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Conference Paper · July 2019

DOI: 10.1109/BHI.2019.8834535

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Non-Invasive In-Home Sleep Stage Classification Using a Ballistocardiography Bed Sensor

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***Abstract*—Longitudinal monitoring of sleep related parameters can be used for early detection of diseases and also as an indication to physicians for effective adjustment of medication and dosage treatments for people at risk. The correlation between sleep disorders and health conditions such as Alzheimer's and Parkinson's diseases has already been reported in the literature. In this paper, we propose the use of a hydraulic bed sensor for sleep stage classification. Our main motivation of using the bed sensor is to provide a non-invasive, in-home monitoring system, which tracks the changes in health conditions of the subjects over time. Regular polysomnography data from a Sleep Lab have been used as the ground truth, with the focus on three sleep stages, namely, awake, rapid eye movement (REM) and non-REM sleep (NREM). A total of 74 features including heart rate variability (HRV) features, respiratory rate variability (RV) features, and linear frequency cepstral coefficients (LFCC) were extracted from the bed sensor data. Support Vector Machines (SVM) and K-Nearest Neighbors (KNN) classification methods were applied to these features. Our results show accuracy as good as 85% with 0.74 kappa, in the detection of these three sleep stages. These results show promise in the ability of the bed sensor to monitor and track sleep quality and sleep related disorders noninvasively.**

Keywords—classification, sleep stages, in-home monitoring

I. INTRODUCTION

Sleep occupies a considerable part of a person's life. Good sleep quality contributes to the repair of the human physiological and neurological systems. Sleep disorders, such as insomnia and sleep apnea, are among the factors that affect people's daily life. Sleep disturbance could be associated with many neurological and psychiatric diseases, such as Alzheimer's Disease [1] and Parkinson's Disease [2] or other ailments such as obstructive lung disease, sleep apnea, and restless legs syndrome [3]. Frequent sleep disruption caused by heartburn affects sleep quality of patients with gastroesophageal reflux disease (GERD) and their daytime functioning [4, 5]. Other studies such as [6, 7] reported among patient with deformity of the spine (kyphoscoliosis), the severe desaturations happen during rapid eye movement (REM) sleep. Stage N3 and REM are reduced and N1 and stage N2 sleep are increased. For patients with Chronic obstructive pulmonary disease (COPD), sleep efficiency and total sleep time may decrease. REM and N3 sleep may also decrease; however, wake after sleep onset may increase [3]. Therefore, monitoring sleep and studying sleep structure has become especially important.

Polysomnography (PSG) is the most accurate and comprehensive method widely used in sleep labs to monitor sleep and diagnose sleep disorders. By placing many electrodes, sensors, tubes, and masks on a patient's body surface, the system is able to simultaneously acquire multiple biological signals. A technician monitors the patient throughout the night and annotates the sleep stages based on 30-second epochs. The sleep scoring follows the American Academy of Sleep Medicine (AASM) Manual [8]. The normal sleep structure is the alternate of REM sleep and NREM sleep. Further, from shallow to deep, the NREM sleep is divided into NREM1 (N1), NREM2 (N2), and NREM3 (N3) sleep. Although the PSG system has great advantages in its accuracy and comprehensiveness, inevitably, it is expensive, and it can only be done by a sleep-credentialed technician in a sleep lab. In addition, wearing all the devices on the body and sleeping in a different bed in a new environment affects the normal sleep pattern of patients and, consequently, the sleep study results to some extent. Non-invasive sleep monitoring systems can greatly facilitate in-home sleep monitoring [9].

A non-invasive hydraulic bed sensor has been developed in our lab to monitor vital signs during the sleep [10]. The sensor is placed under the mattress without any electrodes being connected to the subject's body. Small pressure sensors

connected to each transducer capture movement of the body, including restlessness in bed, respiratory related movement of the chest and abdomen, and the ballistocardiography (BCG) movements of the body center of mass, due to the flow of blood inside the vascular system during each cardiac cycle [11, 12]. Previous research has proposed reliable approaches to estimate the heart rate, respiration rate [13, 14], sleep posture [15] and changes in the blood pressure [16] from the hydraulic bed sensor signals.

Previous studies have used BCG features, such as heart rate and respiration rate variabilities in sleep stage classification [9]. In this study, thirteen heart rate variability (HRV) features, eleven respiratory variability (RV) features, and fifty linear frequency cepstral coefficients (LFCC) were extracted from the bed sensor data. We explored two types of structures for classifying sleep stages, a single classifier versus a multi-layered hierarchical structure. Support vector machines (SVM) with different kernels and k nearest neighbors (k-NN) with a varying number of neighbors and different distance metrics were applied. The results show the potential benefits of using the hydraulic bed sensors in classifying sleep stages.

II. METHODS

A. The Hydraulic Bed Sensor

The hydraulic bed sensor system consists of four hydraulic bed transducers that are placed under the mattress (Fig. 2 (d)). The pressure sensors at the end of each transducer convert the change in the local pressure into a voltage signal at a sampling rate of 100 Hz. These sensors are sensitive enough to be able to capture low amplitude motions such as the BCG movement of the center of mass during each cardiac cycle, or the movement of the rib cage wall during the respiratory cycle (Fig. 2).

B. Data Collection

Five sleep lab patients with a low Apnea-hypopnea index (AHI) have been selected so that each one has REM, NREM, and Wake sleep stages during the night. De-identified and synchronized PSG and bed sensor data of these five patients (2 males, 3 females; mean age 66.2±2.68 years) were collected, as shown in Table I. The data collection took place during regularly scheduled PSG studies conducted by a sleep-credentialed technician at the Boone Hospital Center (BHC) Sleep Center in Columbia, MO. A total of 4202 epochs (2101 minutes) of synchronized PSG and bed sensor signals were collected from 5 patients, under the University of Missouri IRB approval, project number 2008526.

TABLE I. FIVE SUBJECTS AND THE PERCENTAGE OF EACH SLEEP STAGE OVER ONE ENTIRE NIGHT OF PSG STUDY FOR EACH SUBJECT

Subject	Gender / Age	WAKE(%)	REM(%)	NREM(%)
1	F / 69	21.57%	14.13%	64.3%
2	M / 66	14.95%	16.61%	68.44%
3	M / 68	33.76%	12.30%	53.94%
4	F / 66	46.98%	7.32%	45.7%
5	F / 62	29.85%	19.53%	50.63%

C. Sleep Stage Ground Truth

We used de-identified PSG data collected at the BHC sleep center as ground truth for our bed sensor signals. A sleep technician at BHC annotated each patient's clinical events (e.g., respiratory and cardiac events, limb movements, arousals, and sleep stages according to the AASM standards [17]. Fig. 1 shows an example of ground truth sleep stages, exported from the Natus Neuro Works ® Sleep Works interface [18]. Each sleep stage is annotated in 30-second epochs.

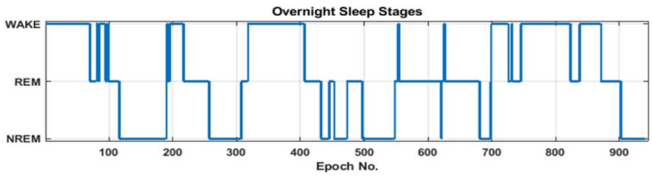

Fig. 1. An example overnight Hypnogram generated by the PSG annotations

D. Data Preparation

In this work, a 6th order Butterworth bandpass filter was implemented. Cutoff frequency ranges of 0.7 Hz and 10 Hz were used to remove most of the low-frequency respiratory components and the high-frequency motion artifacts, resulting in a clean BCG waveform (Fig. 2 (b)). In order to get the respiratory component of the bed sensor signal, a low pass 6th order Butterworth filter with a cutoff frequency of 0.7 Hz was applied on the signals (Fig. 2 (c)).

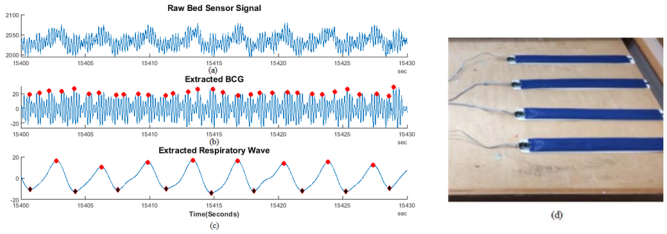

Fig. 2. Heart beats and respiration peaks detected for one epoch and four hydraulic transducers. (a) One epoch raw signal of one transducer, (b) Filtered BCG from raw signal, (c) Respiratory signal extracted from raw signal. (d) Four hydraulic bed transducers.

E. Heartbeat and Respiration Peak Detection

The energy algorithm proposed in [13] was used in this study to detect the heartbeat from the BCG signal. For each 30-second epoch, the algorithm detects the heart beats based on the energy of a 0.3-second moving window. The red circles above the signal in Fig. 2 (b) are the heartbeats detected using the energy algorithm in a 30-second epoch. Also, Fig. 2 (c) shows the peaks and troughs of the extracted respiratory waveform.

F. Feature Extraction

The heart beat locations were obtained to further determine the heart beat intervals (HBI) and HRV features. Time domain HRV features are the statistical measures derived from the HBI and the differences in successive HBI. Table II. contains the definition of the HRV features in the time domain.

A previous study [19] showed that the parasympathetic and sympathetic nervous system activities are related to different frequency bands of power spectral density of the HBI. Moreover, the nervous system's activity level changes during

different sleep stages. The frequency-domain features of the HBI series have been shown to be useful in indicating the sleep stages. Definition of the frequency measures and the ranges for frequency domain HRV features are listed in Table III. Also, Table IV lists the RV features extracted from breath-to-breath intervals, successive differences of intervals, and intervals of inspiration and expiration.

TABLE II. TIME DOMAIN HRV FEATURES AND THEIR DEFINITIONS

Feature	Definition
RMSSD	The square root of the mean of the squares for the successive difference in intervals
PNN50	The percentage of successive difference in interval > 50ms
mHBI	Mean of heart beat intervals
CV	Coefficient of variance
SDNN	The standard deviation of heart beat intervals
maxHBI	Maximum of beat-to-beat intervals
minHBI	Minimum of beat-to-beat intervals
max_minHBI	Differences in the maximum of beat-to-beat interval and the minimum of beat to beat interval
SDSD	The standard deviation of successive difference of heart beat intervals

TABLE III. FREQUENCY DOMAIN HRV FEATURES AND THEIR RANGES

Feature	Definition
Low frequency band (LF)	0.04-0.15Hz
High frequency band (HF)	0.15-0.4Hz
Total power (TF)	0-0.4Hz
The ratio of low and high frequency bands	LF/HF

TABLE IV. RV FEATURES AND DEFINITION

Feature	Definition
RMSSD	The square root of the mean of the squares of the successive difference of breath-to-breath intervals
mDI	Mean of successive differences of breath-to-breath intervals
MADI	Maximum absolute differences of breath-to-breath intervals
mRR	Mean of respiratory rate
SDRR	The standard deviation of respiratory rates
MedianRR	Median of respiratory rate
IQR	The inter quartile range of respiratory rate
MAD	Mean of the absolute deviation value of respiratory rates
CV	Coefficient of variance
RMDA	The ratio of the mean of differences between the amplitudes of expiration and inspiration
RMI	The ratio of the mean of expiration and inspiration intervals

In [20] the LFCC of EEG signals were obtained to classify three sleep stages and showed an average accuracy of 95%. In this paper, we extract similar LFCC features from the BCG waveforms using the steps that are described as follows:

- For each epoch use a sliding window (of 2s with 80% overlap) to segment it into short time frames and compute the power spectrum of each frame.
- Apply a linear filter bank with 26 filters. Since the BCG frequency ranges from 0.7 Hz to 10 Hz, 28 uniformly distributed points were selected in this frequency range and rounded to the nearest FFT bins of the previous step.
- Apply the filter bank to the power spectra. For each time frame of 26 filter bank, energies were generated in total.
- Apply the discrete cosine transform (DCT) on these 26 log filter bank energies to generate 26 cepstral coefficients. Discard the first DC term of each time frame. Compute the mean and standard deviation of the coefficients along the time frames. This results in a total of 25 mean LFCCs and 25 standard deviation LFCCs for each epoch.

G. Evaluation

In a common classification problem, accuracy expresses the proportion of correct prediction. However, as shown in Table I, the sleep stage data are usually imbalanced with regards to the sleep stages. Typically, in such cases, both accuracy and Cohen's kappa coefficient are used to measure the classification performance. The kappa value(κ) measures the inter-rater agreement and is considered to be a more robust way to measure the agreement [21].

III. EXPERIMENTS AND RESULTS

Our experiments consist of two main classification structures to explore hierarchical versus standard classification of the three sleep stages: REM, NREM, and Wake. For each structure setting, we used multiple variants of the SVM and k-NN methods. In this section, we describe the configurations of each setting and their corresponding results, shown in Table V.

A. The single layer classification

In order to detect the sleep stages using the features extracted from the bed sensor signal, we applied SVM with different kernels and k-NN with a varying number of neighbors and different distance metrics.

For SVM, multiple kernels including cubic, quadratic, and Gaussian, have been evaluated using 10-fold cross-validation. Among them, SVM with cubic kernel showed the highest accuracy of 85.3%, with the kappa value equal to 0.74. This result is higher than the results reported by Yang [22], previously done using a similar sensor.

For the k-NN, a varying number of neighbors and different distance metrics have been implemented. The classifier showed the best performance with five nearest neighbors and the Euclidean distance metric with the accuracy reaching 83.7% and the kappa value reaching 0.71.

B. Hierarchical classification

We have also explored the potential of using the hierarchical classification to enhance the detection accuracy. As shown in Fig. 3, our hierarchical structure is composed of two layers. The first layer separates Wake from the union of REM and NREM (a.k.a Sleep) in a binary classification problem. After separating Wake from Sleep, all the epochs classified as Sleep were fed into the next layer to further classify the REM and NREM epochs.

The benefit of hierarchical classification has already been introduced in a paper by Huang [23] for sleep stage detection.

They applied SVM in a hierarchical setting on the forehead EEG signals of ten normal subjects and their reported accuracy was 77% with 0.67 kappa.

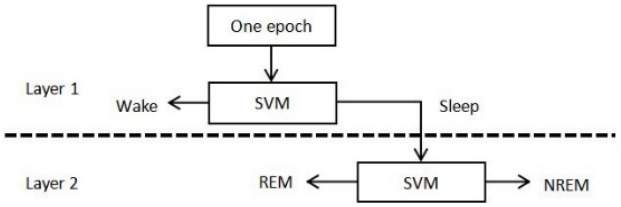

Fig. 3. The structure of hierarchical classification.

TABLE V. THE ACCURACY, KAPPA, AND SENSITIVITY OF THE TWO CLASSIFICATION STRUCTURES

Structure	Classifier	Accuracy (%)	kappa	Sensitivity (%)		
				Wake	*REM*	*NREM*
Single Layer	SVM	85.3	0.74	75.1	80.4	91.6
	k-NN	83.7	0.71	74.5	73.7	90.8
Hierarchical	SVM	84.9	0.64	79.9	78.8	88.8

IV. CONCLUSION

The initial goal of this research was to use noninvasive hydraulic bed sensors to classify sleep stages. The BCG signals collected using hydraulic bed sensors were used in this study. The ground truth sleep stages provided by the BHC sleep lab is considered to be the most accurate available to date. The subjects who participated in this study were elderly people with different severity levels of apnea. The individual differences are more obvious than the data collected from one subject during several entire nights. The heart-beat intervals and breath intervals were calculated from the filtered heart rate signal and the respiratory signal. Then, HRV features and RV features were extracted based on these intervals respectively. The LFCC features were generated from filtered heart rate signals.

The results of the 10-fold cross validation showed potential in classifying the sleep stages. They indicate that the features extracted from the BCG signals contain characteristics related to sleep stages. Both SVM and k-NN showed acceptable performances with about 85% accuracy and a kappa value of 0.7, which are higher than most of the results reported in the literature. The hierarchical method had an overall accuracy of about 85%. The hypothesis that wake is separable from other stages in the first layer had an 88% accuracy rating.

In future work aimed at improving the sleep stage classification, we plan to investigate new noise removal methods and more accurate heart beat detection.

ACKNOWLEDGMENT

We would like to show our gratitude to all staff of Boone Hospital Center Sleep Center at Columbia, Missouri, with a special thanks to Mr. Custer for his patient and helpful advice.

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