Proceedings of the 28th IEEE
EMBS Annual International Conference
New York City, USA, Aug 30-Sept 3, 2006

Signal Processing and Feature Extraction for Sleep Evaluation in Wearable Devices

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Abstract

In this paper we discuss the possibility of performing a sleep evaluation form the heart rate variability (HRV) and respiratory signals. This is particularly useful for wearable devices. The HRV and the respiration were analyzed in the frequency domain and the statistics on the spectral and cross-spectral parameters put into evidence the possibility of a sleep evaluation on their basis. Additional information can be achieved from the number of microarousals recognized in correspondence of typical modifications in the HRV signal.

1. Introduction

The great advances in nanotechnology, internet, wireless technologies, digital signal processing , textile sensors and sophisticated implantable devices gave rise to wide application of wearable devices (WD) for monitoring vital signs. Whenever and wherever those allow the remote and continuous motoring of persons in different circumstances and situations, such as diagnosis procedure, patients with both chronic respiratory and heart diseases, and even healthy people who want to have a view of their status for example during sport, stressing conditions or sleep. The social impact of the WD covers from a better possible diagnosis, due to the patient lives his daily life and is not perturbed psychologically by the hospital environment, until saving economic resources by the reduction in hospitalization costs. However, the huge amount of data produced by prolonged recordings and the increased number of sensors used in WD, needs to be properly interpreted and managed.

In this view a WD must be provided with an "intelligence" able to:

1. extract relevant features from the signal;
2. select from the signal only informative time windows and eventually transmit only those to a remote station for the interpretation;
3. provide a synthesis of the data;
4. provide a feedback to the user, especially in non medical applications, where there is not an expert for signals interpretation.

The signal processing could be carried on off-line, in real-time or by stages: this depends on the information that is necessary to process and on the approaches used for the assessment of the information.

In the present work we face the problem of providing indices on the quality of sleep in healthy subjects. It is well known that the quality of sleep has a great impact on the daily life and on the performances one can obtain at work, in sports, etc. Day time somnolence can be the cause of serious incidents.

Further, many researchers had proven how sleep deprivation or a bad quality of sleep for prolonged periods, could be related to the rise of hypertension, cardiovascular pathologies, obesity, diabetes and to a decrease in the efficiency in the immunitary system [1]. For all those reasons, an indication on the sleep quality may really constitute a good parameter for prevention also in healthy subjects, and the introduction of wearable devices, that can be used at home without the intervention of medical persons, make it reliable.

The points that will be discussed in the present paper deal with:

1. the selection of the better vital signs for monitoring sleep;
2. the information one can achieve from the recorded signals;
3. the possibility to perform sleep evaluation on the basis of the extracted features.

2. Methods

2.1.Signal selection

Sleep is a physiological condition mainly involving the Central Nervous System (CNS), and is usually studied through the EEG signal associated with EMG and EOG. The classical sleep staging, according to [2] is based on those signals, as well as the identification of other relevant events, such as microarousals, CAP sleep, etc. However it is well known that also the Autonomic Nervous System (ANS) is strongly affected by the status of the CNS and many researches testify the presence of autonomic changes related to different sleep stages [3]. The action of the ANS produces spontaneous fluctuations in the blood pressure and in the heart rate, that can be highlighted and quantified through the frequency domain analysis of the heart rate variability (HRV) signal. It was stated by numerous

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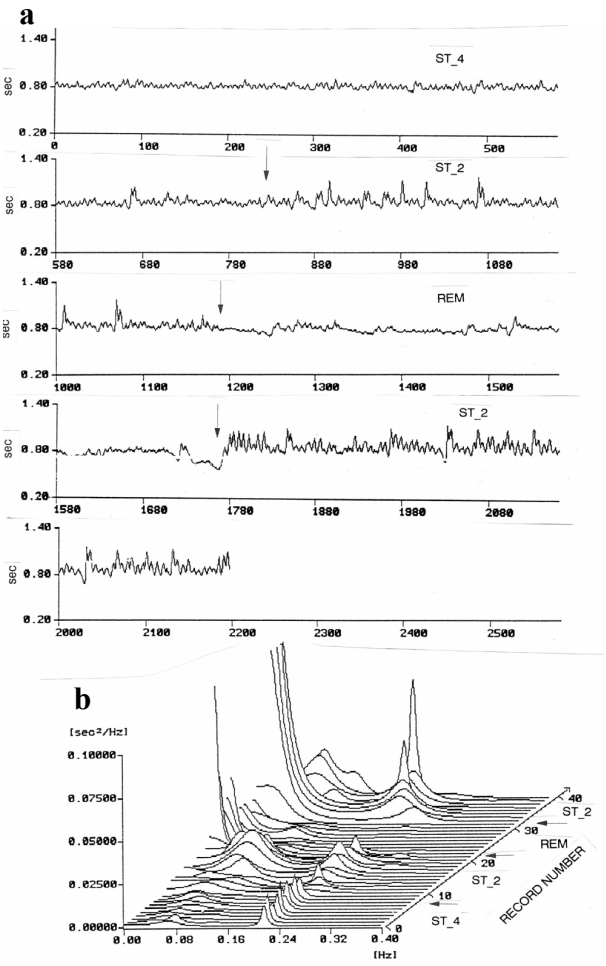

Fig.1 a) half a hour recording of HRV signal while the subject was switching between different sleep stages (the transitions are marked by arrows). b) corresponding spectra plotted in compressed array form.

researches that three main components contribute in the HRV:

- the very low frequency (VLF) component is assumed to be due to long-term regulatory mechanismis such as humoral factors, temperature, and other slow components;
- the rhythm corresponding to vasomotor waves and present in heart period and arterial pressure variabilities is defined as the low frequency (LF) component. Since it increases during sympathetic stimulation, it can be considered a marker of sympathetic activation;
- the respiratory rhythm, synchronous with the respiration rate, defined as high frequency, (HF) is generally considered a marker of vagal modulation.

A reciprocal relation do exist between the power of the LF and HF rhythms. This balance can be quantified by the LF/HF ratio [4, 5].

In [3] for example, the frequency analysis of the HRV signal was applied during sleep after the sleep staging performed through the classical procedure based on [2]. Fig.1a in effect, shows a half an hour recording of the HRV signal while the subject was switching between different sleep stages (stage 4, stage 2, REM, stage2; transitions marked by arrows). Fig.1b shows the corresponding spectra plotted in compressed array form: the LF and HF components and their ratio is strongly modulated by the sleep stages. Notice that this modulation, controlled by ANS, also afflicts the respiration signal and its rhythms. So, dealing with wearable devices, it is important to keep in mind that the recordings must present good signal to noise ratio, must be robust to movements, and their information content should not strictly depend on the correctness of the position of the sensors (the user should be able to wear the sensors by himself, without the help of an expert). From this point of view the HRV signal is much better then the EEG and thus we decided to base the sleep evaluation on its analysis. We also considered respiration behavior and the correlation levels with HRV in order to add more information and improve the sleep quality estimation.

2.2.Signal processing

Data come from the polysomnograpy of 5 normal subjects and 4 patients that underwent the examination for the control of the effects of OSA's therapy (CPAP). Notice that no statistic differences are shown in the behavior of the ANS between normal and OSA subject [6]. The registration was performed after one night of adaptation in the same conditions they used to have at home, meaning same diet, drugs and environmental condition. The polygraph was a Grass. Telefactor and the signals were recorded at a sampling rate of 100 Hz. Registrations obtained with the polysomnography were divided in the classical sleep stages (Wake, 2, 3, 4 and REM sleep) by experts who applied [2]. Then the R-R intervals were extracted from ECG using an own developed algorithm, which implements a parabolic interpolation on the R peak in order to reduce the low sampling rate error [7]. Stationary sequences of the R-R intervals (tachogram) with a length between 180 to 450 beats were identified to guarantee the correctness of the analysis through an Autoregressive model. The respiratory signal extracted form thorax movements was re-sampled in correspondence with each R peak in order to obtain the respirogram. Batch analysis mono and bivariate were applied to the tachogram and the respirogram for the calculation of the spectral and cross-spectral parameters of interest. The following spectral indexes were obtained: Total Power (TP), Very Low Frequencies power in 0.003 – 0.04 Hz band (VLF), Low Frequency (0.04 – 0.15 Hz, LF) and High Frequency (0.15 – 0.5 Hz, HF), the values are

expressed in absolute and normalized units; Low to High frequency ratio (LF/HF) was also computed. The indexes computed with the bivariate analysis were: maximum Coherence in both LF and HF bands (LFC and HFC respectively), frequency of maximum coherence at LF and HF (FMC in LF and HF) [10], power of the tachogram coherent and not coherent with respiration (CRP and NCRP), both in absolute and in percentage units. For the statistical analysis the power values were root squared (a measure equivalent to an amplitude was obtained) for making the data more suitable for the statistical analysis. We also used, as measure of sleep fragmentation, the number of microarousals They, usually detected on the EEG, produce a typical pattern on the HRV signal (Fig.2).

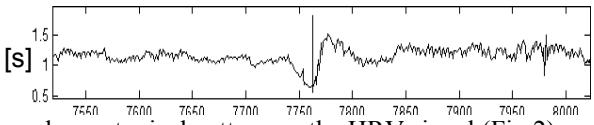

Fig2. typical pattern of an arousal correctly detected by our algorithm.

An arousal on HRV is defined as a series of HR falls and consequent rises of about 15% above a previous baseline within a time window of 10 sec. So, our algorithm scans the whole tachogram obtaining a moving-average (with a window of 20 beats) and then it evaluate when the signal falls more than 15% respect the previous mean value. When this happen it jump 10 beats later and evaluate the end of the possible arousal. If it rises more than 10% respect the initial baseline than it is recognized as an arousal and the beat of the recognized falls is considered its beginning.

2.3.Statistical Analysis

Repeated Measure ANOVA was performed to evaluate the spectral and crss-spectral indexes grouped by sleep stages. Bonferroni's post hoc test analysis was performed if significant statistical differences were found. Values of $p<0.05$ were considered statistically significant.

3. Results

Table I summarizes the results obtained form the statistical analysis of the spectral and cross-spectral parameters in the different sleep stages. Three sleep stages were considered: light sleep (L), that corresponds to stege 2; deep sleep (D), that corresponds to stages 3 and 4 grouped together; REM sleep (R). The table shows the mean values and the standard errors in the three conditions, and the significant differences ($p<0.05$) between pairs of sleep conditions are put into evidence. Three of the parameters listed in the table are able to differentiate the three stages: the percentage power in the VLF, the percentage power in the HF, and the percentage CRP (the percentage NCRP is complementary to this latter, thus is not considered). A great number of parameters is able to discriminate between REM and non REM sleep, while only a few parameters do not discriminate any sleep stage. It is worth noting how the better indices are related to measures of synchronization between HRV and respiration, while the LF do not contain enough information for discrimination.

Fig.2 shows an example of tachogram containing the typical waveforms related to microarousals. The lines marks the detection performed by the described algorithm.

4. Discussion and Conclusion

In this paper we demonstrated that some spectral and cross-spectral indexes from the cardio-respiratory system are significantly related to sleep stages and they could be the basis of a sleep evaluation instead of the more classical EEG. That is motivated by the need of using signals that can be obtained from wearable systems, which the user can wear by himself at home, without the help of anybody. Further, HRV is less sensitive to noise then EEG. The statistical analysis put into evidence that many of them seem suitable for segregating between REM and non REM sleep, while only a few can discriminate between Light and Deep sleep. Additional information can be achieved from the counting of microarousals identified on the HRV signal. The next step will be the implementation of a robust classifier for the automatic evaluation of the sleep on the basis of the selected parameters. Aim of the study is to provide a sleep profile, that is not the hypnogram (by definition obtained from EEG, EMG and EOG), but that could be of help in defining the quality of the sleep during the night and to the early identification of sleep disorders.

Table I Indexes obtained applying autoregressive mono and bivarate batch analysis on stationary sequencies from 17 polisonnographies

Index	Light Sleep	SD from	Deep Sleep	SD from	Rem Sleep	SD from
Mean RR (ms)	938.813±4.755		928.612±6.167		935.325±7.171	
r_TP	35.491±1.643	R	30.139±2.131	R	51.876±2.478	L,D
r_VLF	22.734±1.712	R	16.983±2.220	R	41.503±2.582	L,D
VLF %	50.324±1.830	R,D	41.526±2.374	R,L	67.189±2.760	L,D
VLF f. (Hz)	0.014±0.001	R	0.014±0.001	R	0.006±0.001	L,D
r_LF	11.753±0.747	R	8.990±0.968	R	17.191±1.126	L,D
LF %	18.196±1.442		16.927±1.870		17.421±2.175	
LF f. (Hz)	0.068±0.003		0.074±0.004		0.076±0.004	
r_HF	18.297±0.585		18.055±0.759		16.108±0.883	
HF %	31.480±1.352	R,D	41.550±1.754	R,L	15.394±2.040	L,D
HF f. (Hz)	0.273±0.001	R	0.275±0.002	R	0.286±0.002	L,D
LF/HF	0.702±0.109	R	0.529±0.142	R	1.634±0.165	L,D
LFN (n.u.)	0.288±0.023	R	0.214±0.030	R	0.433±0.035	L,D
HFN (n.u.)	0.648±0.024	R	0.701±0.032	R	0.397±0.037	L,D
HFC	0.929±0.012	R	0.946±0.016	R	0.766±0.019	L,D
HFC f. (Hz)	0.247±0.002		0.247±0.002		0.247±0.003	
r_CRP (ms)	19.427±0.849		18.070±1.102		19.893±1.281	
CRP %	32.141±1.114	R,D	36.904±1.445	R,L	19.226±1.680	L,D
r_NCRP (ms)	29.072±1.373	R	23.509±1.781	R	43.304±2.071	L,D
NCRP %	67.859±1.114	R,D	63.096±1.445	R,L	80.773±1.680	L,D

Data are presented as mean ± SE. r_TP : root square (r) of Total Power; r_VLF, r_LF, r_HF : r. of Very Low, Low and High Frequencies, presented in their absolute, percentuage and frequency form; LF/HF : Low to High frequency ratio; LFN, HFN : Low and High Frequencies in Normalized unit; HFC : High Frequency level of Coherence, in absolute and percentage form; r_CRP,r_NCRP: r. of Coherent/Not Coherent Respiratory Power in absolute (a) and percentage form (%). SD from: Statistically Different from Light (L), Deep (D) and REM (R) sleep stage valutated with $p<0.05$

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Acknowledgments

This paper was supported by the MyHeart Project IST 507816 of the European Community.