An approach for deriving continuous health assessment indicators from in-home sensor data

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Abstract. Recently, a number of projects have been undertaken to collect continuous behavioral data from elderly individuals using unobtrusive in-home sensors. An important challenge facing these projects is the development of approaches for interpreting these data. One approach, based on statistical process control, is to model each individual's behavior as a random process whose mean and variance may change over time. The sensor data then provide specific measures of the process that can be used to identify changes in patterns of behavior. The approach is presented and applied to measures of sleep hygiene in a group of 14 community-dwelling elders monitored over a six month period. Both acute and slow changes in the patterns of sleep were successfully identified in individuals using this approach.

Keywords. Aging in place, Monitoring, Remote monitoring, Smart home

1. Introduction

In 1997, more than 6 million elders in the United States received in-home care due to a limited capacity for independent living, with an additional 7 million residing in assisted living and skilled nursing facilities. The Congressional Budget Office (CBO) estimates that total expenditures in 2004 for long-term care services for the elderly was $135 billion, 60% of which was paid for by Medicare and Medicaid [1]. Some of this cost could be avoided by helping the elderly remain independent as long as possible, which has led to a recent research focus on technologies for facilitating remote monitoring of the elderly [2]. Many of these approaches are based on the use of unobtrusive wireless sensors, including magnetic switches, passive infrared sensors, and environmental sensors, which provide continuous data about activity in the home [3-8].

In this paper we present an approach for identifying trends in these continuous assessment data. We use this approach to estimate parameters of sleep behaviors, derived from motion sensor data. It is generally accepted that disrupted sleep, including nighttime awakenings, difficulty falling asleep, and early awakening, are common in the elderly. Estimates of the prevalence of sleep disturbances in the elderly range from 23-54% [9]. Many sleep disturbances are reflective of health problems such as congestive heart failure or back problems, and the greater prevalence of sleep disturbances among the elderly does not appear to be simply due to normal aging changes [10]. Thus, trends in patterns of sleep may be of particular importance in assessing health changes, and provide a good example of the utility of the approach.

2. General Approach

The analysis technique described here draws on concepts from statistical process control [11]. Each individual's behavior is modeled as a random process whose mean and variance may change over time. The sensor data then provide specific measures of the process that can be used to identify changes in patterns of behavior. The basic approach is to (1) develop a baseline model of typical measures for each individual; (2) monitor these measures on an ongoing basis for trends away from the norm – these trends provide "continuous assessment indicators" or CAI; and (3) record the slope of the trend, and the duration (trends must stabilize over time, since the data are bounded).

2.1. *Estimation of the baseline*

In statistical process control, data is collected for a single individual over a short period of time (called a *run*) for each measure of interest *x*, giving *n* data points x_i. We then take a measure of location $\bar{x}$ (e.g. the mean or median) and a measure of spread $\bar{r}$ (e.g. range or standard deviation) for that run. By tracking changes in these values over time, we form a picture of how consistent these measures are for that individual. Thus, trends and outliers in the data are reflective of changes in behavior for *that individual*, without reference to others in that person's cohort.

In order to detect those changes, an initial period of time is used to establish a baseline for each individual. For example, if we used bedtime each night over a 7-day period for our run data, we would average these $\bar{x}, \bar{r}$ values over a period of time – say 12 weeks – to establish typical values for the individual. This allows us to set *control limits* – to identify values that represent outlier boundaries. A common choice for determining control limits is to calculate the mean $\bar{\bar{x}}$ and standard deviation $\hat{\sigma}$ of the run values for this initial period. Then, upper and lower control limits on the measures are defined as $\left\{\bar{\bar{x}} + {3\hat{\sigma}}\big/{\sqrt{n}}, \bar{\bar{x}} - {3\hat{\sigma}}\big/{\sqrt{n}}\right\}$. These *control limits* can be used to identify outliers in the data throughout the monitoring period. Similarly, upper and lower control limits can be set on the measure of spread $\bar{r}$. Plots of the mean values with the overlay of control limits (*Control Charts*) are used to determine when the process is "out of control" – in the case of a health behavior, when an important change has occurred which affects the measure of interest.

The choice of measures to be tracked clearly depends on the characteristics of the data and the changes of interest. Charts tracking the mean (Shewhart $\overline{X}$ charts) or the spread (typically the range or standard deviation, using an *R* chart) are useful for detecting acute changes in a measure not expected to drift over time. To detect a small or large drift in the process mean, a cumulative sum chart (CUSUM, see section 2.2) [12] or an exponentially-weighted moving average chart (EWMA, see section 5.1) [13, 14] is more appropriate.

2.2. *Using a CUSUM plot to identify trends*

After the initial period a model has been established for each subject that characterizes the normal variance in the parameters of interest. At that point, we can begin to track trends away from the estimated process means, as well as identify individual weeks in which the data contain outliers. Identifying outliers is important for identifying incident events (for example, breaking a hip) which may mask trends relevant to the detection of longer term changes (for example, cognitive decline). In order to look for longer-term trends, we can use a procedure in which the difference between the run means and the process mean is calculated for each point, and then summed cumulatively: $S_i = S_{i-1} + (\overline{x}_i - \hat{x})$. The magnitude of any change in the process can be calculated by first calculating the difference between the maximum and minimum values of the cumulative sum $S_{\max} - S_{\min}$, and then using bootstrapping to estimate the significance of that difference. The point of change m is determined by minimizing the mean square error $MSE(m) = \sum_{i=1}^{m} (\overline{x}_i - \overline{\overline{x}}_1)^2 - \sum_{i=m+1}^{N} (\overline{x}_i - \overline{\overline{x}}_2)^2$, where $\overline{\overline{x}}_1$ and $\overline{\overline{x}}_2$ are means of all values $\overline{x}_i$ to the left and right of point *m*. Additional change points can be identified recursively.

3. Experimental setup

The use of process control techniques to monitor behavioral data collected with unobtrusive in-home sensors was evaluated in a study of the patterns of sleep behaviors of fourteen adults aged 65 or older (mean 89.3 ± 3.7 years), who were ambulatory and living independently and alone in the community. All subjects provided informed consent to participate (Oregon Health and Science University Institutional Review Board protocol 1487). Subjects were assessed using the global Clinical Dementia Rating (CDR) scale and the Mini-Mental State Exam (MMSE), and placed in either the *healthy* group (n=7; global CDR = 0, MMSE > 24) or the *MCI* group (n=7; Mild Cognitive Impairment: CDR = 0.5, MMSE>24).

Continuous assessment data were collected unobtrusively in each home for at least six months, using a wireless sensor-based system described previously [8]. Using magnetic sensors on the doors to detect movement into and out of the home, together with pyroelectric motion sensors (MS16A, x10.com) placed in each room of the home to detect movement, we estimated a number of sleep measures (Figure 1):

a) Time of awakening in the morning (estimated risetime), defined as the start of the first period of activity in the bedroom after 4am lasting 2 minutes or longer, followed by activity anywhere in the home for at least 60 minutes, or by a departure from the home during that 60 minutes;

b) Time to bed at night (estimated bedtime), defined as the end of the last bedroom activity after 8pm followed by at least 20 minutes of inactivity in the home;

c) Time spent in bed at night (estimated hours in bed), defined as the time between when the person went to bed and their time of awakening.

Both the mean and the Coefficient of Variation were calculated for each of these measures.

4. Results

4.1. Group Comparisons

In order to do baseline comparisons of the sleep measures between groups, we first looked at these measures for a common six-month period during which all subjects were being monitored. Comparisons between groups showed no significant differences between the MCI and healthy elders in these mean values for bedtime, hours in bed at night, or rise time. However, the coefficient of variation (CofV) of the hours in bed was significantly higher in the MCI group as compared to healthy controls (*healthy: 0.16 ± 0.025, MCI: 0.22 ± 0.070, p=0.02*), and in fact, in general, the greatest differences between the groups were in the CofV of the measures.

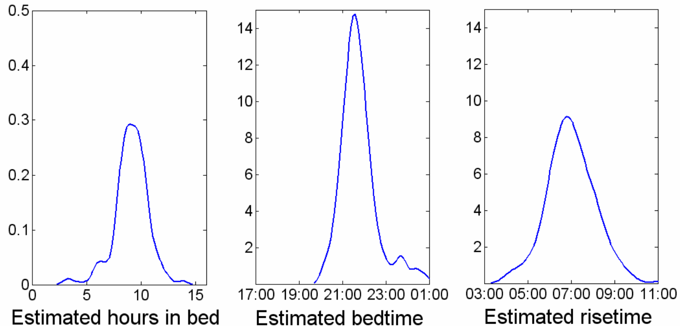

Figure 1. Probability densities of the sleep measures, estimated over the entire monitoring period (subject 7).

4.2. Identifying acute events

Data from the initial twelve weeks of monitoring for each subject were used to establish that individual's baseline, to allow setting of control limits. Then, each individual was monitored for an additional 3-9 month period. During that time, weeks in which the means exceeded the control limit were identified. A surprisingly large number of weeks (25.8% ± 10.8%) were identified as out of control using the mean and standard deviation of the CofV to set the process control limits. This emphasizes the importance of choosing appropriately robust measures for use in tracking changes (see discussion).

4.3. Finding change points

Both acute and slow changes in the patterns of sleep were successfully identified in individuals through the use of control charts. A small number of subjects showed a gradual change in parameters over time, suggesting a more subtle change in environmental or health parameters over time. For example,

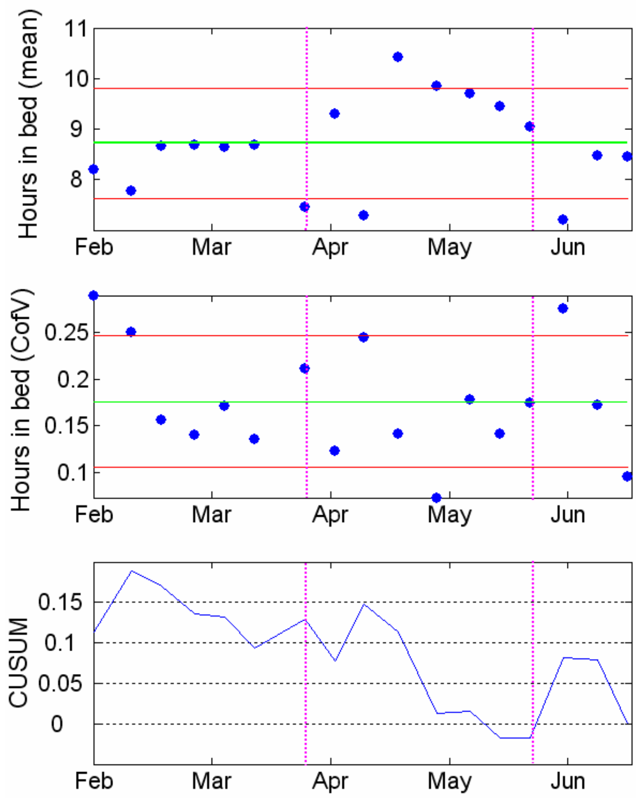

Figure 2. Control charts and cumulative sum plot for a subject suffering from depression in the period from late March until late May. Her hours of sleep were much more variable during this period.

one subject experienced a period of depression lasting a couple of months, which was reflected in increased variability in her hours of sleep (Figure 2). Three subjects showed a seasonal response to the time change in April; not only did they rise earlier during the summer months, but the variance in their rise time was significantly reduced (see example, Figure 3).

5. Discussion

5.1. Selection of appropriate process control parameters

Human subject (and patient) data sets often contain many potential outliers. For example, in the case of sleep, a short night's sleep could be due to anything from an arthritis flare-up to depression to a good book. A key goal in the case of continuous health assessment indicators is to be able to detect variation in subgroup means in the presence of outliers. Thus, it is important to choose statistical measures that yield control limits that are resistant to such outliers, and yet allow for accurate determination of trends away from the process norm [15].

Many variations on standard control charts and cumulative sum charts have been proposed. Each of these has advantages and disadvantages. Risk-

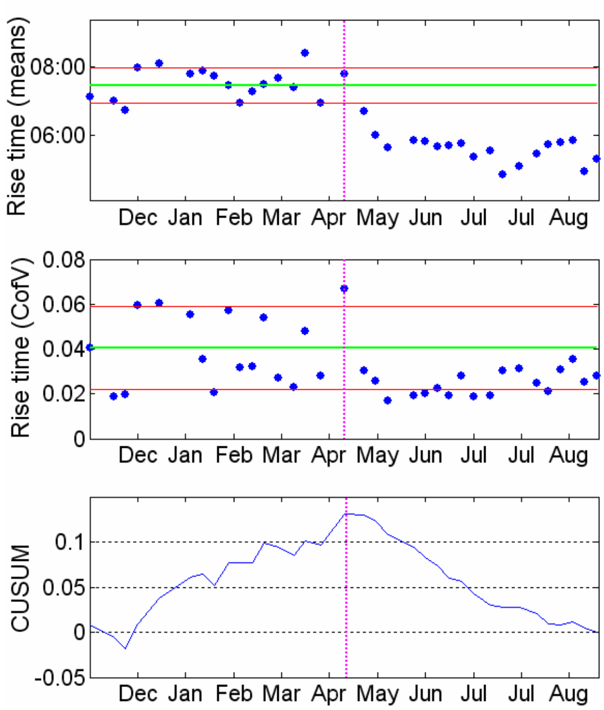

Figure 3. Control charts and cumulative sum plot for a healthy subject (S1) who showed significant seasonal variation in rise time. Dashed vertical line indicates a change point, which corresponded to the time change.

adjusted control charts, in which the baseline and control limits are determined from appropriate population norms (for example, norms of blood pressure) have been used to provide better estimates of outliers in medical data [16]. However, this is not effective for measures that do not have established norms, or for cases where what is normal (and healthy) for one individual differs significantly from another, as with the sleep behaviors described here. In that case, what is of interest is variation from the norms for a single individual, and thus data from that individual can serve as their own baseline. Clearly, the problem with this is that establishing a baseline assumes the process is in control – i.e. that the baseline data reflect typical behavior for the individual being monitored - something that may require substantial effort to determine.

When it is important to detect trends in the data – that is, when there is an expectation that the process mean is slowly changing over time – an exponentially-weighted moving average chart (EWMA chart) may provide an earlier indication of this change in the process mean than a CUSUM chart. Such charts take into consideration a weighted average of previous values in estimating the current data point, which allows for detection of small shifts in the process mean [13, 14].

5.2. Potential applications of the Approach

Statistical process control has been used to monitor both mortality due to particular procedures, and physiological parameters such as blood pressure and weight change, in a clinical setting [11]. Applying this approach to measures collected within the home provides an opportunity to put in place an alerting system to help determine when medical intervention may be needed.

Both acute and slow changes may be monitored with this approach. For example, in a situation in which weight is monitored daily in patients at risk for congestive heart failure, acute changes are of particular interest. Similarly, for medications in which the interval between doses is of particular importance, tracking the mean and range of inter-dose intervals may be appropriate. In contrast, when tracking sleep patterns over time, a much more variable range of values is likely to be typical, and both acute changes (reaction to medication changes or an arthritic flare-up, for example) and longer terms trends (e.g. depression) may be of more interest.

The visual presentation of information about patterns of behavior may also serve to provide patients with incentive to keep that behavior under control. In a recent study we conducted of medication adherence in the elderly [17], subjects were surprised to learn just how often they missed taking a dose. When presented with a graph of that adherence, they began to identify why they had missed particular doses. We hypothesize that providing regular feedback to patients in the form of control charts may help them monitor and modify their behavior.

It should be stressed that these charts are not diagnostic. Rather, they are intended to provide a means of alerting to the need for additional follow-up. However, as continuous in-home monitoring of daily behaviors becomes more common, and as more commercial systems become available, tools which provide such summaries of the data will become increasingly important.

Acknowledgements

The authors thank Brad Stenger, Andre Adami, and Tracy Zitzelberger for their help with data collection. This work was supported by grant from the National Institute on Aging (P30AG08017). Dr. Kaye's time was supported by grant P30-AG08017 from the National Institute on Aging and by the Merit Review Grant, Office of Research and Development, Department of Veterans Affairs.

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