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A Subject State Detection Approach to Determine Rest-Activity Patterns Using Load Cells

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Abstract

A patient's sleep/wake schedule is an important step underlying clinical evaluation of sleep-related complaints. Aspects related to timing of a person's sleep routine provide important clues regarding diagnosis and treatments. Solutions for sleep complaints may sometimes rely solely on changes in habits and life style, based on what is learned from daily rest-activity patterns. This paper describes an approach for determining two states, in-bed and out-of-bed, using load cells under the bed. These states are important because they can help characterize rest-activity patterns at nighttime or detect bed exits in hospitals or nursing homes. The information derived from the load cells is valuable as an objective and continuous measure of daily patterns, and it is particularly valuable in sleep studies in populations who would not be able to remember specific hours to complete sleep diaries. The approach is evaluated on data collected in a laboratory experiment, in a sleep clinic, and also on data collected from residents of an assisted-living facility.

I. Introduction

Good sleep hygiene has as much importance as a balanced diet and the amount of exercise for our health. The assessment of the regularity of rest-activity patterns such as bedtimes, get up times, and daytime naps is important because it helps promote effective sleep [1]. Lack of regularity and the common practice of cheating hours from sleep can lead to chronic fatigue.

Sleep diaries represent a simple and inexpensive method for assessment of rest-activity patterns. The patient needs to record, on a daily basis, actual sleep times and daytime activities, as well as the occurrence of symptoms such as nocturnal arousals [2]. This subjective account of daily patterns is valuable when symptoms are not easily accessible to laboratory testing, and has great value for assessing treatment effects and other factors that affect the consistency of a person's sleep. However, there is evidence to suggest that people have difficulty assessing their own sleep especially when suffering from insomnia [3] and

depression [4]. Sleep diaries also have limited usefulness for patients with frequent fluctuations in daytime vigilance, as is seen in elderly persons [5].

Actigraphy also has been used to study rest-activity patterns [6–8]. 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, and patients have to keep records of the times when it is taken off. They provide the opportunity to conduct longitudinal sleep studies. However, data loss occurs when the person does not wear it.

Given the drawbacks of sleep diaries and actigraphy, researchers have looked for alternative ways to obtain information about rest-activity patterns at nighttime from unobtrusive sensors installed in the bedroom. Chan et al. [9,10] proposes a system that uses motion sensors installed in areas such as the bedroom and bathroom to monitor activity during the night. The system consisted of 10 infrared motion sensors installed on the ceiling that included one above the bed and in areas adjacent to the bed. A number of different activities such as going to bed, restlessness in bed, getting out of bed, and getting out of the room were monitored. The activities were detected by the pattern of the sensor activations, and by setting thresholds. They found good agreement with the nurse staff annotations in an 8-month study that monitored 4 subjects. Although motion sensors represent a cheap technology, the proposed system has to be reconfigured every time the environment changes. In addition, the proposed system cannot discriminate the patient being in bed from them standing near the bed, and it recognizes the latter as restlessness in bed.

In this work, we propose an approach for determining two states, in-bed and out-of-bed, using load cells under the bed. These states are important because they can help characterize rest-activity patterns at nighttime or detect bed exits in hospitals or nursing homes. The information derived from the load cells is valuable as an objective and continuous measure of daily patterns, and it is particularly valuable in sleep studies in populations who would not be able to remember specific hours to complete sleep diaries or who would depend on subjective reports from caregivers or family members. This approach can be employed only for single bed occupancy. We evaluate the approach on data collected in a laboratory experiment, in a sleep clinic, and also on data collected from residents of an assisted-living facility.

II. Methods

A. Determination of In-Bed and Out-of-Bed States

Load cells are strain gauge transducers that convert applied force into a resistance change. They are widely deployed in industrial systems and also commonly used in electronic scales. They can be manufactured to measure loads on nearly any scale, ranging from measuring ingredients for pharmaceutical productions in milligrams, to the weight of a freight train with several hundred tons [11]. They are of relatively low cost, and represent a simple and durable technology.

Load cells have been used to detect movements in bed [12] as well as to classify breathing events [13]. The forces sensed by the load cells placed under each support of a bed i at each discrete time t , $x_i(t)$, are related to the instantaneous distribution of the mass of the body when someone is lying on bed. The sum of the load cell data, defined as

$$\sum_{i=1}^M x_i(t),$$

where M is the number of supports, is the total force sensed. Fig. 1 shows a load cell installed under a bed. Fig. 2. shows an example of load cell data collected during one night for a subject.

It is straightforward to identify the in- and out-of-bed states with load cells due to the drop in the total force sensed when someone gets up. 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 by minimizing the within-cluster variability and maximizing the between-cluster variability [14].

Given that k-means is an unsupervised clustering method, no training phase is necessary. 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.

B. Performance Measure

The problem of determining the in-bed and out-of-bed states can be formulated as a hypothesis testing of two mutually-exclusive hypotheses:

H_0 : the subject is in bed,

H_1 : the subject is out of the bed.

Two types of errors may occur in a detection system. Type I error occurs when the null hypothesis (H_0) is rejected when it is true. The errors of this type are referred to as “misses”, meaning that the subject is detected as out of bed when he or she is in bed. Type II error occurs when the null hypothesis is not rejected when it is false. The errors of this type are referred to as “false alarms”, meaning that the subject is detected as in bed when he or she is out of bed. Fig. 3 shows an example of false alarm and miss detection errors. The miss detection errors can be further divided into two classes. In the first class, the errors happen at the in-bed boundaries (such as the miss detection error in the left side of Fig. 3). The other class is the miss detection of a whole in-bed event. The difference between these two classes of errors is that the second one can be more damaging for systems that depend on the in-bed events. That is, the information during that period is completely lost because of such miss detection. The same issue can happen for the false alarm.

The missed detection rate (MDR) and the false alarm rate (FAR) are used to characterize the performance of the system. The MDR is computed as the ratio between the total time of wrongly undetected in-bed events and the total in-bed event time. The FAR is computed as the ratio between the total time of wrongly detected in-bed events and the total out-of-bed event time.

C. Laboratory Experiment Dataset

Fifteen adults (7 men and 8 women), age ranging from 22 to 45 years (mean age 30.4 ± 6.1 years old) participated in a laboratory study. Load cell data were collected from 4 single point load cells (AG100 C3SH5eF, ScaimeTM, France) sampled at 200 Hz and downsampled to 10 Hz. Data were collected using two different protocols, *free movement* and *fixed movement*, to allow both diversity and uniformity of movements. The main difference between these two protocols is that the latter required the subject to perform a pre-determined set of movements in bed. A video technique was used as the ground truth for this experiment [15].

This dataset contains 145 in-bed states, corresponding to approximately 25.5 hours of data, and approximately 4.5 hours of out-of-bed state data.

D. Sleep Clinic Experiment Dataset

Twelve patients (8 men and 4 women) from the Oregon Health and Science University (OHSU) Sleep Disorders Program, with ages ranging from 30 to 69 years (mean age 50.4 ± 11.2 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 polysomnography (PSG). We collected data from 6 resistive load cells (16-bit digitization) placed under the supports of the bed. The load cell data was collected at 2 kHz for the entire length of the patient's sleep study, and downsampled to 10 Hz for analysis. Trained sleep technicians made annotations of the times when patients got in and out of the bed during the night. The ground truth for this experiment was the technicians annotations.

This dataset contains 25 in-bed states, corresponding to approximately 99 hours of data, and approximately 1.5 hours in out-of-bed state.

E. Assisted-Living Facility Experiment Dataset

Three residents of Elite Care (2 men and 1 woman), an assisted-living facility located in Milwaukie, Oregon, participated of the study. The subjects had ages ranging from 88 to 92 years (mean age 90.3 ± 2.1 years-old). The load cell setup for this experiment was the same setup described in Section II.C. Data were collected for three weeks. Ground truth for this experiment was the sleep diaries completed by caregivers [15].

This dataset contains 458 in-bed states, corresponding to approximately 551.5 hours of data, and approximately 202.5 hours in out-of-bed state. The data was excerpt from the period when every subject goes to sleep and wakes up in the morning. Nighttime period, defined by the bedtime and get up time, was identified by manual labeling.

III. Results

The performance of the subject state detection approach, evaluated on the three datasets, is shown in Fig. 4. The false alarm error rate ranged from 0% (on the assisted-living facility dataset) to 0.97% (on the laboratory experiment dataset). The miss detection error rate ranged from 0.01% (on the sleep clinic dataset) to 1.64% (on the assisted-living facility dataset).

The results show that the proposed approach achieves a very high accuracy for in-bed and out-of-bed state detection. One of the reasons for the miss detection errors is that subjects seated before laying down or getting up. In such cases, the data was labeled as out-of-bed because a small total force was produced when part of the body weight was supported by the feet on the floor. Since such events are very common in the assisted-living facility dataset due to the elder subjects and the large number of bed entering and exits, the miss detection rate was the largest among all three datasets. Another reason is attributed to the differences produced by the manual labeling and the hard-decisions made by the clustering method.

The false alarm errors were mainly caused by the bed exits in the laboratory and sleep clinic datasets, at the end of the experiment. A very interesting result is that none of the miss detection and false alarms errors were caused by missing or giving a false positive of an entire in-bed event. This means that all in-bed events were detected (with a small variance in the beginning and ending times), providing a very reliable decision for systems that depend on such information to characterize rest-activity patterns at nighttime or detect bed exits in hospitals or nursing homes.

IV. Conclusions

This paper presented an approach for determining two states, in-bed and out-of-bed, using load cells under the bed. The load cell data was clustered into two groups using the unsupervised clustering method k-means. The results show that the approach provided an average error below 1% for miss detection and false alarm. In addition, no whole in-bed or out-of-bed event was missed or falsely detected by the approach. Therefore, the approach can be used by systems that require such information.

The proposed approach requires that the data from the time period to be analyzed must be available beforehand. An extension to our approach is to perform the state detection in real-time using methods like, for example, the cumulative sum algorithm with an adaptive threshold [16]. Real time detection will allow systems that depend upon the detected information to perform some more specialized measurement, such as number of bed enterings/exits, bedtime, get up time, and current total time in bed. In addition, the method must be evaluated with systems that require such subject state information to produce relevant information about the bed activity of a subject.

The subject state detection could also be used in other applications besides sleep hygiene, where the knowledge about a person's habits could be helpful, for example, for localization.

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References

1. Culebras, A. Clinical Handbook of Sleep Disorders. 1. Newton, MA: Butterworth-Heinemann; 1996.
2. Aldrich, MS.; Naylor, MW. Approach to the Patient with Disordered Sleep. In: Kryger, MH.; Roth, T.; Dement, WC., editors. Principles and Practice of Sleep Medicine. 3. Philadelphia, MA: W. B. Saunders Company; 2000. p. 521-525.
3. Carskadon MA, Dement WC, Mitler MM, Guilleminault CG, Zarcone VP, Spiegel RS. Self-reports versus Sleep Laboratory Findings in 122 Drug-free Subjects with Complaints of Chronic Insomnia. *American Journal of Psychiatry*. 1976; 133:1382–1388. [PubMed: 185919]
4. Tsuchiyama K, Nagayama H, Kudo K, Kojima K, Yamada K. Discrepancy between Subjective and Objective Sleep in Patients with Depression. *Psychiatry and Clinical Neurosciences*. 2003; 57:259–264. [PubMed: 12753564]
5. Rogers AE, Caruso CC, Aldrich MS. Reliability of Sleep Diaries for Assessment of Sleep/Wake Patterns. *Nursing Research*. 1993; 42:368–372. [PubMed: 8247821]
6. Ancoli-Israel S, Cole R, Alessi C, Chambers M, Moorcroft W, Pollak CP. The Role of Actigraphy in the Study of Sleep and Circadian Rhythms. *Sleep*. 2003; 26:342–392. [PubMed: 12749557]
7. Sadeh A, Acebo C. The Role of Actigraphy in Sleep Medicine. *Sleep Medicine Reviews*. 2002; 6:113–124. [PubMed: 12531147]
8. Verbeek I, Klip EC, Declerck AC. The Use of Actigraphy Revised: The Value for Clinical Practice in Insomnia. *Perceptual and Motor Skills*. 2001; 92:852–856. [PubMed: 11453214]
9. Chan M, Campo E, Laval E, Estève D. Validation of a Remote Monitoring System for the Elderly: Application to Mobility Measurements. *Technology and Health Care*. 2002; 10:391–399. [PubMed: 12368559]
10. Chan M, Campo E, Estève D. Assessment of Activity of Elderly People Using a Home Monitoring System. *International Journal of Rehabilitation Research*. 2005; 28:69–76. [PubMed: 15729100]

11. Scaime. Load Cells. 2003. http://www.scaime.com/english/pages_e/loadcells.html
12. Adami AM, Pavel M, Hayes TL, Singer CM. Detection of Movement in Bed with Unobtrusive Load Cell Sensors. *IEEE Transactions on Information Technology in Biomedicine*. 2010; 14:481–490. [PubMed: 19171523]
13. Beattie, ZT.; Hagen, CC.; Pavel, M.; Hayes, TL. Classification of Breathing Events Using Load Cells under the Bed. 31st Annual International Conference of the IEEE EMBS; Minneapolis, Minnesota. 2009. p. 3921-3924.
14. Duda, RO.; Hart, PE.; Stork, DG. *Pattern Classification*. 2. New York, NY: John Wiley & Sons, Inc; 2001.
15. Adami, AM. PhD, Electrical Engineering. Oregon Health & Science University; Beaverton: 2006. *Assessment and Classification of Movements in Bed Using Unobtrusive Sensors*.
16. Basseville, M.; Nikiforov, IV. *Detection of Abrupt Changes - Theory and Application*. Englewood Cliffs, N. J: Prentice-Hall, Inc; 1993.

Fig. 1.
Load cell installed under a bed.

Fig. 2.
Total force sensed by load cells (in Newtons), during a night, for a subject.

Fig. 3.
Example of false alarm and miss detection errors.

Fig. 4.
Detection performance on the three datasets.