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On the Verification of Power Nap Associated with Stage 2 Sleep and Its Application

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***Abstract*—**One of the most important causes of accidents is driver fatigue. To reduce the accidental rate, the driver needs a quick nap when feeling sleepy. Hence, searching for the minimum time period of nap is a very challenging problem. The purpose of this paper is twofold, i.e. to investigate the possible fastest time period for nap and its relationship with stage 2 sleep, and to develop an automatic stage 2 sleep detection and alarm device. The experiment for this investigation is designed with 21 subjects. It yields the result that waking up the subjects after getting into stage 2 sleep for 3-5 minutes can efficiently reduce the sleepiness. Furthermore, the automatic stage 2 sleep detection and alarm device yields the real-time detection accuracy of approximately 85% which is comparable with the commercial sleep lab system.

***Keywords*—**Stage 2 sleep, nap, sleep detection, real-time, EEG

I. INTRODUCTION

SLEEP is important and essential for human life such that it enhances the memories and also daily restores the body to the normal stage [1]. Lack of sleep is also one cause of drivers' fatigue which often leads to the severe car accidents. To reduce the accidental rate, the driver needs a quick nap when feeling sleepy. Hence, searching for the minimum time period of nap is a very challenging problem.

In the last four decades, the classical method used for classifying sleep stages is called the Rechtschaffen and Kales (RK) sleep scoring standard [2]. According to the RK sleep scoring standard, sleep stages can be divided into two patterns, i.e. Non-Rapid Eye Movement (NREM) sleep and Rapid Eye Movement (REM) sleep. To make a distinction between the NREM and REM, both amplitude and frequency of the electroencephalogram (EEG) are generally employed. For NREM sleep, it can be divided into four stages, i.e. stage 1, 2, 3, and 4. In this paper, we mainly focus on the sleep stages up to stage 2 which are the stages before the deep sleep. In other words, investigation on finding the possible fastest time period for nap and its relationship with stage 2 sleep will be studied.

The stage 1 sleep is a light sleep or drowsiness which is the transition stage from full consciousness to the beginning of sleep. It usually takes approximately 5-10 minutes. This stage is constituted of low amplitude EEG waves with predominantly 4-7 Hz activity, vertex sharp waves (V waves), and slow eye movement (SEM) [3]. The average appearance of this stage is approximately 4 to 5% of the total sleep time. The stage 2 sleep is considered as the first true sleep stage. The characteristic of this stage is the occurrence of sleep spindles which are episodic bursts with frequencies between 11-16 Hz (most commonly 12-14 Hz) and last for a minimum of 0.5 sec. Moreover, K-complexes and a relatively low-voltage are also combined in frequencies of EEG waves in this stage 2 sleep. The K-complexes are the large waves starting with negative deflection followed by a positive component with total duration more than 0.5 sec. Since K-complex is sometimes can be used as the marker of stage 2 sleep, many authors are therefore work on the automatic detection of the patterns of K-complex, e.g. to employ the time domain analysis in [4] and [5]. Other works have preferred to detect K-complexes based on the filter-based features extraction e.g. in [6]. Stage 2 sleep may occur for 45 to 55% during the complete sleep. Since stage 2 sleep is the last stage before the deep sleep, waking up during this stage is likely to be efficient for napping. Some researchers have also mentioned about this assumption [14-16]. However, more scientific and real-time experiments as well as clinical verification still need more investigation.

Furthermore, regarding the overall sleep stages, significant researches have been made in the field of automated sleep analysis, starting with successful pioneering hybrid system [7], [8], and recently, with comprehensive and effective software systems using the theory of evidence [9] and knowledge approach [10]. In [11], the automatic sleep stage classification is designed based on visual analysis by using multiple electrodes of EMG, EOG, and EEG. In [12], the study of automatic sleep classification based on heart rate variability (HRV), respiration, and movement signals are illustrated. This study employs the time variant-autoregressive (TVAR) model and the discrete wavelet transform (DWT) as the feature extraction methods. Even though the literatures yield impressive results, however, real-time sleep stage detection still needs further investigation.

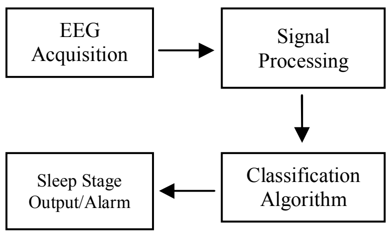

Fig. 1 The overview system of automatic stage 2 sleep detection and alarm

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The purpose of this paper is twofold, i.e. to further investigate the possible fastest time period for nap and its relationship with stage 2 sleep, and to develop a real-time automatic stage 2 sleep detection and alarm system. The experiment for this investigation is designed with 21 subjects. The overview of the proposed real-time stage 2 sleep detection system is shown in Fig. 1. There are four main parts, i.e. EEG acquisition, signal processing, classification algorithm, and sleep stage output/stage 2 alarm.

II. The Study on Waking up During Stage 2 Sleep

A. Design of Experiment

In order to investigate the possible time period for the most efficient nap, we designed the experiment by using five healthy subjects with 20-22 years old male. Each subject had to take a nap on the desk as shown in Fig.2. In each trial, the subjects have to wake up at various sleep stages. We designed the period of waking up for each subject into five periods, i.e.

1) Waking up when the subject reach into stage 1 sleep for 3 minutes,
2) Waking up when the subject reach into stage 2 sleep for 1 minute,
3) Waking up when the subject reach into stage 2 sleep for 3 minutes,
4) Waking up when the subject reach into stage 2 sleep for 5 minutes,
5) Waking up when the subject reach into stage 2 sleep for 10 minutes.

Each sleep stage was judged by the sleep specialist based on RK sleep scoring standard.

B. EEG Acquisition and Processing

The Ag-AgCl electrodes were used in the EEG acquisition process. A single channel EEG at C_3-A_2 position according to the international 10-20 system was employed as recommended in [1]. In this experiment, the BIOPAC™ amplifier was used for amplifying the EEG. The 0.1-35 Hz bandpass analog filter was also employed together with the 50Hz analog notch filter. For the analog to digital converter, we used NI-DAQ™ mx (NI USB 6008) with the sampling rate of 1,000 Hz. We also used another digital bandpass filter with range 0.05-35Hz to further denoise the acquired EEG signal. LabVIEW 8.5 was used to develop the detection and recording algorithms. In this paper, we performed two experiments the results of both experiments are shown in Sections II.C and II.D, respectively.

C. Experiment 1 and Results

In the first experiment, the five subjects took a nap on the desk by using the molar-shaped pillow. We attached electrodes on their scalps at the mentioned position. We then recorded the EEG signal while they were sleeping. The subjects were waked up at various sleep stages according to the opinion from the sleep lab specialist. After waking up, the subject immediately took a questionnaire which has three levels of opinion. Level 1 represented sleepy, Level 2 represented normal, and level 3 represented fresh. The experimental set up was shown in Fig. 2. According to Table I, most of the subjects felt fresh after waking them up 3-5 minutes after the get into stage 2 sleep.

D. Experiment 2 and Results

According to the result in Table I from Section II.C, we set up another experiment to verify our claim that waking up the subject 3-minute after stage 2 sleep will make them feel fresh. The experiment was set up similar to Experiment 1 except that we wake the 21 subjects up 3-minute after stage 2 sleep. All participants in experiment 1 are excluded in experiment 2. The questionnaire that we used is now divided into 5 levels of alertness, i.e. level 1 means sleepy while level 5 means fresh. According to Table II, more than 50% of the subjects had the alertness levels 4 and 5 which can preliminary prove our claim. More subjects are still needed to further prove this claim to avoid the bias of some subjects on filling in the questionnaires. It should be noted that we actually had 40 subjects. To reduce time consumption of the experiment, if a participant did not reach stage 2 sleep within 20 minute, he or she was woken up and excluded from the result. Therefore, only 21 of them can sleep into stage 2 within 20 min.

Fig. 2 Overview of the experiment: The blue box is our EEG acquisition module

TABLE I
RESULT OF WAKING UP DURING VARIOUS SLEEP STAGES OF 5 SUBJECTS: LEVEL1 IS SLEEPY, LEVEL2 IS NORMAL, AND LEVEL3 IS FRESH

	Period of waking stage 2				
	Stage 1	1 min	3 mins	5 mins	10 mins
Subject 1	1	2	3	2	2
Subject 2	1	2	3	3	1
Subject 3	1	1	3	2	1
Subject 4	2	2	3	3	2
Subject 5	1	1	3	2	2

TABLE II
THE ALERTNESS LEVEL OF
WAKING THE SUBJECTS UP 3 MINUTES AFTER SLEEP STAGE 2 OF 21 SUBJECTS

	Sleepy				Fresh
Levels of alertness	1	2	3	4	5
Number of subjects	1	1	6	5	8

III. Automatic Stage 2 Sleep Detection System

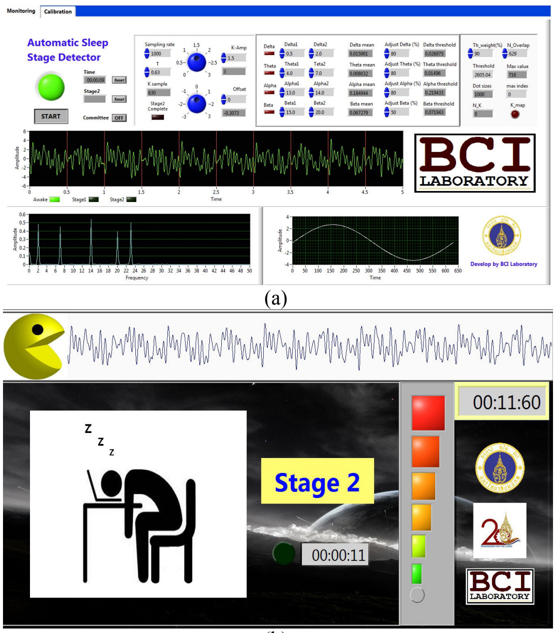
In order to make our claim becomes the device that can be used to reduce the accidents cause by drivers fatigue, we designed the real-time system that can minimize their napping time. The proposed device aims to wake up the users when they take a nap and achieve 3-minute after stage 2 sleep.

A. Hardware

We used the same devices as Section II.B except that it is portable because the power supply was changed to 12 volt battery. Laptop with the designed software was used as the processing and alarm units as well.

B. Real-time Stage 2 sleep Detection Algorithm

The proposed algorithm was divided into two parallel processes, i.e. 1) frequency domain analysis and 2) time domain analysis. These proposed algorithms are implemented and can be used via our designed user friendly GUI as in Fig.3.



(a)

(b)

Fig. 3 The GUI of the program: (a) Control page, (b) Display page.

1) Frequency Domain Analysis

This process was used for two purposes, i.e.

1) Detecting Theta wave (4-7 Hz) of *sleep stage one*,
2) Detecting Theta wave (4-7 Hz) as well as spindle (12-14 Hz) wave of *sleep stage two*.

We used the power spectrum (PS) to accurately fine the frequency of each sleep stage. The magnitude of power spectrum was calculated via FFT with Hanning window. We processed the signal every 1 second. Each time, 10 seconds signal per epoch was acquired, i.e. the signal was acquired with 9 seconds overlapping time. We separated the frequency bands of interest into four intervals. The average of magnitude of each interval can be defined as follows:

- P_δ was defined as the average power spectrum in delta band (0.5-2Hz).
- P_θ was defined as the average power spectrum in theta band (4-7Hz).
- P_μ was defined as the average power spectrum in alpha band (12-14Hz).
- P_β was defined as the average power spectrum in beta band (16-20Hz).

Prior to the experiment, some thresholds need to be set via our calibration process, i.e. the P_δ, P_μ, P_β, and P_θ was acquired and 180% of their magnitudes are set as their corresponding thresholds, $P_{\delta\ threshold}$, $P_{\mu\ threshold}$, $P_{\beta\ threshold}$, and $P_{\theta\ threshold}$. To discriminate the sleep stages, higher magnitude of P_θ compare with its threshold indicates sleep stage 1 whereas higher magnitudes of P_θ and P_μ (spindle) compare with their threshold indicate stage 2 sleep. This process of decision making will be summarized in Section III.C

2) Time Domain Analysis

This process was used to detect the K-complex waveform which is another component of stage 2 sleep. The general waveshape of the K-complex can be widely modeled as in Fig.4 and its invert. The parameters T, T_1, T_2, and A are unfixed but can be changed within empirically established bounds. From the previous work [5], according to the data from over 50 subjects, the average T of K-complexes was approximately 0.63 second, with the bounds of approximately 0.50 to 1.00 second and A >100 μV. The shape of the real K-complex may in some instances differ in other respects as well. This variability of waveshape is true in general for all events found in EEGs and would lead to the difficulty to accurately describe any waveform with a mathematical method.

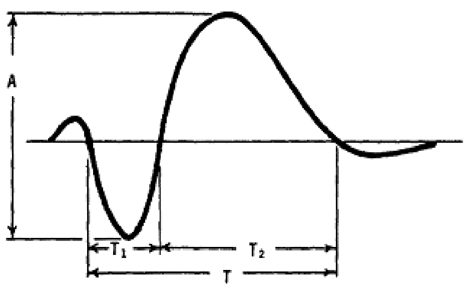


Fig. 4 The approximated waveform representation of K-complex; 0.5 < T< 1.0 seconds; A >100 μV [5]

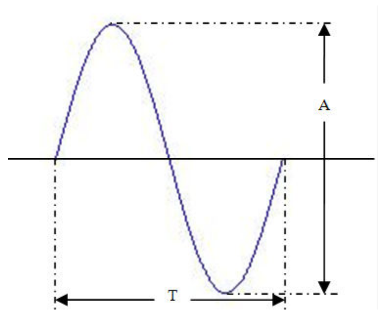


Fig. 5 K-complex mathematical model used as basis for detection scheme. 0.5 < T< 1.0 seconds; A > 100 μV

Instead of using the K-complex model as in Fig.4, in this paper, we employed the simple K-complex model as in Fig. 5 for the purpose of real-time processing. This simple K-complex model that we employed is a one cycle of a sine wave of minimum peak-to-peak amplitude of 100 μV. The period is adjustable between 0.5 and 1.0 second, with the default value of 0.63 second according to [5].

To detect the K-complex, we used this model to compare with the acquired real-time signal. The absolute value of the inner product (dot product) [13] was used for comparing the correlation between the model and the EEG waveform. The absolute of the inner product can be shown as follows:

$$Absolute\ of\ Inner\ Product = |a \cdot b| = \left|\sum_{i=1}^{n} a_i b_i\right|,$$

where a represents the generated model and b represents the acquired real-time EEG. Absolute value is needed since K-complex waveform can be inverted from the model (180 degree phase shift).

In this paper, we compared the dot product value in real-time between the real-time acquired EEG waveform and the model. The default model parameters were set prior to the recording while the subject was in the relax behavior. The K-complex threshold was calculated as 80% of the absolute value of the inner product of the default model with itself. The K-complex is found, if the absolute of the inner product is more than the threshold.

C. Decision Making

The decision rule of the system can be summarized as follows:

1) The decision is made as stage 1, if $P_\theta > P_{\theta_{threshold}}$and the magnitude of others power spectrum, P_δ P_μ P_β, are less than their corresponding thresholds.

2) The decision is made as stage 2, if $P_\theta > P_{\theta_{threshold}}$and spindle (12-14Hz) or K-complex waves are found at least 3 times within 20 seconds. Spindle (12-14Hz) is found, if $P_\mu > P_{\mu_{threshold}}$. The K-complex is found, if the absolute of the inner product is more than its corresponding threshold.

3) Otherwise, the decision is made as awake.

After the subject is detected as getting into stage 2 sleep, the device will alarm when 3 minutes have been past.

D. Classification Results

In order to verify the proposed real-time detection method, three subjects (excluded from experiments 1 and 2) were asked to sleep for the whole night. With the justification of the sleep lab specialist, sensitivity and specificity were calculated. The sensitivity measures the proportion of actual positives which are correctly identified (the percentage of real stage 2 which is correctly identified as having the condition). The specificity measures the proportion of negatives which are correctly identified (the percentage of out of stage 2 which are correctly identified as not having the condition). The results are shown in Table III.

TABLE III
THE RESULTS OF AUTOMATIC STAGE 2 SLEEP DETECTION SYSTEM

	Specificity	Sensitivity
Subject1	89.8	78.7
Subject2	90.6	83
Subject3	88.7	76.3

According to Table III, the system can classify stage 2 sleep with high accuracy. The specificity of each subject was approximately 89% with the sensitivity ranging from 76.3 to 83%. It should be noted that these results are more accurate than the ones we get from the automatic detection in the commercial software of the polysomnography system which yields only approximately 70% sensitivity.

IV. CONCLUSION

In this paper, we have presented the results to verify that the possible period that effective nap (power nap) can be occurred is 3-5 minutes after stage 2 sleep. According to 21 subjects, the time average to reach the effective nap is 12 minutes. However, more subjects need to be included to further verify the results. Furthermore, this paper has proposed the *real-time* automatic stage 2 sleep detection and alarm system. Instead of using the complex theory, we try to simplify the algorithm so that the real-time processing is possible. The system is developed for verifying the power nap theory. For our future work, some other evaluation methods besides the questionnaire will be employed, e.g. letting the subjects perform basic calculation to observe their levels of alertness.

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