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Sleep Stage Classification for Healthy Individuals and Patients with Elman Neural Network

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Abstract: Sleep plays an important role in human health. A sleep stage classification method for healthy people and patients with Elman neural network was proposed in this work. The classification process included four essential steps: data acquisition, signal preprocessing, feature extraction, and classification. Wavelet threshold denoising and wavelet packet transform were applied for the signal preprocessing. With the Elman network, the accuracy for healthy people is 90.48% and 82.36% for patients, respectively. Besides, the skewness and kurtosis of six characteristic waves were selected with higher relevance to the sleep stages and less redundancy to other features. This study presented a sleep stage classification method with well generalization performance and conclusions, which contribute to the EEG signal analysis for healthy and slight sleep disorders individuals.

1. Introduction

Sleep, which is critical to mental and physical health, contributes to the reconstruction of the human body, maintaining the immune system, and upholding brain function [1]. On the contrary, sleep disorder is usually associated with work productivity decline, coronary artery disease, and impaired neurobehavioral performance [2]. Therefore, sleep treatment is widely and increasingly needed. To treat somnipathy effectively, it is of great significance to analyze the sleep stages and cycles [3]. With the development of the deep learning models, Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) models have been applied to the sleep stage classification [4]. With LSTM Recurrent Neural Network, Nicola Michielli achieved an accuracy of 86.8% for healthy people [5]. It shows the potential to develop a more general deep learning model for sleep stage classification. However, the majority of sleep stage classification is based on the EEG signals of healthy people [6], only a few studies had tested the generalization performance of their sleep stage classification methods on patient subjects [7]. Nowadays, there are not enough convincing results for the difference of the EEG signals between healthy people and sleep disorders.

To address the aforementioned challenges, we presented a method to classify the sleep stage for healthy people and patients with Elman neural network. Besides, it was found that both for healthy people and patients, the skewness and kurtosis of EEG signals performed the best with higher relevance to the sleep stages and less redundancy. Our generalization performance for healthy people got an accuracy of 90.48% and 82.36% for patients which were assessed by 5-fold cross-validation.

2. Materials and Methods

2.1. The General Process for Sleep Stage Classification

The general scheme of the sleep stage classification process in this study is described in Figure. 1. Firstly, data acquired from the Sleep-EDF database. After that, the wavelet threshold de-nosing method and wavelet packet transformation (WPT) method were applied in the process of signal preprocessing to get the six characteristic waves. Then, 39 features were extracted in four different domains. Eventually, taking all features as inputs, we got a trained Elman neural network and applied it to classify sleep stages for healthy people and patients.

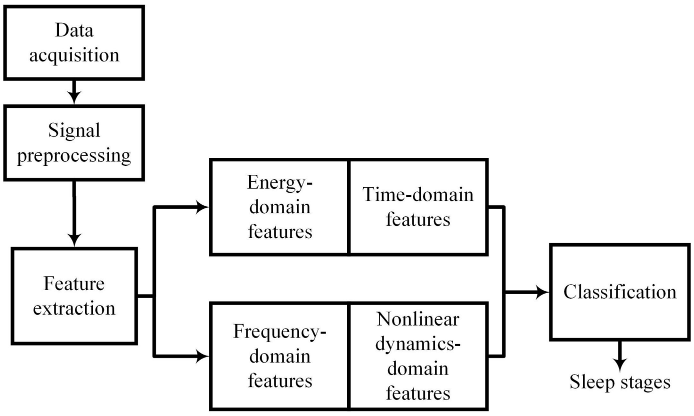

Figure 1: The general process scheme for sleep stage classification.

2.2. Data Collection

The raw sleep recordings were collected from the Sleep-EDF database, which is publicly available from PhysioBank directly [8]. These recordings are EEG signals from the Fpz-Cz channel and recorded with a 100Hz sampling rate. We collected the sleep recordings from 8 healthy people and 8 patients aged 18 to 35. These patients had a slight difficulty in falling asleep. Following the R&K rules, all EEG signals were divided into 30s epochs. Every epoch was assigned to one of the five sleep stages: wakefulness (W), non-rapid eye movement 1 (NREM1), non-rapid eye movement 1 (NREM2), slow-wave sleep (SWS), and rapid eye movement (REM). We composed two datasets for healthy people and patients, each dataset is composed by the 2880 epochs from eight subjects to make each subject contributes equally. The generalization performance of the model was assessed by 5-fold cross-validation.

2.3. Signal Preprocessing and Feature Extraction

First of all, wavelet threshold denoising method was applied to the original EEG signal denoise. After that, wavelet packet transform (WPT) was used to extract the six characteristic waves which are composed into EEG signals, including alpha (α = [8-13Hz]), beta (β = [14-30Hz]), theta (θ = [4-8Hz]), delta (δ = [0.5-2Hz]), spindle ([12-14Hz]), sawtooth ([2-6Hz]).

For any EEG related analysis, feature extraction is the most important procedure. In this study, there were a total of 3000 samples in each 30s epoch since the sampling rate was 100Hz. To get a comprehensive feature system, we found 39 features in four domains:

1)Energy features: the energy of six characteristic waves: $E\alpha$, $E\beta$, $E\theta$, $E\delta$, *Esaw-tooth, Espindle* the ratio of alpha and delta to theta wave: $Q\delta/\theta$, $Q\alpha/\theta$.

2)Time-domain features: the skewness, kurtosis, standard deviation of six characteristic waves: skew(Xi), kurt(Xi), Std(Xi), $i = \alpha, \beta, \theta, \delta$, *saw-tooth, spindle*.

3)Frequency-domain features: the power of six characteristic waves calculated with power spectral density in the frequency domain: $P\alpha$, $P\beta$, $P\theta$, $P\delta$, *Psaw-tooth, Pspindle* and mean frequency of denoised EEG signals.

Nonlinear features: Spectral entropy, Renyi entropy, Fuzzy entropy, Sample entropy, Lempel-ziv complexity, and Multi-scale entropy of denoised EEG signals.

2.4. Classification

In this study, the Elman neural network was composed of four layers: the input layer, hidden layer, context layer, and output layer. Took the 39 features as the inputs of the Elman neural network, the five different sleep stages as the output. The adaptive moment estimation algorithm was adopted in this study for backpropagation.

3. Results

Through the above processes, for healthy people and patients, we calculated the average accuracy in each fold, in Figure. 2(a). What's more, the average accuracy of each sleep with 5 folds is presented in Figure. 2(b).

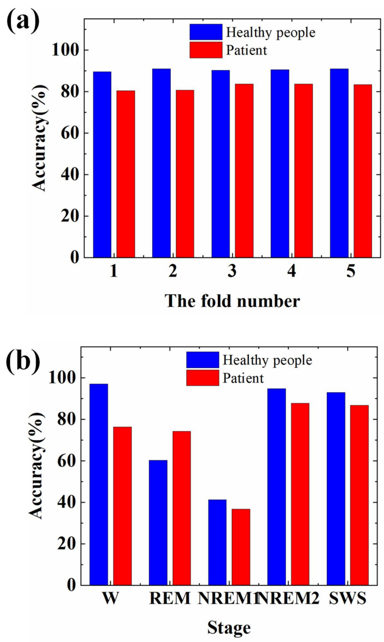

Figure 2: The average accuracy for healthy people and patients

(a) in different fold, (b) for different stage.

For healthy people, the average accuracy of five folds was 90.48% and 82.36% for patients, which indicated our method was available for two kinds of people. However, the accuracy of REM and NREM 1 were much lower than other stages, which may owe to the inadequate number of REM and NREM 1 recording.

4. Discussion

Considering the feature system has overmuch features making the calculation inefficiency, we selected the most effective feature and discuss the performance of two kinds of people. In this study, minimum redundancy maximum relevance (mRMR) algorithm was applied to select the effective features. According to this algorithm, the relevance of each feature was examined. Take some of the most related features as the inputs of the Elman network and the features were permuted. After that, the changing curves of accuracy for healthy people and patients were obtained. According to the maximum accuracy for two kinds of people, we confirmed the most effective features for healthy people and patients which are shown in Table 1. For healthy people, the accuracy after the feature selection is 90.03%, while for patients, it is 81.74%.

Table 1: The most effective features for two kinds of people.

Domain	Healthy people	Patients
Energy	Qδ/θ, Qα/θ	Eα, Eδ, Esaw-tooth, Qδ/θ, Qα/θ
Time	Std(Xsaw-tooth), skew(Xα), skew(Xβ), skew(Xθ), skew(Xδ), skew(Xsaw-tooth), skew(Xspindle), kurt(Xβ), kurt(Xδ), kurt(Xspindle), kurt(Xsaw-tooth)	Std(Xδ), Std(Xθ), skew(Xα), skew(Xβ), skew(Xθ), skew(Xδ), skew(Xsaw-tooth), skew(Xspindle), kurt(Xα), kurt(Xβ), kurt(Xβ), kurt(Xθ), kurt(Xδ), kurt(Xsaw-tooth), kurt(Xspindle),
Frequency	Pα, Pβ	Mean frequency, Pβ
Non-linear features	Spectral entropy, Fuzzy entropy, Multi-scale entropy, LZC sample entropy	Multi-scale entropy, Fuzzy entropy, Spectral entropy Lempel-Ziv complexity

In Table 1, it is clear to discover that both for healthy people and patients, the skewness and kurtosis of six characteristic waves are all preserved, indicating that they have higher relevance to the sleep stages and less redundancy than other features. Additionally, nonlinear dynamics features are both effective for two kinds of people.

5. Conclusions

This study presented a sleep stage classification applicable method for healthy people and patients, using Elman neural network. After the four essential steps: data acquisition, signal preprocessing, feature extraction, and classification, the accuracy was 90.48% for healthy people and 82.36% for patients. Besides, after feature selection with the mRMR algorithm skewness and kurtosis had higher relevance to the sleep stages and less redundancy than other features. However, in the future study, it is necessary to establish a more comprehensive feature system and expand the number of subjects to select the features which indicate the difference between the healthy people and sleep disorders and to improve the accuracy for sleep disorders.

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