Sleep Staging Based on Signals Acquired Through Bed Sensor

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***Abstract*—We describe a system for the evaluation of the sleep macrostructure on the basis of Emfit sensor foils placed into bed mattress and of advanced signal processing. The signals on which the analysis is based are heart-beat interval (HBI) and movement activity obtained from the bed sensor, the relevant features and parameters obtained through a time-variant autoregressive model (TVAM) used as feature extractor, and the classification obtained through a hidden Markov model (HMM). Parameters coming from the joint probability of the HBI features were used as input to a HMM, while movement features are used for wake period detection. A total of 18 recordings from healthy subjects, including also reference polysomnography, were used for the validation of the system. When compared to wake–nonrapid-eye-movement (NREM)–REM classification provided by experts, the described system achieved a total accuracy of $79 \pm 9\%$ and a kappa index of 0.43 ± 0.17 with only two HBI features and one movement parameter, and a total accuracy of $79 \pm 10\%$ and a kappa index of 0.44 ± 0.19 with three HBI features and one movement parameter. These results suggest that the combination of HBI and movement features could be a suitable alternative for sleep staging with the advantage of low cost and simplicity.**

***Index Terms*—Automatic classification from vital signs, human health screening, no-contact sensors, pattern classification, signal processing.**

I. Introduction

DURING the past years, the importance of sleep evaluation has increased due to a considerable number of pathologies that implies sleep disorders. Furthermore, the performance of many basic activities in the normal life, such as memorization, learning, productivity, and concentration, are closely connected to a good sleep quality [1]–[4]. In addition to the sociological and physiological consequences produced by low sleep quality, the sleep evaluation is a time-consuming task that has to be done by expert clinicians. This evaluation consists in defining different sleep stages through visual scoring of the polysomnography (PSG). PSG includes the recording of many signals such as EEG, electromyography (EMG), ECG, electrooculagram (EOG), pulse oximetry, and respiration. With the PSG procedure, it is possible to observe sleep efficiency, sleep quality [1], and sleep disorders [4]. Although the PSG is an accurate procedure, some inconveniences rise; for instance, we can cite the need for specific equipment, dedicated sleep centers and specialized and trained personnel. All these PSG requirements have generated underestimation of the sleep disorders and low accessibility for the general population. Thus, the development of unattended and portable monitoring systems could be of great help. However, until a few years ago, the sleep evaluation was available only in sleep centers; this situation was mainly generated by technological limitations. Nowadays, these limitations have been partially overcome with the introduction of new technologies that allow the acquisition of physiological signals with high precision in different environments [5]–[8].

In sleep medicine, the standard practice is to divide the sleep time in epochs with length of 30 s, and based on the EEG, EOG, and EMG behavior each epoch can be scored as stages 1, 2, 3, 4, and rapid eye movement (REM) and wake. The representing plot of the tagged epochs is called hypnogram. Generally stages 1–4 are merged in one stage named NREM (non-REM). The intrinsic dynamic of NREM–REM–wake stages (here macrostructure) carries valuable information about sleep quality since this is highly modified during sleep disorders. Thus, a system able to evaluate this structure over sleep time from signals of simple measurement can contribute to fast and accurate sleep screening.

ECG can be recorded at home more efficiently than most of the PSG signals. ECG has been applied for sleep modeling in many studies by calculating first the heart rate variability (HRV) out of R-R intervals (ECG RRIs), and then analyzing the different spectral components of HRV [9]–[11]. HRV also gives information about the cardiovascular and respiratory functions during sleep [9], [10]. These interesting characteristics of HRV can be analyzed with automatic procedures [12], and thus, the HRV analysis can constitute the basis for sleep evaluation at home. New nonintrusive systems and procedures to study the cardiorespiratory behavior during sleep have been published [13], [14]. Ballistocardiographic (BCG) signal can be recorded unobtrusively through a pressure-sensitive sensor integrated into the bed mattress, and sleep analysis can be done, e.g., with one-channel static charge-sensitive-bed (SCSB) method by Alihanka *et al.*, which is based on the extracted body movements, respiration and heart-beat signals [15]. Accuracy of the extraction of the heart-beat interval (HBI) from BCG signals can be improved

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by using multichannel bed sensor and spectral averaging [5], which enables us to make HRV-based sleep modeling with a bed sensor, using similar algorithms as in the previous studies with the standard ECG recordings [16]. A noncontact bed sensor is easy to use, as it does not require placement of sensors on the subjects body, and it enables sleep monitoring also at home. In addition to the analysis of the HRV obtained from the HBI, the bed sensor can also measure information related to body movements and respiration [5].

The movement actigraphy measurement have been broadly used as a portable monitoring method to evaluate the sleep quality and this procedure is well accepted in clinics [17]. However, the movement actigraphy method presents typically an overestimation of the sleep time. This occurs because the subject can be awake during the bed time but without any motion [17].

This paper describes a system to automatically recognize the sleep macrostructure from HBI and body movement signals, which are calculated from multichannel BCG recordings from a bed sensor. The sleep stages are automatically detected using a TVAM as feature extractor, and a hidden Markov model (HMM) as probabilistic classifier. First, this study compares the HRV analysis between the bed sensor BCG and standard ECG recordings, and second, the automatic sleep classification is compared with the expert visual sleep scoring of PSG recordings.

II. Material and Methods

A. Bed Sensor

The bed sensor was composed of multiple pressure-sensitive Emfit foil electrodes. Emfit is a porous polypropylene foil including large internal voids that are permanently electrically charged. When thickness of the foil is altered by a change in the pressing force, the strength of the internal electrical field varies and generates charge on the outer surfaces. Conducting electrodes on the opposite surfaces are used for measuring the cumulated charge. The laminated structure includes both Emfit foil and several insulating layers using printed electrodes for signal conducting and shielding [18]. Sensor development was done by VTT in cooperation with the sensor manufacturer Emfit Ltd. Overall sensor area was 1 m $\times$ 2 m with 160 electrodes [5], and the Emfit foil matrix was placed in between two foam plastic mattress resulting with total thickness of 4 cm. This sensor mattress was then placed below the normal foam plastic mattress having thickness of 12 cm. High spatial resolution of bed sensor matrix is needed for both sleep posture detection and body- and limb-movement analysis. For example, the sleep posture classified into four groups, supine, left side, right side, and prostrate, could be detected correctly for 92% of cases with the bed sensor, having reference posture measurement from inclinometer sensor in the thorax position [19]. However, for the heart-beat extraction, a reduced number of electrodes and a small sensor area can be used.

We made a comparison between different number and shape of electrodes to find the optimum between reliability and complexity of the sensor. The selected cost-efficient design has eight lateral-direction electrodes with size of 7 cm $\times$ 34 cm each, placed in two columns and four rows, and covering overall area of 72 cm $\times$ 72 cm under the middle body of the subject. This reconfiguration of the bed sensor electrodes was tested afterward for the collected data of the original 160-channel bed sensor, by averaging the neighborhood channel signals to compose a signal from a larger, combined electrode area. The applied A/D converter, i.e., switched integrating IC DDC112 from Texas Instruments, integrates each sample value during the whole sampling period, hence causing no time delays between different measuring channels. Therefore, we could directly sum up the neighboring measuring channels afterward, to present the signal from a combination of electrodes.

B. HBI Extraction From Bed Sensor Signals

Bed sensor measures BCG signals with pressure sensitive Emfit foils. The sampling rate of the BCG signal is 50 Hz for each measurement channel. In the most applications using BCG for sleep analysis, the signal will be exploited for the average heart rate, by counting up the heart beats based on the filtered heart pulse estimator. However, it is very difficult to extract individual HBIs from the BCG signal, because of high variance in the shape of the BCG signal, when the accuracy should be comparable with the reference ECG R-R peak interval. The largest markers in the BCG complex can be located by a manual tracking with the help of the ECG signal, as being most likely the minimum and maximum of the BCG signal between 0.1 and 0.25 s after the ECG R-peak. The first five markers denote the systolic deflections and the last three the diastolic deflections [20]. Ideally, the BCG HBI algorithm should be based on tracking of the location of the selected BCG complex markers, but there seems to be no solutions performing this fully automatically, yet. We have applied another principle to calculate the HBI from BCG signal, by using Fourier transform (FT) based cepstrum method [5]. Cepstrum C_x is defined in the homomorphic deconvolution theory [21]. It is the inverse FT of the logarithm of spectrum S_x:

$$S_x = F\{x\} \tag{1}$$

$$C_x = \text{real}(F^{-1}\{\log_e(|S_x|)\}). \tag{2}$$

The spectrum computed from the BCG heart-beat signal is composed of the peaks at the harmonic frequencies of the fundamental heart-beat frequency. This periodicity in the spectrum is shown as a peak value in the cepstrum located at the corresponding BCG HBI lag time value. We found out that for a nonstationary BCG signal, the optimal selection of the FT time window includes exactly the two consequent heart beats. Fig. 1 shows the BCG signal during a time period of three heart beats including two BCG HBI values to be estimated. The uppermost graph shows one measurement channel of the bed sensor. Wide gray curve shows the FT time window for the first BCG HBI period and narrow black curve shows the following period. The middle graph shows the logarithm of the spectrum and the lowermost graph shows the Cepstrum calculated for the corresponding time windows. The first BCG HBI result with gray curve is 1.14 s and the following is 0.96 s. This method benefits of multichannel BCG measurements, as

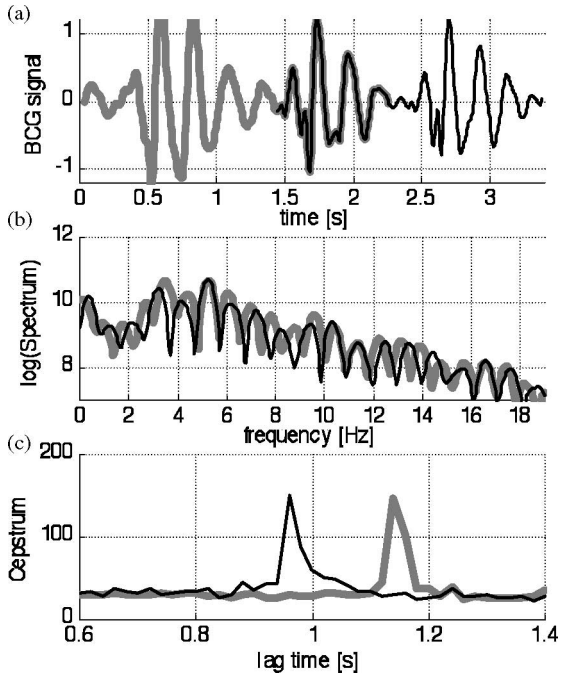

Fig. 1. Two consequent heart beat on: (a) BCG signal, and corresponding (b) spectra and (c) cepstra.

the Fourier transform can be averaged between measurement channels improving the estimation without impairing the spectral resolution. An algorithm called adaptive cepstrum method was previously presented for the extraction of HBI from the bed sensor signals [5]. The method first selects the time window including two consequent heart beats, and then calculates the cepstrum with FT. The selection of the time window was done with adaptive method: first, calculating filtered pulse train of the heart-beat signal, and then, selecting a time window for each pair of consequent heart beats. In this study, a new cepstrum method was applied for the HBI extraction. First, multiple spectra estimates are calculated by looping over different time window lengths, and the final cepstrum is composed from these spectra. The sliding discrete FT algorithm (SDFT) is applied to update each spectrum efficiently [21]. The main benefit of the new SDFT-based method is a better robustness for the BCG signal variation, which may arise between subjects, different sleep postures, or different sensor assemblies. The new algorithm has also more straightforward implementation. The drawback of the new method is a higher complexity processing as compared to the adaptive method. Nevertheless, we have implemented the real-time calculation separately both for a standard PC and for a DSP (model TMS320F2833 by Texas Instruments).

C. Movement Detection

Bed sensor measures also the movement activity, which can be applied in a similar way as the standard activity recordings for identifying the wake stage during the bed time [17]. However, it is necessary to preprocess the bed sensor activity signal by smoothing before the wake and sleep stages can be separated with a threshold analysis. The following procedure was implemented to find the best preprocessing and threshold parameters that maximized the agreement for wake and sleep scoring between the reference PSG and movement activity signal. The movement activity was calculated from the bed sensor BCG signals by first calculating the standard deviation with 4-s-long sliding time window for each sensor channel and then taking the average between all channels. This movement signal was scaled such that the 16-bit unsigned integer values for the A/D converter output equals with range from 0 to 1. The optimizing procedure begins with a threshold in the movement signal equal to zero. After that the sample-by-sample series was converted to epochs of 30 s according to the standard epoch length on which the sleep staging is based. An epoch was defined as wake if at least one sample inside the epoch was higher than the threshold, and otherwise, this epoch was defined as sleep. Then, to the new epoch-by-epoch series a median filter was applied. Different window lengths were used for median filtering, from 2 to 15 epochs. Thereafter, PSG classification was compared with each wake–sleep series after each median filter, and sensitivity, specificity, and accuracy were evaluated. This process was repeated again with thresholds from 1% until 20% of the maximum value on the movement signal with increasing steps of 1%. Fig. 2 shows the results. Here, the selected threshold was 4% and median filtering was not used.

D. Recording Protocol

Sleep recordings from nine female (age 20–54 years) shift working subjects were performed at the sleep laboratory of Finnish Institute of Occupational Health. Each subject participated with two recordings and these were obtained after baseline night, once during daytime sleep after a night shift of work and once during nighttime sleep. Signals were scored using standard R&K criteria on EEG, EOG, and EMG [1]. The sleep scoring was done by expert personnel based on standard polysomnographic recordings. RRIs were computed from the standard ECG signal with the Somnologica software. In addition, the multichannel BCG was recorded with the bed sensor using multiple Emfit electrodes, as described in the previous Section II-A. Both the HBI, with coverage of 88%, and movement activity were extracted from the bed sensor signals with the method described in Section II-B.

E. Feature Set

Since HBI as well as RRI become nonstationary for a long-term sleep recording, it is important to select methods, which are robust for such variability in the signal properties during time. The time-variant autoregressive model (TVAM) is an optimum candidate to this task, since it presents interesting properties able to track the nonstationary signals [22], [23]. TVAM shifts a moving window across the data and adapts its coefficients at each signal sample. The use of a proper forgetting factor allows to set a higher weight for the most recent data and to decrease the weight for the old data when updating the model parameters. This characteristic allows TVAM to analyze time series with variable temporal behaviors.

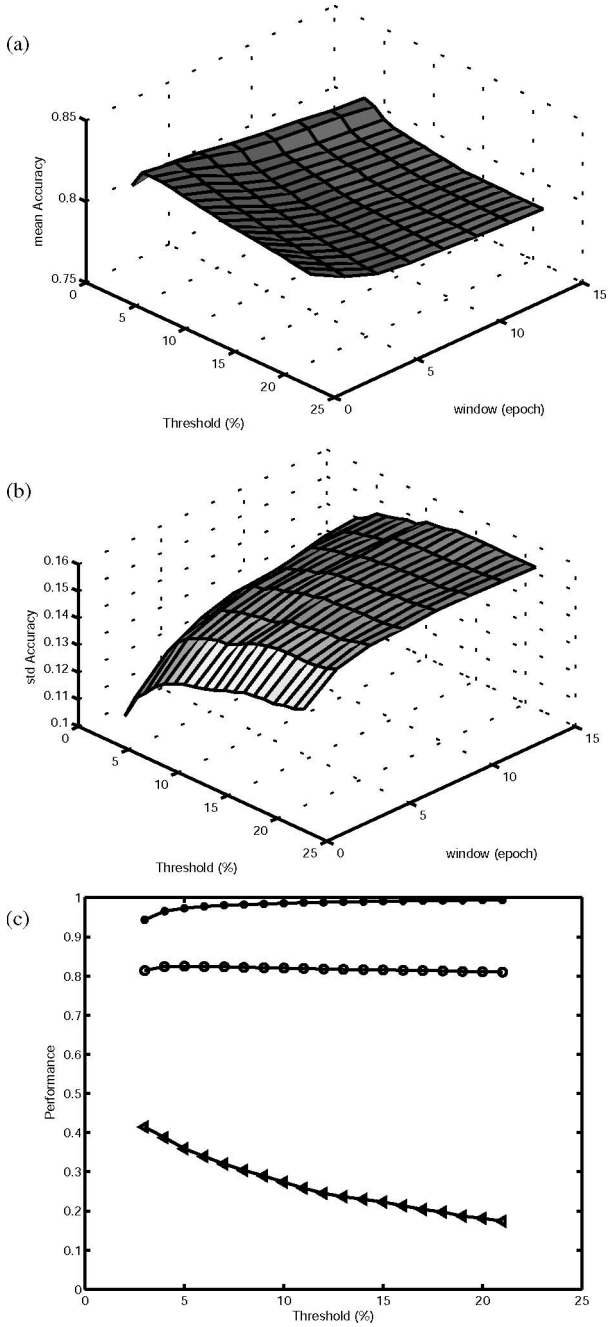

Fig. 2. [(a)–(c)] Threshold selection to detect the wake stages from movement signal (see text for details). (c) Circle represents accuracy, point represents sensitivity, and triangle represents specificity.

The HRV spectrum was directly computed from the obtained time-variant autoregressive parameters [11], [22] on a beat-by-beat basis. A model order of eight and a forgetting factor of 0.98 were used for all sleep recordings. The following beat-by-beat features were obtained from the time-variant HRV spectrum:

1) total power—TP (0.003–0.5 Hz);
2) very low frequency power—VLF (0.003–0.02 Hz);
3) low-frequency power—LF (0.02–0.15 Hz);
4) high-frequency power—HF (0.15–0.5 Hz);
5) modulus of the HF pole;
6) phase of the HF pole.

LF and HF indexes are related to the sympathovagal balance and present characteristic values at the different sleep stages. However, these sympathovagal values may be different among subjects due to the biovariability. This intersubject variability has to be eliminated in order to obtain values that can be comparable between subjects and to enable the sleep stage classification. This normalization process eliminates some inconsistencies and assures that the noise produced by the biodiversity of subjects is reduced or damped. The HRV spectral parameters (HF, LF, and VLF) were normalized beat-by-beat as the percentage power with respect to the TP. Module and phase of the HF pole were not normalized since these present values between 0–1 and 0–π, respectively. Finally, in order to establish a direct comparison of the normalized beat-by-beat features with the reference PSG-based hypnogram, all the features were resampled by averaging method to epoch-by-epoch resolution. We applied an epoch length of 30 s, which corresponds to the time window considered to evaluate the reference hypnogram.

F. Selection and Transformation of the Features

Normal sleep presents a well-defined dynamic pattern in its macrostructure, containing sequential periods of REM and NREM sleep. This cyclical process can be parametrized by models that are able to recognize the dynamic patterns in time. One of the most suitable is the HMM, which uses the pattern temporality of a time series to define the most probable state based on the history of observations [24], [25].

In order to obtain features with normal distribution, which is desirable condition for the good performance of the HMM classifier, the logarithmic transformation was used for spectral features and the square-root transformation for the modulus of the pole. Also a discretization process is needed before entering the features for the HMM model. Each transformed feature was divided into M equal values (here, $M = 10$), which range from the minimum to the maximum value of the feature. After discretization, the joint probability distribution was computed for each possible tuple of two or three features in each recording. From each joint probability distribution, a 1-D sequence of symbols was obtained to feed the HMM. The 1-D sequence of symbols v was computed applying the following code book for the bivariate case:

$$v = (o_1 * M) + o_2 \tag{3}$$

where o_1 and o_2 are the first and second discretized observations (features) that form the bivariate joint probability distribution. For the trivariate case, the sequence of symbols was obtained as follows:

$$v = (o_1 * M) + (o_2 * M) + o_3 \tag{4}$$

where o_1, o_2, and o_3 are the first, second, and third discretized observations (features) that make up the trivariate joint probability distribution

Fig. 3 shows the joint probability distributions obtained from VLF and pole observation. The red color represents wake, blue represents NREM, and green represents REM. Note that these

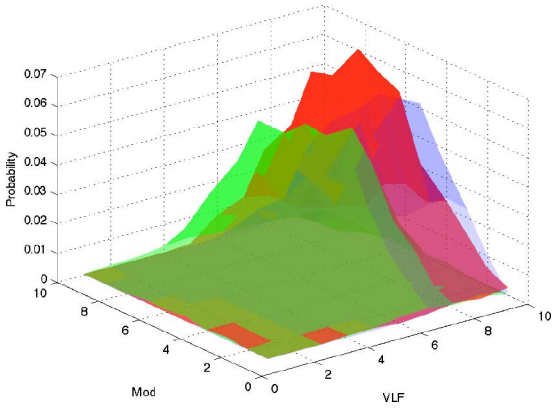

Fig. 3. Joint probability of VLF and HF pole during wake–NREM–REM. The red color represents wake, blue represents NREM, and green represents REM.

two features present interesting characteristics as related to the different sleep stages, i.e., REM presents higher values of VLF than wake and NREM, while NREM shows different values of module with respect to wake.

G. HMM—Model Selection

The learning and performance procedure was carried out from the whole database using leave-one-out cross-validation technique (LOOCV). The transition matrix was computed from the hypnograms and the emission matrix from the sequence of symbols as follows.

1) Leave the symbol sequence v and the hypnogram out of one recording from the total 18 sleep recordings.
2) Evaluate the emission matrix and transition matrix from the symbol sequences and hypnograms from the remaining recordings.
3) Decode the symbol sequence of the recording that was left out to calculate the statistical classification measures of kappa index, accuracy, sensitivity, and specificity by comparing the hypnogram and the sequence of states obtained from the HMM decoding. Please note that the hypnograms were simplified in: wake = wake and stage 1, NREM = stages 2–4, and REM.
4) Finally, again from the whole set another recording (never the same) was left out and the transition and emission matrices and the measures of classification were again evaluated.

This procedure was repeated until each recording was left out once. Finally, we obtained the mean performance of the 18 recordings. The same procedure was done for the joint probabilities composed by two and three features. The performances for all possible combinations of features were obtained.

The best performances were obtained with the following combination of features:

1) VLF—Modulus pole (bivariate model);
2) VLF—Modulus pole: TP (trivariate model).

TABLE I
MEAN AND STANDARD DEVIATION OF THE POWER SPECTRAL INDEXES OF HEART-RATE FLUCTUATIONS OBTAINED FROM STANDARD ECG AND VTT SYSTEM

Index	HBI	RRI
LF (ms^2/Hz)	0.4211± 0.15	0.4137±0.15
HF (ms^2/Hz)	0.4326± 0.21	0.4399±0.21
pLF (Hz)	0.0578±0.03	0.0580±0.04
pHF (Hz)	0.2304±0.06	0.2300±0.06

H. Sleep Profile, HBI, and Movements

After selecting the best combinations of two and three observations that maximized the classification performance between the reference and their respective sleep profiles, we merged the classification obtained with the movements with those sleep profiles of the joint probabilities. Then, we calculated the statistical classification measures of kappa index, accuracy, sensitivity, and specificity by comparing the hypnogram and the sequence of states obtained from the joint probabilities and movements.

Finally, sleep efficiency was computed from the sequence of stages given by the HMM. This is defined as the number of epochs in REM–NREM divided by the total number of epochs.

III. RESULTS

A. Reliability of HBI Signal

We compared the spectral parameters of signals obtained from the ECG and from bed sensor. To this comparison, ten segments from each recording were randomly chosen, where HBI and RRI do exist. The segments were taken such that RRI and HBI belonged to the same time interval. Each time series was resampled by a cubic spline with sample frequency of 1 Hz. From each estimated HRV spectrum, TP, LF, HF, and their respective frequency peak (pHF and pLF) with the maximum power were computed.

The spectral content between HBI and RRI is compared as follows. Fig. 4 shows segments of RRI and HBI during sleep and their respective PSDs (black solid line is for the HBI signal, while dotted gray line is for the RRI). One can observe, in Fig. 4(a), that HBI follows roughly RRI. Our suggestion is that the small differences in the RRI and HBI might be caused by small body or respiration movements that modify the phase relation between the electrical and mechanical activity of the heart. This phenomenon would refer more to the measurement techniques than the physiology. If the PSD is analyzed [see Fig. 4(b)], spectra are also quite similar. This is also true for LF and HF spectral components. Fig. 4(c) and (d) shows that HBI is completely overlapping to RRI in time and power. Fig. 4(e) and (f) shows that RRI and HBI are quite similar also in case of stronger low-frequency fluctuations of HRV. Table I shows the obtained results as mean and standard deviation of the spectral indexes. To quantify statistical differences, *t*-test was used between RRI and HBI spectral indexes. Indexes did not show statistical differences. We also compared the difference between the ECG and BCG heart-rate measurements. First, the artifact periods were removed from the data with fixed threshold level on the movement activity signal. The achieved coverage was 88% averaging among subjects. The relative error (δx) of BCG

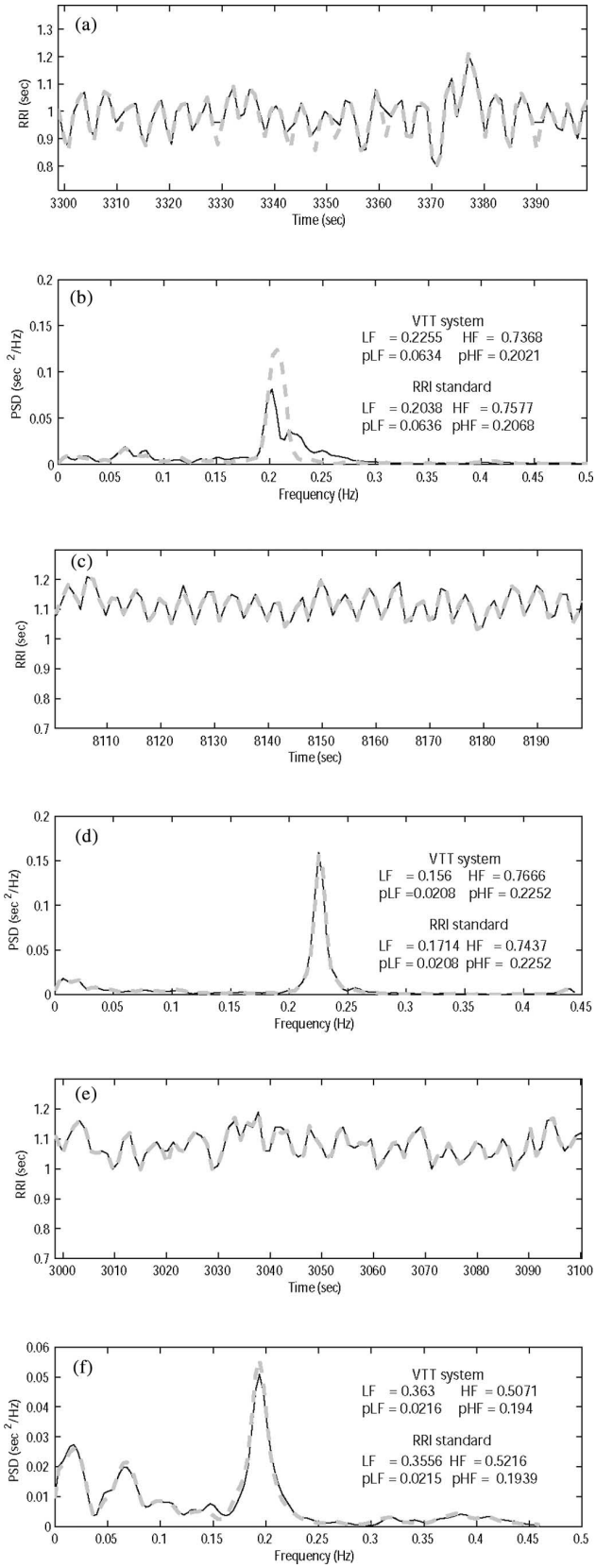

Fig. 4. Typical examples of RRI and HBI segments during sleep stage 2 as well as their respective PSDs. One can observe in (a) that HBI follows roughly RRI. If the PSD is analyzed (b), spectra are also quite similar. This is also true for LF and HF. (c) and (d) HBI is completely overlapping to RRI in time and power. (e) and (f) Quite good overlapping is present also in case of low-frequency fluctuations. Solid black line is HBI and dotted gray line is RRI.

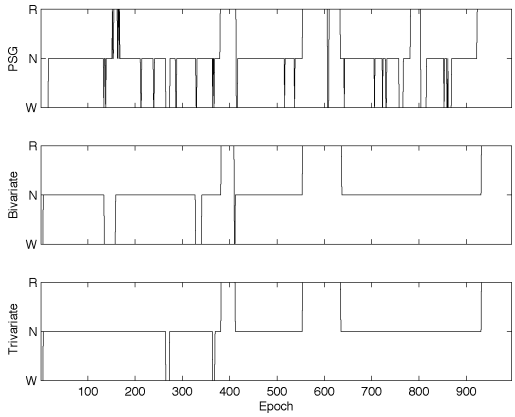

Fig. 5. Example of an automatic sleep classification based only on HBI features for a single night. The top plot shows the hypnogram evaluated by an expert based on PSG but simplified to three stages. Middle plot shows the automatic scoring with joint bivariate distribution and bottom panel illustrates the scoring obtained with joint trivariate distribution. R represents REM, N represents non-REM, and W represents wake.

HBI, in reference with the ECG RRI, was obtained with the following equation:

$$\delta = \frac{|\Delta x|}{x} = \frac{|x_0 - x|}{x} \tag{5}$$

where Δx is the absolute error, x the reference value of the quantity (ECG RRI), and x_0 the measured value (BCG HBI). The average value for the relative error of HBI was $1.1\% \pm 0.38\%$, which is almost threefold higher than in the previous study [5], where the average relative error was 0.4% between subjects. Main difference with our new dataset is that we reduced the number of BCG channels down to 8. However, the result is still acceptable, as statistical difference in the spectral content was small, and further analysis shows that the sleep classification succeeds as well with both the BCG HBI and the ECG RRI.

B. Sleep Staging

Mean performances of the studied automatic systems to identify the sleep macrostructure from the heart-rate fluctuations are presented in Table II. The reference gold standard for assessing the classification performance was the visual scoring of PSG (hypnogram) by an expert sleep technician. Accuracy, sensitivity, and specificity of the classifier were obtained as a comparison with PSG evaluation. Bivariate and trivariate joint distributions with movement detection showed accuracy close to 80%. However, the agreement level is around 0.44, which means a moderate agreement. Mean sleep efficiency (see Table II) was similar to the one given by the reference PSG visual scoring, independently if either a bivariate or a trivariate joint distribution was used.

From top to bottom, Fig. 5 shows the hypnogram and the sleep profiles obtained with the bivariate and trivariate probability distributions. One can observe that the dynamic of the hypnogram is maintained by the automatically obtained sleep profiles, for both the bivariate or the trivariate probability distributions. One can also observe from Fig. 5 that fast state transitions (i.e., when there is one wake epoch between two NREM

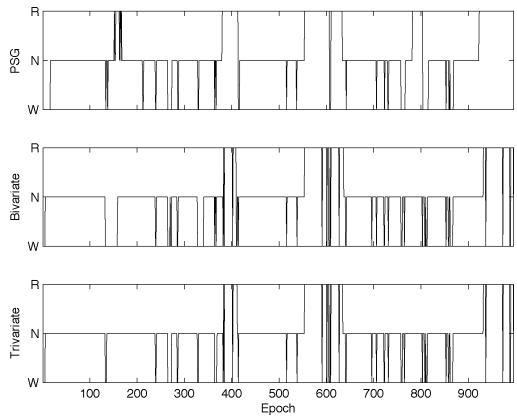

Fig. 6. Example of an automatic sleep classification based only on HBI features and movements for a single night. The top plot shows the hypnogram evaluated by an expert based on PSG but simplified to three stages. Middle plot shows the automatic scoring based on joint bivariate distribution and movements and bottom panel illustrates the scoring obtained with joint trivariate distribution and movements. R represents REM, N represents non-REM, and W represents wake.

epochs) were not detected by HMM. This is practically driven by the emission and transition matrix, and as a result, we shall obtain a smoothed version of the hypnogram. Fig. 6 shows the hypnogram obtained by the joint probability distribution and movement together. Movement detection adds valuable information especially to detect the wake epochs. This is also shown in Table II, where accuracy, specificity, and sensitivity in wake recognition are improved when movements are included. In addition, the last two columns in Table II show the sleep efficiency evaluated from the hypnogram and sleep profile, respectively. Note that the values are similar; however, these values differ largely in the classification approaches where movement is not included.

IV. Discussion

We have presented an automatic system for the sleep evaluation, based on BCG recordings with bed sensor, robust feature extraction from HRV signal, and classification model for sleep modeling. Our main claims are as follows.

1) Bed sensor seems to be a suitable device to acquire, in a simple way, vital signals to enable portable monitoring of the sleep quality.
2) TVAM is an optimal and robust tool to extract spectral parameters from the nonstationary HRV signal.
3) HMM presents interesting properties to evaluate sleep macrostructure and track the sleep dynamic.
4) Joint probability distributions offer good discriminatory power for sleep staging.
5) Movement activity adds valuable information to detect wake stage from sleep.

In a previous study by Kortelainen and Virkkala [5], the HBI from multichannel BCG signal with bed sensor (BCG HBI) was compared directly with the reference ECG RRI for each beat-to-beat values. The relative error of BCG HBI was 0.4% in comparison with the ECG RRI reference, when averaged between subjects. In the present study, we have analyzed a new dataset using similar kind of bed sensor. We reduced the number of BCG channels down to eight before calculating the HBI with the cepstrum method, which is probably the main reason why the error of BCG HBI increased to 1.1%, when averaged between subjects. The eight-channel sensor enables a more cost-efficient system, and the achieved accuracy is still feasible for further analysis. For a typical HBI value of 1 s, this relative error would correspond with 11 ms, which is still much better than the resolution of the BCG sampling time of 20 ms. This has been achieved by averaging the signal channels in the frequency domain and by interpolating the cepstrum maximum search. We compared the BCG HBI results with the reference ECG RRI results also both on HRV and the modeling of the sleep and wake stages. Table I shows that the difference between the BCG HBI and ECG RRI is small on HRV, which supports the achieved good accuracy of BCG HBI, and both methods give about similar result for sleep classification in Table II.

We have calculated the spectral parameters of the HRV signal with a TVAM method, which is a robust choice for nonstationarities, in contrast to the standard spectral analysis techniques such as FT. Spectral powers in different frequency ranges VLF, LF, and HF, and characteristics of AR-model pole at HF frequency were selected as features for the HMM model. As a first attempt, we classified the wake, NREM, and REM sleep stages by feeding each features separately [11]. In this study, we improved the classification by combining the features with their joint probability distribution, which is shown in the Table II. This improvement was achieved using a still sufficiently low-dimensional feature space and maintaining low computational cost. These results are in line with the recent study from Redmond *et al.* [12], which presented an interesting algorithm to detect wake–NREM–REM stages based on features extracted from HRV and respiratory surrogates.

The separation of REM from wake or NREM seems to be a challenging problem when only HRV or any peripheral signal (based on heart fluctuations, respiration and vascular activity) is used. The ECG presents similar characteristics during the wake and REM stages. However, the accuracy is considerably improved by including also the movement activity signal for the classification model features. Because the movement activity can be measured with the bed sensor in addition to the heart beat, this gives a significant benefit for the sleep monitoring system presented here. On the other hand, detection of wake periods from movement activity is well accepted in clinics, where actigraphy is already a standard for insomnia diagnosis.

It is interesting to compare the sleep-wake separation between our results and those obtained by Redmond et. al. [12]. The best approach from Redmond reached an accuracy of 89% and Kappa index of 0.6, which is superior to our best classifier with accuracy of 81% and Kappa index of 0.4. The possible explanation for this difference is that Redmond's approach classifies very often the REM by NREM (see Fig. 3 of the Redmond study), and also REM accuracy is very low (27.9%) in Table 3 for three classes [12]. On the contrary, in our case, the REM stage is often classified as wake, as can be found from the Fig. 6, which is the reason for the low kappa index in the two-class separation problem. Thus, these results suggest that the Redmond's

TABLE II
MEAN AND STANDARD DEVIATION OF THE SLEEP STAGERS BASED ON HBI AND MOVEMENT SIGNAL

Bivariate													
	Wake			**REM**			**NREM**					**Sleep Eff**	
JointFeat	Sen	Spe	Acc	Sen	Spe	Acc	Sen	Spe	Acc	AccTot	kappa	Algor	Med
VLF-Pole	17±12	92±10	80±12	73±31	80±16	79±11	74±23	66± 23	73±12	77±10	0.36±0.19	91±10	83±9
Bivariate + Movement													
	Wake			**REM**			**NREM**					**Sleep Eff**	
JointFeat	Sen	Spe	Acc	Sen	Spe	Acc	Sen	Spe	Acc	AccTot	kappa	Algor	Med
VLF-Pole	46±16	90±10	82±11	69±30	82±16	80±10	73±23	72± 20	75±12	79±9	0.43±0.17	85±10	83±9
Trivariate													
	Wake			**REM**			**NREM**					**Sleep Eff**	
JointFeat	Sen	Spe	Acc	Sen	Spe	Acc	Sen	Spe	Acc	AccTot	kappa	Algor	Med
VLF-Pole-TP	22±19	90±15	80±14	66±33	83±14	80±10	76±24	65± 23	74±13	77±11	0.36±0.21	89±15	83±9
Trivariate + Movement													
	Wake			**REM**			**NREM**					**Sleep Eff**	
JointFeat	Sen	Spe	Acc	Sen	Spe	Acc	Sen	Spe	Acc	AccTot	kappa	Algor	Med
VLF-Pole-TP	48±18	89±15	81±13	63±33	85±13	80±9	75±23	71± 20	75±12	79±10	0.44±0.19	84±14	83±9

classifier works better for two-class separation. One important difference between these methods is the number of features used in the classificator, while Redmond used all together 31 features derived from ECG and inductance plethysmography, we have used only three features, which implies advantage as a reduced computational complexity.

Based on classification between sleep and wake stages, we have also compared the sleep efficiency in Table II. Note that a considerable difference with the reference PSG scoring is obtained when sleep staging is done without including the movement activity feature in the classification. The main reasons for this are the difficulties in detecting the heart beat during the strongest body movements. Interpolation of the missing HBI values during these movement periods cannot generate the missing HRV spectral parameters correctly. However, the movement activity itself has a good correlation with wake periods, and thus, the sleep efficiency evaluated from both HBI spectral features and movement activity together give us better accuracy.

The bed sensor is noncontacting and unobtrusive for the user, which is an important benefit for the sleep recording, when compared with, e.g., a wearable ECG recording having contact electrodes. The sensor mattress comprises materials and dimensions of normal top mattress and can be supplied with different widths, so it does not change the appearance of the bed. The bed sensor prototype applied in this study was connected to a PC for data logging and further processing. However, we have reduced the system complexity since this preliminary testing, and in the next version, all the processing and data storage is done with DSP in a separate electronics box, having 2-m-long cable from the bed sensor.

The main drawback of BCG HBI method is the excessive noise during the body movements that prevents the heart-beat detection. However, we could apply an automatic method to discard the noisy signal during the movement artifacts, using a fixed threshold for the movement activity signal calculated directly from the bed sensor signals. On the average, about 12% of the total recorded sleep time was removed, caused mainly by the normal movements during sleep, but this number had very high interpersonal variation. It is expected that obtaining the HBI data during the movement artifacts cause strongest difference in the HRV LF and VLF components between the BCG HBI and ECG RRI methods. This is because the heart rate normally has smoothly increasing trend during the movement activities, which may last for time periods between 10 s up to several minutes, and is shown in the LF component of the HRV spectra at the frequencies below 0.15 Hz. On the other hand, it is worth mentioning that the movements during the night are related mainly to wake periods, thus discarding the HRV spectral analysis during the movement periods, so we do not introduce excessive errors for the sleep classification. Another problem for BCG HBI method, in comparison with ECG RRI, is that the ectopic beats during arrhythmia periods are missed. In fact, in some cases, the ectopic beats are present in the ECG signal only, and do not influence any pumping mechanism of heart, and thus, cannot be extracted from BCG signal by any means. However, these anomalies do not cause strong difference in the HRV analysis, as the standard methods remove the arrhythmia periods from the ECG RRI data as well before performing the spectral calculation for the HRV. In this study, the subjects did not present strong arrhythmia, but this problem should be taken into account in case of pathological subjects.

The suggested sleep analysis system enables portable recording at home. The system could be used as a support tool especially for those cases where the patient cannot attend the clinics due to immobility, safety, or critical illness. The current system, even if it is in an early stage, would belong to the type 4 given by the guidelines of Task Force of Unattended Portable Monitors for sleep apnea [26], since only one signal type is measured (BCG). It must fulfill some of the basic concerns dictated by the Task Force such as safety, easy use, reliability, durability, economy, and diagnosis accuracy. The system also has to be recommended by an expert clinician in order to define the applicable patient groups, and to take into account that some pathologic conditions may decrease the accuracy of the diagnosis.

The benefits of the proposed system are unobtrusive measurement and minimal operations needed after the system has been installed. The quantity and characteristics of the collected data, i.e., HBI and movement activity, force us to look for automatic methods to calculate the sleep efficiency and sleep profile, which would then be analyzed by the experts. The respiratory movements could potentially be measured as well, which

allows detection of different respiration-related sleep problems. In the future, we have intention to add new algorithms to diagnose pathologies such as sleep apnea, periodic leg movement, or insomnia.

V. Conclusion

The combination of bed sensor with signal processing and classification offers a portable monitoring system, which makes it possible to screen the sleep quality also outside of the sleep centers. This would be of great benefit to the population and could break technological limits for a large number of applications for sleep evaluation. Heart-rate fluctuations include valuable information about the sleep macrostructure. TVAMs seem to be useful to capture the time-variant characteristics of the HRV, which are then linked to the central nervous activity during sleep. HMM offers interesting characteristics to evaluate the sleep macrostructure using both the movement activity and features from the heart rate. Bed sensor is a simple device able to monitor these physiological variables by unobtrusive way.

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