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A Method for Classification of Movements in Bed

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Abstract — **Sleep is characterized by episodes of immobility interrupted by periods of voluntary and involuntary movement. Increased mobility in bed can be a sign of disrupted sleep that may reduce sleep quality. This paper describes a method for classification of the type of movement in bed using load cells installed at the corners of a bed. The approach is based on Gaussian Mixture Models using a time-domain feature representation. The movement classification system is evaluated on data collected in the laboratory, and it classified correctly 84.6% of movements. The unobtrusive aspect of this approach is particularly valuable for longer-term home monitoring against a standard clinical setting.**

I. Introduction

Sleep is characterized by long periods of immobility interrupted by brief episodes of movement. Low motor activity levels and prolonged episodes of uninterrupted immobility are associated with increasing sleep depth, whereas high activity levels are related to intermittent wakefulness during sleep, and arousals are often associated with movement [1]. Changes in the pattern of motor activity during sleep can be a disease marker. There are also sleep disorders associated with abnormal movements, like restless legs syndrome (RLS) and periodic limb movements (PLMS), that may adversely affect sleep.

Overnight polysomnography (PSG) is the gold standard for diagnosing sleep disorders associated with abnormal movements, but is obtrusive because patients have to sleep in a lab. Actigraphy has been used for in-home assessment of movement disorders in sleep for many years. With actigraphy, activity monitors are attached to a person's wrist, leg, ankle or feet [2] to assess nocturnal activity. The collected data 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. In addition, the patient must record the time at which they go to bed and get up in the morning. Thus, although actigraphy has the advantage that it can be used for extended periods of time, it places a burden on the patient with all the data collection requirements.

An alternative approach is to assess mobility in bed is by instrumenting the bed itself. Many solutions have been proposed [3-5]. Our research focuses on a solution that employs load cells installed at the corners of the bed. We developed a system that allows both detection of body movement (i.e., identification of the time intervals when a movement in bed occurs) and classification of the type of movement (i.e., determination of the type of movement performed in a given time interval). The well-proven load cell technology, based on strain gauge sensors, provides stable and reliable data and therefore it is a practical solution for long-term monitoring that can be valuable in sleep studies in populations who would not be able to wear a sensor during a study (like, for example, the elderly and patients with dementia). It offers advantages over actigraphy in terms of the ability to confirm and document times in bed. Another benefit is that it can provide a complete picture of types of movements in bed. This paper describes an approach to classify movements in bed into postural shifts, smaller position changes, and limb movements. We evaluate the approach on data collected in a laboratory experiment.

II. Methods

The goal of a movement classification method is to determine the type of movement (with respect to physical changes in posture) performed in a time interval. It is assumed that the time intervals where a movement in bed is detected are known *a priori*. Details about the movement detection algorithm used in this work can be found in [6]. In this work, movements in bed are classified into three classes that include the most typical movements found in the medical literature [7,8]:

- **Class 1** (major posture shifts): changes in body position that involve a torso rotation larger than 45 degrees. These large movements may represent movements related to getting into or out of bed, or large movements associated with wakefulness.
- **Class 2** (small and medium amplitude movements): changes in body position involving the head, arms, torso rotations smaller than 45 degrees, any combination of upper and lower limbs, and any combination of limbs and torso rotations smaller than 45 degrees. These medium amplitude movements may represent restlessness.
- **Class 3** (leg movements: isolated movement of lower limbs - thighs, legs and feet): these leg movements can be associated with PLMS or RLS.

The movement classification approach uses a statistical model estimated from the subject's movement data to

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characterize a person's motion patterns, producing three movement-class models for each subject. Details of the steps of the movement classification approach are described next.

A. Pre-Processing

In the pre-processing step, the coordinates of the body center of mass are estimated from the raw load cell signal of a detected movement. In this application, for a movement defined over a time interval $[t_0, t_1]$ that is obtained through the movement detection algorithm, the trajectory of the body center of mass is given by the coordinates of the body center of mass $x_{CM}(t)$ and $y_{CM}(t)$. The trajectory is represented by a finite number of segments connecting the coordinates of the points (in this case, bed coordinates) representing all the positions taken by the center of mass of the body during a movement. Given the weights measured at each corner of the bed at each time t, $w_i(t)$, i = 1, 2, 3, 4, the length and width of the bed ($x_{\max}$ and $y_{\max}$, respectively), and according to the two-dimensional Cartesian system illustrated in Fig. 1, the center of mass can be calculated, following the law of levers, as

$$x_{CM}(t) = x_{max}\left(\frac{[w_2(t) - w_2(t_0)] + [w_3(t) - w_3(t_0)]}{\sum_{i=1}^{4}\big(w_i(t) - w_i(t_0)\big)}\right)$$

$$y_{CM}(t) = y_{max}\left(\frac{[w_3(t)-w_3(t_0)]+[w_4(t)-w_4(t_0)]}{\sum_{i=1}^{4}(w_i(t)-w_i(t_0))}\right),$$

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. The constant terms $w_2(t_0)$, $w_3(t_0)$, and $w_4(t_0)$ correspond to the weight of the bed measured by corners 2, 3 and 4, at time t_0, just before the person goes to bed. The goal of such normalization is to remove the effect of the unequal weights measured at the corners due to differences in the bed frame built or linens that can be on top of the bed.

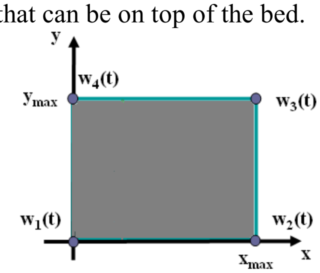

Fig. 1. Representation of the bed coordinates in a Cartesian system.

An example of the trajectory of the body center of mass is illustrated in Fig.2. The "Beginning" and "End" arrows in Fig. 2 point, respectively, to the position of the body center of mass at the beginning and at the end of the movement, i.e., the initial and end points of the trajectory. The intermediary points used to approximate the body center of mass trajectory are estimated by the sampled measurements provided by the sensor.

B. Feature Extraction

Three features were extracted from the trajectory of the body center of mass: (1) the Euclidean distance between initial and end points of the trajectory, (2) the trajectory length, and (3) the variance of the trajectory in the y-direction perpendicular to the sleeper's body axis. The choice of features was motivated by considering the nature of the movements to be discriminated.

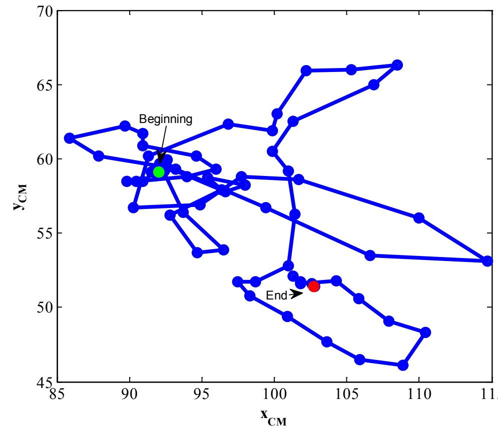

Fig. 2. Coordinates of the trajectory of the body center of mass during a postural shift movement (class 1 movement). The "Beginning" and "End" arrows point, respectively, to the position of the body center of mass at the beginning and at the end of the movement. x_{CM} and y_{CM} are given in centimeters.

The Euclidean distance between the initial and end points of the trajectory provides spatial information about a movement in terms of the displacement of the body center of mass as a result of the movement. Class-1 movements usually generate larger values for this feature than the other two classes because posture shifts produce larger displacement of the body center of mass.

The trajectory length, L, is estimated by summing the distances between adjacent (in time) positions of the body center of mass during the body movement, as

$$L = \sum_{t=0}^{T-1}\sqrt{\big(x_{CM}(t+1) - x_{CM}(t)\big)^2 + \big(y_{CM}(t+1) - y_{CM}(t)\big)^2}$$

where T is the duration of the movement. Intuitively, it is reasonable to assume that the trajectory length is considerably larger for class-1 movements, and smaller for class-3 movements. The trajectory length is very short for arm and head movements in class 2 because there is not a considerable displacement of mass during such movements. The trajectory length is not necessarily proportional to the duration of a movement because it depends on the parts of the body that were involved in the movement (different body parts affect the center of mass differently). For example, a movement that involves arms and head can last as long as other movements, but the observed changes in the position of the body center of mass during movement are likely to be small.

The sample variance of the trajectory in the y-direction, which corresponds to the motion from one side of bed to the other, also provides spatial information about a movement. The sample variance of the trajectory in the y-direction $\hat{\sigma}_y^2$ is calculated as follows:

$$\hat{\sigma}_y^2 = \frac{\sum_{i=1}^{N}(y_{CM}(i) - \bar{y}_{CM})(y_{CM}(i) - \bar{y}_{CM})^T}{N-1}$$

where N corresponds to the number of observations over the interval of the movement and $\bar{y}_{CM}$ corresponds to the estimated mean over the interval. This feature is particularly useful in discriminating movements involving upper and lower body in class 2 from lower body movements in class

3. A displacement of the torso in the y-direction occurs more frequently when adjusting position for class 2 (medium amplitude) than when performing a leg movement.

C. Statistical Modeling

The goal of the statistical modeling step is to estimate the parameters of a probability distribution that represents a certain movement class c_k, using training data from movement k. In this work, each movement class is modeled using Gaussian mixture model (GMM), which describes the probability distribution of a given data set as a linear combination of several Gaussian densities [9]. The reason for using GMM is that it is capable of forming smooth approximations of arbitrarily shaped densities.

In order to reduce the number of parameters, we use GMMs with diagonal covariance matrices. Although the use of a diagonal covariance matrix has the underlying assumption that the features are uncorrelated, this simplified representation is sufficient for the purpose of the classification task, since we have observed that the performances of the diagonal matrix GMMs are not significantly different that the performances of the full matrix GMMs.

The maximum likelihood (ML) decision rule is used to classify every movement.

III. EXPERIMENTAL SETUP

In this section, we describe the sensors, data collection protocols, labeling, data preparation and performance measure.

A. Sensors

The load cells used in this work were single point load cells, model AG100 C3SH5eF (Scaime™, France). The nominal load or capacity of each load cell was 100 kg, and the combined error (error due to non-linearity and hysteresis measured by the manufacturer) was 0.017 kg. An acquisition board (Elektrika Inc., model 335-2001 Rev. C) was connected to the load cells. Data from load cells under the bed were collected at 200 Hz, and downsampled to 10 Hz. The dowansampling was performed because the voluntary movements assessed in this work rarely exceed 3-4 Hz, and the energy of the load cell signal for the set of movements performed was mostly concentrated below 5 Hz.

B. Subjects and Data Collection Protocols

Fifteen adults (7 men and 8 women), ranging from 22 to 45 years (mean age 30.4 ± 6.07 years old) and with no mobility problems participated in the laboratory study. Each subject signed a consent form approved by the university's Institutional Review Board (OHSU IRB#7983), and received a compensation of $20.00 for his/her participation.

Data were collected from 15 subjects that participated in an experiment with a twin size bed (size 99 cm x 190 cm). A group of 5 subjects also participated in an experiment with a full size bed (size 137 cm x 190 cm). Both beds had a box spring mattress. The goal for collecting data in different beds is to assess the generalizability of the approach proposed in this work. Since we have not found a significant difference in the classification performances across beds, the results shown are calculated based on combination of these datasets.

Since the subjects were awake during the experiment, data were collected using two different protocols, *free movement* and *fixed movement,* to allow both diversity and uniformity of movements. In the *fixed movement protocol,* each subject performed 5 trials composed of 20 pre-defined movements each, done in different order in each trial. Each of the 5 trials performed comprised a different combination of the movement sets found in [10]. In the *free movement protocol,* each subject was asked to lie in bed and freely move 10 times. Subjects were instructed to move accordingly to the types of movements typically seen during sleep. Subjects were prompted to move by a beep, and had approximately 15 seconds to perform a movement and then to rest in a still position.

C. Assessment of Actual Movements

We used a video technique as the ground truth for this experiment. To allow a quantitative measure of body movement using video, subjects wore cloth bands of different colors on the head, arms, legs, and torso. The actual movement intervals were estimated by tracking the trajectories of the cloth bands. The location of every cloth band, consequently the respective part of the body, is estimated using template matching [11]. Details about the analysis of video data can be found in [10].

D. Data Preparation

For each subject, movement data from the trials were randomly split into 2 sets: training (3/5 of the dataset) and testing (2/5 of the dataset). The training data contained 1711 movements and the testing data contained 1107 movements.

E. Performance Measure

The performance measure used in this work was the classification rate across all subjects, which is the proportion of test samples from all subjects that are correctly classified. The classification rate across all subjects was used because we want to measure the overall performance of the classifier independently of the subject. Unless indicated otherwise, all comparisons between different classifier conditions were done with the McNemar's test [12] ($\alpha = 0.05$).

IV. RESULTS AND DISCUSSIONS

This section presents and discusses the movement classification performance. The effect of training size in the classification performance is also analyzed.

A. Movement Classification Performance

Each class was modeled by a diagonal-covariance GMM estimated over some training data from the respective subject. The number of mixture components in the GMMs was estimated using 3-fold cross-validation of the training data. Training data from each subject were randomly split into 3 disjoint sets, each containing roughly the same number of data samples. Each set was used in turn as an independent test set while the remaining 2 sets were used for training. The classification rate was estimated over all sets.

The results showed that two mixture components yielded the best performance in the training data for all subjects.

The overall classification rate on the test data was 84.6%, and the corresponding confusion matrix is presented in Table 1. The most frequent errors were between classes 2 and 3 (medium movements versus leg movements). A closer examination of the errors showed that, in many cases, the classifier mistakenly classified movements consisting of leg movements and very small adjustments of head or torso (class 2) as leg movements (class 3). In such cases, the small movements in the upper body did not substantially affect the overall trajectory of the center of mass.

TABLE 1
CONFUSION MATRIX FOR THE 3-CLASS MOVEMENT CLASSIFICATION PROBLEM: LARGE, MEDIUM AND LEG MOVEMENTS

		Estimated Label		
		Large	**Medium**	**Legs**
True Label	**Large**	325	9	2
	Medium	13	391	101
	Legs	2	44	220

The classification rates for individual subjects ranged from 76.7% to 95.3%. The χ^2 test for differences among proportions [13] showed a difference in classification performance between subjects, at a significance level of 0.05 and with 14 degrees of freedom. We speculate that there are differences in the classification performance across subjects because the intra-subject movement variability may be larger in some subjects, which results in a larger intra-class variance.

B. *Effect of Training Set Size*

The use of subject-dependent models requires learning parameters for each subject with data of each subject. The disadvantage of this approach is that it takes time to collect subject-dependent data. To select the most appropriate parameterization, it is important to know the minimum amount of data necessary to train the model for each person.

We examined how the classification rate on the testing data changed as we progressively increased the number of training samples per class. Because the number of samples per class is different for each subject, we included in this analysis only those subjects who had at least 30 movements per class. The overall classification rate, which was calculated on the test data previously selected for each subject, was computed as a function of the number of training samples, with the number of samples increasing from 5 to 30 in increments of 5. Using ten samples per class, the classification rate was 81.5%, which was significantly greater than the classification rate using only five samples ($p < 0.01$). However, the classification rate did not increase significantly when all available samples were used (83.2%), and we therefore concluded that at least 10 samples per class are necessary to train the model for each person.

V. CONCLUSIONS

We presented a method for subject-dependent classification of movements in bed from load cell signals. The approach used Gaussian mixture models estimated on different features from the body center of mass to represent each class. We showed that this approach is applicable in real settings because it does not require a large amount of training data (a minimum of 10 samples per class is necessary to achieve comparable classification results). The classification performance was 84.6%.

Since the evaluation of the system was based mostly on voluntary movements that were performed during wake periods, an important advance in this work is to evaluate the system in real sleep conditions. We have started a new study to evaluate the system with load cell data from patients being monitored with PSG in a sleep laboratory.

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