31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

Comparison of Load Cells and Wrist-Actigraphy for Unobtrusive Monitoring of Sleep Movements

Adriana M. Adami, Tamara L. Hayes, *Member, IEEE*, Misha Pavel, *Member, IEEE* and André G. Adami, *Member, IEEE*

Abstract — **Accurate assessment of mobility in bed presents challenges to clinicians and researchers alike. Mobility is traditionally assessed by either overnight polysomnograph recording or wrist actigraphy. This paper describes an alternative system for unobtrusive and continuous monitoring of sleep movements that uses load sensors installed at the corners of a bed. This work is focused on the detection and classification of clinically relevant types of movement based on the forces sensed by load cells. The accuracy of the system for detecting movement has been evaluated using data collected in a laboratory setting. We also present a comparison of the proposed system with wrist-actigraphy.**

I. Introduction

BODY movements in normal sleep constitute a very regular pattern that is characteristic of the sleeper. Any alteration in this pattern may reflect internal or external changes in the sleep-wake cycle [1-3]. A sufficiently detailed record of nightly movement, preferably obtained from non-invasive monitoring devices, may help to identify motor disturbances that affect sleep quality. The assessment of sleep-related motor disturbances is traditionally performed by overnight polysomnograph (PSG) recording or actigraphy. PSG is an expensive method that involves at least a full night's stay in a sleep laboratory attended by properly trained technicians, which may not provide a representative sample of typical movements. 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. Physical motion is translated to a numeric representation, sampled at a certain rate and aggregated at a constant interval usually referred as an epoch (e.g. 15 seconds), which varies according to the manufacturer [4]. The exact nature and the number of movements that occur are not recorded [5]. Data loss occurs when the person does not wear it. Therefore, the actigraph has to be worn all the time and patients have to keep records of the times when it is taken off. Also, with actigraphy, the exact time in bed is not recorded, relying instead on patient report.

An alternative approach is to assess body movements in bed in a continuous and unobtrusive way by instrumenting the bed itself. Our research focuses on an alternative for unobtrusive assessment of movement in bed that employs four 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).

Load cell technology, based on strain gauge sensors, provides stable and reliable data and therefore it is a practical solution for long-term monitoring. The system is designed to detect postural shifts, smaller position changes, and limb movements based on changes in the magnitude of the load cell signals. We show evidence that the system can differentiate types of movements that are relevant to clinical disorders, and present a comparison of the proposed system with wrist-actigraphy.

II. Methods

A. Monitoring of Sleep Movements

Our goal is to monitor sleep movements by determining the type and frequency of movements performed by a patient during the night. Movement of a person in bed generally results in rapidly changing values in the load cell signals. From these changing load cell signals, we can derive parameters that describe the trajectory of the center of the person's mass during movement and the characteristics of that trajectory. We use these parameters to detect the movements and classify them into one of the following 3 classes:

- **Class 1:** major posture shifts - changes in position that involve a torso rotation larger than 45 degrees that may represent movements related to getting into or out of bed, or 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. They may represent restlessness or position changes associated with non-rapid eye movement (NREM) sleep stage I.

This work was funded by Intel Corporation and the Oregon Opportunity.

A. M. Adami and André G. Adami were with Oregon Health and Science University Portland, OR 97239 USA. They are now with University of Caxias do Sul, Caxias do Sul, RS 95070-560 Brazil (phone: +55 54 3218 2100; e-mail:amiorell@ucs.br).

M. Pavel and T. L. Hayes are with Oregon Health and Science University Portland, OR 97239 USA (e-mail: pavel@bme.ogi.edu, hayest@bme.ogi.edu).

- **Class 3**: leg movements - isolated movement of lower limbs (thighs, legs and feet) that may be associated with periodic limb movements during sleep (PLMS) or restless legs syndrome (RLS).

The choice of classes was based on movement descriptions used in the literature to analyze the distribution of movements during sleep [1, 6, 7]. The analysis of data is performed offline, and data can be recorded continuously for many nights. Movement detection and classification frameworks are described in Sections II.B and II.C, respectively.

B. Movement Detection Framework

A movement of a person in bed is generally characterized by rapidly changing forces at the load cells. Therefore, the general idea underlying the movement detection is based on the assessment of the weighted variability in the short-term energy across the load cells.

In its simplest form, the problem of detection of movement in bed consists of computing a set of features *f(t)* at each time *t*, and determining whether someone is moving or not at a given time *t*. It is formulated as a likelihood ratio test (LR) between two mutually-exclusive hypotheses: H_0: that a movement has not occurred at time *t*, and H_1: that a movement has occurred at time *t*. The LR test is a comparison between the likelihood ratio of two hypotheses and a threshold, and it is given by $\frac{p(f \mid H_1)}{p(f \mid H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \lambda$, where $p(f \mid H_j)$ is called the likelihood function for the j^{th} hypothesis, for $j = 0, 1$, evaluated for an observed feature value *f(t)* at time *t*, and λ is the fixed decision threshold. $p(f|H_0)$ and $p(f|H_1)$ are the likelihoods that the feature *f* is generated under the two competing hypothesis. H_1 is accepted if the ratio is larger than a threshold λ and, in general, this ratio can range between zero and infinity

The set of features is computed by estimating the energy in the short-term variability in each load cell. The individual load cell signals $w_i(t)$, for $i = 1, 2, 3, 4$, are then combined by weighting the load cells by their distance from the calculated center of mass of the person on the bed. Estimation of the short-term variability is based on the means of the load cells, calculated over an analysis window of length *L* samples

$$\overline{w}_i(t) = \frac{1}{L} \sum_{k=-\left(\frac{L-1}{2}\right)}^{\frac{L-1}{2}} w_i(t-k), \quad i = 1,2,3,4$$

where *L* is an odd number. Then, the mean-square difference for each $w_i(t)$ is calculated as:

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

We then estimate the scaling coefficients for a weighted combination of the mean-square differences $s_i^2(t)$. The goal is to assign degrees of relevance to modulate the contribution of each load cell signal based on its "gain", i.e., the distance from the estimated center of mass of the body. The notion is that the leverage of the signal from each load cell is inversely proportional to the distance of the moving body part. The center of mass is computed by treating the fixed location of the load cells as a two-dimensional Cartesian system so the center of mass is estimated using the law of moments or law of levers [8] as

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

and

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

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 $w_i(t_0)$ 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.

The set of features *f(t)* is an one-dimensional vector given by a weighted sum of the mean-square differences:

$$f(t) = \sum_{i=1}^{4} c_i(t) s_i^2(t).$$

The scaling coefficients $c_i(t)$ reflect the distance of the center of mass from the i^{th} corner, and were calculated based on the distance $d_i(t)$ between load cell *i* and the center of mass of the body

$$c_i(t) = \frac{1}{d_i(t) + 1}.$$

A kernel density estimation procedure is used to estimate the likelihood functions for the hypotheses $p(f|H_j)$, for j = 0,1. More details can be found in [9].

C. Movement Classification Framework

The subject-dependent movement classification framework consists of a training module and a testing module. The first step in the training module consists of pre-processing the load cell data from each movement, from the data of each subject, to estimate the trajectory of the center of mass during movement. In the second step, the feature extraction step, descriptors of the trajectory of the center of mass during movement are extracted: (1) the distance between initial and end points of the trajectory, (2) the length of the trajectory, and (3) the variance of the trajectory in the y-direction perpendicular to the sleeper's body axis. These features provide a simple characterization of the spatial and (indirectly) temporal aspects of the movements in bed. In the third step, the statistical modeling step, the goal is to estimate the parameters of each Gaussian Mixture

Model [10] that represents a certain movement class. In the testing module, after the testing data are pre-processed and features are extracted as it was done in the training module, the system estimates a likelihood score for each class for every test pattern, based on the model parameters estimated during the training module. A class label is assigned based on the maximum likelihood rule [11].

D. Laboratory Evaluation

The system was evaluated on data collected in laboratory. A convenience sample of fifteen participants (ages 22 to 45 years, mean age 30.4 ± 6.07 years old) was selected from faculty and students at Oregon Health and Science University (OHSU). Data were collected using two different protocols, *free movement* (where subjects were instructed to make a natural transition from one position to another when prompted by a beep) and *fixed movement* (where subjects were instructed to perform pre-defined movements when prompted by a beep), to allow both diversity and uniformity of movements. Each subject performed 10 natural transitions, plus 5 trials composed of 20 pre-defined movements each. These pre-defined movements include 6 large movements of torso and limbs (posture shifts) and 14 small movements (6 isolated movements of the head or arms, and 8 leg movements). The selected set of movements is related to the movement classes chosen for this study. All participants provided written informed consent (OHSU IRB #7983).

E. Ground truth measurements

Video was used as ground truth for this experiment. A Creative web cam NX Ultra camera was mounted on the ceiling, 2 m above the bed. Uncompressed 640x480 pixels RGB images of the bed were recorded at a rate of 10 frames per second, time-aligned with the load cell data, for offline analysis. 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 using template matching [12].

F. Sensors

Load cell data were collected using single point load cell (AG100 C3SH5eF, Scaime™, France) with a nominal load of 100 kg and an output ranging from 0 to 9.5 mV per 100 kg. Data were collected using an USB acquisition board (335-2001 Rev. C, Elektrika Inc.) Data were sampled at 200 Hz and digitized using a 13-bit analog-to-digital converter, and then downsampled to 10 Hz because the energy of the load cell signal for the set of movements performed is most concentrated below 5 Hz. Since voluntary movements rarely exceed 3-4 Hz, this choice was appropriate for the current study but does not prevent the use of higher sampling rates when analyzing involuntary movements.

Actigraphy data were collected simultaneously using an Actiwatch64 (Mini-Mitter Company Inc., Bend, Oregon). With each movement of the wrist, an accelerometer inside the Actiwatch generates a variable voltage that is sampled at a frequency of 32 Hz. The signal is integrated over a user-selected epoch, and a value expressed as "activity counts" is recorded on local memory. As defined by the manufacturer, the activity count is zero if no movement has been detected in an epoch. Therefore, we considered movement to occur any time the activity count for an epoch as greater than 0. The epoch used in the study was 15 seconds.

III. Results

A. Results of Movement Detection by Load Cells

In a decision process that minimizes errors, the LR of each data sample is compared to a threshold, producing a sequence of decisions that reflect the time periods when the subject is either moving or not. The decision threshold is estimated *a posteriori* by searching a value that produces the EER when applied to the likelihood ratio estimated from the testing data. In practice, the threshold is obtained by varying its value across all available values of LR and determining which value better satisfies the EER condition.

A common measure of the accuracy of a detection system is its equal error rate (EER), which is the operating point where the number of missed detections (false negatives) is equal to the number of false positives. The decisions of the detector are discrete, and false alarm rates and miss detection rates are defined by the counts of correct and incorrect sample decisions. For our load cell system, the EER was 3.22%. Of a total of 890 movements tested, only 11 movements were missed and 14 were falsely detected. The missed movements include 7 head movements, 2 arm movements, and 2 medium amplitude movements that include arm and leg movements to adjust position. For an average miss detection rate of 3.22%, 2.69% accounts for miss detections at the movement onsets and offsets, and only 0.53% accounts for missed movements. For the false alarm rate, 2.77% accounts for false alarms at the onsets and offsets, and only 0.45% accounts for falsely detected movements. This shows that most of the errors come from errors at the estimation of the onsets and offsets.

B. Results of Movement Classification by Load Cells

The performance measure used in the classification of movements 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. 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). For each subject, the classifier was designed using the training set, and the performance was evaluated on the test set. The system correctly classified 84.6% of these movements. 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.

C. Comparison to Wrist-Actigraphy Data

In order to do the comparison with actigraphy, the load cell detection results (sampled at 10 Hz) and the ground truth video data (sampled at 10 frames per second) were converted into 15 second epochs. To compare the actigraphy data to the ground truth video data, we recorded a "hit" by the Actiwatch for every epoch in which there was an activity count larger than zero, and during which an actual movement was recorded on the video within the time interval of the respective epoch. To compare the load cell data to the ground truth video data, we recorded a "hit" by the load cell detector for every epoch in which a movement was detected, and during which an actual movement was recorded on the video within the time interval of the respective epoch. The probabilities that a given movement was detected by the actigraph or the load cell detector given that the movement had occurred according to the video assessment are shown in Table 1. These probabilities show that, whereas most of the posture shifts are detected by the actigraph, head and arm movements (when moving the arm that does not have an actigraph) are missed. Approximately 44% of the leg movements were detected, and the actigraph detected very small movements of the wrist that could not be seen from video during leg movements. The results show that the load cell detection system yields more accurate detection of movements in bed than wrist-actigraphs and, in particular, that it can detect a wider range of movements in bed rather than the movement of a specific limb.

TABLE I
ACTIGRAPH AND LOAD CELLS HIT RATES FOR THREE TYPES OF MOVEMENTS

	Posture Shifts	*Medium Amplitude Movements*	*Leg Movements*
Actigraph	1	0.732	0.438
Load Cells	1	0.974	1

IV. CONCLUSION

This paper presented a system for assessment and classification of movement in bed with load cells. The main goal of this work was to examine the extent to which the load cell signals can be used to infer clinically meaningful aspects of movement and sleep quantity. Although the evaluation of the system was based on voluntary movements that were performed during awake periods, the system has great potential for clinical use. One of the aspects that could most benefit from further study is to determine how the system can be used to document RLS and PLMS. Since RLS patients constantly move their legs to relieve the tingling sensations caused by this disorder, we speculate that our system could be used as an aid for diagnosis or treatment of RLS because it can differentiate leg movements from other movements. Our system can be employed in such cases to monitor the frequency of leg movements. Also, we have shown that the load-sensor system compares favorably with wrist-actigraphs for the determination of lower extremity movement, but a comparative study of the bed-based system with ankle or calf-actigraphy is needed. We believe the system offers advantages over actigraphy in terms of comfort and ability to confirm and document times in bed, in addition to the potential to accurately classify limb movement.

ACKNOWLEDGMENT

The authors acknowledge the participants of the study, and the staff of the Point of Care Laboratory for their technical assistance.

REFERENCES

[1] A. Muzet, "Dynamics of Body Movements in Normal Sleep," in *Eighth European Congress on Sleep Research*, Szeged, Hungary, 1986, pp. 232-234.

[2] F. Giganti, G. Ficca, S. Gori, and P. Salzarulo, "Body movements during night sleep and their relationship with sleep stages are further modified in very old subjects," *Brain Res Bull,* vol. 75, pp. 66-9, Jan 31 2008.

[3] S. Gori, G. Ficca, F. Giganti, I. Di Nasso, L. Murri, and P. Salzarulo, "Body movements during night sleep in healthy elderly subjects and their relationships with sleep stages," *Brain Res Bull,* vol. 63, pp. 393-7, Jun 30 2004.

[4] G. Jean-Louis, D. F. Kripke, W. J. Mason, J. A. Elliott, and S. D. Youngstedt, "Sleep Estimation from Wrist Movement Quantified by Different Actigraphic Modalities," *Journal of Neuroscience Methods,* vol. 105, pp. 185-191, 2001.

[5] S. Chokroverty, W. A. Hening, and A. S. Walters, *Sleep and Movement Disorders*, First ed. Philadelphia, PA: Elsevier Science, 2003.

[6] S. T. Aaronson, S. Rashed, M. P. Biber, and A. Hobson, "Brain State and Body Position," *Archives of General Psychiatry,* vol. 39, pp. 330-335, 1982.

[7] J. Wilde-Frenz and H. Schulz, "Rate and Distribution of Body Movements during Sleep in Humans," *Perceptual and Motor Skills,* vol. 56, pp. 275-283, 1983.

[8] G. Strang, *Calculus*. Wellesley, MA: Wellesley-Cambridge Press, 1991.

[9] A. M. Adami, M. Pavel, T. L. Hayes, and C. M. Singer, "Detection of Movement in Bed with Unobtrusive Load Cell Sensors," *IEEE Transactions on Information Technology in Biomedicine,* p. in press, 2009.

[10] R. O. Duda, P. E. Hart, and D. G. Stork, *Pattern Classification*, Second ed. New York, NY: John Wiley & Sons, Inc., 2001.

[11] D. H. Kil and F. B. Shin, *Pattern Recognition and Prediction with Applications to Signal Characterization*, First ed. Woodbury, NY: American Institute of Physics, 1996.

[12] A. M. Adami, "Assessment and Classification of Movements in Bed Using Unobtrusive Sensors," Ph.D., Electrical Engineering, Oregon Health & Science University, Beaverton, 2006.