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Unobtrusive Classification of Sleep and Wakefulness Using Load Cells under the Bed

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Abstract

Poor quality of sleep increases the risk of many adverse health outcomes. Some measures of sleep, such as sleep efficiency or sleep duration, are calculated from periods of time when a patient is asleep and awake. The current method for assessing sleep and wakefulness is based on polysomnography, an expensive and inconvenient method of measuring sleep in a clinical setting.

In this paper, we suggest an alternative method of detecting periods of sleep and wake that can be obtained unobtrusively in a patient's own home by placing load cells under the supports of their bed. Specifically, we use a support vector machine to classify periods of sleep and wake in a cohort of patients admitted to a sleep lab. The inputs to the classifier are subject demographic information, a statistical characterization of the load cell derived signals, and several sleep parameters estimated from the load cell data that are related to movement and respiration. Our proposed classifier achieves an average sensitivity of 0.808 and specificity of 0.812 with 90% confidence intervals of (0.790, 0.821) and (0.798, 0.826), respectively, when compared to the "gold-standard" sleep/wake annotations during polysomnography. As this performance is over 27 sleep patients with a wide variety of diagnosis levels of sleep disordered breathing, age, body mass index, and other demographics, our method is robust and works well in clinical practice.

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I. Introduction

Poor quality of sleep has been linked to many adverse health outcomes. For example, shorter sleep duration has been linked to increased risk of stroke and chronic disease [1], and also poor metabolic control [2]. Sleep disordered breathing – including obstructive and central sleep apneas - cause daytime drowsiness, decreased executive function, and increased risk of cardiovascular disease [3, 4]. Periodic limb movements during sleep cause reduced sleep efficiency [5], a measure of quality of sleep. As a result, studying sleep and identifying sleep disorders is important for treatment and improved health outcomes.

The current gold standard for studying sleep and assessing sleep disorders is polysomnography (PSG). PSG is an overnight sleep study conducted in a sleep lab where a patient is hooked up to multiple devices measuring eye movements, electroencephalography (EEG), airflow, electrocardiography (ECG), and electromyography (EMG) at multiple locations. Frequently, additional measurements are made based on the suspected diagnosis. PSG has been widely and successfully used for both research and clinical applications, but has some serious shortcomings. PSG is expensive, obtrusive (requiring a patient to be hooked up to many devices through electrodes and other interfaces), measures sleep in an unfamiliar and artificial environment, does not lend itself to longitudinal studies, and requires visual analysis and manual scoring/annotation by a trained expert for adequate data interpretation.

To overcome some of the limitations of PSG, many groups have proposed both alternative methods of measuring sleep parameters of a patient in their own bed, and automatic scoring algorithms to assess different characteristics of sleep. The primary methods most often employed are based on instrumenting the patient or instrumenting the bed, although other methods have been used [6]. Actigraphy, the most common method of instrumenting a patient, relies on a body worn accelerometer or actigraph typically placed on the wrist [7, 8]. While actigraphy based sleep monitoring is used regularly in clinical practice, the method requires that the patient wear the device during sleep and requires that the patient keep records of the time they go to bed and get up in the morning. For long term monitoring, regular charging of the device, regular downloading of the data captured by the device, and consistent device placement on the body are all required to prevent data loss and promote correct data interpretation. In terms of instrumenting the bed, the static charge sensitive bed has been used extensively in Scandinavia to assess sleep unobtrusively in clinical studies [9]. This approach, which places a sheet between a 2-inch foam mattress and the bed platform, has had partial success in classifying sleep and wake periods [10]. However, no studies have used it with other types of mattresses, and in the United States, where 8–10 inch spring, memory foam, and air mattresses are common, other approaches are needed.

Recently, a load cell based approach has shown considerable promise. Typically, load cells are placed under the bed supports and measure the force applied at each support. Load cell data has been successfully analyzed to classify breathing events [11], lying position [12], and bed movements [13]. Other studies have used load cells to estimate heart rate variability [14], and to separate slow wave and non-slow wave sleep [15]. In this paper, we extend these prior results by describing our lab's use of load cell data to classify segments of in-bed time into periods of sleep and wakefulness. In particular, we demonstrate that a support-vector machine (SVM) based classification approach using features derived from load cell signals and patient demographics has good sensitivity and specificity over 27 sleep patients with varying levels of sleep disordered breathing. This was validated against gold standard PSG records of sleep and wakefulness.

II. Methods

A. Subjects and Data Collection

Twenty-seven subjects participated in this study. All subjects provided written informed consent before participating in study activities (OHSU IRB #6308). Subjects were selected from a larger cohort of patients who had been admitted to the sleep lab for routine PSG and who had undergone simultaneous load cell data collection. The entire cohort was not used as some subjects' load cell and PSG data had not been time aligned prior to this study. However, the subset used possessed a wide range on the PSG-scored Apnea-Hypopnea Index (AHI), which provided a wide range of sleep apnea severity and therefore a range of sleep/wake behaviors. Load cells were placed under each of the five existing supports of the bed at the Pacific Sleep Program. All patients received standard overnight polysomnography and the load cell data was collected simultaneously. PSG records were scored by an experienced sleep technician, including annotation of the sleep stage for each 30 second epoch of the record. We then re-coded all sleep stages as "sleep", to make sleep/wake a binary variable. These binary sleep stages were then used as ground truth for our evaluation.

The 27 subjects (mean age 51 ± 14) had an average body mass index (BMI) of 31.9 kg/m^2 ranging from 47.8 kg/m^2 to 22.2 kg/m^2, 18 were male, 7 had an AHI of less than 5, 9 had an AHI between 5 and 15, and 11 had an AHI of greater than 15. Across the 27 subjects a total of 23972, 30 second epochs were recorded.

B. Load Cells and Data Processing

The load cells used in this study were model AG 100C3SH5eU (SCAIME, Annemasse, France). The output of each of the 5 load cells was prefiltered with a 4-pole analog Butterworth filter with a cutoff frequency of 50 Hz before being digitized at a sampling frequency of 500 Hz by a 16 bit A/D converter (USB-1608FS, Measurement Computing, Norton, MA). For the analysis described here, the digital signals were further low pass filtered with a 5 Hz cut-off frequency and decimated to a sampling rate of 10 Hz prior to further processing. After time aligning the load cell data to the PSG data, the load cell data was also segmented into 30 second epochs corresponding to the ground truth PSG data.

From the load cell data, we derived three additional signals. First, we calculated a center of pressure (COP) signal [12], which is a vector valued signal containing an estimate of the location of the COP on the bed with respect to a Cartesian coordinate system on the bed. This signal is calculated as

$$\mathbf{x}_{cop}(t) = \frac{\sum_{i=1}^{5} x_i(t)\mathbf{d}_i}{\sum_{i=1}^{5} x_i(t)} \quad (1)$$

where $\mathbf{d}_i$ is the (x,y) coordinate of the ith load cell and x_i is the force measured by the ith load cell at time t. From this signal we estimated the respiration signal, x_r, by lowpass filtering the y component of the $\mathbf{x}_{cop}$ signal with a cutoff (-3 db) frequency of 0.367 Hz. The final signal we derived is a mean-square difference (msd) signal, which has been shown to contain information about movement in the bed [16]. This signal is calculated separately for each load cell as

$$x_{i,msd}(t)=\frac{1}{L-1}\sum_{j=-(k-1)/2}^{(k-1)/2}(x_i(t-j)-\bar{x}_i(t))^2 \quad (2)$$

where $\bar{x}_i(t)$ is the local average of the signal calculated over the same window set by the window size, L, constrained to be an odd number and set to 11 for our analysis. We further summarized the individual msd signals into a composite signal by summing the msd pointwise over all load cells. Figs. 1 and 2 show examples of each of the signals for epochs of wake and sleep, for one of the subjects.

C. Feature Selection and SVM Classification

In order to use load cell data to classify subject's in-bed periods into epochs of sleep and wake, we first summarized the previously described signals into a set of load cell features and combined these with demographic information to generate a set of 26 variables that characterized each 30 second epoch. This set of 26 variables, or feature vector, fits loosely into three different categories of data: demographics, statistical representations of the signals, and sleep parameters.

The demographic variables included age, height, weight, sex, body mass index, and race (coded as Caucasian or non-Caucasian). While these variables were constant for a given patient, it is possible that measures such as weight and age could influence how the load cells capture respiration during sleep and wake differentially across patients. We also included the patients' AHI as estimated from PSG, since AHI unquestionably influences the respiration signal. In practice, the AHI could be estimated from the load cell data instead [11]. The statistical variables consisted of the sample mean and variance of the following signals: COP in both x and y directions, the respiration signal, the sum of the individual load cell signals, and the composite msd signal. The sleep parameters consisted of multiple variables characterizing measures of movement and respiration during in-bed time. Two variables were used as measures of movement: the sum over time and range of the composite msd signal. To characterize breathing, we detrended and estimated the peak frequency of the respiration signal, and the COP signal in both the x and y directions, using the fast Fourier transform (FFT). We also calculated the maximum amplitude, full and 90% range, and autocorrelation at one lag of the respiration signal.

To classify periods of sleep and wake from the features described above, we used an SVM. SVM is a machine learning algorithm commonly used for binary classification problems, and is well described in the literature ([17], for example). SVM is a supervised learning algorithm, and requires training on labeled data prior to being used for classification. In our study, we used a Gaussian radial basis function (RBF) as the kernel for the SVM. We also tried SVM with a linear kernel and logistic regression for classification, but neither method was competitive with the RBF-SVM. To train the SVM, we first split the feature vectors into sets corresponding to epochs of sleep and wake. We then randomly subsampled one third the total number of wake epochs (1491) and the same number of sleep epochs to make the training set. This resulted in 2982 vectors – approximately 12.5% of the total data – in the training set. The remaining 87.5% of the data was used to test the classifier. The results were quantified in terms of specificity and sensitivity of the classification. The training and testing was repeated 100 times to calculate confidence intervals for the classifier performance. We note that leave one out cross-validation is often used in this context. Our choice of repeated random subsampling was driven by the desire to use a smaller proportion of the data set to train the classifier (we used approximately 12.5% of the data as opposed to the 96% that would have been used) and because we wanted to have enough test and training splits to estimate assumption free confidence intervals from the data.

III. Results

The results of the classification when compared with PSG labeled epochs are summarized in Table I. The classifier achieved a mean sensitivity of 0.902 and a mean specificity of 0.923 on the training sets. The 90% confidence intervals were (0.891, 0.911) and (0.911, 0.932), respectively. This shows that the training data was fairly separable, although there were still a number of cases where sleep and wake were confused based on the features we used. The classifier also showed good generalization when applied to the testing sets. Specifically, the classifier achieved a mean sensitivity of 0.808 and a mean specificity of 0.812, with corresponding 90% confidence intervals of (0.790, 0.821) and (0.798, 0.826), respectively.

IV. Discussion

As Table I shows, the classifier performed very well in delineating periods of sleep from periods of wake. In particular, this classifier generalized well to the out-of-sample test sets with sensitivities and specificities of over 0.8, on average. Additionally, the tight confidence intervals suggest that this classifier is robust and performed consistently on out-of-sample data when trained over a large range of different training data. This is especially promising for practical application as we used patient data collected from 27 patients with a wide variety of sleep-disordered breathing profiles, BMI index, heights, weights, and ages.

There have been two other load cell based methods that have tried to estimate periods of sleep and wakefulness. The first method is based on what is referred to as bed actigraphy, or BACT [18]. This approach consisted of estimating the intensity and duration of movements in the bed, and classifying periods as wakefulness if the duration of movement exceeded a threshold. This method was validated on 10 healthy volunteers and had a high agreement between epochs of sleep and wake compared to PSG (95.2%). However, the average sensitivity was 0.644 (SD 0.133), indicating that sleep was not detected very well. This suggests that the agreement with PSG was good primarily because periods of sleep were classified well, and most of the epochs from the sleep lab were periods of sleep. Also, the use of healthy subjects frequently results in an overestimate of algorithmic performance when applied to patient data. The other load cell based method for estimating sleep and wakefulness was based on the ballistocardiogram derived from a load cell equipped bed [19]. This study also used 10 healthy volunteers and achieved a mean sensitivity of 0.717 and a specificity of 0.989. No confidence intervals or standard errors were included to assess the variability in the results. In addition, the study appears to have optimized the decision threshold to minimize the discrepancy between the PSG and the algorithm. This makes it unclear how well the algorithm would generalize to unseen data, as it appears to have been optimized on the same data used to train the optimal threshold. Additionally, as with the prior method, the use of healthy volunteers may have resulted in an overestimate of algorithm performance compared to the “real-world” application with sleep patients.

Despite our promising results, we expect that some improvements will increase the performance of this classifier. In particular, heart rate information obtained from load cell data has been shown to be useful in detecting periods of sleep and wakefulness[19] and sleep stage[15]. We are currently working on implementing an algorithm for heart rate estimation and expect that features derived from the heart rate signal will increase classifier performance. We also plan to study the respiration signal in more detail and investigate a more comprehensive characterization of this signal than those used here.

In addition to improving the classification of wake versus sleep, we plan to implement automatic feature selection to determine the relative contribution of each of the features used

in this study. This will help determine which signals are the most important for detecting periods of sleep.

V. Conclusion

In this paper, we discussed an approach for classifying periods of sleep and wakefulness from patient demographics combined with unobtrusively derived sleep parameters from load cell data. We showed a high sensitivity and specificity with narrow confidence intervals for out-of-sample classification when compared to ground truth PSG data. Our study used data collected from 27 patients with different demographics, including a wide range of AHI, a measure of sleep disordered breathing. In addition, we compared our method with previously described work and outlined the benefits of our study. Finally, we discussed future work to improve classifier performance and generalize the approach described here for the problem of classifying periods of sleep by sleep stage and wakefulness.

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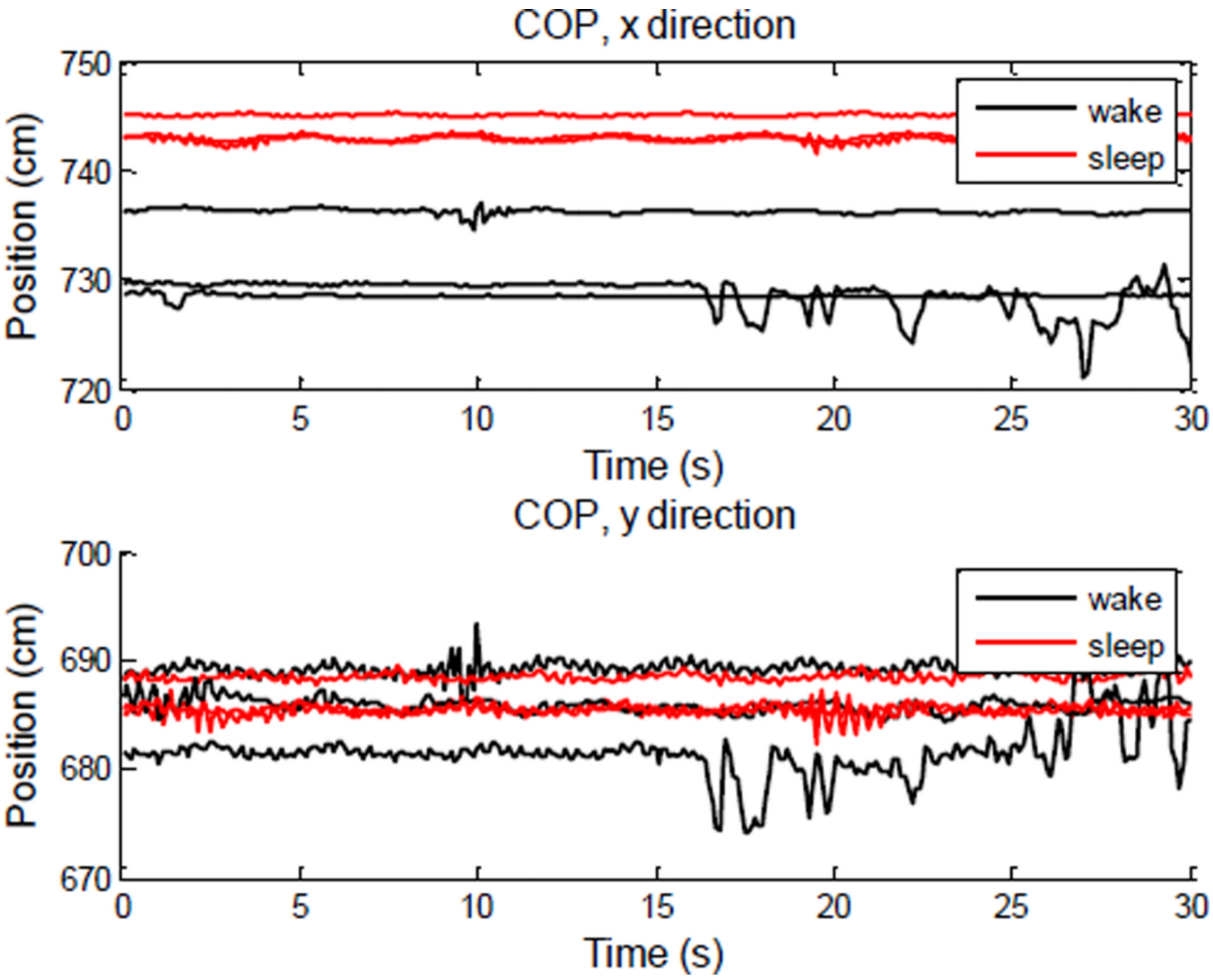

Figure 1.
Three example traces from one subject for the center of pressure signal, x_{cop}, in both the x (top) and y (bottom) directions for periods of sleep (red) and wakefulness (black). Sleep and wake epochs were labeled by an experienced sleep technician using the polysomnography data.

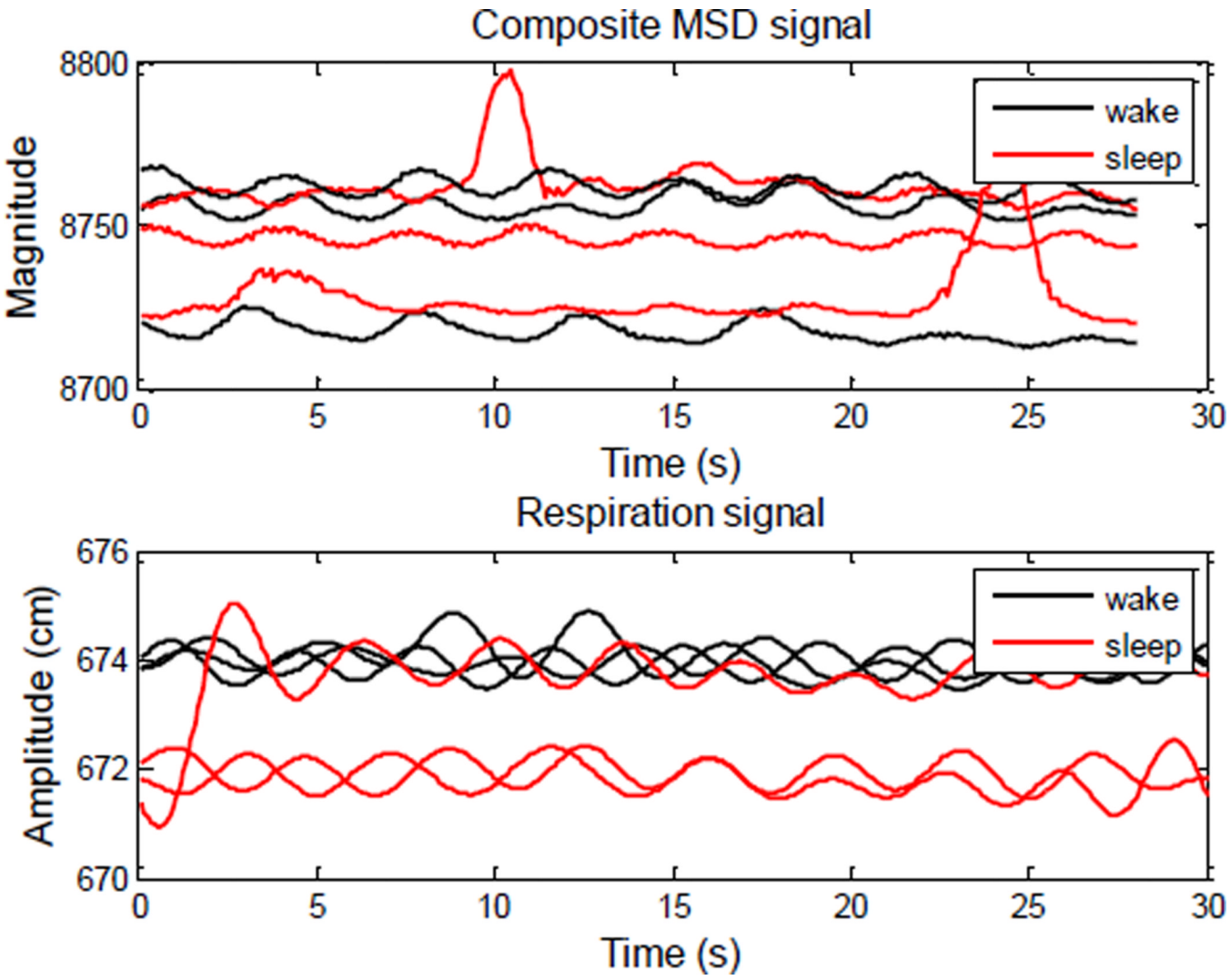

Figure 2.
Three example traces from one subject of the composite msd signal (top) and respiration signal (bottom) for periods of sleep (red) and wakefulness (black). Sleep and wake epochs were labeled by an experienced sleep technician using the polysomnography data.

Table I

SVM classification results for training and testing sets. CI stands for confidence interval.

	Mean Sensitivity	90% CI Sensitivity	Mean Specificity	90% CI Specificity
Training	0.902	(0.891,0.911)	0.923	(0.911,0.932)
Test	0.808	(0.790,0.821)	0.812	(0.798,0.826)