, the fifth layer (D5) represented theta waves, the sixth (D6) and seventh (D7) layer represented delta waves. We calculated energy ratio between D3, D4, D5, D6 and D7 and 0~30 Hz, which got four frequency domain characteristics of EEG. There are respectively $\eta_\alpha$, $\eta_\beta$, $\eta_\theta$, and $\eta_\delta$.

The frequency range of 30~125 Hz represented high frequency of muscle movements in EMG signal. In this paper, we selected "sym3" wavelet base to decomposed EMG signals into 3-layer decomposition.
wavelet, which got wavelet coefficients from each layer that the first (D1) layer and second (D2) layer represent 30~125 Hz. The frequency domain features ($\eta_n$) were calculated by equation (2) and (3).

**The Sample Entropy**

Sample entropy is defined as:

$$\text{SampEn}(m,r) = \lim_{N \to \infty} \left\{ \frac{-\ln \left( \frac{B^{m+1}(r)}{B^m(r)} \right)}{\ln B(r)} \right\}$$  \hspace{1cm} (2)

When $N$ is a finite value, sample entropy can be written as:

$$\text{SampEn}(m,r,N) = -\ln \left( \frac{B^{m+1}(r)}{B^m(r)} \right)$$ \hspace{1cm} (3)

To calculate sample entropy, $m$, $r$ and $N$ should be selected first, which $m$ is the embedded dimension that is usually 1 or 2. $R$ is the similar tolerance and the value is too large to lose a lot of detailed information. After extensive and analysis, the results are better when $r=0.2\text{SD}$ (SD is the standard deviation of the original data). In this study, $r=0.2\text{SD}$ is selected. $N$ is the data length, and it is concluded by experiments that $N=1000$ works well.

**Support Vector Machine Classification Algorithm**

The support vector machine (SVM) minimizes the empirical risk and confidence range by seeking the minimum structural risk and makes its classification more extensive. The basic idea of SVM is map data put into high-dimensional space, and then build the optimal classification hyperplane in the new space.

In this paper, radial basis kernel function is selected:

$$K(x,x_i) = \exp(-\gamma \|x-x_i\|^2)$$ \hspace{1cm} (4)

70% data was selected as training data, and the expert interpretation results in the database were taken as classification labels. And the training data and labels were input into the SVM classifier to obtain the classification model. The remaining 30% data was selected as testing data, the expert interpretation results in the database were taken as test labels. And the training data were input into the SVM classification model to get the classification results, compare classification results and the test labels, then, calculated the classification accuracy.

**Experiments and Results**

**Feature Extraction Results**

In this paper, the features of the sample slp45 were analyzed by selecting a piece of data of each sleep period (including Wake, N1, N2, N3 and REM). Sleep time of sample slp45 is 380 minutes, each group of data length is 7500 points (30 s). EEG, EMG, ECG and respiration signal of different sleep stages in 20 minutes (group a total of 40 * 5) data feature were selected to extract, feature extraction result is shown in figure 2. The variance of the characteristic value of respiratory signal was calculated, and the rest features were averaged, and table 2 was obtained.
The Classification Results

Extracted all night sleep data of slp32, slp41, slp45, slp48 samples, which is respectively 620 groups, 750 groups, 730 groups and 740 groups after eliminating the useless data. Obtained 2840 groups sample characteristics, of which 70% (1988) as the training sample were used to establish the SVM classification model, the remaining 30% (852) were used to test classification effect.

To verify the superiority of this method, three methods of comparative experiments were designed. Firstly, we used sleep classification method based on EEG. Then, we used sleep classification methods based on EEG and ECG. Lastly, we used sleep classification method based on multi-parameter feature fusion. The classification effect of the three methods is shown in table 3. Compared with sleep staging methods based on EEG, the improvement rate of the accuracy of the other two methods in each sleep stage is shown in table 4.

| Sleep Stage | Training Samples | Testing Samples | Correct | Accuracy | Correct | Accuracy | Correct | Accuracy |
|-------------|------------------|-----------------|---------|----------|---------|----------|---------|----------|
| W           | 638              | 274             | 257     | 93.80    | 260     | 94.89    | 269     | 98.18    |
| N1          | 378              | 162             | 105     | 64.81    | 109     | 67.28    | 140     | 86.42    |
| N2          | 707              | 303             | 275     | 90.75    | 281     | 92.74    | 286     | 94.39    |
| N3          | 125              | 53              | 37      | 69.81    | 35      | 66.04    | 43      | 81.13    |
| R           | 140              | 60              | 39      | 65.00    | 41      | 68.33    | 55      | 91.67    |
| Total       | 1988             | 852             | 713     | 83.69    | 726     | 85.21    | 793     | 93.08    |
Table 4. The Increase rate of based on the EEG and ECG method and based on the multi-parameter method compared with based on the EEG sleep staging method.

| Sleep Stage Methods | Increase rate /% | Total |
|---------------------|------------------|-------|
|                     | W    | N1   | N2   | N3   | R    |
| EEG, ECG            | 1.09 | 2.47 | 1.99 | -3.77| 3.33 | 1.52 |
| Multi-parameters    | 4.38 | 21.61| 3.64 | 11.32| 26.67| 9.39 |

To verify the generalization ability of this method, cross-validation was used to train and test different samples. The sample slp32 has no REM period, it is easy to cause misjudgment, resulting in lower accuracy of test samples, so sample slp32 was excluded in this experiment. The experimental results are shown in table 5.

Table 5. The generalization ability test results of based on multi-parameter features fusion sleep staging method.

| Training samples | Testing samples | The average accuracy |
|------------------|-----------------|----------------------|
| Slp41            | Slp45           | Slp48                |
|                  | 86.28           | /                    | 86.23 |
| Slp45            | 84.09           | /                    | 85.16 |
| Slp48            | 85.14           | 82.25                | /     | 84.26 |
| The average accuracy | 86.34       | 84.25                | /     | 85.25 |

In summary, the accuracy of sleep staging method based on EEG was 83.69%, that of sleep staging method based on EEG and ECG was 85.21%, that of sleep staging method based on the multi parameter accuracy was 93.08% in table 3. Therefore, the sleep staging method based on multi-parameter feature fusion designed in this paper can achieve a high accuracy of sleep staging.

It can be seen from table 3 and table 4 that the multi-parameter sleep staging method has great influence on sleep stages. Compared to sleep staging method based on EEG, the accuracy of sleep staging method based on EEG and ECG increased by 1.52%, the accuracy of sleep staging method based on multi parameter increased by 9.39%.

The generalization ability test results in table 5 shown that the cross-validation effect is ideal between different samples, and the average accuracy rate was 85.25%.

**Conclusion**

Sleep staging is the important objective indicators to study sleep disorders and related conditions. In order to improve the accuracy and generalization ability of sleep staging, in this paper, a method based on multi-parameter features fusion is proposed. The experimental results show that this sleep staging method based on EEG, ECG, EMG and respiratory signal fusion has obvious advantages in accuracy and generalization ability, significantly improves the accuracy of N1 and REM period compared to the method based on EEG sleep staging. This method can accurately complete sleep staging, meanwhile, it has certain generalization ability.

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