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Sleep-Wake Detection based on Respiratory Signal Acquired through a Pressure Bed Sensor

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Abstract— **This study proposes an automatic method for the sleep-wake staging in normal and pathologic sleep based only on respiratory effort acquired from a Pressure Bed Sensor (PBS). Motion and respiratory movements were obtained through a PBS and sleep-wake staging was evaluated from those time series. 20 all night polysomnographies, with annotations, used as gold standard and the time series coming from the PBS were used to develop and to evaluate the automatic wake-sleep staging. The database was built up by: 10 healthy subjects and 10 patients with severe sleep apnea. The agreement of the statistical measures between the automatic classification and the human scoring were: 83.59 ± 6.79 of sensitivity, 83.60 ± 15.13 of specificity and 81.91 ± 6.36 of accuracy. These results suggest that some important indexes, such as sleep efficiency, could be computed through a contact-less technique**

I. Introduction

The importance of sleep-wake cycle lies in its ability to predict onset of diseases, as well as its severity. Patients with some sleep-related disorder have been known to have worsening sleep-wake cycles, and in healthy subjects could be useful to identify sleep disorders like insomnia. Polysomnography (PSG) is the traditional method to assess the sleep quality and sleep disorders by the recording of many physiological signals during an entire sleep night. The recordings are visually scored by experienced technicians according to the sleep staging criteria defined by the American Association of Sleep Medicine (AASM) guidelines. Although highly accurate, PSG requires specialized sleep centers with dedicated personnel, adequate infrastructure, and special acquisition systems, which make the sleep evaluation an intrusive, expensive, complicated and time consuming procedure.

The high prevalence of sleep disorders, as well as PSG inconveniences have sparked the introduction of new technologies which mostly rely on a relatively small number of physiological signals and allow a simpler acquisition with high precision in different environments. However, most of these systems still require sensors attached to the body and wires around the subject. To have more comfort and robust measurement, new techniques have been developed to acquire vital signs by non-contact sensors. One example is the pressure sensor integrated into a bed mattress (PBS – Pressure Bed Sensor) which records unobtrusively ballistocardiographic (BCG) signals and enables analysis of heart beat, respiration and body movements [1]. PBS has been proposed as an alternative method to investigate the sleep physiology, sleep disorders, sleep-related cardiovascular impairments and respiratory pathologies such as sleep apnea. In earlier investigations this method was used to analyze the sleep physiology, showing that the amount of movement detected by the PBS vary according to the sleep stage [2]. Visual inspection of the BCG patterns [2][3] and investigations were done to demonstrate the validity of the PBS signals in detecting obstructive sleep apnea [4][5]. The improvement of these results was achieved by combining the PBS with other signals such as oxygen saturation [6]. Recently, the idea of PBS has been improved due to the development of small and more sensible sensors [7][8][9] with new materials that together with a better instrumentation and pre-processing provide more reliable signals.

Respiration is one of the key measurements in monitoring sleep-disordered breathing. One of the most common is sleep apnea, which has in the general population prevalence around 3% [10]. As previously commented, the respiration signal could be obtained from the PBS, and it is well known that this signal presents specific characteristics at the different sleep stages and wake [11]. For example, the respiratory signal presents higher variability and irregular patterns during wake and REM sleep, and very regular patterns during NREM sleep. In addition, it is highly evident the affects produced by sleep apnea. However, respiratory effort acquired through PBS has been mostly used in the evaluation of sleep-related apneas, how we can found in [4] [6] [12].

Therefore, based on these ideas it seems feasible to develop an automated method to determine the sleep-wake dynamic, in normal and pathologic situations, based only on the respiratory signal obtained from the PBS. This study describes the application of an automatic sleep-wake

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algorithm based on PBS respiratory movement to monitor healthy and sleep apnea patients.

II. USED MATERIALS AND SIGNAL DESCRIPTION

A. Pressure Bed Sensor (PBS)

PBS development was done by VTT in cooperation with the sensor manufacturer Emfit Ltd. Overall sensor area was 1 m × 2 m with 160 electrodes [14], and the Emfit foil matrix was placed in between two foam plastic mattress resulting with total thickness of 4 cm. This sensor mattress was then placed below the normal foam plastic mattress having thickness of 12 cm. A comparison was made between different number and shape of electrodes to find the optimum between reliability and complexity of the sensor. The selected cost-efficient design has eight lateral-direction electrodes with size of 7 cm × 34 cm each, placed in two columns and four rows, and covering overall area of 72 cm × 72 cm under the middle body of the subject. This reconfiguration of the bed sensor electrodes was tested afterward for the collected data of the original 160-channel bed sensor, by averaging the neighborhood channel signals to compose a signal from a larger, combined electrode area [15].

B. Respiratory Movement (RM) Signal

During resting sleep the main source for the middle body movements is respiration. PBS measures the dynamic force caused by respiration movements, which can be converted to movement amplitude by integrating the force signal. The multichannel BCG signals were high pass filtered for heart beat extraction and low pass filtered for the respiratory signal extraction with filter corner frequency of 1 Hz. A simple averaging between all the eight signal channels would not provide the optimal result, because the respiration signal can have phase difference and even different polarity depending on the sensor electrode locations and the subjects sleeping posture. Therefore, it was applied an adaptive principal component (PCA) model for extraction of respiration signal. From all possible linear projections for multichannel signal, the first principal component will give the maximum variance for the composed output signal [7]. The adaptive PCA modeling was embedded into DSP processing, and the final respiration signal is composed on-board as the PCA model score output signal with 10 Hz sampling rate.

To update the adaptive PCA model coefficients, data were divided into one minute long epochs and checked the quality of each model by testing the regularity of the resulted scores signal over the epoch length. Any additional body movements, shown as strong variation in the signal, would cause poor quality for the PCA modeling, and for those epochs we removed the short movement period from the epoch and run the model again. During the longer body movement periods we kept the old PCA model parameters until the new epoch contained enough relevant data to update the respiration model again. The PCA model coefficients behave steady during the long resting sleep periods, and the major changes in the model occur normally while switching the sleeping posture.

Because the PCA model is affected by the variance of the signal but not by the polarity, we had to track for the correct polarity by the assumption that the inhalation shows a sharp peak in the signal in comparison with the longer exhalation valley. By this way, the PCA model was automatically biased in the correct polarity for 90 % of time epochs in our test data, and for the rest of the epochs, we could easily correct the polarity by comparing the model load coefficients with the preceding epochs. PBS respiration was compared with reference RIP (Respiratory Inductive Plethysmogram) signal firstly by respiration cycle, and secondly by ratio between inhalation period and respiration cycle.

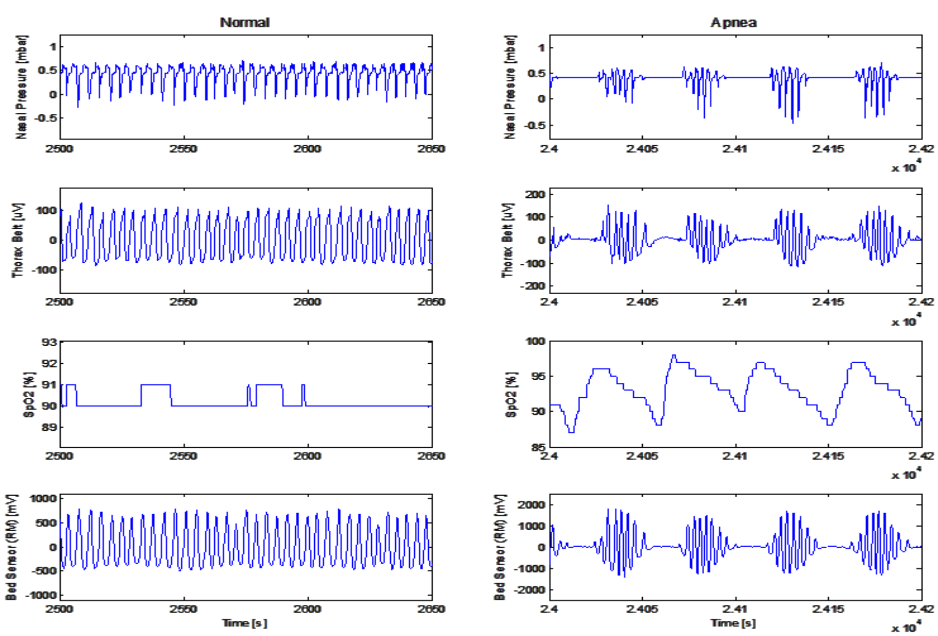

Figure1. Two segments of different signals in normal and apneic respiration, in a sleep apnea patient. The left panels show a segment of normal breathing and right panels plots a segment with consecutive apneic events.

Figure 1 shows a visual comparison between RM signal and reference signals during sleep apnea. From the top to the bottom: air flow (Nasal pressure), oxygen saturation (SpO2) and respiratory effort with thorax belt. It can observe that RM signal could be comparable with the other respiratory signal, and also reflects the sleep apnea effects.

C. Protocol

In total, 20 sleep recordings were used, divided in two different databases. The first one contains sleep recordings from five female (age 20-54 years) shift working subjects acquired at the sleep laboratory of Finnish Institute of Occupational Health. Each subject participated with two recordings and these were obtained after baseline night, once during daytime sleep after a night shift of work and once during nighttime sleep. The sleep scoring was done by expert personnel based on standard polysomnographic recordings using standard R&K criteria. The second one is composed of 10 patients (age 50-68 years) referred to sleep laboratory for suspected sleep apnea. All participants underwent a full-night PSG study and simultaneous recording with the bed sensor described in previous sections. The PSG recordings were scored through the computer using Somnologica software (Medcare, Reykjavik, Iceland) for sleep stages and respiratory events (apnea/hypopnea).

III. MATHEMATICAL METHODS

The algorithm has been adapted from [14], it has several steps that eventually provide an automatically adaptive decision-making process that differentiates between sleep and wake:

1) For each 30 seconds epoch of the normalized RM signal (the RM is normalized by the maximum), based on the observation that RM signal is more spiky, saturated, and entropic during wakefulness while having an overall denser, lower amplitude, and/or periodic patterns during sleep. The function TH is determined with the typical activity of the patient through the night. This function gives a threshold for each 30 seconds and is a simple average.

$$TH_k = \frac{1}{t}\sum_{i=1}^{t} RM(i,k) \quad (1)$$

where t=30 seconds and k is the actual 30 seconds epoch.

2) The RM signal is filtered with a digital band-pass between 1.5 and 2 Hz by a ninth order Butterworth IIR filter, to remove physiological signals like cardiac one.
3) For each 30 second epoch, values of filtered RM below a threshold (TH) determined in 1 are disregarded, and the remaining is integrated using a symmetrical weighted sliding window (Hanning) of 5 minutes' duration. The window is centered at each epoch and provides the level of activity the surroundings of the select epoch. The result is termed here the *Integrated Local Movement*. A wake epoch is defined by comparing the level of activity with the TH threshold.

$$ILM_k = \sum_{i=1}^{t} W(i) * EM\,(i) \quad (2)$$

Where W=Hanning window and $t = 5$ minutes.

4) For each 30 second epoch, the algorithm searches a kind of "periodicity" in RM signal within a 10 minutes symmetrical window. If the algorithm detects periodicity (such as expected during periodic apneic events), this epoch is declared a sleep state overruling the decision made in step 3. Thinking in RM signal as a modulated signal by the apnea; it was used Hilbert transform to envelope detection. The Hilbert Transform is a process by which signal negative frequencies are phase-advanced by 90 degrees and the positive frequencies are phase-delayed by 90 degrees. Shifting the results of the Hilbert Transform (+j) and adding it to the original signal creates a complex signal known as the Analytic Signal. If $m_i[n]$ is the Hilbert Transform of $m_r[n]$, then:

$$m_c[n] = m_r[n] + jm_i[n] \quad (3)$$

is an analytical signal.

5) For each Wake state, a rectangular window of 10 minutes duration is applied to the envelope signal detected in step 4, and calculated the power spectral density by Welch's Method. A threshold was determined to discriminate the periodicity of the signal by analyzing 0.01 to 0.04 frequencies. Figure 1 shows different segments of the respiration signal in which one can observe a modulation in the RM signal caused by periodic apnea events or airflow amplitude reduction coupled with oxygen desaturation lower than 4% that cannot be categorized like hypopnea. The power spectral density shows, a clear difference in each segment.

IV. RESULTS

The records were stratified into two groups: Normal and apneic. We calculated percentage of statistical measures of performance: sensitivity, specificity and accuracy. Sensitivity measures the proportion of actual positives (sleep stage) which are correctly identified as such. Specificity measures the proportion of negatives (wake stage) which are correctly identified and accuracy measures the proportion of true results (both positives and negatives) correctly identified.

Table 1 shows sensitivity, specificity and accuracy for each group. There was a high accuracy between the respiratory effort-based sleep/wake detection and the PSG scoring in healthy and apneic patients. Specificity was more affected by sleep apnea; since RM signal has a greater number of spikes and variations caused by the effects of the pathology. These are the results of an epoch-by-epoch validation for both groups.

TABLE 1. RESULTS SLEEP/WAKE DETECTION

Level of apnea severity	No	Sensitivity %	Specificity %	Accuracy %
Normal	10	83.60 ± 4.85	91.72 ±13.24	83.56 ±4.60
Apneic	10	82.59 ± 8.56	75.49 ±12.72	80.27 ±7.63
All	20	**83.59 ± 6.79**	**83.60 ±15.13**	**81.91 ±6.36**

Figure 2 shows a comparison between PSG reference and sleep/wake detection by a patient with severe sleep apnea.

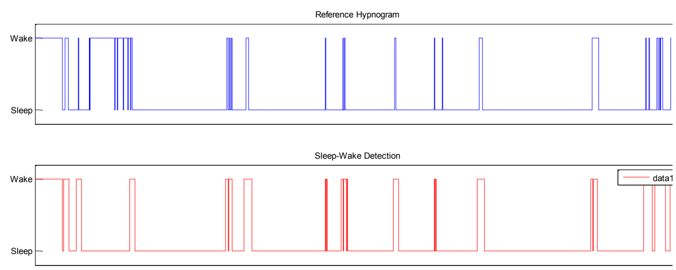

Figure 2. Upper curve shows reference hypnogram and lower curve shows sleep/wake detection.

V. Discussion

The goal of this study was to implement a method to sleep-wake staging based solely on RM signal extracted trough a pressure bed sensor, which gives the possibility of analyze sleep recordings without the need of electrodes, wires or other devices connected to the subject's body. RM signal is an indirect lecture of the subject respiration, but also reflects corporal movements that could be exploited to wake identification.

Compared with other sleep-wake classifications, this was a very simple algorithm that does not involve any complicated mathematical technique. This study has demonstrated that PBS signals may be used to accurately identify sleep and wakefulness on an epoch-by-epoch validation. The algorithm was reasonably stable across two groups of patients, and shows comparable and better results than original actigraphy-based algorithm [14]. Furthermore, the RM signal conveys information that can be used to explore the REM-NREM staging and apnea detection. Additionally to RM signal, PSB provides other signals like beat interval, body posture and body movements, that could be analyzed and combined looking for a better detection.

It is important noting that a large percentage of sleep apnea subjects also suffer of cardiac problems, thus they may present important modifications in heart activity. Thus, all the algorithms based on heart activity could suffer a significant reduction in their performance. Then the application of RM signal to evaluate the sleep staging could be a fine option since it could be robust to some cardiac dysfunctions. The main disadvantages of this study is the small number of patient and the performance could be improved by adding new features such as spectral or complexity measures.

VI. Conclusion

The obtained, results encourage the analysis of PSB signals for sleep staging and sleep apnea detection. These results further open the way to a free contact sleep diagnosis, eliminating some of the drawbacks that traditional method presents. In addition, respiratory signal, obtained from the PBS, seems a robust and simple signal that could be used for clinical screening.

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