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Estimation of Rest-Activity Patterns using Motion Sensors

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Abstract

Disrupted sleep patterns are a significant problem in the elderly, leading to increased cognitive dysfunction and risk of nursing home placement. A cost-effective and unobtrusive way to remotely monitor changing sleep patterns over time would enable improved management of this important health problem. We have developed an algorithm to derive sleep parameters such as bed time, rise time, sleep latency, and nap time from passive infrared sensors distributed around the home. We evaluated this algorithm using 404 days of data collected in the homes of 8 elderly community-dwelling elders. Data from this algorithm were highly correlated to ground truth measures (bed mats) and were surprisingly robust to variability in sensor layout and sleep habits.

I. INTRODUCTION

It has been estimated that more than 50% of seniors have disrupted sleep patterns [1], which have been associated with increased cognitive dysfunction, cardiovascular and pulmonary co-morbidities, and decreased quality of life. Furthermore, loss of sleep can lead to increased falls and an increased risk for nursing home placement. Therefore, there is considerable interest in understanding sleep behaviors in the elderly.

Assessment of sleep behavior for research is typically done through self-report using questionnaires on which people are asked to report on the frequency of certain behaviors over some period in the past, such as “taking more than 30 minutes to fall asleep” or “having restless sleep”. Self-report is known to be unreliable [2], particularly in cognitively impaired populations, and so a number of alternatives have been proposed for collecting objective

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This potential conflict has been reviewed and managed by OHSU.

measures of rest/activity cycles, including actigraphy [3], load cells under the supports of the bed [4,5], bed mats [6], and the Static Charge Sensitive Bed [7]. However, actigraphy requires patient compliance, and the other methods have limitations for long-term wide-scale use due to ease of deployment and the possibility of displacement of the device during changes of bed linens and cleaning. Furthermore, although these methods capture in-bed activity, they give no insight into activities at night that occur out of bed. Over the past few years, we have developed a system for continuously collecting activity data in the home [8,9] that has now been collecting data in the homes of more than 230 participants for an average of 144 weeks. As part of this study we monitor the activity in each room of the home using inexpensive passive infrared motion sensors. We have developed an algorithm for estimating sleep parameters such as bed time, rise time, sleep latency, and total sleep time that integrates the data from multiple low-cost sensors to provide accurate estimates of these important parameters.

This paper reviews the approach and our initial evaluation of it in the Oregon Center for Aging and Technology (ORCATECH) Living Laboratory (OLL). The OLL is a population of community-dwelling seniors who have agreed to participate in a variety of research studies related to the use of in-home technologies for health monitoring, intervention, and support of independent living. We have installed an extensive suite of “base” sensors in their homes, including motion sensors in each room and contact sensors on the outside doors and the refrigerator. Here, we describe the algorithm used to derive the sleep parameters, and evaluate it on data collected in the OLL.

II. METHODS

A. Approach

The motion sensors used to detect room activity are both noisy (they do not always fire) and relatively inaccurate (they have a six second refractory period). However, the firings of sensors in different rooms are independent, and by combining data from multiple sensors we are able to estimate the probable state of the subject. We do this by representing the activities of the subject as a finite state machine. The states of interest are awake in the bed (IB), asleep in the bed (AB), or out of the bed (OB). The transitions between states are determined by a set of context-sensitive grammars which describe the sequence of sensor firings that determine if a transition between states has occurred at any particular time. The parser incorporates the timing of sensor firings by introducing *temporal tokens*, and the primary goal of the parser is to reduce the input string to determine the next state of the subject. Thus, we extend the traditional definition of the grammar to include these temporal tokens and output states: $G = (V, S, \Sigma, \tau, R, \sigma)$, where V is a finite set of non-terminal variables, S is the set of states of interest, Σ is the set of terminals (sensor firings), τ are the temporal tokens, R is the set of rewrite rules, and σ is the starting token.

For examining sleep in the bedroom, we start parsing at a time point when we are reasonably assured that the subject is out of bed (e.g. noon), and find the first bedroom firing after that point. Therefore, the starting state S_0 is OB, and the starting token $\sigma=b$ (bedroom firing). We then apply the rewrite rules at each firing of the bedroom sensor. That is, we walk through the series of bedroom firings, determining the appropriate set of rewrite rules based on the subject's current state, and then apply those rules to determine the next state of the subject. In rare cases, a rewrite rule required that the subject's previous state be updated; in such cases, we did not reapply the rewrite rules after changing the previous state.

The rewrite rules capture various sensor firing sequences due to placements of the sensors. There are five categories of rewrite rules that were used to determine state transitions. We

present an example (Figure 1) to help demonstrate the use of the temporal tokens and output states.

For subjects in the state OB:

1. The first category captures people's normal going-to-bed patterns: 20 minutes of inactivity prior to a bedroom firing, where the previous 4 sensor firings prior to the inactivity included at least one bedroom firing. In this case the time of the most recent firing prior to the quiescent period is marked as an OB→AB transition).
2. The second category captures people who are active in bed (e.g. read or watch television in bed): All firings within the previous 20 minutes have been in the bedroom with no more than 1.5 firings per minute over the entire IB period. In this case each bedroom firing going back to the last non-bedroom firing is marked as IB, and the next non-bedroom firing after the current one is marked as the transition IB→OB.

For subjects in the state IB or AB:

- 3) The third category captures restlessness at night: If the next firing sequentially is also a bedroom firing, then the subject state is not changed.
- 4) The fourth category captures missed activity from a non-instrumented room: If there have been more than 15 non-bedroom firings immediately prior to the current bedroom firing, then the previous bedroom firing is corrected to be OB, and the current bedroom firing is marked as OB. In this case apparent inactivity when in the bedroom (category 1) was actually due to missed activity in a non-instrumented location.
- 5) The final category captures peoples' normal wakeup behaviors. If the current bedroom firing is followed by a bathroom firing, more than 2 living room firings, or more than 1 of any other non-bedroom firing, then the time of the firing is marked as a transition to OB.

The algorithm can be applied to any room, but we use the bedroom as an example since that is the most common location for sleeping.

B. Data collection

Eight subjects from the ORCATECH Living Lab (mean age 77.3 ± 4.7 years) participated in this study. All subjects provided written informed consent before participating in study activities. The protocol was approved by the OHSU Institutional Review Board (IRB #2765). All subjects living alone, although one subject had a cat. One subject has Restless Leg Syndrome and two subjects had back problems during the monitoring period; these subjects did not always sleep in their bed at night. One subject broke her arm during the monitoring period. The home sizes ranged from four to fourteen rooms.

Ground truth about in and out of bed measures was provided by pressure mats placed under the mattress (BAM Labs, Los Gatos, CA). These mats provide pressure, heart rate, and respiration data every 10 seconds. The pressure information was used to determine when the subject was lying on the bed. Data from the existing motion and door sensors in the subject's homes were collected simultaneously with the mat data for at least four weeks (mean 59.1 ± 41.8 days, range 26–141 days). Days during which the subject was away at night (36), had overnight guests (19), did not sleep in their own bed (44), or the data was not collected due to problems with the Internet connection, sensors, or mat (126) were excluded from analysis. A total of 405 days of data were included, including at least 29 days for each subject.

C. Evaluation of in-and-out-of-bed estimation

For the purposes of evaluating how well the PIR sensor algorithm estimated in and out of bed events, we treated in bed as a “positive” event and out of bed as a “negative” event. The state estimation of awake in the bed (IB) and asleep in the bed (AB) are both considered positive events. The BAM mat reports the pressure on the bed every 10 seconds. Therefore, we determined the ground truth of positive and negative events from those data. We then formed a contingency table containing the false positives (FP), false negative (FN), true positive (TP) and true negatives (TN) arising from our algorithm and used a χ^2 test of independence to determine the relationship between the algorithm estimates and the ground truth. We measure the strength of the association using Cramer’s Phi (ϕ), which determines the proportion of the variance ($=100\%*\phi^2$) that is accounted for by the relationship identified by the χ^2 test.

D. Calculation of sleep measures

We used the in- and out-of-bed estimations to calculate a number of traditional sleep measures. Note that asleep in bed (AB) events can happen at any time of day, since people nap, but many sleep measures of interest typically refer to nighttime sleep. The measures reported here were derived from application of the algorithm to bedroom firings.

- a. Transition to bed: transition from out-of-bed (OB) to in-bed (IB). For determining bedtime, we choose the last transition IB before the first asleep-in-bed (AB) event after 6pm at night.
- b. Sleep latency: the time between IB and the first AB event that immediately follows it. For determining sleep latency when the subject first goes to bed, we chose the latency for the first AB event after 6pm.
- c. Transition out of bed: transition from IB to OB. For determining rise time, we choose the first OB transition following the last AB event prior to 1pm in the afternoon.
- d. Number of times up at night: the number of OB to IB transitions excluding bedtime.
- e. Time up at night: the total amount of time spent OB between bedtime and rise time.

III. RESULTS

Figure 2 shows examples of one night of sleep for two subjects, one who sleeps well, and one who gets up a night and then falls asleep in their living room. The lines in the plot show the estimates of IB and OB from the mat and the PIR sensor algorithm. Results of the a χ^2 analysis are shown in Table 1, together with the average estimated bedtime, rise time, number of times up at night, and total time up at night for each subject. We also calculated the correlation between the time to bed and the rise time estimated from the mat and using the PIR sensor algorithm (see Figure 3). The correlation coefficients were 0.99 (bed time) and 0.96 (rise time).

IV. DISCUSSION

We have presented an algorithm that can be used to unobtrusively monitor sleep behavior parameters on an ongoing basis over extended periods of time. The algorithm accurately estimated in and out of bed states as compared to a bed mat that provided this information directly. However, the algorithm could also be used to capture naps, by applying it to other rooms such as the living room. It also provides information about what people are doing

when they get out of bed (going to the bathroom, kitchen, etc.), which is an advantage over bed mats and similar devices placed on or under the bed.

The accuracy of the algorithm varied depending on the quality of the sensor placement and the activity of the participants. So, for example, in one home in which the walk-in closet did not contain a sensor, our ability to accurately infer sleep and in-bed states was compromised. However, in spite of this, we achieved extremely good estimates of bedtime and rise time using the algorithm.

This algorithm does not work well for multi-person homes, since the additional sensor firings due to other residents make the rewrite rules inapplicable. We are experimenting with placement of additional sensors, such as restricted field motion sensors on either side of the bed, to improve our ability to detect sleep patterns in multi-person homes.

We are now applying our algorithm to our ongoing longitudinal study, to gather objective information about how sleep patterns relate to cognitive status and other health states.

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Figure 1.
Example of a rewrite rule for category 1.

Figure 2.

Two examples of one night of raw motion sensor data (dots), together with the results of the algorithm to detect bed/sleep times (lines). The solid pink line shows time in bed as determined from the BAM mat; the dashed blue line shows estimated periods of sleep inferred from the motion sensors. The top plot shows a subject who slept well at night; the bottom plot shows one night from the subject with RLS during which they got up after a period of sleep, likely fell asleep in the living room, and then returned to bed later in the night. In this case the mat clearly shows the person is out of bed; however, we infer that the person is sleeping in the living room based on the PIR sensor activity.

Figure 3. Correlation between the time of transitions into bed (top) and out of bed (bottom) between the mat data and the estimates of the PIR sensor algorithm.

Summary of daily sleep parameters for each subject, together with the χ^2 results of the comparison of the in and out of bed profiles produced by the PIR sensor algorithm to the data from bed mats. Mean time up and Mean latency reported in hours:minutes.

Table 1

Subj. ID	Median Bedtime	Median Rise time	#times up	Mean time up	Mean latency	χ^2	Variance	Notes
311	00:42	7:31	1.94	0:05	0:01	1.46E+06	87.2%	Back problems, doesn't always sleep in bed
315	21:34	7:58	1.52	0:17	1:16	3.28E+05	68.7%	Has a cat
317	23:48	5:30	1.50	0:46	3:13	3.67E+05	80.5%	Restless leg syndrome
373	20:01	8:22	2.82	1:23	2:08	9.83E+05	57.5%	Watches TV in bed in the evenings
517	23:07	7:01	1.37	0:02	0:23	5.12E+05	97.1%	
776	00:14	8:44	1.60	0:08	3:46	4.83E+05	87.7%	Broke her arm
777	21:59	4:47	2.14	0:13	0:27	3.95E+05	74.4%	Back problems, doesn't always sleep in bed
1075	23:01	7:47	1.19	0:03	0:01	3.10E+05	40.8%	Home was missing sensor in walk-in closet