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Automatic Detection of sleep macrostructure based on bed sensors

M.O. Mendez, M. Matteucci, S. Cerutti, A.M. Bianchi and Juha M. Kortelainen

Abstract— **This study analyses the spectral components of the heart rate fluctuations of a new contact-less technology for sleep evaluation. Both heart beat interval (HBI) and movement activity were extracted from the multichannel ballistocardiographic (BCG) measurements, based on Emfit sensor foils placed into bed mattress. Powers spectral densities (PSD) of HBI have been compared with the ones obtained from the standard ECG during sleep stage 2. In addition, spectral features obtained from the contact-less technology and standard ECG has been used to automatically classify the sleep macrostructure through a time-varying autoregressive model and a Hidden Markov Model. Whole night recordings from six subjects were analyzed in this study. Spectral components did not show significant differences between the two measurements. Further, contactless technology achieved a total accuracy of 83 % and kappa index of 0.42, while standard ECG achieved an accuracy of 84 % and kappa index of 0.43 when compared to clinical sleep staging from polysomnography.**

I. Introduction

In the recent past, the interest in introducing new technologies for sleep evaluation has been increased. This necessity appears as an attempt to simplify the time consuming procedure required from clinicians and to provide the possibility of assessing sleep evaluation in the general population for screening purposes. The usual practice in sleep medicine is to perform the sleep staging procedure through the visual scoring of the polysomnography (PSG). PSG includes the recording of many signals. Electroencephalography (EEG), electromyography (EMG), electrooculagram (EOG) and respiration are some examples. The recording takes place during the whole duration of a night in a specialized sleep centre and allows the evaluation of the sleep quality [1] and the diagnosis of sleep disorders [2]. However, PSG presents some drawbacks; among them we can cite the necessity of dedicated equipment, dedicated sleep centers and specialized and trained personnel. Then the sleep diagnosis often requires long waiting lists and is not useful for screening purposes on the general population. So, the development of new and accessible methodologies to evaluate sleep in different environments out hospitals could be only of benefit. Some studies have observed that some peripheral measures, such as Heart Rate Variability (HRV), blood pressure and respiratory activity, present specific characteristics in the different sleep stages [3]. In order to capture these features, it is necessary to use proper mathematical approaches which can lead to a reliable classification. Further, new technologies for non obtrusive signal recording have been developed. Ballistocardiographic (BCG) measurement can be done with sensors integrated into bed mattress, and HRV can be estimated from the extracted heart beat interval (HBI) signal [4]. Non-contact bed sensors are easy to use, as they do not require placement of sensors on the subject's body, and enable sleep monitoring also at home.

The aim of the current study is to analyze the reliability of the heart rate fluctuations (HBI) obtained from bed sensors prepared at VTT to classify the sleep macrostructure. This analysis is done by: 1) assessing the classical spectral components of the standard HRV and the correlated HBI extracted from the system developed at VTT (bed sensor) and 2) evaluating the sleep stages by an automatic classifier developed at the Politecnico of Milano, this classifier is based on a time varying autoregressive model (feature extractor) and a Hidden Markov Model (HMM) (classifier). As a second step, the movements detected from the same bed sensor were included in the classification process to observe their discriminative power between WAKE and REM stages. The automatic classifier was previously developed using data presented in protocol 1 as training set and applied to protocol 2 data.

II. Methodology

A. Protocol 1

17 standard ECG recordings of healthy subjects were used to develop the classifier system. Age of the subjects ranges between 40 and 50 years. Subjects had a body mass index less than 29Kg/m^2. All subjects had AHIs (apnea hypopnea index) of zero and were drug-free. Each subject participated with one night recording. Mean sleep efficiency (total sleep time/time in bed) was 85%. All experiments were conducted at the sleep clinic of the San Raffaele Hospital. Sleep evaluation was done by expert personnel and assessed following the standard PSG recommendations [1]. The acquisition system was a Heritage Digital PSG Grass Telefactor and all data was acquired with 128 Hz as sampling rate. Polysomnographic data were scored in epochs of 30 seconds each. The hypnogram was obtained as a result

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M. O. Mendez is with the Politecnico di Milano, Milano, IT 20133 Italia (phone: 0039 02 3399 3322; fax: 0039 02 3399 3360; e-mail: martin.mendez@ biomed.polimi.it).

A. M. Bianchi is with the Politecnico di Milano, Milano, IT 20133 Italia (e-mail: annamaria.bianchi@polimi.it).

S. Cerutti is with the Politecnico di Milano, Milano, IT 20133 Italia (e-mail: sergio.cerutti@polimi.it).

M. Matteucci is with the Politecnico di Milano, Milano, IT 20133 Italia (e-mail: matteucc@elet.polimi.it).

J. M. Kortelainen is with the Machine Vision, VTT Technical Research Center of Finland, Tampere, Finland (e-mail: juha.m.kortelainen@vtt.fi).

of this procedure. Only hypnogram and ECG signal were used to develop the classifier system.

From the ECG, R peaks were detected. Distances between consecutive R peaks were evaluated (RRI). Some R peaks were misdetected and some ectopic beats were found in the ECG. Then, those erroneous beats were manually corrected and the new tachogram recalculated.

B. Protocol 2

Sleep recordings from 6 female subjects was performed at the sleep laboratory of Finnish Institute of Occupational Health. The sleep scoring was done by expert personnel based on standard polysomnographic recordings. RRI was calculated from the ECG signal with the Somnologica software. In addition, the multichannel BCG was recorded with the bed Emfit sensor. Both the heart beat interval (HBI), with coverage of 88 %, and movement activity were extracted from the bed sensor signals. This study compares the sleep classification based on HRV obtained from the standard ECG and with that obtained from the bed sensor.

Bed sensor development was done by VTT in co-operation with the foil sensor manufacturer Emfit Ltd. Previously, a large sensor with altogether 160 electrodes has been presented to enable sleep posture and movement analysis with good spatial resolution [4]. However, for the extraction of heart beat interval and movement activity, the number of sensors could be reduced, by combining the selected neighborhood electrodes and removing most of the sensor area. This more cost-efficient design had 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.

An algorithm called *Adaptive Cepstrum method* was previously presented for the extraction of HBI from bed sensor signals. The method firstly selects the time window including two consequent heart beats, and then calculates the cepstrum with FFT. The selection of the time window was done with adaptive method: firstly calculating filtered pulse train of heart beat signal and then selecting time window for each pair of consequent heart beats.

A new cepstrum method was applied in this study for the HBI extraction. Firstly, multiple spectra estimates are calculated by looping over different time window lengths, and the final cepstrum is composed from these spectra. The Sliding Fourier Transform algorithm (SDFT) is applied to update each spectrum efficiently [5].

The main benefit of the new SDFT based method is better robustness for the BCG signal variation, which may arise between subjects, different sleep postures or by different sensor assembly. New algorithm has also more straightforward implementation. The drawback of the new method is higher processing need in comparison with the adaptive method. Nevertheless, we have implemented the real-time calculation separately for both standard PC and a DSP (model TMS320F2833 by Texas Instruments).

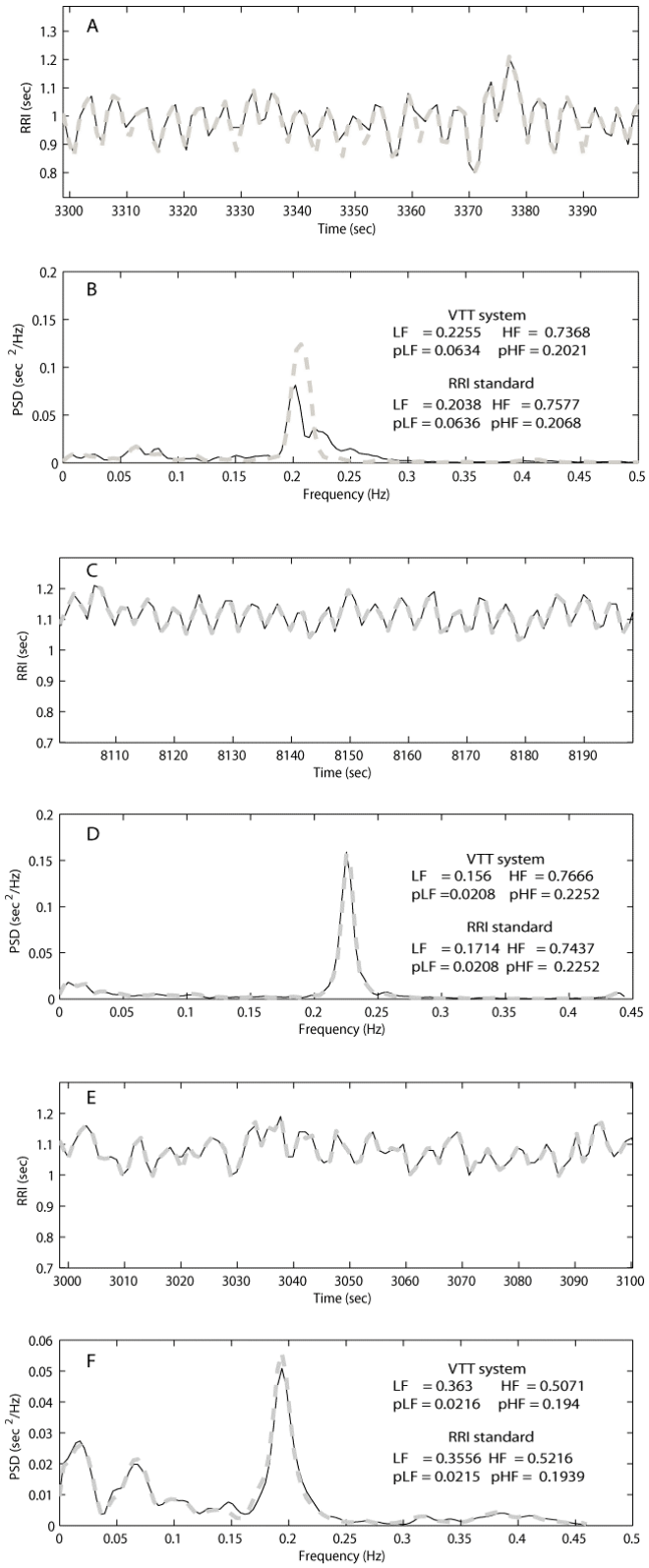

Figure 1. Examples of heart rate fluctuations and their spectra from standard ECG (RRI) and VTT system (HBI) during sleep stage 2. Thin black line represents HBI while bold gray line is RRI. LF and HF are low and high spectral powers normalized respect to the total power. pLF and pHF represents their respective peaks at the maximum power.

C. Powers Spectral Density (PSD) Assessment

In order to test the similarity between the PSD of the heart rate fluctuations obtained from the standard ECG (RRI) and bed sensor (HBI), 12 segments (two belonging to each recording) were chosen randomly from recordings of the Protocol 2 during sleep stage 2. The segments were taken such that RRI and HBI belonged to the same time interval. From each estimated spectrum [6], the following spectral indexes were computed:

- TP; Total Power (0.003–0.6 Hz)
- LF; low-frequency component (0.02–0.15 Hz)
- HF; high-frequency component (0.15–0.5 Hz)
- pLF; frequency peak to the maximum power in the low frequency band.
- pHF; frequency peak to the maximum power in the high frequency band.

Mean and standard deviation of the spectral indexes were computed for the 12 segments. Table I shows the results obtained. To quantify statistical differences, t-test was used between RRI and HBI indexes. t-test did not show any statistical differences between RRI and HBI Indexes. Then we can conclude that these measures are tie similar.

Table 1. Power spectral indexes of heart rate fluctuations obtained from standard ECG and bed sensor.

Index	HBI	RRI
LF	0.2717±0.10	0.2770±0.12
HF	0.6360±0.14	0.6317±0.17
pLF	0.0458±0.03	0.0414±0.02
pHF	0.2702±0.07	0.2705±0.08

LF and HF are low and high frequency components respectively normalized with the total power. pLF and pHF represent the frequency of the maximum peak of each component. t-test did not show statistical differences.

Fig. 1 shows segments of RRI and HBI during sleep stage 2 as well as their respective PSDs. One can observe, in Fig. 1A, that HBI roughly follows RRI. If the PSD is analyzed (Fig 1B), spectra are quite similar. This is also true for LF and HF. Figs. 1 C-D show that HBI is completely overlapping to RRI in time and power. Figs. 1 E-F show that quite good overlapping is present also in case of low frequency fluctuations.

D. Comparison based on application

In order to compare the usability, of HBI with respect to RRI in a possible application related to sleep evaluation, features extracted from HBI or RRI were used to feed an automatic macrostructure classifier.

1) *Feature Extraction:* a Time-Variant Autoregressive Model (TVAM) was used to calculate, on a beat-to-beat base, the spectral components of the RR series [7]. The spectral components were used to obtain the feature subset to separate the different sleep stages: WAKE-NREM-REM. In this study the forgetting factor was chosen to be 0.98 and the model order was equal to 8. The power spectrum was computed from the autoregressive parameters for each time series. Therefore, from each beat-by-beat estimated spectra, the following time variant spectral indexes were computed: TP; Total Power (0.003 - 0.5 Hz), VLF; very low frequency component (0.003 - 0.04 Hz), LF; low frequency component (0.04 - 0.15 Hz), HF; high frequency component (0.15 - 0.5 Hz), LF/HF; Low to high frequency components ratio. In addition to the classical spectral indexes, two new indexes were extracted from the model parameters. The modulus and phase of the representative pole in the high frequency band were extracted [8]. Spectral features were normalized respect to the total power for each recording. These features where transformed by a logarithm function in order to obtain a Gaussian distribution. Modulus was transformed by square root. All the beat-by-beat normalized and transformed features from each recording where converted to epochs of 30 s resolution by evaluating the mean value. Features were quantized to values ranging from 1 to 10. Hidden Markov Model [9] was used to evaluate WAKE-NREM and REM stages based on the bivariate probability distribution of VLF and pole modulus.

2) *Training and Testing Process:* The 17 recordings coming from the protocol 1 were used to evaluate the elements of the emission and transition matrixes of the HMM. Only VLF-Pole modulus couple was used to evaluate WAKE-NREM-REM classification. The test classification process was done by applying Viterbi decoding algorithm (the best path of states that describes the observed physiological parameters) [9] to the bivariate probability distribution (VLF-Pole modulus) to each recording from Protocol 2. recordings.

Table II. Mean and standard deviation of accuracy and agreement measure of sleep staging obtained from HBI and RR intervals.

	Heart Rate Fluctuations						
	ACC	**Kappa**	**SeHMM**	**SeHyp**	**%Wake**	**%REM**	**%NREM**
bed sensor	0.8324±0.06	0.4193±0.18	0.97127±0.02	0.8965±0.04	0.1034±0.04	0.1785±0.06	0.7179±0.02
ECG	0.85891±0.03	0.42808±0.23	0.9488±0.06	0.8950±0.05	0.10495±0.05	0.1783±0.06	0.7166±0.02
	Heart Rate Fluctuations and Movements						
	ACC	**Kappa**	**SeHMM**	**SeHyp**	**%Wake**	**%REM**	**%NREM**
bed sensor	0.83466±0.05	0.4583±0.13	0.9198±0.03	0.8965±0.04	0.1034±0.04	0.1785±0.06	0.7179±0.02
ECG	0.8585±0.05	0.4700±0.13	0.9002±0.03	0.8950±0.04	0.1049±0.04	0.1783±0.06	0.7166±0.02

ACC means general accuracy, kappa is kappa index, SeHMM is the sleep efficiency obtained by the automatic system, Sehyp represent the sleep efficiency obtained from the standard hypnogram. % Wake, %REM and %NREM are the percentage for wake, REM and NREM epochs found in all recordings.

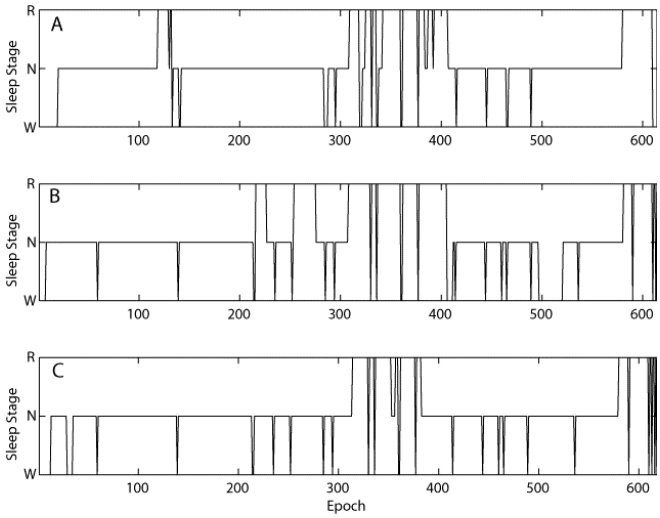

Figure 2. Single night example of a hypnogram. The top plot shows the hypnogram evaluated by an expert based on PSG but simplified to 3 stages. Middle plot shows the scoring using heart rate fluctuations and movements (coming from VTT system). Bottom panel illustrate the scoring obtained using heart rate fluctuations (form standard ECG) and movements (coming from VTT system). R is REM, NR represents non REM and W is wake.

Sleep Efficiency was computed from the sequence of stages given by HMM. This is defined as the number of epochs in REM-NREM divided by the total number of epochs. Finally, in order verify if the considering also movements (obtained from the bed sensor) could improve the classification performance; epochs with movements were considerate as WAKE stages and again the classification performance and the sleep efficiency were recomputed.

This procedure was done for RR series coming from standard ECG signal (RRI) and from heart rate fluctuations obtained by the bed sensor (HBI). The classification algorithm is an extension of the system presented in [6] but for 3 stages and bivariate probability distributions.

III. RESULTS

Sleep macrostructure classification based only on heart rate fluctuations was done by an automatic system. Sleep classification with features coming from standard ECG and bed sensor have been compared. From the top to the bottom Fig. 2 shows: the simplified hypnogram obtained by an expert based on PSG data, sleep profile computed using HBI and movements, and sleep profile calculated from RRI and movements. One can observe that the sleep profiles obtained with the automatic system with eirther RRI or HBI are similar to the hypnogram given by the expert, however some differences appear. Sleep profile obtained from HBI seems to overestimate REM and wake while sleep profile obtained from RRI seems to underestimate REM. However, the main sleep macrostructure is quite maintained. This recording had a kappa index [10] around 0.42 and accuracy of 80. Table II shows mean and standard deviation of the classification measures obtained with the automatic system with features obtained from bed sensor and standard ECG from the database defined in protocol 2. The first part of the table shows the classification performance using only heart rate fluctuations. All the results obtained for RRI and HBI are similar. When movements obtained from the bed sensor where included in the classification process, as wake stages, the results were improved.

IV. CONCLUSIONS

Heart rate fluctuations coming from a novel acquisition system (HBI) has been compared with the standard RRI. This comparison was carried out by analyzing the time and frequency domain analysis of both measurements.

Further, RRI and HBI spectral parameters were used to classify automatically the sleep stages. Our main observations are: 1) the spectral characteristics of RRI and HBI are similar, 2) the classification performance of the automatic system using features coming from HBI or RRI was similar, and 3) movements coming from bed sensor seem to give valuable improvement to detect wake stages. The performances of the presented systems are comparable to other ones found in literature [10]. It is worth noting that the same classification performance, kappa = 0.46, was obtained using indifferently signals coming from standard ECG or from bed sensor.

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