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A Gaussian Model for Movement Detection during Sleep

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***Abstract* — Quality of sleep is an important attribute of an individual's health state and its assessment is therefore a useful diagnostic feature. Changes in the patterns of mobility in bed during sleep can be a disease marker or can reflect various abnormal physiological and neurological conditions. This paper describes a method for detection of movement in bed that is evaluated on data collected from patients admitted for regular polysomnography. The system is based on load cells installed at the supports of a bed. Since the load cell signal varies the most during movement, the approach uses a weighted combination of the short-term mean-square differences of each load cell signal to capture the variations in the signal caused by movement. We use a single univariate Gaussian model to represent each class: movement versus non-movement. We assess the performance of the method against manual annotation performed by a sleep clinic technician from seventeen patients. The proposed detection method achieved an overall sensitivity of 97.9% and specificity of 98.7%.**

I. Introduction

The quality of sleep is an important attribute of an individual's health state and its assessment is therefore a useful diagnostic feature. Changes in the patterns of motor activities during sleep can be a disease marker or can reflect various abnormal physiological and neurological conditions. There are motor disturbances that are triggered by sleep such as restless legs syndrome (RLS) and periodic limb movements during sleep (PLMS). Patients with RLS report feelings of discomfort in the legs, and they feel compelled to move (for example, tossing and turning in bed) to relieve the discomfort [1]. PLMS are involuntary, repetitive movements, most typically seen in the lower limbs but sometimes seen in the arms, and may provoke frequent arousals or even awakenings. Therefore, body movements are generally used as an indicator of sleep quality and depth, and their assessment is important.

The assessment of mobility in bed is traditionally performed by either overnight polysomnography (PSG) or actigraphy. PSG consists of continuous recordings of several physiological measures including brain waves (electroencephalography), electrical activity of muscles, eye movements (electro-oculogram), breathing, blood pressure and blood oxygen saturation. Although there are portable PSG units that can be used in home and community settings, it is best done in a sleep laboratory, and it remains an expensive and intrusive method that involves properly trained technicians [2] and, therefore, it is unfeasible for long term monitoring.

With actigraphy, activity monitors are attached to a person's wrist, leg, ankle or feet to assess nocturnal activity [3-5]. The data collected are very sensitive to where the device is worn, and to gather a complete picture of types of movements in bed, the devices must be worn on multiple limbs. Thus, although actigraphy has the advantage that it can be used for extended periods of time, it places a burden on the patient because the patient has to wear them all the time.

Since the traditional methods are intrusive, researchers have been studying unobtrusive approaches to assess mobility in bed by instrumenting the bed with sensors [6-9]. Cheng et al. [6] propose a system that uses conductive mats to detect movement times and determine sleep and wake periods. Three conductive mats are placed under the chest, hip and legs to detect physical activities with the resistance changes of the mats. Jones et al. [7] propose a system based on a pad with 24 pressure sensors to determine movement onset times. Watanabe et al. [8] use a pneumatics-based system, placed under the bed mattress, for measurement of heartbeat, respiration, snoring and body movements. Shin et al. [9] use an air-mattress with balancing tube method to monitor heartbeat, respiration, snoring and body movements.

Our research focuses on the unobtrusive assessment of movements in bed using data from load cells installed under each support of a bed. Load cell data can be collected continuously without interfering with the patient or their sleep. Load cells have been used in our laboratory to assess sleep hygiene [10], classify lying position [11], and to distinguish normal respiration from disordered breathing [12]. We have also developed a system that allows detection of body movement, i.e., identification of the time intervals when a movement in bed occurs [13]. In this paper, we have extended our previous work on movement detection and describe a method for detection that uses a Gaussian model to discriminate movement and non-movement and that is independent from the subject. We evaluate the method on data collected from patients admitted for regular PSG in a sleep clinic.

II. Approach

In this section, we present an approach for detection of movement in bed from load cell signals. Load cells are strain gauge transducers that convert applied force into a resistance change. They are widely deployed in industrial systems and are also commonly used in electronic scales. They are of relatively low cost, and represent a simple and durable technology.

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In its simplest form, the problem of detection of movement in bed consists of determining whether someone is moving or not at a given time *t*. The purpose is to determine whether a sample belongs to one of two classes: movement and non-movement. It employs a supervised classification based on Gaussian models to assign the class labels to each sample.

The approach comprises four stages: pre-processing, feature extraction, statistical modeling and decision, as illustrated in Fig. 1. During the pre-processing stage, the collected data is segmented in order to extract the periods when the subject is in bed. In the feature extraction stage, a one dimensional representation for the load cell data is estimated by assessment of the weighted variability in the short-term energy across the load cells. In the statistical modeling stage, the Gaussian model parameters are estimated for each class (only in the training phase). In the testing phase, after the test data are pre-processed and features are extracted, the decision stage estimates a likelihood score for each class for every test sample, based on the model parameters estimated during the training phase. A class label is assigned based on the maximum likelihood rule.

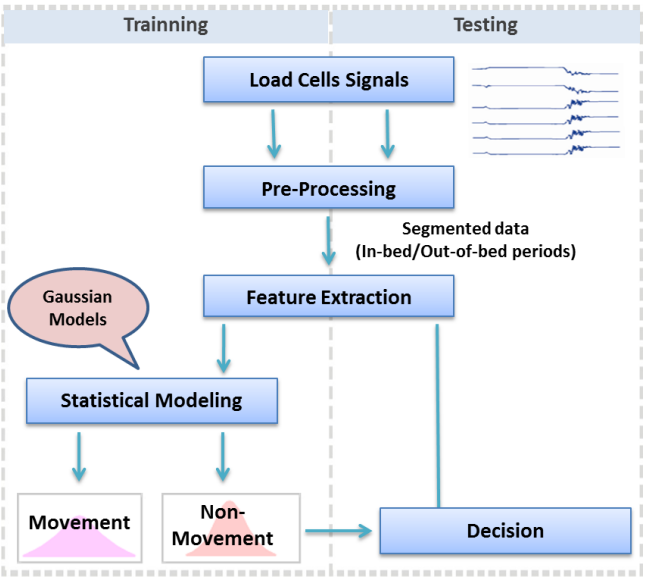

Figure. 1. Movement Detection Framework.

A. Pre-Processing

The first stage of the analysis consists of a segmentation process to extract the data from the periods when the subject is in bed. The forces sensed by the load cells placed under each support of a bed are related to the instantaneous distribution of the mass of the body when someone is lying on bed. It is straightforward to identify the in- and out-of-bed periods with load cells due to the drop in the total force sensed when someone gets up. We used the k-means algorithm to divide the data from each subject into two clusters representing the two states in- and out-of-bed. The k-means algorithm is an unsupervised clustering method that aims to partition m observations into k clusters [14]. After the data from every subject was clustered into two groups, the time intervals with data from the group with the smallest centroid (represented by the mean of the total force sensed by the load cells) are labeled as out-of-bed. More details about this stage can be found in [10].

B. Feature Extraction

A movement of a person in bed is generally reflected by rapidly changing forces at the load cells. Therefore, the idea underlying the movement detection is to assess the weighted variability in the short-term energy across all load cells. The feature used for detection was computed by estimating the energy in the short-term variability in each load cell. The mean-square difference for each load cell signal $w_i(t)$, for $i = 1, 2, \ldots, 6$, was estimated by

$$s_i^2(t) = \frac{1}{L-1} \sum_{k=-\frac{L-1}{2}}^{\frac{L-1}{2}} [w_i(t-k) - \overline{w}_i(t)]^2 , \qquad (1)$$

where

$$\overline{w}_i(t) = \frac{1}{L} \sum_{k=-\frac{L-1}{2}}^{k=\frac{L-1}{2}} w_i(t-k)$$

was calculated over an analysis window of length L samples (L is an odd number).

The individual mean-square difference signals were then combined by weighting the load cells by their distance from the calculated center of mass of the person on the bed. We estimated the feature space using a one-dimensional vector given by a weighted sum of the mean-square differences

$$x(t) = \sum_{i=1}^{6} c_i(t) s_i^2(t) .$$

The scaling coefficients $c_i(t)$, which reflect the distance of the center of mass from the bed support where load cell i is located, are computed based on the distance $d_i(t)$ between load cell i and the center of mass of the body at time t $c_i(t) = 1/(1 + d_i(t))$. The center of mass was computed by considering the fixed location of the load cells as a two-dimensional Cartesian system so the center of mass was found using the law of moments or law of levers [15] as

$$x_{CM}(t) = x_{\max} \frac{\hat{w}_2(t) + \hat{w}_3(t) + \hat{w}_4(t)}{\sum_{i=1}^{6} \hat{w}_i(t)}$$

$$y_{CM}(t) = y_{\max} \frac{\hat{w}_4(t) + \hat{w}_5(t) + (\hat{w}_3(t) + \hat{w}_6(t))/2}{\sum_{i=1}^{6} \hat{w}_i(t)} .$$

where $x_{CM}(t)$ and $y_{CM}(t)$ are the coordinates of the body center of mass when someone is lying in bed, at a given time t, and x_{max} and y_{max} represent the length and the width of the bed, respectively. Also, $\hat{w}_i(t) = w_i(t) + w_i(t_0)$, where $w_i(t_0)$ represents the load cell values when the bed is empty. Subtraction of the empty-bed load cell values removes any asymmetry in the bed weight distribution to avoid its potential effects on the location of the center of mass of the

system.

C. Statistical Modeling and Decision

The goal of the statistical modeling stage is to estimate the parameters of a probability distribution that represents each class. Given the characteristics of the class distribution of the data, as shown in Fig. 2, a single univariate Gaussian model is used to model each class [14].

A maximum likelihood decision rule is used to determine the class for each sample feature. For each test sample, a likelihood score is estimated for each class model. The test sample is then labeled as belonging to the class with highest likelihood score. Thus, assuming that both classes are equable probable, that decision rule takes the form

$$P\left(x\middle|\Theta_{Movement}\right) \geq P\left(x\middle|\Theta_{Non-Movement}\right)$$

where Θ represents the model parameters.

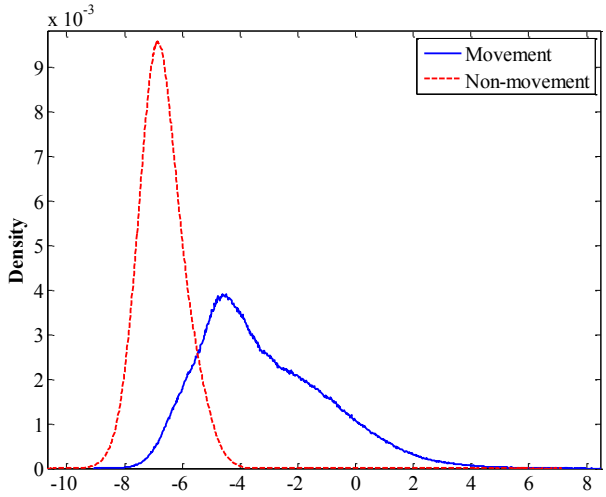

Figure 2. Class density distribution of the features.

III. Experimental Setup

A. Subjects and Data Collection

Seventeen patients (10 men and 7 women) from the Oregon Health and Science University (OHSU) Sleep Disorders Program, with ages ranging from 29 to 74 years (mean age 50.4 ± 12.3 years-old) participated of the study. The Body Mass Index (BMI) for this group of patients varied between 23 kg/m^2 and 56.8 kg/m^2. The data were collected during regularly scheduled single-night sleep studies at the OHSU sleep clinic, where the patients were admitted for regular PSG.

We collected data from 6 resistive load cells (AG100C3SH5eU, SCAIME Annemasse, France) that were placed under the supports of the bed and that had capacities of 100 kg each. The load cell data was collected at 2 kHz for the entire length of the patient's sleep study, and downsampled to 50 Hz for analysis. The dataset consist of 27.3 hours of movement data and 110.8 hours of non-movement data.

B. Training and Testing Procedure

Since data was collected for only one night from each subject, a proper method for dealing with small datasets was applied to ensure independency between the training and testing data, while maintaining sufficient data for training a classifier. Using a leave-one-out method [16], each class was modeled by a single Gaussian model estimated over training data from 16 subjects, and the excluded subject is tested by the classifier. This procedure is performed 17 times to test all subjects. The overall performance measurements are estimated using the errors obtained for each test sample.

C. Performance Measurement

The performance is evaluated by comparing the decisions taken by the linear classifier to a ground truth measure derived independently from the PSG exam and from the technicians' annotations of when movements were performed (movement segment boundaries defined by onset and offset times) during the night.

Given that the movement detection problem is formulated as a two-class classification, the sensitivity and specificity can be used to measure the performance of the method. Sensitivity measures the proportion of positive samples (i.e., the patient is moving) correctly labeled by the classifier, and is given by

$$Sensitivity = \frac{True\ \ Positive}{True\ \ Positive\ + False\ \ Negative},$$

where *True Positive* is the total time period labeled as movement, and *False Negative* is the total time period labeled as non-movement for the period when the patient was moving in bed. Specificity measures the proportion of negative samples (i.e., the patient is not moving) correctly labeled by the classifier, and is given by

$$Specificity = \frac{True\ \ Negative}{True\ \ Negative\ + False\ \ Positive},$$

where *True Negative* is the total time period labeled as non-movement, and *False Positive* is the total time period labeled as movement for the period when the patient was not moving.

These statistical measurements are independent of the population of interest subjected to the test. They are also related to false alarm (Specificity = 1 – False Alarm Rate) and miss detection (Sensitivity = 1 – Miss Detection Rate) errors used in detection problems.

Since the technicians' annotations of movements for PSG do not have precise boundaries, 500 milliseconds around each movement boundary were necessarily excluded from analysis.

IV. Results

Before any result can be produced, a decision must be made about the length of the analysis window L required (Equation (1)) by the feature extraction step. In order to determine a value for L that would provide better classification results, a series of experiments were performed varying the L parameter from 0.5 to 2 seconds on part of the training data (results were obtained from held-out data from the training data). Results show that an analysis window length of 0.5 seconds provides the highest sensitivity and specificity rates.

Using the leave-one-out method, the overall performance is a sensitivity rate of 98% and a specificity rate of 99%. The achieved high performance rate and the subject-independent model training make the approach practical for application in residential and clinical settings.

The performance for each subject is shown in Fig. 3. For all subjects the sensitivity was equal or superior to 89% and the specificity was equal or superior to 87%. No correlation could be found between BMI and the results, indicating that the system provides a weight-invariant detection, as was suggested in our previous work.

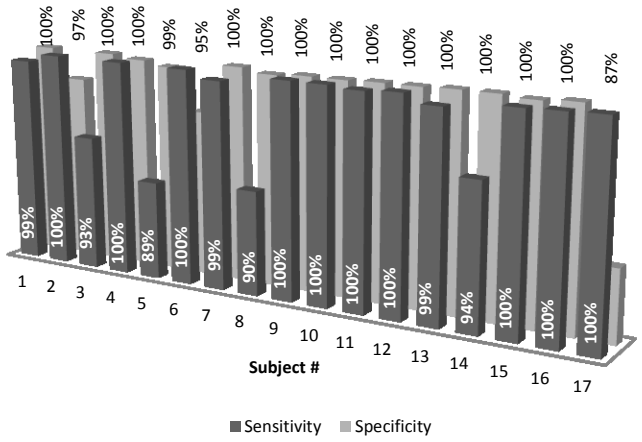

Figure 3. Performance measurements for each subject.

The results show that the Gaussian model provides an accurate modeling of the classes. In our previous work, a likelihood ratio test using a kernel density estimator was used to detect movement. The problem with kernel density estimators is the processing time and storage requirements for the classification process. In addition, the class condition densities are estimated using a finite number of samples. Therefore, the Gaussian model provides a simplistic way to design a classifier without requiring high computing power.

V. CONCLUSIONS

We presented a method for detection of movement in bed that is independent from the subject and it is based on a pattern classifier. The method uses a single univariate Gaussian model designed using features estimated from a weighted combination of the short-term mean-square differences of each load cell signal, which capture the variations in the signal caused by movement.

The method was evaluated against manual annotation performed by a sleep clinic technician on data collected from seventeen patients during a PSG exam. Using a leave-one-out approach, the method achieved an overall sensitivity of 97.9% and specificity of 98.7%. A high performance rate was achieved on realistic data, and the simplicity of the approach makes it practical for application in residential and clinical settings.

The subject-independent model training is also an important extension of our previous work, and it is an important feature when dealing with small datasets. No correlation could be found between BMI and the results, indicating that the system provides a weight-invariant detection, as was suggested in our previous work.

A natural extension of this work should include the classification of movements to distinguish, for example, periodic leg movements from normal movements. The information obtained about the detected movements (onset, duration and frequency, for example) could be used in addition with other information (such as respiration) to determine when the subject is sleeping/awake.

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