Activity Density Map Visualization and Dissimilarity Comparison for Eldercare Monitoring

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***Abstract*—In this paper, we present a methodology for analyzing passive infrared motion sensor data logged in the homes of seniors. The objective is to capture activity patterns that represent different health conditions. Recognizing changes in the activity patterns can then be used to provide early detection of health changes. A visualization of motion sensor data is introduced in the form of a density map that uses different colors to show varying levels of activity. For evaluating the activity density level accurately, time away from home is determined first using a system of fuzzy rules. In addition, a dissimilarity between two density maps is computed using texture features for automatically determining changes in activity patterns, which may indicate a health problem. The activity density maps are being used in an aging in place senior housing community to aid clinicians in early illness detection. Three case studies of elderly residents are included to illustrate how the density map and dissimilarity measure can be used to track general activity level and daily patterns over time, showing changes in physical, cognitive, and mental health.**

***Index Terms*—Co-occurrence matrix (CM), early illness detection, eldercare technology, fuzzy logic, motion density map.**

I. Introduction

TECHNOLOGY that can help seniors "age in place" has been spotlighted in recent years, spurred by an aging population. With this demographic trend, there is a desire to keep older adults healthy and living independently in the home of their choice. Aging in place offers a better quality of life for seniors; they prefer to live in their own home. In addition, aging in place can provide a more cost-effective alternative at a time when the dramatic population shift will stress current resources, and facilities designed to care for older adults. However, there are huge challenges in keeping older adults healthy and functionally able so that they can age in place.

One approach to these challenges is technology in the form of Ambient Assisted Living, that is, the use of systems that provide daily support unobtrusively. In this paper, we present a methodology for analyzing passive infrared (PIR) motion sensors in the context of continuous monitoring of activity patterns in the home. The objective is to use the PIR sensors to capture activity patterns that represent different health conditions. Recognizing changes in the patterns can then be used to provide early detection of potential illness and functional decline. Recognizing health problems while they are still small can provide a window of opportunity for interventions that will address the problem areas before they become catastrophic and thus, aid in keeping seniors healthy and functionally independent [1].

This strategy is being tested in a senior living community called TigerPlace. To date, 42 sensor networks have been installed in TigerPlace apartments since Fall, 2005, with an average installation time of about two years. This longevity in sensor data collection is allowing us to develop algorithms for identifying sensor data patterns that correspond to activity and health conditions. For example, the sensors can be used to capture sedentary versus active "puttering" lifestyles, nights of restful sleep versus restlessness or wandering at night, and consistency in sleep and meal times versus irregular patterns. Changes in a lifestyle pattern can be an indicator of deteriorating health conditions. In this paper, we first describe related study and then present our work on activity monitoring, including a visualization of the PIR sensor data with a dissimilarity measure based on texture features. Three case studies illustrate the use of the methods for tracking health.

II. Background and Related Work

Technologies to support independent living for older adults have been available for several years. The focus of many systems is to alert caregivers when emergencies happen. For example, some systems have a pull cord attached to the wall or a wearable pendant with an alert button. However, when an older person is unable or reluctant to give an alert, this type of system becomes useless. To address this problem, sensors are introduced to monitor activities in the home, with the goal of tracking patterns and generating alerts automatically.

Glascock and Kutzik proposed the use of motion sensors to infer activities of daily living [2]. The Independent Life Style Assistant (ILSA) developed by Honeywell was also an early system which proposed passive monitoring (e.g., mobility, sleeping, and toilet usage), as well as the learning of environmental preferences (e.g., temperature) [3]. Ogawa *et al.* monitored two participants for over a year, logging motion activity, sleep time, and appliance use (with wattmeters) [4]. Beckwith studied nine residents with dementia in assisted living housing, using motion and door sensors, and bed load cells; residents and staff each wore a badge for location tracking [5]. Barger *et al.* report a monitoring system with eight PIR sensors to infer a person's behavioral patterns using probabilistic mixture model analysis [6]; the approach was validated with one user and a manual log documenting activities such as sleeping, changing clothes, and meals.

Lundell *et al.* proposed a medication prompting system that uses context and previous behavioral patterns [7]. Cuddihy

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et al. collected data in the homes of seniors, using motion sensor density to determine the level of movement; family members could be alerted when the motion density was very low, indicating little or no movement [8]. Kaye *et al.* introduced a system to estimate walking speed from noisy time and location data collected by PIR sensors; walking speed was investigated as a proxy to detect early signs of cognitive problems [9].

Wearable health monitoring devices have also been proposed. Actigraphy is a method of monitoring human rest/activity cycles, typically used with a wrist sensor worn like a watch [10]. Paavilainen *et al.* studied a telemetric actigraphy system to monitor the circadian activity rhythm of elderly nursing home residents [11]. Howell *et al.* investigated the daily maximum activity collected using actigraphy to evaluate the clinical utility in patients with heart failure [12]. Philipose *et al.* used RFID gloves in the home to recognize activities through object proximity [13]. Korhonen *et al*. introduced a model which used wrist-worn sensors to measure health and wellness status of an individual [14]. Sensing has also been incorporated into textiles for wearable systems [15]–[17]. There are advantages to wearable sensing systems, such as the ability to collect data outside of the home. However, there are problems in relying on wearable sensing for continuous, long-term monitoring of seniors, as many find them intrusive [18]. Also, older adults with cognitive problems may either forget to wear the devices or intentionally remove them.

There have been a variety of machine-learning approaches applied to in-home sensor data. Kim *et al.* compared hidden Markov models (HMM), conditional random fields, skip chain conditional random fields and emerging patterns in activity recognition, and proposed a topic model based on daily routine discovery [19]. Rashidi *et al.* introduced an adaptive smart home system and the frequent and periodic activity miner algorithm to find patterns of daily activities [20]. Helal *et al.* introduced a smart environment to monitor activities, diet, and exercise compliance of diabetes patients, using HMMs for task recognition [21].

Barnes *et al.* used motion and door sensors to extract a 24-h activity profile [22]. An alert could be generated if newly logged data deviated significantly from the stored profile. However, due to the brittleness of the alarms, a voice messaging system was incorporated to send a confirmation. Majeed *et al*. used fuzzy rules to classify motion and door sensor data into one of six activities, such as sleeping, preparing or eating food, and receiving visitors [23].

This body of work shows that activity behavior can be captured with sensors. However, what is largely missing is a relevant interpretation for the purpose of detecting early health changes in a generalizable way. Many researchers try to capture activities of daily living (ADL). Knowing whether an aging adult is able to feed, dress, and bathe himself is important for determining whether independent living is possible. However, the sensor patterns associated with each ADL are often different in different housing configurations; a normal ADL pattern might be different for each monitored resident depending on the size of the residency, the chronic condition(s) being managed, or simply preferences. Also, explicit ADL recognition may be unnecessarily complex to capture early signs of health changes or be too late in some cases for early interventions. For example, we have observed changes in night time activity as a result of urinary tract infections without seeing changes in ADLs [24].

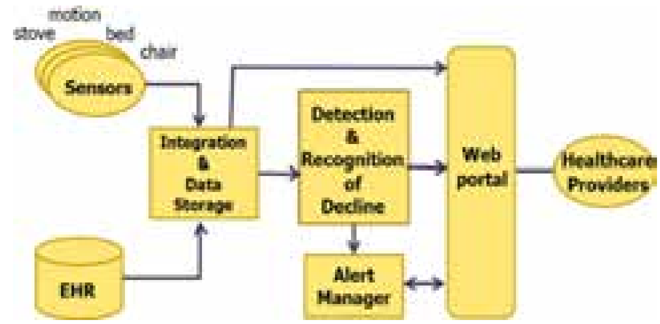

Fig. 1. Integrated sensor network deployed in TigerPlace.

Our approach is to capture sensor data patterns that are typical for an elderly resident and offer a clinically relevant perspective, and then look for changes in the sensor patterns. Whatever the pattern was, a change provides an indication of a possible health decline that warrants a closer look by healthcare providers. Our goal is to investigate features that are clinically relevant regardless of the floorplan, the lifestyle pattern, or chronic condition. To test this approach, we have installed sensor networks in the homes of elderly residents with a variety of different conditions and with floorplans of different sizes. It is also important that we capture the natural activity patterns of residents, so we do not require them to wear any sensors or do anything outside of their normal daily routines. Residents in our studies report that, after an initial adjustment period, they no longer consciously think about the sensors but rather go about their regular daily activities [25].

III. Integrated Sensor Network

The sensor network deployed in TigerPlace apartments is shown in Fig. 1. Residents are recruited to participate in a study approved by the University of Missouri Institutional Review Board. Sensors include PIR motion sensors, a stove sensor, and a bed sensor that can also be installed in recliner chairs [26]. Sensor data are logged and analyzed automatically to look for possible alert conditions; if a significant change in the sensor patterns is determined, an alert is generated in the form of an email sent to the nursing staff [27]. An Electronic Health Record (EHR) is used to log health-related events, vital signs, health assessments, and other medical-related data [28]. Both the EHR and the sensor data can be viewed through web-based interfaces, which were developed iteratively with clinicians and the research team.

Motion sensors detect presence in a particular room as well as specific activities, such as a ceiling-mounted sensor over the shower or a sensor installed in the refrigerator. A motion sensor is also installed on the ceiling above the front door to detect movement through the doorway (e.g., for apartment exits). For social reasons, residents sometimes leave their front door open so magnetic door sensors are not reliable for this purpose. The motion sensors are commercially available PIR HawkEye sensors which transmit using the wireless X10 protocol [29]. The sensors detect movement of warm bodies and will transmit an event every 7 s when movement is still detected. This artifact is used to capture the activity level as a density (the number of sensor events per unit time) at different times of the day. For example, a pattern of consistently low motion density (about 50 events/h) indicates a sedentary lifestyle, whereas a high density (over 400 events/h) indicates an active puttering lifestyle.

The bed sensor is a pneumatic strip that detects low, normal, and high pulse and respiration rates and restlessness in bed [30]. The stove sensor detects motion in the kitchen as well as the temperature of the stove/oven unit; this is accomplished by adding a thermister to a PIR motion sensor. These additional sensors contribute to the pattern of activity logged for each resident [26]; however, here, we focus on the PIR motion sensor events to generate the activity density map.

IV. Computing Time Away From Home (TAFH)

To evaluate the activity density accurately, TAFH is first detected using the wall-mounted PIR sensors and the ceiling-mounted PIR sensor above the front door. The PIR data are preprocessed into three features in units of seconds. The parameter *exit* represents the duration of door sensor events after other in-home sensors fire and before leaving, *away* is the duration of no sensor events, and *return* is the duration of door sensor events after returning. Although the TAFH algorithm is designed for a single exit point, the algorithm could be extended for additional exits. The proposed approach is independent of the number of PIR sensors in the home.

A TAFH confidence is computed using a set of fuzzy rules with the three features described previously as inputs [31]. Trapezoidal-shaped functions are used to define fuzzy memberships for Short, Long, and Very Long; these memberships provide inputs to the fuzzy rules [31]. A linear combination of variables is used per the Takagi–Sugeno–Kang model [32], where the output is a confidence [0,1]. The membership functions and rules were developed empirically. Here, a confidence of 0.75 or higher is considered to be a TAFH; the TAFH periods are subtracted from the hour when computing the motion density (PIR events per time).

Validation was performed with three datasets. The first set was collected in a test apartment configured with a typical sensor network. Researchers lived in the apartment in shifts. Videos were recorded, and a log file was written by the occupants to record their activity; both were used as ground truth for validation. A second set was generated using a simulator designed for generating motion and bed sensor data with known patterns over long periods of time [33]. The third set is from a test apartment in TigerPlace. A web camera was installed in the living room of the apartment for four days; silhouettes of the residents were extracted [34] and used as ground truth to verify the TAFH periods. Results are shown in Table I for the complete set of TAFH events and for those with a duration longer than 5 min. Although the algorithm missed some short TAFH periods, the results indicate the algorithm works well for TAFH periods longer than 5 min.

V. Activity Density Map

In the density map, different colors are used to represent different levels of motion sensor density. The density is computed as the number of all motion sensor hits during 1 h divided by time at home during that hour. Examples of density maps are shown in Fig. 2. The *X*-axis represents days in a month. The

TABLE I
TAFH Validation Results

			> 5 minutes		All	
Validation Data #1	Sum	Detected	11	11	21	16
	Accuracy Rate		1		0.76	
	False Positive		0			
Validation Data #2	Sum	Detected	8	8	14	12
	Accuracy Rate		1		0.86	
	False Positive		0			
Validation Data #3	Sum	Detected	9	9	10	10
	Accuracy Rate		1		1	
	False Positive		0			

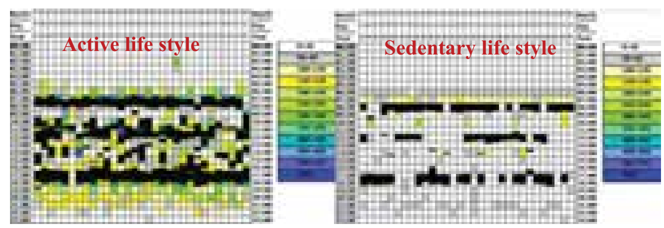

Fig. 2. Examples of activity density maps.

Y-axis represents hours in a day, from midnight (top) to 11 PM (bottom). The colorbar on the right of the figure shows the colors by density range. Black represents TAFH. White corresponds to very low density. Colors change from light gray (at the low end of 50 events/h), yellow, green, light blue to dark blue at the high end (550 events/h or more). In the density map, the density is calculated for each hour block; TAFH is computed to the second.

Fig. 2 shows examples of different lifestyles. The map on the right is less colorful, showing a sedentary lifestyle. The TAFH periods (black) are infrequent. The sedentary resident mostly left the home only for meals, and sometimes skipped the meal in the dining room. In contrast, the left map represents an active lifestyle. The active resident left home more frequently which also tends to indicate a higher level of activity. The overall day time activity is higher for the active resident, as indicated by the color. Activity density maps are now used operationally by the TigerPlace clinical staff to observe or confirm changing health trends of the residents.

VI. Dissimilarity Using Texture Information

The density maps illustrate the patterns of the residents' daily activity, including the periodicity of daily activity that may correspond to health changes. A co-occurrence matrix (CM)-based dissimilarity measurement is proposed for evaluating changes in daily patterns as shown in the density maps [35]. The average density and average TAFH provide useful information on the activity level of residents but does not provide information about the periodicity of daily activity. We propose the use of CM texture information to capture periodicity patterns of daily activity.

A. CMs of Activity Density Maps

The gray-level co-occurrence matrix (GLCM) is derived from gray scale images to extract textural features [36]. However, here, we use the original density and TAFH data directly to generate the activity density map co-occurrence matrix (ADMCM). The horizontal direction N_X refers to the number of days and the vertical direction N_Y refers to the hours of the day (1440 min). Each resolution cell in the vertical direction represents the density of a specific hour in that minute except the minutes away from home. Normally, the density is less than 550 events/h; in the rare case of higher densities, they are capped to 550. The TAFH minutes are set to a larger number such as 750, which gives enough contrast to the maximum density. Suppose the density value is quantized to N_m levels separately. Let $L_x = \{1, 2, \ldots, N_x\}$, $L_Y = \{1, 2, \ldots, N_y\}$, and $M = \{1, 2, \ldots, N_m\}$. The original data D can be represented as a function which assigns a value M to each resolution cell or pair of coordinates in $L_Y \times L_X$; $D : L_Y \times L_X \rightarrow M$. The ADMCM is defined similarly with the GLCM [35].

B. Feature Extraction

All textural information is contained in the set of CMs. The equations which define a set of textural features are given in [35] and [36]. According to the density map properties, the textural features are chosen from

$$f_1 = \sum_i \sum_j \{Q(i,j,d)\}^2 \tag{1}$$

$$f_2 = \sum_{n=0}^{N_g-1} n^2 \left\{ \sum_{i=1}^{N_g} \sum_{\substack{j=1 \\ |i-j|=n}}^{N_g} Q(i,j,d) \right\} \tag{2}$$

$$f_3 = \sum_i \sum_j \frac{1}{1+(i-j)^2} Q(i,j,d) \tag{3}$$

$$f_4 = -\sum_i \sum_j Q(i,j,d) \log(Q(i,j,d)). \tag{4}$$

The angular second moment feature, (1), is a measure of homogeneity. The contrast feature, (2), measures the amount of local variations. The inverse difference moment, (3), also measures homogeneity, achieving its largest value when most of the occurrences are concentrated near the main diagonal. Entropy, (4), measures the disorder. The textural features measure regularity in the activity behavior and capture shifts. In addition, the average motion density per hour and the average TAFH per day are also used as features in the dissimilarity measure.

C. Distance Measure

The dissimilarity of two density maps is computed in feature space as the distance from one map to another, i.e., the smaller the number, the more similar the density maps. The weighted normalized Euclidean distance is used as the distance measure, with the six features described previously. Given a feature vector **x**, $\{x_1, x_2, \ldots, x_m\}$, the weighted normalized Euclidean distance d_{rs} between the normalized vector x_r^* (reference activity map) and x_s^* (current activity map) is defined as follows:

$$x_r^*(i) = \frac{x_r(i)}{\max[x_r(i), x_s(i)]} \qquad x_s^*(i) = \frac{x_s(i)}{\max[x_r(i), x_s(i)]} \qquad \text{for } i = 1, \ldots, 6$$

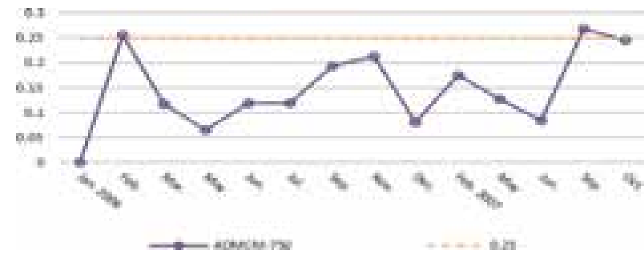

Fig. 3. Weighted normalized Euclidean distance measures for the density maps shown in Fig. 4 (single resident). Each month is compared to the baseline month, January 2006.

$$d_{rs} = \sqrt{\left\{ \sum_{i=1}^{6} w_i \left[x_{rn}(i) - x_{sn}(i)\right]^2 \right\}} \qquad \text{where } w_1, w_2, \ldots, w_6 = \frac{1}{6}. \tag{5}$$

We tested six distance measures for comparison (Euclidean, Cityblock, Minkowski, Cosine, correlation distance, and weighted normalized Euclidean distance). The different distance measures show similar trends in computing dissimilarity. In empirical results, the weighted normalized Euclidean distance was shown to be the most sensitive and thus, was chosen for the dissimilarity measure of the density maps. Sample test results are shown in the following section.

D. Results and Analysis

Data from motion sensors installed in the living room, kitchen, dining room, den, bedrooms, bathrooms, shower, closets, laundry, and front door are used in the density map. The apartments include a range of floorplan designs, sizes, and number of bedrooms and bathrooms, which also means a variable number of PIR sensors. A typical configuration has one PIR sensor per room except for the bathroom which also has a shower sensor. Results are generated for a single resident over time and across multiple residents to investigate the sensitivity. Here, we have selected one month as the window size for illustration. However, any window size can be used.

1) *Single resident results:* Fig. 3 shows the dissimilarity results for a resident, using the map of January 2006 as a baseline month and compared to other months (shown in Fig. 4). A value of 750 is used for the TAFH; different values were tested (650, 750, 1000, and 1500) and they follow a similar trend.
2) *Cross-resident results:* Fig. 5 shows the dissimilarity results across nine residents. Residents 2–9 are compared to resident #1 (see Fig. 5). A value 750 is used for the TAFH; different TAFH values were again shown to follow a similar trend. For the single resident results (see Fig. 3), the dissimilarity measurements are almost all less than 0.25, whereas for the cross-resident results (see Fig. 5) the dissimilarity measurements are almost all greater than 0.25. The nonimage-based CMs give adequate contrast between different activity patterns as illustrated by the different residents.

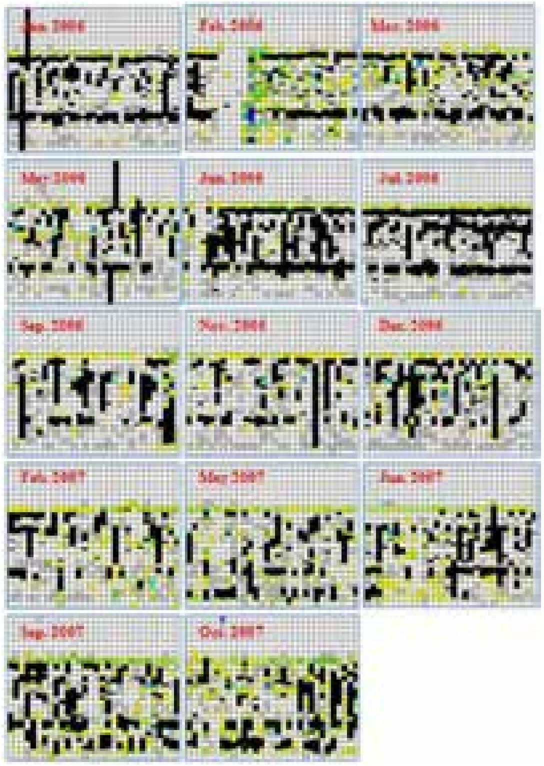

Fig. 4. Density maps used for Fig. 3 (single resident).

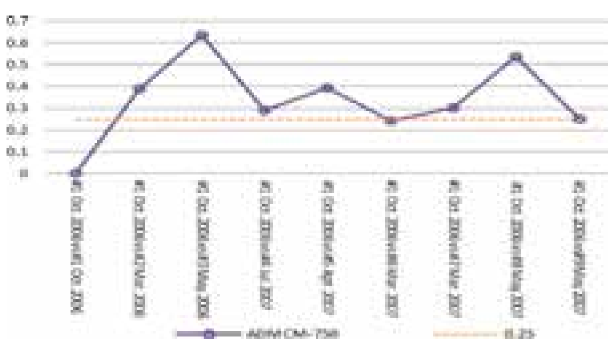

Fig. 5. Weighted normalized Euclidean distance measures for the density maps shown in Fig. 6 (multiresident). Each month is compared to the baseline month, Resident #1.

VII. Case Studies

The activity map visualization and dissimilarity measure were applied to data logged in the homes of elderly TigerPlace residents. Case studies for three residents are included next. The dissimilarity is computed using the weighted normalized Euclidean distance with a one-month window size.

A. Case Study #1

The left part of Fig. 7 shows the density map of a resident for March 2006. The map indicates activity starting around 7 AM most days, suggesting the resident woke up regularly in the morning. Similarly, he went to bed regularly around 9–10 PM. The TAFH areas (in black) suggest that he had three meals in the dining room most days, but not always. In addition to mealtime, this resident left home at other times. The right

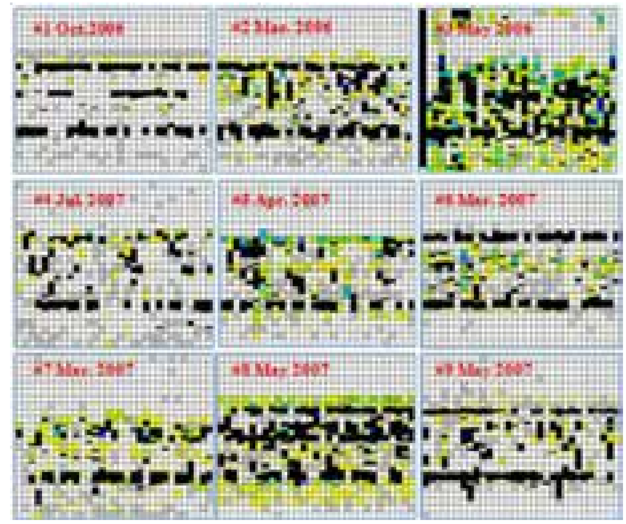

Fig. 6. Density maps used for Fig. 5. Each density map represents the pattern of a different resident.

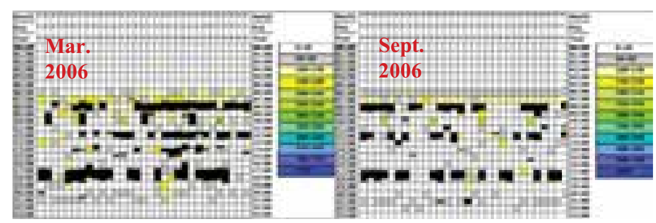

Fig. 7. Case study #1: density maps, showing a decline in activity.

part of Fig. 7 shows the density map of the same resident for September 2006 after depression was diagnosed. The color of the September density map shows a lower level of activity, and the TAFH areas are less frequent. These changes indicate that the general activity level decreased from March to September.

The average TAFH of March 2006 and September 2006 is 178 and 168 min per day, respectively. The average density of March 2006 and September 2006 is 96 and 77 sensor events/h, respectively. From these two features alone, it is evident that the activity level of this resident decreased. The dissimilarity measure between March 2006 and September 2006 is 0.21 which represents a significant change, although not dramatic. The density maps for the two months show similar patterns in daily life, but the color shows decreased motion density, which is consistent with the higher dissimilarity measure.

In Fig. 7, there is a high-density hour in green at 10–11 AM every Monday. These correspond to the weekly cleaning schedule when a housekeeper is in the apartment. Also, note that the first two waking hours tend to have a higher density than the rest of the day. This is consistent for most of the residents; thus, the morning hours after waking might be used to set a baseline activity level for the day to look for activity changes that may correspond to health changes.

B. Case Study #2

Fig. 8 shows four months of density maps from another resident. The January 2006 map shows a relatively active lifestyle. From February 6–10, the resident had knee replacement surgery,

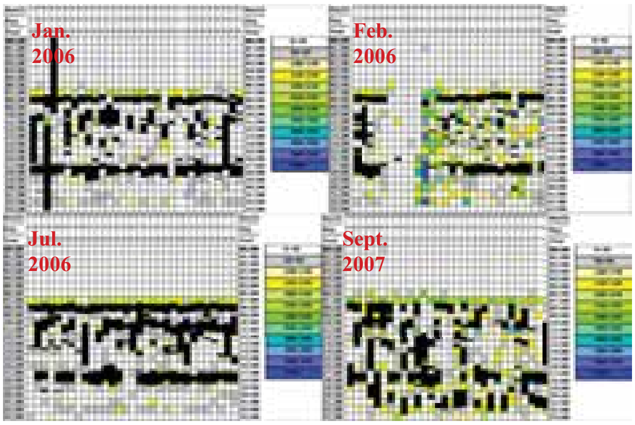

Fig. 8. Case study #2: density maps tracking knee replacement surgery.

which is shown mostly as white in the February 2006 density map, representing the extended absence of the resident. There are a few areas of activity during this time, e.g., caused by the housekeeper. The resident returned in the afternoon of February 10. From February 11–13, his family took care of him, and because there are several people in the apartment, the map shows a higher density during these days. He did not go out for meals until breakfast on February 13. After the surgery, the resident's TAFH was less frequent compared to the previous month, mostly for breakfast and dinner only. The early morning density is reduced to 150–199 events/h. During the day time, the higher density corresponds to more people in the apartment helping the resident in his recovery.

The July 2006 map shows a return to a more active life. Compared to February, he had improved considerably from the knee surgery. The September 2007 map shows even more activity, including evening activities. Compared to the previous density maps, this map indicates a higher level of activity, even higher than the month before surgery. Although he did not go out for meals as regularly, his TAFH increased overall. The motion sensors in the kitchen indicated that he prepared more meals in the home (this is not shown in the density map). At the end of 2007, he had recovered from the knee surgery very well.

Table II shows the dissimilarity measures of the density maps in Fig. 8. The dissimilarity of February 2006 compared to January 2006 is 0.26, which indicates a substantial change, due to the resident's knee surgery and help during recovery. Comparing July 2006 to January 2006, the TAFH and the average density are very similar. However, comparing density maps for these months, one can see changes in the regularity of the TAFH. The dissimilarity measure of the two months is 0.12, which indicates moderate change in his daily life pattern, as captured by the textural features. Comparing September 2007 to January 2006, both the TAFH and the density increase, and the pattern of daily life changes; these lead to the dissimilarity increase of 0.27. His general activity level was higher after rehabilitation than it had been before the knee replacement, as evidenced by the average sensor events/h in Table II.

C. Case Study #3

May 2006, September 2006, and October 2007 in Fig. 9 are three months of density maps for a third resident, with a different

TABLE II
CASE STUDY #2 DISSIMILARITY OF DENSITY MAPS

	Ave TAFH min/day	Ave Density sensor events/hour	Dis-similarity to Jan. 2006
Jan.	226	87	0
Feb.	117	128	0.26
July	242	87	0.12
Sept.	243	106	0.27

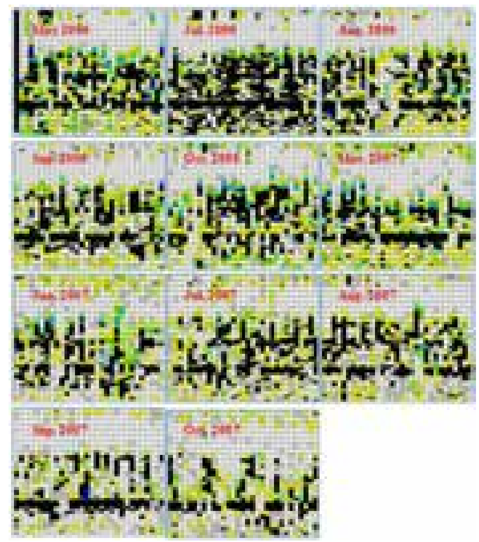

Fig. 9. Case study #3: density maps used for Fig. 10.

TABLE III
CASE STUDY #3 DISSIMILARITY OF DENSITY MAPS

	Ave TAFH min/day	Ave Density sensor events/hour	Dis-similarity to May 2006
May 2006	247	203	0
Sept. 2006	247	150	0.13
Oct. 2007	168	132	0.24

lifestyle pattern and a higher level of activity than the previous residents discussed. The resident has a puttering lifestyle and moves from room to room frequently, possibly due to early dementia. The density maps also show frequent periods of TAFH, including in the late night hours, which was confirmed by the staff. The dissimilarity results for these months are shown in Table III. The activity level shows a significant decrease from May 2006 to October 2007. The dissimilarity measure reflects this change along with the periodicity changes shown in the density maps.

For further investigation, we also look at the trend of the density maps over several months, from May 2006 to October 2007. This resident was absent from TigerPlace for several months; thus, some months are excluded in the study. Fig. 10 shows the dissimilarity results for the density maps in Fig. 9, comparing each month to May 2006. The map for July indicates a much higher number of TAFH blocks and, as a result, is substantially different from May. The month of October 2006 is the most similar to May. Over time, this resident's pattern begins to shift. The periodicity changes, there are fewer TAFH periods, and the overall activity level declines. Thus, the later months of

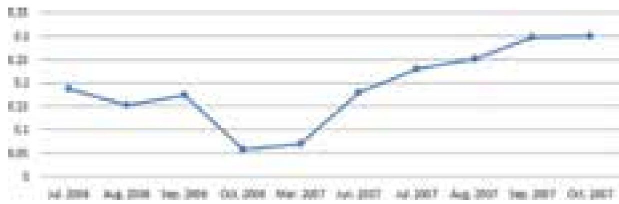

Fig. 10. Dissimilarity results for case study #3, comparing each month to May 2006. Density maps are shown in Fig. 9.

TABLE IV
CROSS-RESIDENT DISSIMILARITY COMPARISON

Comparison months	Dis-similarity
Case #1 Sept., 2006 to Case #2 Jan., 2006	0.39
Case #1 Sept., 2006 to Case #3 May, 2006	0.52
Case #2 Jan., 2006 to Case #3 May, 2006	0.30

September and October of 2007 indicate a higher dissimilarity measure compared to May 2006.

D. Cross-Resident Dissimilarity Comparisons

As a further test of the density map dissimilarity measure, we also compare representative monthly density maps from the three case study residents discussed previously. Table IV shows the dissimilarity comparison among the three cases. The resident in case study #1 has a somewhat sedentary pattern of activity. The resident in case study #2 is relatively active with a regular daily pattern. The resident in case study #3 shows a quite different pattern of activity with frequent movement in a puttering style but less regularity compared to the other residents. As shown in Table IV, the dissimilarity results range from 0.30 to 0.52. The results show that the dissimilarity measure is sensitive enough to catch lifestyle changes.

VIII. DISCUSSION AND CONCLUSIONS

Visualization of activity density maps and comparisons using the proposed dissimilarity measure are used to monitor the long-term daily activity level of older adults. The approach is independent of the floorplan, the number of sensors, or the firing sequence, as it looks for changes from a baseline that provides a personalized pattern of the resident. The color density map displays the activity level in an intuitive way and illustrates trends in changing health conditions. The visualization of the color density map has received good responses from the nurses and other clinicians on our team and is now used by the clinical staff at TigerPlace to monitor health changes of the residents. The analysis through the dissimilarity measure provides an automated method for detecting changes in the patterns of residents that will aid caregivers in the monitoring process. Different window sizes can be selected as desired, with a fixed baseline period or even a sliding baseline. It is unclear what the optimal baseline strategy is for early illness detection. This will require further investigation.

There are limitations in using the PIR data. The PIR motion sensor cannot identify specific individuals. Thus, the system will contain a degree of ambiguity as to who performed the activity (e.g., resident or visitor), and it is also a challenge to identify the number of persons in an apartment. Second, the motion sensor fires at most every 7 s if there is motion nearby, and useful information can be lost because of the 7 s resolution. On the other hand, the motion sensors used in this project are inexpensive and readily available. The system is affordable, easy to deploy, and nonintrusive.

Future research will expand on feature extraction and automated reasoning at different time scales using the logged sensor data, focusing especially on early detection of pattern changes. Although the dissimilarity measure does not indicate the direction of the change, we will investigate the use of the average density per day and the TAFH events for assessing whether the health condition is improving or declining. We have also begun to investigate circadian patterns using the PIR data, similar to approaches used with actigraphy data [12].

Automated reasoning will provide cues of potential problems in mobility or cognition as suggested by the logged data. The decision-making process for this type of sensor network will always be associated with some uncertainty. Thus, fuzzy logic systems provide a good strategy for managing the uncertainty by exploiting a tolerance for imprecision in order to interpret ambiguity. The main goal of our extended research team is to introduce advanced sensor reasoning, novel signal and image processing, and high level reasoning to enhance the independence and safety of older people while maintaining privacy and minimizing interference.

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