Contact Pressure Monitoring Device for Sleep Studies

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Abstract— This project implements a non-invasive sleep monitoring system using a bed pressure sensor array. The system detects changes in the contact pressure between a subject and the bed and is able to automatically select the sensor with the best respiratory signal, determine the respiratory rate (RR), count number of sleep apneas and count body position changes through the night. The respiratory signal is validated with an airflow sensor using Pearson's correlation coefficient. To determine the performance of body position and apnea detection algorithms, the sensibility and positive predictivity is computed on preliminary data and known records from a Physionet database. Real data is obtained from 5 subjects totaling 39 hours measured at home during a full night sleep, in a non-invasive way. The data is used to calculate relevant parameters to estimate a sleep quality. Cumulative frequency of sleep interval duration is proposed as a novel metric for sleep assessment.

I. INTRODUCTION

People sleep about a third of their lives. During sleep, the body restores metabolic functions and stores information collected on the day [1]. When normal conditions of sleep are affected, also the functionality of the subject is impaired, causing problems such as somnolence, decrease of reaction time, loss of coordination that may cause traffic accidents, irritability, cardiovascular disease (CVD) such as hypertension, arrhythmia, and others affecting the life quality of the subject [2], [3]. The most common nocturnal disease is the sleep apnea hypopnea syndrome (SAHS), present in 2% of women and 4% of men between 20 and 40 years old [4]. SAHS patients use at least twice as many medical resources compared to a normal patient. Sleep quality is defined as the ability to generate rest and recover brain functionality to perform optimally during the daily activities, and is used as a life quality or health index [5]. Sleep quality is normally determined with indexes based in questionnaires. The most common are the Pittsburgh index [6], which evaluates the patient sleep perception during the last 2 weeks, and the Epworth Sleepiness Scale [7], which inquires which daily activities produce sleepiness. However these indexes are subjective evaluations, unlike the polysomnography study that allows to diagnose a patient with objective, measured parameters [6].

Polysomnography is the standard test used to diagnose most sleep disorders. This study connects multiple sensors to the subject to record parameters during sleep and determine if the patient suffers some disorder [8], [9]. However, too many sensors connected to the body may affect the measurements.

EP, AD, PA, JC and AM are with the Department of Electrical Engineering, Universidad de Concepción, Concepción, Chile epino@ieee.org Furthermore, polysomnography is an expensive exam, that requires hospital admission for the night. The number of people who undergo this exam are few compared to the potential number of subjects who could benefit from some sleep disorder screening.

An alternative to monitoring patients during sleep is a pressure sensor array [10] to observe the respiratory signal [11] and body movements [12]. The respiratory signal contains parameters such as respiratory rate (RR), measured in respirations per minute (RPM), and number of apneas, which is used to calculate the apnea hypopnea index. RR variability is also used as an estimate of the sleep depth [13] and sleep cycles (SC). From the body movements it is possible to estimate sleep depth, detecting sleep intervals (SI) between movements longer than 20 min $(SI_{>20})$ and shorter than 20 min $(SI_{\leq 20})$. From the pressure sensors, the time in bed (TB) can also be easily calculated [14]. Different combinations of these parameters have been used to estimate sleep quality by different authors. However, there is no single non–invasive device that monitors all these objective parameters at the same time.

This paper shows the implementation of a non–invasive monitoring system that provides enough parameters to conduct sleep studies based on objective measurements. Such a device would allow comparing sleep quality between patients and/or follow the evolution of a patient in time. The device is implemented with a pressure sensor array, allowing its use in non–hospital environments, reducing costs and facilitating access to a larger population. The respiration signal is validated using an airflow sensor. The algorithms are tested on standard Physionet [15] database records from *slpdb* [16]. The system is tested during full night sleep with 5 subject, totaling 39.0 hours. Some metrics for objective evaluation are proposed.

II. ACQUISITION SYSTEM

The acquisition system is divided into four stages: 1) sensor array, 2) analog signal multiplexing, 3) resistance– voltage transducer and 4) microcontroller with digital to analog conversion (ADC), multiplexer and serial communication to a data logger.

A. Sensor array

The design of the sensor array considers the following requirements:

- It has to cover the width of the thorax.
- It has to be comfortable to the patient during sleep.
- It has to be safe for the patient.

Fig. 1. Sensor mat positioned between the mattress and the sheet. The sensing area is 300 x 900 mm. The arrows show the three rows of 8 sensors.

A pressure sensor array with 24 force sensing resistors (FSR \mathbb{B}) from Interlink Electronics are positioned in 3 rows and 8 columns. Each sensor has an active area of 38.1 x 38.1 mm. The total sensing area is 300 x 900 mm. Fig 1 shows the prototype sensor mat in a single size bed.

B. Analog signals multiplexing

Three 8–channel analog multiplexers are used to leverage the available ADC ports in the ATMega64 microcontroller and to reduce the size of the hardware.

C. Resistance–Voltage Transducer

An inverting amplifier is used for resistance-voltage transduction. The $FSR^@$ lowers its resistance as more force is applied to it. The converted values range from 0 V when the sensor is not pressed, to about +4 V under maximum pressure.

D. Microcontroller with ADC, multiplexer and serial communication with a data logger

Three ADC channels of the microcontroller ATMega64 are used, which are configured with 8 bits of conversion. The sampling frequency of the ADC is 250Hz per channel. Since each channel samples 8 sensors, the final sampling rate of each sensor is 32.9Hz. After conversion, data are sent by the serial port at 38.4Kbauds to the data logger, Logomatic v2 from SparkfunTM Electronics, and saved in a microSD card.

III. SIGNAL PROCESSING AND ANALYSIS

After recording the pressure distribution signals during a night sleep, some signal processing is required to end up with relevant parameters to estimate sleep quality. The required steps to compute parameters such as TB, RR, SC, number of apneas, total movements (TM) and SI duration are:

- a) Body movement detection
- b) Automatic signal selection
- c) Apnea detection
- d) RR calculation
- e) RR variability

Fig. 2 shows a segment of a record with body movements,

Fig. 2. Apneas, respiratory signal and body movements recorded by the pressure sensor array. The best signal for RR calculation among the 24 sensors is automatically selected.

Fig. 3. (a) Pressure distribution in the sensor array showing 3 different positions during night sleep at 285, 310 and 330 minutes. Pressure distribution is obtained from the individual sensors in the first row (b), the second row (c) and the third row (d).

respiratory signal fluctuations from which the RR signal is obtained.

A. Body movement detection

The automobility interesting the signal of the control of the signa There are 2 kinds of movements in the recorded signals: body movements and respiratory movements. Body movements correspond to changes in position and are seen as abrupt changes in pressure distribution or high frequency, high amplitude signals. Respiratory movements are acquired when the subject is at rest, still, and the changes in bed sensor pressure are due to inhalation and exhalation. Respiratory movement is similar to a sine wave, with a defined range of frequencies and amplitudes. Body movement detection algorithm is implemented detecting large amplitude changes during a 2 s. window in at least 3 signals to determine if a movement event has occurred. Fig. 3 shows a segment of a measurement during a night sleep, where the subject changes position 2 times, at 296 minutes and 320 minutes. Fig. 3-a shows the pressure distribution in the sensor array at 285 minutes, 310 minutes and 330 minutes, depicting 3 different sleeping positions during the night.

Fig. 4. Example of a 7 h night sleep. a) Pressure sensor signal. b) Body movements and RR series. c) moving RR_{sd} , and d) number of movements in a 20 minute window.

B. Automatic Selection of the Respiratory Signal

Every time the subject changes positions, the best respiratory signal available appears in a different channel. Between body movement detections, an automatic channel selection algorithm evaluates and selects the channel with the best respiratory signal. The automatic selection is divided in 2 stages: 1) Discard signals with the mean and standard deviation above and below a previously determined threshold, in order to reject saturated, disconnected and/or uninformative signals, and 2) Selection of the signal with the smallest kurtosis along the segment, provided that it is smaller than 10. In some cases the algorithm may not select a respiratory signal because no channel satisfies these requirements.

C. Apnea Detection

An apnea is defined as a suspension of the airflow for 10 seconds or more [8]. In the respiratory signal, apnea is defined as a decrease in signal variance to 10% or less of its normal value. The normal variance of the selected channel is computed as the mean variance along the segment between two body movements.

D. RR Calculation

RR is defined as the instantaneous number of RPM. It may change with age, sex or the wake/sleep stage. RR is calculated as the inverse of the time between peaks in the respiratory signal. Fig. 4 shows a full night record along the calculated RR series. Body movements are also shown to identify SI.

E. RR variability

RR variability is also related to the sleep stage [13]. As a measure of variability, the standard deviation (RR_{sd}) is computed in 20 minute windows, with a 25% overlap.

F. Analysis

As mentioned, several relevant sleep parameters and time series can be calculated from the processed signals:

TABLE I PARAMETERS FROM SUBJECTS DURING FULL NIGHT SLEEP.

Rec.	TB	RR	RR_{sd}	SC	TM	$SI_{>20}$	$\overline{\mathrm{SI}}_{<20}$
	[min]	[RPM]	[RPM]				
s1n1	389.5	16.96	1.73	4	33		26
s1n2	368.4	17.21	1.56	4	30		21
s1n3	439.31	16.86	1.31	5	30	11	18
s2n1	300.79	17.37	1.52	4	30	6	23
s2n2	421.16	16.13	1.42	5	88	4	83
s3n1	417.31	17.74	2.26	4	141		135
s4n1	434.99	15.39	1.79	6	55	6	48
s5n1	554.90	14.04	1.70	5	32	9	22

- *TB:* Time in bed is computed by counting the minutes while at least a sensor is pressed $(> 0 \text{ V})$.
- RR_{sd} : is the moving standard deviation of the RR series for 20 minute windows with 25% overlap.
- *Mov.*: is the moving count of body movements in a 20 minute window with 25% overlap.
- *SC:* is derived from the cycles observed in RR_{sd} .
- *Number of apneas:* is counted directly from the apneas detected.
- *TM:* are counted from the body movements detected.
- $SI_{\geq 20}$: is the number of intervals longer than 20 min.
- $SI_{<20}$: is the number of intervals shorter than 20 min.

As an example, Fig. 4 shows a processed signal, from which all the relevant parameters can be obtained.

IV. RESULTS

A. Validation of the respiratory movement signal

To validate the respiratory signal obtained with the sensor array, 15 volunteers are measured in the laboratory with the sensor array and an airflow sensor simultaneously for 6 minutes, changing to prone, lateral and supine positions. The instantaneous RR from both sensors is compared using Pearson's correlation coefficient, and obtaining $\rho = 0.904$. A Student's t-test for $\rho = 0.904$ rejects the null hypothesis at $\alpha = 0.001$ significance level, meaning that both signals are correlated.

B. Evaluation of Body Movement and Apnea Detection Algorithm

To test the body movement algorithm, 15 volunteers perform 3 position changes at specific times, while laying in the bed. The algorithm output is compared to the known body position changes, obtaining a sensibility (Se) of 100% and a positive predictivity (+P) of 100%.

The *slpdb* database from Physionet is used to test the apnea detection algorithm. Only records *slp48*, *slp59*, *slp60* and *slp67x* are considered because they present central apnea events and a respiratory effort signal, comparable to the respiratory signal obtained with the pressure sensor array. It this case, apnea detection algorithm has $\text{Se} = 83.1\%$ and $+P = 92.19\%$.

Fig. 5. Cumulative frequency of the sleep intervals duration. Frequency at 20 min indicates the percentage of time spent sleeping in short–time intervals.

C. Analysis of full night sleep records

Tests with 5 healthy subjects, 3 men and 2 women ranging from 22 to 57 years old (s1 to s5), produced 8 full night records, totaling 39.0 hours. Table I shows the parameters obtained with the pressure sensor array. None of the subjects presented sleep apneas. Comparing between records, some relative measure of sleep quality can be established. Record s3n1 presents the worse results. Despite having a large TB, his RR_{sd} is the largest, suggesting a restless sleep, with important variations in RR. Also, the number of movements during the night exceeds largely the average among all the subjects. Of those, 96.4% correspond to frequent movements (less than 20 min apart), suggesting that there are few opportunities to achieve a deep sleep state. On the contrary, s5n1 has the largest TB, with a low TM. Of those, 71.0% are frequent movements. The lowest proportion of short–time intervals to long–time intervals is achieved by s1n3, with 62.1%. This result indicates that there is a higher chance of attaining deep sleep, conclusion supported by the fact that it is also the record with lowest RR_{sd} . These observations can be corroborated by Fig. 5, where the normalized cumulative sum of the sleep intervals is shown for each record. Looking at the 20 min. threshold, it can be seen that s3n1 has 59% of the total sleep intervals under 20 min., s5n1 has 36% and s1n3 has about 28% under 20 min., corroborating the previous observations. However, s2n2 appears this time as the worst result, because 70% of the time sleeping is spent in short intervals (less than 20 min).

V. CONCLUSIONS

This work shows the feasibility of contact pressure sensing for sleep studies. The designed system show promising results to allow an objective evaluation of sleep quality. Respiration signal, movement and apnea detection are successfully validated. Intermediate steps necessary to compute objective sleep parameters are achieved.

Actual full night sleep records were obtained from multiple subjects and compared using calculated sleep parameters. These parameters allow evaluating sleep performance both between patients or to follow a single patient's evolution in time. A novel metric based on the cumulative frequency of sleep interval durations is presented as a good single indicator of sleep quality.

Future work include validating the device as a prescreening for polysomnography studies. Once validated, such a system would lower costs and time required to reach sleep disorder diagnoses by providing a portable, simple alternative that patients may even use at home.

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