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Detection of Sleep-Disordered Breathing with Pressure Bed Sensor

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Abstract— **A Pressure Bed Sensor (PBS) can offer an unobtrusive method for sleep monitoring. This study focuses on the detection of the sleep related breathing disorders using a PBS in comparison to the methods used in a sleep laboratory. A newly developed PCA modeling approach for the eight sensor signals of the PBS is evaluated using the Reduced Respiratory Amplitude Index (RRAI) as a central measure. The method computes the respiration amplitude with the Hilbert transform, and then detects the events based on a 20% amplitude reduction from the baseline signal. A similar calculation was used for the sleep laboratory RIP measurements, and both PBS and RIP were compared against the reference based on the nasal flow signal. In the reference RRAI method, the respiratory-disordered events were obtained using RemLogic respiration analyzer to detect over 50% amplitude reduction in the nasal respiratory flow, but removing the RemLogic standard hypopnea event associations on the oxygen desaturation events and the sleep arousals. The movement artifacts were automatically detected based on the movement activity signal of the PBS. Twenty-five (25) out of 28 patients were finally analysed. On average 87% of a night measurement has been covered by the system. The correlation coefficient was 0.92 between the PBS and the reference RRAI, and the performance of the PBS was similar with the RIP belts. Classifying the severity of the sleep related breathing by dividing RRAI in groups according to the severity criteria, the sensitivity was 92% and the specificity was 70% for the PBS. The results suggest that PBS recording can provide an easy and un-obstructive alternative method for the detection of the sleep disordered breathing and thus has a great promise for the home monitoring.**

I. Introduction

According to epidemiological studies, sleep apnea-hypopnea syndrome (SAHS) is the most frequent sleep related breathing disorder with prevalence estimated at 5% of adult men and 2% of women in the western countries [1]. SAHS is a condition characterized by recurrent episodes of cessation (apnea) or considerable reduction (hypopnea) of respiratory flow during sleep often resulting in oxygen desaturation and arousals from sleep. The classic manifestation is excessive sleepiness and other symptoms such as unrefreshing sleep, poor concentration and fatigue during the day are commonly reported [2]. Besides of these manifestations SAHS has been related with other diseases such as hypertension, atrial fibrillation, stroke cardiac failure, aortic dissection and sudden cardiac death [3]; elicited by repetitive cycles of lack of airflow that causes strong sympathetic activation and rapid blood pressure elevation.

Sleep apnea is usually classified, according to its cause, in: obstructive (OA), central (CA) and mixed (MA). OA is caused by the repetitive obstruction of the upper airway, here the effort generated to produce airflow increases causing the rib cage and abdomen to distort and move out of the normal respiratory phase. In contrast, CA is caused by the lack of central respiratory drive, in which respiratory movements are absent or attenuated, but in phase [3]. Finally, MA is caused by the combination of both central and obstructive factors, the absence of airflow is initially associated with an absence of the respiratory effort and then persistent upon resumption of the respiratory effort indicating upper airway obstruction [2]. In routine clinical practice it is not necessary to distinguish between the obstructive hypopneas and apneas because both types of events have the similar pathophysiology.

Currently, the most reliable method for the assessment of sleep disorders and sleep quality is the overnight polysomnography (PSG), using of the continuous monitoring of many physiological signals recorded in a sleep centre. These signals are visually and manually scored by experienced technicians or neurophysiologists. However, recent advances in software development have provided new tools that analyze the PSG signals and assist clinicians in their diagnosis, such as Remlogic™ developed by EMBLA (Embla Systems, Denver CO). The number of apneas and hypopnea events per hour of sleep, the apnea-hypopnea index (AHI), is the index most commonly used measurement to determine the severity of SAHS. Current criteria consider mild, moderate and severe categories, with: 5 to 15, 15 to 30 and more than 30 events per hour, respectively [4].

Due to the expensive, complex and time-consuming nature of PSG, portable monitoring devices have been investigated and utilized as an alternative diagnostic test for SAHS [5]. Those portable systems reduce the number of physiological signals needed, thus increasing patient comfort and decreasing the complexity and costs of the procedure. However, portable systems like wearable ECG [6], sensors integrated into user's clothing [7], wearable wrist-sensor [8], among others, have still the limitation that they are attached

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to the subject's body. To improve these conditions, the Pressure Bed Sensor (PSB) is presented as a contactless sensor for sleep analysis.

The purpose of the current study was to analyze the potential of the respiratory movement signals derived from PBS for SAHS estimation. The estimated Reduced Respiratory Amplitude Index (RRAI) was compared with the references obtained with the polysomnography nasal airflow signal and with the Respiratory Inductive Plethysmogram (RIP) on thorax and abdomen. The latter signals provide an indirect measurement of the respiration air flow through the respiration effort in a similar way as the PBS.

II. Material

A. Pressure Bed Sensor (PBS)

The PBS measures multiple ballistocardiographic (*BGC*) signals with eight channel force sensing piezoelectric foils with PVDF (Polyvinylidene Fluoride) material, acquired from Measurement Specialties Inc. The sensor foils are placed into four rows and two columns covering a measurement area of 64 cm × 64 cm, placed in between two foamed rubber sheets and covered with hygienic fabrics, having overall dimensions of 100 cm × 72 cm and 2 cm thickness when not compressed (see Fig. 1). The sensor assembly is installed under the normal bed mattress which normally has a thickness of about 10 cm. From this sensor configuration, the eight channel pressure signals are acquired at 50 Hz and the respiratory, heart rate and movement activity signals are extracted with the on-board algorithms implemented by VTT [9].

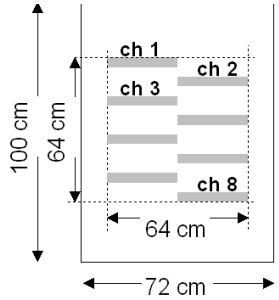

Figure 1. PBS assembly with eight PVDF sensors.

B. Recording Protocol

A total of 28 subjects (age 50-68 years) referred to the sleep laboratory of Tampere University Hospital for suspected sleep problems were recorded for testing of the PBS against the PSG references. However, three patients were using the CPAP (Continuous Positive Airway Pressure) device during the sleep and thus their recordings were not suitable for the calculation of the RRAI, leaving 25 subjects; 12 female and 13 male, with BMI= 29.33±5.34 and age between 48 to 63 years. All participants were recorded overnight: a full PSG study using the sleep laboratory's standard methods and a simultaneous recording with the PBS. Afterwards, the reference RRAI was calculated with the automatic RemLogic procedure (Embla Systems LLC) by detecting the respiratory events of the nasal air flow signal, having at least 50% amplitude reduction from the baseline with duration of 10 seconds or more, and calculating the index by dividing with the total analysis time for the each patient recording. The RemLogic applies proprietary methods for the detection of flow events and artifact removal. In comparison with the standard AHI definition given in [10], the associations with both desaturation events and arousals were not used, and the total analysis time was applied instead of the recommended total sleep time (TST). The simplified RRAI was selected instead of AHI for the reference because the PBS analysis in comparison did not include the estimation of the desaturation events, arousals and sleep/wake stage.

III. Methods

A. Respiration Amplitude Estimation

A common way for respiration amplitude estimation is to detect minimum and maximum values for each respiration cycle based on the zero-crossings of the derivative of the signal. However, the noise and irregular respiratory movements may cause false detections, especially during apnea periods. To improve robustness we applied the Hilbert transform strategy [11] for the estimation of the amplitude of the PBS respiration signal by using the hilbert.m function of Matlab (The Mathworks, Matick MA). The method is based on calculating firstly the Discrete Time Fourier Transform (DTFT), setting the spectrum values at the negative frequency bins to zero, rescaling the rest spectrum values accordingly to maintain the total signal energy, and then performing the inverse DTFT. The method can be used efficiently with the FFT algorithm. Hilbert transform is a non-causal operation, however this is not a problem for the apnea detection, as the sleep analysis is performed for the recorded data off line. If $m_i[n]$ is the Hilbert Transform of the original real-valued measurement signal $m_r[n]$, then the complex valued summation gives:

$$m_c[n] = m_r[n] + jm_i[n] \quad , \qquad (1)$$

where the resulted $m_c[n]$ is known as the analytic signal. The analytic signal is useful in calculating instantaneous attributes of a time series, e.g. amplitude or frequency at any point in time. To estimate the respiration amplitude we smoothed the magnitude of the analytical signal with a 3rd order Butterworth low-pass filter having 0.1 Hz corner frequency.

Fig. 2 shows firstly the nasal airflow signal as respiratory reference, the on-board calculated channel averaged respiration signal (PBS_resp) in the uppermost left and right chart respectively, and then the eight different PBS respiration signals together with the estimated amplitude curves. In the middle part of the nasal signal a period of absence of the respiratory flow can be seen. This is detected by the RemLogic as an obstructive apnea event. The channel-averaged PBS_resp signal shows only a minor decrease in the amplitude of the respiratory movements, calculated with the Hilbert method. However, some of the individual sensor channels are more sensitive than others for the reduced respiration amplitude, which can be seen by comparing the eight signal channels in the lower part of the Fig. 2.

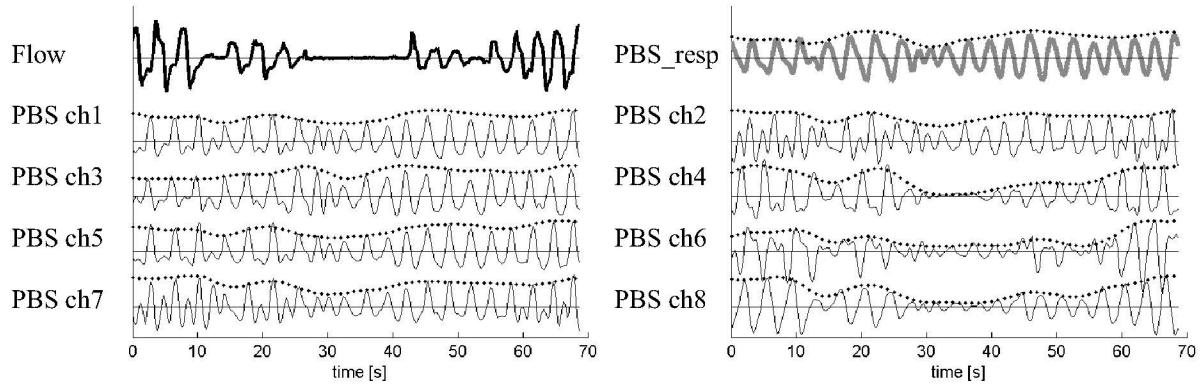

Figure 2. Reference nasal airflow signal during apnea period in the uppermost left graph, the PBS averaged respiration signal on the top of the right panel, and the eigth different PBS respiration signals are shown below them including the amplitudes calculated with the Hilbert transform method.

B. Principal Component Analysis (PCA)

In addition to the on-board calculated channel averaged PBS_resp signal we developed a new method to calculate an enhanced multichannel PBS respiration amplitude signal (PBS_mult) to improve the sensitivity of the PBS for the apnea/hypopnea events. Firstly, we low-pass filtered the eight sensor signals, using a corner frequency of 1 Hz, and calculated the amplitude curves separately for each signal channel with the Hilbert method. Then we estimated the maximum variance signal by using the principal component analysis (PCA) model for the amplitude curves.

PCA is a data reduction procedure, where the projected data values on each PCA coordinate are called *scores*, and the vectors including the linear equation coefficients to carry out the projection are called *loads*. The definition for the first principal component loads w_1 of a dataset x can be given as [12]:

$$w_1 = \text{argmax}_{\|w\|=1} E\{(w^T x)^2\} \quad (2)$$

From all possible linear projections for dataset x, the first principal component will give the maximum variance. The corresponding scores vector s_1 is:

$$s_1 = w_1^T x \quad (3)$$

The first scores vector of the PCA was calculated with singular value decomposition method (SVD) on data blocks using a window length of five minutes and these were overlapped by updating the model for each minute. Finally, we applied the maximum variance amplitude signal for the apnea detection in a similar way as with the original signals, explained in the following subsection.

C. Detection of reduced respiration amplitude (RRA) events

Having calculated the respiration amplitude signal with the Hilbert method, and PCA for PBS_mult, the amplitude baseline was calculated as the mean value of the preceding 100 seconds. A RRA event was detected when the ratio with the baseline was less than a selected percentage threshold value for a period of at least 10 seconds. The PBS movement activity signal was used to remove any movement artifact periods according an established threshold before calculating the baseline signal. The RRAI was calculated for each recording as a sum of the detected RRA events divided by the analysis time subtracted with the cumulated artifact periods time. For comparison, the RRAI was calculated for the original PBS respiration signal PBS_resp, enhanced multichannel method PBS_mult and also for the PSG respiratory belt (RIP) signals with the same method using Matlab. Because the sensitivity of the respiratory movement signals is much weaker for the apnea/hypopnea events than with the nasal airflow signal, we had to select different thresholds for the detection. The reference RemLogic method uses 50% amplitude reduction for the flow events, and we selected correspondingly 20% amplitude reduction threshold to achieve similar RRAI for the PBS and RIP respiration movement signals.

IV. Results

Fig. 3 upper row shows the RRAI of PBS respiration signals plotted against the reference RemLogic nasal airflow RRAI. The left hand side graph shows the PBS respiration signal and the right hand side graph shows the enhanced multichannel PBS_mult method, with the latter having better correspondence against the reference.

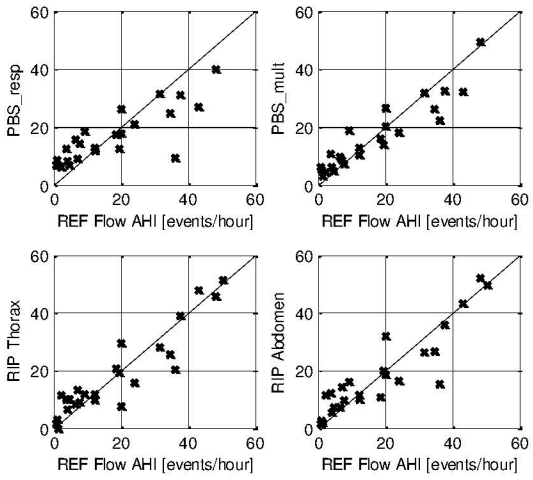

Figure 3. RRAI detection for PBS and RIP respiration signals compared with reference flow RRAI.

The lower graphs show the RRAI of RIP respiratory belt signals at Thorax and Abdomen positions in *versus* the reference. The overall accuracy is similar for both RIP signals and the enhanced multichannel PBS_mult method.

In the study group of *N=25*, the reference RRAI was between *0* to *50* events/hour, and the average error given in Table I was about 10 % of the whole range. The accuracy was calculated as the average absolute difference and correlation coefficient between the reference and tested RRAI results. All the found correlations were significant at p=0.001. To measure the sensitivity and specificity, the subjects were classified with the RRAI into four severity groups, resulting 7 subjects in healthy class, and amount of 6, 5, and 7 subjects in the classes mild, moderate and severe, correspondingly. The two lower rows in Table I show the average sensitivity and specificity readings over all RRAI severity groups for each measurement. As a result, the sensitivity of the original averaged PBS respiration signal was poor, which can be seen in the left hand side graph of the uppermost row in the Fig. 3 also. The enhanced PBS_mult method performed much better and with similar accuracy as the RIP sensors on both sensitivity and specificity. The average measurement coverage of the PBS RRAI was *87 %*, including also two restless sleeping subjects having less than *70 %* measurement coverage.

TABLE I. RRAI ACCURACY FOR N=25 SUBJECTS

Performance measure	**Measurement Method**			
	PBS respir-ation	***PBS Multi-channel***	***RIP Thorax***	***RIP Abdomen***
Abs error (events/h)	6.67	4.47	4.53	4.57
Correlation Coefficient	0.83	0.92	0.92	0.91
Sensitivity (%)	86	92	89	89
Specificity (%)	46	70	72	69

V. DISCUSSION AND CONCLUSION

During different types of the obstructive breathing it is quite normal that the respiratory effort is still found in the movement signals although the respiratory air flow is strongly reduced or absent due to e.g. airway blockage or paradoxical breathing phenomena. However, the sleep disordered breathing events in most cases also affect the respiratory movements to some extent, and the difference can be seen if compared with the regular respiration. Although the measurement coverage of the system is directly affected by the strong body movements, such as change of body position or leg movements. In here, we found a good correlation between the multichannel PBS respiratory movements and the reference respiratory flow.

As a first approximation we used as a reference the annotations of the respiratory events obtained by using the PSG nasal flow signal only and removing the default association with the blood oxygen desaturation events. This was done to simplify the challenge on finding correspondence from the respiratory movement measurement, i.e. both PBS and RIP sensors, for the nasal airflow measurement. Modeling error between these different physiological measurements might include also artifacts in the flow measurement, i.e. in case of mouth breathing. For the next step, we shall investigate the merits of adding the heart rate variability analysis based on the PBS signals to find correspondence with the reference desaturation events, and consider using the standard AHI as a final reference.

It was demonstrated that some of the individual PBS sensor channels are more sensitive for the apnea-hypopnea events than the averaged respiration. The most sensitive sensor channel seemed to be strongly dependent on the sleeping posture, e.g. when sleeping on the sides the more apnea sensitive respiratory movements were found on the front side of the sleeper (channels 2, 4, 6 and 8 in the Fig. 2). An automatic method was developed to improve the sensitivity on the reduced respiration amplitude events, by calculating the maximum variance estimator for the eight channel PBS respiration amplitude signals with an adaptive PCA model. Results from the new method show similar accuracy to the RIP respiratory belt signals and also has a good correspondence with the nasal airflow signal. These results suggest that PBS recording can provide an easy and un-obstructive alternative method for the detection of the sleep disordered breathing and thus has a great promise for the home monitoring.

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