PHOTOPLETHYSMOGRAPHY-BASED BRACELET FOR AUTOMATIC SLEEP STAGES CLASSIFICATION: PRELIMINARY RESULTS

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ABSTRACT
In this ongoing study we present the preliminary results of a fully automatic sleep stages classification based on acceleration and photoplethysmography signals recorded at wrist. The device consists in a bracelet integrating sensors, processing unit, communication capabilities, and power management. The bracelet has been worn by two healthy volunteers during a night period at hospital in combination to a complete polysomnograph. Spectral analysis of heartbeat intervals in standard HRV frequency bands, as well as movement activity level have been performed and used to differentiate 3 sleep states: WAKE, REM and NREM. The automatic classification has been compared to the hypnogram provided by a professional clinician using standard polysomnography procedure. Classification rates up to 90% have been achieved for NREM state and between 44% and 72% for REM state. High confusion coefficients for WAKE state is reported and results from hypnographic misalignment with the algorithm output.

KEY WORDS
Photoplethysmography; sleep stages; REM; NREM; hypnogram, heart rate variability.

1. Introduction

Modern lifestyles are irremediably associated with increased incidence of sleep disorders. Only in the US more than 18 Million people are accounted to suffer from chronic sleep apnea, and 70 Million from insomnia. Unfortunately, the diagnosis and follow-up of sleep disorders requires still nowadays the use of bulky and cumbersome monitoring devices. There is a clear demand for new technologies that allow assessing vital signs during sleep without interfering with user comfort.

With respect to wakefulness, sleep is characterized by a higher parasympathetic activity, a lower body metabolism, a lower body temperature, and a lower responsiveness to stimuli.

Large individuals sleep behavior variability is common. Their sleep structure and organization are influenced by biological (*e.g.* age, gender, body mass index) and environmental factors (*e.g.* work schedule, cultural traditions, socioeconomic condition and health history). It is thus impossible to determine optimal sleep characteristics reflecting the habits of the entire population. Researchers are used to stratify the population and characterize each sub-population separately. For example, it is reported that the majority of healthy young adults sleep approximately 7.5 hours and 8.5 hours on weekday and weekend respectively.

Since more than 50 years now, sleep is classified in two categories: rapid eye movement (REM) and non-rapid eye movement (NREM) sleeps. The REM sleep is also called paradoxical sleep and is characterized by rapid and random movement of the eyes and dream activity. In healthy young adults, REM sleep normally occupies between 20% and 25% of the total night sleep duration. NREM sleep constitutes 70% to 80% of the total night's sleep period and is characterized by low body metabolism and increased regularity in heart rate and breathing rate. Remaining 5% of the total night sleep duration is normally scored as wakefulness [1].

In a whole normal night sleep period, four to six REM-NREM cycles (ultradian cycles) lasting 90 to 110 minutes each are observed. Ultradian cycles depict a particular structure evolving from one cycle to the other. The standard way to monitor sleep structure is polysomnography (PSG), consisting in simultaneously recording electroencephalogram (EEG), elecrooculogram (EOG), electromyogram (EMG), electrocardiogram (ECG), and respiration. The information provided by PSG allows professionals to distinguish each sleep category and sub-category in order to establish a sleep profile commonly called hypnogram.

Sleep scoring rules are complex and require a long and accurate visual inspection by specialized personnel. Algorithm for automatic sleep scoring have been studied and developed, as well as alternative devices for automatic sleep profile estimation based either on single lead EEG (as claimed by Zeo, Inc, and Neurovigil,

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Inc), on single lead ECG [2], on breathing activity, on actigraphy [3], or on a combination of some of them [4].
In the present work, we have monitored sleep with a bracelet-like device integrating acceleration and optical sensors to acquire signals related to body movements and cardiac activity, respectively [5-6]. These signals have been automatically processed to obtain a sleep profile, consisting in REM, NREM, and WAKE stages. The following sections described the methodology, preliminary results and observations related to this ongoing study.

2. Methodology

2.1 Recording protocol

The first phase of our study was conducted during 2013 in collaboration with the University Hospital of Lausanne (Switzerland). So far, two young healthy females participated to the study.

After the installation of the ambulatory recording setup, the subjects were asked to enter home for a full night and come back to hospital the successive day. PSG was started between 22:00 to 23:00 and was terminated by spontaneous awakening between 06:00 and 08:00. The recording setup consisted in a PSG system and the bracelet (placed at the left wrist). PSG was done using Embla titanium recording system and signal analyzed with Somnologica software (both Natus Medical, Inc, products) to obtain the hypnogram. The bracelet integrates three-axial accelerometer, optical sensors, processing unit, communication capabilities, and power management [7]. The optical sensor includes one infrared LED (940 nm) and three photodiodes in contact with skin and providing three photoplethysmography (PPG) signals acquired at 21.33 Hz. The total weight of the portable sensor (Figure 1) of about 25 g and its reduced size (34x40x12 mm^3) make it a comfortable device for minimally obtrusive ambulatory sleep studies [5-6]. The sensor is equipped with an LCD showing cardiovascular indicators in real time, and depicts 50 hours of data logging autonomy.

Data recorded during the entire night without interfering with subjects was further downloaded into a PC platform for off-line processing.

2.2 Features extraction

From the two records, two families of features have been extracted to classify sleep stages (WAKE, REM, NREM) and design sleep profiles (hypnogram): 1) acceleration- and 2) PPG-based features (see **Figure 2**).

The acceleration-based feature #1 is used to determine "sleep" (REM and NREM) and "wake" (WAKE) classes. It is performed by estimating the energy and comparing its low-pass filtered version to a threshold. Magnitudes below the threshold are classified as "sleep" (REM, NREM), in the opposite case as "wake". The acceleration-based feature #2 consists in an estimation of the night movement level which is extracted by low-pass filtering (cut-off frequency at 0.1 Hz) the energy (square of the norm-2) of the first derivatives of each axis. Feature #2 is used to classify sleep stages (REM, NREM and WAKE).

Features based on PPG signals are derived from heartbeat interval time series. PPG signals are processed as described in [5] to obtain pulse-to-pulse intervals. Outliers are then rejected from the pulse-to-pulse intervals series by applying lower (300 ms) and upper thresholds (2000 ms) reflecting normal physiological conditions of a healthy human. Pulse-to-pulse time series are then resampled at 2 Hz, band-pass filtered (0.02-0.5 Hz), and analyzed in the frequency domain as performed in Heart Rate Variability (HRV). Various methods exist to estimate the power spectral density of a signal. In this study we used the Yule-Walker algorithm to estimate parametric spectral densities by fitting autoregressive (AR) prediction models of a given order to pulse-to-pulse time series. An AR model of order 20 was fitted on 50-seconds segments at each sample to evaluate the power in the very low frequency (VLF<0.04 Hz), low frequencies (LF in [0.04, 0.15] Hz, and high frequency (HF>0.15 Hz) ranges [6].

Figure 1 - CSEM's proprietary wrist device for fully automatic sleep stage classification.

2.3 Sleep profile

Classification of sleep stages (REM, NREM and WAKE) based on HRV and acceleration signals has been performed using a decision tree [8]. Nodes, branches, and leafs of our decision tree are defined as follow:

- WAKE class is accessible when "wake" is detected by the *sleep/wake classification* module;
- REM class is reached when 1) "sleep" is detected, 2) night movement level is extremely poor, and 3) spectral analysis indicates high parasympathetic activity;

- NREM class is entered when 1) “sleep” is detected by *the sleep/wake classification* module, 2) night movement level is poor, and 3) spectral analysis indicates high sympathetic activity.

The sleep profile is then obtained by using the outcome of the *sleep stage classification* module and consists in an estimated hypnogram with REM/NREM/WAKE durations.

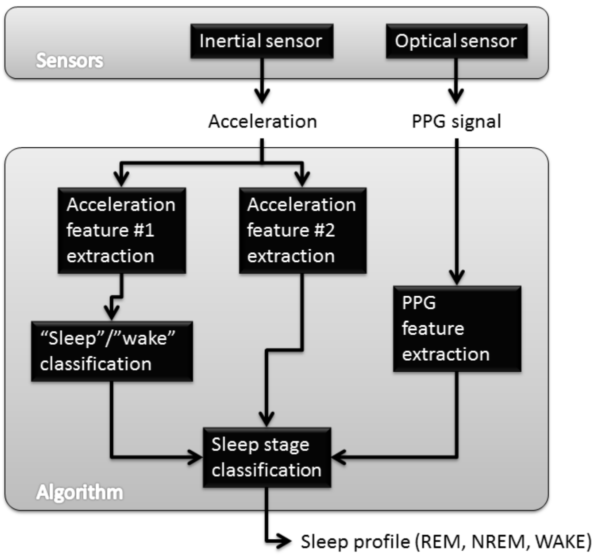

Figure 2 - Block scheme of the algorithm for automatic sleep profile estimation.

3. Results

Figure 3 shows a comparison between the PSG-based and proposed approach hypnograms. As can be seen, subject 1 displays more false positives, especially for the WAKE state, compared to subject 2. The false positives for the WAKE state can be explained by an increased SNR in the PPG signal due to muscle activities and possibly lower skin blood perfusion in the arm that is mistaken for body movement.

As shown in **Tables 1** and **2**, the proposed classification algorithm performs rather well for classifying REM and NREM as displayed by the diagonal elements of the confusion matrices. The WAKE state is poorly discriminated with classification rates of 37% and 20%. This is due to the misalignment of the hypnogram and the output of the algorithm. Indeed, while rules have been elaborated for the determination of the sleep stages (REM, NREM and WAKE), the subjective assessment from the sleep clinician result in these misalignments. Confusion between WAKE and the other sleep states can result as shown in **Tables 1** and **2**.

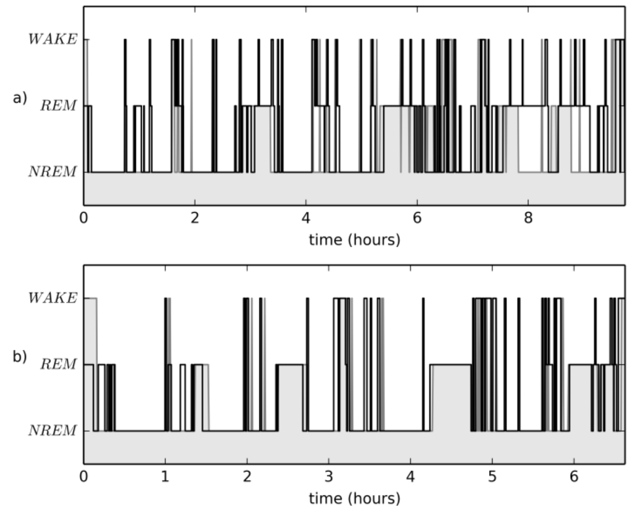

Figure 3 - Comparison of PSG-based (grey area) and wrist-worn device-based (black line) hynograms for: (a) subject #1 and (b) subject #2.

Table 1 – Confusion matrix for subject #1 [%]

		PSG		
		REM	NREM	WAKE
PPG	REM	**44**	52	4
	NREM	12	**82**	6
	WAKE	16	47	**37**

Table 2 – Confusion matrix for subject #2 [%]

		PSG		
		REM	NREM	WAKE
PPG	REM	**72**	20	8
	NREM	7	**91**	2
	WAKE	12	68	**20**

4. Conclusion

This paper presented encouraging preliminary results for the determination of the 3 fundamental and standard sleep states of REM, NREM and WAKE solely from the measurement of body movement and heart pulse rate using PPG from the wrist. The wrist-worn sensor and processing device makes our approach very attractive for applications related to screening and compliance to treatment of sleep disorders, mental stress and depressive states. Improvement of classification rates will be achieved by using a larger database and strategies for improving SNR in the PPG signal.

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