A New Method for Detecting Sleep Apnea

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A new method for detecting sleep apnea

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Abstract: Sleep apnea is a sleep disorder that can induce hypertension, coronary heart disease, stroke and other diseases, so the detection of sleep apnea is clinically important for the prevention of these diseases. In order to improve the detection performance and verify which physiological signals are better for sleep apnea detection, this paper uses multi-channel signal superposition and channel summation to improve the content of valid information in the original signal. Thirty features are analyzed by Relief feature selection algorithm. Finally, 15 features were used to build a classification model and support vector machine (SVM) was used for classification. The experimental results showed that the highest accuracy of 96.24% was achieved when electrocardiogram (X2) and electroencephalogram (C3-A2) channels were used for channel summation.

Keywords: sleep apnea; wavelet threshold; Relief algorithm; support vector machine

1. Introduction

Patients suffering from sleep apnea often feel demoralized and depressed in their lives [1]. Undiagnosed sleep apnea has a significant impact on the quality of human life and can lead to heart disease, hypertension, pre-diabetes and diabetes, depression and long-term stroke [2]. Polysomnography (PSG) is one of the most commonly used methods in sleep apnea diagnosis [3]. Polysomnography (PSG) is a method of simultaneous recording of multiple physiological parameters related to sleep to detect sleep apnea by measuring different parameters (Respiratory Disturbance Index (RDI), Apnea Hypoventilation Index (AHI), etc.)..

In recent years, many researchers have used different physiological signals for the automatic

diagnosis of sleep apnea. For example, song et al. used Markov models to detect sleep apnea by extracting features such as time and frequency domains from respiratory (EDR) signals and electrocardiogram (ECG) signals with a correct rate of 86.2% [4]. Xie et al. Used electrocardiogram (ECG) and peripheral blood oxygen saturation (SPO2) signal detection. Through the combination of classifiers, the accuracy rate reached 82% [5]. Nishad et al. Used electrocardiogram (ECG) signal and adopted an algorithm based on tunable-Q factor wavelet transform (TQWT), with an accuracy of 92.78% [6].Li et al. introduced a stacked SAE automatic feature extraction method with 84.7% accuracy for classification [7].Sharma et al. extracted a RBF kernel based on hermit basis function to extract features from RR interval LS-SVM large segmented SA detection method with an accuracy of 83.8% [8].Hassan et al. proposed a normal inverse Gaussian (NIG) pdf model method based on tunable-Q factor wavelet transform (TQWT) domain using electrocardiogram (ECG) signals with an accuracy of 90.72% [9].

The aforementioned studies on sleep apnea have made good progress, but the focus of the work has been on how to improve the detection of sleep apnea. In the part of choosing physiological signals, some of them used ECG signals, as in [5, 6]; some used electroencephalogram (EEG) signals, as in [13]; some used ECG+EDR signals, as in [4]; some used ECG+SPO2 signals, as in [5]; none of these studies conducted a comparative study of the performance of physiological signals for the detection of sleep apnea. In order to verify which physiological signals are better for the detection of sleep apnea, this study chose ECG and 6-channel EEG signals for a comparative study. In addition, the superposition of different source signals can attenuate the white noise interference and enhance the synchronous effective information in the signal [10]. Therefore, this study proposes the method of channel summation

and signal superimposition to detect sleep apnea. In order to improve the performance of sleep apnea detection, time domain features, frequency domain features and nonlinear features are calculated, and the Relief algorithm is used to filter the optimal features to improve the detection results. Among them, channel addition is to extract features by combining data from multiple channels, and signal superposition is to extract features after summing data from multiple channels.

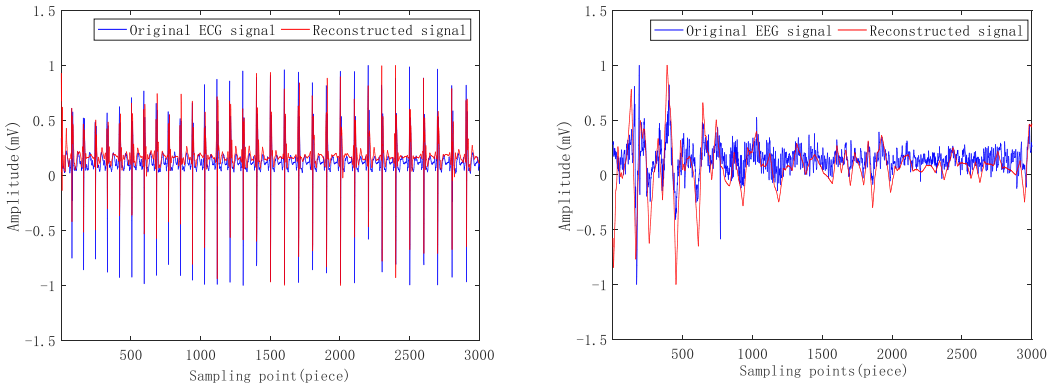
2. Materials and methods

The data for this study were obtained from the ISRUCG-SLEEP dataset [11]. One ECG channel (X2) and six EEG channels (F3-A2, C3-A2, O1-A2, F4-A1, C4-A1, and O2-A1) were selected from 100 patients with sleep apnea and the sampling frequency was 200 Hz. all data were divided into 30s segments and labeled by two experts. In this study, wavelet thresholding is used to remove the noise, and signal superposition and channel summation are used to enhance the effective information in the multi-channel signals. Then 30 features of three types, including time domain features, frequency domain features and nonlinear features are filtered by Relief algorithm. The screened 15 features were then used and the support vector machine (SVM) was employed to classify the sleep apnea segment and the normal segment.

2.1 Signal pre-processing

The wavelet threshold method can effectively reduce the interference of noise on the signal. In the actual clinical sleep breathing test, usually only the spectrum between [10] 0.5 ~ 30Hz is concerned. In order to reduce the effect of high frequency sub band noise, the original signal is decomposed by db3 wavelet, and the threshold estimation method with stein unbiased likelihood estimation and soft threshold function is used, and then reconstructed by using db3

wavelet. Figure 1(a) and (b) shows the comparison of ECG with the reconstructed signal and EEG with the reconstructed signal, respectively.



(a) ECG versus reconstructed signal (b) EEG versus reconstructed signal

Figure 1 Comparison of the original signal and the reconstructed signal

In this study, signals from a total of seven channels, ECG (X2), EEG1 (F3-A2), EEG2 (C3-A2), EEG3 (O1-A2), EEG4 (F4-A1), EEG5 (C4-A1), and EEG6 (O2-A1), were used to detect sleep apnea. Both types of signals (ECG, EEG) in principle contain valid sleep apnea information, which allows the two types of signals to be combined with each other for sleep apnea detection. Therefore, we chose to combine the raw ECG signal with the EEG signal to detect sleep apnea. The combination consists of two to seven channels of signals combined with each other.

2.2 Feature extraction and screening

The extraction of features is important for the detection of sleep apnea, and there are a large number of features for the detection of sleep apnea in different studies, including some time domain features [1, 12, 19, 21], frequency domain features [1, 12] and nonlinear features [1]. In this study, a total of 30 features were extracted in three types of features, which are maximum value, minimum value, mean and variance in time domain features, absolute mean value of power spectral density, signal power in alpha rhythm band in frequency domain features, and sample

entropy, alignment entropy, spectral entropy in nonlinear features. The specific features are shown in Table 1.

Table 1 Extraction of initial features

Feature Type	Features
Time domain characteristics	Maximum, minimum, mean, root mean square, peak-to-peak, variance, standard deviation, skewness, Degree, kurtosis, waveform factor, peak factor, impulse factor, margin factor, coefficient of variation, first quartile, second quartile, third quartile, energy
Frequency domain characteristics	Absolute mean of power spectral density, signal power of alpha rhythm band, signal power of beta rhythm band, signal power of delta rhythm band, signal power of theta rhythm band
Non-linear characteristics	Sample entropy, permutation entropy, fuzzy entropy, spectral entropy, excess zero rate, fractal dimension

Different features have different abilities to detect sleep apnea. Some features may be redundant, so it is important to reduce the dimensionality of the extracted features and select the optimal ones while maintaining the classification performance [13]. Therefore, it is necessary to screen the features.

Table 2 Relief algorithm

Algorithm 1 Relief algorithm pseudo code

```
Input: dataset D, sample sampling number m, threshold value of feature weights δ
Output: weights T of each feature
Put 0 all feature weights, T[F]:= 0;
for i = 1 to m do
A randomly selected sample R
Find the nearest neighbor sample H of R from the set of similar samples
Find the nearest neighbor sample M from different sample sets
for F = 1 to n do
        W(F)=W(F)-diff(F,R,H)/m + diff(F,R,M)/m
for F = 1 to n do
If W(F)> δ
Adding F features to T
end
end
end
```

This study uses the Relief algorithm for feature selection .Relief is an effective feature

selection algorithm [14].The Relief algorithm was first proposed by Kira as a feature weighting algorithm that gives features different weights based on the relevance of each feature and category. A threshold can be set and if the weight is less than the threshold, the feature will be removed. The correlation between features and categories in the Relief algorithm is based on the ability of features to discriminate between close samples. The pseudo-code of Relief algorithm is shown in Algorithm 1 in Table 2.

In Algorithm 1 of Table 2, T[F] is the vector of weights corresponding to the features. The higher the weight, the better the corresponding feature, the stronger the classification ability of that feature; conversely, the worse the corresponding feature, the weaker the classification ability of that feature. The algorithm randomly selects a sample R from the data set D. It will find the nearest neighbor sample H, called Near Hit, from the samples of the same kind as R and the nearest neighbor sample M, and called Near Miss, from the samples of the same kind as R. If the distance between R and Near Hit on a feature is smaller than the distance between R and Near Miss, it means that the feature is useful for distinguishing the nearest If the distance between R and Near Hit on a feature is smaller than the distance between R and Near Miss, the feature is beneficial to distinguish the nearest neighbors of similar and dissimilar categories, and the weight of the feature is increased. Repeat m times, and finally the average weight of each feature is obtained. The formula for calculating diff is shown in Equation 1.

$$\mathrm{diff}(F, R_1, R_2) = \begin{cases} \dfrac{\left|R_1[F] - R_2[F]\right|}{v}, if\ \ F\ is\ continuous \\ 0, if\ \ F\ is\ discrete\ and\ R_1[F] = R_2[F] \\ 1, if\ \ F\ is\ discrete\ and\ R_1[F] \neq R_2[F] \end{cases} \tag{1}$$

Where V is the normalization unit, normalizing the diff values are normalized to the [0, 1] interval

and F is one of the features.$R1$, $R2$ is the sample.

2.3 Classification

Support vector machine (SVM) is a tool developed on the basis of statistical learning theory to solve supervised classification problems [15]. In this study, a Gaussian kernel function (RBF)-based support vector machine (SVM) is used for classification. In addition, to verify the accuracy of the model, the sensitivity, specificity and F1-score are calculated in addition to the accuracy. The calculation equations are as shown in Equations 2-5.

$$accuracy = \frac{TR + TN}{TP + TN + FP + FN} \tag{2}$$

$$sensitivity = \frac{TP}{TP + FN} \tag{3}$$

$$specifity = \frac{TP}{TP + FN} \tag{4}$$

$$F1 = \frac{2TP}{(2TP + FN + FP)} \tag{5}$$

Where, TP, FP, TN, and FN are the number of true positives, false positives, true negatives, and false negatives, respectively. In addition, the area under the recursive operating curve (ROC) (AUC) is used to visualize the performance of the classifier. The Kappa coefficient is then used to calculate the agreement between the expert labels and the classifier output. the value of Kappa ranges from -1 to 1, and the closer to 1 indicates better performance. The calculation formula is shown in Equation 6.

$$Kappa = \frac{p(0) - p(e)}{1 - p(e)} \tag{6}$$

Where P(0) denotes observation consistency and P(e) denotes opportunity consistency. The calculation formula is shown in Equations 7-8.

$$P(0) = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

$$P(e) = \frac{(TP + FP)(TP + FN) + (TN + FN)(TN + FP)}{(TP + TN + FP + FN)} \tag{8}$$

3. Results

3.1 ECG signal detection results using individual features

Table 3 Accuracy and Kappa coefficient of sleep apnea detection by a single feature

Serial number	Name	Accuracy (%)	Kappa (%)
1	Minimum value	76.70	53.40
2	Displacement entropy	57.21	14.42
3	Spectral entropy	58.41	16.82
4	First quartile	72.71	45.42
5	Skewness	54.66	09.32
6	Fractal dimension	75.52	51.04
7	Fuzzy entropy	60.30	20.60
8	Average value	70.11	40.22
9	Maximum value	79.36	58.72
10	Sample entropy	67.35	34.70
11	Signal power in the alpha rhythm band	79.86	59.72
12	Signal power in the beta rhythm band	80.95	61.90
13	Signal power in the theta rhythm band	79.87	59.74
14	Absolute average of power spectral density	76.19	52.38
15	Second quartile	74.10	48.20

We selected the minimum value, alignment entropy, spectral entropy, first quartile, fractal dimension, skewness, fuzzy entropy, mean value, maximum value, sample entropy, signal power in the (α, β, θ) rhythm band, absolute mean of power spectral density and second quartile, a total of 15 features to verify their effectiveness for sleep apnea detection, and the same data set and classifier are used for testing. Table 3 shows the accuracy and kappa coefficients for sleep apnea detection using a single feature.

From Table 3, we can see that the accuracy and Kappa coefficient of individual features are low, with accuracy below 85% and Kappa coefficient below 65%. The differentiation of single features is not effective.

3.2 Performance of sleep apnea detection when channels are summed and signals are superimposed

In this subsection, we compare the results of sleep apnea detection using single channel signals and signals with different number of channels in combination with each other. A 4-fold cross-validation was used and the average of the four predicted results was taken as the final result, and the test results were the final model evaluation metrics. Different metrics such as area under the recurrent working curve (ROC), F1-score, Kappa coefficient, sensitivity, specificity, and accuracy were used to evaluate the classification results of ECG, ECG summed with EEG channels, and ECG superimposed with EEG signals. The results of single-channel signal and two-channel signal sleep apnea showed that the combination of ECG and EEG was more effective than single-channel ECG, and the results are shown in Table 4. The results of ECG, ECG and EEG combination are listed in Table 4, where Accuracy, AUC, Sen, Spe, and F1 indicate the accuracy, area under the ROC curve, sensitivity, specificity, and F1-score, respectively. Figures 2 and 3 indicate the accuracy and Kappa coefficient of raw ECG signal, ECG and EEG Channel added, and ECG and EEG signal superimposed.

As shown in Table 4 and Figures 2 and 3, when using the EEG signal for sleep apnea detection, it is evident that the classification of the ECG signal reached 95.92% and the Kappa coefficient was 91.84%. Therefore, the overall performance of sleep apnea was improved with the fusion of multiple features.

The best classification performance was achieved by ECG and EEG2 channel addition with 96.24% accuracy and 92.48% Kappa coefficient, when the signals are superimposed, the classification performance of ECG and EEG2 is better, with an accuracy of 96.18% and a kappa coefficient of 92.36%.Overall, channel addition and signal superposition can enhance the simultaneous effective information in the signal, thus improving the classification performance.

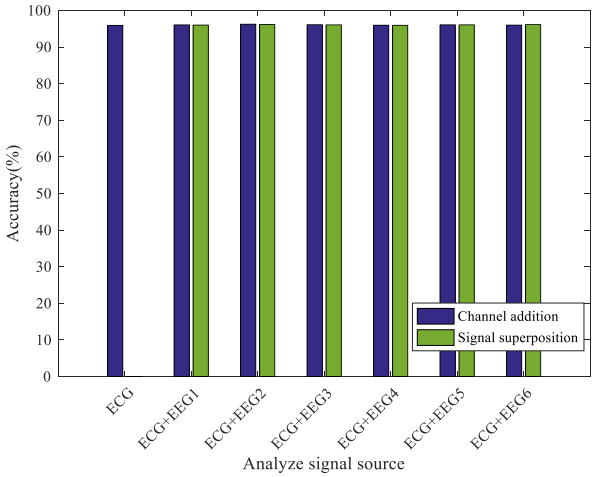


Figure 2 Accuracy of sleep apnea detection with signal channel addition and signal superimposition

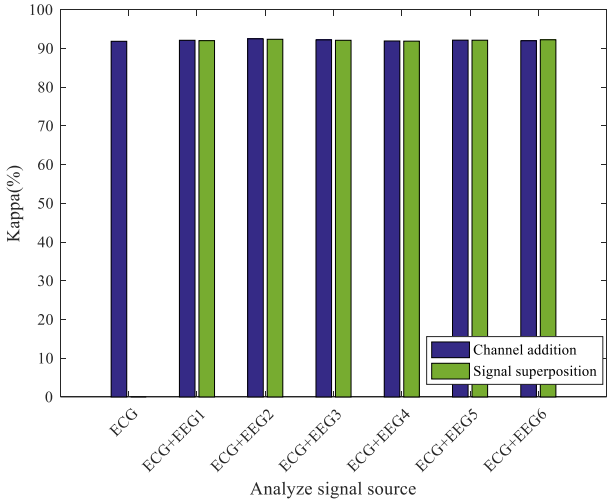


Figure 3 Kappa coefficient of sleep apnea detection with signal channel addition and signal superposition

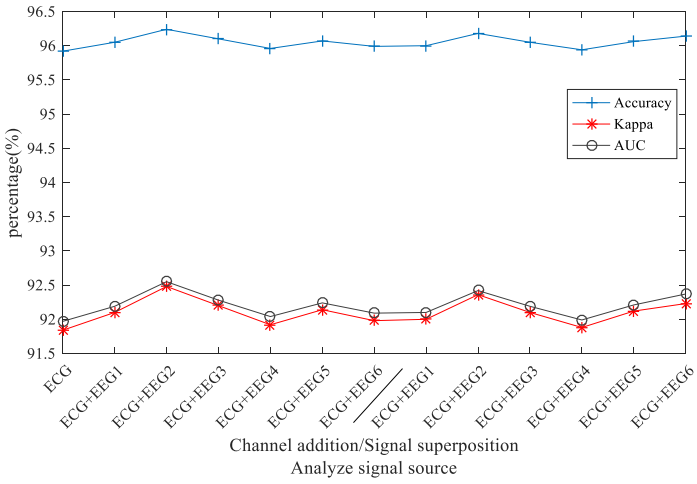


Figure 4 Accuracy, Kappa coefficient and area under the ROC curve curves for different signals

Figure 4 compares the accuracy, Kappa coefficient and area under the ROC curve when ECG, ECG and EEG channels are added and ECG and EEG signals are superimposed. It can be seen from the figure that the accuracy, Kappa coefficient and area under the ROC curve curves show the same trend.

The above shows that the highest accuracy was achieved when ECG and EEG2 channels were added under the two-channel signal combination, on the basis of which the number of channels was increased to detect sleep apnea, and Table 5 shows the results of sleep apnea detection under the multi-channel signal combination. It shows that the best classification performance was achieved when ECG, EEG2 and EEG6 channels were added under the combination of multi-channel signals, with an accuracy of 96.13% and a Kappa coefficient of 92.26%. The results show that adding ECG and EEG channels can obtain better detection results of sleep apnea. Compared with using ECG signals for sleep apnea detection, better sleep apnea detection performance can be obtained using multi-channel ECG and EEG signals.

Table 4 Performance of combined ECG and EEG sleep apnea testing

Serial number	Combination method	Analyzing signals	Accuracy (%)	Kappa (%)	Sen (%)	Spe (%)	F1 (%)	AUC (%)
1	Original signal	ECG	95.92	91.84	98.40	93.75	96.02	91.97
2		ECG+EEG1	96.05	92.10	98.60	93.50	96.15	92.19
3		ECG+EEG2	96.24	92.48	98.73	93.76	96.33	92.55
4	Channel	ECG+EEG3	96.10	92.20	98.70	93.50	96.20	92.28
5	summation	ECG+EEG4	95.96	91.92	98.13	93.80	96.05	92.04
6		ECG+EEG5	96.07	92.14	98.55	93.59	96.17	92.24
7		ECG+EEG6	95.99	91.98	98.33	93.66	96.08	92.09
8		ECG+EEG1	96.00	92.00	98.55	93.45	96.10	92.10
9		ECG+EEG2	96.18	92.36	98.78	93.59	96.28	92.42
10	Signal	ECG+EEG3	96.05	92.10	98.53	93.58	96.15	92.19
11	superimposition	ECG+EEG4	95.94	91.88	98.33	93.56	96.03	91.99
12		ECG+EEG5	96.06	92.12	98.63	93.50	96.16	92.21
13		ECG+EEG6	96.14	92.23	98.65	93.63	96.23	92.37

Table 5 Performance of sleep apnea detection based on multi-channel signal combination

Serial number	Analyzing signals	Accuracy (%)	Kappa (%)	Sen (%)	Spe (%)	F1 (%)	AUC (%)
1	ECG+EEG2+EEG1	96.00	92.00	98.50	93.50	96.10	92.09
2	ECG+EEG2+EEG3	95.94	91.88	98.63	93.26	96.05	91.98
3	ECG+EEG2+EEG4	96.02	92.04	98.38	93.67	96.11	92.15
4	ECG+EEG2+EEG5	95.94	91.88	98.48	93.40	96.04	91.98
5	ECG+EEG2+EEG6	96.13	92.26	98.85	93.39	96.22	92.32
6	ECG+EEG2+EEG6+EEG1	95.57	91.14	98.25	92.89	95.69	91.30
7	ECG+EEG2+EEG6+EEG3	95.55	91.10	98.33	92.78	95.67	91.24
8	ECG+EEG2+EEG6+EEG4	95.81	91.62	98.28	93.35	95.91	91.76
9	ECG+EEG2+EEG6+EEG5	95.69	91.38	98.28	93.10	95.80	91.47
10	ECG+EEG2+EEG6+EEG4+EEG1	95.24	90.48	97.95	92.53	95.37	90.62
11	ECG+EEG2+EEG6+EEG4+EEG3	95.34	90.68	98.25	92.43	95.47	90.58
12	ECG+EEG2+EEG6+EEG4+EEG5	95.40	90.80	97.88	92.93	95.51	90.94
13	ECG+EEG2+EEG4+EEG1+EEG2+EEG4	95.32	90.64	98.10	92.54	95.45	90.79
14	ECG+EEG3+EEG6+EEG1+EEG2+EEG5	95.11	90.22	98.35	91.87	95.26	90.36
15	ECG+EEG1+EEG2+EEG3+EEG4+EEG5+EEG6	94.86	89.72	98.15	91.57	95.02	89.87

4. Discussion

There are many studies on sleep apnea. Usually, they focus on classification methods. Some studies used a single classifier for sleep apnea detection [21], and some studies used multiple classifiers for sleep apnea detection [2, 13]. Compared with some past studies such as [4, 5, 6, 7, 9, 16, 17, 18, 19, 20] the final accuracy of the method used in this paper is significantly better. Table 6 compares the accuracy of this method with some past sleep apnea tests. However, it is important to note that the signal sources and methods used in these studies are not identical. For example, we used the overall accuracy as a measure of sleep apnea detection, but the literature [7] used the categorical accuracy of each segment of detection. In order to improve the performance of sleep apnea detection and to verify which physiological signals perform best for sleep apnea detection, this study was conducted in terms of feature screening and analyzing the results of different channels and different superimposed signals for sleep apnea detection.

Table 6 Comparison of accuracy rates

Literature	Year	Signal Source	Accuracy (%)
[17]	2011	ECG	91.90
[5]	2012	ECG+SPO2	82
[4]	2016	ECG+EDR	86.2
[18]	2016	ECG	85.97
[9]	2016	ECG	90.72
[16]	2017	ECG	89.80
[19]	2017	ECG	88.88
[6]	2018	ECG	92.78
[7]	2018	ECG	84.6
[20]	2019	ECG	82.12
This study	—	ECG+EEG2	**96.24**

It can be found that the addition of the original ECG signal itself and EEG channel plays an important role in sleep apnea; In addition, the superposition of EEG signals can also improve the detection results of sleep apnea. Specifically, compared with single channel ECG signals, summing ECG and EEG channels and signal superposition can improve the effect of sleep apnea detection.

Feature screening is also an important factor affecting sleep apnea detection. In this paper, 15 features were screened from 30 initial features by Relief algorithm. Through this study, we can find that different features have different effects on sleep apnea. Single features are also poorly differentiated, while feature fusion can improve the overall classification.

In the follow-up, we can also study the ocular electrical signal and blood oxygen saturation signal, and study the impact on sleep apnea performance by adding different physiological signals. In addition, different preprocessing methods will also affect the final classification results. The use of a single classifier, multiple classifiers and the combination of multiple classifiers will also affect the effect of sleep apnea detection.

5. Summary

Sleep apnea is a common clinical respiratory disease [22], detection work is currently relying

on polysomnography to complete the detection, due to the wearing aspects of inefficiency, so the signal feature extraction, screening, fusion and automatic detection in the clinical significance, can reduce the workload of medical workers. Considering that the superposition of signals can attenuate white noise interference and enhance the synchronous effective information in the signal and the combination of multiple features can make the sleep apnea detection complement each other. In this study, we used multi-channel data and multiple features to detect to improve the effectiveness of sleep apnea detection. In the current study, we have the highest accuracy of 95.92%, 96.24% and 96.18% by comparing ECG signal, ECG and EEG channel addition, and ECG and EEG signal superimposition, respectively, for improving the detection of sleep apnea.

Availability of data and materials

The datasets generated and/or analyzed during the current study are available in the [data] repository, [https://pan.baidu.com/s/1V4A_kLNftfbcXjf_u0wAIQ?pwd=4fi9]

Abbreviations

SVM: Support vector machine

PSG: Polysomnography

RDI: Respiratory Disturbance Index

AHI: Apnea Hypoventilation Index

EDR: ECG-Derived Respiratory Signal

ECG: Electrocardiogram

SPO2: Peripheral blood oxygen saturation

TQWT: Tunable-Q factor wavelet transforms

SAE: Stacked Auto-Encoder

RBF: Radial basis function

LS-SVM: Least squares-Support vector machine

NIG: Normal inverse Gaussian

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Contributions

Xin Xiong put forward research ideas; Yaru Zhang was responsible for the experiment and wrote the text; Sanli Yi completed the content of Figure 1; Chunwu Wang and Ruixiang Liu are responsible for Figure 2,Figure 3 and Figure 4; Jianfeng He is responsible for the revision of the final version.

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Ethics declarations

Ethics approval and consent to participate

All data included in this study can be found in the ISRUC-Sleep dataset （https://sleeptight.isr.uc.pt/?page_id=48）Publicly available on. Therefore, this study does not require ethical approval.

Consent for publication

Not applicable.

Competing interests

All authors declare no competing interests in this current study.

Supplementary Information

Additional file 1

Performance of sleep apnea detection based on EEG

Supplementary Files

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