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Classification of sleep apnea based on EEG sub-band signal characteristics

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Sleep apnea syndrome (SAS) is a disorder in which respiratory airflow frequently stops during sleep. Alterations in electroencephalogram (EEG) signal are one of the physiological changes that occur during apnea, and can be used to diagnose and monitor sleep apnea events. Herein, we proposed a method to automatically distinguish sleep apnea events using characteristics of EEG signals in order to categorize obstructive sleep apnea (OSA) events, central sleep apnea (CSA) events and normal breathing events. Through the use of an Infinite Impulse Response Butterworth Band pass filter, we divided the EEG signals of C3-A2 and C4-A1 into five sub-bands. Next, we extracted sample entropy and variance of each sub-band. The neighbor composition analysis (NCA) method was utilized for feature selection, and the results are used as input coefficients for classification using random forest, K-nearest neighbor, and support vector machine classifiers. After a 10-fold cross-validation, we found that the average accuracy rate was 88.99%. Specifically, the accuracy of each category, including OSA, CSA and normal breathing were 80.43%, 84.85%, and 95.24%, respectively. The proposed method has great potential in the automatic classification of patients' respiratory events during clinical examinations, and provides a novel idea for the development of an automatic classification system for sleep apnea and normal events without the need for expert intervention.

Sleep apnea, a common sleep disorder, is characterized by the frequency of more than five apneas per hour during sleep or the stopping time of respiratory airflow for more than 10 s^{1,2}. Sleep apnea can cause daytime fatigue, a lack of energy, impaired memory, and may also cause several diseases, including high blood pressure, coronary heart disease and stroke³. There are three types of sleep apnea, including obstructive sleep apnea (OSA), central sleep apnea (CSA), and mixed apnea (MSA)⁴. Among these, OSA accounts for the largest proportion. It manifests as repeated upper respiratory tract attacks, where the respiratory rhythm is still maintained. In CSA, respiration is either diminished or is completely absent. MSA is a mixture of these two types, defined as a central apnea in a relatively short time interval followed by obstructive apnea⁴. When conducting a diagnosis, the type of sleep apnea that each patient has is determined by the specific type of sleep apnea event. Patients with OSA mostly experience events obstructive events, while patients with CSA mostly experience central events. Mixed events are usually accompanied by both central and obstructive events. In the event of mixed events, if obstructive event is dominant, it is diagnosed as OSA. Otherwise, it is diagnosed as CSA⁵. Sleep apnea hypopnea index (AHI) refers to the number of apneas plus hypopneas per hour of sleep, and is related to the severity of apneas. According to Chicago standards, the severity of apnea is classified into four categories, including normal (AHI<5), mild sleep apnea syndrome (5<AHI<15), moderate sleep apnea syndrome (15<AHI<30), and severe sleep apnea syndrome (AHI>30)⁶.

The gold standard for conducting a diagnosis of sleep apnea is through the use of sleep polysomnography⁷, which is a set of variables that record a variety of electrophysiological and pneumological signals continuously and simultaneously⁸. The signals that are recorded include electroencephalogram (EEG), electrocardiogram (ECG), electromyogram (EMG), electro-oculogram (EOG), oronasal airflow, ribcage movements, abdomen movements and oxygen saturation⁹. However, this method of diagnosis requires sleep technologists to monitor and diagnose sleep apnea events, which is complicated, expensive, and time-consuming¹⁰. Therefore, there is a

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need for an automatic method of diagnosis for sleep apnea events that are both low cost and can be carried out in a relatively simple manner.

In recent years, an increasing number of studies have used the characteristics of a single signal to carry out an automated diagnosis of sleep apnea events¹¹. Using respiratory airflow, oxygen saturation (SpO₂), and photoplethysmography (PPG) alone can help identify apnea events, which have achieved many research results^{12,13}. Although these signals have the advantage of being easily acquired, they have certain limitations. First, the diagnosis of sleep apnea is based on sleep staging¹⁴. These methods cannot judge a patient's sleep state and sleep stage, while may cause deviations with regards to diagnosis of sleep apnea. EEG signals are commonly used in sleep staging, as the use of EEG signals can help ensure the patient's sleep state, and the classification of sleep apnea events is relatively accurate. Secondly, in certain scenarios, such as during any chest and abdomen surgeries or limb surgeries, there is no or inconvenient respiratory airflow monitoring, SpO₂ monitoring, and PPG monitoring. Even for patients that suffer from irregular breathing or obvious arrhythmia, respiratory airflow monitoring, SpO₂ monitoring, and PPG monitoring may lose their utility. However, the use of EEG signals alone in the above cases can help identify sleep states, as well as various apnea events, which have important clinical significance. In addition, EEG signals reflect electrical activity of the brain and can obviously be used to evaluate sleep stages and problems^{15–17}. At the same time, sleep quality is affected by sleep problems such as sleep apnea events¹⁸. In summary, the main purpose of this research is to classify sleep apnea events based on EEG signals.

Many studies emphasize the function of EEG signals in the automatic classification and detection of sleep apnea^{19,20}. Talluk et al. used bispectrum analysis to extract the secondary phase coupling amount of each frequency band as a feature of EEG²¹. Almuhammadi et al. used the energy and variance of brain electronic band signals as characteristics that would allow identification of OSA patients from normal control groups, and achieved an accuracy of 97.14%²². Zhou et al. used trend fluctuation analysis (DFA) to extract the scale index of EEG signals as features, and used support vector machine (SVM) to identify apnea patients, which led to an average accuracy of 95.1%²³. These studies are able to distinguish sleep apnea patients from healthy subjects, but the automatic detection of sleep apnea patients' apnea events is an important task. There has been abundant literature reporting use of EEG signals to study the automatic classification of sleep apnea events. What these studies have in common is that they are only able to distinguish between sleep apnea and non-apnea events, but do not involve the specific subclassification of apnea event types (OSA or CSA). Bhattacharjee et al. used the Rice density function to model the feature changes of sub-frames, and used these modeling parameters and other statistical parameters as the input of the K-nearest neighbor (KNN) classifier, which led to an accuracy rate of 98.02%²⁴. Saha et al. proposed feature extraction using multi-band entropy methods, and reported 87.64% as the average accuracy of the KNN classifier. They also characterized the energy ratio between frequency bands of multi-band EEG signals, which led to an average accuracy of 92.21%²⁵. Ahmed et al. obtained statistical features from the time pattern of beta band energy and applied them to the classifier, leading to an average accuracy of 82.28%²⁶. Shahnaz et al. adopted the feature extraction method based on the power ratio of incremental frequency band of the Delta sub-frame. When using SVM and KNN, the average accuracy was found to be 84.07% and 84.83%, respectively²⁷. Sachin et al. proposed a Hermite decomposition algorithm based on particle swarm optimization (PSO), which utilized the Hermite function (HFs) optimized by particle swarm optimization to extract Hermite coefficients from EEG signals to identify SA events. The classification accuracy rate was 98.82%²⁸. Additionally, the Hermite function (HFs) optimized by the evolution technology (ETS) was utilized to represent the EEG signal, and the artificial bee colony (ABC) algorithm was carried out for feature extraction based on Hermite coefficients, which led to an accuracy as high as 99.53%²⁹.

Correctly detecting and distinguishing apnea events is the first step in diagnosing the type of apnea. The main purpose of this study is to develop a method for automatic classification of OSA events, CSA events and normal breathing events, based on feature extraction of EEG sub-band signals. After preprocessing the data, the features of the EEG signal were obtained, and the set after feature selection was used as the input for the classifiers. Finally, the effectiveness of the method was evaluated.

Materials and methods

EEG data. The data used in this study was obtained from the night polysomnography monitoring database of patients in the Tianjin Chest Hospital. The data is composed of overnight polysomnography data recorded by the PHILIPS RESPIRONICS ALICE5 sleep monitor, that was made in the United States. The C3-A2 and C4-A1 EEG signals of 30 patients were selected on random as the research subjects. The 30 patients included 23 men and 7 women, between the ages of 37–78 (average 55.17 ± 11.90 years), with a BMI range of 19.83–39.26 kg/m² (average 29.20 ± 4.47 kg/m²), and an AHI range of 8.2–68.9 (average 29.18 ± 4.46 events/h). All normal breathing events or apnea events were taken during the patient's sleep and were marked by experienced sleep experts according to the AASM 2012 guidelines. Among them, from the overnight sleep data of 30 patients, there were 1229 epochs of OSA events, 812 epochs of CSA events, and 1418 epochs of normal breathing events. The sampling frequency of the EEG signal was 100 samples/second.

Ethics approval and consent to participate. This study was approved by the Ethics Committee of Tianjin Chest Hospital and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed consent. Informed consent was obtained from all individual participants included in the study.

The proposed method. First, EEG signals were deconstructed into five sub-bands, after which the sample entropy and variance of each sub-band are extracted. Next, we applied the nearest neighbor component analysis

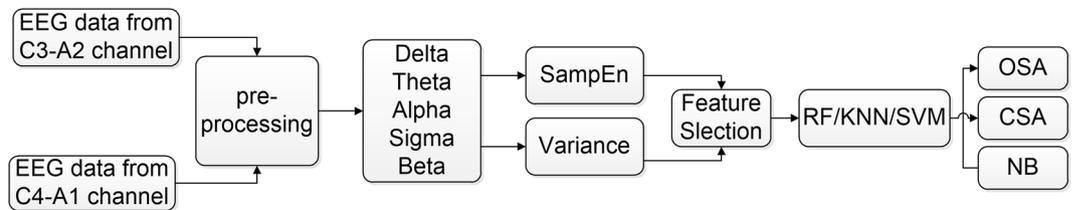


Figure 1. Flow chart of the proposed method, where NB is referred to as normal breathing.

(NCA) algorithm to feature selection in order to acquire the optimal feature set. Finally, the results were utilized as inputs for the classifiers. The steps for the method are shown in Fig. 1, All procedures of data processing were written in MATLAB R2019b. Figure 1 was obtained with Microsoft Visio 2010.

Data pre-processing. For data pre-processing, we used an Infinite Impulse Response Butterworth Band pass filter to deconstruct the EEG signals of C3-A2 and C4-A1 into five sub-bands: delta (δ , 0.5–4 Hz), theta (θ , 4–8 Hz), alpha (α , 8–12 Hz), sigma (σ , 12–16 Hz) and beta (β , 16–40 Hz), while filtering out the sensed noise interference outside the frequency band of interest.

Sub-band feature extraction. *Sample entropy.* The EEG signal is a standard non-linear signal, and the state of the signal may appear randomly on the time scale. Sample entropy, a non-linear statistical method for measurement of the complexity of time series, can effectively handle the randomness of EEG signal³⁰. The larger the value of the sample entropy of the signal x , the more complex the sample sequence. The definition of sample entropy is outlined below³¹.

If there is a time series of N sample points $\{x(i)\} = x(1), x(2), \dots, x(N)$, where the dimension is m (the value of m is generally 1 or 2; in this study the value of m is 2):

$$X(i) = [x(i), x(i+1), \dots, x(i+m-1)], i = 1, 2, \dots, N-m+1 \quad (1)$$

Then, the distance between the vector $X(i)$ and $X(j)$ can be calculated as:

$$d[X(i), X(j)] = \max_{k=0, \dots, m-1} |x(i+k) - x(j+k)| \quad (2)$$

For a given $x(i)$, we can calculate the number of j so that the distance between $x(i)$ and $x(j)$ is lower than or equal to r (r is a real number, which represents the measure of "similarity"). Generally, $r=0.1 \sim 0.25 \cdot \text{std}(\text{data})$; herein, we select 0.2 times. For each i , we can calculate:

$$C_i^m(r) = \frac{\text{num}\{d[X(i), X(j)] \leq r\}}{N-m+1} \quad (3)$$

$B^m(r)$ and $B^{m+1}(r)$ is defined as follows:

$$B^m(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} C_i^m(r) \quad (4)$$

$$B^{m+1}(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} C_i^{m+1}(r) \quad (5)$$

Therefore, the sample entropy is calculated as:

$$\text{SampEn}(m, r, N) = -\ln \left[\frac{B^{m+1}(r)}{B^m(r)} \right] \quad (6)$$

Variance. Variance refers to the measure of dispersion of a random variable or a set of data. It is the average of the squared of deviations (the differences between each data point and the mean of the variable). The greater the variance, the greater the deviation from the mean of each sample of signal x , and the greater the degree of dispersion. The formula is for variance is:

$$\sigma^2 = \frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^2 \quad (7)$$

where σ^2 refers to the variance, N refers to the total number of samples, x_i refers to the sample value of each epoch, \bar{x} refers to the average.

Feature selection. Feature selection is a technique that eliminates irrelevant or repetitive features from the original feature set, and chooses a small feature subset, thus decreasing the data dimension and improving the algorithm's execution speed³². The objective of the NCA algorithm, a non-parametric feature selection algorithm for supervised learning, is to learn feature weighing vectors through the use of optimized regular parameters that will allow maximization of the classification accuracy³³. The algorithm can provide the weight of features, which will allow us to select important features. The steps of NCA algorithm are listed as follows:

1. Divide the data into a training set and a test set
2. Divide the training data into 5 folds (four as the training set and one as the test set) for NCA feature selection
3. Use fivefold cross-validation to tune the regularization parameter λ .
4. For each λ , use the corresponding training set to train the NCA model.
5. Use the trained NCA model to measure the loss of classification of the corresponding test set and obtain the loss value.
6. Repeat steps 2-4.
7. Calculate the average loss of each λ worth 10% cross-validation.
8. Identify the best λ that corresponds to the minimal average loss.
9. Use the test data to determine the weight of each feature using the best λ .
10. Select important features based on feature selection criteria using the relative threshold (T):

$$T = \tau * \max(w) \quad (8)$$

In which τ is a fixed value of 0.02 and ω is the characteristic weight³⁴.

In this algorithm, the best λ is associated with the best classification loss. The average loss of cross-validation is dependent on the choice of λ . When λ gets too large, all the feature weights tend to be 0, which causes redundant or irrelevant feature subsets. Hence, the value of λ should be adjusted to minimize the average loss³⁴. Herein, we selected a λ value of 16, with equally spaced points from 0 to 15/N.

Classifiers. Support vector machine (SVM) and K-nearest neighbor (KNN) are the more common classifiers that are utilized in apnea classification problems, largely due to the fact that the supervised model has learning ability to distinguish binary categories. The random forest (RF) model is an ensemble algorithm, which combines multiple weak classifiers. Then, the final result is voted or averaged, and the result of the overall model has higher accuracy and generalization performance³⁵. Therefore, we used RF in this study, as well as SVM and KNN, as classifiers to validate the features obtained above. Due to the imbalance of the data used, the traditional learning algorithm has greater limitations. To solve this problem, we adopted the class weighting method to improve the classification performance by adjusting the weights of different classes to favor minority classes.

K-nearest neighbor. The KNN classification algorithm, an extension of the nearest neighbor method, is a supervised learning method that belongs to a nonlinear classifier within the classification process^{36,37}. KNN classifies by measuring the distance between various feature values. Specifically, if the data and labels of the training set are known, then the characteristics of the test data are compared to the corresponding features within the training data, which can help determine the most similar top k data within the training set. Hence, the test data will belong to the most frequent category among the top k data³⁸. The similarity between test data and training data is generally determined by the Euclidean or cosine distance. Herein, we used Euclidean distance.

Support vector machine. Support vector machine (SVM) is a supervised machine learning algorithm that develops an optimal hyperplane that allows classification of input data³⁹. This algorithm was originally designed for solving binary classification problems. The basic principle of SVM is that if the data are points that are distributed on a two-dimensional plane, then they are gathered in different areas as per their classification. The goal of this algorithm is to determine the hyperplane between these categories through training⁴⁰. For multi-class classification problems, a multi-class classifier needs to be developed. Currently, there are two methods for constructing multi-class classifiers, including the direct and the indirect method. In this study, we used the indirect method, which allows division of the multi-class classification problem into multiple two-classification problems. The main idea is to design an SVM for classification into two types of samples. In this study, we carried out SVM classification using LibSVM.

Random forest. Random forest is an integrated learning algorithm that uses multiple decision trees for prediction. For classification problems, it is the voting of all decision tree prediction results⁴¹. During training, the training set of each decision tree is constructed using randomly sampling. When training every node of each decision tree, the features that are utilized are also a part of the features that are extracted from the entire feature vector⁴². Through integration of multiple decision trees and training each decision tree with feature components each time, the variance of the model can be efficiently decreased. Theoretically, as the number of decision trees increase, the classification capability of the model also increases. However, at the same time, if the correlation between any two trees increases, then the error rates also increase. Therefore, the optimal number of decision trees also needs to be selected. Herein, the classification of the tree with the best classification effect is 85.

Performance measures. In order to further assess the performance of each of the three feature sets in the RF classifier, we implemented recall, precision, F_1 -score and kappa coefficient as the evaluation indicators for the classification performance. A confusion matrix contains all the data about the actual label, as well as the predicted label. The Kappa coefficient is utilized for consistency testing, but can also be utilized for measurement of classification accuracy. Its calculation is based on a confusion matrix. The evaluation indicators are defined:

$$\text{recall} = \frac{TP}{TP + FN} \quad (9)$$

$$\text{precision} = \frac{TN}{TP + FP} \quad (10)$$

$$F_1 - \text{score} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \quad (11)$$

Here, TP refers to true positive (when positive class is classified as positive class), FP means false positive (when negative class is classified as positive class), and FN refers to false negative (when negative class is classified as positive class).

$$k = \frac{p_o - p_e}{1 - p_e} \quad (12)$$

In this calculation, p_o refers to the sum of the number of samples that are correctly classified within each category, divided by the total number of samples, which provides overall classification accuracy. For p_e , if we assume that the number of real samples within each category are a_1, a_2, \dots, a_C , the predicted number of samples in each category are b_1, b_2, \dots, b_C , and the total number of samples is N , then:

$$p_e = \frac{a_1 \times b_1 + a_2 \times b_2 + \dots + a_C \times b_C}{N \times N} \quad (13)$$

Usually, the calculation of kappa coefficient is between 0 and 1, and the larger the coefficient, the higher the consistency and accuracy.

Results

Herein, we utilized EEG data from 30 different individuals to detect and classify sleep apnea, as well as analyze the performance of the classifier. The data set contained 3459 epochs, which includes 1229 epochs of OSA events, 812 epochs of CSA events, and 1418 epochs of normal breathing events.

After feature extraction, we obtained 20 feature points for each epoch (Table 1). These 20 feature points constitute the original feature set, and the features of all these epochs form 3459*20-dimensional data.

During the feature selection stage, we first determined the minimum average loss when selecting different training set and test set ratios. Hence, we randomly selected 45%, 40%, 35%, 30%, 25%, and 20% of the original feature set as the test set (Table 2). When 25% of the test set and 75% of the training set were selected, the average loss was found the most minimal.

The correlation between the average loss and the λ value is shown in Fig. 2. The minimum average loss that corresponded to the 16 lambda values is 0.1445, while the corresponding optimal λ value was 0.0011.

Figure 3 showcases the feature weight of each feature index, and the meaning of the feature that corresponds to each serial number is shown in Table 1. The obtained feature weight that is relative to the threshold T is 0.0567, and 15 important features are screened out according to this value (Table 3).

Within the classification stage, we selected the training set as well as the test set by 10-fold cross-validation, allowing us to select the training set and the test set, and input the features into KNN, SVM, and RF for classification. Then, we took the average accuracy of 10-fold cross-validation as the final result. The average confusion matrix of the 10-fold cross-validation of each classifier is given in Figs. 4, 5 and 6.

Table 4 indicates the specific classification results of the three classifiers for obstructive apnea, central apnea and normal breathing. It can be observed from the table that out of three classifiers, RF has the highest classification accuracy, followed by KNN, and SVM has the lowest.

Table 5 demonstrates the classification performance of the three classifiers. RF was shown to have the highest classification accuracy and the best classification effect. It can be seen that the random forest classifier has better recall, accuracy, F_1 -score and kappa coefficient than the other two classifiers, and has the best classification performance.

Discussion

In this study, we propose a method that will allow classification of sleep apnea by applying classifiers to EEG signals. In order to obtain a high performing classifier, it is necessary to eliminate the non-contributing elements within the original feature data set. Therefore, we utilized NCA to carry out feature selection in the original data set to acquire a data set that contained 13 features. Finally, three classifiers are utilized to detect and classify sleep apnea. The results of this feature selection indicate the presence of six features in the important feature subset from the left hemisphere EEG signal (C3-A2), and seven features from the right hemisphere (C4-A1). This indicates that patients with sleep apnea have different changes in the EEG of the central scalp area of the left (C3-A2) and right (C4-A1) during sleep, specifically, the right cerebral hemisphere is more active than the

No	Feature vector		
	feature	Channel	sub-band
1	Variance	C3	Delta
2			Theta
3			Alpha
4			Beta
5			Gamma
6		C4	Delta
7			Theta
8			Alpha
9			Beta
10			Gamma
11	Sample Entropy	C3	Delta
12			Theta
13			Alpha
14			Beta
15			Gamma
16		C4	Delta
17			Theta
18			Alpha
19			Beta
20			Gamma

Table 1. The specific meaning of the 20 characteristics.

Test percentage	45%	40%	35%	30%	25%	20%
Best loss	0.1487	0.1594	0.1530	0.1557	0.1455	0.1510
Best lambda	0.0021	0.0009	0.0013	0.0012	0.0011	0.0022

Table 2. The corresponding best loss and best lambda when selecting different test sets.

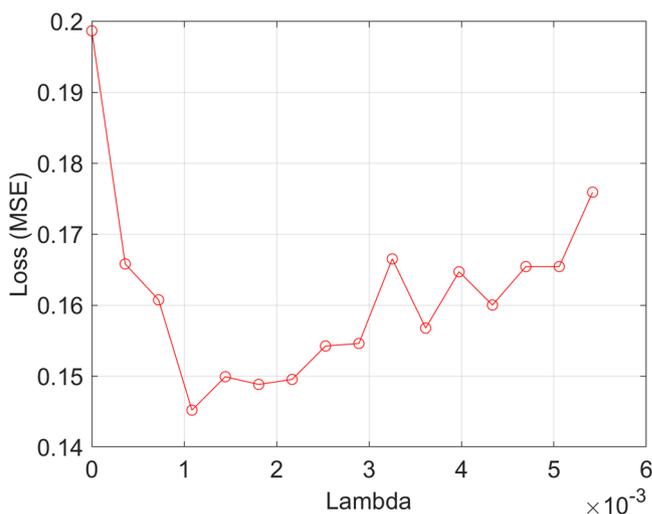


Figure 2. Relationship between average loss and λ value.

left hemisphere during sleep. Additionally, it can be concluded from Fig. 3 that the feature weight that is taken from the sub-band theta is the larger of all the five sub-bands, and the feature weight of the low-frequency sub-band is bigger than that of the high-frequency sub-band. This illustrates the importance of low-frequency EEG components that allow detection of sleep apnea, which is consistent with literature⁴³.

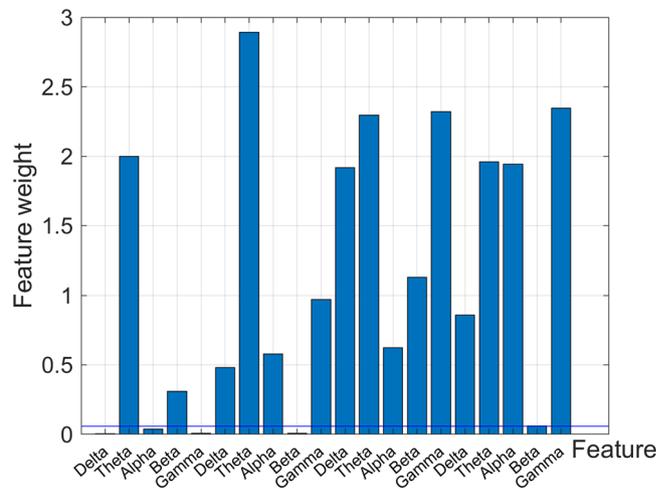


Figure 3. Feature weights after NCA feature selection.

No	Feature vector		
	feature	Channel	sub-band
2	Variance	C3	Theta
4			Beta
6		C4	Delta
7			Theta
8			Alpha
10			Gamma
11	Sample Entropy	C3	Delta
12			Theta
13			Alpha
14			Beta
15			Gamma
16		C4	Delta
17			Theta
18			Beta
19			Gamma
20			Gamma

Table 3. The specific meaning of the 15 important features.

There are also the studies that devoted to automatic classification of OSA events, CSA events and normal breathing events based on EEG signals. Monika et al. used discrete wavelet transform and Hilbert transform in order to extract statistical characteristics, including instantaneous amplitude, instantaneous frequency, and weighted instantaneous frequency from EEG epochs. In order to select features, they utilized variance analysis and multiple regression analysis. Then, using a feed-forward neural network, they reported that the average accuracy was 77.27%, while the accuracy for normal breathing, OSA, and CSA were 71.21%, 86.36% and 74.24%, respectively¹⁴. They also used the same feature extraction and selection method to analyze the EEG signals of C3-A2 and C4-A1 channels, and concluded that combining the two EEG channels together is more effective at automatic detection and discrimination of sleep apnea⁴³. In comparison to these studies, the proposed automatic classification method for sleep apnea has high accuracy.

Conclusion

In this study, a classification algorithm that was based on EEG sub-band signal feature extraction is proposed to help classify sleep apnea events. The EEG signals used in this study came from a database of night polysomnography among patients treated at the Tianjin Chest Hospital. The results of this study show that the average accuracy of random forest classifier classification can reach 88% after feature selection using the NCA feature selection algorithm, while the accuracy, the recall rate, and the F1-score was 0.86, 0.89, and 0.87, respectively. Hence, this method can automatically detect the occurrence of sleep apnea events, determine the type of apnea

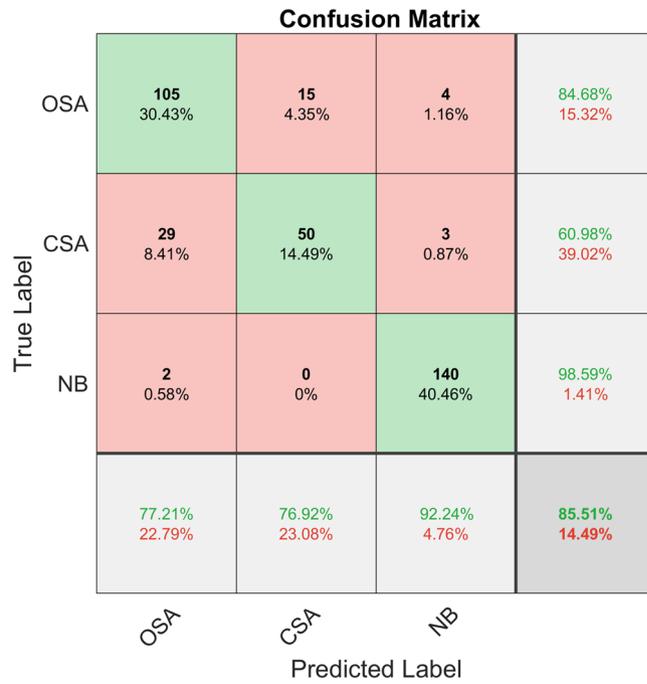


Figure 4. Confusion matrix of KNN classifier classification accuracy.

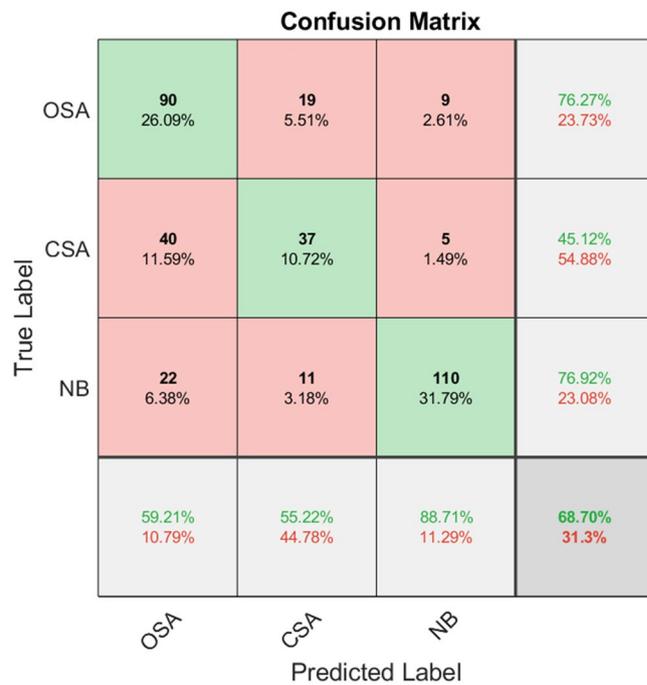


Figure 5. Confusion matrix of SVM classifier classification accuracy.

event, and, to some extent, replace sleep experts to complete the diagnosis of respiratory events, thereby saving medical resources and time. The classification of apnea events based on EEG signals is only a preliminary study for now. In the future research, we will further improve accuracy on this basis, and work on classifying sleep apnea types and severity to develop a set of methods determining sleep apnea and severity based on EEG.

Confusion Matrix

True Label	OSA	111 32.08%	10 2.90%	2 0.58%	90.24% 9.76%
	CSA	25 7.25%	56 16.23%	1 0.29%	68.29% 31.71%
	NB	2 0.58%	0 0%	140 40.46%	98.59% 1.41%
		80.43% 19.57%	84.85% 15.15%	95.24% 4.76%	88.99% 11.01%
		OSA	CSA	NB	
		Predicted Label			

Figure 6. Confusion matrix of RF classifier classification accuracy.

Classifiers	Average	OSA	CSA	NB
KNN	85.51%	77.21%	76.92%	92.24%
SVM	68.70%	59.21%	55.22%	88.71%
RF	88.99%	80.43%	84.85%	95.24%

Table 4. Classification results of three classifiers.

Classifiers	Recall	Precision	F1-score	kappa
KNN	0.81	0.82	0.82	0.83
SVM	0.67	0.68	0.67	0.54
RF	0.86	0.89	0.87	0.85

Table 5. Classification performance of three classifiers, including accuracy, recall, F1-score and Kappa coefficient.

Data availability

The data used and analyzed during the current study are available from the corresponding author on reasonable request.

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Author contributions

All authors contributed to the study conception and design. X.Y.Z. conceived, developed and validated the method; recorded data. X.H.W. analyzed data and wrote the manuscript. T.S.Y. and S.Y.J. researched literature. H.Q.W. and J.H.W. reviewed the manuscript. Y.W. and Q.W. supervised the research, provided comments. All authors reviewed and approved the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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