Unobtrusive Movement Detection during Sleep based on Load Cell Dynamics

Adriana Miorelli Adami [1], André Gustavo Adami[1], Tamara Hayes[2], Zachary Beattie[2]

[1]Laboratório de Tecnologias em Saúde – Universidade de Caxias do Sul – (UCS)
Rua Francisco Getúlio Vargas, 1130 – 91.501-970 – Caxias do Sul – RS – Brazil

[2]Biomedical Department – Oregon Health and Science University
Portland, USA

{amiorell, agadami}@ucs.br, {hayesta, beattiez}@ohsu.edu

Abstract. *Changes in the pattern of motor activities during sleep can be a disease marker, or can reflect various abnormal physiological and neurological conditions. Currently, there are no unobtrusive ways to assess the quality of sleep at point of care outside of a clinic. In this paper, we propose an alternative method of detecting movements during sleep that can be deployed unobtrusively in a patient's own home by using load cells sensors. This subject-independent method uses a linear discriminant function to detect periods of movement in a cohort of 17 patients admitted to a sleep lab. The system yields a sensitivity of 97.5% and a specificity of 99% when compared to technicians' annotations.*

1. Introduction

Body movements in normal sleep constitute a very regular pattern that is characteristic of the sleeper, and the alteration of this pattern might reflect the deterioration in sleep process [Muzet 1986]. The alteration of the pattern or amount of motor activity can also be a disease marker [Muzet 1986; Chokroverty, Hening et al. 2003]. It can reflect illnesses ranging from flu to depression, pain, or the side effects of certain treatments [Hyyppa and Kronholm 1987; Chokroverty, Hening et al. 2003]. Many neurological disorders are presented with abnormal movements during day and nighttime that may adversely affect sleep [Chokroverty, Hening et al. 2003]. For example, normal body movements in Parkinson's disease patients may be repressed by motor daytime symptoms that persist during sleep such as a decreased ability to start and continue movements, and impaired ability to adjust body position. These symptoms worsen sleep quality, and can cause discomfort and pain [Phillips 2004].

The assessment of nocturnal motor disturbances in sleep is traditionally performed using overnight polysomnograph recording or actigraphy. Overnight polysomnograph recording (PSG) is the gold standard to evaluate motor events occurring during sleep [Chokroverty, Hening et al. 2003]. PSG consists of continuous recordings of several physiological measures including brain waves (electroencephalography), electrical activity of muscles, eye movement (electro-oculogram), breathing rate, blood pressure, blood oxygen saturation, and heart rhythm. Additional leads are applied to other parts of the body (for example, arms and legs) if there is a specific motor complaint [Chokroverty, Hening et al. 2003]. It involves at least a full night's stay in a sleep laboratory attended by properly trained technicians

[Culebras 2004]. PSG has been widely and successfully used for both research and clinical applications [Guimarães, Silva et al. 2006], but it is expensive, obtrusive and it is done in an unfamiliar environment.

Long-term assessment and behavior therapy require an inexpensive technique for which wrist actigraphy is a reasonably economical method that is commonly used [Tryon 2004]. Actigraphs are wristwatch-like devices that measure acceleration, and provide information on the activity level of the user. They are usually placed on the non-dominant wrist, although they can also be placed at the site of movement to examine specific movements. Although they have the advantage that they can be used for extended periods of time, the exact nature and the number of movements that occur are not recorded [Chokroverty, Hening et al. 2003]. In addition, the patient has to keep records of bedtimes and getup times, as well as times out of bed during the night, because the device cannot differentiate between times in bed from out of bed.

Since traditional methods are obtrusive, researchers have been studying unobtrusive approaches to assess mobility in bed by instrumenting the bed with sensors [Watanabe, Watanabe et al. 2005; Jones, Goubran et al. 2006; Cheng, Hsu et al. 2008; Shin, Chee et al. 2010; Verhaert, Haex et al. 2011]. Cheng et al. [Cheng, Hsu et al. 2008] 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. [Jones, Goubran et al. 2006] propose a system based on a pad with 24 pressure sensors to determine movement onset times. Shin et al. [Shin, Chee et al. 2010] use an air-mattress with balancing tube method to monitor heartbeat, respiration, snoring and body movements. Watanabe et al. [Watanabe, Watanabe et al. 2005] use a pneumatics-based system, placed under the bed mattress, for measurement of heartbeat, respiration, snoring and body movements. Verhaert et al. [Verhaert, Haex et al. 2011] propose an algorithm that detects movements based on the time derivate of mattress surface indentation. Our research focuses on the unobtrusive assessment of movements in bed using data from load cells installed under each support of a bed. Load cells have been used in our laboratory to assess sleep hygiene [Adami, Adami et al. 2010], classify lying position [Beattie, Hagen et al. 2011], classify sleep and wakefulness [Austin, Beattie et al. 2012], and to distinguish normal respiration from disordered breathing [Beattie, Hagen et al. 2009]. Load cell data can be collected continuously without interfering with the patient. This paper describes a system for unobtrusive detection of movement in bed that employ load cells installed at the corners of a bed. The system focuses on identifying when a person is in bed and when a movement occurs based on the forces sensed by the load cells. The performance of the system was evaluated using data collected from 17 patients during regularly scheduled single-night sleep studies at a sleep clinic.

2. System for Unobtrusive Detection of Movements during Sleep

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*. This problem can be formulated as a two-class classification problem (movement and non-movement). Our approach comprises three stages: pre-processing, feature extraction and detection, as illustrated in Figure 1. The pre-processing stage consists of a segmentation process to extract the data from the periods when the subject is in bed. In the feature extraction

stage, a six dimensional representation of the load cell signals is estimated by assessing the variability in the short-term energy across the load cells. In the decision, a linear discriminant function is applied to the features so that a decision of whether the subject is moving or not moving while in bed is made. Details about the three stages and about the load cells used in the experiment are presented next.

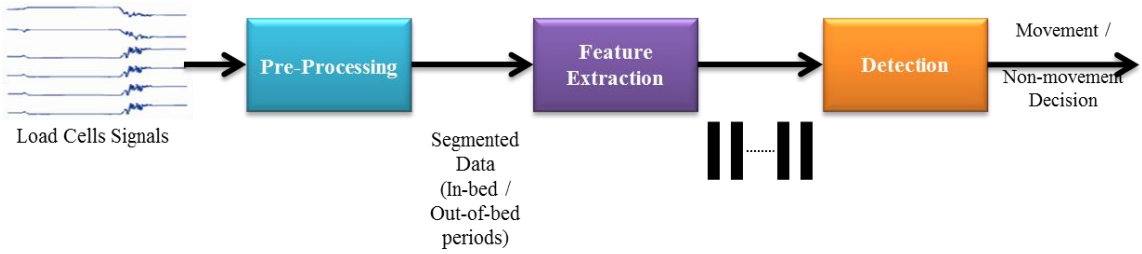

Figure 1. Movement detection framework.

2.1 Load Cells

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. Although forces are not directly measured, but inferred from the resultant strain, the output is linearly proportional to force, with the relationship determined by calibration. After calibration the raw data is converted to force values (in Newton).

The sleep laboratory bed used for this study is equipped with load cells under the bed supports. Given the number of bed supports, 6 load cells (AG100C3SH5eU, SCAIME Annemasse, France) with capacities of 100 kg each are used for data collection. The load cell signals were collected at 2 kHz for the entire length of the patient's sleep study using a 16 bit A/D converter (USB-1608FS, Measurement Computing, Norton, MA). Then, the signal is downsampled to 20 Hz to reduce the computational cost during analysis. Figure 2 shows an example of data collected from one subject. The highlighted intervals are intervals when the subject made a movement.

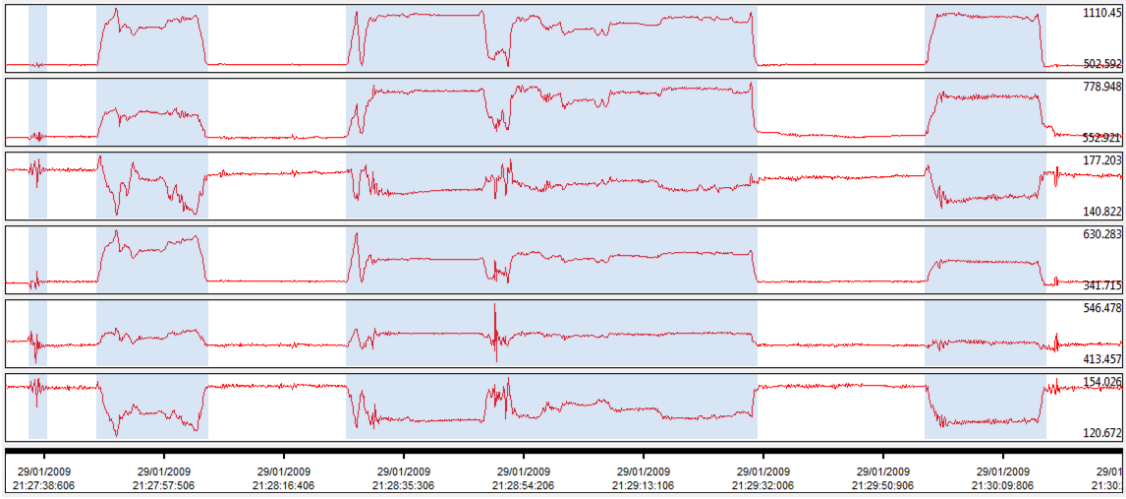

Figure 2. Six load cell signals collected from a subject during the study. The highlighted intervals are intervals where a movement occurred.

2.2 Pre-Processing

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 exits the bed. We used the k-means algorithm to separate 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 [Duda, Hart et al. 2001]. After the data from every subject was clustered into two groups, the time intervals with data from the group with the smallest centroid (the centroid representing the mean of the total force sensed by all the load cells) are labeled as out-of-bed. More details about this step can be found in [Adami, Adami et al. 2010].

2.3 Feature Extraction

A movement of a person in bed is generally reflected by rapidly changing forces at the load cells. Therefore, the general idea underlying the movement detection is the assessment of the variability in the short-term energy across the load cells. The six dimensional feature vector is estimated as the energy in the short-term variability in each load cell that can be estimated through the mean-square difference. The mean-square difference for each load cell signal $\mathbf{x}_i(t)$, for i = 1, 2, …, 6, and it is calculated as

$$\mathbf{x}_{i,msd}(t) = \frac{1}{L-1} \sum_{k=-\frac{L-1}{2}}^{\frac{L-1}{2}} \left[\mathbf{x}_i(t-k) - \bar{\mathbf{x}}_i(t)\right]^2 \quad (1)$$

where L is an odd number that represents the length of the analysis window, and $\bar{\mathbf{x}}_i(t)$ represents the local average of the signal calculated over the analysis window. We discuss later the selection of an appropriate value for L.

2.4 Decision

The problem of movement detection can be formulated as a two-class classification problem (movement and non-movement). Among all approaches to two-class problems, linear discriminant functions designs decision rules based on functions estimated from the data. That is, a linear discriminant classifier tests a linear combination of the features given by a linear discriminant function

$$h(\mathbf{x}) = \mathbf{V}^T\mathbf{x} + v_0 \begin{matrix} C_1 \\ > \\ < \\ C_2 \end{matrix} 0, \quad (2)$$

where $\mathbf{x}$ is the feature vector, $\mathbf{V}$ is the weight vector, v_0 is the threshold value, and C_i is a class, for i = 1, 2. This function indicates that $\mathbf{x}$ is assigned to C_1 if $h(\mathbf{x})$ is larger than 0, and vice versa.

The parameters $\mathbf{V}$ and v_0 of the linear discriminant function can be estimated, in a supervised mode using the criterion that measures the between-class scatter normalized by the within-class scatter [Fukunaga 1990], as follows

$$\mathbf{V} = \left[P_1\boldsymbol{\Sigma}_1 + P_2\boldsymbol{\Sigma}_2\right]^{-1}\left(\mathbf{M}_2 - \mathbf{M}_1\right) \quad (3)$$

$$v_0 = -\mathbf{V}^T\left[P_1\mathbf{M}_1 + P_2\mathbf{M}_2\right] \quad (4)$$

where P_i is a prior probability of class i, $\mathbf{M}_i$ is the mean from class i, and $\boldsymbol{\Sigma}_i$ is the covariance matrix.

3. Experimental Setup

In this section, we describe the subjects that participated in the study, the training and testing procedure, and present the performance measurement used to evaluate the system.

3.1 Subjects

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 data were collected during regularly scheduled single-night sleep studies at the OHSU sleep clinic, where the patients were admitted for regular PSG. The protocol was reviewed and approved by OHSU (IR4345). Table 1 shows the number of hours of movement and non-movement for each subject, with a total of 27.3 hours of movement data and 110.8 hours of non-movement data.

Table 1. Number of hours of movement and non-movement for each subject.

Subject	Movement Time (Hours)	Non-Movement Time (Hours)
1	1.5	5.7
2	1.8	6.9
3	1.1	6.4
4	2.0	7.6
5	2.3	4.6
6	2.0	6.0
7	1.1	7.5
8	1.5	6.9
9	1.0	7.5
10	1.1	7.0
11	1.4	8.2
12	4.2	2.7
13	0.8	7.0
14	0.7	6.9
15	1.8	6.0
16	0.5	7.3
17	2.5	6.6
Total	**27.3**	**110.8**

3.2 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 [8], a linear classifier is designed using 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. Despite the disadvantage of designing 17 classifiers, the problem was alleviated by the simplicity of the linear classifier.

The values of the prior probabilities for estimating the parameters of the linear discriminant function (Equations (3) and (4)) where estimated from the collected data. The prior probability for the movement class is 0.4 and, consequently, 0.6 for the no-movement class.

3.3 Performance Measurement

The performance is evaluated by comparing the decisions taken by the linear classifier to a ground truth measure derived from the technicians' annotations of when movements were performed (movement segment boundaries defined by onset and offset times) during the night. Given that the linear classifier provides a decision on a feature sample level, such decisions divide the data into segments that belongs to a movement or a no-movement class. The resulting segments can be described by time periods that can be easily compared to the technicians' annotations. Since the technicians' annotations of movements for PSG do not have precise boundaries, 500 milliseconds around each movement boundary were necessarily excluded from analysis.

The movement detection problem is formulated as a two-class classification problem, and 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. The 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 (*Sensititvity* = 1 – *Miss Detection Rate*) errors used in detection problems.

4. Results

Before any result can be produced, a decision must be made about the length of the analysis window L required, as defined in Equation (1), in the feature extraction step. Before estimating each linear classifier, the analysis window parameter is estimated

through a series of experiments with varying analysis window lengths using a leave-one-out method on the subjects belonging to the training data (i.e., on the data from the 16 subjects). The analysis window length with the best performance on the training data was used in the training and testing procedure for each subject. In all experiments, the analysis window length of 0.5 second provided the highest sensitivity and specificity.

Using the leave-one-out method, the system yields an overall sensitivity of 97.5% and specificity of 99%. The achieved high performance and the subject-independent modeling make the approach practical for application in residential and clinical settings. The use of load cell sensors installed under the bed posts provides an unobtrusive way of monitoring subjects during their sleep. In addition, the system can be readily installed because no subject model training is required.

Table 2 shows the age, height, weight, body mass index, and the performance for each subject. Even though the subjects show a large variability in the BMI (from 23.0 kg/m^2 to 56.8 kg/m^2), the detector performance is not affected by the subjects' BMI.

Table 2. Individual Results and Patient Demographics.

Subject Number	Age	Height (m)	Weight (kg)	Body Mass Index (kg/m^2)	Sensitivity (%)	Specificity (%)
1	44	1.75	98.4	32.1	98.1	100.0
2	63	1.70	164.2	56.8	99.9	98.8
3	30	1.70	69.4	24.0	93.4	100.0
4	47	1.70	99.3	34.3	99.8	99.6
5	69	1.63	87.1	32.8	89.0	99.2
6	51	1.88	134.7	38.1	100.0	94.3
7	46	1.65	92.1	33.8	98.7	100.0
8	53	1.68	67.1	23.8	92.3	99.6
9	55	1.88	141.1	39.9	100.0	99.4
10	49	1.85	151.5	44.3	100.0	99.6
11	61	1.85	128.4	37.5	91.0	99.9
12	36	1.64	151.1	56.2	99.9	99.8
13	29	1.63	71.2	26.8	99.6	99.9
14	55	1.63	61.2	23.0	91.2	100.0
15	49	1.75	86.2	28.1	99.5	99.8
16	45	1.70	94.3	32.6	99.8	99.9
17	74	1.88	138.8	39.2	100.0	92.6

5. Conclusions

We presented a movement detection system based on load cells installed under the supports of a bed on data collected during a PSG exam. The short-term mean-square differences of each load cell signal were used to capture the variations in the signal caused by movement. The system used a supervised detection method based on a linear classifier, and the performance of the method was assessed against manual annotation performed by a sleep clinic technician from seventeen patients.

Using a leave-one-out approach, the method achieved a sensitivity of 97.5% and a specificity of 99%. 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 an important feature when dealing with small datasets. The individual performance showed that the detection performance is not affected by the variability of the subjects' BMI.

This work provides several directions in which the assessment of movement in bed can be pursued further. One direction is to include the classification of movements to distinguish, for example, involuntary and repetitive movements (caused by the Periodic Limb Movements disorder) from normal movements.

References

Adami, A. M., Adami, A. G., Schwarz, G., Beattie, Z. T. and Hayes, T. L. (2010). A Subject State Detection Approach to Determine Rest-Activity Patterns Using Load Cells. In 32nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Buenos Aires, Argentina.

Austin, D., Beattie, Z. T., Riley, T., Adami, A. M., Hagen, C. C. and Hayes, T. L. (2012). Unobtrusive Classification of Sleep and Wakefulness Using Load Cells Under the Bed. In 34th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, San Diego, California, USA.

Beattie, Z. T., Hagen, C. C. and Hayes, T. L. (2011). Classification of lying position using load cells under the bed. In Engineering in Medicine and Biology Society,EMBC, 2011 Annual International Conference of the IEEE.

Beattie, Z. T., Hagen, C. C., Pavel, M. and Hayes, T. L. (2009). "Classification of Breathing Events Using Load Cells under the Bed". 31st Annual International Conference of the IEEE EMBS Minneapolis, Minnesota: 3921-3924.

Cheng, C. M., Hsu, Y.-L. and Young, C. M. (2008). Development of a Portable Device for Telemonitoring of Physical Activities During Sleep. Telemedicine and e-Health 14(10): 1044-1056.

Chokroverty, S., Hening, W. A. and Walters, A. S. (2003). Sleep and Movement Disorders. Philadelphia, PA, Elsevier Science.

Culebras, A. (2004). Who Should be Tested in the Sleep Laboratory? Reviews in Neurological Diseases 1(3): 124-132.

Duda, R. O., Hart, P. E. and Stork, D. G. (2001). Pattern Classification. New York, NY, John Wiley & Sons, Inc.

Fukunaga, K. (1990). Introduction to Statistical Pattern Recognition, Academic Press, 2nd ed.

Guimarães, G. M. N., Silva, H. B. G. d., Ladeira, M. and Viegas, C. A. d. A. (2006). "Aprendizagem de Classificadores para Diagnóstico da Síndrome da Apnéia Obstrutiva do Sono". VI Workshop de Informática Médica. Vila Velha, ES: 193-202.

Hyyppa, M. T. and Kronholm, E. (1987). Sleep Movements and Poor Sleep in Patients with Non-Specific Somatic Complaints - II. Affective Disorders and Sleep Quality. Journal of Psychosomatic Research 31(5): 631-637.

Jones, M. H., Goubran, R. and Knoefel, F. (2006). "Identifying Movement Onset Times for a Bed-Based Pressure Sensor Array". International Workshop on Medical Measurement and Applications. Benevento, Italy: 111-114.

Muzet, A. (1986). Dynamics of Body Movements in Normal Sleep. In Eighth European Congress on Sleep Research, Szeged, Hungary, Gustav Fisher Verlag.

Phillips, B. (2004). Movement Disorders: A Sleep Specialist's Perspective. Neurology 62: S9-S16.

Shin, J. H., Chee, Y. J., Jeong, D. U. and Park, K. S. (2010). Nonconstrained Sleep Monitoring System and Algorithms Using Air-Matress with Balancing Tube Method. IEEE Transactions on Information Technology in Biomedicine 14(1): 147-156.

Tryon, W. W. (2004). Issues of Validity in Actigraphic Sleep Assessment. Sleep 27(1): 158-165.

Verhaert, V., Haex, B., De Wilde, T., Berckmans, D., Vandekerckhove, M., Verbraecken, J. and Sloten, J. V. (2011). Unobtrusive Assessment of Motor Patterns During Sleep Based on Mattress Indentation Measurements. Information Technology in Biomedicine, IEEE Transactions on 15(5): 787-794.

Watanabe, K., Watanabe, T., Watanabe, H., Ando, H., Ishikawa, T. and Kobayashi, K. (2005). Noninvasive Measurement of Heartbeat, Respiration, Snoring and Body Movements of a Subject in Bed Via a Pneumatic Method. IEEE Transactions on Biomedical Engineering 52(12): 2100-2107.