An Accurate Sleep Staging System with Novel Feature Generation and Auto-Mapping

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***Abstract*—Traditional sleep monitoring conducted in professional sleep labs and scored by sleep specialist is costly and labor intensive. Recent development of light-weight headband EEG provides possible solution for home-based sleep monitoring. This study proposed a machine learning approach for automatic sleep stage detection. A set of effective and efficient features are extracted from EEG data. The utilization of a collection of well annotated sleep data ensures the quality of learning model. A feature mapping algorithm is proposed to map the feature spaces generated from EEG data acquired through different electrodes. We collected headband EEG data for 1 hour naps in experiments conducted in our sleep lab. Preliminary result shows that sleep stages detected by proposed method are highly agreeable with the sleepiness score we obtained.**

I. Introduction

Sleep plays an important role in a person's overall health and well-being. To quantitatively assess the sleep quality, the American Academy of Sleep Medicine (AASM) [1] developed a guideline of terminology and scoring rules for sleep, based on the former R&K score proposed by Rechtschaffen and Kales in 1968. The different stages of a sleep cycle include rapid eye movement (REM) sleep (stage R, corresponding to REM in R&K rule) and non-rapid eye movement sleep (NREM). NREM sleep can be further classified into stages N1, N2 and N3 (corresponding to S1, S2 and S3+S4 of R&K rule respectively). N3 is the deepest stage of sleep, also called slow wave sleep (SWS). A sleep hypnogram as shown in Figure 1 shows the stages of sleep as a function of time. Traditionally, sleep monitoring can only be conducted in sleep labs using polysomnographic (PSG) equipment recording electroencephalogram (EEG), electrooculograms (EOG) and elecromyograms (EMG). With the recordings from multiple sensors a trained specialist mark the sleep stages using AASM standard. PSG-based sleep monitoring has limited applications due to its high cost involving manual annotation and the bulky set up of sleep labs. In recent years, the development of light-weight EEG sensors, e.g., EEG headbands has made home-based sleep monitoring systems possible. In this study, we focus on automatic sleep stage detection, with the hypothesis that an well designed machine learning model for sleep staging can adapt itself for various sensors (EEG electrodes) and different loci.

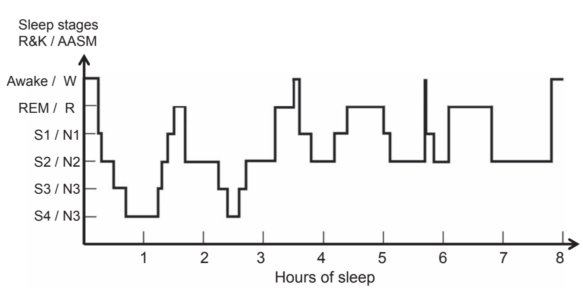

Figure 1. Hypnogram showing the sleep stages in a sleep cycle

A number of groups have been working on single channel based sleep stage detection. Rossow et. al. [2] develops a EEG model using HMM and kalman filter and report 60.14% agreement rate. Huang et. al. [3]proposed autoregressive Hidden Markov Models (HMM) to detect arousal states through the mean frequency feature, which acheives a 70% detection rate for wake vs. drowsiness. Novak et. al [4] develops a HMM sleep staging model using a set of combined features, including autoregressive parameters, spectral entropy and complexity stochastic measurements, which works for N3 and N4 prediction but do not work well in detecting wake-N1-N2 stages. Based on a recent review [5], home sleep scoring systems displayed big deviance from the standard measure especially in the wake-N1 transition stage. The author concludes that home based sleep staging systems have yet to arrive reliably.

In this study, we propose a computational model for accurate sleep stage detection based on a set of highly efficient and effective features extracted from EEG signals. We then apply the model in the headband EEG-based sleep monitoring and verified that the model can accurately predict sleep stages using a feature space mapping approach.

II. Method

A. Proposed framework

We propose a machine learning framework using bipolar EEG signal data acquired from EEG cap in a PSG sleep lab setting, where the data is well annotated with standard recording procedure. We then compare the cap EEG signal with EEG signal acquired from different electrodes, e.g., head-band EEG on forehead, by mapping the features space we are able to apply the model in sleep stage prediction. Figure 2 illustrates the framework

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of the proposed sleep Staging system. The boxes linked by double red lines form the process of building the computational model called iStaging. The boxes linked by dashed blue lines are the sleep Staging process using the iStaging model.

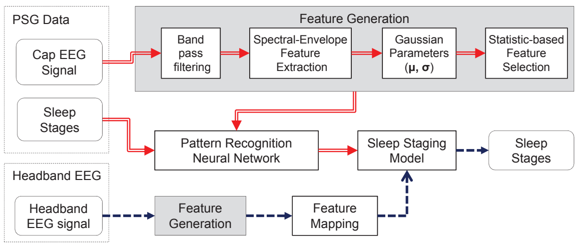

Figure 2. Framework of the proposed sleep staging system

B. iStaging feature generation

iStaging Feature Generation conducts Band pass filtering from the PSG data containing whole night EEG with sleep stage annotation, raw EEG of bipolar (PFz-Cz) signal is first processed with a Butterworth band-pass filter to remove artifacts resulted from occasionally poorly contacted EEG electrodes. The cutoff frequency is set to 0.35-48 Hz, upper bounded by the sampling rate.

1) Spectral power ratio extraction: It is known that EEG properties, particularly amplitude, vary among different subjects. We calculate the energy power ratio instead of absolute energy power in order to produce robust and subject-independent quantity measurements of the spectrum power. Temporal shifting windows of 2s with 50% overlap are used to compare consecutive temporal segments, which represent data of current instance of time under analysis, with relation to past and future data. The spectral features are extracted along the 2s shifting window using fast Fourier transformation (FFT). The total power spectrum is calculated by summing up the power spectrum among the cutoff frequency bands: $P_{total} = \sum_{f=F_{min}}^{F_{max}} P(f)$, Where $P(f)$ is the power of frequency f, with $F_{max} = 48$Hz and $F_{min} = 0.35$Hz. The power ratio of each frequency band is defined as: $Pr(i) = \frac{\sum_{f=f_{low}(i)}^{f_{high}(i)} P(i)}{P_{total}}$, Where $f_{low}(i)$ and $f_{high}(i)$ indicate the range of the respective spectral power band. We represent the boundaries as an vector of frequency bands $B = \{0.35\ 2\ 4\ 8\ 12\ 16\ 24\ 48\}$, from which we can get any band pass definition, e.g. the $f_{low}(2) = 2$Hz and $f_{high}(2) = 4$Hz. The vector B was chosen after many rounds of experiments for the optimal setting, which well matches the bands that plays important roles in different sleep stages, e.g., Delta(0.5-4 Hz), Spindle $(12 - 16\text{Hz})$, Beta$(12-30\text{Hz})$, Alpha $(8-12\text{Hz})$ etc, as described in table I. This step yields 7 spectral power ratios $Pr = pr(i)$, $i = 1..7$. that are further processed by spectral envelope feature extraction.

2) Spectral envelope feature extraction: The concept of a spectral envelope for spectral analysis is commonly used in automatic speech recognition (ASR). Such a feature serves as an efficient tool for exploring the periodic nature of a categorical time series with minimum loss of information. We have design a novel feature extraction method with envelope-based spectral filtering, aimed at suppressing the color noise appearing in the spectral power periodogram. We first create the pass and stop bands edge frequencies for a Chebyshev filter, a specially defined spectral space of 0-0.5 Hz is further divided into 2 bands in a log-space. Chebyshev type II filter is applied to the 7 spectral power bands acquired from the above step, yielding another 14 parameters.

3) Extracting Gaussian parameters to form the feature space: The standard sleep staging window size is 30 seconds according to the AASM scoring. The 21 parameters extracted along a 2 second shifting window exhibit Gaussian distribution in the 30 second window. We extract the mean and variations of the parameters to form the feature space with 42 features. In comparison to the established feature set which has been previously developed for EEG based sleep stage detection, the spectral envelope-based features, comprised of spectral powers and their spectral derivatives form a better representative feature space, which are further analyzed in the experiment section.

C. iStaging model generation for sleep stage detection

Automatic sleep stage detection is a multi-class classification problem. We define a 3-layer pattern recognition neural network with 10 hidden nodes to model the problem. Pattern recognition networks are feedforward networks that can be trained to classify inputs according to target classes. The target data for the networks consist of vectors of all zero values except for a 1 in element s, where s is the sleep stage. Input to the network is the feature space as described above.

D. Apply iStaging model in a new EEG sensor

1) Sleep stage detection: The iStaging model contains parameters of the weight matrix and bias vectors for hidden layer and output layer (W_i, B_i, W_o, B_o), which are used to infer a sleep stage from the input features. The calculation of sleep stage can be realized by the following :

$$\mathbb{O} = logsig(W_o * (tansig(W_i * \mathbb{I} + B_i) + B_o) \quad (1)$$

Where $\mathbb{I}$ and $\mathbb{O}$ are input and output of the system respectively. The transfer functions used in the pattern recognition network are the log-sigmoid (logistic) and tan-sigmoid, which are given by $logsin(x) = \frac{1}{1+e^{-x}}$ and $tansin(x) = \frac{2}{1+e^{-2x}} - 1$, the output is a vector containing 4 values, with each representing the posterior probability of sleep stage s.

2) Automatic feature mapping for a new EEG sensor: Applying the iStaging model learned from cap EEG sensor to a new scenario where signals are acquired from a new EEG sensor is a transfer learning problem. To address the problem, we have invented a novel feature range mapping