Non-invasive Sensors based Human State in Nightlong Sleep Analysis for Home-care

M Smolen, K Czopek, P Augustyniak

AGH University of Science and Technology, Krakow, Poland

Abstract

In this paper we present methodology used in a non-invasive, easy-to-use and low-cost monitoring system for nightlong human sleep quantification. Our system uses simultaneous measurement of three different signals representing the activity of the human body: infrared video-recorded subject motion, audio-recorded acoustic effects and the three-leads electrocardiogram. Signal-specific interpretation methods yield parameters selected as most discriminative for the sleep quality, synchronized and combined as a sleep record.

In the experimental stage the nightlong sleep was supervised by a reference EEG recordings and particular components of the sleep record were correlated to the presence of delta wave representing deep sleep. Significant correlation values in most subjects allows to validate the proposed sleep record as comparable to the standard polysomnogram.

1. Introduction

Average human spends one third of his live in sleep. This justifies the investigation of the sleep quality as an important component of the quality of life. Unfortunately, sleep studies today require specialized equipment and qualified personnel, therefore cannot be easily transferred to the home care conditions.

A pursuit for an intelligent health surveillance infrastructure embedded in the subject's premise motivated us for investigation of possible integration of cheap off-shelf components to a sleep-quality assessment system. The research presented in this paper aims at:

- optimal selection of the system components,
- estimation of convergence of sleep descriptions to results from clinical methods.

2. Material and Methods

The system is targeted to healthy and diseased users as well, therefore in our studies we investigated selected modalities of nightlong sleep recorded from eight healthy volunteers (three females and five males, aged 21-59). Characteristic pattern of each of the acquired signals and video frames were analyzed by means of dedicated software. Final conclusions about the state and activity of every investigated patient are presented by setting-up and comparison specific parameters: ECG-derived HRV and breathing parameters, snoring parameters and body motion index referenced to the presence of delta waves, representing the deep sleep in the EEG.

2.1 Recording equipment

For basic electrocardiographic recording three-leads (III, V1 and V5) battery operated personal recorder with 12-bit 128 sps was used (Aspekt 702, Aspel).

Brain electrical activity data were acquired from C4-A1 (or C3-A2 backup) derivations according to the 10-20 system, two mastoid electrodes (A1 and A2) in reference and a ground electrode placed between Fp1 and Fp2. The maximum value of skin resistance was 5 kΩ. An EEG amplifier (ISO1032, Braintronics) uses a 16 bit analog-to-digital converter (500 sps). The acquired signal was filtered with a bandpass filter (0.3-35 Hz) and a power line frequency (50 Hz) notch filter accordingly to the desirable digital specifications in [1]). The baseline (mean value) was subtracted from the signal and then in order to reduce calculation time quadruple resampling to 125 Hz was applied.

Small microphone attached to the patient chin measured acoustic effects recorded with the sample rate set to 44100 Hz in Cool Edit Pro software.

Nightly video motion measurements were possible due to setting up black/white CCD (Charge Coupled Device) camera with additional kit of nine infrared diodes which role was to illuminate the research area.

2.2 Heart rate variability and respiratory wave

The ECG recordings were used to acquire electrocardiogram-derived respiratory (EDR) and the pattern of heart rate variability (HRV) in dependence of time domain. The typical tachogram and its main parameters were calculated: RMSSD, SDANN. The square root of the mean squared differences of successive NN intervals (RMSSD) calculated over 2.5 min and the standard deviation of the average NN interval calculated

over ten minutes periods (SDANN) represented short-time and long-time variability respectively.

The respiratory signal (EDR) was calculated with cubic splines within the detected QRS area, based on RS amplitude, measured as the difference between the minimum of the S and maximum of the R waves (fig. 1):

$amp(i) = R_{amp}(i) - S_{amp}(i)$, i=1, 2, . . . , n. [2].

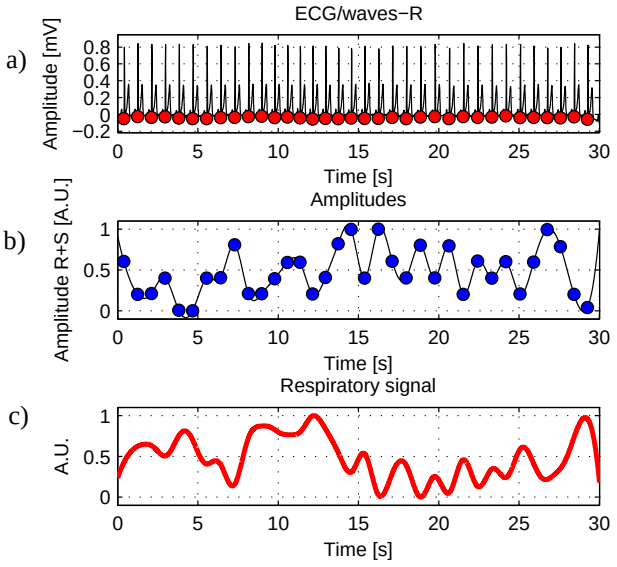

Figure 1. a) ECG removal of baseline b) RS amplitude c) respiratory signal from a subject breathing at 26 bpm.

2.3. Brain waves decomposition

Analysis of the electroencephalographic signal consisted in basic brain waves decomposition into stochastic time-frequency dictionaries of Gabor functions $G = \{g_1, g_2, ..., g_n\}$, where $\|g_i\| = 1$ [3]. For that aim free MP4 application proposed by Ircha and Durka [4] was used. This software is based on the iterative method of Matching Pursuit (MP) [5]. First, the waveform g_{γ_0} which creates a maximal scalar product with the signal, is selected from the dictionary. Thus the fitting to the signal is most significant. In each successive step, the analytic function g_{γ_n} (pattern) is made running along the analyzed signal $R^n x$, yielding as a result the correlation and residual functions. The best matching pattern and the corresponding time distribution of pattern-to-signal likelihood are adopted as decomposition coefficients, while the residual function is subject for further decomposition. After n steps of decomposition, the signal is expressed as a convolution of n analytic signals weighted by the (time-pattern) decomposition coefficients and the residual signal not sufficiently well fitting to any of the dictionary component. These operations are presented below by the following set of equations [6]:

$$\begin{cases} R^0 x = x \\ R^n x = < R^n x, g_{\gamma_n} > g_{\gamma_n} + R^{n+1} \\ g_{\gamma_n} = \arg\max_{g_{\gamma_i} \in G} | < R^n x, g_{\gamma_n} > | \end{cases}$$

When the particular time-frequency waveforms have been fitted to the analyzed signal, the procedure is convergent to x:

$$x = \sum_{n=0}^{\infty} < R^n x, g_{\gamma_n} > g_{\gamma_n}$$

Waveforms $g_\gamma(t)$ are generated by translating (u), scaling (s) and modulating window function $g(t)$:

$$g_\gamma(t) = \frac{1}{\sqrt{s}} g\left(\frac{t-u}{s}\right) e^{i2\pi ft}$$

$$g_\gamma(t) = K(\gamma, \phi) e^{-\pi\left(\frac{t-u}{s}\right)^2} \sin(2\pi f(t-u) + \phi))$$

where:

$K(\gamma, \phi)$ – normalizing factor such that $\|g(\gamma, \phi)\| = 1$

ϕ – phase

After the MP decomposition, each sample of the EEG signal in a given time period of 30 seconds was verified for matching the time range of any atoms corresponding to exact wave. Then all samples which satisfied this criterion were totalized and the percentage contributions depending on time were prepared for each wave.

2.4. Acoustic effects analysis

Snoring is produced in the vocal tract, similarly to speech. Thanks to that analogy, existing techniques for speech analysis have been applied to evaluate snoring sounds.

The transformation of data from the time domain to the frequency domain was performed by the Short-Time Fourier transform algorithm implemented in the Matlab programming environment. Sampling frequency of the analog-to-digital converter (44100 Hz) determines the maximum time duration of the sample. Frequency range of 12 kHz can completely describe the snoring phenomenon. Snoring sounds were analyzed using the short-time Fourier transform (STFT) to determine the frequency and content of local sections of the samples. It can be described using the following equation [7]:

$$STFT_x^T = X(\tau, f) = \int_{-\infty}^{\infty} x(t) w(t-\tau) e^{-i2\pi ft} dt$$

where $w(t)$ is the window function, commonly a

Hamming window (width N = 353 samples), centered around zero, and $x(t)$ is the signal to be transformed. Essentially $X(\tau, f)$ is the Fourier Transform of $x(t)\cdot w(t-\tau)$, a complex function representing the phase and magnitude of the signal over time and frequency.

Time variation of the frequency spectrum is calculated by dividing the analyzed signal into short, overlapping segments. Signal in 10ms segments becomes stationary, so short time Fourier transform can be performed. After raising the resulting spectrum to the second power these segments can be combined. Time variation of the frequency spectrum is defined as square module of STFT [4, 5]. It can be described using the following equation:

$$G_x(t, f) = \left|STFT_x = (t, f)\right|^2$$

The STFT is a complete description of the signal and it is an important procedure for further analysis.

2.5. Motion index

Quantitative evaluation of the movements activity during nightlong sleep were performed by means of processing the absolute value of difference images from the consecutive video frames at 1 sec. intervals in respect to the changeable in time background signal [8].

Firstly, the relationship between all pixels mean brightness sum (y) in dependence of sleep time for obtained difference images was calculated. This operation yields supportive signal (ss) representing the noise level by local minima of the signal y in time window $2d$:

$$ss(i) = \min(y(i-d : i+d))$$

To estimate movements activity of the human body the percentage contribution of pixels with ss overthreshold brightness was calculated over 1s periods. Motion index (MI) defined in that way reveals both the value and the frequency of the patient movements during sleep.

3. Results

Complete quantitative analysis of nightlong sleep was made for all volunteers participated in this study. In order to characterize the sleep during its various stages, based on ECG, motion, respiration and acoustic methods we calculated several specific parameters: RMSSD, SDANN, motion index MI, snoring index SI and breathing index BI. These parameters were calculated for periods of at least 20 minutes during deep sleep with presence of delta waves (tab. 1) and for periods after deep sleep stage determined by absence of delta waves. Motion index was integrated whereas other parameters were averaged in those chosen intervals for each subject.

Table 1. Sleep quantitative analysis during deep sleep (delta waves).

Parameters/ Patients	1	2	3	4	5	6	7
RMSSD	52.2	173.0	12	10.3	122.3	88.6	35.7
Std RMSSD	12.6	44.6	1.5	0.7	16.7	4.8	11.1
SDANN	14.2	13.7	7.0	2.6	10.2	9.7	3.3
Std SDANN	4.7	7.2	9.2	3.6	14.5	15.6	1.4
MI	8.5	0	0.9	3.2	6.9	0	0
Snoring events/min	none	none	16, more than 65dB	17, 50-65dB	none	none	none
Breathing events/min	19	15	16	17	20	18	19

Joint analysis of different modalities of biosignals recorded during the whole sleep period yields several observations and statements. Figure 2 presents the relation of ECG-derived short-time HRV parameter RMSSD and motion index. Figure 3 displays the example of relation of delta waves contribution percentage and motion index MI during nightlong sleep. Figure 4 presents the respiratory signal calculated with use of two methods: acoustic analysis and EDR. Comparison of the breath signal calculated by these methods indicates their equivalence in the assessment of breath during sleep.

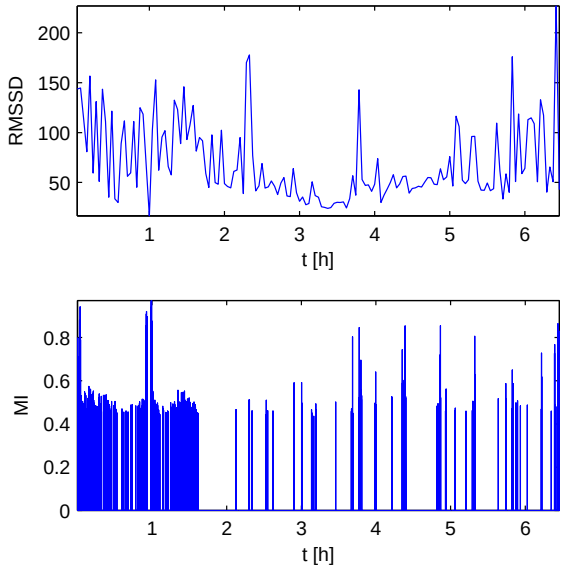

Figure 2. Presentation of RMSSD and MI parameters in dependence of whole sleep time.

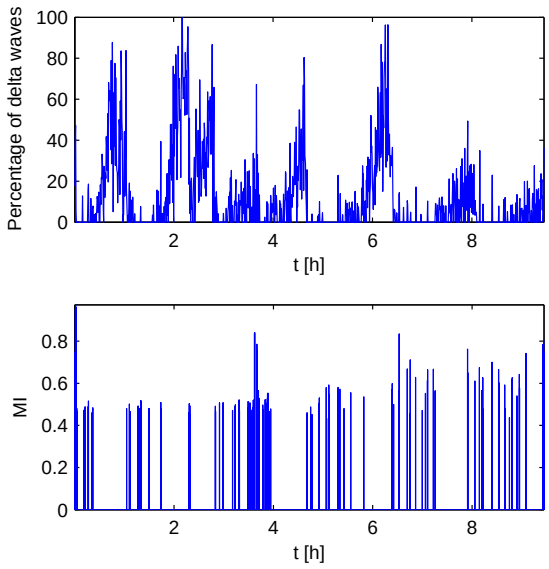

Figure 3. Correlation of delta waves and MI value during the whole sleep time.

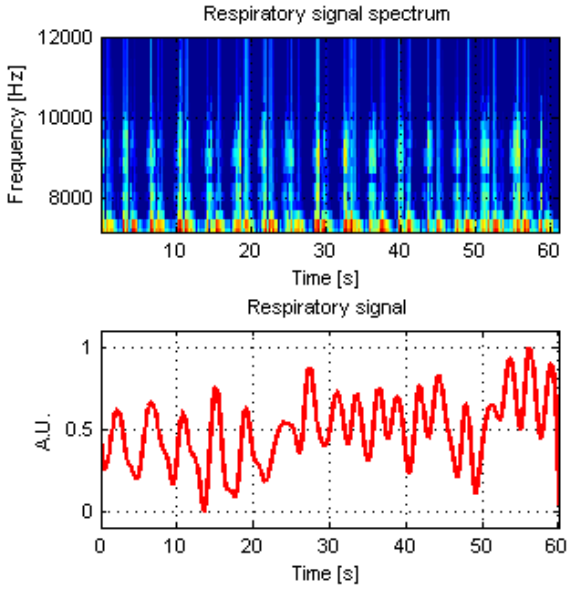

Figure 4. Correlation of sound-derived respiratory and EDR signals from a subject breathing at 18 bpm during deep sleep stage (delta waves).

4. Discussion

In the study several methods were presented and few basic parameters sufficient to sleep evaluation were proposed. Analysis of RMSSD and SDANN during deep sleep and non-delta waves episodes revealed inter-subject variability as well as variability in time of the same patient. Significant negative correlation between body movements amount and percentage contribution of delta waves could be seen.

Acoustic methods and EDR are very important in identifying sleep apnea and other abnormalities during sleep. Thanks to a complete acoustic analysis we were able to observe that during the deep stages of sleep breathing is steadier then in any other period.

Quantitative sleep analysis shows significantly lower RMSDD parameter values during and after the deep sleep stages for subjects presenting measureable snoring events.

In authors' opinion the proposed multimodal home-care nightlong sleep analysis system is not equivalent to the standard polysomnogram, however is sufficiently accurate for identification of human state and evaluation of nightlong sleep quality.

Acknowledgements

Scientific work supported by the Polish State Committee for Scientific Research resources in years 2009-2012 as a research project No. N N518 426736.

References

[1] Iber C, Ancoli-Israel S, Chesson AL, Quan SF. The AASM manual for the scoring of sleep and associated events 2007.

[2] Langley P, Bowers EJ, Murray A. Principal Component Analysis as a tool for analyzing beat-to-beat changes in ECG features: application to ECG-Derived Respiration. IEEE transactions on biomedical engineering 2010;57.

[3] Smolen MM, Analysis of EEG acivity during sleep – brain hemisphere symmetry of twoclasses of sleep spindles. Pol J Med Phys Eng 2009;15(2):65-75.

[4] Durka PJ, Malinowska U, Szelenberger W, Wakarow A, Blinowska KJ. High resolution parametric description of slow waves sleep. Journal of Neuroscience Methods 2005; 147:15-21.

[5] Mallat S, Zhang Z. Matching Pursuit with time-frequency dictionaries. IEEE Trans Signal Process 1993;41:3397-3415.

[6] Malinowska U, Durka PJ, Blinowska KJ, Szelenberger W, Wakarow A. Micro- and macrostructure of sleep EEG. Engineering in Medicine and Biology Magazine 2006, IEEE;25:26-31.

[7] Zielinski T. Digital Signal Processing. (in Polish) Warszawa: WKiL, 2005.

[8] Smolen M, Czopek K, Augustyniak P. Sleep evaluation device for home-care. Information Technologies in Biomedicine;2:367-378.

Address for correspondence:
AGH University of Science and Technology
30 Mickiewicza Ave.
30-059 Krakow
Poland

E-mail addresses:
m-smolen@wp.pl
klaudia.czopek@gmail.com
august@agh.edu.pl