

Sleep Stage Classification in Children Using Photoplethysmogram Pulse Rate Variability

Parastoo Dehkordi¹, Ainara Garde¹, Walter Karlen¹, David Wensley², J. Mark Ansermino³,
Guy A. Dumont¹

¹Department of Electrical and Computer Engineering,

²Department of Pediatrics, and

³Department of Anesthesiology, Pharmacology & Therapeutics,
the University of British Columbia, Vancouver, Canada

Abstract

Human sleep is classified into Rapid Eye Movement (REM) and non-REM sleep. In non-REM sleep, the heart rate and respiratory rate decrease whereas during REM sleep, breathing and heart rate become more irregular. As such, identification of sleep stages by monitoring the autonomic regulation of heart rate is a promising approach. In this study we analysed the standard features of heart rate variability extracted from the pulse oximeter photoplethysmogram (PPG) to identify different sleep stages. The overnight PPG signals were recorded from 146 children with the Phone Oximeter™ in addition to overnight polysomnography. The recordings were divided into 1-min segments and labelled as wake, non-REM and REM based on the event log file of the polysomnography. For each segment, six standard time and frequency domain features of heart rate variability were estimated. Two support vector machine classifiers were separately trained to classify wake from sleep and non-REM from REM sleep. Wake and sleep were classified with an accuracy of 77% and REM and non-REM were classified with an accuracy of 80%.

1. Introduction

Human sleep is classified into three major stages: wakefulness, non-Rapid Eye Movement (non-REM) and Rapid Eye Movement (REM). In polysomnography (PSG), the recordings of brain activity (EEG), eye movement (EOG), muscle activity (EMG) and other physiological parameters during sleep are used for determining sleep stages. Although PSG is considered as the gold standard for assessing sleep, it requires an overnight stay of patients in the sleep laboratory with specialized equipment and all-night attending sleep technicians. The complex set-up and overnight stay in hospital may further affect sleep conditions, resulting in inaccurate outcomes.

The activity of the autonomic nervous system (ANS) undergoes various changes when transiting between wake and sleep stages. In non-REM sleep, sympathetic activity of ANS reduces and parasympathetic activity predominates, as a result, the activity of cardiorespiratory decreases [1]. While sleep progresses from non-REM to REM, sympathetic activity increases, parasympathetic activity decreases and breathing and heart rate become more irregular. Autonomic activity during wakefulness was found to be situated between non-REM and REM sleep.

Heart rate variability (HRV), the variation of the time interval between consecutive heartbeats, is a physiological indicator that partially reflects the autonomic regulation of the cardiorespiratory system [2]. There are three frequency components of HRV associated with ANS: very low frequency (< 0.04 Hz, VLF), low frequency (0.04-0.15 Hz, LF) and high frequency (0.15-0.4 Hz, HF) components [3]. The physiological interpretation of these components is not completely known; however, HF power is frequently used to quantify the parasympathetic activity. The LF power may reflect both sympathetic and parasympathetic activity [2]. The ratio between the LF and HF power is known as an index of sympathetic/parasympathetic balance [2].

HRV has recently been used as a reliable tool for identifying sleep stages in adults [4], [5], [6], [7]. Penzel et al. investigated the different linear and non-linear features of HRV in subjects with and without sleep apnea [5] in different sleep stages. Lisenby et al. classified REM and non-REM by analysing heart rate in time and frequency domain [6]. Karlen et al. used the spectral analysis of electrocardiogram (ECG) and respiration signal recorded by a wearable sensor to classifying sleep from wake [7]. These studies showed that sleep classification by monitoring the variation of heart and respiratory rate could attain results similar to sleep scoring achieved by technicians using PSG recordings.

Traditionally, HRV is obtained from measuring the intervals between the consecutive peaks of QRS complexes of the ECG. Previous studies conducted by us and other groups have shown the feasibility and accuracy of extracting the variation of heart rate from pulse oximeter photoplethysmogram (PPG) [8], [9]. PPG is a simple non-invasive technique for detecting blood volume changes in body tissues (e.g. fingertip or earlobe). Each pulse wave of PPG arises from blood volume changes in arterial tissues due to each heartbeat. Therefore the variation of beat to beat intervals can be estimated from the variation of pulse to pulse intervals of the PPG signal (pulse rate variability, PRV).

Most studies [4], [5], [6],[7] have investigated HRV extracted from ECG during sleep; in contrast, the use of PRV for classification of different sleep stages is less well characterized. Furthermore, the influence of sleep transition on HRV has been more extensively studied in adults than in children. In this study, we estimated the different features of PRV from PPG in different sleep stages. The PPG signals were recorded from children using the Phone Oximeter™ [10]. The Phone Oximeter™ is a mobile device that integrates a pulse oximeter with a smart phone. In contrast to recording ECG, the recording of PPG is more convenient and has the potential to be conducted at home.

2. Materials and Methods

2.1. Participants

This study was approved by the University of British Columbia Clinic Research Ethics Board. Following informed parental consent, 160 children were recruited for this study. The children were suspected of having Sleep Disordered Breathing (SDB) and referred to the British Columbia Children’s Hospital for overnight PSG. Children with an arrhythmia, abnormal haemoglobin and inadequate length of sleep (less than 3 hours) were excluded from the study. The data set comprises the physiological signals record from 146 children (Age = 9.1 years \pm 4.2, Body Mass Index = 21.1 kg/m² \pm 7.3).

2.2. Data Collection and Preprocessing

The standard PSG recordings included overnight measurements of electrocardiography, electroencephalography, oxygen saturation (SpO₂), photoplethysmogram (PPG), chest and abdominal movement, nasal and oral airflow, left and right electrooculography, electromyography and video recordings. The PSG included post hoc labelling of sleep phases and all events (apnea, hypopnea, arousal, etc.) by a sleep technician (PSG event log file).

In addition to the PSG, the PPG (sampled at 62.5 Hz), and SpO₂ (sampled at 1 Hz) were recorded simultaneously

with the Phone Oximeter™.

After baseline removal and smoothing with a Savitzky-Golay FIR filter (order 3, frame size 11 samples), each PPG signal was divided into 1-min segments. A signal quality index [11] was assigned to each segment and the segments with low signal quality index were automatically rejected from further analysis. To eliminate the effects of SDB and arousal on variation of heart rate, segments with any period of disordered breathing such as obstructive sleep apnea or central sleep apnea were removed from the dataset. All segments were scored as wake, non-REM and REM based on the 30-s epochs of the labels in the PSG event log file. The segments with any sleep state transition containing multiple sleep state labels (e.g. from wakefulness to non-REM or from non-REM to REM) were also removed from the data set.

2.3. Features of Pulse Rate Variability

In order to obtain the time series of pulse to pulse intervals (PPIs), a simple zero-crossing algorithm was used to locate the pulse peaks in the PPG signals, and then the intervals between successive peaks were computed. The PPIs with the length less than 0.33 second and more than 1.5 were considered unphysiological and deleted from the time series. The mean (meanPP) and standard deviation (SDPP) of PPIs and the root mean square of difference of successive PPIs (RMSSD) were computed for each segment.

PRV was obtained by converting each sequence of PPIs into an equivalent uniformly spaced time series sampled at 4 Hz using a resampling method based on Berger et al. algorithm [12]. The power spectral density of the PRV was calculated through a parametric PSD based on autoregressive modelling, with 1024 points and order 16. The power in each of the following frequency bands was computed by determining the area under the PSD curve bounded by the bandwidth in interest: VLF (0-0.04 Hz), LF (0.04-0.15 Hz) and HF (0.15-0.4 Hz). Normalized LF (nLF) and normalized HF (nHF) were determined by dividing LF and HF powers by the total spectral power of HRV between 0.04 and 0.4 Hz, respectively. The ratio of LF power to HF power (LF/HF Ratio) was also computed.

2.4. Statistical learning

We organized the labelled segments into two data sets: The wake/sleep data set containing all segments labelled as wake and sleep and non-REM/REM data set containing the segments scored as non-REM and REM only. Subsequently, each data set was randomly divided into 10 equal sized data sets. To avoid overestimation of the test performance, a 10-fold cross validation was performed, with one data set serving as test set and the other nine sets as

training sets. This was repeated until all sets served as a test set at least once. A support vector machine (SVM) classifier was trained over the sleep/wake training set to classify wake from sleep (wake/sleep classifier) and another SVM classifier was trained over the non-REM/REM training set to classify non-REM from REM sleep (non-REM/REM classifier). For each SVM classifier, the parameters γ and $cost$ were tuned using a 10-fold cross validation over the training set only. To evaluate the performance of the classifiers, we calculated the accuracy, sensitivity and specificity using the respective test sets.

3. Results

All temporal and spectral features of PRV were compared in sleep and wake states (Table 1) and also during non-REM and REM sleep (Table 2) using the Wilcoxon rank sum test. The meanPP, SDPP and RMSSD were higher during non-REM sleep compared to the wakefulness. When the sleep progressed from non-REM state to REM, meanPP and RMSSD decreased but SDPP did not change significantly. The nLF and LF/HF ratio reached their lowest values in non-REM sleep (Figure 1.a and Figure 1.c); nHF was more pronounced in non-REM than in wake or REM sleep (Figure 1.b).

The sleep/wake data set contained 25,447 segments in the training set and 2,828 segments in the test set. The sleep/wake test set was classified with an accuracy of 77%, a sensitivity of 78% and a specificity of 72%.

The non-REM/REM data set contained 21,719 segments in the training set and 2,413 segments in the test set. The non-REM/REM test set was classified with an accuracy of 80%, a sensitivity of 82% and a specificity of 78%.

Table 1. Descriptive results for the PRV features in wake/sleep data set

	Sleep	Wake	mean difference	%95 CIs (low,high)	p-value
meanPP	0.78	0.72	0.065	0.06,0.07	2e-16
SDPP	0.05	0.04	0.001	0,0.002	0.001
RMSSD	0.05	0.04	0.006	0.005,0.006	2e-16
nLF	0.23	0.39	-0.12	-0.13,-0.14	2e-16
nHF	0.72	0.54	0.15	0.14,0.16	2e-16
LF/HF	0.33	0.70	-0.30	-0.31,-0.27	2e-16

4. Discussion and Conclusions

When the sleep state progressed from wake to non-REM, we found that the meanPP increased, indicating a lower mean heart rate which may reflect the reduced sympathetic activity during non-REM sleep. In addition, the decrease in nLF and LF/HF ratio indicated a reduction in sympathetic activity during non-REM sleep. Higher nHF

Table 2. Descriptive results for the PRV features in non-REM/REM data set

	non-REM	REM	mean difference	%95 CIs (low,high)	p-value
meanPP	0.80	0.76	0.03	0.03,0.04	2e-16
SDPP	0.05	0.05	0	0,0.001	0.41
RMSSD	0.05	0.04	0.005	0,0.01	1e-09
nLF	0.22	0.36	-0.1	-0.1,-0.09	2e-16
nHF	0.73	0.60	0.11	0.10,0.12	2e-16
LF/HF	0.30	0.56	-0.2	-0.21,-0.18	2e-16

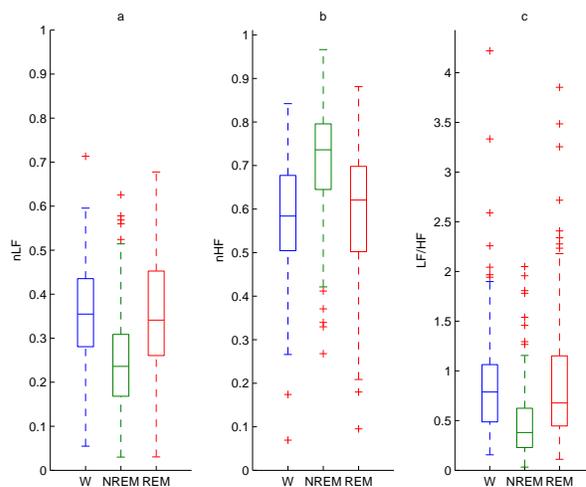


Figure 1. The boxplot shows (a) nLF, (b) nHF and (c) LF/HF ratio in wake (W), non-REM (NREM) and REM sleep in children. Lower quartile, median, and upper quartile values are displayed as bottom, middle and top horizontal line of the boxes. Whiskers are used to represent the most extreme values within 1.5 times the interquartile range from the quartile. Outliers are displayed as crosses.

values in non-REM sleep relative to wakefulness might reflect lower parasympathetic activity in non-REM sleep. When sleep progressed from the non-REM state to REM, nLF and the LF/HF ratio increased, indicating the possibility of higher sympathetic activity during REM sleep. The lower meanPP in REM sleep also reflected a higher heart rate and pronounced sympathetic activity. The decrease in nHF, when sleep progressed from non-REM to REM, may reflect lower parasympathetic activity in REM. These findings are in line with the results of other studies which investigated the variation of heart rate measured from ECG during sleep and wakefulness [1], [5].

The classification of sleep from wake in children showed the accuracy of 78%. Penzel et al. [5] obtained an accuracy of 54% in adults by analysing the spectral features of HRV. However, they improved the performance by

adding the non-linear parameters of HRV to the feature set. Lewicke et al. [13] improved the accuracy further to 85% by automatically rejecting unreliable beat to beat intervals of ECG.

REM and non-REM stages were classified with the accuracy of 80% as has been shown by Lisenby et al. who also achieved the accuracy of 80% classifying REM and non-REM sleep by analysing heart rate in time and frequency domain [6].

For identifying sleep from wake and non-REM from REM states, we trained two separate classifiers. In a practical implementation these two separate classifiers will need to be combined; either using a single classifier with multiple outputs to identify wake, non-REM and REM states together or staging two classifiers, one for identify wake from sleep and a second sub-classifier to identify non-REM from REM from the sleep classes obtained from the first classifier. This will necessarily lead to a degradation of classification performance and needs further investigation.

Autonomic regulation of the cardiorespiratory system has a multivariate dynamic based on the interrelationship of heart rate, respiratory rate, and blood pressure which are not completely achievable through univariate analyses of PRV or HRV, submitting this study to the same limitations as the analysis performed in [5], [6].

In this study, we classified different sleep stages in children by analysing the standard features of PRV estimated from PPG. The PPG signals were recorded by the Phone Oximeter™ in addition to the overnight PSG. Six time and frequency features of PRV were fed to two SVM classifiers to classify wake from sleep and non-REM state from REM. This method would offer lower cost, less time and higher portability than the PSG-based manual scoring techniques. Compared to ECG recordings, PPG recordings are more convenient to obtain, with the potential of being used at home. Home screening will cause less sleep disturbances, facilitate natural sleep patterns, and can be performed over several consecutive nights at minimal cost.

Acknowledgements

This work was supported in part by NSERC/ICICS People & Planet Friendly Home Initiative at UBC and NSERC/CIHR under the CRRP program and the Institute for Computing.

References

[1] Busek P, Vankova J, Opavsky J, Salinger J, Nevsimalova S. Spectral analysis of heart rate variability in sleep. *Physiol Res* 2005;54:369–76.
 [2] Malliani A, Pagani M, Federico L, Cerutti S. Cardiovas-

cular neural regulation explored in the frequency domain. *Circulation* 1991;84:482–92.

- [3] Task Force of the European Society of Cardiology the North American Society of Pacing Electrophysiology. Heart rate variability : Standards of measurement, physiological interpretation, and clinical use. *Circulation* 1996;93:1043–65.
 [4] Boudreau P, Yeh WH, Dumont GA, Boivin DB. Circadian variation of heart rate variability across sleep stages. *Sleep* 2013;36(12):1919–28.
 [5] Penzel T, Kantelhardt JW, Grote L, Peter JH, Bunde A. Comparison of detrended fluctuation analysis and spectral analysis for heart rate variability in sleep and sleep apnea. *IEEE Trans Biomed Eng* 2003;50(10):1143–51.
 [6] Lisenby MJ, Richardson PC, Welch AJ. Detection of cyclic sleep phenomena using instantaneous heart rate. *Electroencephalogr Clin Neurophysiol* 1976;40(2):169–77.
 [7] Karlen W, Floreano D. Adaptive sleep-wake discrimination for wearable devices. *IEEE Trans Biomed Eng* 2010; 58(4):920–6.
 [8] Dehkordi P, Garde A, Karlen W, Wensley D, Ansermino JM, Dumont GA. Pulse rate variability in children with sleep disordered breathing in different sleep stages. In *Conf. Proc. Computing in Cardiology*. 2013; 1015–18.
 [9] Khandoker AH, Karmakar CK, Palaniswami M. Comparison of pulse rate variability with heart rate variability during obstructive sleep apnea. *Med Eng Phys* 2011;33(2):204–9.
 [10] Karlen W, Dumont G, Petersen C, Gow J, Lim J, Sleiman J, Ansermino M. Human-centered phone oximeter interface design for the operating room. In *Conf. Proc. Health Informatics*. 2011; 433–8.
 [11] Karlen W, Kobayashi K, Ansermino MJ, Dumont G. Photoplethysmogram signal quality estimation using repeated gaussian filters and cross-correlation. *Physiol Meas* 2012; 33(10):1617–29.
 [12] Berger RD, Akselrod S, Gordon D, Cohen RJ. An efficient algorithm for spectral analysis of heart rate variability. *IEEE Trans Biomed Eng* 1986;33:900–4.
 [13] Lewicke A, Sazonov E, Corwin M, Neuman M, Schuckers S. Sleep versus wake classification from heart rate variability using computational intelligence: consideration of rejection in classification models. *IEEE Trans Biomed Eng* 2008;50(1):108–18.

Address for correspondence:

Parastoo Dehkordi
 950 West 28th Avenue, V5Z 4H4,
 Vancouver, BC, Canada
 pdekordi@ece.ubc.ca