DENSITY MAP VISUALIZATION FROM MOTION SENSORS FOR MONITORING ACTIVITY LEVEL

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Abstract

This paper describes ongoing work in capturing and analyzing sensor data logged in the homes of seniors. Sensor networks have been deployed in TigerPlace apartments, to promote aging in place. Here, we introduce a visualization of the sensor data in the form of an activity density map which includes time away from home. The visualization is intended to aid caregivers in understanding the sensor data. In the density map, different colors are used to represent different levels of density in motion sensor data. For evaluating the activity density level accurately, time away from home was determined first using a system of fuzzy rules. Three case studies are included to illustrate how the density map can be used to track general activity level over time.

1 Introduction

Technology that can help seniors "age in place" has been spotlighted in recent years, spurred by an aging population. In response to this trend, the University of Missouri has been investigating new approaches in caring for the elderly. One example of this research focus has resulted in TigerPlace, a 31-unit apartment complex for seniors in Columbia, Missouri. A joint venture between MU's Sinclair School of Nursing and Americare Systems Inc., TigerPlace is one of four projects granted state approval to operate under the "aging in place" model of care giving [1]. Under that model, residents who would otherwise be required by state law to live in nursing homes may have health services brought to them in their apartments instead.

Current methods used by caregivers for determining changes in elders are based on observation and asking them relevant questions about their everyday lives. However, many elders are scared to face their functional decline and may not always be willing to provide honest answers. One focus of our research is the creation of "intelligent software" that uses sensors to uncover patterns of activity helpful to caregivers [2]. Our current work is focused on monitoring older adults through a network of sensors placed in the environment ranging from simple motion sensors to video sensors to a bed sensor that captures sleep restlessness and pulse and respiration levels. We believe that it is possible to provide more detailed information about elders by using a sensor network to monitor activities in the home. Sensor networks have been installed in fifteen apartments in TigerPlace. Data collection has been ongoing for over two years in some apartments. This longevity in sensor data collection is allowing us to study the data and develop algorithms for identifying alert conditions and extracting typical daily activity patterns for an individual. The goal is to capture patterns representing physical and cognitive health conditions and then recognize when activity patterns begin to deviate from the norm. A critical part of this effort is being able to sense, detect and assess changes in activity levels. In this paper, we focus on the visualization of motion activity density and time away from home (TAFH).

Much has been written about the population becoming older. By the year 2030, the elderly population will double [3]. The development and introduction of new eldercare technologies are increasing. In fact technologies to support independent living for older adults have been available for several years. The basic idea of many systems is to alert caregivers when emergencies happen. For example, some of these systems have a pull cord attached to the wall. However, when an older person is unable to give an alert, this type of system becomes useless. To solve this problem, sensors are introduced to monitor particular 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 [5]. The Independent Life Style Assistant (ILSA) developed by Honeywell was also an early system which proposed to incorporate passive monitoring [6]. A field study was conducted in 11 elderly homes for six months, focusing on monitoring of mobility and medication compliance. Ogawa et al. also document an early study in which two individual participants are monitored for motion activity, sleep time, and appliance use (through wattmeters) for more than a year [7].

In other work, Beckwith describes a study in an assisted living facility with nine residents of varying degrees of dementia [8]. Residents and staff each wore a badge for location tracking. The system also included motion and door sensors as well as load cells on the bed. Barger et al. report a monitoring system with eight passive motion sensors to infer a person's behavioral patterns using probabilistic mixture model analysis [9].

In work especially relevant to our research, Barnes et al. used motion and door sensors to extract a 24 hour activity profile [10]. An alert could be generated if newly logged data deviated from the stored profile. Majeed and Brown described the "well-being" monitoring of elderly residents with passive sensing from door and motion sensors [11]. Logged sensor data were classified via fuzzy rules into one of six activities, such as sleeping, preparing or eating food, and receiving visitors. The system was tested with two elderly participants.

Live-in laboratory smart homes with sensors and actuators have also been established such as the Aware Home at Georgia Tech [12] and MIT's PlaceLab [13]. The PlaceLab has a particularly large array of sensors, including cabinet and door sensors, accelerometers installed on objects, and sensors measuring water flow.

Our work differs from many of the above projects in that (1) ours is not a demonstration project, but rather we have installed the sensor networks in the homes of elderly volunteers and have achieved longevity of data spanning years, (2) we are focusing on passive sensing and reasoning, i.e., the participants do not wear sensors and the system does not use actuators, (3) we are also collecting data on health events in an effort to correlate the sensor data with the health record, and (4) we are exploring novel visualization methods to aid caregivers in understanding the sensor data.

In this paper, we propose a visualization of daily activity level in the form of a density map for monitoring the movement patterns of older adults. This density map can help caregivers track changes of activity level and patterns of daily life. The methods used to create the density map which includes TAFH are described in this paper. Three case studies of actual residents are included to illustrate how the density map can be used to track changes over time.

2 Integrated sensor network

The sensor network under development is shown in Figure 1. The network includes three main components: (1) a data logger with bed, motion and stove sensors (developed by collaborators at the University of Virginia [14]); (2) an event-driven, video sensor network that hides identifying features of the residents; (3) a reasoning component that fuses sensor and video data and analyzes patterns of behavioral activity. The system (without video) has been installed in 15 TigerPlace apartments.

The network currently installed in TigerPlace consists of a set of motion sensors, a stove temperature sensor, and a bed sensor. Motion sensors are installed to detect presence in a particular room as well as for specific activities. For example, a motion sensor installed on the ceiling above the shower detects showering activity; motion sensors installed discretely in cabinets and the refrigerator detect kitchen activity. The bed sensor is a pneumatic strip (installed under the bed linens) which detects presence in the bed, as well as pulse, respiration, and restlessness [15].

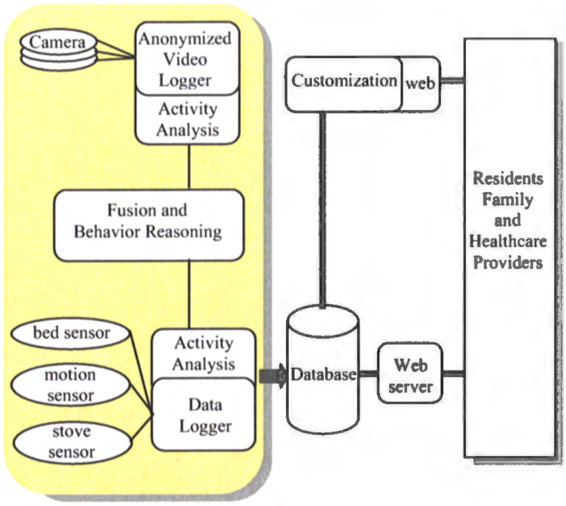

Figure 1:The integrated sensor network. The density maps described here are derived from the motion sensors.

The Data Logger collects data from the sensors, date-time stamps the data and logs it into a file that is regularly sent to a secure server which stores the database. The data is sent as binary streams stripped of identifiers, to ensure HIPAA compliance. The system is non-invasive and exploits simple low-cost sensor technologies coupled with specialized filtering and analysis.

A secure web-based interface was developed to display the sensor data for health care providers, residents, and researchers. The web-interface was refined with input from nursing, health informatics, social work, and residents to ensure it was user friendly and easily interpreted. The interface allows users to select a specific participant and a date range. Sensor data is grouped by category: motion, pulse, breathing, and restlessness. Users can further drill down in the interface to view data from individual sensors. The total number of sensor firings may be aggregated in increments ranging from fifteen minutes to daily and the data can be displayed in a variety of ways including line graphs, histograms, and pie charts.

To detect falls and to track pertinent data on gait, range of motion, and balance (which may indicate a risk of falling), we are also developing a video sensor network. The video network complements the data logger by collecting more detailed information that is not available in the current sensor suite. To preserve the privacy of the residents, several techniques are being investigated. One strategy is to identify a moving person in the image and create a silhouette.

3 Algorithm to determine time away from home

For evaluating the activity density level accurately, time away from home (TAFH) must be determined first. Especially, long periods of TAFH need to be found, as these have even more effect on the activity density level. To determine this event, motion sensors which represent different locations need to be evaluated. Location motion sensors fire every 7 seconds if there is motion near the location. In addition, a motion sensor was mounted on the ceiling above the front door to identify activity near the door way.

Figure 2 displays one of room plans of a TigerPlace apartment. There are six location motion sensors marked from one to six in this apartment. Sensor 6 is the door sensor. Generally, for a leaving-home sequence, a resident must go through a pass of 1 -> 2 -> 3 -> 4 -> 5 -> 6 if the resident leaves from the bathroom area as shown in Figure 2. This indicates that the sensor fires in an order from 1 to 6. In a leaving-home sequence, sensor 6 (door sensor) must fire last. Similarly, in a returning-home sequence the door sensor must fire first.

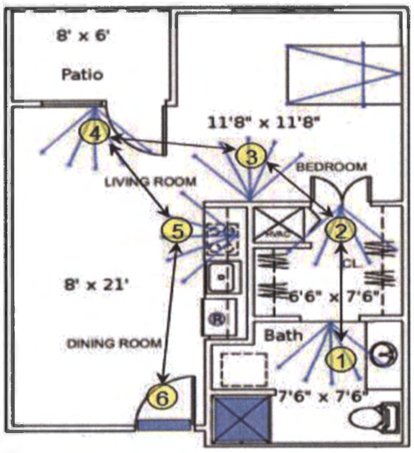

Figure 2: Room plan of an apartment

There are three steps in the away-from-home sequence. The first is leaving home; sensors in the home fire and then the door sensor fires last. In the second step there is nobody in the apartment and thus, no sensor firings during this period of time. The last step is returning home; the door sensor fires first and then other sensors fire. The three steps can be translated to three features which represent the three steps, as shown in Figure 3. A is the duration of door sensor events before leaving, B is the duration of no sensor events, and C is the duration of door sensor events after returning. The raw motion sensor data was pre-processed into this format.

The extracted features represent possible time periods away from the home, but some may be false positives. For example, if someone sits at a table near the door and has a rest without any motion, we can find a feature set similar to an actual TAFH.

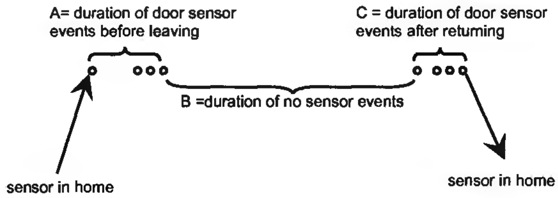

Figure 3: Extracted features from raw sensor data

The differences between an actual TAFH and a false TAFH are the durations of the door sensor events before leaving (A), the durations of no sensor events (B) and the durations of the door sensor events after returning (C). Consider when someone is leaving or returning, the time she spends near the door to put on or take off her coat should be much shorter than the duration of out of the apartment. For a typical TAFH, the length of B is much longer than A and C. For a false TAFH, the length of A, B and C might be similar, or A or C might be much longer than B. It is important to distinguish between actual and false TAFH. For this purpose, the extracted features are classified into actual and false TAFH events using a set of fuzzy rules [16]. Fuzzy logic [16] provides a methodology that simulates human thinking by explicitly modelling and managing the imprecision and inherent uncertainty.

3.1 Membership Functions

Based on the characteristics of the TAFH features, we used trapezoidal-shaped membership functions [17]. The membership value is a function of a feature, x, and depends on four scalar parameters a, b, c, and d (the vertices of the trapezoid), as given by

$$f(x,a,b,c,d) = \max\left(\min\left(\frac{x-a}{b-a},1,\frac{d-x}{d-c}\right),0\right) \quad (1)$$

The fuzzy logic system of discriminating TAFH has three inputs (A, B and C) and one output, the confidence of a TAFH event. Figures 4, 5 and 6 show the membership functions for the linguistic variables used. For all membership functions, the abscissa represents time in seconds.

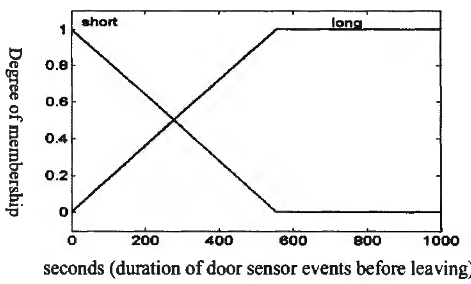

Figure 4: Membership functions for the duration of door sensor events before leaving (A)

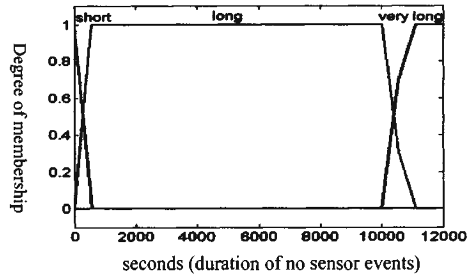

Figure 5: Membership functions for the duration of no sensor events (B)

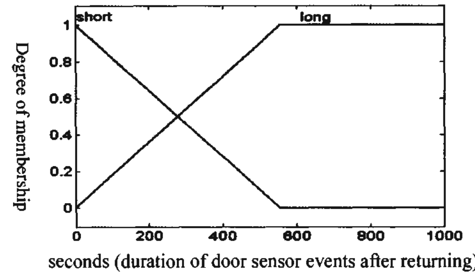

Figure 6: Membership functions for the duration of door sensor events after returning (C)

3.2 Fuzzy Rules and Inferencing

Table 1 displays the rules of the fuzzy system which discriminates TAFH. A, B and C represent the three features described above, which are durations (in seconds). "Confidence of away from home" which changes from very poor to excellent represents the fuzzy output membership functions from 0 to 1. The rules were developed empirically.

rule	A	B	C	Confidence of away from home	
				Linguistic	Member-ship
1	Short	Short	Long	Very poor	0
2	Short	Long	Short	Excellent	1
3	Short	Long	Long	Good	0.75
4	Long	Short	Short	Very poor	0
5	Long	Short	Long	Very poor	0
6	Long	Long	Short	Good	0.75
7	Long	Long	Long	Poor	0.25
8	N/A	Very long	N/A	Excellent	1
9	Short	Short	Short	Very poor	0

Table 1: Fuzzy rules for TAFH discrimination

The most popular models of fuzzy inferencing are the Mamdani models [18] and the Takagi-Sugeno-Kang (TSK) models [19]. The main difference between them is the consequent part of the fuzzy rules. The Mamdani models describe the consequent part using the linguistic variables, while the Takagi-Sugeno-Kang models use the linear combination of the input variables. Both models use linguistic variables to describe the antecedent part of fuzzy rules. For classifying TAFH, we use a Sugeno inference system.

3.3 Validation

An apartment was set up with the sensor network for test purposes. Researchers lived in the apartment in shifts. Videos were recorded, and a log file was written by researchers to record their activity during the day time. Both videos and the log file were used as ground truth to validate the algorithm of discriminating TAFH.

During 22 days of testing, 21 away-from-home events were recorded during the day time, and 16 were found by the algorithm. The accuracy rate is 76% with no false positives. In the 21 away-from-home events, 11 of them were longer than five minutes, and the algorithm found all of these 11 events. The accuracy rate to find TAFH larger than five minutes is 100% with no false positives. This validation result indicates the algorithm for discriminating TAFH works very well for out-of-home time longer than 5 minutes. This result is sufficient for us to apply the algorithm to the density map, because TAFH shorter than five minutes does not significantly affect the evaluation of the activity density level.

4 The activity density map

In the density map, different colors are used to represent different levels of density in the motion sensor data. The density is computed as the number of all motion sensor hits during an hour divided by time at home during that hour. An example of a density map is shown in Figure 7. The X-axis represents hours in a day. The Y-axis represents days in a month. The colorbar on the right of the figure shows the colors of the different densities. Black represents TAFH. White means that no sensor fires. Colors change from light grey, yellow, green, light blue to dark blue as the density per hour increases. The dark blue color represents the highest density of 550 or more events per hour. In the density map, the density is calculated for each hour block; TAFH is accurate to the second.

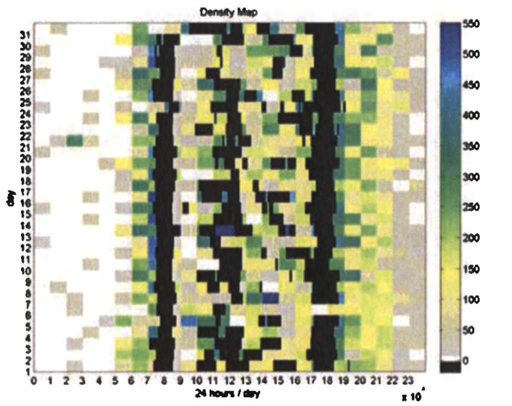

Figure 7: An example of a density map showing an active life style

Figure 8 displays a density map of one day. Several observations can be made. The black area means TAFH, and we can see this resident went out 4 times during day, around 8 am for breakfast, around noon for lunch and around 6 pm for dinner; at around 2 pm, the resident went out for a short period of time. The highest density appeared in the morning around 7 am, and from the yellow green color we know the density is around 170 events per hour.

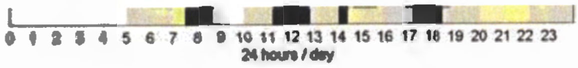

Figure 8: density map of a day

Figure 9 shows another example of a density map. Compared to Figure 7, this map is much less colorful, Green is the darkest color in the map, and the corresponding density is around 300 times per hour. The black areas of Figure 9 cover much less time than Figure 8 too. The resident in Figure 9 only went out for three meals a day, and sometimes skipped the meal. The resident in Figure 7 went out more frequently which also tends to indicate a higher level of activity. Comparing the time from 0 to 6 am, the resident in Figure 7 has less motion activity than the resident in Figure 9; that is, the Figure 7 map indicates better sleep and less motion during night time. In comparison, the overall day time activity and the night time pattern of the map in Figure 7 is better than the map in Figure 9.

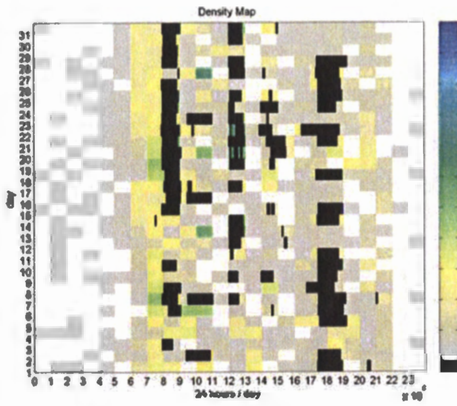

Figure 9: An example of a density map showing a sedentary life style

5 Case studies

The density maps have been applied to logged sensor data from TigerPlace apartments. Examples of three residents are given in the following sections. We are less concerned here with comparing one resident's life style to another resident's life style but rather we want to highlight changes in an individual resident's activity over time. Each resident is followed over several months to show changes in the resident's motion density pattern.

5.1 Case study #1

Figure 10 displays the density of Mar., 2006 for one resident. Several observations can be made. First, there are some grey areas during the night, indicating the resident had motions during the night time. Second, the density color gets darker to yellow starting at around 6 am most days. This indicates that he woke up regularly in the morning. Similarly, he went to bed around 10-11 pm. Third, the black areas indicate that he had three meals outside regularly, but sometimes skipped. In addition to regular meals, this resident also went out of the home at other times during the month of Mar., 2006.

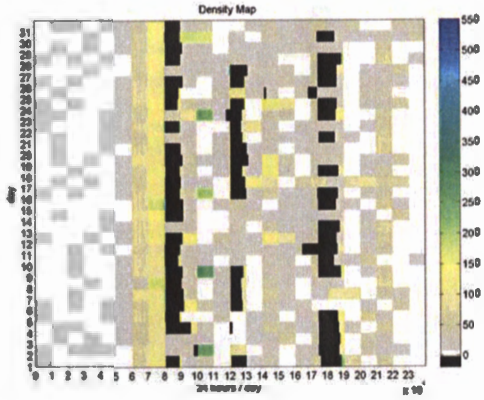

Figure 10: Case study #1, Mar., 2006

Figure 11 shows the density of Sept., 2006 for the same resident. Compared to the density map of Mar., 2006, similar conclusions can be made. However, the color of the density map fades over time, and the black areas are less frequent. These changes indicate that the activity level of the resident decreased over time.

In Figures 10 and 11, there is a high density in green at 10-11 am every week. These dates of high density are all on a Monday. Every week on Monday from 9:45-10:45 am, the apartment is cleaned by a housekeeper. Also, in Figures 10 and 11, the first two waking hours from 6-7 am have a higher density during 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.

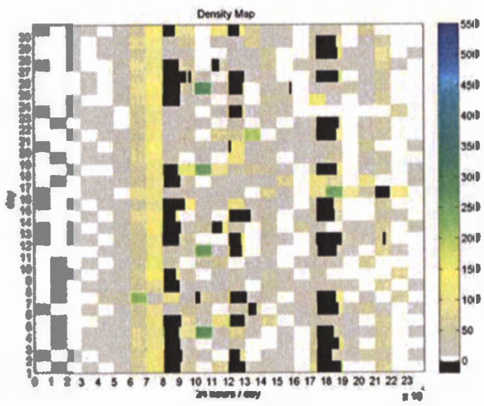

Figure 11: Case study #1, Sept., 2006

5.2 Case study #2

Figures 12, 13, 14 and 15 show four months of density maps from another resident. Figure 12 displays the density map of Jan., 2006. During this month, the resident had a relatively active life. There are some night time movements, but those are in the reasonable range compared to the day time activity. The density color becomes darker to yellow or green in the morning around 6-7 am; this indicates he woke up regularly in the morning and did his morning routine. Around 8-9 am, there is a black area normally, indicating he went out for breakfast regularly. There are some other black areas in the morning or noon, and this indicates he went out sometimes. Each week on Tuesday, from 11 am to noon, there are high density areas, which were caused by the weekly housekeeping. From around 6-7 pm, the resident went out for dinner almost every day. At 11 pm, the person went to bed normally. Overall, the resident had an active life.

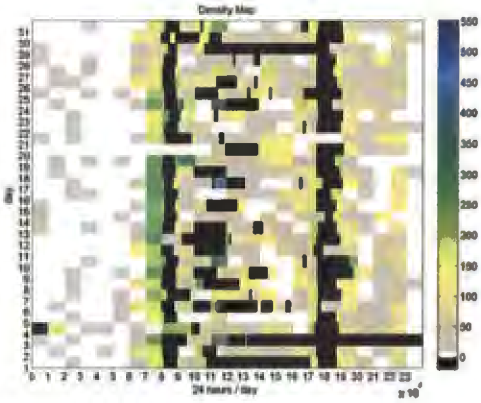

Figure 12: Case study #2, Jan., 2006

Figure 13 displays the density map of Feb., 2006. From Feb. 6th to 10th, he had a total knee replacement surgery. This period of time is white in the density map. There are several color blocks in this white area also. The green block on Feb. 7th is caused by the housekeeper, and others are caused by other people who entered the apartment.

The resident came back to the apartment in the afternoon of Feb. 10th. From Feb. 11th to Feb. 13th, his family took care of him, and because there are several people in the apartment, the density map has darker colors during these days. He did not go out for meals except the breakfast time on Feb. 13th. Later this month, the resident's TAFH was less compared to the previous month, only the breakfast time and most of the dinner time, and the density in the early morning fades. But during the day time, the density color is darker than the previous month, and this indicates someone took care of him during the day time.

Figure 14 displays the density map of July, 2006. The density color darkens to yellow or green in the morning from 7-8 am; he woke up regularly in the morning and the density color in the morning is mostly darker compared to Jan., 2006. Around 8-9 am, he went out for breakfast regularly. Around 9 am to noon or afternoon, there are black areas normally every day, and this means he had some other activities outside the apartment. From around 6-7 pm, he went out for dinner almost every day. At 11 pm, he normally went to bed. Compared to Feb. he recovered from the knee surgery very well and his life went back to normal as before the surgery.

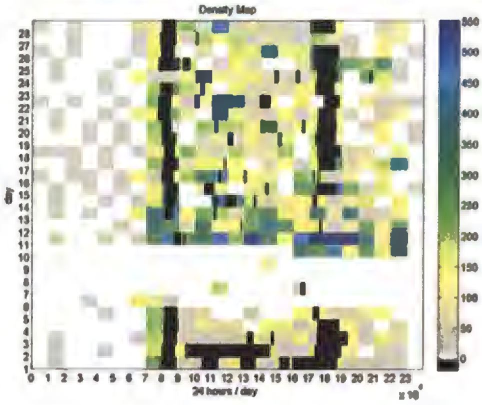

Figure 13: Case study #2, Feb., 2006

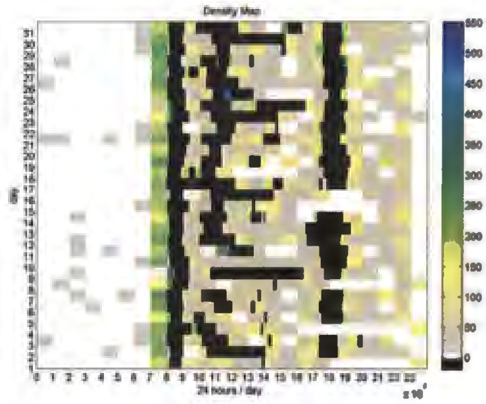

Figure 14: Case study #2, July, 2006

Figure 15 displays the density map of Sept., 2007. Compared to the density maps before, this map is more colorful, and the density color in the morning is close to green. The activity level is even better than the month before surgery. Although he did not go out for meals as regularly, his TAFH during other times increased. 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 recovered from the knee surgery very well. From Figures 12 to 14, the procedure of recovery from the knee surgery can be seen clearly.

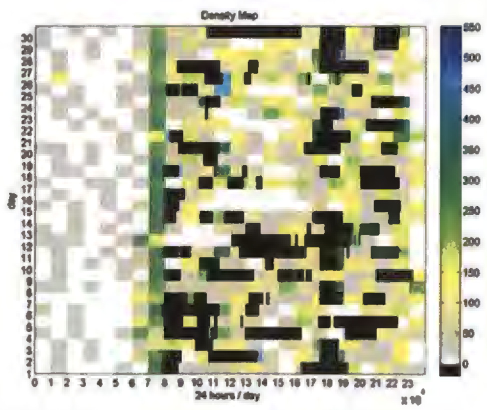

Figure 15: Case study #2, Sept., 2007

5.3 Case study #3

Figures 16, 17 and 18 display three months of density maps for a third resident. From these figures, we can see this resident has a dramatically different style of density map. The color of the density map is much darker than the others discussed in previous sections. She has a puttering style, and likes to move around in high frequency.

From Figure 16, we can see many black blocks, and this indicates she went out of the apartment very often, sometimes for short periods. This has been confirmed by TigerPlace staff that she often left her apartment for short walks in the hall and common areas.

From the color of the density map, it can be seen that she has a very high activity level. It also can be seen that she went out for lunch and dinner normally. She had a lot of motions during the night time, and from the density map it can be seen that the resident slept a short time during the night compared to others in the study.

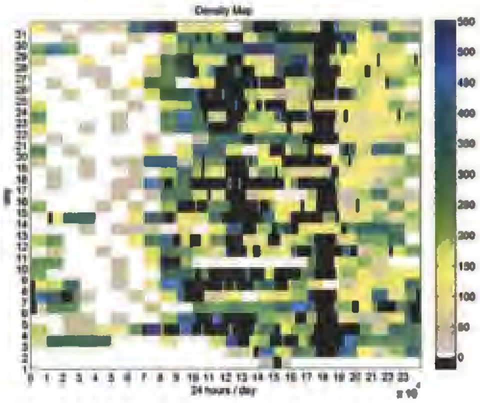

Figure 16: Case study #3, May., 2006

Figure 17 shows the density map of Sept., 2006. Many areas in the map of Figure 17 fade from blue to green compared to Figure 16. Although she still has a very high activity level, her activity level began to decrease. Her sleep pattern still indicated a short sleeping time at night.

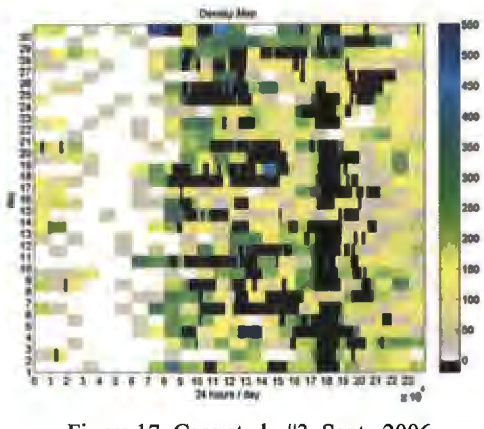

Figure 17: Case study #3, Sept., 2006

Figure 18 shows the density map of Oct., 2007. Compared to the previous months, the activity level of this resident decreased, and the TAFH periods also decreased. From 2006 to the end of 2007, her overall activity level decreased dramatically.

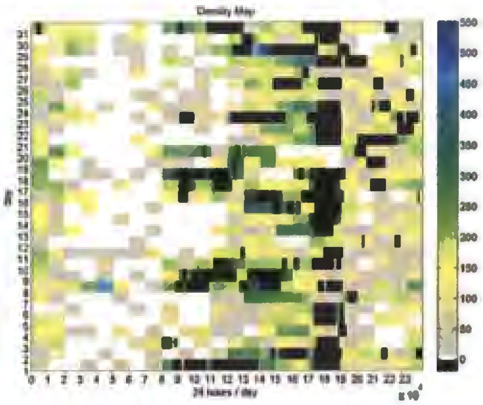

Figure 18: Case study #3, Oct., 2007

6 Conclusion

Visualization of motion density maps is used to monitor the long term daily activity level of older adults living at TigerPlace. The color density map can display the activity level in an intelligible way and make the density issues easy to understand for caregivers. The visualization of the color density map also received good responses from the nurses and other gerontology specialists in our team. In this paper, we explored changes in motion density patterns over several months. The time logged spans different seasons and some of the changes over time may be the result of seasonal changes in living patterns. Nurse gerontology experts in our group have not previously observed seasonal changes in residents' patterns in this type of elder housing. With this data, we can now explore this possibility.

There are challenges in the data analysis also. First of all, the motion sensor in the network cannot tag for personal identification. Thus, the decision made by the system will contain a degree of ambiguity to identify who performed the activity, and it is also a challenge to identify the number of persons in an apartment. Second, the motion sensor fires every 7 seconds if there is motion nearby, and useful information can be lost because of the 7 second resolution. On the other hand, the motion sensors used in this project are inexpensive and readily available. This kind of system is more easily affordable by a majority of older adults and is easy to deploy.

Our future research goals will focus on feature extraction and automated reasoning using the logged sensor data. The features will be extracted from the sensor data for classification and assessment. Automated reasoning will provide cues of potential problems in mobility or cognition as suggested by the logged data. The fact is that the decision-making process for this type of sensor network will always be associated with some uncertainty. 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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