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Wakefulness evaluation during sleep for healthy subjects and OSA patients using a patch-type device

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ABSTRACT

Objectives: Obstructive sleep apnea (OSA) is a major sleep disorder that causes insufficient sleep, which is linked with daytime fatigue and accidents. Long-term sleep monitoring can provide meaningful information for patients with OSA to prevent and manage their symptoms. Even though various methods have been proposed to objectively measure sleep in ambulatory environments, less reliable information was provided in comparison with standard polysomnography (PSG). Therefore, this paper proposes an algorithm for distinguishing wakefulness from sleep using a patch-type device, which is applicable for both healthy individuals and patients with OSA.

Methods: Electrocardiogram (ECG) and 3-axis accelerometer signals were gathered from the single device. Wakefulness was determined with six parallel methods based on information about movement and autonomic nervous activity. The performance evaluation was conducted with five-fold cross validation using the data from 15 subjects with a low respiratory disturbance index (RDI) and 10 subjects with high RDI. In addition, wakefulness information, including total sleep time (TST), sleep efficiency (SE), sleep onset latency (SOL), and wake after sleep onset (WASO), were extracted from the proposed algorithm and compared with those from PSG.

Results: According to epoch-by-epoch (30 s) analysis, the performance results of detecting wakefulness were an average Cohen's kappa of 0.60, accuracy of 91.24%, sensitivity of 64.12%, and specificity of 95.73%. Moreover, significant correlations were observed in TST, SE, SOL, and WASO between the proposed algorithm and PSG ($p < 0.001$).

Conclusions: Wakefulness-related information was successfully provided using data from the patch-type device. In addition, the performance results of the proposed algorithm for wakefulness detection were competitive with those from previous studies. Therefore, the proposed system could be an appropriate solution for long-term objective sleep monitoring in both healthy individuals and patients with OSA.

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1. Introduction

Insufficient sleep influences both mental and physical health as well as daytime performance because sleep not only provides physiological restoration from daily fatigue [1–3] but also plays a role in memory consolidation [4] and hormone acceleration [5,6]. Insufficient sleep is caused by various factors such as sleep disorders, which usually impair normal sleep architecture. Patients with primary insomnia have problems with sleep initiation and maintenance [7]. Thus, their sleep is characterized by longer sleep onset latency (SOL)—the time taken to reach the first epoch of sleep from wakefulness—longer wake time after sleep onset (WASO), and lower sleep efficiency (SE)—defined as the ratio of total sleep time (TST) to time in bed—compared to that of a healthy sleeper [8,9]. Obstructive sleep apnea (OSA) is a breathing-related sleep disorder that is caused by partial or complete blockage of the upper airway during sleep [7]. Apneic or hypopneic events increase respiratory effort, which causes arousal and sleep fragmentation, disrupting normal sleep structure [10–12]. Thus, low SE and short TST

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are frequently observed in patients with OSA, resulting in insufficient sleep [13]. Most patients with those sleep disorders complain of daytime sleepiness, which is linked with cognitive function [14–16] and propensity for accidents [17,18]. Therefore, long-term sleep monitoring can provide meaningful information for understanding the sleep process itself and overall health management.

Polysomnography (PSG)—a standard measure for examining sleep—is used to evaluate sleep architecture and diagnose disorders based on characteristics of multiple physiological signals such as an electroencephalogram (EEG), an electrooculogram (EOG), an electromyogram (EMG), respiratory signals, and sleep position [19]. Even though PSG provides various information related to sleep, trained experts should be involved throughout the entire procedure from preparation to data analysis, which is a laborious and time-consuming process [20]. In addition, the patient's sleep pattern may be altered by an unusual sleep environment and numerous sensor attachment [21]. In this sense, PSG is difficult for application in long-term home-based sleep monitoring.

Actigraphy, which is a simple method of sleep monitoring, is widely used in clinical and healthcare areas [22]. It discriminates wakefulness from sleep based on the level of an individual's movement using accelerometer data [22]. Although actigraphy is applicable to long-term monitoring owing to its ease of use, it generally underestimates the SOL because of the patient's inactive period prior to initiating sleep [22,23]. Although previous studies reported that the correlation between SE from actigraphy and that from PSG was high in healthy groups, it was low in groups of patients with OSA [24]. More specifically, it was revealed that actigraphy provided better results at detecting sleep, with a specificity of 94%, than detecting wakefulness, with a sensitivity of 43% [25]. According to a recommendation from the American Academy of Sleep Medicine (AASM), sleep parameters from actigraphy can assist in the evaluation of sleep disorders such as circadian rhythm disorders; however, only TST is accessible for patients with OSA [26]. An alternative to actigraphy could be the use of heart rate. Various studies reported that the activity of the autonomic nervous system (ANS) is associated with sleep transition [27–30]. Specifically, increased sympathetic activity is observed in wakefulness and it gradually decreases with parasympathetic dominance as sleep progresses from N1 to N3 stages [31–34]. Therefore, several studies developed methods for distinguishing between sleep and wakefulness using heart rate variation, which is influenced by autonomic control [35–39]. However, most methods were evaluated with data from healthy subjects; therefore, an algorithm needs to be developed for both healthy subjects and patients with sleep disorders such as OSA.

In summary, long-term sleep monitoring is necessary for clinical purposes and daily health management. Various methods that classify between sleep and wakefulness have been developed and assessed; however, there are still challenges to estimating more accurate sleep parameters, such as TST, SOL, WASO, and SE, in patients with sleep disorders using portable devices. Therefore, we propose an automatic algorithm for distinguishing between sleep and wakefulness using the data recorded from a patch-type device. In detail, six separate methods are introduced to determine different types of wakefulness based on movement and autonomic nervous activity. The proposed algorithm is applicable to both healthy subjects and OSA patients, and it provides multiple types of sleep-related information; therefore, it could be appropriate for long-term monitoring. Furthermore, it might be possible to provide more concrete sleep–wakefulness information in home and ambulatory circumstances by combining the proposed algorithm with automatic algorithms for detecting rapid eye movement (REM) sleep and slow-wave sleep (SWS).

2. Methods

2.1. Data recording

Thirty participants (male: 16, female: 14) underwent night time PSG at the Center for Sleep and Chronobiology of Seoul National University Hospital. Data from PSG (NEUVO, Compumedics Ltd., Victoria, Australia) included EEG at the O2-M1, C4-M1, and F4-M1 positions, EMG at the chin and tibialis anterior muscles, bilateral EOG, body posture, oronasal airflow, nasal pressure, abdominal and thoracic volume changes, lead II electrocardiogram (ECG), oxygen saturation, and snoring status. In addition, all subjects were asked to attach a T-REX (Taewoong Medical, Co., Ltd, Gyeonggido, Korea) [40], which is a patch-type device for recording a single lead ECG and 3-axis accelerometer signals, with the left side of electrode placed at the anticardium, as shown in Fig. 1. Simultaneous with PSG recording, the device measured ECG at 256 Hz and accelerometer signals at 32 Hz with an acceleration range from −6 g to 6 g (−58.84 m/s^2 to 58.84 m/s^2). The study protocol was approved by the Institutional Review Board of Seoul National University Hospital (IRB No. H-1405-124-582).

2.2. PSG scoring

Following AASM guidelines [19], a PSG technician scored sleep stages at every 30 s epoch. An apnea was recorded when the amplitude decrease in the oronasal thermal signal from pre-event baseline exceeded 90% with a duration of at least 10 s [19]. A hypopnea was recorded when the amplitude decrease in nasal pressure exceeded 30% from the pre-event baseline, its duration is more than 10 s, and oxygen desaturation decreased by more than 3% from the pre-event baseline or the event is associated with arousal [19]. In addition, respiratory effort–related arousal (RERA) was recorded when a sequence of breaths lasting more than 10 s characterized by increasing respiratory effort or by flattening of the inspiratory portion of the nasal pressure led to arousal from sleep but did not meet criteria for an apnea or hypopnea [19]. Finally, the respiratory disturbance index (RDI) was defined as the total number of apneas, hypopneas, and RERAs per hour of sleep [19]. Finally, all scored results were reviewed and confirmed by two clinicians. The data from five subjects were excluded from the analysis because two sets of data were not properly gathered from the device, one subject showed narcolepsy symptoms, and two subjects presented insomnia symptoms. Finally, the data from the 25 subjects were divided into two groups: a low-RDI group (RDI $<$ 15) and a high-RDI group (RDI $\geq$ 15). Table 1 presents a summary of the sleep variables and demographics. No values were statistically different between the two groups except for the proportions of stages N1 and N2, the proportions of stage N3, and the RDI.

2.3. Parameter extraction

2.3.1. Heart rate parameter

ECGs from the PSG and T-REX were high-pass filtered at 1 Hz, then low-pass filtered at 30 Hz with 5th order infinite impulse response (IIR) Butterworth filter. R-peaks from each ECG were found using an automatic algorithm [41] and manually corrected. R-R intervals were obtained from the duration between sequential R-peaks. The data from separated systems were synchronized with R-peak locations and R-R intervals. The OSA is characterized by cardiac arrhythmias such as bradycardia and tachycardia [42]. Although arrhythmias generate abnormal R-R intervals, they could also be meaningful information for distinguishing between sleep and wakefulness. Therefore, all valid R-R intervals are used for feature extraction, except for motion artifacts. Finally, the mean of R-R

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