Recognition of Sleep/Wake States analyzing Heart Rate, Breathing and Movement Signals*

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***Abstract*— This document presents an algorithm for a non-obtrusive recognition of Sleep/Wake states using signals derived from ECG, respiration, and body movement captured while lying in a bed. As a core mathematical base of system data analytics, multinomial logistic regression techniques were chosen. Derived parameters of the three signals are used as the input for the proposed method. The overall achieved accuracy rate is 84% for Wake/Sleep stages, with Cohen's kappa value 0.46. The presented algorithm should support experts in analyzing sleep quality in more detail. The results confirm the potential of this method and disclose several ways for its improvement.**

I. Introduction

Sleep is a state in which our body rests and recuperates [1]. For human's normal physiological, mental and emotional functioning during waking hours, it is necessary to have a good sleep. There is a common belief that it is possible to have only a few hours of sleep per night over a long period of time without suffering negative consequences, which is just a misconception [2]. In fact, even smaller sleep abnormalities can result in psychological problems or physical illness. [3].

Most adults have a sleep duration of 7 to 8 hours each night to regenerate properly, while children should have much more sleep. Indeed, the sleep requirements are very individual for each person. In addition, many hours of sleep do not always guarantee a healthy and restorative state, because the crucial point here is not quantity, but quality. [2]

Sleep studies for obtaining trustworthy data on a person's sleep quality are usually carried out in sleep laboratories. For this procedure, the gold standard method is the overnight polysomnography (PSG) according to the guidelines of the American Academy of Sleep Medicine (AASM) [4]. This method is a resource-consuming and high costly procedure [5]. Several electrodes have to attach to the head in order to record EEG, EOG, and EMG signals for sleep staging [4]. In addition, sleeping in a sleep laboratory and sleeping at home in a familiar environment are two different situations. These reasons can affect the sleep structure and sleep quality of the person in sleep laboratory [6].

However, there are several scientific studies, confirming the relationship between the movement, breathing and heart rate with the sleep stages [7, 8, 9]. And these parameters can be obtained in a more comfortable way, than the PSG [10]. Using these bio vital data, with the appropriate algorithmic background, at least initial investigation of sleep-wake structure as a diagnostic step could be performed in home environments. This would enable to investigate sleep in a much higher number of persons than it is possible nowadays. Although, with this tools the need for sleep laboratories and the sleep experts remain very relevant for a full medical diagnostic of sleep, but medical doctors will receive important information for choosing the appropriate diagnostic and therapeutical pathway in patients suffering from sleep disorders. The main aim of presented project work is to develop a software system supporting a recognition of Sleep/Wake states when analyzing few human body signals, which could be obtained in a non-obtrusive way. According to [7, 10, 11, 12] heart rate, breathing and movement data are qualified signals.

II. State of the Art

Classification of sleep stages is a topic of a high number of scientific articles [8, 9, 13]. This summary mentions just a few but relevant publications due to their similarity in input signals.

As in [11] presented, ECG, heart rate variability (HRV) and heart rate itself could be used for the recognition of sleep stages. HRV and actigraphy (both, wrist and chest sensor) for the recognition of Wake and Sleep states is presented in [14]. 78% of correct recognition rate for the chest and 77% for wrist actigraphy in combination with HRV were achieved in this research.

The article of [7] presents an approach for the identification of Wake and Sleep states using the ECG signal

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and a neural network-based algorithm. 16 PSG records from the MIT-BIH database were used for the evaluation. HRV was calculated from the initial signal for the further processing with an Extreme Learning Machine neural network algorithm using a single hidden layer [15]. The results after the training indicated the accuracy of about 90%.

Evaluating the algorithms of sleep stage classification, it is necessary to be aware, that even in sleep laboratories, some parts of sleep records classification results may be considered with some variations due to the subjective interpretations of particular sleep-stage evaluators [16].

III. METHODOLOGY

As mentioned in the section State of the Art, research has indicated that there is a relation among some bio vital signals (heart rate, breathing and movement) and sleep stages. Furthermore, this fundamental relationship was taken as a baseline for our project approach.

Regression analysis is widely used for calculations of relationships between one dependent and several independent variables. As in the described case, it is necessary to analyze the nominal outcome, multinomial logistic regression (MLR) was chosen as the mathematical technique. MLR is a form of logistic regression from the category of multiple regressions. The outcome of an MLR method is the probability of a dependent variable being a member of a category. In the specific case, the output of the algorithm it is the probability of being in the Sleep or Wake state. [17]

To increase the accuracy, signals of heart rate, breathing and movement are not being directly analyzed, but they are derived from those signals:

- heart beat interval – the value of mean RR interval for every 30s epoch (HBI)
- the number of heartbeats per 30s epoch (HB)
- heart rate variability – mean difference of lengths between successive R peaks per 30s (HRV)
- R/RA - algorithm (RA)
- D(k)-algorithm (DA)
- Body movement signal (BM)
- Mean respiratory depth of inhalation (P_{sdm})
- Mean respiratory depth of exhalation (T_{sdm})
- Median respiratory volume during breathing cycles (V_{br})
- Median respiratory volume during inhalation (V_{in})

Whereas some of the derived parameters do not need any complex calculation (HBI, HB, HRV), other features need a more detailed explanation, stated with the mathematical descriptions below.

The RA algorithm is described in [8]:

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

where the discrete time for every 1 min is defined as k, H_{k+i}^{former} and H_{k+i}^{latter} are the heart rate values from the former and latter 30 seconds of the time interval *(k+i)* and *i* represents the movement inside the window (moving average) with the size *2q*, where *q* is equal 10 according to [8].

The derived parameter BM value is calculated as:

$$BM(k) = \frac{1}{n} \sum_{i=0}^{n-1} Body_i , \quad (2)$$

where n is equal 30 (one movement record per second for 30-second epochs) and $Body_i$ is calculated as the square root of (X*X+Y*Y+Z*Z) where X, Y and Z are the values of signals per axis of a 3D actigraphy-sensor, used for the measurement of the body movement.

DA is the derived parameter, calculated using the heartbeat and body movement signals [8]:

$$DA(k) = \log_2 \frac{A_k^{body}}{A_k^{heart} + A_k^{body}} . \quad (3)$$

In this formula, A_k^{body} and A_k^{heart} are representing the mean amplitudes of the body movement and heartbeat signals for the time k. A logarithm is used in this algorithm for the increasing of the effect of slighter body movements.

The next four formulas are mathematically representing the four parameters derived from the breathing signal (P_{sdm}, T_{sdm}, V_{br} *and* V_{in}) [9]:

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

$$T_{sdm}(k) = \frac{median(t_1, t_2, \ldots t_n)}{IQR(t_1, t_2, \ldots t_n)} \quad (4\text{-}7)$$

$$V_{br}(k) = median\left(\sum_{s_x \in \Omega_1^{br}} s_x, \sum_{s_x \in \Omega_2^{br}} s_x, \ldots, \sum_{s_x \in \Omega_k^{br}} s_x\right)$$

$$V_{in}(k) = median\left(\sum_{s_x \in \Omega_1^{in}} s_x, \sum_{s_x \in \Omega_2^{in}} s_x, \ldots, \sum_{s_x \in \Omega_k^{in}} s_x\right),$$

with $p = p_1, p_2, \ldots, p_n$ and $t = t_1, t_2, \ldots, t_n$ – the peak and trough sequences from a chosen time window, the k^{th} breathing cycle is declared with Ω^{br}_k , the k^{th} inhalation and exhalation cycles with Ω^{in}_k and Ω^{ex}_k with k consecutive breathing cycles ($k = 1, 2, ..., K$).

A possible dependence of derived parameters one from another is not relevant according to [18].

Before the computation of derived parameters takes place, the initial ECG signal has to be filtered to remove the disturbances. A linear high-pass filter algorithm was chosen [19]. The results of its work are presented on Fig. 1 with the blue line illustrating the ECG before and the orange one after the filtering.

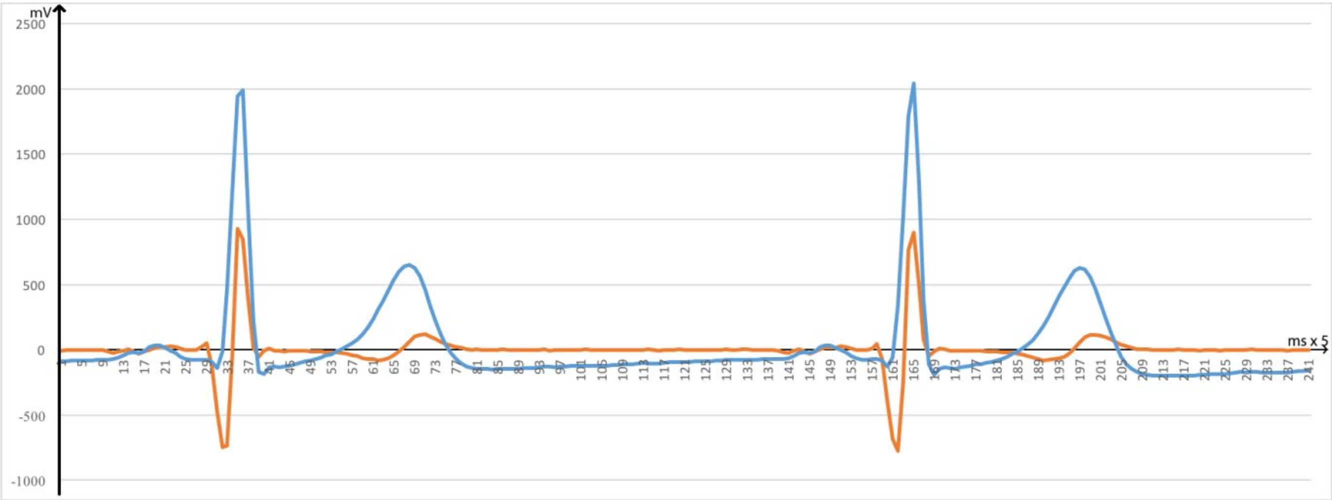

Figure 1. Overlap of the same ECG signal before and after filtering

IV. Results and Outlook

For the evaluation of the approach, a PSG dataset from the Center of Sleep Medicine at Charité clinic in Berlin was used. In total, about 230 hours of sleep records were analyzed. Data were collected from 30 adults (15 male and 15 female) with the average age of 38.5 +/- 14.5 years old and the BMI of participants averaged 24.4 +/- 4.9 kg/m². No significant health disorders were present on the test subjects. The experimental procedures involving human subjects described in this paper were approved by the Institutional Review Board of the Charité-Universitätsmedizin Berlin (application number: EA1/320/114).

The PSG records from dataset were initially sleep staged for every 30 seconds of data by visual expert analysis and was used as a reference. From the available PSG records, the heartbeat signal was extracted from the ECG signal after the filtering process that has been described in the previous section. The respiration signal was substituted by a thoracic (VTH) inductive plethysmography record and the movement signal was replaced by the signal, measured by a 3D acceleration sensor placed on the chest of the test subjects.

In addition to the 30 test records for the evaluation of the algorithm, five PSG records were used to train the classification algorithm. After the training, the test classification in Sleep/Wake states with sleep records from 30 persons was performed: 27 662 time intervals @30 seconds were analyzed. The results are presented in the Table 1.

TABLE I. State Recognition Results

		Stage (developed SW-System)	
		WAKE	SLEEP
Stage (expert)	WAKE	2649	1845
	SLEEP	2482	20686
		Accuracy:	0.84357602
		F1 score (W)	0.55044156
		F1 score (S)	0.90531521
		Cohens Kappa:	0.45625838

The discrepancy between the high accuracy and moderate Cohen's Kappa is caused by imbalance between Sleep and Wake stages, which is typical for PSG recordings because of their specifics. Nevertheless, this point will be investigated in the future research to increase the significance of results.

V. Conclusion

The described approach has several unique features: Firstly, it is using only bio vital signals of human body, which can be measured in a non-obtrusive way: breathing, heart rate and movement. This enables future development of sleep study systems for the use in home environments [20]. In order to capture the signals, a hardware must be used, as for example described in [10]. It can be connected to the presented software algorithm, and this part will be the next step in the project work-plan. Secondly, the proposed set of derived parameters should be mentioned as a novel approach. This selection is a result of an executed exploratory data analysis. Finally, a further unique feature is the application of multinomial logistic regression for the recognition of Sleep/Wake states.

The already achieved results (with accuracy equal to 84%) have confirmed the potential of the chosen approach. Nevertheless, there seem to be several ways to improve the accuracy of the algorithm:

First of all, other derived parameters should be tested for their significance in the MLR-algorithm. A reduction of the amount of derived parameters is possible and the influence on the classification should be reviewed. However, the study with a higher amount of test persons would be necessary to get the significant results in comparison of different sets of derived parameters because the differences in the dataset with only 30 test persons could result from personal characteristics of persons and are less significant. Also, the evaluation with the higher amount of sleep records can be considered to obtain more statistical data. Another way to improve the accuracy could be the introduction of 'trust anchors', which would be set and thus influence the probability of possible follow-up sleep states. Furthermore, the training database could be tested with the balanced amount of Sleep and Wake stages to investigate the influence of currently unbalanced dataset.

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