

Sleep and Wake Classification Based on Heart Rate and Respiration Rate

W Li^{1,a}, X D Yang^{1,b}, A N Dai^{1,c} and K Chen^{1,d}

¹Department of mechanical engineering, Tsinghua University, Beijing 100084, China

^aweili16@mails.tsinghua.edu.cn

^byangxd@tsinghua.edu.cn

^cdaian15@mails.tsinghua.edu.cn

^dkenchen@tsinghua.edu.cn

Abstract. Sleep plays a significant role in human health. Along with the emergency of diseases related to sleep, sleep monitoring is becoming a hotspot. Traditionally, Polysomnography (PSG) is considered as the gold standard for sleep monitoring, but it is expensive, time-consuming, and uncomfortable, especially not ideal for long-term sleep studies. Thus, exploring alternative sleep monitoring method has drawn much attention of researchers. Currently most of the sleep monitoring methods require complicated signals and feature extraction process. However, this paper innovatively proposes a method using simple signal of heart rate and respiration rate, and integrating the prior knowledge of experts to simplify the feature extraction process, which can make the subsequent classifier distinguish wake state and sleep state easily. In this paper, we used multi-layer neural network as a classifier, getting a Cohen's kappa value of 0.739, and the overall accuracy of classifying sleep and wake state reached to 88%. Furthermore, we improved the ability of detecting wake states greatly by oversampling method, and the sensitivity and specificity reached to 91.3% and 82.3% respectively. Nowadays, the development of various bed sensors makes it easy to obtain the heart rate and respiration rate signals of human beings. Therefore, the method proposed in this paper is conducive to people's long-term sleep monitoring more conveniently and has great significance to people's health.

1. Introduction

Sleep is one of the most important physiological activities of human body. Recently, some studies have found that lack of sleep may cause many diseases such as hypertension and cardiovascular diseases [1-2], which brings sleep monitoring more and more attention. Currently the most standard sleep monitoring method is PSG, but the recording process is costly, and many electrodes can interfere sleep process as well. So researchers have shown great interest in finding other effective ways to replace PSG.

At first, people use signals similar to those in PSG such as EEG and ECG signals, which get a classification accuracy of 90% [3-4]. But these signals are also collected from the electrodes attached to the human body, thus will interfere people's sleep, which makes these sleep monitoring methods not ideal for long-term practice. Actigraphy, on the other hand, is able to measure the body's motion through acceleration sensors. The wristband-style Actigraphy is popular with researchers because it greatly reduces the disturbance of sleep when collecting information [5]. However, motion signal alone often fails to recognize sleep states correctly, so additional signals need to be acquired to get



more accurate results [6]. And then researchers, for instance Xi Long, start to use cardiorespiratory signals to classify sleep states. He extracted a large number of features from body motion and respiration, which made the accuracy improved a lot [7]. Nevertheless, most of these methods introduced above require sophisticated instruments to get signals and complex feature extraction processes such as time-frequency analysis [8], wavelet transformation and dynamic time wrapping [7], and those will cost tons of money and time. Besides, the accuracy of detecting wake state is lower compared with sleep state. Therefore, a simpler and more practical method to classify the state of sleep needs to be studied urgently.

With the development of various bed sensors, it becomes easy to extract the physiological signals of people in bed, including heartbeat, respiratory, etc. These signals are quite accurate and contain information of sleep, but unfortunately they have not been further utilized so far. As we all know, heartbeat and respiratory will both slow down and become more stable after people fall asleep, which means that heartbeat and respiration are related to sleep states. Therefore, this paper proposes a method of recognizing the human sleep states through heart rate and respiration rate based on the above background information. This method has a simple and fast feature extraction process, and uses neural networks as the final classifier. Besides, this method also balances the number of sleep and wake state in the training process, improving the ability of distinguishing wake state.

2. Methodology

The sleep monitoring method introduced in this paper has three steps, including data preprocessing, feature extraction and neural network construction. Data showed in this paper was collected from 10 healthy experiment volunteers using Ann Pollen PSG. Acquisition frequency of heart rate and respiration rate is 1 Hz, and the images of corresponding sleep states are saved in PDF. After processing the image, we can get the state of a certain heart rate and respiration rate. Due to the image resolution problems, a state label will correspond to about 20 seconds' heart rate and respiration rate, which will lead to some errors in the place of state transition. Fortunately, there is few transitions between wake state and sleep state under normal circumstance, so it can be considered that we get accurate heart rate, respiration rate and the corresponding state of the original data.

2.1 Data Preprocessing

Some raw data of heart rate and respiration rate from Ambler PSG can be abnormal sometimes, which should be modified to avoid affecting subsequent classification. This paper set a threshold 40 to 110 for heart rate and 10 to 30 for respiration rate to make sure the data applied in analysis is within a reasonable range. The raw data will be considered as the boundary value if it falls out of the range. With consideration of reducing jitter of raw data, data of heart rate and respiration rate are smoothed by the method of moving average. At each time point, a rectangular window of 60 seconds with the time point as midpoint is applied, and the calculation formula shows below:

$$\bar{x}_i = \frac{1}{60} \sum_{j=i-30}^{i+30} x_j \quad (1)$$

In addition, the original label of polysomnography is divided into five states. But the goal of this paper is to distinguish sleep and wake state, which means that we also need to change the labels to two states. After preprocessing, the dataset of October 20th, 2016 shows below in figure 1.



Figure 1. October 20th, 2016 dataset's heart rate, respiration rate and corresponding sleep states

2.2 Feature extraction

To some extent, the instantaneous value of heart rate and respiration rate are random, but after statistical process, they become useful to classify sleep states. What is known to people is that when the human body fall in asleep, the heartbeat and breathing will become slow and steady. According to above prior knowledge, we can use mean to indicate the trend of slowing down, and use variance to indicate the trend of becoming steady. Further, this paper proposes a simple but effective feature extraction method that can be seen in table 1. These features are based on statistical characteristics of heart rate and respiration rate for a period of time, including mean, variance, skewness and kurtosis. And the length of time used in this paper is 400 seconds ($t = 400$). Higher-order statistics skewness and kurtosis represent more detailed information about data distribution. Skewness shows the deviation of data distribution from normal distribution, and kurtosis shows the sharpness of data distribution relative to the normal distribution. They are calculated as: (\bar{x} , σ represent the mean and variance of corresponding period, and n is the length of one period)

$$\text{skewness} = \frac{1}{n-1} \sum_{i=1}^n \left(\frac{x_i - \bar{x}}{\sigma} \right)^3 \quad (2)$$

$$\text{kurtosis} = \frac{1}{n-1} \sum_{i=1}^n \left(\frac{x_i - \bar{x}}{\sigma} \right)^4 - 3 \quad (3)$$

However, these calculation is a little complicated which will slow down the feature extraction process. Fortunately, experiments show that the accuracy improved by these two features is less than 1%, so it is acceptable to abandon these two features. The last feature of heart rate and respiration rate measures the similarity of two adjacent periods. It is more likely to be classified as sleep state if the

two adjacent periods are similar, so we choose this as an important feature, which is calculated as: (x , y represent the value of adjacent period.)

$$\text{feature} = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y}) \quad (4)$$

On the other hand, different people's heartbeat and breathing will have different basic values, and the features extracted from data will have different scales. In order to make classification better, the features of data must be normalized. In this paper, the data normalization method is as follows,

$$x_{\text{new}} = \frac{x - \mu}{\sqrt{\sigma + \varepsilon}} \quad (5)$$

where μ and σ represent the mean and variance, and ε is generally a small number to prevent the occurrence of the divided-by-zero error. And such a normalization method changes the data into a zero-mean, unit variance distribution. Figure 2 shows all features extracted from dataset of October 20, 2016.

Table 1. Description of all kinds of features

Feature number	Calculation method ($t = 400$)
1	The average of heart rate for a length of t
2	The variance of heart rate for a length of t
3	The skewness of heart rate for a length of t
4	The kurtosis of heart rate for a length of t
5	The average difference of heart rate between two adjacent periods
6	The variance difference of heart rate between two adjacent periods
7	The similarity of heart rate between two adjacent periods
8-14	Above process operated on respiration rate

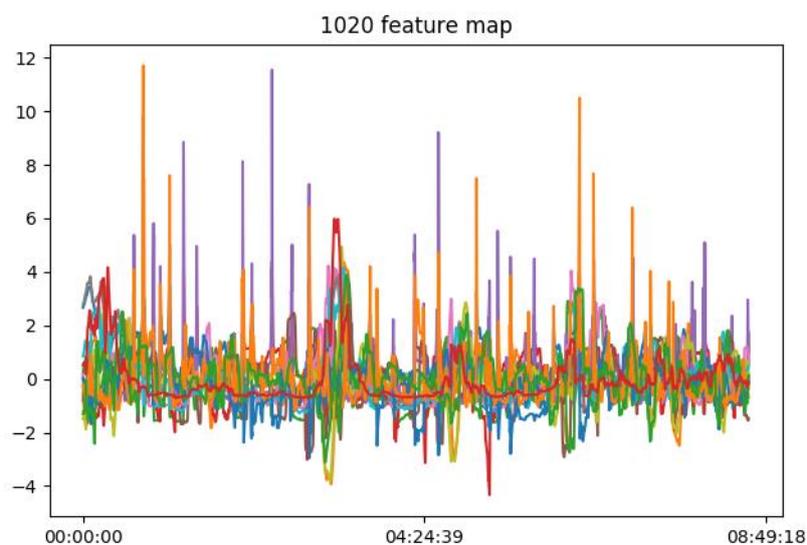


Figure 2. October 20th, 2016 dataset's feature map including 14 features

2.3 Build neural network

In this paper, the structure of neural network is the 14-32-16-4-1, with the hidden layers taking Relu as activation function while the last layer taking sigmoid as activation function. Due to the depth of the neural network, this paper uses Batch Normalization method to solve the problem of training deep network. Because there is a large amount of data (more than one million) that can be utilized, this paper does not use any regularization method. What's more, in order to speed up the training process, this paper adopts the gradient optimization method with momentum. The momentum factor is 0.9, the initial length of step is 0.01, and the decay factor is $1e-6$. It is found that the loss drops slowly after 50 epochs and then we can choose to stop the optimization.

The amount of sleep state and wake state in the dataset acquired from the original data is quite different, so the previous classifier [9] tends to be more sensitive and less specific. In this paper, we use an oversampling method to double the wake state, and then merge them with sleep state to form the final dataset. This dataset will be shuffled and divided into three parts, including training set, validation set and test set, which account for 64%, 16%, 20% respectively. The training set will be trained in neural networks to solve the problem of low specificity. Although oversampling makes accuracy drop down slightly, the model is even more powerful. And figure 3 shows the change of loss and accuracy in training process.

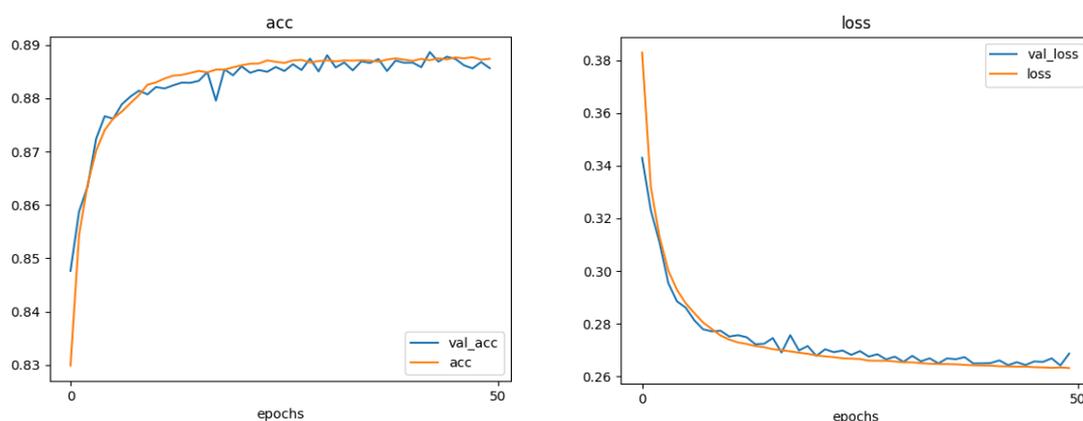


Figure 3. Training process on data including training set and validation set. Left is loss curve, right is accuracy curve.

3. Results and discussion

Following the above steps, we can get the final neural network classification model. This model achieved an overall accuracy of 88% in training set, as well as in validation set and test set. By balancing the number of sleep states and wake states, we got the confusion matrix as table 2, and the sensitivity and specificity reached to 91.3% and 82.3% respectively. And this classifier got a Cohen's kappa value of 0.739, showing the high coherence of the ground truth. Compared with the similar method for classifying the states of sleep in which pressure sensors are installed on a bed [10], the accuracy is improved by about 9% and the specificity is improved by nearly 20%. In table 3, we show the results of 20 subjects randomly selected from all data, which is also better than the classification results of Bayesian approach using heart rate and surplus pulse O₂ signals in [9]. And there is comparison of these methods mentioned above in table 4.

Table 2. Confusion matrix on all data

Prediction \ ground truth	sleep states	wake states
	sleep states	567588 (TP)
wake states	54176 (FN)	268161 (TN)

$$\text{sensitivity} = \frac{TP}{TP + FN} = 0.913 \quad (6)$$

$$\text{specificity} = \frac{TN}{TN + FP} = 0.823 \quad (7)$$

$$\text{kappa} = \frac{p_o - p_e}{1 - p_e} = 0.739 \quad (8)$$

This paper proposes a new model using heart rate and respiration rate signals that people can easily and inexpensively acquire to classify sleep states. What's more, the statistical characteristics of heart rate and respiration rate are used as features, which simplifies the feature extraction process greatly and reduces the time cost at the same time. Because we have found the hidden relation between heart rate, respiration rate and sleep states by neural network, people can use bed sensors to collect the data of heart rate and respiration rate, and then get the state of sleep. Therefore, sleep monitoring can be used more widely.

Table 3. Sensitivity, specificity and accuracy of 20 nights' data randomly selected from data

ID	sensitive	specificity	accuracy
1	0.9550	0.8727	0.9430
2	0.9520	0.8020	0.9195
3	0.9363	0.9134	0.9349
4	0.9376	0.7903	0.8902
5	0.8824	0.6321	0.8413
6	0.9085	0.9127	0.9097
7	0.9234	0.9263	0.9239
8	0.8961	0.8352	0.8887
9	0.9091	0.8544	0.8952
10	0.9292	0.8639	0.9111
11	0.9212	0.7262	0.8761
12	0.9435	0.8841	0.9321
13	0.9255	0.9248	0.9254
14	0.8328	0.7998	0.8252
15	0.8844	0.9078	0.8896
16	0.9653	0.7721	0.8805
17	0.8559	0.7238	0.8199
18	0.9322	0.8757	0.9245
19	0.9002	0.8980	0.8994
20	0.8660	0.7309	0.8368
mean	0.9128	0.8323	0.8933

Table 4. A comparison of methods

method	sensitive	specificity	accuracy
This paper	0.9128	0.8323	0.8933
Bayesian approach [9]	0.9274	0.5917	0.8269
Pressure-Based [10]	0.955	0.532	0.743

4. Conclusion

Nowadays, sleep has drawn great attention due to its close relation with health. At the same time, the monitoring of sleep states has naturally become a hot topic. In this paper, a method of using heart rate and respiration rate to classify sleep states is proposed. Through simple feature extraction process based on prior knowledge and multi-layer neural network, we got an overall accuracy of 88%. Moreover, by the way of oversampling, we enhanced the ability to detect wake state and improved the specificity obviously. With the trend of the development of various kinds of bed sensors, this method makes it possible to monitor sleep at low cost, as well as to prevent various sleep-related diseases. On the basis of this method, people can improve the accuracy by adding more useful features, and we will search for these features to make the classification better in the future.

Acknowledgment

Thank my tutor Yang for his patient guidance and help, and also thank Softide for its support and thanks for the experimenters who provided the data.

Reference

- [1] Yan C. Sleep monitoring for prevention of cardiovascular and cerebrovascular diseases[J]. *Medical information management*, 2011, 24(6):2587
- [2] Lei W. Research on relation between sleep quality and blood pressure rhythm in hypertensive patients[D]. Beijing University of Chinese Medicine, 2014.
- [3] Fraiwan L, Lweesy K, Khasawneh N, et al. Automated sleep stage identification system based on time-frequency analysis of a single EEG channel and random forest classifier[J]. *Computer Methods & Programs in Biomedicine*, 2012, 108(1):10-19.
- [4] Da S T, Kozakevicius A J, Rodrigues C R. Single-channel EEG sleep stage classification based on a streamlined set of statistical features in wavelet domain[J]. *Medical & Biological Engineering & Computing*, 2017, 55(2):343.
- [5] Morgenthaler T, Alessi C, Friedman L, et al. Practice parameters for the use of actigraphy in the assessment of sleep and sleep disorders: an update for 2007.[J]. *Sleep*, 2007, 30(4):519-29.
- [6] Paquet J, Kawinska A, Carrier J. Wake Detection Capacity of Actigraphy During Sleep[J]. *Sleep*, 2007, 30(10):1362-9.
- [7] Long X, Fonseca P, Foussier J, et al. Sleep and Wake Classification With Actigraphy and Respiratory Effort Using Dynamic Warping[J]. *IEEE Journal of Biomedical & Health Informatics*, 2014, 18(4):1272-1284.
- [8] Xiao M, Yan H, Song J, et al. Sleep stages classification based on heart rate variability and random forest[J]. *Biomedical Signal Processing & Control*, 2013, 8(6):624-633.
- [9] Fu C, Zhang P, Jiang J, et al. A Bayesian approach for sleep and wake classification based on dynamic time warping method[J]. *Multimedia Tools & Applications*, 2015, 76(17):1-20.
- [10] Walsh L, Mcloone S, Ronda J, et al. Noncontact Pressure-Based Sleep/Wake Discrimination[J]. *IEEE Transactions on Biomedical Engineering*, 2016, 64(8):1750-1760.