Parameter Set Selection and Classification of Sleep Phases Tracing Biovital Data·

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Abstract

To assess the quality of a person's sleep, it is essential to examine the sleep behaviour by identifying the several sleep stages, their durations and sleep cycles. The established and gold standard procedure for sleep stage scoring is overnight polysomnography (PSG) with the Rechtschaffen and Kales (R-K) method. Unfortunately, the conduct of PSG is time-consuming and unfamiliar for the subjects and might have an impact of the recorded data. To avoid the disadvantages with PSG, it is important to make further investigations in low-cost home diagnostic systems. For this intention it is necessary to find suitable bio vital parameters for classifying sleep stages without any physical impairments at the same time.

Due to the promising results in several publications we want to analyse existing methods for sleep stage classification based on the parameters body movement, heartbeat and respiration. Our aim was to find different behaviour patterns in the several sleep stages. Therefore, the average values of 15 whole-night PSG recordings -obtained from the 'DREAMS Subjects Database'- where analysed in the light of heartbeat, body movement and respiration with 10 different methods.

1 Introduction / Motivation

Sleep has effects on physical and mental health in a variety of ways. Sleep deprivation induces significant reductions in performance and regular poor sleep increases the risk of serious medical conditions like obesity, heart disease and diabetes [HHS, 2008]. In order to assess the quality of a person's sleep, it is vital to examine the sleep behaviour by identifying the several sleep stages, their durations and sleep cycles. The established and gold standard procedure for sleep stage scoring is overnight polysomnography (PSG) according to the Rechtschaffen and Kales (R-K) method. The used technologies for PSG are eletroencephalogram (EEG), electrooculogram (EOG), electromyogram (EMG), electrocardiogram (ECG), blood oxygen saturation (SpO2), respiratory airflow and respiratory effort [Anthony, 2008]. To perform PSG, subjects have to sleep within a hospital or at a sleep center with a minimum of 22 wire attachments to their bodies [Karmakar, 2013].

The conduct of PSG is time-consuming and unfamiliar for the subjects and might not reflect the usual sleep behaviour of the patient. Recorded data might be different compared to sleeping at home. Therefore, low-cost home diagnostic systems are likely to be advantageous. This presumes to find non-invasive recording methods to avoid impacts on the recorded data and to reduce the number of parameters. Achieving these objectives involve to find suitable bio vital parameters which allow inferences to the certain sleep phases. Our aim is to find different behaviour patterns in the several sleep stages to classify the sleep stages WAKE, REM, Light Sleep (LS) and Deep Sleep (DS) as accurately as possible. However, by choosing the parameters, the possibility to receive the related data non-invasive must also be taken into account to guarantee a natural sleep to the patients. For this, we analysed already defined algorithms that calculate sleep stages with fewer sensors than the R-K-Method needs. All of these methods are based on the parameters heartbeat, respiration or body

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movement, which have the potential to be recorded in a non-invasive way.

2 State of the Art

In this chapter we name three scientific publications, which had relevant content to our researches.

One publication describes a non-invasive algorithm to estimate sleep stages with only heartbeat and body movement signals. They describe two main indices, that indicate the condition of REM sleep and the sleep depth. In consideration of these indices they developed two main algorithms to calculate the sleep stages. In addition to several assumptions about the characteristics of REM and NREM sleep, they take into account to several statistics and heuristical examinations about the sleep behaviour of different age groups, too. Thus, for each age group of the subjects, they determined functions, which obtain the incidence ratio and the standard deviation of the extracted elements for each sleep stage. They classified the subjects sleep stages in Wake, REM, NREM-1, NREM-2, NREM-3 and NREM-4 and reached an agreement ratio of 51.6% [Kurihara and Watanabe, 2012].

In another scientific paper, an automatic sleep-wake stages classifier based on signal ECG and ELM tools was developed. They discovered that the use of heart rate variability (HRV) produces good results in the sleep-wake-classification because HRV changes during the stages of sleep [Hayet and Slim 2012].

In one study the depth and volume of respiratory effort was analysed and quantified during nighttime sleep to differ across the sleep stages. It emerged that the respiratory depth is more irregular and the tidal volume is smaller during REM sleep than during NREM sleep as seen in Figure 1. A set of 12 novel features were proposed which should reflect respiratory depth and volume, respectively and can be an additional support for classifying sleep stages. It has been shown that adding the new features into their existing feature set improved the results in classifying the stages WAKE, REM, Light Sleep and Deep Sleep [Long et al., 2014].

3 Proposed Approach

Due to the findings and promising results in several publications and in our previous studies [Klein et al., 2015] we want to analyse existing methods for sleep stage classification based on the following physical functions:

- Body Movement
- Respiration
- Heartbeat

The aim of this project is to combine existing methods and create a new algorithm which is able to evaluate sleep stages based on these parameters. To verify the results we used 15 digital whole-night PSG recordings of healthy subjects from the 'DREAMS Subjects Database' of University of MONS and Université Libre de Bruxelles [Devuyst et al., 2011]. The recordings are suitable for the verification because they are annotated in sleep stages according to Rechtschaffen and Kales criteria. In detail, we used ECG for the heartbeat signals, EMG as substitute for body acitivity and both abdominal (VAB) and thoracic (VTH) inductive plethysmography for respiration signals. The 15 subjects (3 men) we analysed are between 20 and 65 years old.

3.1 Methods and Algorithms

First of all, we analysed the existing R(k) and D(k) algorithms presented in the paper 'Sleep-Stage Decision Algorithm by Using Heartbeat and Body-Movement Signals' [Kurihara and Watanabe, 2012]. Both algorithms were already explained in greater detail in our prior studies [Klein et al., 2015]. The R(k) algorithm (1), which indicates the condition of REM, is based on the variations of the heart rate variability and relies on the fact that heartbeat becomes more frequent and less rhythmical during REM sleep.

$$R(k) = \frac{1}{2q+1} \sum_{i=-q}^{q} |H_{k+1}^{former} - H_{k+1}^{latter}| \quad (1)$$

On the other hand the D(k) algorithm (2), indicates the condition of the sleep depth and take the body movement signals into account. In this process, D(k) considers the fact that when sleep deepens body movement becomes smaller and less frequent.

$$D(k) = log_2 \left(\frac{A_k^{body}}{A_k^{heart} + A_k^{body}} \right) \quad (2)$$

From the 12 novel features proposed in the publication 'Analyzing respiratory effort amplitude for automated sleep stage classification' [Long et al., 2014] we picked 4 promising algorithms T_{sdm}, P_{sdm}, V_{br} and V_{in} (3 - 6) to analyse respiratory effort and respiratory depth as an additional parameter to estimate sleep stages.

$$P_{sdm} = \frac{median\ (p_1, p_2, \ldots, p_n)}{IQR(p_1, p_2, \ldots, p_n)} \quad (3)$$

$$T_{sdm} = \frac{median\ (t_1, t_2, \ldots, t_n)}{IQR(t_1, t_2, \ldots, t_n)} \quad (4)$$

T_{sdm} and P_{sdm} consider the mean respiratory depth and its variability at the same time in terms of inhalation (P_{sdm}) and exhalation (T_{sdm}). For both algorithms it is necessary to calculate the median and interquartile range (IQR) of the peaks (p) and troughs (t) of each recorded respiration cycle.

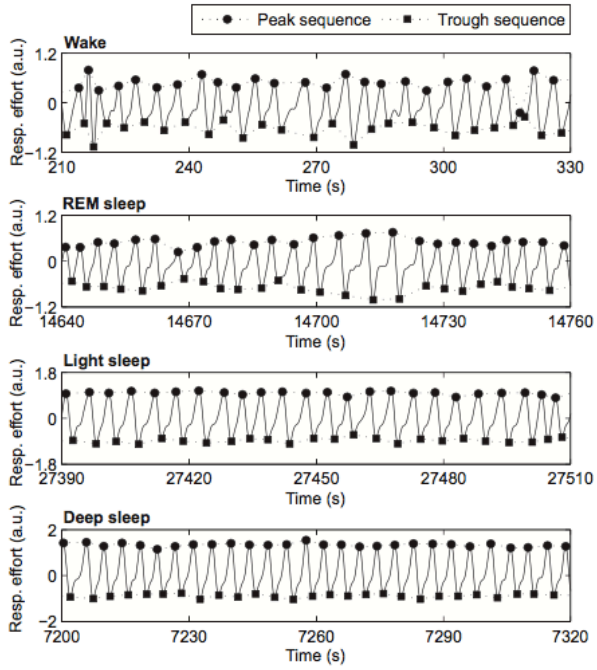

Figure 1: Typically respiration behaviour during the sleep phases WAKE, REM, Light and Deep sleep [Long et al., 2014].

V_{br} and V_{in} are volume-based features and should reflect the respiratory effort. Ω_k^{br} means the kth breathing cycle and Ω_k^{in} the kth inhalation period.

$$V_{br} = \sum_{S_x \epsilon \Omega_1^{br}} S_x \, , \sum_{S_x \epsilon \Omega_2^{br}} S_x \, , \ldots , \sum_{S_x \epsilon \Omega_K^{br}} S_x \quad (5)$$

$$V_{in} = \sum_{S_x \epsilon \Omega_1^{in}} S_x \, , \sum_{S_x \epsilon \Omega_2^{in}} S_x \, , \ldots , \sum_{S_x \epsilon \Omega_K^{in}} S_x \quad (6)$$

Furthermore, we analysed the following mean values:

- Body movement (BM) (7)
- Number of heartbeats (HB) (8)
- Heart rate interval ($HR_{interval}$)
- Heart rate variability (HR_{var})

The $HR_{interval}$ (9) expresses the time between two beats which is shown in Figure 2. The variability between two intervals will be computed with HR_{var} (10).

$$HR_{interval} = \frac{1}{k} \sum_{i=0}^{k-1} R(t)_i \quad (9)$$

$$HR_{var} = \sum_{i=0}^{k-1} |R(t)_{i-1} - R(t)_i| \quad (10)$$

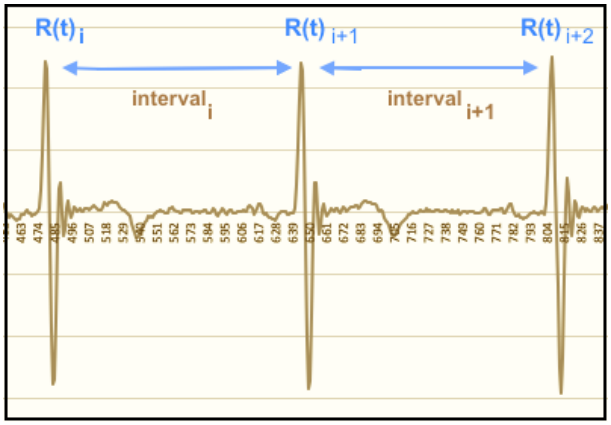

Figure 2: Beat-by-beat heart rate intervals ($HR_{interval}$) measured between the highest peaks 'R-Peaks' of the QRS complex.

Every PSG recording was devided in 30 second intervals with $i_0 = 30$, $i_1 = 60$, ... i_n = recordtime. The presented algorithms and methods (1-10) were applied to each interval and ordered in several lists. The reason for this approach is that the recordings are evaluated according to Rechtschaffen and Kales criteria in 30 second intervals, too. This permits a correct assignment of our results and the estimated sleep stages from the experts.

3.2 Expected results

There are several characteristics that indicates REM and Non-REM sleep which is listed in Table 1 and 2. Due to the usage of only heartbeat, body movement and respiration signals we can verify just a few of these characteristics.

One important characteristic of REM sleep is, that heartbeat becomes more frequent and less rhythmical. If sleep deepens, heart rate becomes less frequent and body movement is concentrated before and after REM sleep. The characteristics of NREM sleep we can examine are the facts, that when sleep deepens from the wake stage, body movements become smaller and less frequent and the deeper the sleep, the less frequent the heart rate [Kurihara and Watanabe, 2012]. With the parameter respiration we expect the typically respiration behaviours which are shown in Figure 1. During the wake phase, the inhalation, exhalation and the respiration volume are irregular. However, this pattern changes when sleep deepens and the deeper the sleep, the more regular and deeper the several breathing becomes. Finally, the respiration behaves less rhythmical during REM phase but more regular than in the wake phase.

With the results we want to analyse the full extent of these variations and how remarkable they are. Furthermore, with this approach we are possibly able to determine which algorithms are especially suitable to detect the variations between the parameters and the sleep stages WAKE, REM, LS and DS.

No.	Characteristicas of REM sleep
1	Brainwaves similar to those shown in Non-REM 1 and Wake stages
2	The incidence ratios of delta wave and spindle wave decrease
3	The tension of anti-gravitiy muscles completely disappears
4	Rapid eye movement appears
5	Heartbeat and respiration become more frequent and less rhythmical, and the blood pressure becomes high
6	With regard to adults, REM sleep occurs once every 90 to 100 minutes on average
7	Body movement is concentrated before and after REM sleep

Table 1: Characteristics of REM Sleep [Kurihara and Watanabe, 2012]

No.	Characteristicas of Non-REM sleep
1	The deeper the person sleeps, the more frequent the incidence ratio of delta waves
2	In the sleep stage of Non-REM2, spindle waves are recognized
3	When sleep deepens from the Wake stage, body movements become smaller and less frequent
4	The deeper the sleep, the less frequent the heart rate
5	Non-REM1 occasionally is found after Non-REM3, Non-REM4, or REM sleep stages with large body movement

Table 2: Characteristics of NREM Sleep [Kurihara and Watanabe, 2012].

4 Results

In this chapter we analyse the results of the used methods for every calculated list and each 30-second interval which are presented in the Tables 3-6. Our researches are particularly interested in remarkable differences between the several stages. In addition, the results were set in relation to the wake phase for better comparison.

4.1 Heartbeat and Body Movements

The heartbeat signals were examined by HB, $HR_{interval}$, HR_{var} and R(k) algorithms. BM represents the mean value of body movement and D(k) considers the relationship between body movement and heart rate signals.

The number of heartbeats (HB) have their highest values during the WAKE phase and are reduced in LS and DS phases. On the other hand, the values in REM are slightly increased. The heart rate intervals have their longest duration in DS stage. Furthermore, the results of HR_{var} show, that the heart rates have a high variability in WAKE and REM stage and very rhythmical during LS. In general, the heartbeat signals behaves in the several stages as expected. Especially the heart rate variability has probably a great potential to distinguish between the sleep phases.

MEANS	HB	$HR_{interval}$	HR_{var}
WAKE	34.712	847.970	149.598
Light Sleep	31.136	899.791	95.051
Deep Sleep	32.012	918.367	75.575
REM	32.420	913.948	100.325
RELATION to WAKE in %			
Light Sleep	-10.302	+6.111	-36.462
Deep Sleep	-7.778	+8.302	-49.481
REM	-6.603	+7.781	-32.937

Table 3: Summary results of HB in counts, $HR_{interval}$ and HR_{var} in Milliseconds.

MEANS	BM	R(k)	D(k)
WAKE	11733.324	10.624	0.622
Light Sleep	6618.859	6.095	0.872
Deep Sleep	4595.706	3.981	1.127
REM	4356.449	3.547	1.153
RELATION to WAKE in %			
Light Sleep	-43.589	-42.630	+40.193
Deep Sleep	-60.832	-62.528	+81.190
REM	-62.871	-66.613	+85.370

Table 4: Summary values of BM, R(k) and D(k).

MEANS	T_{sdm}	P_{sdm}
WAKE	3.911	-4.813
Light Sleep	3.873	-5.122
Deep Sleep	4.791	-7.182
REM	5.062	-7.970
RELATION to WAKE in %		
Light Sleep	-0.973	+6.406
Deep Sleep	+22.485	+49.197
REM	+29.414	+65.583

Table 5: Summary values of T_{sdm} and P_{sdm}.

MEANS	V_{br}	V_{in}
WAKE	4880.83	1905.10
Light Sleep	4839.10	1523.69
Deep Sleep	4891.64	1366.62
REM	4618.04	1370.37
RELATION to WAKE in %		
Light Sleep	-0.855	-20.020
Deep Sleep	+0.221	-28.266
REM	-5.384	-28.069

Table 6: Summary values of V_{br} and V_{in}.

4.2 Respiration

With T_{sdm} and P_{sdm} the mean respiratory depth and its variability were considered. V_{br} and V_{in} are volume-based algorithms and should reflect the respiratory effort.

The mean values show that all respiration algorithms we have tested, seem to be good additional methods to differentiate between WAKE and REM phases. Unfortunately, LS and DS have very similar values to the WAKE stage. Therefore, it is not possible to distinguish between WAKE, LS and DS with the mean values alone.

5 Conclusions and Future Work

The preliminary results of this project show that body movement, heartbeat and respiration are potentially suitable bio vital parameters to identify the sleep phases WAKE, REM, LS and DS without the usage of PSG. The findings of this project are intended to contribute later researches with the aim to create an algorithm, which is able to classify the sleep phases with only these three parameters automatically.

In the future, we will develop an appropriate sensor array system with pressure sensitive sensors, which will be placed under a mattress to record the data non-invasive to the patient. For the later classification, instruments of machine learning and data mining, like regression analysis, will be used.

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