An EOG-based Sleep Monitoring System and Its Application on On-line Sleep-stage Sensitive Light Control

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Abstract: Human beings spend approximately one third of their lives sleeping. Conventionally, to evaluate a subjects sleep quality, all-night polysomnogram (PSG) readings are taken and scored by a well-trained expert. The development of an automatic sleep-staging system that does not rely upon mounting a bulky PSG or EEG recorder on the head will enable physiological computing systems (PhyCS) to progress toward easy sleep and comfortable monitoring. In this paper, an electrooculogram (EOG)-based sleep scoring system is proposed. Compared to PSG or EEG recordings, EOG has the advantage of easy placement, and can be operated by the user individually. The proposed method was found to be more than 83% accurate when compared with the manual scorings applied to sixteen subjects. In addition to sleep-quality evaluation, the proposed system encompasses adaptive brightness control of light according to online monitoring of the users sleep stages. The experiments show that the EOG-based sleep scoring system is a practicable solution for home-use sleep monitoring due to the advantages of comfortable recording and accurate sleep staging.

1 INTRODUCTION

In recent years, physiologically sensing technologies have been applied to human computer interaction. They can not only help people with disabilities but also be integrated into general user interfaces used by healthy people. They also create more diverse interactive ways and help users keep healthy (Silva et al., 2011). Electrooculography (EOG), which measures our eye movement, is a kind of physiological sensing technologies. Several studies in the human computer interaction (HCI) field have shown that EOG can be used to track eye gazes (Manabe and Fukumoto, 2006; Bulling et al., 2009). In addition to detecting eye gazes, a recent study also suggested that EOG can be used to classify people's sleep stage(Virkkala et al., 2007).

Sleep is important for human health. Sleep diseases, such as insomnia and obstructive sleep apnea, seriously affect quality of life. Sleep is not a static stage but a dynamic process (Rechtschaffen and Kales, 1968). Sleep can be divided into six periods: wakefulness (Wake); the four stages of non-rapid eye movement (NREM, numbered 1-4); and rapid eye movement (REM). Stages 3 and 4 have also been combined, and referred as the slow wave sleep stage (SWS). Conventionally, to evaluate a subjects sleep quality, all-night PSG tests including electroencephalograms (EEG), EOG, and electromyograms (EMG) are usually recorded and scored by a well-trained expert (Rechtschaffen and Kales, 1968). Due to their high cost and bulk, conventional PSG systems are not suitable for sleep recording at home. Some easy-to-use alternative products such as Fitbit, Bodymedia Fit, and Zeo, along with the corresponding analysis software, have been developed for home sleep testing.

The HCI field has begun to take note of sleep-related issues (Aliakseyeu et al., 2011; Choe et al., 2011), and additional interaction designs to aid sleep have been proposed. Several studies identify factors that would affect sleep quality, and provide suggestions to improve it (Stepanski and Wyatt, 2003). In addition to self-management, advances in interaction designs may assist users to achieve better sleep quality and habits (Aliakseyeu et al., 2011). One prior

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study (Bauer et al., 2012) applied the concept of peripheral display to the design of mobile applications that can encourage users to keep good sleeping habits. There are also various systems using sensors on mobile phones to help users record sleep stages (Lawson et al., 2013) and to understand their sleep quality. Some products focus on waking users up by adjusting light levels during the period near the preset wake-up time, e.g., the Philips Wake-up Light.

Choe et al. (2011) have indicated many factors affecting sleep quality, including caffeine, the bedroom environment, and fears. Aliakseyeu et al. (2011), meanwhile, have suggested several design opportunities for improving sleep, some of which would need the support of real-time sleep-stage monitoring. Indeed, the results of these studies inspired us to develop an automatic scoring system. Recently, several proposals have been made for phone-based applications (apps) and wearable devices to monitor sleep efficiency (wake-sleep states), using accelerometers to detect body movements during sleep. These devices are easy to use, but cannot accurately recognize sleep stages and they may not function at all if used other than in bed, e.g. while having a nap in the office. The development of an online sleep-staging system that does not require the mounting of a bulky PSG system on the head will allow PhyCS to progress toward easier sleep and more comfortable monitoring.

This paper proposes an EOG-based sleep monitoring system including EOG acquisition and a sleep-staging method based on EOG signal analysis. Compared to all-night PSG or EEG recordings, EOG has the advantage of easy placement, and can be measured by the individual user without assistance. An automatic EOG sleep-scoring method integrating the time-domain EOG feature analysis and a linear classifier is proposed. The agreement between the proposed method and the expert scoring is higher than 83%, placing it within the range of inter-score agreement (Norman et al., 2000). Active control of environmental light/brightness, based on online monitoring of the users sleep stages by the proposed system, is also demonstrated.

2 BACKGROUND AND RELATED WORK

2.1 Stages of Sleep

Depending on whether EEG, EOG, or EMG has been utilized, sleep states can be roughly separated into NREM and REM sleeps, which alternate throughout a night in a roughly 90-minute cycle. In wakefulness with the eyes closed, alpha rhythms (8-13 Hz) can be observed using EEG in more than 50% of each epoch (i.e. each 30 seconds of data). According to the American Academy of Sleep Medicine (AASM) manual for the scoring of sleep (Iber, 2007), NREM sleep can be further classified into three stages: stage 1 (S1), stage 2 (S2) and SWS. S1 is a transitional stage from wakefulness to sleep. In S1, alpha rhythms are attenuated and replaced by low-amplitude, mixed-frequency activity (4-7 Hz) for more than 50% of the epoch, coupled with slow eye movements (SEM) and vertex sharp waves (V waves). S2 is characterized by sleep spindles with frequencies of 11-16 Hz, and/or K complexes. Stage SWS is defined by 20% or more of an epoch consisting of slow wave activity, that is, waves of frequency 0.5-2 Hz and peak-to-peak amplitude $> 75\ \mu$ V. In REM sleep, low-amplitude, mixed-frequency activity (4-7 Hz) similar to that in S1 can be observed via EEG, in combination with rapid eye movements and low chin EMG tone. Therefore, sleep stages can be distinguished from one another by observing different waveform patterns in EEG, EOG and EMG.

2.2 PhyCS for Sleep

In addition to assistive technologies for healthy living, researchers have started to develop PhyCSs that integrate sensing and computing technologies to support healthy sleep. Choe et al. (2011) conducted large-scale surveys and interviews to identify the design opportunities for supporting healthy sleep. According to their study, healthy people care almost as much about their sleep quality as insomnia patients do. Instead of clinical sleep diagnosis based on all-night PSG recording (including EEG, EOG and EMG), new portable recording devices with automatic analysis software have been developed for home applications; these include Zeo®, Fitbit®, and Bodymedia®. In addition, a number of phone apps have been developed to help users analyze their sleep processes (Lawson et al., 2013). The main purposes of these technologies are to monitor users sleep quality and to remind them of their sleep problems. Prior study (Aliakseyeu et al., 2011) has suggested some interaction designs for sleep applications, which may help people to enhance sleep quality, and accommodate the differing sleep habits of individuals.

2.3 Sleep Monitoring Devices

Recently, many novel techniques for online monitoring of physiological signals have been developed to help patients with sleep disorders (Chandra et al., 2012). Patients can wear wireless sensors that allow caregivers to monitor their conditions and provide help when needed (Silva et al., 2011). Some products for improving sleep quality have already reached the market, and these include both sleep-management systems and sleep clocks (Kay et al., 2012). It is reasonably clear that people have begun to pay particular attention to their sleep efficiency and quality. A sleep-management system usually consists of one or more sensors and a monitoring system (or a user interface). A user wears the sensors on their body and pre-sets up a wake-up time; the system will then wake up the user at a proper sleep stage at or before the wake-up time.

Zeo is a sleep-management product, shaped like a sports headband with three sensors attached on the forehead. Fitbit provides the user with a sleep quality score by measuring how long they sleep and how many times they wake up. Fitbit also has a silent wake-up alarm that gently vibrates to wake up the user by their preset time. The functionalities of Bodymedia Fit are similar to those of Fitbit. It lets users know the quality and efficiency of their sleep. In general, Zeo, Fitbit and Bodymedia Fit provide users with helpful information such as sleep efficiency (wake-sleep states) for sleep management; however, they may not be able to accurately recognize the whole range of sleep stages.

2.4 EOG-based Sleep Scoring Method

Wearable EOG systems have been used for eye tracking in the past. They are easy to use and do not obscure users field of view. For example, Bulling et al. (2009) embedded an EOG system into goggles that can recognize eye gestures in real time (Bulling et al., 2009). Manaby and Fukumoto also attempted to design an all-day-wearable gaze detector based on EOG (Manabe and Fukumoto, 2006). These systems show that EOG can potentially be used in our daily life.

Besides eye tracking, Virkkala et al. (2007) further proposed that EOG can be utilized to classify sleep stages effectively. The agreement between computer analysis/scoring of EOG signals, on the one hand, and the expert scoring of PSG signals is nearly 73%. This is not in the range of inter-score agreement (>82%, Norman et al., 2000), but if its accuracy can be improved, the EOG-based sleep staging system will be a very practicable solution for home-use sleep monitoring, due to the advantages of comfortable recording (as compared to PSG) and complete sleep staging (as compared to actigraphy).

3 AN EOG-BASED AUTOMATIC SLEEP SCORING METHOD

Our EOG-based sleep-stage scoring method includes three parts: preprocessing, feature extraction, and classification. The following subsections introduce each part in greater detail.

3.1 Preprocessing

The sampling rate of our EOG signals is 256 Hz. According to Rechtschaffen and Kales (1968) (hereafter, R&K rules), the major brain activity during sleep consists of low-frequency rhythms (< 30 Hz), and therefore an eighth-order Butterworth band-pass filter with a 0.5-30 Hz pass-band is used to filter the recordings for artifact rejection and enhancement of sleep-related physiological activities. Multi-scale entropy (MSE) has been used to analyze the filtered signals, as recommended by (Costa et al., 2005). In addition, an eighth-order Butterworth band-pass filter with a 4-8 Hz pass-band is utilized to extract the theta band components for the autoregressive (AR) model, as recommended by (Pardey et al., 1996).

3.2 Feature Extraction

Our feature extraction process includes: (a) MSE, (b) AR modeling, and (c) multi-scale line length (MLL). The MSE is the principal foundation of the method; the AR model and the MLL are complementary features for increasing the classification accuracy of S1 and REM.

a) Multi-scale Entropy. MSE is a signal-analysis method recently proposed by Costa et al. (2005). It estimates the complexity associated with the long-range temporal correlation of a time series. Instead of using a single scale, MSE measures the complexity of a time series by considering entropy at multiple temporal scales. MSE has been used to analyze the complexity of various biomedical signals such as EEG (Kang et al., 2009; Liang et al., 2012; Takahashi et al., 2009), ECG (Costa et al., 2005), and heart rate (Costa et al., 2003; Norris et al., 2008).

Given an EOG time series with N samples, $x = \{x_1, x_2, x_3, \cdots, x_N\}$, the original time series is divided into non-overlapping time windows of length τ, which is defined as the scale factor. A coarse-gained time series $y_\tau(j)$ is then calculated by averaging the data points inside a time window,

$$y_\tau(j) = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} x_i, \; 1 \le j \le \left\lfloor \frac{N}{\tau} \right\rfloor \tag{1}$$

After obtaining each element of the coarse-gained time series for each scale τ, the entropy of each coarse-gained time series is calculated. Theoretically, if the complexity of the signal is greater, the entropy value will be higher. Relatively, the entropy value is smaller. Two popular approaches for physiological time series analysis are approximate entropy (ApEn)(Pincus, 1995) and sample entropy (SampEn) (Richman and Moorman, 2000). SampEn was proposed to overcome some limitations of ApEn, such as bias caused by incorrect counting of self-matches to avoid the occurrence of a natural logarithm of zero in the calculation. Therefore, in this paper, SampEn has been utilized to calculate the entropy of the EOG time series. More details of SampEn can be found in Richman and Moorman (2000). The windows of length τ are set as 1-8, and therefore we have eight entropy values corresponding to different time resolutions, extracted as the features after MSE analysis.

b) Autoregressive Model. An AR model is a parametric model used to describe a stationary time series. It is a popular tool for EEG analysis (Berthomier et al., 2007; Olbrich et al., 2003; Thakor and Tong, 2004). AR models represent the current value of a time series $x(t)$ as the weighted sum of its previous values $x(t-i)$ and an uncorrelated error $\varepsilon(t)$,

$$x(t) = \sum_{i=1}^{p} a_i x(t-i) + \varepsilon(t), \tag{2}$$

where $a(i)$ is the AR coefficients and p is the order of the AR model. In this paper, we compute $a(i)$ and p from the theta band signals (4-8 Hz) extracted by an eighth-order Butterworth band-pass filter in the preprocessing phase. The computed $a(i)$ and p are used to determine EOG states.

c) Multi-scale line length. MLL calculates the line length for each coarse-gained time series. The line length LL of a time series is the sum of the vertical distance (absolute difference) between successive samples of the time series (Esteller et al., 2001),

$$LL = \frac{1}{N-1} \sum_{i=1}^{N-1} |x_{i+1} - x_i|, \tag{3}$$

where x is the time series considered, i represents the temporal index of the time series, and N is the total length of the time series.

Line length reflects changes of waveform dimensionality and is a measurement sensitive to variations of signal amplitude and frequency (Guo et al., 2010). MLL has the advantage of low computational complexity and is therefore suitable for online applications. It has also been used for automatic epileptic-seizure detection in EEG (Esteller et al., 2001).

A total of 24 features, including 13 MSE values, eight AR coefficients, and three MLL values are extracted from the EOG signals and fed in to a linear classifier for sleep-stage classification.

3.3 Classifier

Due to its low computational cost, we chose to utilize linear discriminant analysis (LDA) to classify five sleep stages based on the extracted MSE values, AR coefficients and MLL values. In addition, we wanted to ensure that the proposed EOG features were effective to a point that sleep stages could be determined simply using a linear classifier.

a) Linear discriminant analysis. LDA finds a hyperplane that best separates two or more classes of objects or events by adjusting the linear weighting of their features. Usually, the within-class, between-class, and mixture scatter matrices are used to formulate the criteria for searching the hyperplane (Lin et al., 2008; Kuo and Landgrebe, 2004). In order to test the generalization ability of the proposed method, the EOG data of 16 subjects were used to train the LDA classifier, while the EOG data of a different group of 16 subjects were used to verify the performance of our proposed method.

b) Smoothing. Sleep-stage scoring has periodicity and continuity from light to deep (R&K rules). After classifying the sleep stage using LDA, some misclassified epochs can be corrected according to temporal contextual information and R&K rules, which refer to the relation between epochs prior and posterior to the current epoch. For example, three consecutive epochs consisting of S2, REM, and S2 should be followed by the sequence S2, S2, S2. Similarly, consecutive epochs of REM, S1 and REM should be followed by the sequence REM, REM, REM. Following the protocols established by Iber (2007) and Virkkala et al. (2007)(Iber, 2007; Virkkala et al., 2007), a total of 10 rules were utilized to smooth the final results and increase the accuracy of our method. Table 1 shows the 10 smoothing rules we followed.

4 SLEEP-STAGE SCORING EXPERIMENT

4.1 Subjects and Recordings

All-night PSG sleep recordings were obtained from 32 healthy subjects (18 males and 14 females) ranging in age from 18 to 24 years. The subjects were interviewed about their sleep quality and medical history. Their sleep efficiency ranged from 56% to 97%.

Table 1: List of smoothing rules.

Rule No.	Modification
1	An REM Epoch before the very first appearance of SWS are replaced with Wake epochs.
2	Wake, REM, S2 → Wake, S1, S2
3	S1, REM, S2 → S1, S1, S2
4	S2, S1, S2 → S2, S2, S2
5	S2, SWS, S2 → S2, S2, S2
6	S2, REM, S2 → S2, S2, S2
7	SWS, S2, SWS → SWS, SWS, SWS
8	REM, Wake, REM → REM, REM, REM
9	REM, S1, REM → REM, REM, REM
10	REM, S2, REM → REM, REM, REM

None of them reported any history of neurological or psychological disorders. The PSG recordings of each subject were made using six EEG channels (F3-A2, F4-A1, C3-A2, C4-A1, P3-A2, and P4-A1, following the international 10-20 standard system), two EOG channels (the above-right and below-left outer canthus), and a chin EMG channel, and were acquired through the Siesta 802 PSG (Compumedics, Inc.). The sampling rate was 256 Hz with 16-bit resolution. The filter settings of the cut-off frequencies were 0.5-30 Hz for EEG/EOG, and 5-100 Hz for EMG. These nine-channel signals were used for manual scoring, as suggested by the R&K rules, whereas only the EOG data were used for the single-channel sleep-stage scoring system being developed.

The 32 PSG sleep recordings were visually scored by a sleep specialist using the R&K rules. Each 30-second epoch was classified into Wake, REM, S1, S2, SWS, and movement artifacts. In our experiments, only epochs of the five sleep stages were used; epochs of movement artifacts were rejected (Berthomier et al., 2007; Schaltenbrand et al., 1996).

4.2 Performance Evaluation

Next, we evaluated the performance of our automatic EOG-based sleep-scoring method. The performance criterion was the agreement between computer scoring, on the one hand, and expert scoring based on all PSG channels. The proposed systems sensitivity corresponding to each sleep stage is shown in Table 2. The rows represent the results arrived at by the experts visual scoring, and the columns represent the results of our method. The sensitivities of the proposed automatic stage-scoring method that were associated with the five sleep stages were 81.45% (Wake), 28.05% (S1), 88.12% (S2), 83.06% (SWS) and 81.05% (REM), yielding an overall sensitivity of 83.33%. The sensitivities for all stages except for S1 were higher than 81%. S1 can easily be mis-categorized as any of the other stages except SWS, and the number of S1 epochs is significantly lower than that of other stages epochs. As such, it is difficult to create a model with a high sensitivity for S1. Rosenberg et al. (Rosenberg et al., 2013) report that inter-scorer agreement in a large group is approximately 83% under current manual scoring rules, a level similar to that reported for agreement between expert scorers.

Comparing the recognition results achieved by the present study against the existing, purely EOG-based sleep-stage scoring method proposed by (Virkkala et al., 2007), overall agreement has increased from 73% to 83%. The results of the method in Virkkala et al. are Wake, 79.7%; S1, 30.6%; S2, 79.7%; SWS, 75.9%; and REM, 75.6%. As detailed in the preceding paragraph, our method performed better in four of the five stages (Wake, S2, SWS, and REM), and with regard to the remaining stage, the results are similar (28% vs. 30.6%).

5 LIGHTING CONTROL SYSTEM BASED ON SLEEP STAGES

In addition to sleep quality evaluation, it is worth considering whether a comfortable sleep monitor can be utilized to control the sleep environment. Accordingly, the present research also incorporated an active brightness-control system governed by online monitoring of the users sleep stages.

People can now purchase various lighting products that mimic the effect of natural sunlight. For example, the Philips Wake-up Light © is a dawn-simulation product that allows users to set up their wake-up time, the period of dawn or dusk simulation, and the maximal light intensity. This and other dawn-dusk simulation products gradually modify light intensity to simulate natural ambient light and help users fall sleep and/or wake up (Fontana Gasio et al., 2003; Fromm et al., 2011; Giménez et al., 2010). However, these dawn-dusk simulation products do not take any account of the users sleep stages. In particular, since every persons sleep pattern is different and may vary from time to time, changing light intensity according to a preset fixed program may not be appropriate, and even disturb a users sleeping partners who have different bedtime or wake-up time. Hence, it is desirable to develop an adaptive system that can dynamically adjust its lighting to let each user sleep and wake up gradually and individually.

Table 2: Confusion matrix of five-stage classification comparing the proposed EOG-based sleep scoring and manual sleep scoring based on PSG recordings.

	EOG system	Wake	S1	S2	SWS	REM	SE(%)
Expert	Wake	1094	55	33	11	150	81.45
	S1	100	124	76	8	134	28.05
	S2	28	203	5880	380	177	88.18
	SWS	5	1	376	1884	2	83.06
	REM	39	326	116	2	2129	81.05
	Overall						83.33
	Kappa						0.75

As a separate issue, light is important for safety, and especially for avoiding falling injuries at night. According to the American Association of Neurological Surgeons (AANS), falling down is the most common cause of death for people aged 65 or older. Children under the age of 4 are also at a high risk of head injury from falling in and around the home. To reduce the risk of falls, a function that automatically turns on appropriate lighting when a user wakes up at midnight must be considered.

5.1 System Requirements and Design Concept

In order to extend the PhyCSs-based sleep analysis for actively controlling the sleep environment, we have developed a lighting-control system that adaptively varies its brightness based on the users sleep stage. Following on from the discussion in the previous section, our system was intended fulfill the following requirements: a) Use online technology to classify a users sleep stages; b) Use online technology to adjust the lighting of the sleep environment according to the users sleep stages; c) During hours of darkness, provide faint light when the user wakes up and moves, to avoid falling; d) Wake up the user during a proper sleep stage (i.e. S1, S2 and REM) at or before the user-specified wake-up time; and e) Record and provide sleep information including sleep period, total sleep time, sleep latency, and sleep efficiency so that the user can learn about their sleep pattern. Figure 1 shows the concept and architecture of our adaptive light system. The processing steps were as follows:

1. A portable wireless EOG recording unit was used to record the users sleep EOG online.
2. The EOG signal was sent to a personal computer via wireless transmission.
3. An automatic sleep-scoring method based on EOG signals was utilized to classify the users sleep stage online. The output of the automatic sleep-scoring method is the users current sleep stage.
4. According to the users current sleep stage, the lighting-control algorithm gradually adjusts the brightness of light. The lighting-control algorithm also considers the situation of the user moving about during the night, e.g. to go to the toilet, and supplies adequate lighting to avoid falls.

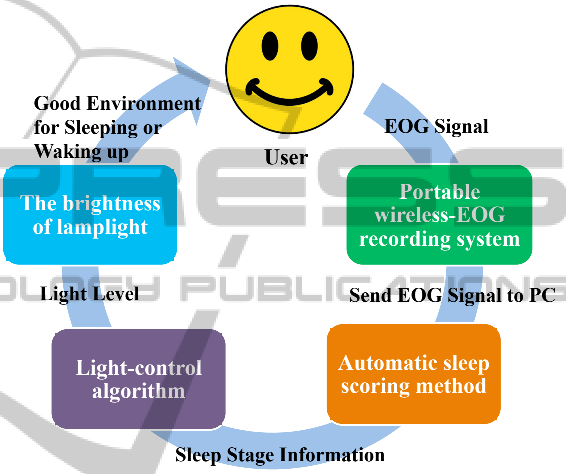

Figure 1: The concept and architecture of the proposed adaptive light system.

5.2 Portable Wireless EOG Recording Unit

In our design concept, a portable wireless EOG recording unit (as shown in Figure 2) is integrated with our sleep-scoring system to perform online sleep-stage monitoring. It consists of three components: Part A is a CC2530 wireless sender; Part B is the amplifier circuit of electrocardiography; and Part C is a CC2530 wireless adapter. Because the device is designed for online automatic sleep-stage scoring, most of the signals are in the low frequency band. Therefore, we chose the range of 0.3-35Hz as the passband of the analog filter. This system can continuously operate for, at most, 30 hours.

5.3 Control Module

Our lighting-control module consists of a circuit board with micro-controller and a sleep-stage-based lighting-control algorithm to control the brightness of an LED bulb. The circuit board we used is *Arduino Uno*, which has a micro-controller with a 16 MHz clock rate and 14 digital I/O pins (of which six provide PWM output). It can be connected to a computer via a USB cable for both data transmission and power supply, but it can also be run on a stand-alone basis, powered via an AC-to-DC adapter. The specifications of the LED bulb are, Color temperature: warm white 3500 K; current: 700 mA; voltage: 3.2-3.7v; brightness: 130-150 lm.

Our sleep-stage-based lighting control algorithm is illustrated in Figure 3. When the user wears our portable wireless-EOG recording unit and goes to bed, the brightness decreases from 200 lux to 100 lux over the course of 90 seconds. When the users sleep stage first reaches S1, the brightness decreases from 100 lux to 50 lux over a period of 150 seconds. Similarly, when users sleep stage enters its first S2, the brightness decreases from 50 lux to 25 lux in 60 seconds. The light is turned off 60 seconds after users sleep stage enters its first SWS epoch. Then, if the user appears to experience three continuous Wake epochs, indicating that they are likely to get up, the algorithm turns on the light and the brightness increases to 50 lux in 5 seconds. When the user goes to sleep again, the lighting control algorithm would check the first S2 and SWS, and the light is turned off gradually again. On the other hand, if the users sleep stage does not show three consecutive Wake epochs, it means that the user has continued sleeping. Five minutes before the user-set wake-up time, the lighting control algorithm checks the users sleep stage. If the users stage is Wake, the brightness increases to 255 lux in 60 seconds. If, on the other hand, the users stage is S1, S2, or REM, the brightness increases to 255 lux in 300 seconds. If there are no Wake, S2, or REM

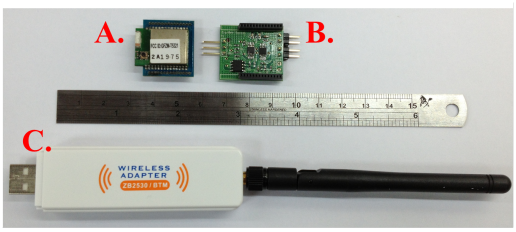

Figure 2: The three components of the portable wireless-EOG recording unit.

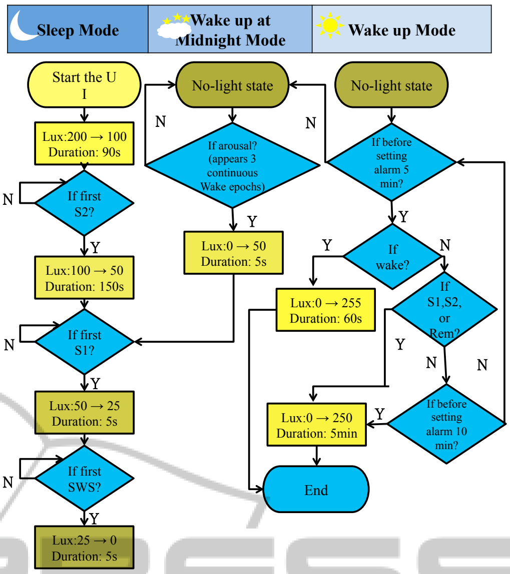

Figure 3: The flowchart of our light control algorithm, which has three modes: sleep, wake up at the middle of the night, and wake up.

stages within the 10 minutes immediately preceding the wake-up time, the brightness also increases to 255 lux in 300 seconds. The voice alarm rings when the brightness of the light reaches 255 lux.

6 LIGHTING CONTROL EXPERIMENT

We recruited three male subjects aged 23 $\pm$ 1.1 years old via the Internet. All three subjects had a habit of taking a nap at noon. They were asked about their sleep quality. None of them reported any history of sleep disorders. They were instructed to keep a regular sleep-wake schedule for three days prior to the experiment. Subjects were required to abstain from caffeine and alcohol throughout the course of the study. All subjects gave written informed consent before entering the study and were paid for their participation. The experiment began at about 1:00 PM.

6.1 Procedure

A darkened, quiet room was built for the sleep experiment. A camcorder was set up to record the experimental process. Two EOG channels, placed right/above and left/below outer canthus, were connected to our portable wireless EOG recording unit. The LED blub was placed next to the subjects pillow. The total sleep time was 80 minutes for each subject, this being the usual length of a persons first

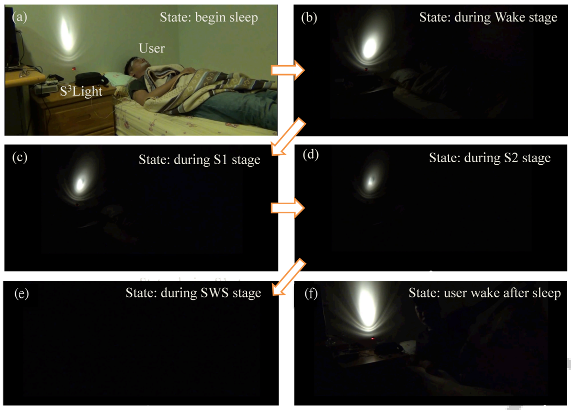

Figure 4: Illustration of the actual environment and experimental process. (a)-(e) show the brightness was gradually decreased when the user transitioned from waking to deep sleep. (f) shows how the light automatically turned on when the user woke up.

sleep cycle. Usually, sleep stages are not stable in the first sleep cycle; in particular, they change more frequently in the first sleep cycle than in the later cycles. Therefore, our experimental design focused on the first sleep cycle to verify the stability of the system in more difficult cases. Figure 4 shows the experimental environment and process, where (a)-(d) indicate how the brightness was gradually decreased in the periods when the users sleep stage transited from wake to light sleep (S1 and S2), and that the light was turned off in the SWS stage. Figure 4 (e) shows that the light was automatically turned on when the user woke up.

6.2 Results

In Figure 5, (a)-(c) show the sleep hypnograms and light levels for subjects 1, 2, and 3, respectively. The experiments of all subjects can be deemed successful, as the light was gradually turned off when their sleep stage changed from Wake to SWS, and was turned on when they woke up or were in the light sleep stage 10 minutes before the pre-set wake-up time.

From Figure 5(a), one can observe that brightness decreased at the beginning of sleep and during the first S1, S2, and SWS stages. The brightness of light remained zero until 71 minutes into the experiment, that is, nine minutes before the wake-up time set by the subject. The sleep stage of Subject 1 at 71 minutes was S2. Therefore, the brightness increased to 255 lux over the following 5 minutes. However, some Wake stages did appear between 30 minutes and 70 minutes, but all were less than three epochs in length. They may have been caused by body movement without awareness, or by misclassification by the sleep-scoring method. In any case, as these periods were

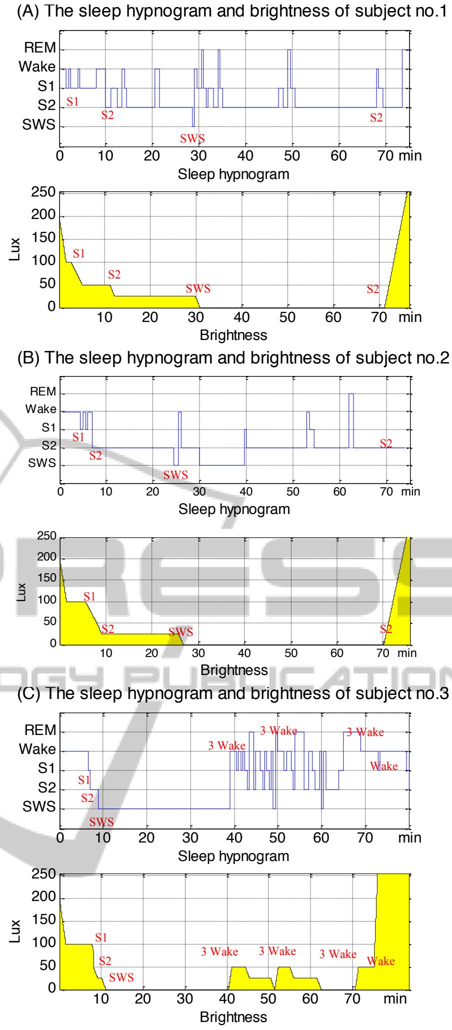

Figure 5: The sleep hypnogram and brightness of the three subjects.

less than three consecutive epochs, the light did not turn on. The results from Subject 2 were similar to those of Subject 1.

Figure 5(c) shows that Subject 3 achieved SWS quickly; however, he woke up two times between the 39-minute mark and the 51-minute mark. Our system provided faint light for purposes of safety when the user woke up, and turned off again when his sleep stage had returned to SWS. It is worth mentioning that the sleep stage of Subject 3 changed quickly between minute 40 and minute 60. Such rapid changes of sleep stage often result in incorrect sleep-stage scoring. To avoid mistakenly turning on the light when it is not needed, the lighting control algorithm may be adjusted according to a users sleep pattern and efficiency. Other factors affecting the sleep environment, such as music and temperature, can also be considered in the future.

7 DISCUSSION

Comfortable recording and accurate sleep-stage cassification are two essential criteria for sensing and computing technologies designed to support healthy sleep. Due to their high cost and bulk, conventional PSG systems are not suitable for sleep recording at home. Expert scoring of PSG recordings is also a time-consuming process. Recently developed phone apps and wearable devices for sleep monitoring are easy to use, but none claim to accurately recognize the full range of sleep stages. In this paper, an EOG-based sleep-scoring system has been proposed. Compared to PSG or EEG recordings, our EOG-based device has the advantage of easy placement and can be operated by the individual user with minimal training. The accuracy of the proposed method as compared with manual scoring can reach 83.33%. This solution balances the criteria of comfortable recording and accurate sleep staging.

In addition to sleep-quality evaluation, our system incorporates active light control. Our results demonstrate that light can be adjusted automatically based on the sleep stages of human subjects. Sleep hypnograms show that the time-points of different subjects sleep stages from awake to light sleep or from light sleep to deep sleep were very different. Hence, a dawn-dusk simulation should ideally control the brightness of light based on the users sleep stage, in order to overcome individual differences in their sleep patterns.

Prior work (Choe et al., 2011) indicated that users were not accustomed to wearing biosensors while asleep. This suggests that we must improve the comfort of this type of device in the future. Furthermore, there is lack of long-term (i.e. month-long or longer) studies of the use of portable sleep-monitoring devices in daily life (Fontana Gasio et al., 2003). With improvements to devices and increased user familiarity, negative user experiences can be expected to decrease.

Previous studies (Fromm et al., 2011; Giménez et al., 2010) have also suggested that simulated dawn-dusk light influences sleep quality. However, the main purpose of our work is to demonstrate that our method can adjust the brightness of light automatically based on users real-time sleep stages. How best to adjust the light to improve users sleep quality needs further studies for verification.

7.1 Benefits of Adaptive System

Most of the existing work in this area (Lawson et al., 2013; Kay et al., 2012) only recorded users sleep stages and helped them to analyze their sleep quality, without providing an active system to modulate the sleeping environment appropriately in harmony with users individual sleep stages.

Kupfer and Reynolds (1997) indicated that television was seen as a cause of disrupted sleep (Kupfer and Reynolds, 1997). However, it may help those who fear sleeping alone, or who need to be shielded from outside noise (Aliakseyeu et al., 2011; Choe et al., 2011). An adaptive system similar to the one we propose could adjust the brightness and contrast of TV screens to guide users to sleep, and shut down the TV automatically when users fall asleep. Since it has been demonstrated that lights can be adjusted and turned on and off automatically based on individuals sleep stages in real time, adaptive lighting adjustment could also help children who are afraid of the dark. A sleeping environment that is actively attuned to users sleep stages will allow them to have a better quality of sleep.

Besides improving sleep quality, an adaptive system might bring other benefits. For example, users could show their sleep stages to flight attendants on long air journeys, so that the flight attendants could avoid disrupting their rest when they are in deep sleep. For users who sleep with a partner, timely detection of sleep stages could modulate the sleeping environment appropriately, for example by adjusting the light level and TV volume once the partner is asleep. These automatic control systems need further design work and verification, but are certainly worthy of future research exploration.

7.2 Limitations

Our system still has some limitations. First, new EOG recording devices that can be easily worn would have to be developed if extensive use of our system was to be made. A long-term sleep monitoring system should be evaluated in the near future. Second, there is still much scope for improvement of the lighting-control algorithm, which can and should be fine-tuned to suit different subjects and scenarios.

8 CONCLUSIONS

This paper proposed a comfortable, accurate EOG-based sleep-monitoring system. In addition to offline sleep quality evaluation, its usefulness extends to dynamic control of light levels based on users sleep stages. This study demonstrates the feasibility of using online and closed-loop PhyCS to control a sleeping environment adaptively.

It is hoped that this work may open up new research horizons and strategies with regard to both sleep monitoring and environmental control. When a comfortable online sleep monitor is available, this system can be utilized to control the sleep environment for easy sleep. A system that automatically and adaptively adjusts environmental factors based on a users sleep stages for the purpose of sleep quality enhancement is feasible.

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