Automatic Sleep Onset Detection Using Single EEG Sensor

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***Abstract*— Sleep has been shown to be imperative for the health and well-being of an individual. To design intelligent sleep management tools, such as the music-induce sleep-aid device, automatic detection of sleep onset is critical. In this work, we propose a simple yet accurate method for sleep onset prediction, which merely relies on Electroencephalogram (EEG) signal acquired from a single frontal electrode in a wireless headband. The proposed method first extracts energy power ratio of theta (4-8Hz) and alpha (8-12Hz) bands along a 3-second shifting window, then calculates the slow wave of each frequency band along the time domain. The resulting slow waves are then fed to a rule-based engine for sleep onset detection. To evaluate the effectiveness of the approach, polysomnographic (PSG) and headband EEG signals were obtained from 20 healthy adults, each of which underwent 2 sessions of sleep events. In total, data from 40 sleep events were collected. Each recording was then analyzed offline by a PSG technologist via visual observation of PSG waveforms, who annotated sleep stages N1 and N2 by using the American Academy of Sleep Medicine (AASM) scoring rules. Using this as the gold standard, our approach achieved a 87.5% accuracy for sleep onset detection. The result is better or at least comparable to the other state of the art methods which use either multi- or single- channel based data. The approach has laid down the foundations for our future work on developing intelligent sleep aid devices.**

I. INTRODUCTION

Studies have shown that soothing music can help improve the quality of sleep in different age groups [1], [2], [3]. However, if music is left playing after the onset of sleep, it may interfere with sleep by increasing the probability of arousal. An ideal sleep aid tool, e.g. a music-induced sleep-aid device, should be able to stop playing the music when sleep onset has been detected automatically.

Sleep onset is a complex process, which can be identified by several kinds of markers: behavioral features such as decrease of attention; physiological features such as changes in electrical resistance and temperature of skin; and changes in Electroencephalogram (EEG) [4]. Traditionally, sleep monitoring have been only conducted in professional sleep labs, using polysomnographic (PSG) equipments recording EEG, electrooculograms (EOG) and elecromyograms (EMGs); and a trained specialist who manually annotates the sleep stage according to the American Academy of Sleep Medicine (AASM) scoring [13]. The high cost of PSG setup and trained experts have restricted the applications of sleep research. The advancement of light weight EEG sensors, as well as automatic sleep scoring / staging systems, have made home-based sleep monitoring possible.

Various approaches have been reported on automatic sleep staging based on single EEG channel data. Huang et. al. [14] detects the arousal states of human using mean frequencies of a single EEG for autoregressive Hidden Markov Models (HMM), the approach achieves a wake-drowsiness detection rate of 70%. Novak et. al [15] employed the use of more features, including spectral entropy, autoregressive parameters, and complexity stochastic measure to build a HMM model for sleep staging. This approach works for predicting sleep stage N3 and N4 but it was not able to distinguish well among wake-N1-N2 stages. Rossow et. al. [16] described an approach using a single-channel EEG modeling by use of kalman filter and HMM, and the agreement rate in the testing set was reported to be 60.14%. Griessenberger et. al evaluated the sleep staging accuracy of a home sleep scoring system and discovered that the system showed a big deviance from the standard measure, especially in the wake-N1 transition stage. It concludes that reliable home based sleep scoring systems are still awaited [20]. Flexer et. al. [21] proposed a Gaussian Observation HMM to detect sleep stages, and achieved a accuracy of 86% for wake but only 22% for stage N1.

Unlike most sleep staging systems which analyze the recordings of whole night's sleep data and categorize epochs into five stages (including N1-4, REM), the objective of this study focuses on detecting the transition between wake and (N1-N2), which can provide a control mechanism for applications such as sleep aid devices.

Spectral analysis has been applied on EEG data during wake-sleep transition by several studies. Germain et. al. [12] reported that during the sleep onset power decreased in all frequency bands except delta (0-4Hz), and the decrease was observed most significantly in the frontal area of the brain. Tichy et al [18] found that during good concentration and attention the dominant power was in alpha band (8-12Hz), and that during micro sleep, the prominent peak was shifted to lower frequencies to the delta band. Although many features can be extracted from EEG signals for sleep staging, some show little correlation with sleep onset, some are redundant; some require high order computational power, the latter of which is inapplicable to real-time processing.

In this study, we propose a simple rule-based approach for sleep onset prediction, which is based on the trend detection of alpha and theta slow waves. This approach has minimum computational cost, yet displays high accuracy. We describe

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the method and experiment results in the following sessions.

II. Method

A. Data Acquisition and Annotation

Polysomnographic (PSG) and wireless headband EEG data were obtained from 20 healthy male adults ranging from 20 to 45 years of age (mean=29.7 ± 7.5 year) after obtaining the approval from a local Institutional Review Board (National University of Singapore). The subjects have signed informed consent forms for the experiments, which were conducted in the afternoon at the sleep laboratory of the Institute for Infocomm Research, Singapore. All subjects had at least 7 hours of sleep the night before the experiment and did not consume any alcoholic or caffeinated drinks on the day of experiment. Also no medications were used to induce sleep. Each subject underwent 2 sleep sessions on 2 different days. 40 sessions of sleep data were collected. The recordings were then analyzed offline by a PSG technologist via visual observation of PSG waveforms, and sleep stages N1 and N2 were annotated by using the AASM scoring rules based on 30 second (30s) epoch. The time labels of N1 and N2 are used as the gold standard to evaluate our algorithm.

B. Processing of EEG data

The sample rate of headband EEG signals used in this study is 256 samples/second. The continuous data is first processed with a notch filter followed by a Butterworth band pass filter with a cutoff frequency of 0.3-64Hz. The filters normalize the EEG data with zero-mean and remove motion artifacts which resulted from the occasionally poor contact of EEG electrodes.

Temporal shifting windows of 3s with 50% overlap are used to compare consecutive temporal segments, which represent data of current instant of time under analysis, with relation to its past and future data. The spectral features are extracted along the 3s shifting window using fast Fourier transformation (FFT). It is known that EEG properties, particularly amplitude, vary among different subjects [10]. We calculate the energy power ratio instead of absolute energy power in order to produce robust and subject-independent quantity measurement of the spectrum power.

The total power spectrum is calculated by summing up the power spectrum among the cutoff frequency bands:

$$P_{total} = \sum_{f=F_{min}}^{F_{max}} P(f) \tag{1}$$

where $P(f)$ is the power of frequency f. The power ratio for each frequency band is defined as:

$$PR(f) = \frac{\sum_{f=f_{low}}^{f_{high}} P(f)}{P_{total}} \tag{2}$$

where f_{low} and f_{high} indicate the ranges of the respective spectral power band. Association of various spectral bands with the sleep stage have been analyzed ; to simplify the sleep onset detection rule we are only interested in the Alpha band (PR_α, f_{low}=8Hz, f_{high}=12Hz) and the Theta band (PR_θ, f_{low}=4Hz, f_{high}=8Hz).

In order to obtain a reliable trend of changes in a particular spectrum band, a carefully designed 4th-order type II Chebyshev filter is applied to the power ratio data along the shifting 3s windows. The Chebychev filter requires less computational load as it obtains a steeper roll-off than other filters, such as a Butterworth filter of the same order. It has the property that minimizes the error between the idealized and the actual filter characteristic over the range of the filter, yielding a smoother response in the passband [11], which is preferred for our approach. The slow waves are noted as S_α and S_θ, respectively. Figure 1 illustrates the proposed EEG signal processing approach for sleep onset detection.

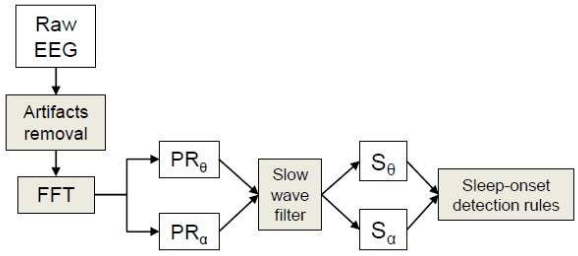

Fig. 1. Flowchart of proposed approach

C. Rule-based Sleep Onset Detection

Slow waves which resulted from the above process, noted as S_α and S_θ, are then send to a rule-based engine for sleep onset prediction. The engine examines whether the energy ratio difference $S_\theta - S_\alpha$ is persistently higher than a certain threshold $\mathbf{V}$ for a particular duration of time λ. If so, the sleep onset is detected, otherwise it carries on searching for next time point. The thresholds, $\mathbf{V}$ and λ are critical parameters for the prediction performance. We search for optimal $\mathbf{V}$ and λ by defining the following objective function:

$$\min \sum_{j=1}^{n} \|t^j_{pred} - (N^j_1 + N^j_2)/2)\|^2$$
$$s.t.\ Sign(S^j_\theta - S^j_\alpha - \mathbf{V}) * H(t^j_{pred} - \lambda) > 0$$

where n is the number of sleep sessions and the sign function is defined as:

$$Sign(x) = \begin{cases} 1 & \text{for} \quad x > 0 \\ 0 & \text{for} \quad x = 0 \\ -1 & \text{for} \quad x < 0 \end{cases}$$

and the step function:

$$H(x) = \begin{cases} 1 & \text{for} \quad x > 0 \\ 0 & \text{for} \quad x \leq 0 \end{cases}$$

The search algorithm is illustrated in following pseudocode:

Data: $S_\theta^i(t), S_\alpha^i(t), N_1^i, N_2^i, i = 1, 2, ...n$
Result: $\mathbf{V}, \lambda$
$Err0 \leftarrow \infty$;
for λ_j *in* $(\lambda_{min} : \lambda_{max})$ **do**
  for V_k *in* $(V_{min} : V_{max})$ **do**
    for i *in* $(1 : n)$ **do**
      $f_1 = Sign(S_\theta^i(t) - S_\alpha^i(t) - V_k)$;
      $f_2 = H(t - \lambda_j)$;
      $t_{pred}^i = \underset{t}{\operatorname{argmin}}(f_1 * f_2) > 0$;
    end
    $err = \sum_{i=1}^{n} \|t_{pred}^i - (N_1^i + N_2^i)/2)\|^2$;
    if $err < Err0$ **then**
      $\mathbf{V} = V_k$;
      $\lambda = \lambda_j$;
      $Err0 = err$;
    end
  end
end
return $\mathbf{V}, \lambda$;

Algorithm 1: Grid Search for optimal $\mathbf{V}$ and λ

D. Analysis method

To evaluate the proposed method, we use the N1 and N2 timings marked by PSG technologist to formulate the durations of real sleep onset. The correct detection of sleep onset should fall in the range between N1 and N2. However, when taking into consideration the inter-expert rating variability [9] and the inter-subject variability, we extend a 1 epoch (30s) buffer on both sides. In this paper, we define the true prediction of a session as $epoch_{N1} - 1 < epoch_{pred} < epoch_{N2} + 1$. Finally, accuracy is defined as the number of sessions with correctly predicted sleep onset divided by total experiment sessions.

III. Experiment and Result

A. Experiment Data Annotated by Sleep Expert

Table I lists the sleep stages N1 and N2 annotated offline by PSG technologist according to ASSM rules, based on visual observation of PSG signals.

In the sleep experiment we conducted, the set up of PSG electrodes took around 40 minutes. Such a duration of setup time, along with the complexity of physical set up, may have induced sleepiness. Consequently, all subjects fell sleep within 20 minutes after lying down. The time in table I is noted in [mm]:[ss] format, e.g., 03:20 stands for 3 minutes 20 seconds from the point where data acquisition started. On average, it took 03:18 for a subject to transit to sleep stage N1, and 06:02 to start N2, starting from the time when data acquisition started. The mean transition time from N1 to N2 was 02:44.

B. EEG Signal Processing for Sleep Onset Prediction

Figure 2 illustrates the overall procedure of the proposed method. 2.(a) shows a fragment of raw EEG signal; (b) represents the corresponding EEG signal that has been cleaned by artifacts removal and normalized with zero-mean; (c) shows the alpha and theta power ratio extracted by FFT and in (d) the slow waves of alpha and theta bands are generated for rule-based sleep onset detection.

TABLE I
Time of sleep stage N1 & N2 annotated manually

Session	N1	N2	Session	N1	N2
1	09:06	14:10	21	01:36	02:36
2	11:34	15:08	22	01:39	03:00
3	01:43	04:01	23	00:36	02:00
4	02:32	05:00	24	01:03	02:32
5	01:42	02:30	25	02:05	03:06
6	01:41	02:04	26	02:00	02:39
7	11:07	18:03	27	03:00	04:30
8	10:01	14:07	28	03:42	06:00
9	04:41	08:37	29	05:37	10:01
10	02:30	04:36	30	00:34	03:30
11	02:03	05:01	31	02:35	06:38
12	05:00	07:36	32	03:03	07:32
13	03:11	10:30	33	02:32	03:37
14	00:30	02:31	34	04:13	04:34
15	01:31	11:05	35	01:39	03:30
16	01:05	03:34	36	00:34	04:00
17	00:31	01:07	37	01:33	05:09
18	01:30	05:07	38	04:37	06:04
19	10:00	11:00	39	01:07	03:38
20	01:14	01:30	40	00:30	02:30

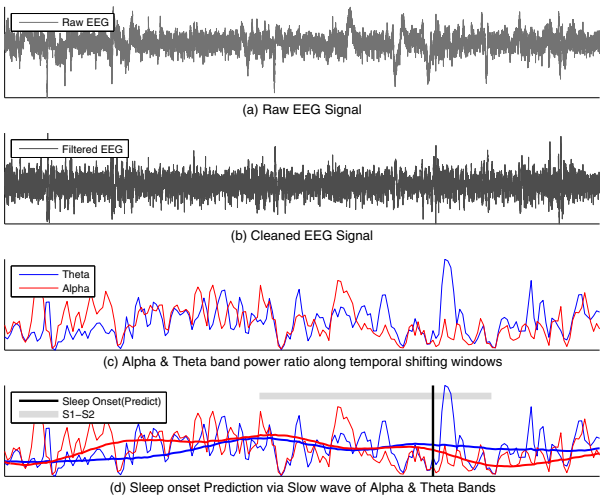

Fig. 2. EEG signal processing

From 2.(d) we can observe a clear trend of decline of alpha and uplifting of theta power, which can be associated with sleep onset [12], [18].

C. Accuracy of the Sleep Onset Prediction

Figure 3 shows the prediction results across all sleep events. Each gray bar represents the duration of N1-N2 $\pm$ 1-epoch in a sleep event. The blue star markers are the sleep onset time points detected by the proposed method. If a marker falls inside the gray bar, the onset is predicted correctly for that event, as explained in section II-D. Overall accuracy is 87.5% (35 out of 40 onsets detected). Among the

5 misses, 3 are very close to the N1-N2 period, if we relax the buffer to ± 2 epochs, there are only 2 misses, corresponding to an accuracy of 95%.

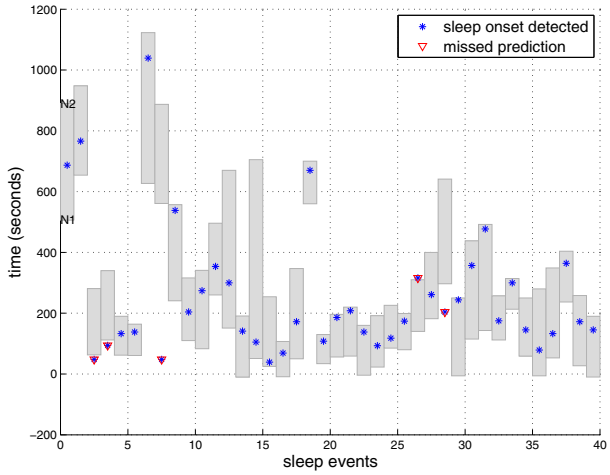

Fig. 3. Sleep onset predicted for all experiment events

IV. Discussion and Future Work

In this work we describe a rule-based algorithm for sleep onset detection, which uses EEG data from a single electrode. We conducted sleep experiments with sleep stages, which were manually annotated to assess the performance of our approach. With the criteria of N1-N2 $\pm$ 1 epoch setting, our approach can predict sleep onset with an accuracy of 87.5%.

A number of research articles reported the implementation of Artificial Neural Network (ANN) or Hidden Markov Model (HMM) for automatic sleep staging [14], [15], [19]. However, sophisticated learning algorithms such as HMM require a large set of training data and the preprocessed data from a set of manually crafted features. Such models may not work satisfactory in another conditions, such as across different sleep labs [22]. Furthermore, there are no clear physical meanings inferred from such prediction results due to their black-box manner. ANN or HMM methods are more suitable for a multi-staging purpose. This study does not attempt to detect the standard multi-stages of sleep. Instead, it focuses on sleep onset detection using a single channel EEG, and it can be used in applications such as music-induce sleep-aid devices. The proposed rule-based algorithm has several advantages. It is simple, yet accurate. It is fast enough for effortless online deployment. The mechanism is obvious, and the parameters can be easily calibrated upon change of conditions.

The accrate detection of sleep onset provides a control signal to sleep-aid devices we are currently developing. We have been continuously collecting sleep experiment data, and to further improve the proposed algorithm, we plan to do so in a different sleep lab and in different conditions, such as with background music.

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