Behavioral Patterns of Older Adults in Assisted Living

Gilles Virone, *Member, IEEE*, Majd Alwan, *Senior Member, IEEE*, Siddharth Dalal, *Member, IEEE*, Steven W. Kell, Beverely Turner, John A. Stankovic, *Fellow, IEEE*, and Robin Felder

***Abstract*—In this paper, we examine at-home activity rhythms and present a dozen of behavioral patterns obtained from an activity monitoring pilot study of 22 residents in an assisted living setting with four case studies. Established behavioral patterns have been captured using custom software based on a statistical predictive algorithm that models circadian activity rhythms (CARs) and their deviations. The CAR was statistically estimated based on the average amount of time a resident spent in each room within their assisted living apartment, and also on the activity level given by the average number of motion events per room. A validated in-home monitoring system (IMS) recorded the monitored resident's movement data and established the occupancy period and activity level for each room. Using these data, residents' circadian behaviors were extracted, deviations indicating anomalies were detected, and the latter were correlated to activity reports generated by the IMS as well as notes of the facility's professional caregivers on the monitored residents. The system could be used to detect deviations in activity patterns and to warn caregivers of such deviations, which could reflect changes in health status, thus providing caregivers with the opportunity to apply standard of care diagnostics and to intervene in a timely manner.**

***Index Terms*—Behavioral science, biometrics, chronobiology, circadian/seasonal activity rhythms, healthcare, pattern mining, smart homes.**

I. Introduction

HUMAN beings are influenced by two principal types of rhythms, social and biological. Social rhythms can be defined as those rhythms that are dependent on the requirements of normal daily life (working, commuting, business opening and closing times, bed time, leisure time, etc.) and are strongly influenced by the individual's overall social environment (culture, education, environmental conditions, stress levels, etc.). Biological rhythms are internal, physical rhythms that govern physiological functions, such as metabolism and cellular activity. Chronobiology, the study of these temporal structures, has demonstrated that human beings normally follow an approximate 24-h fluctuating rhythm known as a circadian rhythm [1].

Manuscript received June 14, 2006; revised August 29, 2006, February 1, 2007, and May 21, 2007. This work was supported in part by the National Science Foundation under Award 0428420, Grant CNS-0435060, and Grant CCR-0329609 under a research license agreement of U.S. Patents 5629215 and 6108685.

G. Virone and J. A. Stankovic are with the Department of Computer Science, University of Virginia, Charlottesville, VA 22904 USA (e-mail: gv6f@cs.virginia.edu; stankovic@cs.virginia.edu).

M. Alwan, S. Dalal, S. Kell, B. Turner, and R. Felder are with the Medical Automation Research Center (MARC), Department of Pathology, School of Medicine, University of Virginia, Charlottesville, VA 22908 USA (e-mail: alwan@virginia.edu; dalal@virginia.edu; swk3f@virginia.edu; bt2h@virginia.edu; raf7k@virginia.edu).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TITB.2007.904157

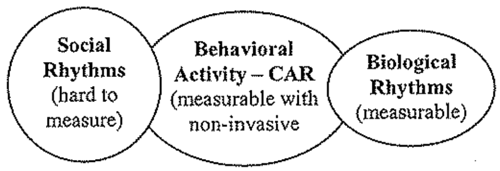


Fig. 1. Relationship among social and biological rhythms, and behavioral activity through the CAR.

Some interdependence can be noticed between social and biological rhythms manifested by the individual's exhibited physical activity levels. It is evident that biological rhythms are also influenced by society, culture, and, sometimes, climate (for example, an afternoon siesta is more prevalent in warmer countries). Studies of the rhythms of daily life are currently underway using accelerometers to measure body movements while in bed to evaluate the quality of sleep [2]. Other researchers have attempted to predict daily behavior in a similar way using motion detectors and switches to monitor events such as opening and closing of doors [3].

Glascock and Kutzik [4] described a non-intrusive system that is similar in principle and some basic hardware components to one of the technologies used in this study. In their proof of concept phase, this system was validated in the activity of daily living (ADL) suite of an urban hospital where a video camera and recorder captured the actual activities carried out by the participants. In 1998, an in-home testing phase was conducted in the homes of several participants, with the longest monitoring data collected for 13 consecutive days [4]. The system applied simple statistics to the first motion sensor firing in the morning, indicating wakeup time, and the last sensor firing at night, signifying bedtime, as well as the frequency and times of access to medications, which was monitored via an instrumented medication caddy; the paper also presented and examined trends of these variables [4].

We postulate that a person's behavior during the daily cycle of life at home, tends to fall into basic and regular patterns measurable by monitoring residents' cyclic physical activity inside the home using wireless passive sensors. We use some infrared motion sensors in the study presented in this paper. The appellation "circadian activity rhythms" or CARs (see Fig. 1) was defined in [5] and [14] to describe the measurement of this in-home rhythmic behavioral activity that the resident engages in the habitat. CAR are influenced by social rhythms, but also interacts with the biological rhythms of the organism. They provide a rich source of information about the resident activity patterns such as his or her wake/sleep cycles, ADLs, meal periodicity, etc. This new approach to understanding and measuring the in-home

1089-7771/$25.00 © 2008 IEEE

rhythmic behavioral activity has, so far, been mostly ignored in the literature. These rhythms at home often represent external manifestation of the resident's internal medical condition, and hence are of potential value for long-term health status monitoring. The objective of our pattern mining software program, called Software for Automatic Measurement of Circadian Activity Deviation (SAMCAD), which is based on a statistical model of data gathered from an in-home monitoring system (IMS), is to determine whether such activity monitoring allows us to discern behavioral patterns, and differentiate between normal behavior and behavior indicative of an underlying pathology. In the process of knowledge discovery in databases (KDD), data mining techniques such as machine learning [6], [7], Bayesian Networks [8], or fuzzification [9], for example, are often employed for pattern discovery in medical databases to help clinical decision making. CAR proposes a novel approach based on the rhythm by analogy to the biological rhythms. CAR variations have also been modeled and implemented in the SAMCAD in order to observe behavioral changes over time. Identification of the relationship between these behavioral changes and the medical conditions the resident presents is not addressed in the paper. A study is ongoing to render SAMCAD as a better aid for diagnosis and disease inferences using a data fusion approach.

In what follows, we describe the SAMCAD software tool applied to data collected from an IMS designed to monitor health status and now the behavior of an individual within their living environment. The system comprises wireless sensors (infrared motion sensors and magnetic switches, temperature sensors, and a bed monitoring unit), and, currently, characterize and differentiate between normal and irregular activity/behavioral patterns. The automatic detection and prediction of specific disease onset or pathological patterns is not part of the system yet. The paper examines how this system is capable of capturing these behavioral models (patterns) and detecting behavioral deviations in an assisted living care setting, where persons who need an intermediate level of care and some assistance in some of their ADLs transition to from independent living settings. The detected behavioral deviations are validated against the reports of the IMS system as well as clinical and behavioral notes of the professional caregivers' observations regarding health status and changes in functional abilities, as opposed to activity levels, of the monitored residents; these notes were collected throughout the data collection period.

II. Methods

A. System Description

Motion activity data were collected from an IMS comprised of wireless passive infrared motion sensors placed in every room (bathroom, shower area, etc.), in addition to a stovetop temperature sensor and a passive bed-based vital sign monitor [10]; however, only the motion sensor data is used in the CAR analysis presented in this paper. All motion sensors were installed to detect activity inside a specific room or area without being triggered by motion outside that area by pointing the motion sensor and in some cases limiting the detection area. The sensors transmitted data wirelessly to a personal computer-based data

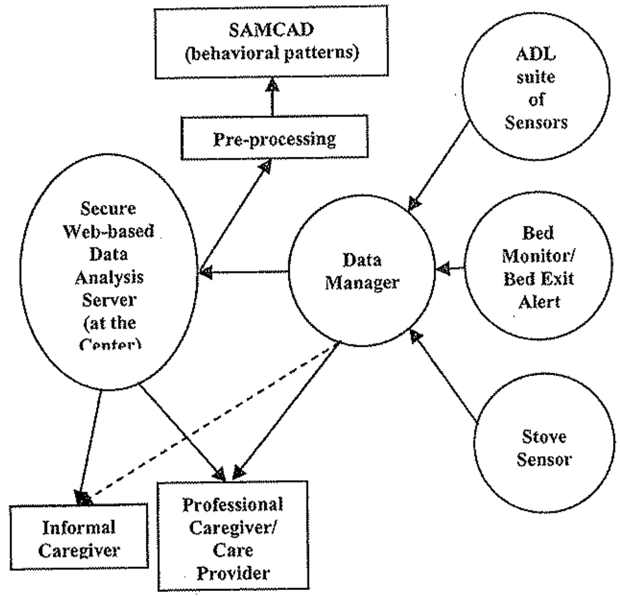


Fig. 2. Connection between the IMS and the SAMCAD.

manager linked to a secure Web-based server for data storage and analysis, as illustrated in Fig. 2.

The data manager collected data from the separate sensor modules, date/time stamped and logged the collected data continuously. Periodically, every 3.5 h, data logs were transferred to a secure central data analysis server, housed at the University of Virginia, via the participant's phone line through a point-to-point dial-up connection. Logs were sent as binary streams stripped of identifiers, to ensure the Health Insurance Portability and Accountability Act (HIPAA) compliance, and recorded into a secure database that can be accessed by a web server dedicated to presenting the reports, which are accessible via a secure socket layer (SSL) to authorized individuals with a valid log-in name and password. The system was designed to monitor the activities of individuals living alone. Codes were used to identify data and subjects.

Dedicated preprocessing software read the raw activity data of the monitored individuals from the database on the IMS secure Web server and transformed it into a format suitable for the SAMCAD software that extracted the CAR. Both software programs were written using the NI LabWindows/CVI, which is an American National Standards Institute (ANSI) C development tool for data acquisition, analysis, and presentation.

B. Subjects and Data

The motion data analyzed had been previously collected from 22 IMSs that were installed in assisted living units in St. Paul, MN. Total sample size was 22 participants, seven males, and 15 females. All participants but one were over the age of 65 (mean age 83.78 years, median age 85, minimum age 49, and maximum age 93). All subjects were white. Seven of the participants were memory care unit residents and 15 were nonmemory care residents. All the subjects lived alone in individual assisted living apartments. The data were collected under informed consent and approval of the Institutional Review Board (IRB) for periods of approximately three months to one year, depending on the subject. Inclusion criteria required the participants to be ambulatory, be able to provide for their own hygiene, and be able to transition autonomously to meals. Exclusion criteria included subject or guardian refusal to being monitored, inability to get out of bed, and the requirement for extensive outside assistance in the ADLs. Among the 22 participants, four subjects were selected for presenting their results in details as case studies, and a dozen were used to give general results about the population in assisted living environments. The case study subjects were selected based on the length of continuous data, with minimum gaps due to absence from their residence to provide the maximum of data to the CAR software for statistical calculations, and because they exhibited changes in their activity patterns that warranted investigation, on the one hand, and the availability of nursing staff notes for these subjects to compare to, on the other. The variations observed in the CAR of the four case study subjects were retrospectively compared with the nursing staff notes on the monitored individuals. For all the studied users, we also removed the last day from the study because we wanted to apply the CAR processing on whole days in term of data.

C. Preprocessing, Behavioral Modeling, and Circadian Activity Rhythm Measurement Software

As discussed in the introduction, the system is designed to monitor the resident's overall activity in his/her home. It is, therefore, necessary to create a model of this in-home activity, which will then serve as a reference for the resident's "normal" lifestyle and habits. Once this model is established, activity deviations beyond certain parameters will trigger an alert that the caregivers (or emergency services) can view, investigate, and/or respond to. The motion sensors continuously monitor the resident's activity by reporting the sensors identification, linked to the room the resident is in, whenever that motion sensor is triggered. The IMS date and time stamps the motion data and sends the motion data logs to a database server via a direct telephone link; the database is implemented in MySQL. Since the data was already collected from a real-life assisted living setting environment and stored in a format that was not compatible with the data format of the SAMCAD software, an intermediate program was specifically developed to perform the following functions 1) Migrating the data from the MySQL database into an extensible markup language (XML) file for the SAMCAD software. 2) Detection and elimination of the periods during which the user was outside the residence so as to use only relevant data in the CAR analysis. A parameter h_{ext} was established in order to determine the period of time after which the resident is considered outside the home. After several experiments to calibrate this parameter (by setting h_{ext} to 2, 3, and 4 h consecutively), we finally selected the 4-h value, because we observed that this value has successfully filtered out all short-absence periods (which may correspond with the resident's participation in group activities) and has successfully identified only the long periods of absence from the residence. Our goal was to detect only long periods of absence, as the residents, in some cases, spent some time at the front doorway, possibly chatting with neighbors, or in common areas. 3) Concatenation of all the remaining in-home activity periods, after eliminating periods when the resident was outside their residence, to create a single file to be processed. 4) Reduction of the size of data sets to be processed by considering activities' approximate time, hour and minute only, disregarding the seconds, to save processing time. Using this approach, processing time was significantly reduced; for example, data from a five-month period, approximately 1834 KB, is processed in approximately 1 h.

The SAMCAD reutilizes the XML data set to calculate the CAR, their deviations, and the corresponding deviation alerts, when such deviations exceed preset thresholds (defined in the next section). The deviation is based on an integrated resident-specific statistical model of the CAR, built using the resident's own data as defined next.

1) Behavioral Analysis (CAR Modeling): The CAR behavioral modeling implemented in the SAMCAD software, which permits the extraction of rhythmic activity and their deviation in any type of dwelling (regular apartments, nursing homes, independent living, etc.), has been detailed in [5]. Here, only the essential elements and enhancements are reported.

a) Presence-based CAR: When the resident transitions from one room to another in the residence, their transition triggers the motion sensors in both rooms. The difference in time between two consecutive transition events results in the period of time the person has spent in the room. The first step of the presence-based CAR model is summing all these time periods the resident spent in each room of the residence per hour during 24 h, and for all the days of the stay, which requires sorting beforehand the time periods overlapping several hours, days, or months. This is accomplished by scanning the dynamic XML file, generated by the formatting program. This constitutes a series of values x_i^h for each room i at each hour h of the day. The calculation of the mean values m and standard deviations s for each of these location- and time-specific presence periods x_i^h are calculated over the number of days N of the stay minus 1 (the last day being kept for the alert triggering) providing an hourly activity rhythm, or ultradian rhythm (whose period is inferior to 24 h) [cf. (1)]

$$\forall i, h, m_i^h = \sum_{n=1}^{N-1} \frac{x_i^h}{N-1} \text{ (hourly activity rhythm).} \quad (1)$$

The mean length of stay in a specific room at a certain hour is between 0 and 60 min. We normalize these values by dividing them by 60 min, to convert these values to a probability of presence we call the "*statistical occupancy rate*." The juxtaposition of the 24 statistical occupancy rates per day for each room in the residence produces the CAR. At the end of a learning period, after the acquisition of a sufficient number of data points, typically between two and three weeks from our empirical observations (cf. Section III-B), the occupancy rates provide a good approximation of the person's daily habits, characterized by the low rate of alerts triggered during regular daily life, as verified in previous studies using simulated activity data (see [5]).

From the calculations of m and s, four symmetrical thresholds S_1, S_1^* and S_2, S_2^*, whose parameters are μ_1 and $\mu_2 (\mu_1 < \mu_2)$, are defined as

$$[S_1^*, S_1] = [m - \mu_1 \times s, m + \mu_1 \times s]$$
with μ_1 being "the slight behavioral deviation" parameter (2)

$$[S_2^*, S_2] = [m - \mu_2 \times s, m + \mu_2 \times s]$$
with μ_2 being the "significant behavioral deviation" parameter. (3)

Behavior outside of the interval $[S_1^*, S_1]$ is considered as nonhabitual (slight behavioral deviation alert). Outside of the interval $[S_2^*, S_2]$, the resident's behavior is considered to be more nonhabitual (significant behavioral deviation alert). Deviation alerts above S_1 and below S_1^* correspond to overpresence and underpresence, respectively. The parameters μ_1 and μ_2 for the alert trigger thresholds are set at 1.5 and 2, these values being the current default values for SAMCAD. Assuming a Gaussian law, these parameters make the intervals $[S_1^*, S_1]$ and $[S_2^*, S_2]$ contain 87% and 95% of the observation, respectively [5].

b) Activity-level-based CAR: The activity-level-based CAR characterizes how active the residents are during their presence period in each room. This information, which complements the presence habits, allows determining the resident's activity level as well as identifying variations in these levels during the presence period over an extended period of time. The process to determine the activity-level-based CAR is similar to the process described in the previous section, but, instead, of computing the number of minutes spent in every room every hour, we sum the number of motion sensor firing events per hour. In that case, we can trigger room-specific hyper- or hypoactivity alerts, instead of room-specific under- or overpresence deviation alerts.

2) Behavioral Deviation Alerts: Changes in presence- or activity-based CAR may be indicative of change of health condition, through the exacerbation of these conditions, when reviewed daily by a caregiver as an informational and alerting aid. Similarly, comparing both CAR patterns before and after a treatment could be an efficient aid for the physicians to estimate the effectiveness of treatment. A simple example would be the case where a person would take some sleeping pills recommended by a physician. It would be easy to distinguish their effect on bedroom CAR. It is important to emphasize that the system is not meant to be a diagnostic instrument, but, rather, an informational aid. SAMCAD can automatically generate two types of behavioral deviation alerts as explained in what follows.

a) Presence-based CAR: For the current day and at the end of the current hour, the number of minutes spent in each room in the residence is computed. This number, normalized with a division by 60 min, gives the "*current occupancy rate*" per room and per hour. Deviation of the current occupancy rate from the "learned" statistical occupancy rate for this specific room at this specific hour may produce different deviation alerts (underpresence/overpresence, slight/significant [cf. (1) and (2), daytime/nighttime] if the difference exceeded the preset thresholds (Fig. 3). The "daytime" period was considered between 6 o'clock in the morning and midnight, and the "nighttime" period covers the remainder of the 24-h period.

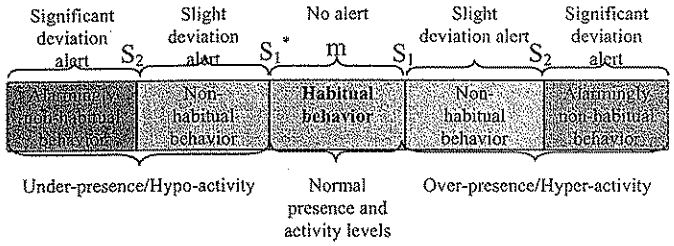


Fig. 3. Illustration of the different alert types within the behavioral limits.

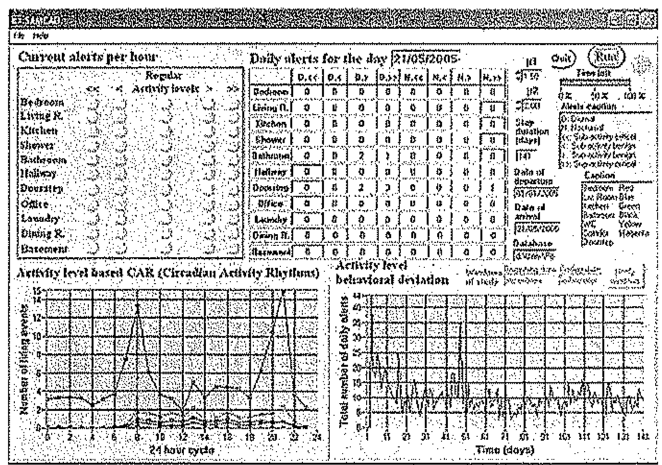


Fig. 4. Front panel of the SAMCAD (note the dates are in the dd/mm/yyyy format).

Continuous monitoring of these alerts allows us to follow the resident's behavioral deviations in real-time and over extended periods of time.

For each hour in the day (hour_i), $i \in [1, N]$, N being the length of stay at home, data being processed in hours until the last hour (hour_N), the SAMCAD runs the XML database from its beginning, updates and generates the CAR, and sets off deviation alerts when behavioral deviations are encountered.

The presence-based behavioral deviation alerts may allow the detection of the flu, for example, trough its exacerbations as an extended stay period in the bed room (in bed, in particular) which could show on the presence-based CAR.

b) Activity-level-based CAR: Using the same method as described in Section II-A to obtain the presence deviations, we compute the number of sensor firing events to establish the "current activity level" at the end of the current hour of the current day. Comparison with the statistical activity level enables the detection of hyper- or hypoactivity (Fig. 3). The presence-based behavioral deviation alerts may allow the early detection of, for example, urinary tract infections, which are characterized by significant increase in bathroom visits, and, hence, may be manifested on the activity level CAR as increase in activity level in the bathroom.

c) General user interfaces (GUI): The following displayed functions are available on a GUI for both the presence- and activity-based CARs (Fig. 4):

1) Display the current behavioral deviation alerts triggered for each hour (as represented by a flashing LED, upper left-hand side of the screen); The signs "<" and ">" are

reserved for one standard deviation, and the signs "≪" and "≫" are reserved for two standard deviations. "<" and "≪" are for the overpresence in a room, and ">" and "≫" for the underpresence;

2) Display daily deviation alerts, the "Current alert rate," which represents the total number of alerts triggered per day, according to each type of alert (under/overpresence/activity, daytime/nighttime);
3) CAR plots (lower left-hand side);
4) Curve showing behavioral deviation (lower right-hand side). This curve represents the total number of behavioral deviation alerts of any type triggered per day. This allows evaluation of the resident's behavior from the beginning to the end of the period the resident stayed in their home;
5) A timer (time left—upper right-hand side) indicates the time remaining to execute the application;
6) A series of information displays concerning the entire stay (whole duration, starting and ending dates) as well as the selected database file;
7) Three initially dimmed controls, located just above the behavioral deviation graph, permit specifying an observation window within the whole stay (start and end dates) to allow a refined CAR analysis centered on an anomaly, for example;
8) Values for the μ_1 and μ_2 parameters that set the behavioral deviation alert thresholds.

The entire CAR measurement process is designed to function with data collected under the assumption that the user is alone in the residence. In other words, the SAMCAD software currently manipulates data for one person at a given time. It is also important to emphasize that IMS requires no active participation on the resident's part and is, thus, completely passive. However, the presence of more than one person in the home can taint the resident's data. One way to avoid the potential effect on the resident's behavioral rhythms is to identify the periods during which the resident had company (visitors, nurses, doctors, etc.) and to exclude data generated during the visitation periods from the analysis. Another way is to assume that the visits are included in the life patterns of the user. In this study, we have chosen to consider the periods during which the resident had company, whether for socialization or care delivery, as part of the user's life pattern.

III. Results

A. *Typical Weekday and Weekend Rhythm*

This section discusses results of two cases selected from the 22 users monitored in assisted living units during their daily life; the first individual, User 1, is representative of monitored individuals who did not have any acute illnesses or any significant change in their health condition or behavior during the pilot, the other, User 2, experienced some change as discussed in the following section. For these results, SAMCAD performed all the statistical calculations according to the respective length of their stay. In our study, we examined the CAR on weekdays (Figs. 5 and 6) separately from the CAR on weekends (Figs. 7 and 8), assuming that the activity patterns during the weekend

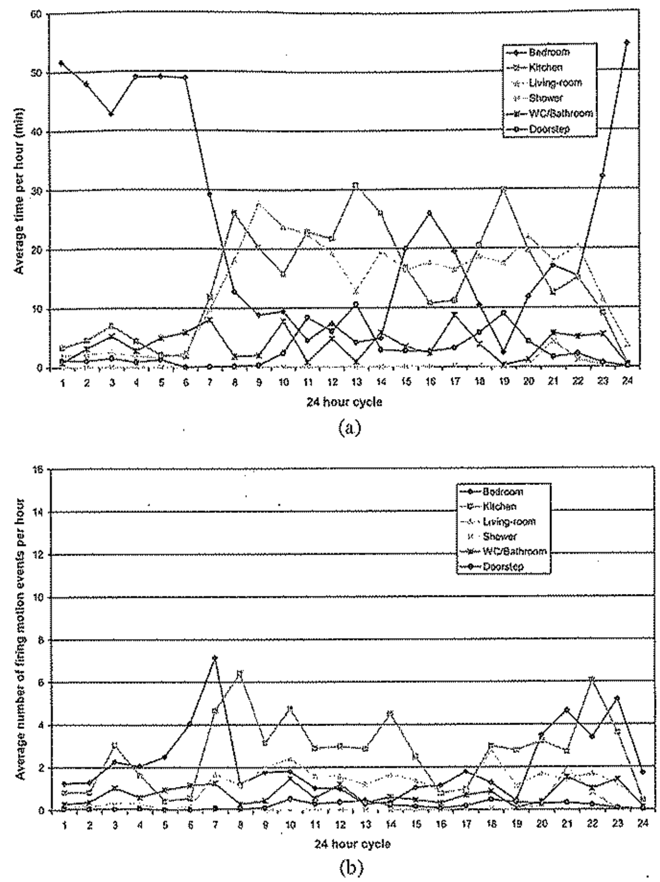


Fig. 5. (a) Presence- and (b) activity-based CAR for the weekdays—User 1.

may be different from that on the weekdays. From the CAR baselines established in these curves, information about quality of sleep can be inferred and sleep disorders as well as wandering subactivity patterns can be tracked. For example, the sleep of User 1 is disturbed around 3:00 a.m. [Fig. 5(a) and (b)] as the monitored individual goes every night to the kitchen possibly to have a snack or take medication, and spends approximately 8 min on average in the kitchen and then goes to the bathroom and spends approximately 5 min [Fig. 5(a)].[1] The sleep/wake pattern for User 2 shows going to the bedroom at night around 7:30 p.m. and leaving the bedroom around 8:00 a.m. the next morning (Fig. 6). The comparison of sleep/wake patterns for both users using both the presence- and activity level-based CAR shows a higher activity level for User 1 who goes to bed much later (around 11:00 p.m., midnight) and gets up earlier, around 6:00 a.m. [Figs. 5(a) and 6(a)]. He also spends less time in the bedroom (gets up more) during the night than User 2. This information is confirmed by studying the activity level-based CAR [Figs. 5(b) and 6(b)], which clearly shows that the sleep of User 1 is more disrupted than that of User 2, who exhibited more restful sleep. Moreover, the activity levels for User 1 are constantly higher than those for User 2.

[1]*Note*: The vertical axis on the presence-based CAR graphs represents the average number of minutes m [cf. (1)] the resident stayed in a specific room. In Fig. 5(a), for example, the kitchen CAR at 3 a.m. is at 8 min.

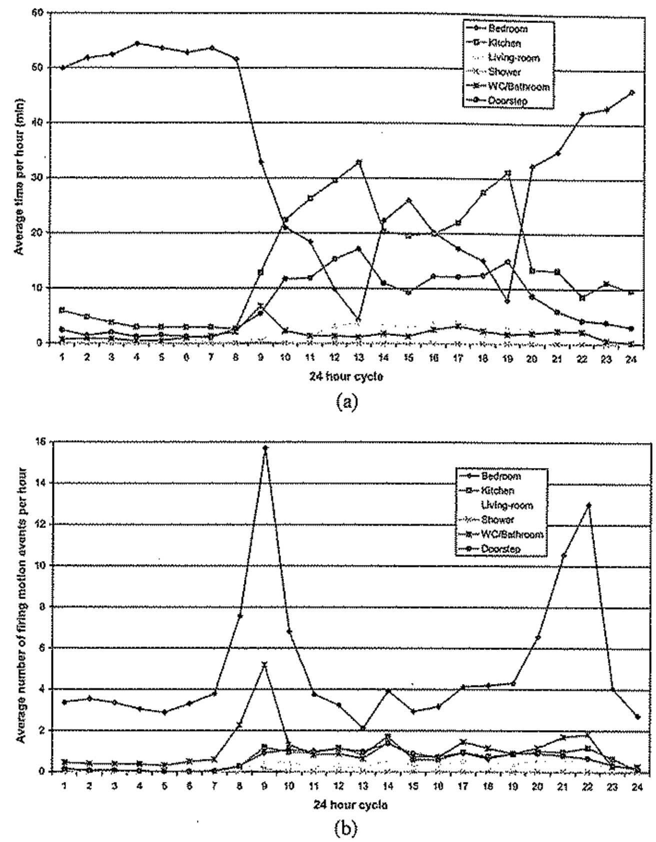


Fig. 6. (a) Presence- and (b) activity-based CAR for the weekdays—User 2.

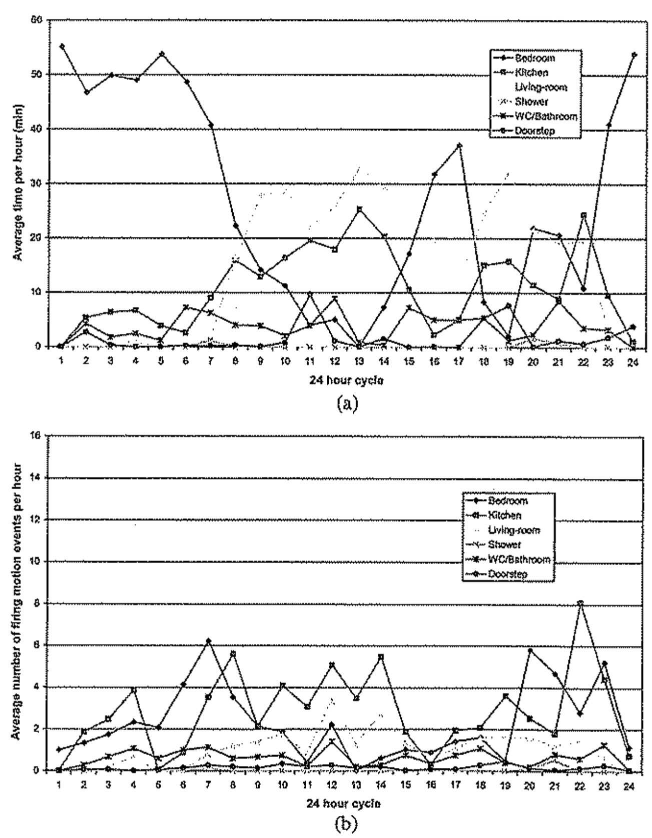


Fig. 7. (a) Presence- and (b) activity-based CAR for the weekends—User 1.

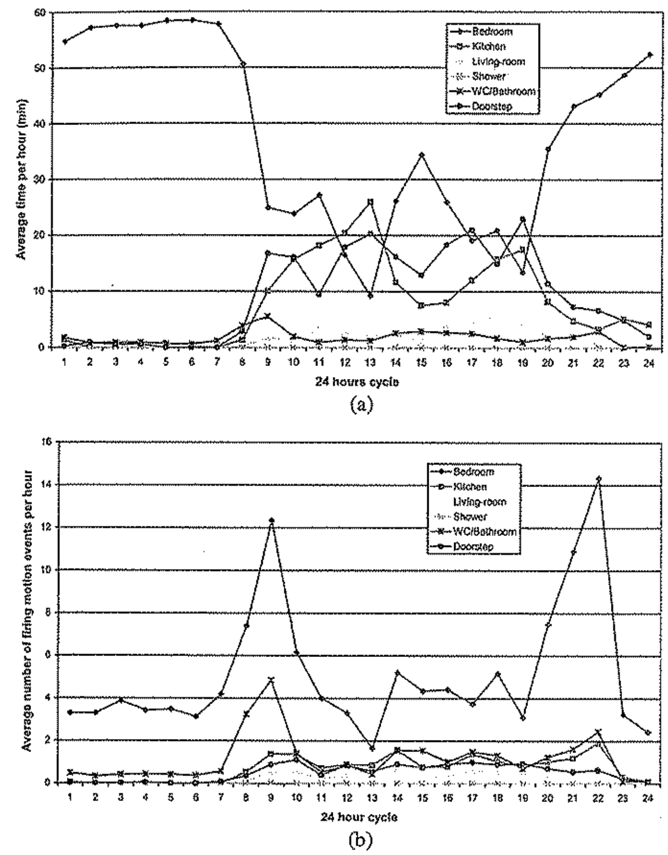


Fig. 8. (a) Presence- and (b) activity-based CAR for the weekends—User 2.

During the day, before going to bed at 11:00 p.m. [Fig. 5(a) and (b)], the rhythmic activity signals also show the periodicity of the meals. Activity spikes emerge for the meal patterns. In Fig. 5(a) and (b), we can see some spikes for breakfast at 8:00 a.m. when the resident leaves the bedroom to the kitchen, lunchtime at 1:00 p.m., and dinner at 7:00 p.m. These usual activities are omnipresent on each of the curves and reflect the variations in the times of the activities following the pattern of the user. For example, in Fig. 6, User 2 had breakfast at around 10:00 a.m., 2 h later than usual, and seemingly needed to get more sleep. The shape of the spikes also confirms this information. In Fig. 5, they are much narrow and more defined than for User 2, and last the same amount of time, approximately half-an-hour each time for every meal centered on 8:00 a.m., 1:00 p.m., and 7:00 p.m. The meal activity spikes are generally wider for User 2 and less defined, indicating that User 2 spends more time in the kitchen, and possibly needs longer time for eating activities.

Comparing the presence CAR of the weekend to that of the weekday, Figs. 5 and 7 show a 30-min delay in bed and wake-up times for User 1. For User 2, the weekday patterns presented were generally similar to the weekend patterns, for both presence- and activity level-based CAR. (cf. Figs. 6 and 8). However, we can notice a slight change during the nocturnal presence-based CAR, which shows less disrupted sleep during the weekend compared to weekdays; this is indicated by a high statistical occupancy rate for the bedroom reaching almost 100% (60 min/h) on weekend nights. This information is

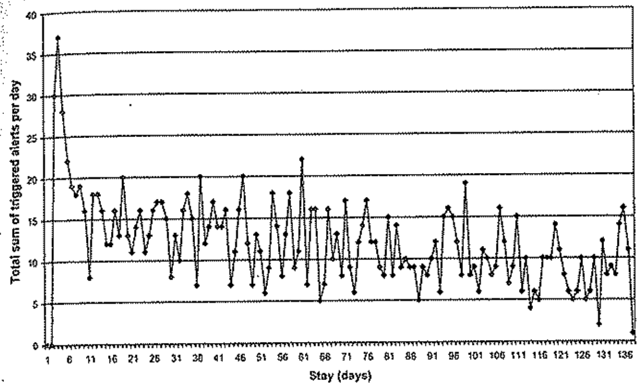


Fig. 9. Typical presence-based CAR behavioral deviation—User 3.

complemented by the activity level graphs [cf. Figs. 6(b) and 8(b)], which show lower activity levels.

Similarly, time spent outside the bedroom during the night on the weekends is generally also reduced for User 1, and more time is spent in the bedroom compared to weekday patterns (Figs. 5 and 7). The analysis of bathroom use demonstrates that User 1's nightly bathroom visit varies more in time over weekend nights than weekday nights with an activity level spike around 9:00 p.m. on Fig. 7. Morning bathroom visits of User 2 on the weekends seem to have more variations in time compared to weekdays, whereas the pattern for User 1 generally remains the same for weekends and weekdays (cf. spikes for the WC/bathroom in Figs. 5–8).

B. Validity of Behavioral Deviation Alerts Through Case Studies

In this section, we present behavioral status assessed by the behavioral deviation measure derived using the SAMCAD for three different users: Users 2–4. The aim is to show how a regular behavioral pattern is characterized (learned) in CAR and refined over time, and how some deviation in behavior could, hence, be detected and tracked. The graph in Fig. 9 shows a typical presence-based CAR behavioral profile for User 3 when no behavioral anomaly is detected. No distinction between the weekday and the weekend were made in this case. This curve shows how many days worth of data were needed for the algorithm to capture repetitive life activity, rhythm, or behavior. From the graph, we can empirically observe that an approximate stabilization period up to 3 weeks of regular activity data was needed for the convergence of the algorithm. This cannot be theoretically explained using the law of the large numbers [11], which requires a mean of more than 30 samples. We can also observe a continued downward trend at the end of the plot, which indicates that the activity pattern is regular, and fits the learned CAR model. Ideally, a perfectly regular behavior would not trigger any behavioral deviation alerts. However, as for User 3, behavior is deemed to be regular by the SAMCAD if it generates less than 25 behavioral deviation alerts. These thresholds have been determined empirically using previous experience with the CAR on simulated data. We obtained similar results with the activity-level-based CAR (same shape for the activity level behavioral deviation graph).

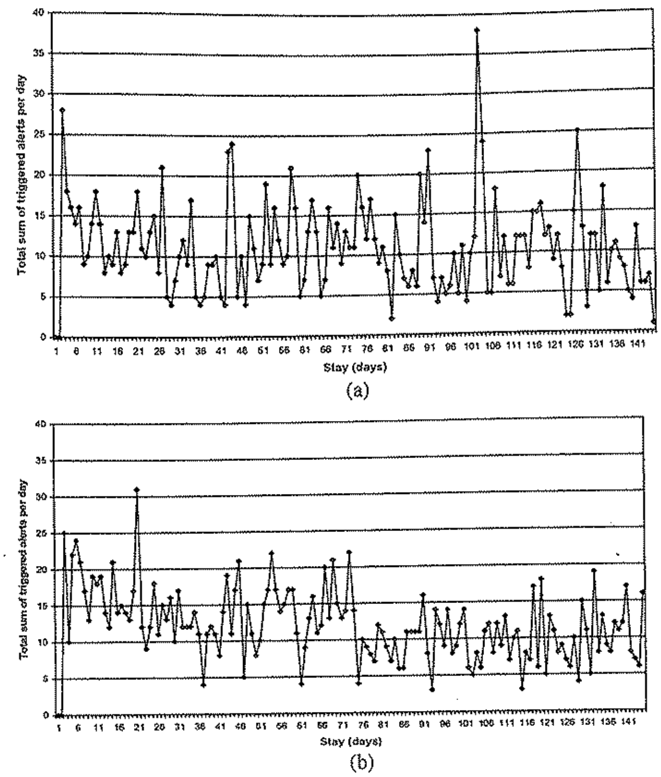


Fig. 10. (a) Presence- and (b) activity-based CAR behavioral deviation—User 4.

Fig. 10 (a) and (b) shows the results for User 4. In Fig. 10(a), a presence spike can be noticed around day 100. In Fig. 10(b), we can easily distinguish two activity level anomalies (the first one from day 1 to day 75, and the second one from day 76 to day 145) starting around day 79, showing the complementary nature of the activity- and presence-based CAR methods. During this period, professional caregivers at the facility were closely following up on the resident, because they were noticing decreased activity levels on the activity reports generated by the IMS (see [10] for more information on these reports), which showed that this resident was spending a lot of time in bed. Caregivers were concerned and suspected a case of depression. Consequently, this reduced activity was detected by the CAR and presented as a spike.

Fig. 11 represents the presence- and activity-based CAR behavioral deviation for User 2 whose regular CAR was presented and analyzed in Section III-A. Fig. 11 incorporates weekdays and weekends. Fig. 12 focuses only on weekdays, where weekends were removed from this analysis to see how they may affect the weekly behavioral deviations. Two spikes appear on the graph presented in Fig. 11(a) after the initial behavioral pattern learning period. Inquiries to the medical staff permitted us to find the cause of these spikes: the absence of the user. Indeed, around the date of the first behavioral deviation spike, the user was out of apartment, in the hospital recovering from severe influenza. The absence period created some gaps in the database, which were detected and subsequently removed from the analysis. After the user returned home, due to the hospitalization period, which has probably disorientated the patient,

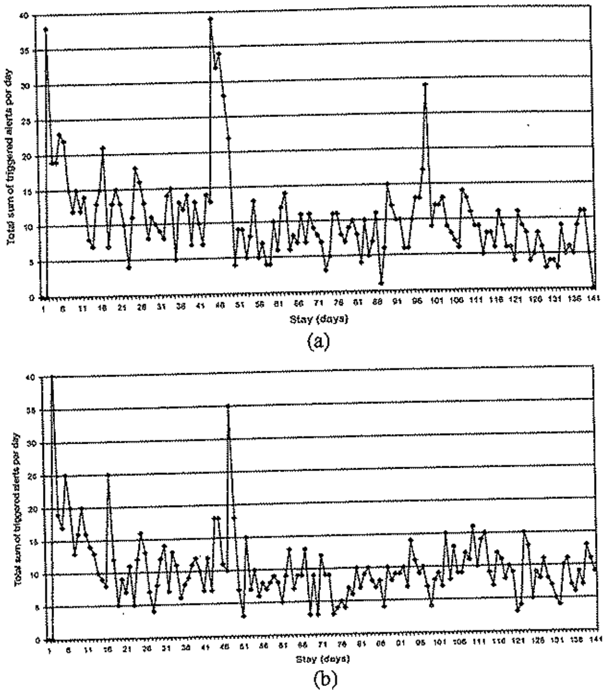


Fig. 11. (a) Presence- and (b) activity-based CAR behavioral deviation—User 2.

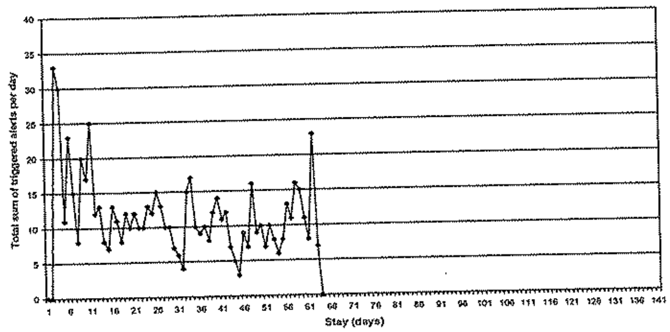


Fig. 12. Compressed presence-based CAR behavioral deviation for the weekdays only—User 2.

it might have taken him/her a few days [cf. the width of the spikes on Fig. 11(a)] to regain his/her habitual life activities. On the days when the second spike appears, inspection of the IMS activity reports revealed that the user regularly spent approximately 4 h during the day, between 10:00 a.m. and 5:00 p.m., outside the home on that long weekend (including the following Monday), possibly visiting family. We can see that the second spike is smaller than the first because the user's second period of absence was shorter than the first. Concerning the activity level deviation in Fig. 11(b), we find, again, the first anomaly around day 46 for the same reasons, but the second anomaly completely disappeared. This can be explained by the fact that the user resumed his habitual activity levels immediately upon return, unlike the case when the resident was hospitalized.

Fig. 12 shows the same behavioral deviation as in Fig. 11 after removing all the weekends' data from the analysis. The first consequence is obviously the reduction of the length of the

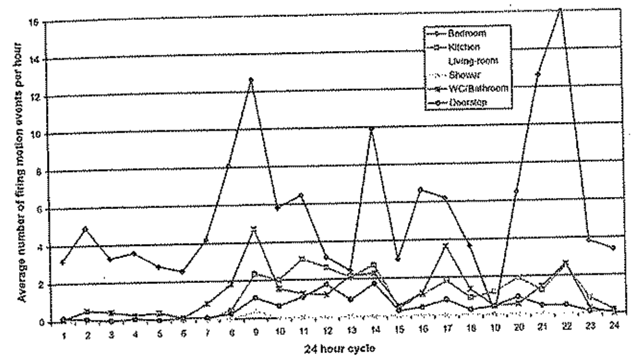


Fig. 13. Activity level-based CAR centered on the first behavioral deviation spike around day 51—User 2.

stay and a shift of the first spike a few days to the left. The second spike of the curve, located at the day 100, disappeared because the deviation occurred on the weekend. Comparison between these two curves shows slower convergence for the weekend and more alerts triggered during the behavior-learning phase. This may be caused by the periodic deduction of the weekend data, every week from a continuous stay data.

To complete this analysis for User 2, we replotted the presence-based CAR on a 1-week window centered on the second spike of the curve mixing weekday and weekend. The main observations are that the user had three distinct meals instead of two (cf. Figs. 6 and 8) and spent less time in the bedroom during the night. The user may have had to get up more often during the night. In any case, the behavior returned to its prior norm within a few days after returning from the hospital. We also replotted the activity level centered on the first spike using a window of 12 days. Fig. 13 shows higher activity levels in the bedroom around 1:00 p.m. and the bathroom around 4:00 p.m. during the period that coincided with the behavioral deviation spike.

In the future, we intend to study the sleep behavior from the bed-monitor data and the CAR during day and night times to detect a diurnal and nocturnal behavioral deviation.

C. CAR Patterns in Assisted Living Facilities

In this section, we discuss common results obtained for a dozen of assisted living environments subjects. Out of 22 cases, around 12 permitted a study with a sufficiently good data quality (maximal cumulated absences in the stay <12%). First, we can generally observe a regular sleep/wake cycle corresponding to a strong presence at night in the bedroom for most of the subjects [Fig. 14(a)], except for one, who presents a strong singularity around 3:00 a.m. in the morning (User X in the figure). Strangely, he gets up normally around 8 o'clock as the average of the residents. Comparing the different wake-up times, which vary from 6:00 a.m. to 9:00 a.m. permits to detect the earliest risers. Same reasoning can be effectuated to the bedtime. We can also clearly see that the bedroom is occupied for half an hour during several hours in the afternoon, which probably corresponds to the nap periods. The meal periods (ADL "eating") were also identified by the CAR for all the residents.

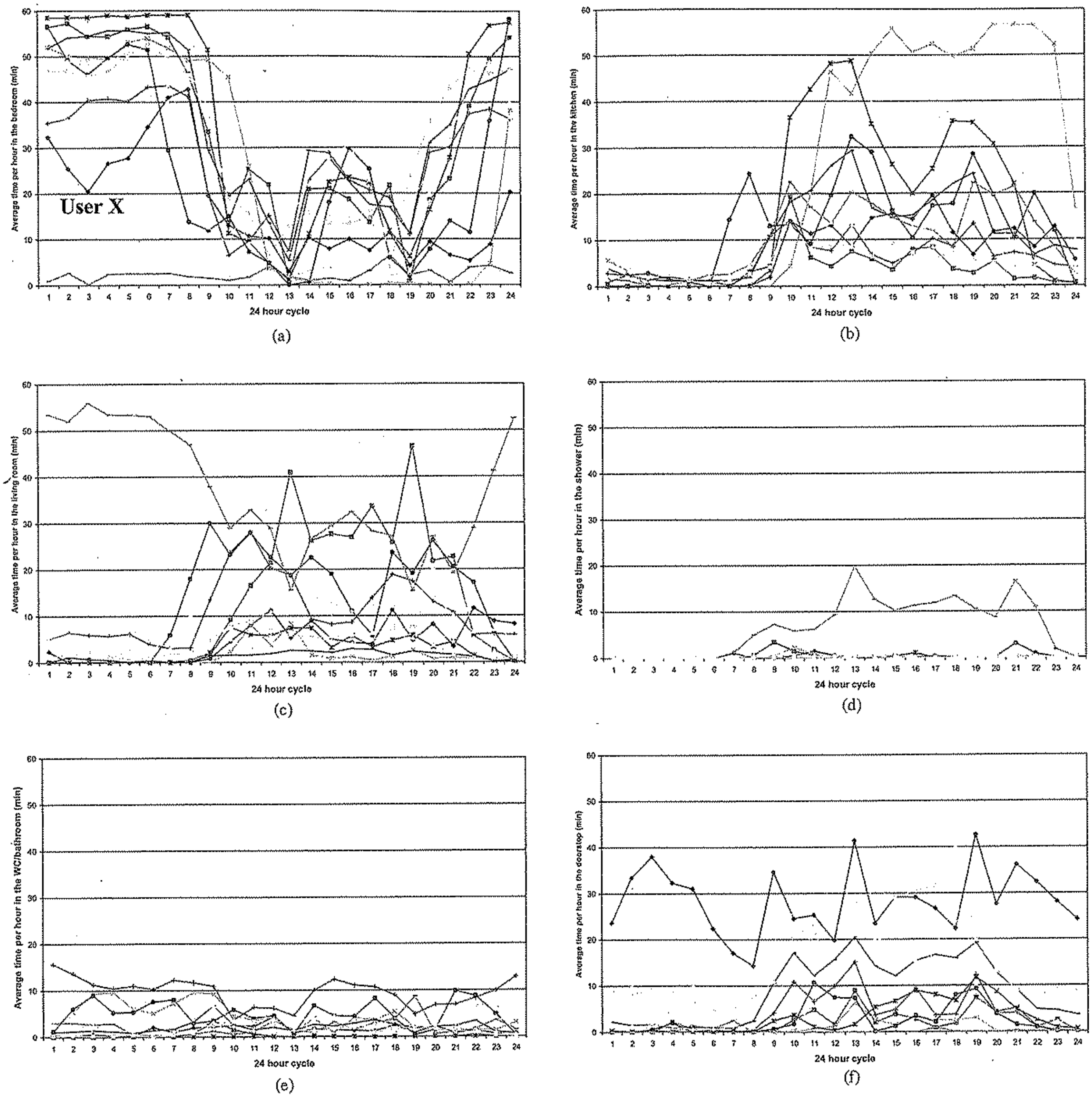


Fig. 14. CAR patterns in assisted living.

They can be observed with accuracy in Fig. 14(f), representing the time spent outside the assisted living unit for less than 4 h. Three spikes emerge with evidence in this figure at 9:30 a.m., 00:30 p.m., and 06:30 p.m., showing directly the meal patterns of the assisted living facility served in the common dining room. Sometimes, some residents may prefer to have their meals in their own unit rather than in the common dining room. Slight differences in terms of length and occurrence of the ADL "eating" can exist among the subjects [Fig. 14(b)]. For example, the lunch and dinner time emerge more strongly on the graphs than the breakfast, which is logical as having breakfast is usually faster than having lunch or dinner. We can also see in this figure a weak presence in the kitchen during the night, and a user who spends a lot of time inside in the afternoon until 10:30 p.m. Fig. 14(c)) shows the results for the living room, which is an important room in terms of user occupancy during the day. A user seems to have his bed inside, and another one to have his meals on it, possibly to watch TV during the meals. Fig. 14(d)) demonstrates that in assisted living, the elders rarely go to the shower area (ADL "hygiene") probably because they are too weak to shower by themselves. However, one resident seems to be more active than the general trend of the elderly

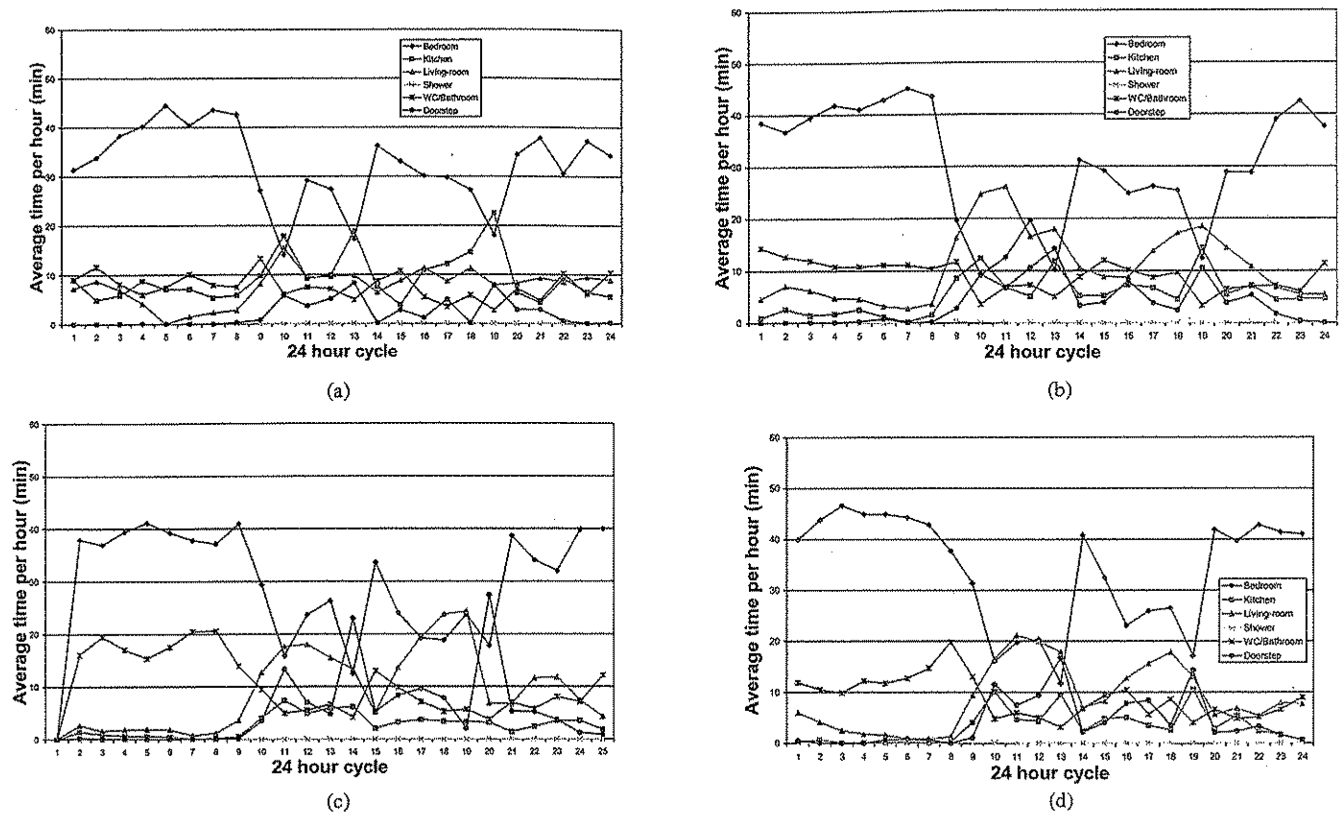


Fig. 15. Example of seasonal CAR.

population. Concerning the WC/bathroom, the residents do not spend more than 10 min in this room at every hour of the day (one of them exceeds a little bit).

D. *Seasonal Activity Rhythms (SAR) Patterns in Assisted Living Facilities*

We have also analyzed a couple of users following their CAR during the seasons to detect stereotypical behaviors that can then be related to any existing known pathologies related with the seasons (depression in the winter, insomnia, etc.). Again, for the same reasons as earlier, no relevant observations were distinguished as, for example, people get up later and go to bed earlier during winter (cf. Fig. 15). This may be due to fixed activity schedules assistive living residents are engaged in, which is not the case for people living in their own homes, for example.

IV. Discussion

The system and analysis method presented here is geared to monitor an individual living alone and does not handle the presence of multiple individuals well. The system does not currently link the collected data to a specific individual through identification or a biometric signature. The system also records, in the same database, all the other measurements from outside sources (other individuals visiting in the habitat, for example, or possibly even sunlight hitting a piece of metal and setting off the infrared sensor). Nonetheless, these results permitted qualitative interpretations. Indeed, an analogy can be made with signal processing where the CAR is considered as the signal and the false detections as noise. Given the nature of the statistical method employed, which is based on averaging over extended periods of time (as opposed to judging individual events), the CAR filters out the background noise. Moreover, it is also possible to assume that these rhythms, within the context of an assisted living facility, the staff's schedule, or the patient's visiting hours, could ultimately be reflected in the resident's own patterns.

It is also important to emphasize the potential impact of the characteristics of the observation window on the results; currently, this is a rectangular 1-h window synchronized with the beginning and the end of each hour of the day. A window width of 1 hour gives a good approximation of the resident's rhythms in light of the fact that it allows for the deduction of certain activities. The sensitivity of the method, and, hence, the resolution of the results, could be significantly enhanced by using a sliding window that shifts every 5 min, for example, throughout the day, although it would require more processing time.

The system also requires certain technical improvements including the introduction of a user identification into the data (using, for example, active identification badges), to differentiate between the movements of the resident and professional caregivers or visitors. Alternatively, activity data could be associated to the individual generating the data through association of the activity data itself with additional measurements that may allow the identification of the person through biometric characteristics, such as height, weight, gait signature, and, possibly, the CAR themselves, which can be acquired passively.

In this paper, the CAR was limited to the indoor environment of all the assisted living units. Time spent outside the home in different places [and localizable using a global positioning system (GPS)], which is part of the rhythms, is deemed more significant for individuals living in independent senior housing or in their own homes in the community; such rhythms will be further investigated in the appropriate settings in the future.

Other approaches using wearable sensors are also investigated to study sleep, circadian rhythms, and activity levels. They are based on wristwatches or actigraphs that measure the number of accelerations exceeding a preset threshold per minute [12], or that estimate the intensity and length of movements [13]. Differences with our system reside in the granularity and sensitivity of the detection. The passive monitoring accomplished with motion sensors within the home is sensitive to the infrareds generated by the body (generally face and hands) within the detection cone of the motion sensor, whereas the actigraphs are sensitive to direct body movements, permitting probably to estimate with a better accuracy the acrophases (maxima of the activity rhythmic signal during a 24-h period) used in drug delivery for cancer diagnosis.

V. Conclusion and Perspective

We validated a method presented in [5] which computes some CARs using data collected from an assisted living care setting. This method establishes some patterns and norms and enables the tracking of deviations from these norms. The results demonstrated that the system can model behavioral patterns and detect deviations in these patterns that may be consistent with disease onset. Typical behavioral patterns were generated using the SAMCAD. These basic behaviors, which have been passively collected in assisted living units, provided invaluable insights about behavioral patterns of the monitored cohort, even in the presence of noise resulting from visitors and professional caregivers in the facility. Currently, this noise is the main weakness of the system/method. Use of active badges or new techniques such as "data association" described in the discussion section, for example, would resolve the problem. In terms of perspective, we envision to use the CAR in real-time in the IMS to provide to the caregivers and the current alert-level status and anomalies detected to calculate the sensitivity and specificity of the method. We also intend to render the model more specific to pathologies using data fusion with other types of sensors, and to mix the model with data mining techniques such as clustering, for example, which can be another approach to identify with accuracy some behavioral deviations over the days. A principal components analysis (PCA), applied on different branches of the CAR, such as the ADL/activity[2] or the CPAR[3] -based CAR [14], could also be envisioned to correlate them with other information typical to pathologies to better estimate the general health status of the resident, and, eventually, to detect disease conditions and progression. Other applications include the potential use as a tool to monitor a person's quality of life and evaluate the efficacy of medical interventions. It is possible to envision future applications based on the different branches of the CAR that could include the diagnosis and evaluation of therapy for various patient populations (based on pathologies like cardiac or respiratory insufficiencies, Parkinson's, Alzheimer diseases, and obesity).

[2]The study of the activity/ADL-based CAR entails applying the CAR algorithm to a particular activity to evaluate its circadian rhythm. Applied to an activity, such as eating, for example, a detected downward trend could reveal, for example, a malnutrition over the time.

[3]Circadian physiological activity rhythm, same as earlier but using a physiological signal such as a heart rate.

Acknowledgment

The authors would like to express their appreciation to W. Holman in helping to maintain the data collection and analysis infrastructure. The research team would like to thank Volunteers of America National Services, for providing in-kind services, and the staff, caregivers, and residents of the Homestead at Maplewood assisted living facility.

References

[1] A. Reinberg, *Les rythmes biologiques, mode d'emploi*. Paris, France: Flammarion, 1994.

[2] H. Hagiwara, T. Nakano, K. Yoshida, K. Fukuyori, A. Michimori, and E. Koyama, "Measurement of human behavior in a daily life based on the understanding of biological rhythm," in *Proc. 41st SICE Annu. Conf.*, Aug., 2002, vol. 2, pp. 5–7.

[3] A. Yamaguchi, M. Ogawa, T. Tamura, and T. Togawa, "Monitoring behavior in the home using positioning sensors," in *Proc. 20th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, 1998, vol. 20, no. 4, pp. 1977–1979.

[4] A. P. Glascock and D. M. Kutzik, "Behavioral telemedicine: A new approach to the continuous non intrusive monitoring of activities of daily living," *Telemed. J.*, vol. 6, no. 3, pp. 33–44, 2000.

[5] G. Virone, N. Noury, and J. Demongeot, "A system for automatic measurement of circadian activity deviation in telemedicine," *IEEE Trans. Biomed. Eng.*, vol. 49, no. 12, pp. 1463–1469, Dec. 2002.

[6] M. E. Cohen and D. L. Hudson, "Neural networks models for biosignal analysis," in *Proc. IEEE Eng. Med. Biol. Soc. Annu. Int. Conf.*, New York City, NY, Aug. 30–Sep. 3, 2006, pp. 3537–3540.

[7] S. Jonic, T. Jankovic, V. Gajic, and D. Popovic, "Three machine learning techniques for automatic determination of rules to control locomotion," *IEEE Trans. Biomed. Eng.*, vol. 46, no. 3, pp. 300–310, Mar. 1999.

[8] S. M. Lee and P. A. Abbot, "Bayesian networks for knowledge discovery in large datasets: Basics for nurse researchers," *J. Biomed. Inf.*, vol. 36, no. 4–5, pp. 389–399, Aug.–Oct. 2003.

[9] J. Xue and M. Krajnak, "Fuzzy expert systems for sequential pattern recognition for patient status monitoring in operating room," in *Proc. IEEE Eng. Med. Biol. Soc. Annu. Int. Conf.*, New York City, NY, Aug. 30–Sep. 3, 2006, pp. 4671–4674.

[10] M. Alwan, S. Dalal, D. Mack, B. Turner, J. Leachtenauer, and R. Felder, "Impact of monitoring technology in assisted living: Outcome pilot," *IEEE Trans. Inf. Technol. Biomed.*, vol.. 10, no. 1, pp. 192–198, Jan. 2006.

[11] H. Freudenthal, "The 'empirical law of large numbers' or 'the stability of frequencies,'" *Educ. Stud. Math.*, vol. 4, pp. 484–490, 1972.

[12] V. Chevalier, M. Mormont, H. Cure, and P. Chollet, "Assessment of circadian rhythms by actimetry in healthy subjects and patients with advanced colorectal cancer," *Oncol. Rep.*, vol. 10, pp. 733–737, 2003.

[13] E. Van Someren, "Actigraphic monitoring of movement and rest-activity rhythms in aging, Alzheimer disease and Parkinson's disease," in *Proc. 18th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Amsterdam, The Netherlands, 1996, vol. 1, pp. 69–70.

[14] G. Virone, "Local architecture and simulation of the health integrated smart home information system for the detection of at-risk situations and decision assistance," Ph.D. dissertation, Université Joseph Fourier (UJF). Grenoble, France, 2003.

Gilles Virone (S'02–A'03–M'04) was born in Grenoble, France, in 1974. He received the M.S. degree in modeling and instrumentation in medicine and biology and the Ph.D. degree from the University Joseph Fourier, Grenoble, in 1999 and 2003, respectively. He served the M.S. and Ph.D. internships at the Traitement de l'Information, Modélisation et Cognition Laboratory (TIMC) he joined in 1998.

In 2001, he had a two-month internship stint at the Department of Computer Science, Université du Quebec a Montréal, Montreal, QC, Canada. In 2004, he worked in collaboration with the Kinesitherapy School of Grenoble, Grenoble, as a Research Associate. Since 2005, he has held a postdoctoral appointment in the Department of Computer Science, University of Virginia, Charlottesville, where he is engaged in research on wireless sensor networks for assisted living facilities. His doctorate and postdoctorate work were devoted to the development of large-scale distributed systems for home healthcare. He is the author or coauthor of more than 30 papers published in international journals or conferences. Spanning the area of medical electronics, sensor networks, and human behavioral modeling, his current research interests also include the development of hardware and software prototypes embedding context aware algorithms for the smart home domain.

Majd Alwan (S'94–M'96–SM'05) was born in Damascus, Syria, in 1966. He received the B.S. degree in electrical engineering from Damascus University, Damascus, in 1988, the M.S. degree (with distinction) in control engineering from Bradford University, Bradford, U.K., in 1992, and the Ph.D. degree in intelligent robotics from Imperial College of Science, Technology, and Medicine, University of London, London, U.K., in 1997.

From 1988 to 1991, he was a Design Engineer and Research Assistant at the Higher Institute of Applied Sciences and Technology (HIAST), Damascus. In 1997, he returned to the HIAST as a Lecturer and Researcher. In the beginning of 2002, he joined the Medical Automation Research Center, Department of Pathology, School of Medicine, University of Virginia, Charlottesville, as an Assistant Professor and Director of the Robotics and Eldercare Technologies Program. He is the author or coauthor of several papers and magazine articles and is the coauthor of a university textbook on computer hardware. His current research interests include passive functional and health assessment, biomedical instrumentation, medical automation, and eldercare and assistive technologies.

Dr. Alwan is the Funding Aging Services Technologies Committee Chair, and serves on the Executive Committee of the Center for Aging Services Technologies. He is a member of the Geriatric Care Workgroup and IEEE-USA's Medical Technology Policy Committee.

Siddharth Dalal (S'98–A'02–M'03) was born in Mumbai, India, in 1979. He received the B.E. degree in electronics engineering from D. J. Sanghvi College of Engineering, Mumbai University, Mumbai, in 2000, and the M.S. degree in computer science from the University of Virginia, Charlottesville, in 2002.

He is currently a Senior Software Engineer at the Medical Automation Research Center (MARC), Department of Pathology, School of Medicine, University of Virginia, where he is engaged in research utilizing the MARC smarthouse technologies. He develops and maintains several Websites for the MARC. He has been the author or coauthor of several conference and journal papers. His current research interests include applications of neural networks to graphics.

Steven W. Kell was born in Sikeston, MO, in 1952. He received the A.A. degree (*summa cum laude*) in electronics from the Piedmont Virginia Community College, Charlottesville, in 1991 after some undergraduate work at Lynchburg College, Lynchburg, VA, in 1973. He also earned Certificates in Microprocessor Technology from the National Radio Institute (1983), obtained professional skills from Xerox Corporation (1981), and customer service training from the American Management Association.

Currently, he is a General Manager at the Medical Automation Research Center, Department of Pathology, School of Medicine, University of Virginia, Charlottesville, with additional roles as Research Engineer and Project Manager on numerous research projects, including regulated research involving human subjects. His past experience includes being an Operations Manager for a national consumer electronics retailer, and owner of his own business for over two decades. His current research interests include the development of passive sensor technologies applied to in-home monitoring of health-related activities, prototype sensor applications, data collection devices, instrumentation and control devices for mobility aids, and technical support for hardware design and circuit topology.

Beverely Turner was born in Tucson, AZ. She received the B.S. degree (*summa cum laude*) in biology/premed from Christopher Newport University, Newport News, VA, in 1983. In addition, she completed selected graduate work at Old Dominion University, Norfolk, VA.

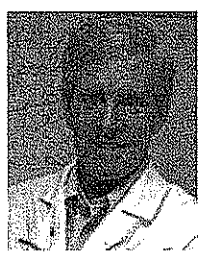
In 1991, she was a Research Specialist at the University of Virginia, Charlottesville, specializing in oncology. Her team established a high-risk cancer clinic, familial cancer genetics program, clinical trials, and a familial oncology research laboratory. In 1999, she was a Clinical Research Coordinator, Project Manager, and Regulatory Consultant, with expertise in human subject research issues. Since 2002, she is with the Medical Automation Research Center, Department of Pathology, School of Medicine, University of Virginia. She is the author or coauthor of many papers, abstracts, educational materials, and lectures covering diverse subjects including the use of low-cost technology to enhance an individual's independence and promote wellbeing. Her current research interests include pharmacokinetics, genetics, and clinical and translational research.

Ms. Turner is a member of the Association of Clinical Research Professionals.

John A. Stankovic (S'77–M'79–SM'86–F'93) received the Ph.D. degree from Brown University, Providence, RI, in 1979.

Thereafter, he was on the faculty of University of Massachusetts at Amherst, Amherst. Since 1997, he has been BP America Professor and Chair of the Department of Computer Science, University of Virginia, Charlottesville.

Prof. Stankovic is a Fellow of the Association for Computing Machinery, and serves as a Treasurer on the Computing Research Association Board of Directors. He was the recipient of an IEEE Award for Outstanding Technical Contributions and Leadership in Real-Time Systems and an Outstanding Scholar Award from the University of Massachusetts. He serves as an Editor-in-Chief for Real-Time Systems and was Editor-in-Chief of the IEEE TRANSACTIONS ON PARALLEL AND DISTRIBUTED SYSTEMS.



Robin Felder received the B.S. degree in chemistry from the College of William and Mary, Williamsburg, VA, in 1977, and the Ph.D. degree in biochemistry from Georgetown University, Washington, DC, in 1983.

He did his postdoctoral work at the National Institutes of Health, Bethesda, MD. Currently, he is a Professor of Pathology, Associate Director of Clinical Chemistry, and Director of the Medical Automation Research Center, Department of Pathology, School of Medicine, University of Virginia, Charlottesville. He is also a Visiting Professor of Pathology at the Johns Hopkins Medical Center, Baltimore, MD, and the Center for Life Sciences Automation, Rostock University, Rostock, Germany. He founded several private ventures that spun out from the University of Virginia including Medical Automation Systems (a medical informatics company), Biophile (a robotic genomic storage solution), Hypogen (a diagnostics and pharmaceutical company), Home Guardian (a home-based telemedicine system), and Global Cell Solutions (a solution for growing cells for pharmaceutical production and orthobiologics). He founded the Association for Laboratory Automation, where he served as Founding President and Editor of its journal. In addition, he serves on the boards of several privately-held medical technology companies. He is the author or coauthor of more than 260 papers published in international journals. He is the holder of 12 patents and has presented over 140 lectures in 15 countries.