**Real time sleep staging from ear-EEG**

# Abstract

Automatic sleep staging in real time is a significant step in the medical research. This monitoring system is based on a long-term wearable in-ear sensor for recording the electroencephalogram (ear-EEG). It can provide sleep stage evaluation compared with manual hypnogram scoring while monitoring a patient’s ear-EEG. The features extracted from the ear-EEG are in the time and frequency domains. In the classification part, the support vector machine (SVM) is chosen as the main classifier, which predicts the real-time ear-EEG compared with the manually scored hypnograms from the related scalp-EEG. The accuracy achieved by standard SVM ranges from 64% to 77.8%. However, when it applies a transition model which uses conditional probabilities, the accuracy is improved to the range of 68% to 82.4%. Additionally, other classifiers are also applied, but their performances are worse than SVM. Moreover, in order to identify the real-time EEG data, the computer program is able to read the data sent by the wearable device at the same time. Therefore, the predicted real-time sleep stage of the user, as well as the predicted result compared to the manually scored hypnogram will be displayed on the screen.

# Acknowledgment

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SWS: slow wave sleep

# Chapter 1. Introduction

## 1.1. General Introduction

Nowadays, an increase number of people suffer from sleep problems. The quality and quantity of sleep affects many real-life activities, such as memorizing, learning and concentrating, and even the cardiovascular health [1], [2]. In medical practice, sleep disorders, such as insomnia and sleep apnoea, require analysis and accurate detection of sleep stages to let researchers have a better understanding of such problems [1]. Thus, sleep scoring plays a key role in the psychiatry and neurology [3]. Traditionally, domain experts usually analyse and score the sleep stages by recording the patient’s over-night polysomnography (PSG), including electroencephalography (EEG), electrocardiography (ECG), electromyography (EMG), blood oxygen percentage and respiration [1]. However, manual sleep stage scoring is time consuming. Therefore, automatic sleep stage detection system is welcome among consumers since the demand for sleep tracking apps is increasing.

The sleep signals are segmented into epochs of 30s and assigned to a sleep stage based on some standard criterions, such as Rechtschaffen and Kales (R&K) rules [4]. According to R&K rules, sleep stages can be divided into wake (W), non-rapid eye movement (NREM) Sleep Stage 1 (N1), NREM Stage 2 (N2), NREM Stage 3 (N3), and rapid eye movement (REM). The following figure shows an example of EEG sleep signals in different sleep stages.

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Fig. 1.1. EEG pattern of different sleep stages [5]

From Figure 1.1, it is obvious that EEG signals in different stages have different frequencies. For instance, stage N2 signals are usually in the theta frequency range (4 – 7Hz), and EEG in stage N3 usually belongs to the delta band whose frequency is lower than 4Hz [5]. Moreover, EEG signals during REM stage are considered to be of mixed frequencies and low amplitudes, and they contain higher activity than that in stage N2 and N3 [6]. In practise, experts need to recognize and score different sleep stages from EEG. Figure 2.2 is an example of a manual sleep stage plot. REM stages have been highlighted in red.

手机屏幕的截图

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Fig. 1.2. Manually sleep staging result [7]

For EEG measurement, the standard method includes the placement of a multielectrode array onto the scalp and requires an electrolyte to enhance the contact between the electrodes and the skin [8]. Usually, such wearable device is obtrusive and inflexible, which is inconvenient for patients, especially for those who need long-term monitoring. Therefore, the ear-EEG system is developed to reduce the complexity of measuring EEG by placing electrodes on an earpiece inserted into the ear [9].

## 1.2. Objective

This project aims to estimate sleep states from real time sleep ear-EEG data. It needs to read the recorded EEG data and predict the sleep stages at the same time. The provided EEG data is recorded through ear canals and has four channels. It also needs pre-processing, such as downsampling and removing noise and interference. To predict sleep states, a classification method of machine learning should be applied. Therefore, some features of EEG data should be extracted and selected, in order to achieve a higher classification accuracy. The project should be done by Python.

The following figure is a flow chart which indicates the general process of this project.

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Fig.1.3. Flow chart of project process

The project mainly focuses on the feature processing and classification part. Several features in the time and frequency domain are extracted, and a statistical tool named analysis of variance (ANOVA) is applied to select useful features. In the classification part, several classifiers consisting of SVM, decision tree and AdaBoost are implemented and compared.

## 1.3. Thesis summary

Apart from the ‘Introduction’ chapter, the following report is mainly divided into other 5 chapters. In Chapter 2, several previous work relevant to sleep staging scoring is summarized and reviewed. An ear-EEG recording method is mentioned, and the process of EEG data acquisition and pre-processing is also introduced. Chapter 3 mainly focused on feature extraction and selection. The database used in this project is introduced, and several extracted features are discussed. Moreover, two ways of selecting significant features with the help of ANOVA method are analysed. In Chapter 5, which is the classification section, SVM is chosen to be the basic classifier after setting its optimum parameters. Additionally, a transition probability model is introduced to improve the classification accuracy. It also discusses the relationship between the confidence score and the accuracy. Moreover, classification results are evaluated and compared by some other classifiers and another ear-EEG dataset. Chapter 5 introduces sleep stage scoring in real time. In the final chapter, it discusses the results of the project and some limitations. Moreover, some improvement of this project is discussed in this part, and the application of this system is also introduced. Finally, a conclusion is provided to summarize the project.

# Chapter 2. Background

## 2.1. Previous work

In the recent years, people have conducted a number of researches on automatic sleep stage prediction. They mainly focus on different classification approaches which have higher prediction accuracy. Moreover, they also commit themselves to exploring effective features that can be used to train the classifier efficiently in order to improve the prediction accuracy. Some other researchers are interested in studying the difference between the ear-EEG and scalp-EEG.

Researchers [10] in Imperial College London has studied automatic sleep monitoring system using ear-EEG. The features selected for sleep state classification are the spectral edge frequency and multi-scale fuzzy entropy which is a complexity feature. They explored the SVM classification of both ear-EEG and scalp-EEG hypnogram labels from ear-EEG recording. Finally, they achieved accuracy ranges from 78.5% to 95.2% and 76.8% to 91.8% respectively. From their research, it can be concluded that the ear-EEG carries sufficient amount of information to represent human sleep patterns. Thus, this indicates that using ear-EEG in this project is faithful.

People [7] from Department of Engineering, Aarhus University, have developed a system to score the sleep into up to five stages automatically using ear-EEG. They would like to compare their results to manual scoring based on a simultaneously recorded PSG. They applied a classifier named ‘Random forest’ [11] which is related to decision trees and achieved accuracy of 76.4%. This study shows that ear-EEG based scoring has clear advantages when compared to both the PSG and other mobile solutions. The information it contains is far superior to a wrist-based actigraph and it is potentially cheaper than the PSG.

Another research conducted by Jose and his group [12] is also about automatic sleep stages classification. However, what is different from other studies is the extracted features. They focused on selecting entropy features, such as Sample Entropy, Shannon Entropy, Approximate Entropy and Multiscale Entropy. Then, they applied J-means approach [13] which is an unsupervised classifier to classify sleep stages. They found that using different entropy features could achieve different accuracies, and the average accuracy was 72.46%.

There are still many other researches related to sleep state scoring. For instance, Oropesa et al. [14] used discrete wavelet transform for sleep staging by dividing EEG waves into 7 specific frequency bands. By applying an artificial neural network (ANN) environment, they achieved 76.6% accuracy finally. Estrada et al [15] employed three

different algorithms, including relative spectral band energy, harmonic parameters and itakura distance and undertook non-linear analysis of EEG signals. In another project, Agarval and Gotman [16] applied segmentation and clustering strategies in EEG classification and reached an 80.6 % accuracy rate.

The number of related researches is increasing recently. The following table shows performance of previous automatic sleep stage classification implementations using different approaches. Different classifiers with different features can lead to a large accuracy difference.

Table 2.1. Examples of precious work in EEG sleep stage scoring

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Author** | **Sleep stages** | **Features** | **Classifier** | **Accuracy** |
| Zoubek et al. [17] | W, N1, N2, SWS, REM | Fourier Transform coefficients | ANN | 71% |
| Fraiwan et al. [18] | W, N1, N2, N3, N4, REM | Time frequency entropy | LDA | 84% |
| Hsu et al. [19] | W, N1, N2, SWS, REM | Energy features | Elman recurrent neural classifier | 87.2% |
| Gunes et al. [20] | W, N1, N2, N3, N4, REM | Welch spectral analysis, k means clustering based feature weighting | Decision tree | 92.4% |

## 2.2. The ear-EEG platform

Ear-EEG, which is an already proven approach to measure EEG from the outer ear, can be a substitute for the normal scalp-EEG. The following figure shows an example type of the ear-EEG recording device.

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Fig. 2.1. An example of the in-ear sensing device [21]

The in-ear sensing device in the figure is consistent of five components: memory-foam substrate, two miniature microphones and two conductive cloth electrodes [21]. The two electrodes Ch1 and Ch2 are used to record EEG signals from the ear canal. The shape of this device is similar to an earphone and the substrate material is a viscoelastic foam, so this device is flexible to fit any ear canal.

The figure below displays EEG signals acquired from both scalp and ear.

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Fig. 2.2. Combined EEG montage showing scalp-channel C4-M1 (top) with three different ear-EEG channels (below) [22]

This figure shows the comparison between scalp-EEG which is the top signal and the remaining three ear-EEG signals. It can be seen that the ear-EEG amplitudes are slightly lower than that of the scalp-EEG, but their shapes are similar. Ear-EEG could have similar performance as traditional EEG measured by the scalp. Therefore, the ear-EEG method is robust to record EEG in the natural environment. It can measure activities from regions of the cortex which are located close to the ears [23]. It can be concluded that ear-EEG method is a better way to measure EEG signals either in researches or in clinic practice, due to its convenience and flexibility.

## 2.3. Data acquisition and pre-processing

Before starting this project, the required EEG data was collected and pre-processed in advance. Several participants were gathered to record both four-channel scalp-EEG and ear-EEG data. The scalp-EEG was recorded by standard gold-cup electrodes, and the ear-EEG was recorded by both the left and right ear. The device to record ear-EEG is similar to the one in Figure 2.1. Both scalp-EEG and ear-EEG were recorded simultaneously with 24-bit resolution, at a sampling frequency fs = 1200 Hz [10].

Since data collected directly is not pure EEG signals which is not suitable to process, pre-processing of EEG data is required. Noise and interference in the EEG data should be removed. First, the ear-EEG data was required to downsampled to 200Hz, which was initially 1200Hz. Then, epochs with amplitudes more than were removed. After that, the data was filtered by a bandpass filter with the passband 0.5 – 30Hz.

# Chapter 3. Feature extraction and selection

## 3.1. Database used in the project

The data used in this project contains four sessions with both scalp-EEG and ear-EEG. In the dataset, it not only contains input EEG signals, but also their corresponding manually recorded hypnogram in order to do the classification. Since feature extraction and selection should be conducted based on epochs, the EEG data after pre-processing should be divided into epochs of 30s, each epoch corresponding to 1 single sleep stage. In the given dataset, the sample frequency of ear-EEG is 200Hz, and each epoch contains 30s data, the total number of data in one epoch should be . Therefore, the total number of epochs of four sessions is 330.

The table below shows the number of EEG epochs and states contained in the dataset.

Table 3.1. Number of epochs and states in the dataset

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **W** | **N1** | **N2** | **N3** | **Total** |
| **Session 1** | 23 | 30 | 36 | 0 | 89 |
| **Session 2** | 7 | 1 | 59 | 22 | 89 |
| **Session 3** | 8 | 6 | 33 | 16 | 63 |
| **Session 4** | 59 | 13 | 12 | 5 | 89 |

The dataset has total 330 epochs and it only contains four sleep stages which are W, N1, N2 and N3. The information about sleep stages is from the manually hypnogram and it is used in the classification section.

## 3.2. Feature extraction and selection

Feature extraction is a significant procedure in the sleep state classification as features can provide information about the underlying structure of a signal. There are numerous features that are suitable for EEG signals to extract, such as temporal features, spectral features and non-linear features [1]. In this project, 7 time-domain features and three types of frequency-domain features are extracted from ear-EEG data. They are listed in the table below.

Table 3.2. Features extracted in the project

|  |  |
| --- | --- |
| **Type** | **Feature** |
| **Time domain** | Kurtosis |
| Skewness |
| Hjorth parameters (activity, mobility, complexity) |
| Zero crossing |
| Detrended fluctuation analysis (DFA) |
| **Frequency domain** | Frequency band power (delta, theta, alpha, sigma, beta bands) |
| Spectral edge frequency (SEF50, SEF95, SEFd) |
| AR model parameters |

### 3.1.1. Time-domain features

***Kurtosis and Skewness***

Kurtosis and skewness belong to statistical measures. They are used to evaluate statistical characteristics of signals in the time domain. Kurtosis can indicate the shape of a probability distribution and measure the distribution’s tailedness while skewness feature measures the asymmetry of a probability distribution [1]. These two features can be calculated by the following equations.

where SD is:

In these equations, N is the number of data samples, SD is standard deviation and is the sample mean. The formula of kurtosis and skewness is similar.

***Hjorth parameters***

Hjorth parameters are popular in feature extraction for EEG data. They provide dynamic temporal information of the PSG signals [5]. They contain three parameters, including activity, mobility and complexity. Considering an EEG epoch X, the three parameters are calculated from its variance , first and second derivatives [24]. Their formulas are shown below.

***Zero crossing***

Zero crossings are the points where the signal waveform goes across the x-axis in the time domain. The zero-crossing rate can provide information in the frequency domain, since a rapid zero-crossing rate is always associated with high frequencies, while signals with low frequencies usually have low zero-crossing rates [25].

**Reference**

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