Detection of Sleep Staging from EEG: A Comparison of Feature Dimensionality Reduction and Classifier Selection

Xiaotong Ding[1,*], Lei Yang[1], Zhongcai Liao[2] and Yanwen Fang[2]
[1]China Academy of Information and Communications Technology, Beijing 100191, China
[2]Zhejiang Heye Health Technology, Anji 313300, China

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Abstract: Sleep is an important part of maintaining human health. With the high incidence of sleep disorders, sleep has attracted much attention. Sleep staging is an effective means to study sleep structure. This paper studies the effect of different feature dimensionality reduction algorithms on the accuracy of sleep analysis, including the influence of principal component analysis, factor analysis and autoencoders on common classifiers, such as random forest and support vector machine for automated sleep stage detection. The combination with the highest accuracy was used to verify the sleep EEG data obtained in our laboratory. The results show that, using autoencoders to reduce dimension can keep the performance of the model, while using principal component analysis and factor analysis can improve the accuracy of the model in most cases.

1 INTRODUCTION

According to the WHO survey, about 30% people worldwide suffer from sleep disorders. The automatic sleep stage classification algorithm helps to improve the detection efficiency and reduce the detection time.

A large number of studies have proposed methods for automatic sleep staging (Chriskos, 2018; Aboalayon, 2015; Sanders, 2014). Features are usually used as the input of classical classification algorithms, such as support vector machine (SVM) (Zhang, 2014), k- nearest neighbor (Malaekah, 2014), RF etc. In recent years, neural networks have also been widely used in automatic classification of sleep stages. Different architectures were created, such as convolution (Tsinalis, 2016), and the deep neural network architecture (Stanislas Chambon, 2018). Different methods are proposed to reduce the content of large data. Fan et al. (Fan, 2018) used multi-scale entropy combined with principal component analysis (PCA) to extract features and automatically detect sleep stages in MIT-BIH database. The final accuracy rate reached 87.9%. Autoencoders (AE) can compress the input data in different degrees (Najdi, 2017).

In this paper, the influence of different dimensionality reduction methods on different types of classifier models will be evaluated. By using less computational load, the memory consumption can be reduced, and more modal information can be fused for sleep staging in the future, which increases the variability of classification model and expands its applicability.

2 MATERIALS AND METHODS

As shown in Figure 1, after feature extraction and dimension reduction technology are applied, the obtained feature data is used to train the classifiers. Then the obtain training classification model is tested. In the case of cross-validation, the performance of each model is evaluated. The best performance model is used to identify the existing sleep EEG data in our laboratory by stages.

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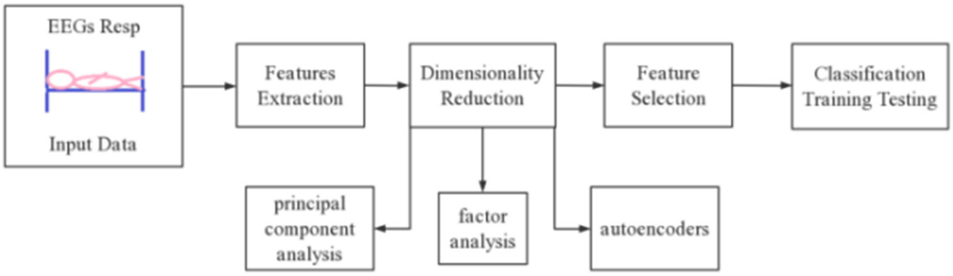

Figure 1: Overview of the method of obtaining the automatic sleep stage model from polysomnographic recordings.

●Data set description: The sleep EEG data in our laboratory includes the sleep EEG data of 41 male students in college for 2 nights each, of which 20 sleep on ordinary mattresses and 21 sleep on sleeping mattresses with magnets. The sampling frequency is 100hz and the acquisition channel is Pz-Oz.

The distribution of sleep stages in the whole sleep is unequal. To provide the classifier with the same amount of data from each sleep stage category, we preprocessed the category distribution in the dataset. We selected the smallest available category and randomly sampled other categories, so that all sleep stages have the same performance in the input seen by the classifier.

●Extracted features: Table 1 lists the general situation of all extracted features. Each sleep stage is represented by different EEG features.

Table 1: The general situation of all extracted features.

id	Feature	Description	id	Feature	Description
1	Spectral power	spectral power: absolute	12	Amplitude env mean	envelope: mean value
2	Spectral relative power	spectral power: relative (normalised to total spectral power)	13	Amplitude env SD	envelope: standard deviation
3	Spectral flatness	spectral entropy: Wiener (measure of spectral flatness)	14	rEEG mean	range EEG: mean
4	Spectral diff	difference between consecutive short-time spectral estimates	15	rEEG median	range EEG: median
5	Spectral entropy	spectral entropy: Shannon	16	rEEG lower margin	range EEG: lower margin (5th percentile)
6	Spectral edge frequency	spectral edge frequency: 95% of spectral power contained between 0.5 and fc Hz (cut-off frequency)	17	rEEG upper margin	range EEG: upper margin (95th percentile)
7	FD	fractal dimension	18	rEEG width	range EEG: upper margin - lower margin
8	Amplitude total power	time-domain signal: total power	19	rEEG SD	range EEG: standard deviation
9	Amplitude SD	time-domain signal: standard deviation	20	rEEG CV	range EEG: coefficient of variation
10	Amplitude skew	time-domain signal: skewness	21	rEEG asymmetry	range EEG: measure of skew about median
11	Amplitude kurtosis	time-domain signal: kurtosis			

●Dimensionality reduction and Classification: The purpose of feature dimension reduction is to reduce the amount of computation and memory requirements, at the same time try to improve the performance through different feature expressions. This paper reduced the total number of features to 10, 20 and 40 components. Three dimensionality reduction methods are used, including PCA, FA and AE (The implementation of AE is shown in Figure 2. The model was fitted with 16 batch size to avoid over-fitting, and was carried out within 100 epochs.).

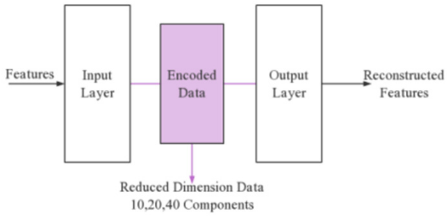

Figure 2: Dimensionality reduction with autoencoders.

We choose two classifiers to evaluate: One is RF (Twenty decision trees were used.). The other is SVM.

Each generated model was evaluated by 10 times cross validation. The average accuracy and $F1_{score}$ of all sleep stage categories were used to compare the performance.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{1}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{2}$$

$$F1_{score} = 2 * \frac{\text{Recall}*\text{Precision}}{\text{Recall}+\text{Precision}} \tag{3}$$

where TP – true positive, TN – true negative, FP – false positive, FN – false negative.

3 RESULTS

Table 2 shows the results. For the automated sleep stage scoring using SVM and RF, after using FA, 20 components are obtained by feature decomposition, and then by using RF the classification accuracy increased to 88%.

Table 2: The change results of different dimension reduction algorithms (PCA, FA, AE).

Classification	Dimensionality	NO.	Precision	Recall	F1-score	Classification	Dimensionality	NO.	Precision	Recall	F1-score
SVM	PCA	10	0.75	0.76	0.75	RF	PCA	10	0.82	0.81	0.81
		20	0.75	0.76	0.75			20	0.83	0.83	0.83
		40	0.75	0.76	0.75			40	**0.88**	**0.88**	**0.88**
	FA	10	0.81	0.82	0.81		FA	10	0.79	0.80	0.80
		20	0.86	0.67	0.70			20	**0.88**	**0.88**	**0.88**
		40	0.86	0.67	0.70			40	0.87	0.87	0.87
	AE	10	0.76	0.77	0.81		AE	10	0.80	0.80	0.80
		20	0.83	0.68	0.70			20	0.86	0.87	0.88
		40	0.81	0.75	0.70			40	**0.87**	**0.88**	**0.87**

20 components were obtained by FA feature decomposition, and the experimental laboratory data were identified by stages using RF classification model. The comparison between the stage results and the original stage results is as figure 3.

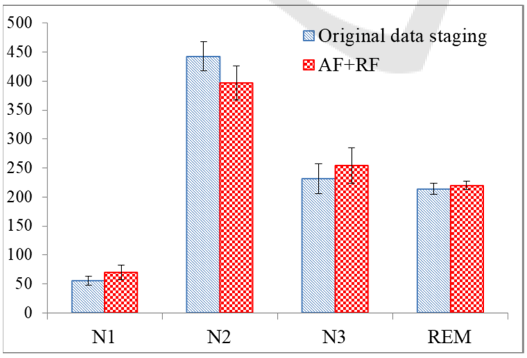

Figure 3: The comparison between the stage results and the original stage results.

4 DISCUSSION

In this paper, the sleep stage was realized according to the steps of feature extraction, feature selection and classification recognition of single lead EEG (Pz-Oz). In the sleep stage recognition experiment, a relatively ideal experimental result has been obtained.

In this paper, three levels of feature quantities are used respectively: 10, 20, 40; Three dimensionality reduction methods: PCA, FA and AE; Two classification methods: SVM and RF. By comparison, it is found that the best classification results are obtained when using the RF classifier in combination with PCA (40 features) and FA (20 features). Among them, FA uses fewer features and occupies less computing space.

The best model in this paper is used to verify and analyze the EEG data in our laboratory. The agreement between the results and the original results reaches 89.26%, among which N1 is 80.00%, N2 is 88.41%, N3 is 91.34% and REM is 97.27%. Among them, N1 has the greatest difference in staging and REM has the highest coincidence.

5 CONCLUSION

In this paper, several dimensionality reduction techniques of EEG data set for automatic detection of sleep stage are analyzed. Among them, FA uses fewer features and occupies less computing space. Dimension reduction technology helps to reshape the input data, thus reducing the computing power and improving the performance for some transformations. The analysis of sleep EEG data in our laboratory supports that static magnetic field can improve sleep quality, whether it is sleep time or sleep structure.

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