

Features and Recognition Algorithms in Sleep Staging and Drowsiness Detection by Using EEG

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Abstract. Sleep quality is a significant problem worldwide, and drowsiness detection is meaningful to sleep staging as it can prevent many accidents with significant loss. Among all the methods, the method that combining the neuron science and the computer science to analyze the EEG signals has the best accuracy. The general steps of sleep staging include gathering the EEG signals, extracting the statistical features, putting the features into the model through recognition algorithms, and evaluating the model. The extraction of features and recognition algorithms are the most important parts of all the steps, which means the two steps can decide the precision of the method. This paper states and compares the different features and recognition algorithms used in this area and introduces some research using the related features and recognition algorithms. Thus, this paper can provide researchers valuable references of the feature and recognition algorithms and therefore develop more useful method for sleep staging in the future.

Keywords: Sleep Staging; EEG Features; Recognition Algorithms.

1. Introduction

Among all the physiological activities of human beings, sleep can be regarded as the most important one. For the entire life, people generally spend one-third of their life sleeping. Thus, many researchers develop experiments and research on sleep. Drowsiness detection (DD) is a significant part of the application of sleep staging. This detection can prevent drowsiness in various situations that may lead to essential accidents, including vehicle driving and crane operating. Drowsiness in these situations may not only lead to the one in danger but also risk the life of surrounding people. In order to prevent the danger from happening, the researchers focus on drowsiness detection. Sleep analysis is another significant part. Since more and more people today are in insomnia, this application can help people to improve their sleep quality and as well can prevent the happening of drowsiness. Researchers have applied different method in DD, such as subjective-based that people report drowsiness when they are tired; vehicle-based, which is similar to the behavior-based, which detect drowsiness through the activities made by humans; and physiological-based, the one can prove that more efficient than other methods.

EEG in the human brain correlates to the physiology signs closely as many people cannot recognize that they are tired, but the signals show different patterns; thus, EEG is widely used in the sleep-related research due to its flexibility. Generally, researchers divide the EEG signals into three features: the feature in the time domain, the feature in the frequency domain, and the feature in the time-frequency domain. The time domain feature can show the EEG amplitude over time as the original EEG signal is a time domain data, reflecting the stimulation correlated to time. Thus, this feature is usually used in the event-related potential analysis. The frequency domain feature usually analyzes the spectral energy of each band in an EEG signal, which is usually transformed from the time domain feature through Fourier Series Decomposition or Fourier Transform. Researchers have already divided the frequency domain feature into different bands, and each band has various frequencies. The analyze of time-frequency domain contains the information of the other two features and requires processing the frequency domain information. This feature is usually used in analyzing the EEG signals and retains temporal information when performing frequency analysis. Many researchers usually adapt one of the features to analyze the signals and get the result of their methods of sleep staging.

In 20th century, the invitation of computer led to the third revolution of science and technology. The convenience of computer algorithms pushed people to seek the prospect that the computer can work as human. Thus, people started to develop the artificial intelligence (AI), where the recognition algorithms are developed from. Recognition algorithms have been widely used in many areas since it is developed, and biomedical engineering, among all the areas, can be regarded as one of the most beneficent areas because the experiment usually collect huge amount of data which is hard to calculate by hand. The recognition algorithms for analyzing EEG signals are mainly machine learning and deep learning. Machine learning is one of the most critical developments in artificial intelligence. The area of machine learning is data science, and machine learning lets the program learn from the data input by itself. Thus, the recognition algorithms can save much time and solve problems that are hard to compute by hand. Deep learning is generally similar to machine learning as it is developed from machine learning. They have the same basic steps: gathering the database, preparing the database, choosing a model, training the model, evaluating the model, parameterizing it, and making a prediction using the model. The difference is that machine learning requires researchers to extract features from the database, while deep learning requires researchers to pay more attention to parameterizing the model.

This paper introduces the features and recognition algorithms used in sleep staging and compares their advantages and shortcomings. The conclusion of this paper can provide a more precise reference for future sleep staging by using EEG signals.

2. Features

Researchers divide features used in the sleep staging using EEG into three kinds: the time domain feature, the frequency domain feature, and the combination of the two features, the time-frequency domain feature. Each feature has its advantages and defects, and the researchers usually adapt the fittest feature in their experiments. Thus, they all are wildly used in sleep staging in EEG today.

2.1 Time Domain

The time domain feature records the change of EED on the time domain, including the statistical features which can represent the shape of the EEG signals, including the mean value, the median, the variance, the standard deviation, and the skewness [1]. By analyzing the period amplitude, the researchers are also able to extract the pattern of the EEG signals, including the number of waves, peak amplitude, wave duration, and other elements through the time domain. Based on the recording, researchers can relate the EED to the stimulation that happens at the same time. Since the statistical features are the most superficial features of the EEG signal and have no treatment on the time domain, the time domain feature is the simplest and fastest feature of the others. As it is the feature that only focuses on the time domain, it has the most accuracy in the time domain.

Two experiments use the time domain feature to analyze the EEG signal.

In order to detect drowsiness during some dangerous work that requires full attention, B and Chinara researched and generalized a new method, a single-channel EEG-based drowsiness detection (DD) model [2]. They developed the new method from the existing methods, usually using the frequency domain feather and the time-frequency domain feature. However, the primary purpose of this kind of research is to notice the DD on time. Thus, they used the time domain feature to record the EEG signal for analysis. They pointed out that using the time domain feature can save time and provide more accuracy. Thus, their model gets high score in total accuracy, sensitivity, precision and F1 score and gets the highest accuracy in Physioet Database and Simulated Virtual Driving Driver Database when containing four features. Besides, by combing the statistic feature in the time domain, they find that the structural graph similarity and the K-means (SGSKM) can better recognize six sleep stages through single-channel EEG signals with the highest accuracy, shortest time and the highest score among the six exiting models proposed before.

2.2 Frequency Domain

The usage of the frequency domain mainly focuses on the computation of the power spectral density (PSD) in a given frequency band [2], which can be computed through different parametric and non-parametric methods [1]. Comparing to the parametric methods, the non-parametric methods are more commonly used in the different areas since they require no parameters for the model. The bands which are usually mentioned in the EEG signals include the gamma band (γ , >30 Hz), the beta band (β , 12-30 Hz), the alpha band (α , 8-12 Hz), the theta band (θ , 4-8 Hz) and the delta band (δ , 0.5-4 Hz), and they are all generated from the frequency domain feature. Meanwhile, the statistic features used in the time domain feature are generally applied in the frequency domain feature.

In 2021, because they wanted to detect drowsiness in different actions, Stancin and his workmates applied the frequency domain feature on the DD [4]. They used the frequency domain feature to estimate the PSD in different bands in the EEG signal because different brain regions have different signals. In order to extract the multichannel ratio index feature based on EEG signal of 28 subjects in the frequency domain, they used a computational method based on multicriteria optimization. Their work provided a new multi-channel indices which can show the statistically significant differences between the wake model and drowsy model and provide a better choice which can save more time and memory during classification for getting the precision of DD and classification accuracy of the XGBoost algorithm and model performance than the existing single-channel ratio indices.

2.3 Time-Frequency Domain

Since the EEG signal is not a stationary signal, the time-frequency domain feature combines the time domain feature and frequency domain feature, which works mainly in experiments, including unsteady data and event-related experiments. This feature's central part is observing the frequency change over time. In the related functions, the short-time Fourier transform is one of the most widely used functions to calculate the frequency components due to its simplicity. The general outcome of this feature is the spectrogram and its available alternative, the wavelet transformation, which can provide a window with variable size dependent on the spectrum frequencies.

In the paper related to the development of a new method for sleep staging, the authors pointed out that though the time domain feature is easy to compute, it lacks accuracy in determining sleep staging [5]. The frequency domain feature cannot indicate the time information when researchers focus on the EEG signals of particular frequency ranges and ignores the inherent model of the signal though it can show the signal clearly. Thus, they apply the time-frequency domain for the experiment and overcome the shortcoming of the single-channel EEG signal by automatic sleep staging. Besides the sleep stage, Güneş and his members used the time-frequency domain to recognize the sleep spindles and got 93.84% accuracy in the classification of sleep spindles by using LM-ANN [6]. Manzano's team, in their reports, constitute a first approximation by combining a single channel with the information from the present period to execute the classification [7]. They combined the time domain feature and the frequency domain feature into the deep learning algorithm and demonstrated that their methods could highly increase the performance of sleep staging problems. In time domain feature, the precision of their work, measured by patient-cross-validation, is 68.6% and the mean F-measure over the different sleep stages is 54.6%. For frequency domain feature, the precision is 68.9% and the mean F-measure is 57.5%.

3. Recognition Algorithms

Though computers are only developed for less than 100 years, this technology already changed human's life a lot. AI is one of the approaches that letting the computer become more intelligence. Due to the lack of ability to possess large amounts of data by hand, humans come up with the recognition algorithm, machine learning, which is an important component of AI. Machine learning is developed since the computers are invented in 1900s, and based on the various derivation of math theorems, it allows humans to process a large amount of data through computer, summarize the

behavior of the data, and make a better decision, usually a more precise prediction, based on the analysis of the data [11]. Based on the development of the recognition algorithm, machine learning is widely used in many areas, and as long as the researchers train the machine learning model, the model can provide the predicted result of the input data. In order to make the model develop by itself, people came up with the algorithm called deep learning, which is from machine learning. This model can correct its algorithm when it detects the difference between the given answer and the result itself predicts, and this process requires more data than machine learning. Both algorithms have their advantages; thus, the researchers usually apply the algorithm to analyze their data in sleep staging by using EEG signals.

3.1 Machine Learning

Machine learning has developed in recent years, and many researchers use this algorithm to solve data with a large amount of data. The research led by Qureshi and Vanichayobon in 2017 is mainly based on machine learning [8]. They applied Random Forest (RF), Support Vector Machine (SVM), and Bagging to improve the classification performance of sleep stages. They clarify that RF can provide correct classification through its algorithm, Bagging can tradeoff overfitting and lower the bias by reducing variance averaging, and SVM mainly focuses on the nonlinear function and solve the classification and regression in the experiment. Besides applying them in the experiment, the researchers also compared the results of the three algorithms and pointed out that RF has the highest accuracy in its classification of sleep staging as the overall accuracy of RF is 97.73%, while the accuracy for bagging is 93.28% and the one for SVM is 81.02%. Aboalayon's team not only used the SVM listed before but also adapted Decision Tree (DT), Neural Network (NN), K-Nearest Neighbors (KNN), and Naïve Bayes (NB) as classifiers in their experiment [10]. They declared that DT has simple and fast steps for learning and classification. Thus, it can play an essential role in managing multidimensional data. For NN, they pointed out that this algorithm can make predictions of the input data by modifying the weights associated with different layers inside the algorithm. KNN is another algorithm used to classify the nonlinear data; it utilizes different distance metrics, including Euclidean and Mahalanobis, to compare the test sample with the training sample in an n-dimensional pattern space to measure closeness and get the k closest neighbors among the most common class. NB is a statistical algorithm which is developed from the Bayes theorem, and it can theoretically provide a faster classification process and higher accuracy for extensive data in experiments. The researchers mentioned in their paper that when they change the training sample size, they get different accuracies for different algorithms. For SVM, they got 85.23% as the highest accuracy when they applied 80% of the database to train the model, while for 50% and 70% of training, the accuracy was less than 70%, while for the other algorithms, they all had no large variation when change the size of training set. The accuracies of the three different data distribution were all about 97% for DT, which is the highest accuracy among all the data, thus, they summed that DT performed best in their experiment.

3.2 Deep Learning

In the experiment mentioned above, Manzano, Rojas, and Herrera applied deep learning to solve the data they got [7]. They stated that they apply deep learning here because it allows the researchers to observe the transformations and relationships that would be hidden at first, and this algorithm does not require a preprocessing stage and saves time. Besides, they used the Leave One Out (LOO) approach to get more accurate results because they have only a few patients, and they cannot provide a large enough database for other approaches. In 2018, Chambon and other researchers introduced a novel deep learning algorithm that can detect various events happen during the night time through analyzing the EEG recordings over the period [9]. The researchers not only recorded the EED signal of humans to analyze the sleep stage, but in 2021, Akada and the researchers held an experiment in which they used deep learning algorithms to score the sleep stage of mice [12]. They mentioned their worries about using existing deep learning algorithms that the databases of wake/REM/NREN are unbalanced, which will lead to difficulties in recognizing the sleep stage. Thus, to assess the sleep

stage, they devised a novel algorithm by sequentially distinguish the differences between the wake-sleep and REM-NREM sleep stages. Their algorithm gains high accuracy in recognizing all three classes. In order to develop the models of each sleep stage, they used the sleep features that they extracted from the recordings of the mouse-derived EMG and EEG signals respectively. The algorithm is built on the long short-term memory (LSTM) network and calculates the time domain data of EMG integral values for time interval selected by the researchers. LSTM is a deep learning algorithm; it usually learns time series trends by simultaneously processing the features of both past-present and future-present by the applying LSTM on two directions. Their results on the two models got high accuracy in both confusion matrix and performance evaluation: wake-sleep model had accuracy of 94.70% and 96.32% of F-measure score and REM-NREM had accuracy of 96.89% and 89.27% of F-measure score. Thus, all three researchers show the use of deep learning in sleep staging using EEG.

4. Discussion

The analysis of DD has become an important and promising area. The related industries, including autonomous driving, are pushing the development of this research further. Hence, this paper focuses on the features and recognition algorithms researchers usually used in recent years and compares their usage in further research.

EEG has three different features in sleep staging using EEG, and each is frequently used. According to the researchers' trade-off in their experiment, the advantages and shortcomings of each feature are clear. Since the time domain feature is similar to the original data collected from the machine, it requires the fewest steps, including filtering the bands, to extract the available data and process the following steps. Thus, it has higher temporal accuracy and precision than frequency and time-frequency domains, and most event-related potential analyses use this feature. However, the time domain can only represent the amplitude changes over time; it cannot sufficiently present the complete information in the EEG signals, such as the change in the frequency range.

In order to analyze the frequency changes in the EEG signals, the frequency domain is a better feature than the time domain. This feature allows researchers to view the different bands in the EEG signals, divided through different frequencies. According to Fourier's theory, any continuous signal can be expressed as an infinite superposition of sine wave signals of different frequencies; thus, by applying Fourier transfer to the time domain feature, researchers can get the frequency domain feature, which reflects the speed of EEG signal changes over time, as well as the amplitude change over frequency. This step naturally makes the frequency domain application slower than the time domain. However, the limitation of the frequency domain is that the Fourier transfer is only available on steady-state data, while most EEG signals are unsteady-state data, and this feature lacks the change over time.

Time-frequency domain is the feature that can show the complete information in a piece of EEG signal. This feature includes the information on the time domain and frequency domain. The method is adding an extra window into the data and assuming that the data is steady state to apply the Fourier transfer and get frequency domain information, then sliding the window along the timeline and applying the same treatment to the data each time window. Thus, the researchers can get the frequency changes over time. When changing the size of the window, the accuracies of time and frequency are also changed. The larger the window, the lower accuracy of time and higher accuracy of frequency, which is suitable for the low frequency with slow waves, and the smaller the window, the higher accuracy of time and lower accuracy of the frequency, which is suitable for the high frequency with fast waves. Since this feature includes the time domain, it can apply to unsteady-state data and event-related experiments. Each step of this feature requires a large amount of computation; thus, it is the slowest feature among all the three.

Table 1. Comparison of different EEG features in sleep staging and drowsiness detection

	Time	Frequency	Time-Frequency
Advantages	Fast, request less time	Allowed researchers to check the distribution of frequency range	Show the thorough information of EEG signal
Shortcomings	Lack the information of the frequency range	Lack the information of time, cannot apply in non-steady data	Slow, need to analyze more data
Application area	Event-related potential	Steady state data	Event-related research, unsteady-state data

As for the recognition algorithms, though machine learning and deep learning are the same in general, the researchers apply them to various databases and areas due to their differences. Machine learning and deep learning are subjects of artificial intelligence, and both are learning from data, which means they can make a prediction based on the input database without being explicitly programmed. The main difference is that machine learning requires a primary function then needs to be trained by the database, while deep learning uses the artificial neuron network, which has a similar function to the human brain's biological neuron network. Based on this difference, deep learning needs to train with more databases to predict as it can learn from data better.

Table 2. Comparison of different recognition algorithms in sleep staging and drowsiness detection

Algorithm	Typical algorithms	Advantages	Disadvantages
Machine learning	ANN SVM	Suit for small samples	Time-saving
Deep learning	LSTM	Suit for large datasets, No need of prior knowledges	Time-consuming

5. Conclusion

Feature extraction and proper recognition algorithms are essential in EEG-based sleep staging and drowsiness detection. This paper summarizes the existing features in the EEG signals and the recognition algorithms, including the time domain, frequency domain, and time-frequency domain for features and machine learning, and deep learning methods for recognition. The usability of each method was also analyzed, which can provide a valuable reference to future works when detecting the sleep state and apply in a real-time scenario.

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