A Machine Learning Approach to Classify Sleep Stages of Rats

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Abstract: Identifying the vigilance states of the mammalian is an important research topic to bioscience in recently years, which the vigilance states is usually categorized as slow wave sleep, rapid eye movement sleep, and awake, etc. To discriminate difference vigilance states, a well-trained expert needs spend a long time to analyze a mass of physiological record data. In this paper, we proposed an automatic sleep stages classification system by analyzing rat's EEG signal. The rat's EEG signal is transferred by FFT and then extracted features. These extracted features are used as training patterns to further construct the proposed classification system. The proposed classification system contains two components, the principle component analysis (PCA) as the first component is used to projects the high dimensional features into lower dimensional subspace, and the *k*-nearest neighbor (*k*-NN) method as the second component is applied to identify the physiological state for a period of EEG signal. By experimenting on 810 periods of EEG signal, the proposed classification system achieves satisfactory classification accuracy of sleep stages.

Key-Words: sleep stages, pattern classification, machine learning, PCA, *k*-NN, FFT

1 Introduction

Sleep is circadian activities composed with repeated cycles of slow wave sleep (SWS) and rapid eye movement sleep (REM). For the research fields related to sleep studies (e.g. sleep depriving, the effect of drugs, circadian clock, etc.), identifying the sleep stages with precision and effectiveness is an important research topic. Scoring vigilance in sleep studies is a time-consuming work to a well-experienced expert. Consequently, how to reduce the human intervention is an significant topic in this research field. A variety of automated sleep staging systems via different analyses have been developed over the past decades [1, 10-17]. Some of proposed methods still required human intervention [1, 17]. For example, the user has to decide the appropriate parameters (thresholds) or participate in the entire classification procedure. However, to select appropriate parameters to different conditions is a very subjective task to each researcher. To solve the problem of selecting parameters, we apply machine learning techniques to develop an automatic sleep stages classification system of rats. By collecting the labeled EEG data in advance, a machine-learning-based classification system is constructed to recognize the testing patterns of different vigilance states with one channel of EEG signal. Through the proposed method, three types of vigilance state could be categorized automatically to save the time of human intervention. In this paper, we roughly category sleep stages into the following three states:

1. Awake (AW)
2. Slow wave sleep (SWS)
3. Rapid eye movement sleep (REM)

During the awake stage, the animal represents a low amplitude and high frequency EEG. Some investigators distinguished active awake from quite awake by high EMG activity. The spectrum of EEG in this stage is with high theta and gamma power density. Slow wave sleep which is defined by high amplitude and low frequency EEG begins with sleep spindle and is dominant with delta waves. In REM, the animal showed the low amplitude and high frequency EEG which is similar to the awake stage and atonic with flat EMG activity. High activities of theta and gamma band were the characteristics of this stage [2-9]. The EEG and EMG signals of three states are as shown in Fig 1.

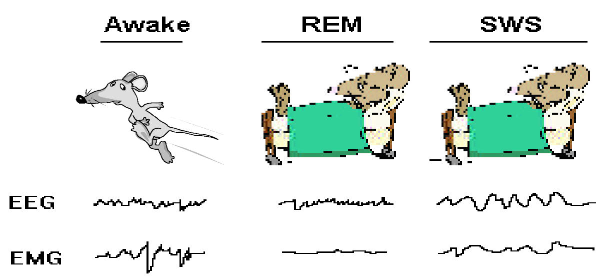

Fig 1. The EEG and EMG signals of three vigilance states.

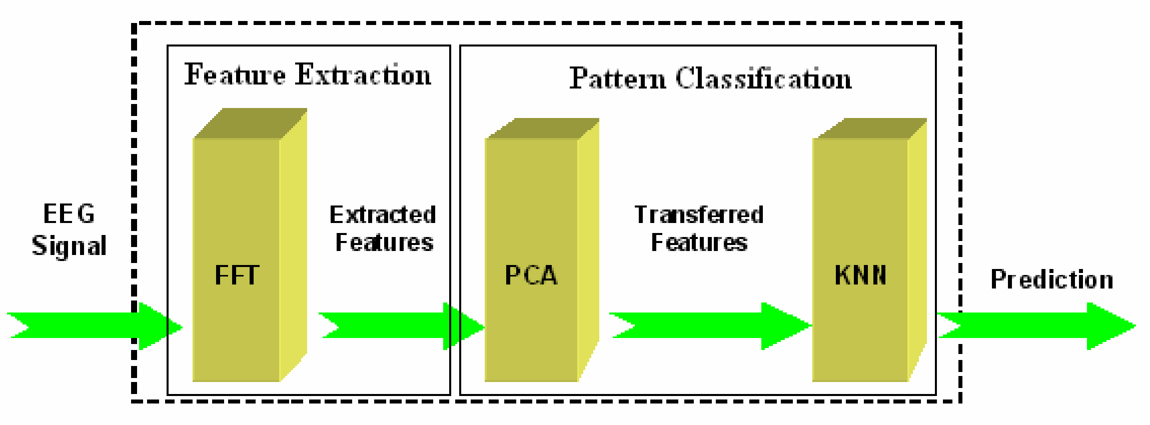

Fig 2. The architecture of proposed classification system.

Table. 1. The frequency range of five frequency bands.

Band	Delta	Theta	Alpha	Beta	Gamma
Frequency Range	0~4 Hz	4~8 Hz	8~13 Hz	13~20 Hz	20~50 Hz

In this paper, we develop a machine-learning-based sleep classification system to classify three mentioned sleep stages. There are two advantages of the proposed system. First, without setting any parameters or thresholds by a user, the classification system is constructed under the discriminative function which is optimized by some criteria, such as high precision rate or minimum false detection rate. Besides, without applying the EMG signal, we only analyze EEG signal to recognize the vigilance state of a rat. The organization of the paper is as follows. In Section 2, we describe system architecture and the proposed techniques. Experimental results of the proposed method are given in Section 3. Finally, Section 4 concludes the paper.

2 The Proposed Classification System

The classification system is composed of two key units: feature extraction unit and pattern classification unit as shown in Fig. 2. Before we introduce the details of two units, we first describe the recording procedure of EEG and EMG signals of a rat.

2.1 The recording of EEG and EMG Signals

For the implantation of recording electrode, the rats were initially anesthetized with sodium pentobarbital (50mg/kg). Ketamine hydrochloride was administrated as necessary to maintain the depth of anesthesia so the animals did not represent the flexor reflex during the surgery. Rats were mounted on the stereotaxic apparatus. For the EEG recording, a parietal electrode was implanted on the same level of bregma and 4mm lateral to the midline. The signal was referenced to a ground electrode implanted over the cerebellum. Two 3-strained stainless steel wires (A-M systems; #793400) isolated with Teflon were embedded in the neck muscle for EMG recording. Those signals were connected to a connector. All of those instruments were sealed and secured with dental cement on the skull and the skin was sutured with wound clips. The rats were usually recovery after one week.

Before the beginning of recording, rats were placed in a test chamber for 4 hours per day to habituate the recording environment. On the recording day, the rats were temporarily anesthetized with halothane (4% in pure oxygen) for connecting the cable and headstage to the connector on the rat skull. After thirty minutes, the EEG and EMG signals started to be recorded when the rats revived from anesthesia and accommodated the recording chamber.

The signals were recorded with a Multi-channel Neuronal Acquisition Processor system (MNAP, Plexon, Dallas, TX) and passed from the headstage to an amplifier and band-passed-filtered (EMG filter: 0.5 ~ 8.8 KHz, gain: 1000-5000; EEG filter: 0.7 ~ 170 Hz, gain: 1000-5000). Each rat was recorded for 2 to 6 hours and the sampling rate is 1K Hz. The recorded files were dealt offline with Neuroexplorer (Nex technology). EEG signal was then transformed with Fast Fourier Transform (FFT). The power spectrum of EEG was calculated for 4 seconds window and the window was shifted 1 second each time.

For most rule-based classification methods of sleep stages, the EEG spectrum is usually divided into five frequency bands [1] as given in Table. 1. This makes researchers effectively to analyze EEG

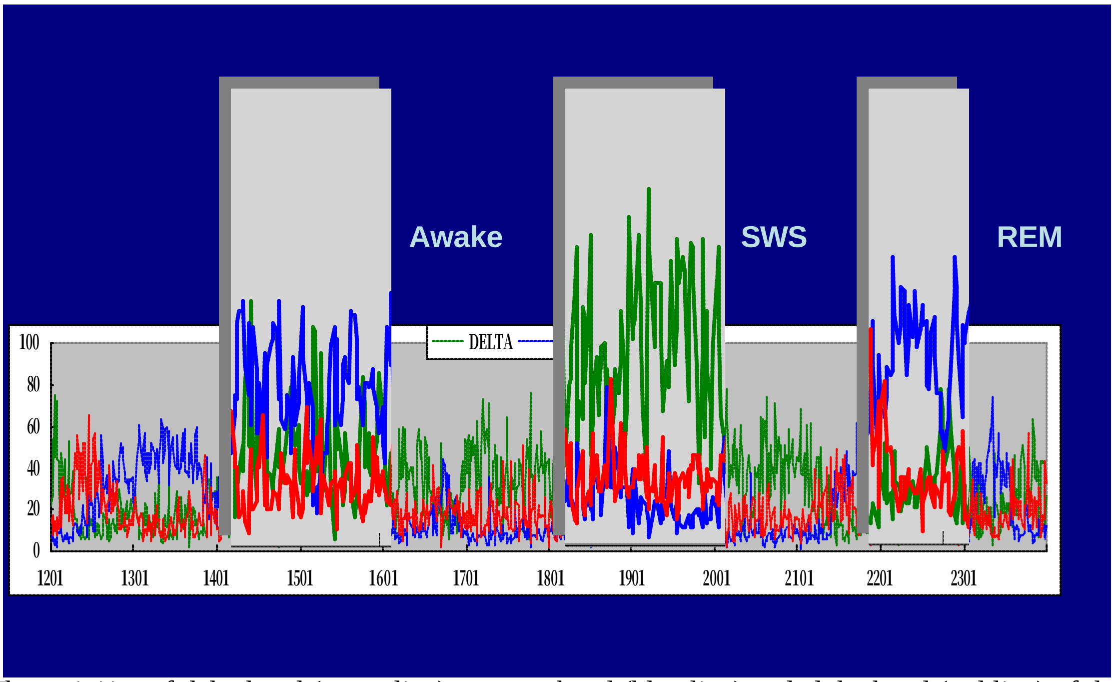

Fig. 3. The activities of delta band (green line), gamma band (blue line) and alpha band (red line) of three sleep stages.

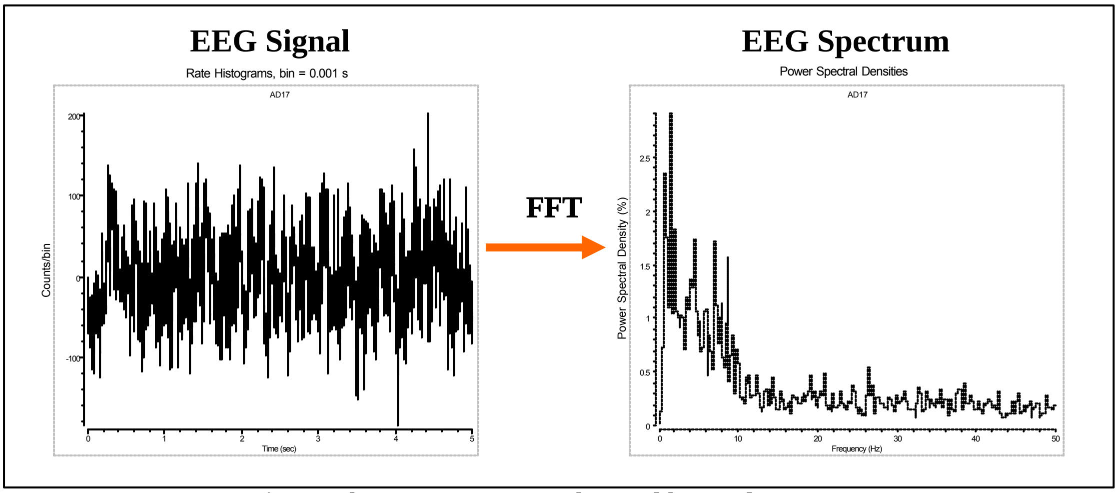

Fig. 4. The EEG spectrum obtained by applying FFT.

signal and reduce the complexity for designing the classification rules. Delta band and gamma band denote the low and high frequency signal, and they are the key bands for classifying sleep stages. In Fig. 3, we measure the power of delta band as delta activity (green line) and the power of gamma band as gamma activity (blue line), respectively. One may find that delta activity is observed more predominant than other frequency bands in SWS state, and gamma activity is more predominant in REM and awake states. To further distinguish REM and awake, most classification methods measure EMG amplitude as key information, because the muscle intensity is lower or not observed in REM stage. One thing should be noticed here; unlike REM stage, we observe that the power strength of gamma band in awake state is close to the power strength of delta and alpha band. This motivates us to classify sleep stages with EEG signal only.

2.2 Feature Extraction

For any machine learning technique, the first work in training procedure is extracting meaningful features from original data. Fast Fourier Transform (FFT) is performed on each period of 4 seconds EEG signal to generate EEG spectrum, as shown in Fig. 4. For example, the EEG spectrum of the sixth second is derived from the EEG signal consisting of the signal between the third second to the sixth second. Different to above rule-based classification methods, the EEG spectrum is separated into 32 uniform frequency bands. We then calculate the relative ratio

ISSN: 1790-5109

ISBN: 978-960-474-114-4

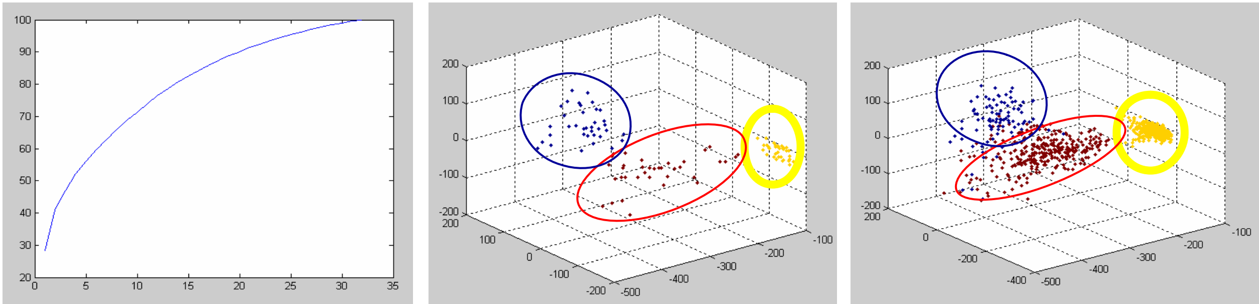

Fig. 5. (a) Percentage of variance explained by the 32 components. (b) Training patterns are projected into 3-dimensional subspace by PCA. (c) Test patterns are projected into 3-dimensional subspace by PCA.

of each band's power to all frequency bands' total power. Finally, the EEG signal in each time point can be extracted 32 relative ratios as features to a training pattern for the following training procedure.

Before constructing the classification system, we need a well-experienced expert decide the label of each data pattern. By examining the activities of gamma and delta band of EEG, the activity of EMG and the captured video, the expert categories each data pattern as one of three sleep stages. Finally, the EEG signals of 108 and 810 seconds are labeled as training and test data patterns, respectively. The time duration of each state is listed in Table 2.

Table. 2. Time durations of each state.

State	Time Duration	
	Training Data Patterns	Test Data Patterns
REM	36 Sec.	97 Sec.
SWS	36 Sec.	403 Sec.
Awake	36 Sec.	310 Sec.
Total	108 Sec.	810 Sec.

2.3 Pattern Classification Methods

The pattern classification unit can be implemented by any algorithm based on linear discriminant function, neural networks, or support vector machines. In this paper, the pattern classification unit contains two components that are principal component analysis (PCA) and k-nearest neighbor (k-NN). PCA is a widely used statistical technique for unsupervised dimension reduction. We apply it as preprocessing to project the extracted high-dimensional features into lower dimensional subspace in a way of maximizing the sum-of-square error. In our dataset, the first 3 components contains about 50% of the variance (Fig. 5(a)). The projections of the three main components into a 3D space are given in Fig. 5(b) and 5(c). The data patterns of SWS, AW and REM state are drawn as yellow, red and blue points, respectively. We observe that data patterns are roughly separated into three elliptical clusters and the data patterns in REM and AW cluster are slight overlap (see Fig. 5(c)). Two benefits of applying PCA are concluded as following. First, PCA could help us to denote which bands might contain important information for classification. Second, projecting the high-dimensional features into lower-dimensional subspace can help user to visualize these data patterns.

After projecting by PCA, each data pattern is then classified by the k-NN method (Dasarathy [19], Levine et al. [20], O'Callaghan [21]), which matches each test pattern with all possible training patterns and considers k-nearest samples, $k \geq 1$, in its classification decision. It has been shown that the asymptotic error rate of k-NN is less than twice the Bayes rate (Cover and Hart [22]). In many applications, k-NN does indeed achieve good accuracy rates and it is also easily to be implemented. .

3. Experimental Results

As shown in Table 2, there are 108 samples for constructing the classification system and 810 samples for testing the performance. Training samples and test samples are collected independently from the same adult rat in different days. This means that the duration of collecting training and test data are occurred at several time points. The training samples are first projected by PCA and then used to construct the k-NN classifier. The proposed classification system spends less than 1 second to category 810 test samples and achieves 95.43% accuracy rate. More details of classification results are given in Table 3. Here we summarize some observations. First, all precision rates are over 90%, especially for SWS state (99.75%). Contrast with

SWS state denoted as the yellow cluster in Fig. 5(c), the higher precision rate of SWS state is expectable. Second, most misclassified errors are occurred in REM and AW states, such situation can be contrast with Fig. 5(c). Third, although most studies in sleep field emphasize that the EMG signal is key factor to discriminate between REM and AW. However, the proposed classification system with EEG signal only provides good performance.

Table. 3. The classification results of proposed method.

		Prediction			
		REM	**SWS**	**AW**	**Precision**
Ground Truth	**REM**	88	0	9	**90.70%**
	SWS	0	402	1	**99.75%**
	AW	17	10	283	**91.29%**
	Recall	**84.80%**	**97.60%**	**96.60%**	

4 Conclusion

In this paper, an automatic sleep stage classification system is developed based on machine learning technique. By simply analyzing EEG signal, the feature extraction of the proposed system is achieved by FFT and classification is performed by PCA and *k*-NN. The proposed system can obtain a prediction of current sleep state for each second and achieve 95.43% accuracy rate with a short period of computational time. The satisfactory performance makes it highly suitable for a real-time application in the future.

Acknowledgement: This work was supported by the National Science Council, Taiwan, R.O.C., under the Grant NSC 98-2218-E-238-001.

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