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A Sleep Stage Classification Method via Combination of Time and Frequency Domain Features based on Single-Channel EEG

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***Abstract*—Sleep staging is an important method to diagnose and treat insomnia, sleep apnea, and other sleep disorders. Compared with the multi-channel automatic sleep staging system, the single-channel EEG signal contains less information, and the traditional single analysis domain feature parameter extraction algorithm cannot meet the requirement of sleep stage classification accuracy. To solve this problem, we propose an automatic sleep staging method based on the combination of time-domain and frequency-domain features based on single-channel EEG signals. Empirical mode decomposition is used to decompose EEG signals in the time domain to obtain the decomposed signals at different time scales. Multiple local features are extracted from each decomposed signal. The frequency-domain features of EEG signals are obtained by using the frequency domain decomposition of EEG signals in various rhythms. The time-domain and frequency-domain decomposition features are combined into eigenvectors and selected for sleep staging. The experimental results show that the sleep staging method proposed in this paper with time-frequency domain features of single-channel EEG signals can approach the accuracy of sleep staging of multi-channel signals on the same data set, and superior to the sleep staging method with the same single-channel EEG signals.**

***Index Terms*—sleep stage classification, Empirical Mode Decomposition, frequency-domain decomposition, time-frequency domain features**

I. Introduction

Sleep is one of the most important physiological activities of human beings. Effective night sleep is vital to human health. In modern society, with the increase of life pressure, more and more people suffer from sleep disorders [1]. Accurate sleep stage classification can better diagnose and treat insomnia, sleep apnea and other sleep disorders. Polysomnography (PSG) is the gold standard for clinical diagnosis of sleep disorders and is widely used in sleep monitoring. According to the physiological signals of electroencephalogram (EEG), electrocardiogram (ECG), electrooculogram (EOG), electromyogram (EMG) and oxygen saturation measured by this instrument, sleep quality is obtained by sleep experts [2]. Manual grading by a sleep expert leads to problems such as high test cost and long sleep assessment time.

Designing a simple and reliable automatic classification system for sleep staging is an effective way to solve the above problems. In recent years, automatic sleep staging has been widely studied. The multi-channel signal sleep staging method according to various physiological characteristics such as EEG waveform type, eye movement, and muscle activity. However, this method requires multiple monitoring circuits to be connected to the subjects, which will affect their normal sleep. Among these physiological signals, EEG signals can reflect the change of sleep pattern in each sleep stage, and play a crucial role in the recognition of sleep stage, which is widely used for sleep staging. The double-electrode device of single-channel EEG signal has the advantages of easy to wear and little sleep interference. Therefore, the single-channel EEG signal is used as the input of our automatic sleep stage classification model.

The EEG sleep staging method based on machine learning includes feature extraction, feature selection and feature classification. The analysis of EEG signals during sleep and effective feature extraction is the key problems in the research. The extracted features mainly include time domain [3]– [5], frequency domain [6]– [9], and time-frequency domain. Time domain analysis method is to perform EMD or Ensemble Empirical Mode Decomposition on EEG signals, extract statistical features such as mean value and variance, and obtain sleep staging results by using a classifier. Although the time domain analysis and calculation is relatively simple, it is difficult to achieve good sleep staging results. Frequency domain analysis is the transformation of brain waves which amplitude changes with time into the spectrum of EEG power changes with frequency. However, the frequency domain decomposition can only reflect the explicit mode of the signal, and ignore the inherent mode of the signal. In addition, the frequency domain decomposition does not reflect the time when the EEG signal occurs in some frequency range.

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TABLE I
THE NUMBER OF EPOCHS OF VARIOUS SLEEP STAGES

Database	Subjects	W	S1	S2	S3	S4	REM	Total
SEDF	4SC+4ST	7927	483	3225	619	500	1383	14137
SEDFX20	10SC+10ST	19024	1359	7464	1319	962	3461	33589
SEDFX20*	20SC	37068	1435	9692	1750	1147	3754	54846
UCD	25	3979	2864	6332	590	1810	2750	18325

Time and frequency domain analysis is a feature extraction method combining time domain and frequency domain. In [10], the most informative features were extracted using discrete wavelet transform, statistical values of sub-bands were calculated and fed into a rotational support vector machine. In [11], three time-frequency techniques were deployed for the analysis of the EEG signal: Choi–Williams distribution, continuous wavelet transform, and Hilbert–Huang Transform. Features were extracted from the time-frequency representation of the EEG signal using Renyi's entropy. However, it is necessary to select the appropriate wavelet basis function for the wavelet transform of EEG. The wavelet function derived from a single basis function is difficult to approximate the local characteristics of the signal accurately at different scales.

Hassan et al. [12] calculated the Gaussian probability density function parameters with the sub-band of the decomposition of tunable Q factor wavelet transform, and used an adaptive boosting algorithm to classify the sleep stages. Sharma et al. [13] conducted three-stage wavelet decomposition of EEG signals, calculated the distinguishing features of sub-bands, and used a support vector machine to obtain sleep staging results. The tunable Q factor wavelet transform can effectively represent the sparsity and non-stationarity of signals in the time-scale domain. However, the decomposition of EEG signals is still limited by three parameters: quality factor, over-sampling rate, and decomposition layer number.

In this work, we propose to use empirical mode decomposition (EMD) method to decompose EEG signals in time domain, and then decompose EEG signals in frequency domain. The temporal and frequency characteristics of EEG signals are fused to improve the accuracy of sleep staging. The single-channel EEG signal automatic sleep staging method overcomes the shortcomings of multi-channel signal sleep staging connections that affect the subject's sleep. With the improvement of sensor performance [14] [15] and the development of mobile sensor algorithm [16] [17], the method we proposed is suitable for portable devices or wearable devices and conducive to the realization of home sleep monitoring systems.

The article is organized as follows: Section II details the experimental data sets. Section III proposes the method via combination of time and frequency domain features. Section IV demonstrates the performance of the proposed method. Section V shows the comparison to other single-channel EEG and multi-channel methods. Finally, section VI gives conclusions.

II. DATASET

PhysioNet [18] is a resource website supported by the National Academy of General Medical Sciences and the National Academy of biomedical imaging and bioengineering. The PhysioNet Resource's original and ongoing missions are to conduct and catalyze for biomedical research and education, in part by offering free access to large collections of physiological and clinical data and related open-source software. Sleep-EDF Expanded (SEDFX) [19] and St. Vincent's University Hospital/University College Dublin Sleep Apnea Database (UCD) [20] are two public data sets widely used in the field of sleep research.

A. SEDFX

The SEDFX database contains 197 whole-night polysomnographic sleep recordings. Two PSGs of about 20 hours each were recorded during two subsequent day-night periods at the subjects' homes in SC group. The PSGs of about 9 hours were recorded in the hospital for two nights in ST group. All the EEG recordings were sampled at the frequency of 100 Hz, then manually annotated by experts into different stages according to the Rechtschaffen and Kales standard [21], which are named as stage 1(S1), stage 2(S2),stage 3(S3),stage 4(S4), REM, wake (W), movement time, or unscored. The movement time and unscored category only mark the start or end time of the record and are not related to the stage studied in this paper. Each subject randomly selects a record for research, using the EEG data of the PzOz channel. The Sleep-EDF (SEDF) database is an early version of SEDFX, and the SC and ST groups each included four PSG records. The standard of sleep stage classification is the same as the SEDFX data set. The number of epochs available for the wake and sleep stages in our data sets is shown in Table I. The SEDFX 20 dataset consists of 10 SC and 10 ST records, the SEDFX 20* dataset consists of 20 SC records.

B. UCD

The UCD database contains 25 full overnight PSG recordings of adults with suspected sleep-disordered breathing. Signals recorded were EEG (C3-A2), EEG (C4-A1), left EOG, right EOG, submental EMG, ECG, oro-nasal airflow, ribcage movements, abdomen movements, oxygen saturation, snoring (tracheal microphone), and body position. Sleep stages were scored by an experienced sleep technologist according to standard Rechtschaffen and Kales rules. We use C3-A2 channel EEG for our research. The number of epochs available for the wake and sleep stages is shown in Table I.

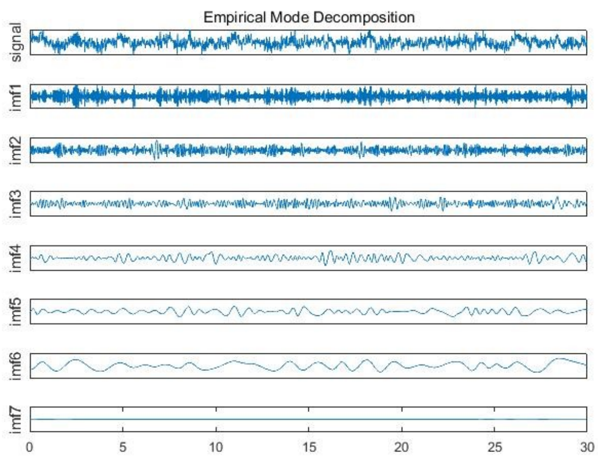


Fig. 1. 7 IMF examples of 30 seconds EEG signals decomposition.

III. METHODOLOGY

A. Preprocessing

While the EEG signal is detected, irrelevant signals such as ECG, EMG, EOG, and respiration are transmitted to the scalp through human skeleton, muscle, fat, and other tissues, which are mixed in EEG signals to form physiological signal artifact. The noise of this irrelevant information as the target signal makes it difficult to collect and analyze the signal and affects the study of EEG signal characteristics. To reduce the influence of artifacts, a Butterworth Bandpass Filter with cut-off frequencies of 0.1 Hz and 50 Hz is used to filter the single-channel EEG signal. The filtered EEG signals are segmented into epochs of 30 seconds.

B. Time-domain decomposition features

EMD is an adaptive time-frequency signal analysis method, which preserves the characteristics of data itself in the decomposition process, and is suitable for extracting the instantaneous characteristics of nonlinear and non-stationary EEG signals. EMD decomposes the signal into a finite number of Intrinsic Mode Functions (IMF). After decomposing the original EEG signals, the form of formula (1) is obtained, in which $EEG(t)$ is the t-th 30 second EEG data, $IMFi$ is the Intrinsic Mode Functions, and $r(t)$ is the residue.

$$EEG(t) = \sum_{i=1}^{n} IMF_i + r(t) \tag{1}$$

The 30 seconds original EEG signals and the first 7 IMFs obtained by EMD are shown in Fig. 1.

Each IMF extracts 10 features including mean, variance, standard deviation, Hjorth mobility (HM), Hjorth complexity (HC), log root sum of sequential variations [22], relative energy, sample entropy, Higuchi fractal dimension, and Katz fractal dimension. Some calculation process is as follows:

- Hjorth parameters: HM is the square root of the ratio of the variance of the first-order difference signal and the variance of the signal itself. HC is the standard deviation of the second-order difference signal of the EEG signal. The calculation process is shown in Formula (2, 3). Where $x(n)$ is the signal, $x^{'}(n)$ and $x^{''}(n)$ are the first and second derivatives of the signal. σ_x, $\sigma_{x'}$ and $\sigma_{x''}$ are the standard deviations of $x(n)$, $x^{'}(n)$ and $x^{''}(n)$, respectively.

$$HM = \sigma_{x'}/\sigma_x \tag{2}$$

$$HC = (\sigma_{x''}/\sigma_{x'})/(\sigma_{x'}/\sigma_x) \tag{3}$$

- Log root sum of sequential variations: The log root sum of sequential variations ($LRSSV$) is proposed in [22] to measure the sequential variations between the samples of the signal. The $LRSSV$ is calculated using the following expression,where N is the length of the signal $x(n)$.

$$LRSSV = \log_{10}\sqrt{\sum_{n=1}^{N-1}(x(n)-x(n-1))^2} \tag{4}$$

- Relative energy: The energy calculation process of each IMF is shown in Formula (5). Where $a_i(n)$ represents the instantaneous amplitude of the i-th IMF Hilbert transform, and n represents the number of data points in each epoch. The total energy is the sum of the energy of each IMF, and the ratio of the energy of each IMF to the total energy, relative energy (E_i), is taken as the characteristic of sleep stages.

$$E_i = \frac{\sum_{n=1}^{N}|a_i(n)|^2}{\sum_i(\sum_{n=1}^{N}|a_i(n)|^2)} \tag{5}$$

- Sample entropy: The sample entropy ($SampEn$) calculation process is shown in Formula (6). Where N represents the number of data in the time series x(N), m represents the reconstruction dimension, r represents the threshold size, and C^m represents the number of data whose distance between two m-dimension reconstruction vectors is less than or equal to R.

$$SampEn(m,r,N) = -\ln[\frac{C^{m+1}(r)}{C^m(r)}] \tag{6}$$

- Higuchi fractal dimension (HFD): Correlation dimension is a common analytical method for one-dimensional time series, which can determine the roughness or irregularity of time-domain signals. The signal $x(n)$ is regrouped into k new series. For any parameter m smaller than k, the k-th series is represented as

$$\begin{aligned} x_k^m = \{&x(m), x(m+k), x(m+2k)... \\ &x(m+\lfloor(N-m)/k\rfloor \times k)\} \\ &m = 1,2,...k \end{aligned} \tag{7}$$

Then the length of the curve by connecting the k-th series x_k^m is

$$L_m(k) = \frac{1}{k} \sum_{i=1}^{\lfloor (N-k)/k \rfloor} \frac{\mid (m+ik) - x(m+(i-1)k) \mid}{\lfloor (N-m)/k \rfloor \times k/(N-1)} \tag{8}$$

The average of $L_m(k)$ across all the possible parameter m is

$$L(k) = \frac{1}{k} \sum_{m=1}^{k} L_m(k) \tag{9}$$

HFD is defined as the slope of the line which best fits the point pairs$(-ln(k), ln(L(k)))$ for all values of k smaller than seven.

- Katz fractal dimension: Katz fractal Dimension (KFD) is a method to calculate fractal dimension based on waveform data. The calculation process is shown in Formula (10), where L refers to the sum of distances between two successive points, and d represents the maximum Euclidean distance between the first point and any other point on the waveform.

$$KFD = \frac{\log N}{\log N + \log(d/L)} \tag{10}$$

C. Frequency-domain decomposition features

The features of EEG signals in the frequency range of different sleep stages are important characteristic parameters in the stages of sleep. Theta wave (4-8 Hz) and alpha wave (8-12 Hz) are present in stage 1. During stage 2, the EEG signal amplitude increases, and theta waves are also more prominent in this stage. Theta wave and delta wave (0-4 Hz) are more noticeable in stage 3. The frequency of the EEG signal during stage 4 varies between 0.5 and 2 Hz. In REM period, sigma wave (12-15 Hz), beta wave (15-30 Hz), and gamma wave(>30 Hz) are more dominant; hence, the frequency content of the EEG signal is greater than 12 Hz. Beta waves are also more predominant during wakefulness.

The results of [23] confirm that the spectral edge frequency of 8-16 Hz, the absolute power and relative power of the signal can effectively identify each sleep stage, especially the REM stage. Therefore, we divide the Alpha wave of the EEG signal into sub-segments separated by 1 Hz in order to effectively distinguish the S1 and REM stages. The results of [24] show that Wake and N1 can be effectively distinguished in the 9-50Hz power range. Therefore, the frequency range is adjusted from the commonly used 0.2-35 Hz to 0.1-50 Hz and the Gamma wave is divided into 4 sub-segments to improve the classification accuracy of S1 and awakening stage. According to the frequency characteristics of EEG signals in different sleep stages, the frequency range of 0-50 Hz is divided into 15 frequency bands. The range of each frequency band is shown in Table II.

TABLE II
FREQUENCY BANDS OF EEG RHYTHMS

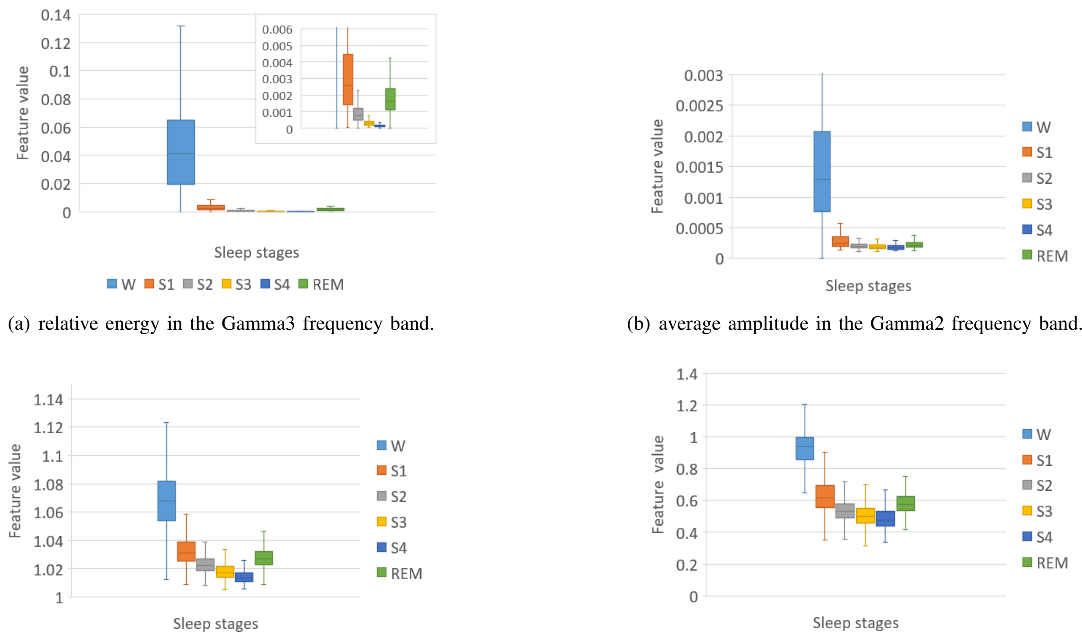
Rhythm	Frequency Band(Hz)
Frequency Range	0-50
Ultra-low Frequency	0.1-1
Delta	1-4
Theta	4-7
Alpha1	7-8
Alpha2	8-9
Alpha3	9-10
Alpha4	10-11
Sigma1	11-14
Sigma1	14-18
Beta1	18-25
Beta2	25-30
Gamma1	30-36
Gamma2	36-41
Gamma3	41-46
Gamma4	46-50

The time-domain signals of each frequency segment are transformed into frequency domain signals by fast Fourier transform. The mean value of frequency amplitude (Amp_Mean) is calculated as the decomposition feature of frequency domain. The power spectral density of each frequency band is calculated to obtain the total power (Pxx). Besides, the relative Energy (Energy) of each frequency band is calculated as the decomposition feature of frequency domain. By calculating the mean amplitude value and total power in the total frequency range from 0 Hz to 50 Hz, a total of 47 frequency domain features are obtained.

D. Feature selection and classification algorithm

The sleep staging model proposed in this paper uses EMD to decompose EEG signals in the time-domain, and the first 7 IMFs extract time domain features such as mean value, variance, standard deviation, Hjorth mobility, Hjorth complexity, log root sum of sequential variations, relative energy, sample entropy, Higuchi fractal dimension, and Katz fractal dimension. The EEG signal is divided into 15 frequency segments according to the frequency range, and the frequency domain features such as amplitude value, power, and energy are extracted by fast Fourier transform.

In this work, features are selected according to the information gain. The specific method is to consider the information representation quantity of the sleep stages when calculating the feature weight and the difference between the two is the information gain of the feature to the sleep stages. The features are selected by using the information gain as the weight of the feature. As a classification model in this paper, random forest is robust to noise and simple to implement. Random forest is a classifier containing multiple decision trees, and the output category is decided by voting on each decision tree. The randomness of both training sets and selected features ensure the diversity of decision trees, resulting in the high robustness against overfitting. Ten fold cross validation method is used to evaluate the accuracy (ACC), recall rate, precision rate, F1 score and Kappa coefficient.



(a) relative energy in the Gamma3 frequency band.

(b) average amplitude in the Gamma2 frequency band.

(c) KFD of IMF4.

(d) HC of IMF2.

Fig. 2. Distribution of features.

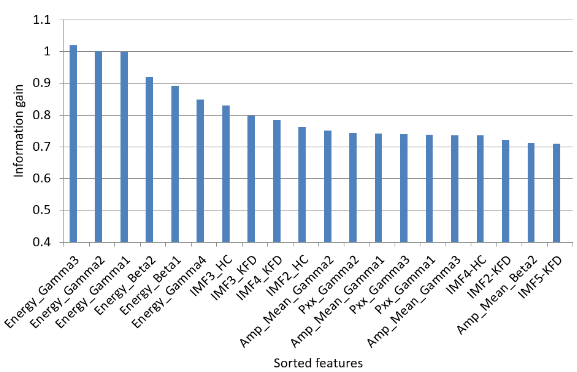


Fig. 3. 7 IMF examples of 30 second EEG signal decomposition.

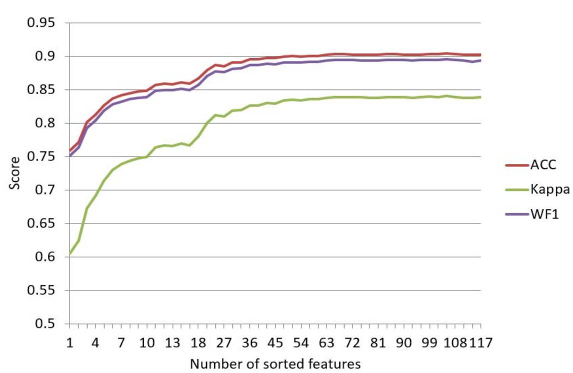


Fig. 4. Classification performance against the numbers of sorted features on SEDFX20 dataset

IV. RESULTS

A. Feature selection and analysis

Features of the SEDFX20 dataset are selected according to information gain. The relative energy of the Gamma3 frequency band, the average amplitude of the Gamma2 frequency band, the KFD of IMF4, and the HC features distribution of IMF2 are shown in Fig. 2. The abscissa represents the 6 sleep stages and the ordinate represents the feature value. The line from top to bottom represents the upper edge (maximum value), the upper quartile, the median, the lower quartile, and the lower edge (minimum value) in turn. The small figure in Fig. 2(a) shows the relative energy feature distribution of the Gamma3 frequency segment in S1, S2, S3, S4, and REM stages. It can be seen from Fig. 2 that the distribution of feature in each sleep stage is obviously different and the average feature value in stage W is larger than those in other sleep stages. With the deepening of sleep, the feature values from S1 to S4 gradually decrease, and then the REM stage increase again. These features are different in different sleep stages and can be used for sleep stage staging.

The feature selection of the top 20 in the SEDFX20 data set is shown in Fig. 3. In the figure, the abscissa represents the feature, and the ordinate represents the information gain score of the feature. It can be seen from Fig. 3 that relative energy, mean amplitude and total power in Gamma and Beta frequency bands play a significant role in classification. Also, the HC and KFD features of IMF2, IMF3, IMF4, and IMF5 can effectively classify different sleep stages. The result of feature selection shows that the Gamma frequency band can effectively distinguish W, S1, and REM stages during sleep

TABLE III
THE CONFUSION MATRIX OF SEDFX20 DATABASE

Alg./Exp.	W	S1	S2	S3	S4	REM
W	18835	61	56	2	2	69
S1	376	331	219	2	4	427
S2	125	51	6807	173	18	290
S3	24	2	487	625	175	6
S4	9	0	42	178	733	0
REM	106	55	451	4	4	2843

TABLE IV
THE CLASSIFICATION RESULTS ON SEDFX20 DATABASE

	Recall	Precision	F-Measure
W	0.990	0.967	0.978
S1	0.244	0.662	0.356
S2	0.912	0.844	0.877
S3	0.474	0.635	0.543
S4	0.762	0.785	0.773
REM	0.821	0.782	0.801
	ACC:0.898	WF1:0.889	Kappa0.8318

stage staging. To obtain the number of feature selections, the feature set is set as an empty set, and the features are added into the feature set one by one according to feature ordering. The classification accuracy rate, Kappa coefficient, and WF1 value are obtained in turn. As shown in Fig. 4, when the feature number is 50, each classification index reaches the maximum value.

B. Classification results

After feature selection, the confusion matrix results of the six-stage sleep stages of the SEDFX20 data set are shown in Table III.The recall rate, accuracy rate, and F1 score of each sleep stage in SEDFX20 are shown in Table IV. The average accuracy rate of sleep staging is 0.898, the score of WF1 is 0.889, and the Kappa coefficient is 0.8318.The high Kappa coefficient shows that the method in this paper is highly consistent with the expert score.

REM stage recognition is usually a difficult task in the stages of sleep. In the diagnosis of REM sleep behavior disorder, the REM stage must be accurately classified. In this paper, REM achieves a high recall rate of 0.821. The classified recall rate of W, S2, S4, and REM sleep stage is above 0.762, and the precision rate is above 0.782. S1 is a transitional stage from awakening to sleep, which accounts for a small proportion and is easy to be misclassified into other sleep stages, with the lowest classification accuracy. The experimental results show that the time-frequency feature analysis method has high accuracy in dividing the REM stage and is also suitable for mixed data sets.

C. Classification performance of time domain and frequency domain features

The 50 features selected contain 26 time-domain features and 24 frequency-domain features in the SEDFX data set. The sleep staging results of time-domain, frequency-domain,

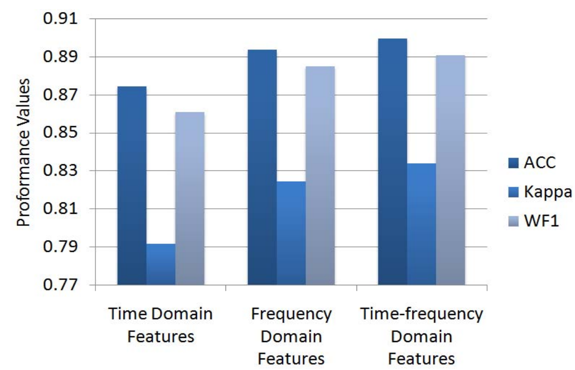


Fig. 5. Comparison of time domain and frequency domain features.

and time-frequency domain features are shown in Fig. 5.The classification accuracy, WF1 score, and Kappa coefficient of time-frequency features are increased compared with the results of using time-domain features and frequency-domain features alone. For example, the Kappa coefficient increases from 0.8024, 0.8244 to 0.8318. The sleep staging method combining time-domain features and frequency domain features is superior to the method using only time domain or frequency domain features.

D. Computation cost

All the experiments have been conducted using the Intel Core i7-6700 processor (3.40 GHz) with 16 GB RAM. The software is Matlab R2017a on Windows 7 OS. The signal decomposition and 50 features extraction for a 30-s EEG epoch cost 0.826s in average. The classifier model takes 19.54 s to build. The 10-fold cross-validation for 20 people takes 175 s. When the data of a new subject comes to test, it takes 9.75 s to obtain the features and classify. The SC data set records the subject's 24-hour data, 50 features require 1M storage space in average. ST data set records sleep data of the subject at night, 50 features require 0.46M storage space in average.

V. DISCUSSION

To evaluate the efficiency of the proposed method, the classification accuracy and Kappa coefficient of different dataset are compared with those of other existing methods. The results are depicted in Tables V and VI. The winning classification results are highlighted. It is observed that the performance of the proposed method is better than the other methods.

A. Comparison to other single-channel EEG methods

The same data set, the same single-channel EEG signal, and the 5-stage sleep staging standard are adopted, so the results of the literature [25]- [29] are directly cited. As shown in Table V, on the SEDF data set, literature [25] adopts the tunable Q-factor wavelet transform in the decomposition of EEG signal, which is limited by three parameters, namely quality factor, over-sampling rate, and decomposition layer number. In [26], the iterative filtering method is used to decompose EEG signals to determine the amplitude envelope

TABLE V
THE OVERALL PERFORMANCE FOR FIVE-CLASS CLASSIFICATION COMPARED WITH STATE-OF-THE-ART WORKS ON SEDF, SEDFX20, AND SEDFX20* DATABASE BASED ON SINGLE-CHANNEL EEG SIGNALS

Database	Authors	Dataset Size	Channels	Method	ACC	Kappa
SEDF	Hassan et al.[25]	8 subjects	EEG	TQWT+ Bagging	0.908	0.854
SEDF	Sharma et al.[26]	8 subjects	EEG	Iterative filtering+ Naive Bayes	0.911	0.862
SEDF	Proposed approach	8 subjects	EEG	Time-frequency domain decomposition+ Random forest	0.914	0.858
SEDFX20	Jiang et al.[27]	20 subjects	EEG	Multimodal decomposition+ Random forest	0.878	0.810
SEDFX20	Proposed approach	20 subjects	EEG	Time-frequency domain decomposition+ Random forest	0.898	0.832
SEDFX20*	Supratak et al.[28]	20 subjects	EEG	CNN+bidirect-LSTM	0.798	0.720
SEDFX20*	Paisarnsrisomsuk et al.[29]	20 subjects	EEG	CNN+generator and discriminator network	0.825	0.76
SEDFX20*	Jiang et al.[27]	20 subjects	EEG	Multimodal decomposition+ Random forest	0.914	0.831
SEDFX20*	Proposed approach	20 subjects	EEG	Time-frequency domain decomposition+ Random forest	0.932	0.863

TABLE VI
THE OVERALL PERFORMANCE FOR FIVE-CLASS CLASSIFICATION COMPARED WITH STATE-OF-THE-ART WORKS BASED ON MULTI-CHANNEL SIGNALS

Database	Authors	Dataset Size	Channels	Method	ACC	Kappa
SEDF	Ozal et al.[30]	8 subjects	EEG, EOG	1D-CNN	0.912	-
SEDF	Proposed approach	8 subjects	EEG	Time-frequency domain decomposition+ Random forest	0.914	0.858
SEDFX20*	Huy Phan et al.[31]	20 subjects	EEG, EOG	CNN+Gated Recurrent Units	0.823	0.75
SEDFX20*	Sokolovsky et al.[32]	20 subjects	EEG, EOG	CNN	0.81	
SEDFX20*	Proposed approach	20 subjects	EEG	Time-frequency domain decomposition+Random forest	0.932	0.863
UCD	Yuan et al.[33]	25 subjects	EEG, EOG, EMG	multi-view convolutional encoder+hybrid attention mechanism	0.733	-
UCD	Langkvist et al.[34]	25 subjects	EEG, EOG, EMG	sparse auto-encoder+LSTM	0.777	-
UCD	Proposed approach	25 subjects	EEG	Time-frequency domain decomposition+Random forest	0.744	0.662

and instantaneous frequency function of signals. This method obtained a higher Kappa coefficient, but its accuracy is lower than that of this method. On the SEDFX20 data set, Literature [27] uses the hidden markov model to modify the sleep staging results, which add extra computational burden. On SEDFX20* data set, the results of sleep staging accuracy and Kappa coefficient of PZ-OZ channel EEG signals using CNN and bidirectional LSTM in [28] are far lower than that of the method presented in this paper. In [29], CNN is used to exact representation features and generator and discriminator network is used for automatic sleep stage scoring. To sum up, the time-frequency domain feature analysis method combining EMD and frequency domain decomposition proposed in this paper is not limited by parameters and has achieved good classification results on SEDF, SEDFX20, and SEDFX20* data sets.

B. Comparison to other multi-channel signal methods

The comparative analysis of multi-channel signal sleep staging methods is shown in Table VI. In [30], the sleep staging accuracy of EEG signals using a one-dimensional convolution neural network is 0.912. The time-frequency domain feature combination method in this paper only uses a single-channel EEG signal, and the sleep staging accuracy is 0.914. On SEDFX20* data set, literature [31] adopts the convolution neural network and the gated circulation unit's sleep staging method, literature [32] adopts the convolution neural network's sleep staging method and the accuracy of sleep staging based on EOG and EEG signals is lower than that of the single-channel EEG sleep staging method in this paper. In [33], [34], the UCD data set has the highest sleep staging accuracy of 0.78 by using EEG, EOG, and EMG signals. In addition to the EEG, the addition of EOG and EMG signals cannot significantly improve the performance of sleep staging. This may be caused by the loss of effective information of the added signal due to the phase difference of the different signals. Compared with the multi-channel sleep staging method, the accuracy of multi-channel sleep staging can be achieved or nearly achieved by using only one channel EEG signal, which is more conducive to the realization of the family sleep monitoring system.

VI. CONCLUSION

In this paper, an automatic sleep staging method of single-channel EEG signals is proposed. The time domain features extracted by EMD and frequency domain features are used to improve the accuracy of the automatic staging of sleep stage. Experimental results show that the proposed algorithm is close to the accuracy of multi-channel sleep staging and better than other single-channel EEG sleep staging methods with the same data set. The 50 features automatic sleep staging system has the advantages of less time consuming and less storage space. In the future, the deep learning method will be used to learn signal features and classify them, and an automatic sleep stage staging system will be realized.

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