Using Sensor Networks to Detect Urinary Tract Infections in Older Adults

Marilyn J. Rantz, Marjorie Skubic, Richelle J. Koopman, Lorraine Phillips,
Gregory L. Alexander, Steven J. Miller, Rainer Dane Guevara
University of Missouri
Columbia, MO, USA
{rantzm, skubicm, koopmanr, phillipslo, alexanderg, millerst, rdg5xc }@missouri.edu

Abstract— **Integrated sensor networks have been installed in apartments of volunteer residents at TigerPlace, an aging in place retirement community that allows residents to remain in their apartments even if their health deteriorates. The sensor networks supplement registered nurse (RN) care coordination provided by Sinclair Home Care by alerting the RN care coordinator about changes in the normal sensor patterns. In several cases, the alerts have prompted the care coordinator to have the resident tested for urinary tract infections. Importantly, the sensor network detected signs of illness earlier than traditional health care assessment.**

Keywords- Aging in Place, Sensor Network, Illness Detection

I. INTRODUCTION

Early illness detection is crucial for early interventions when treatment is most effective and when prevention of dramatic changes is still possible. Early illness recognition and treatment are not only key to improving health status with rapid recovery after an acute illness or exacerbation of chronic illness, but also key to reducing morbidity and mortality in older adults [1] [2] [3]. Sensor technology provides a cost-effective way to remotely monitor older adults at home, detect impending illness, and allow for early intervention. Researchers at the University of Missouri are using passive sensor networks installed in apartments of residents at TigerPlace to detect changes in health status and offer clinical interventions to help residents age in place.

TigerPlace is a retirement community that was developed around the concept of Aging in Place; that is, older adults are allowed to remain in the environment of their choice through supportive services, without the fear of forced relocation as their health status deteriorates [4] [5] [6]. Sinclair Home Care directs the care of the residents of TigerPlace including routinely assessing the residents, providing health promotion and assistive care services when needed, and coordinating all of the residents' medical care with physicians, family members, and other providers, allowing the residents to age in place.

This work was supported in part by the National Institutes of Health, National Institute of Nursing Research under Grant 1R21NR011197-01.

To supplement the care provided by Sinclair Home Care, researchers are investigating the use of integrated, environmentally-embedded passive sensors to monitor the residents and detect early signs of illness and/or functional decline. The current sensor network array at TigerPlace includes passive infrared (PIR) motion detectors, bed and chair sensors that detect pulse, respiration rate and bed restlessness, and stove temperature sensors. TigerPlace provides a real world setting in which to develop and test the integrated sensor network and to explore the efficacy of using passive sensing for early illness detection.

Small investigative studies of sensor networks have been conducted. Glascock and Kutzik tested a system of motion sensors, contact and magnetic reed switches, and vibration detectors to monitor activities of daily living. The system was tested for 13 days in the home of a community-dwelling 71-year old man [7]. In another study, the activities of daily living of 21 assisted living residents were tracked using motion sensors. Heart and breathing rates were also monitored using a bed sensor for three months. The results of this case-controlled study demonstrated reduced hospital days, cost of care to payers and had a positive impact on the caregivers [8]. Chan, Campo, and Esteve reported the findings of a study using 10 infrared sensors on the ceiling of institutional elderly housing to monitor 4 older adults; changes in activity data and correlations between bed restlessness and getting up revealed trends which could be used as a predictive tool [9]. Ogwana, et al. monitored two elderly women continuously for over a year using motion sensors, door switches, watt-meters, and carbon dioxide sensors. The researchers concluded that monitoring may contribute to maintaining the health of older adults [10]. The Independent LifeStyle Assistant (ILSA) by Honeywell was an agent-based monitoring and support system. A pilot field test of the ILSA was conducted for 6 months in the homes of 11 older adults. The system was later retired because the agent-based architecture was difficult to manage and significantly added to the development process [11]. Another study used motion and temperature sensors as well as door switches to create a profile of a person's lifestyle (activity) over time; an alert could be generated if the current data pattern deviated from the stored profile [12]. Most of these projects were primarily focused on validating new technologies and methodologies.

Our research is feasible because of the partnership between the University of Missouri, TigerPlace, and the elderly participants. The sensor networks are installed in apartments of volunteer residents. Based on results of interviews with and observation of residents, our research focuses on environmentally-embedded, passive monitoring, i.e. the residents do not wear any sensors or devices [13] [14]. In addition, we have collected over five years of longitudinal data from a total of 37 TigerPlace apartments. Many networks have been operational for over two years; one resident has been continuously monitored for over five years. Data collection includes both electronic health records as well as sensor data, which makes the investigation of early illness alerts possible. The clinical focus of this research particularly separates this study from other projects [15].

II. Research Components

A. TigerPlace

TigerPlace was designed to nursing home standards, licensed as an intermediate care facility (ICF) with several waivers to allow residents to age in place, and operated as independent living. Residents live in independent apartments with services such as transportation, housekeeping, social activities, and 2 meals per day provided [6]. Health care services are provided by Sinclair Home Care, a specialized home care agency owned and operated by the University of Missouri Sinclair School of Nursing.

Currently, TigerPlace has 63 residents ranging in age from 64 to 97. There are 9 couples and the remaining residents are single. About 90% of the residents have a chronic disease; 60% have more than one chronic illness. Common illnesses include heart disease, arthritis, and diabetes. A few residents have early stage Alzheimer's disease. About 15% of the residents use a walker; several use a wheelchair, and others use canes as needed. In general, the residents are socially engaged in the community and none of the residents have severe cognitive impairment. All of the residents have retained the right to self determination and all have signed IRB-approved consent and HIPAA forms to have their sensor and health information used in aging in place research underway evaluating the clinical outcomes, quality of care, and cost of aging in place as a model of long term care services. Residents participating in the sensor research sign additional, specific IRB consents for the sensor research projects.

B. Sinclair Home Care

The Sinclair Home Care was created to provide services to TigerPlace and other senior congregate housing in the geographical area. Residents of TigerPlace receive a comprehensive assessment upon admission and at least every six months, access to a wellness center five days per week, exercise classes five days per week, social work assistance to help with life transitions, and four prepaid visits per year to assess and help with health issues. Residents may have their vital signs checked, receive assistance with medications, or discuss health related issues with the registered nurse (RN) care coordinator at the wellness center. A RN is on call 24-hours per day, 7 days per week to triage emergency situations. In addition, residents may pay privately for personal care, medication management services, or other services as needed [6]. When warranted, for example, after a hospitalization, residents receive Medicare home health services

A comprehensive electronic health record (EHR) was created to contain the assessment and health records of the residents. It was necessary to develop an EHR in order to integrate the sensor and health data, enhance the RN care coordination at TigerPlace, and advance the research [16]. The RN care coordinator is using both the sensor data and traditional health records to support her clinical decisions.

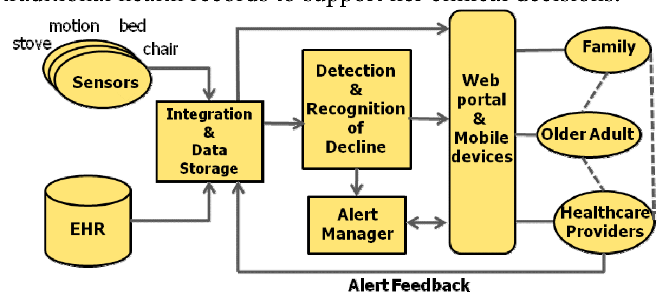

Fig. 1. The integrated sensor network deployed in TigerPlace includes motion, bed, chair, and stove sensors.

C. Integrated Sensor Network

The integrated sensor network installed in TigerPlace (Figure 1) includes (1) bed, chair, stove temperature, and motion sensors; (2) the EHR with resident assessment and clinical records; (3) an integrated database which stores the data from the various components; (4) a detection and recognition module which analyzes the data; (5) an alert manager which notifies clinicians if a problem is detected; and (6) a web portal to graphically display the data, and (7) an alert feedback loop which allows the clinicians to rate the effectiveness of the generated alerts Currently, only the clinicians use the system, although we have plans to include the residents and designated family members.

Inexpensive, commercially-available passive infrared (PIR) motion sensors, which transmit via the X10 protocol [17], are installed in various locations to detect presence in different rooms and to infer specific activities. For example, a motion sensor is installed on the ceiling over the shower to infer bathing. In addition, a stove temperature sensor is installed to monitor cooking activity. Also, a motion sensor is installed on the ceiling by the front door to capture movement out of the apartment; as observed by the staff at TigerPlace, residents often leave their doors ajar so that magnetic door sensors are not reliable for this purpose.

The bed sensor, developed by collaborators at the University of Virginia [18] [19], is a pneumatic strip that lies on the bed on top of the mattress and under the bed linens. The sensor measures four levels of restlessness (based on time of continuous movement) as well as three levels of qualitative pulse and respiration rates (low, normal, and high) [20]. For residents who spend much of their time in a recliner chair, including sleeping at night, the pneumatic bed sensor is installed along the back of the recliner chair.

Figure 2 shows a typical sensor network deployed in TigerPlace for a one-bedroom apartment. The sensor networks vary depending on the size (alcove, one bedroom, two bedroom) and shape of the apartment. Each sensor network includes a bed sensor and motion sensors in the living room, kitchen, bathroom, and closet.

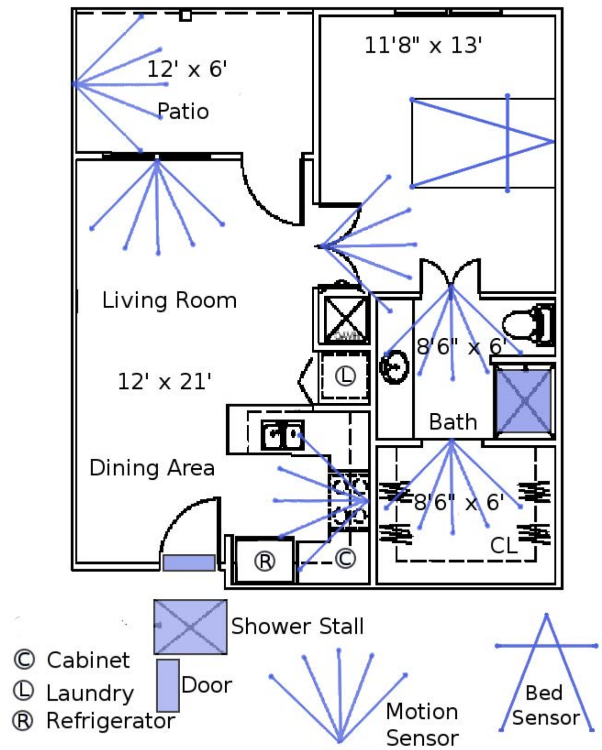

Fig. 2: A typical sensor network deployed in TigerPlace for a one-bedroom apartment.

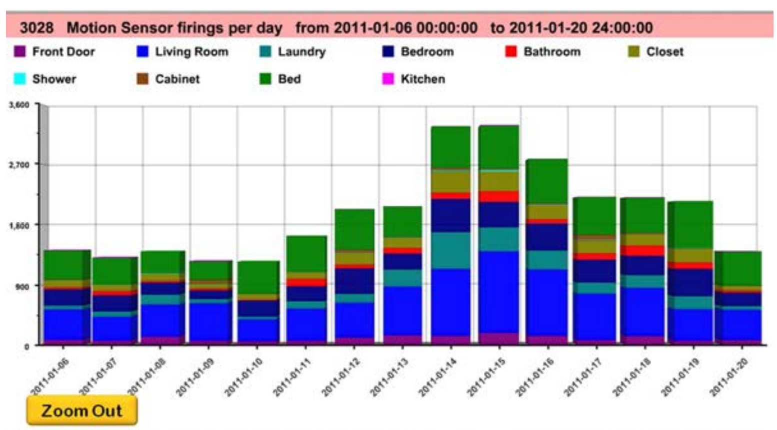

Fig.3. Example of the web-based interface showing motion sensor hits for a resident aggregated to a daily level.

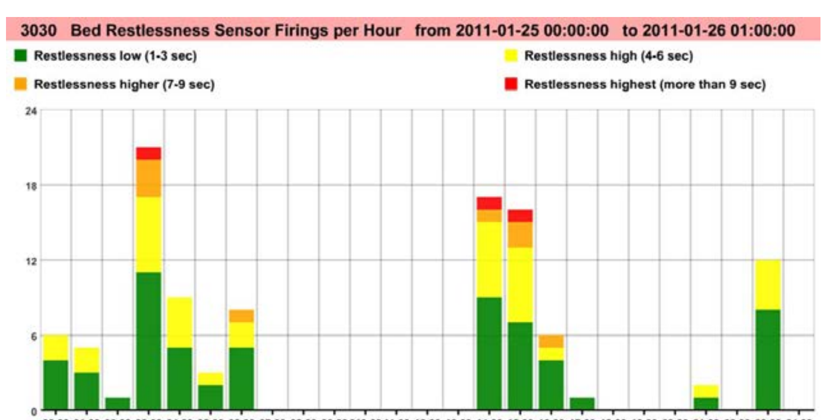

Fig. 4. Example of the web-based interface showing bed restlessness sensor hits for a resident aggregated to an hourly level.

A web-based interface was developed to display the sensor data, currently for clinicians and researchers. The interface allows the user to select a resident and a date range. The sensor data are displayed as histograms and can be aggregated in hourly or daily increments. The sensor data are grouped into categories: motion sensor events, bed restlessness, pulse, respiration, and stove temperature [20]. Examples of the interface are shown in Figures 3 and 4.

An alternative method to display motion sensor data in the form of a density map is shown in Figure 5. The PIR motion sensors generate an event every seven seconds if there is continuous motion detected. As a result, computing motion density as the number of events per unit time captures a general activity level of the resident. For example, a pattern of low motion density corresponds to a sedentary lifestyle, whereas a pattern of high motion density corresponds to a more active lifestyle. The motion density maps provide a visualization of the activity lifestyle through the use of different colors for different motion density levels [21].

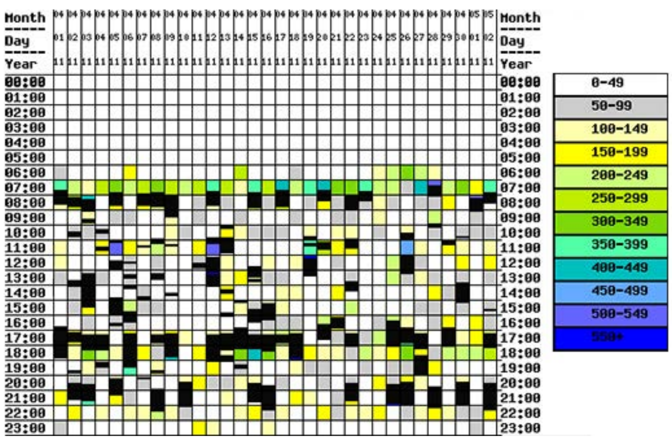

Fig. 5. Motion density map for a resident showing about one month of activity. Black corresponds to time out of the apartment (e.g., for meals in the common dining room). The color bar on the right shows the corresponding color for each density level from white and gray (low density) to green and blue (high density).

The motion density is calculated as the total number of motion sensor hits per hour divided by the total time in the apartment during that hour. As illustrated in Figure 5, the color bar on the right shows colors representing the different levels of density. Black indicates time out of the apartment, which is detected using a system of fuzzy rules as described in [21]. White indicates a very low motion density. The X-axis represents days and the Y-axis represents hours of the day. The density maps are displayed for a six-month time period preceding the ending date that was selected by the user in the web-based interface. Using the density maps, the clinicians may quickly get a graphical representation of the activity level of the resident over time and observe any changes in the activity patterns.

Using a similar format, Figure 6 shows an example graph for bathroom visits as detected by motion sensors. Bathroom visits are plotted on a graph where the X-axis represents days and the Y-axis represents hours of the day. Bathroom visit maps were developed when clinicians on the research team expressed that frequency of bathroom use might be a useful parameter to display in a 2D map showing hourly visits for each day. Using the bathroom visit maps, the clinicians can quickly get a graphical representation of activity in the bathroom over time, including the number and pattern of nighttime trips to the bathroom.

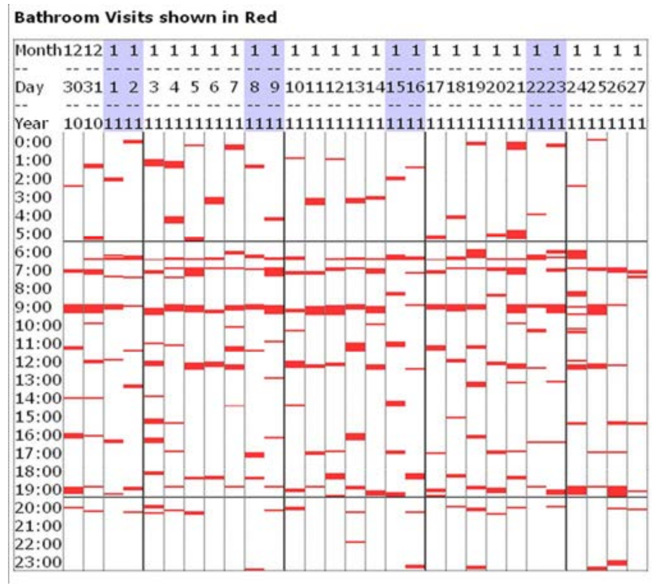

Fig. 6. Bathroom visits for a resident.

D. Study Methods

Thirty-seven people (11 male, 26 female) have been monitored with the integrated sensor network (the group includes two couples). The subjects range in age from 64 to 97 (mean 86.97 ± 6.71). Eleven residents have been discharged; six participants died, four moved to a nursing home, and one moved to a residential care facility. The first network was installed in October, 2005. A network that was installed in November, 2005 is still active; we have continuous longitudinal data for over 5 years for this resident. The average length of monitoring with the sensor network is 1.8 years.

Alerts of potential illness and/or functional decline were developed with input from nursing, medicine, and engineering. Four expert gerontological nurses and a family physician completed a retrospective analysis of sensor data around known health events such as hospitalization, falls, and emergency room visits of all sensor participants. The clinicians viewed sensor data before and after the events to determine initial patterns which could be used as a basis for alerts. After the initial retrospective review, the clinicians routinely viewed the sensor data to monitor the residents' health status and activity levels. The alert algorithms and web-based interface were refined through an iterative

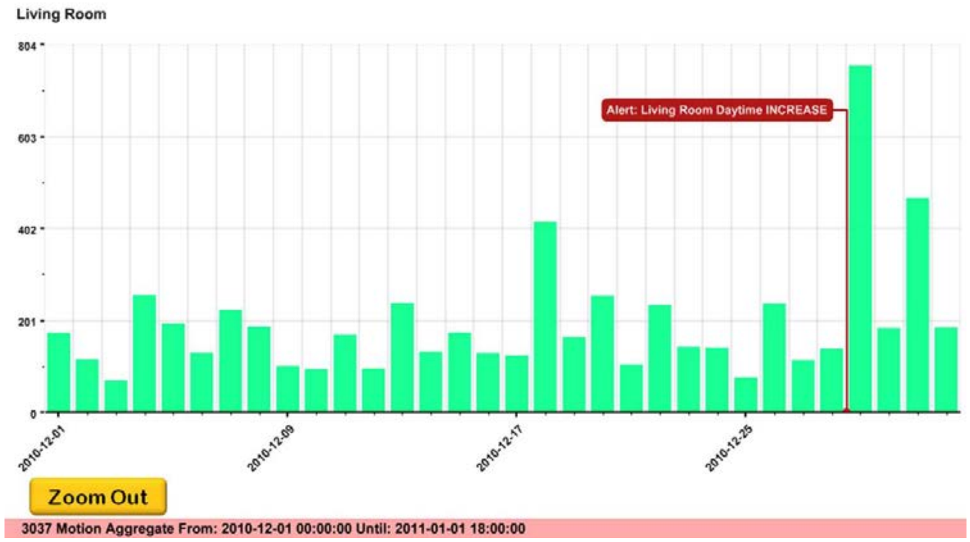

Fig. 7. Example of the web-based interface showing the living room motion sensor hits; an alert was generated on December 29, 2010 for increased living room activity during the day.

process during weekly team meetings of clinicians and computer engineers over a two year period [22]. The retrospective review of sensor data surrounding known health events revealed that changes in sensor data could be visualized by the clinicians, in many cases, up to two weeks before the health event. This time frame became critical for the algorithmic development for automated alerts to clinical staff.

An NIH-funded pilot study prospectively using the alerts to detect early signs of illness and offer early interventions began in June 2010. The alerts used for the pilot study are based on the distribution of total sensor hits per day for a 14-day sliding window. An alert is generated if the total number of sensor hits for the current day is 4 standard deviations outside the mean of the previous 14 days. Three time frames are monitored for alert conditions: daytime (8:00 am to 8:00 pm), nighttime (midnight to 6:00 am), and the 24-hour period (midnight to midnight). Parameters tested for potential alert conditions include living room activity, kitchen activity, bathroom activity, bed restlessness, bed pulse levels 1-3, bed breathing levels 1-3, chair restlessness, chair pulse levels 1-3, and chair breathing levels 1-3. Alerts are delivered via email to the clinicians. As a part of the pilot study, the clinicians are evaluating the clinical value and utility of the alerts. When an alert is received, the RN care coordinator evaluates the resident after reviewing the resident's sensor data and medical record to determine if additional evaluation and possibly treatment are needed. The RN's clinical decision is based upon the results of her nursing assessment; the alerts are not used as a diagnostic tool. She evaluates the resident and makes clinical decisions based on traditional health care methods and coordinates appropriate treatment.

Bathroom activity is classified as the total of the bathroom motion, shower motion, and laundry motion sensors. This was done in an attempt to capture all activity in the bathroom. A specific sensor to monitor toilet usage was not included in the original sensor networks. Bathroom activity was thought to be more useful. The alert is based on the bathroom activity and not specifically on one of the incorporated sensors,

The email alerts contain a link to the web-based interface so the clinicians may quickly view the data which generated the alert; a link is also included for the clinicians to leave feedback and rate the relevance of the alert. The current, simplistic alert algorithm was intentionally chosen to err on the side of generating too many alerts rather than possibly missing crucial alerts. The feedback from the clinicians is being used to develop a database of alerts for future algorithm investigation. The clinician feedback will be used as ground truth to develop more sophisticated algorithms which will eliminate many of the false positive alerts received during the pilot study.

III. Case Studies

Urinary tract infections (UTIs) are a serious health threat for older women [23]. UTIs are common in post-menopausal women [23]. If untreated, a UTI may lead to kidney damage or the infection could spread to the blood stream causing system-wide infection and possibly death. Common symptoms of UTIs include urgency and frequent urination. Alerts from the integrated sensor network have been used to compel residents to be tested for UTIs.

A. *Case Study #1: Early detection of UTI in an 84 year-old woman*

Two alerts were generated for an 84 year-old female who lived alone in her apartment. The first alert was on December 29, 2010 for an increase in living room activity during the day (Figure 7). This alert alone did not alarm the clinicians as the resident may have had company or may have been working on a project in her living room. Daytime motion alerts are often viewed as positive because they indicate an increase in activity or more social interaction with visitors in the apartment. The second alert was on January 1, 2011 for increased activity in the bathroom at night as illustrated in Figure 8. This alert caught the attention of the RN care coordinator because this alert was unusual for this resident and it was the second alert within a few days. Increased bathroom visits, especially at night, may be a sign of a health issue, and have been associated with greater risk for mortality [24]. The care coordinator assessed the resident, and then arranged to have the resident see her physician. Based on the results of a urinalysis (testing the urine for abnormalities), the physician diagnosed a UTI. She was put on antibiotics and made a full recovery. These sensor alerts prompted the RN care coordinator to assess the client and initiate a physician referral. If RN had not received these alerts, the UTI may have gone undiagnosed and caused additional health problems.

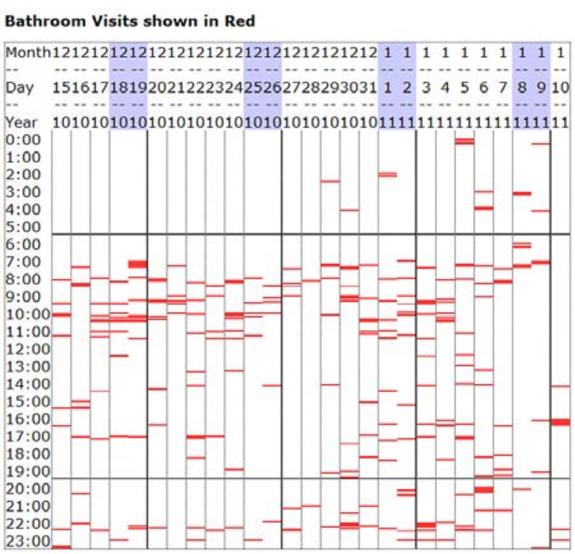

Fig. 8. Bathroom visit map showing increased time in the bathroom at night beginning around January 1, 2011 when an alert was generated

B. Case Study #2: Early detection of UTI in a 75 year-old woman

Similarly, an alert for increased activity in the bathroom at night was generated for a 75 year-old female on December 29, 2010. The RN care coordinator assessed the resident and discussed the increased nighttime activity with the resident's daughter. The daughter took the resident to her physician where she was diagnosed with a UTI. Early treatment with antibiotics eliminated the infection and prevented complications related to the UTI. Similar to Case #1, the resident received treatment because the alert triggered the RN's prompt evaluation.

In both Case 1 and Case 2, the residents received treatment because the care coordinator received an alert generated from the sensor network. The residents received treatment earlier than they would have with the normal health care routines at TigerPlace. Normally, the care coordinator would not have assessed the residents unless the residents or family members reported a health related complaint or a routine assessment was scheduled.

C. Case Study #3: A false positive

In a third case, a 94 year-old female with a history of UTIs and hypertension was tested for a UTI after several alerts were received. Alerts for increase in kitchen activities were received on January 11, 2011 for nighttime activity and January 14, 2011 for daytime activity. In addition, alerts for increase activity in the living room were received on January 14, 2011 (24 hours alert) and January 15 (daytime alert). Finally, an alert for increased bathroom activity at night was generated on January 17, 2011. These alerts created a pattern which compelled the care coordinator to assess the resident, collect a urine sample and request a urinalysis. The results were negative. The resident had family members staying with her from January 13 to January 18 which likely increased activity in the living room and kitchen resulting in the alert conditions. The family members may have also been responsible for the increase in bathroom activity at night on January 17.

This false positive case indicates the need for additional refinement of the algorithms to account for visitors. A recent extension for the algorithm has been developed that provides a confidence of visitor activity [25]; however this has not yet been incorporated into the alert system. The method uses the relative density of motion sensor events (and what it typical for the resident) and the times of motion events in different regions of the apartment as inputs to a system of fuzzy rules [25]. The refined algorithm was run retrospectively for this resident; visitor activity was detected for the period of January 13 to January 18.

IV. DISCUSSION

These case studies demonstrate the potential of the alerts to notify health care providers of signs of illness earlier than traditional health care assessment would have discovered. The RN care coordinator acted on alerts and assessed the residents' conditions. In two cases, a UTI was diagnosed and treated.

However as illustrated by the last case study, the current simplistic alert algorithm is generating too many false positive events. In the current algorithm, an alert is generated if the current daily total of sensor hits is 4 standard deviations outside the mean of the distribution of the daily totals of 14 previous days. While several clinicians intensively reviewed sensor patterns on multiple residents over several years [22], prospective use was needed to determine which alerts are clinically valid. Since the alerts may have implications for the health of these elders, the team decided it was better to generate too many alerts than to miss a critical health event. This simplistic alert was deliberately chosen to start the process with the knowledge that additional work would be needed to refine the algorithm.

A more sophisticated, statistically valid algorithm using feedback from the clinicians on current alerts is under development to reduce or eliminate the false positive events. The clinicians identified several recurring conditions that signify a good alert. The clinicians have classified both nighttime and daytime bathroom activity as a valuable alert condition with two stipulations. 1) Whereas a relatively small increase in nighttime bathroom activity warrants an alert, a much larger increase in daytime bathroom activity is required for a clinically significant alert condition. 2) The bathroom sensor activity overall must be high enough to indicate that someone is staying in the apartment. A fuzzy network algorithm was developed that attempts to model these conditions and determine when an alert should not be generated. The algorithm has been refined using its performance on conditions which have been rated as good or bad by the clinicians. Additional algorithm refinement is needed to reduce the false positive events associated with visitor activity.

In addition to the need for new algorithms, the NIH-funded pilot study has revealed the need for additional improvements in the sensor networks. The clinicians feel it would be valuable to have a sensor to specifically monitor toilet usage. Monitoring toilet use would improve the confidence in detecting symptoms of UTIs and other conditions by potentially reducing false positive alerts.

With additional development and refinement of the alert algorithms, the system has potential to supplement traditional healthcare and enable remote monitoring of older adults. Eventually, the system may be deployed in long-term facilities, other congregate housing, and private homes. With a passive sensor system, illness may be detected and treated earlier, keeping individuals healthy and independent longer.

REFERENCES

[1] K. S. Boockvar and M.S. Lachs, "Predictive value of nonspecific symptoms for acute illness in nursing home resident," *Journal of the American Geriatrics Society*, vol. 51, no. 8, pp. 1111-1115, 2003.

[2] G. Onder, B.W.J.H. Penninx, L. Ferrucci, L.P. Fried, J.M. Guralnik, and M. Pahor, "Measures of physical performance and risk for progfressive and catastrophic disability: Results from the women's health and aging study," Journals of Gerontology: Medical Sciences.,vol. 60A, no, 1, pp. 74-79, 2005.

[3] S. Ridley, "The recognition and early management of critical illness," *Annals of the Royal College of Surgeons of England*, vol. 8, no. 5, pp. 315-322, 2005.

[4] K. D. Marek and M. J. Rantz, "Aging in place: A new model for long term care," *Nursing Administration Quarterly, v*ol. 24, no. 3, pp. 1-11, 2000

[5] M. J. Rantz, K. D. Marek, M. A. Aud, R.A. Johnson, D. Otto, and R. Porter, "TigerPlace: A new future for older adults," *Journal of Nursing Care Quality,* vol. 20, no. 1, pp. 1-4, 2005.

[6] M. J. Rantz, L. Phillips, M. Aud, L. Popejoy, K. D. Marek, L. L. Hicks, I. Zaniletti, and S. J. Miller, "Evaluation of aging in place model with home care services and registered nurse care coordination in senior housing," *Nursing Outlook*, vol. 59, no. 1, pp. 37-46, 2011.

[7] A. P. Glascock and D. M. Kutzik, "Behavioral telemedicine. A new approach to the continuous nonintrusive monitoring of activities of daily living," *Telemedicine Journal,* vol. 6, no. 1, pp. 33-44, 2000.

[8] M. Alwan, E. B. Sifferlin, B. Turner, S. Kell, P. Brower, D. C. Mack, S. Dalal, et al. "Impact of passive health status monitoring to care providers and payers in assisted living." *Telemedicine and e-Health,* vol. 13, no. 3, pp. 279-285, 2007.

[9] M. Chan, E. Campo, & D. Esteve, "Assessment of activity of elderly people using a home monitoring system," International Journal of Rehabilitation Research, vol. 28, no. 1, pp. 69-76, 2005.

[10] M. Ogawa, R. Suzuki, S. Otake, T. Izutsu, T. Iwaya, and T. Togawa, "Long-term remote behavioural monitoring of the elderly using sensors installed in domestic houses," in *Proceeding of the 2nd Joint EMBS/BMES Conference,* Houston*,* 2002, pp. 1853-1854.

[11] K. Z. Haigh, L. M. Kiff, and G. Ho, G, "Independent lifestyle assistant: Lessons learned," *Assistive Technology,* vol. 18, pp. 87-106, 2006.

[12] N. M. Barnes, N. H. Edwards, D. A. D. Rose, and P. Garner. "Lifestyle monitoring: Technology for supported independence." *Computing & Control Engineering Journal,* vol. 9, no. 4, pp. 169-174, 1998.

[13] G. Demiris, M. J. Rantz, M. A. Aud, K. D. Marek, H. W. Tyrer, M. Skubic, and A. A. Hussan, "Older adults' attitudes towards and perception of 'smart home' technologies: a pilot study," *Medical Informatics*, vol. 29, no. 2, pp. 87-94, June 2004.

[14] G. Demiris, D. P. Oliver, G. Dickey, M. Skubic, and M. Rantz, "Findings from a participatory evaluation of a smart home application for older adults," *Technology and Health Care*, vol. 16, pp. 111-1108, 2008.

[15] M. J. Rantz, K. D. Marek, M. Aud, H. Tyrer, M. Skubic, G. Demiris, and A. Hussam. A technology and nursing collaboration to help older adults age in place. *Nursing Outlook*, vol. 53, no. 1, 40-45, 2005b.

[17] Z. Yuejun and W. Mingguang, "Design of wireless remote module in X-10 intelligent home," *Proceedings of the IEEE Int. Conf. on Industrial Technology*, 2005, p. 1349-1353.

[18] M. Alwan, S. Kell, S. Dalal, B. Turner, D. Mack, and R. Felder, "In-home monitoring system and objective ADL assessment: Validation study," *International Conference on Independence, Aging, and Disability*, Washington DC, 2003.

[19] D. Mack, M. Alwan, B. Turner, P. Suratt, and R. Felder, "A Passive and Portable System for Monitoring Heart Rate and Detecting Sleep Apnea and Arousals: Preliminary Validation," in *Proc. of the Transdisciplinary Conf. on Distributed Diagnosis and Home Healthcare (D2H2)*, Arlington, 2006, p. 51-54.

[20] M. Skubic, G. Alexander, M. Popescu, M. Rantz, and J. Keller. "A smart home application to eldercare: Current status and lessons learned." *Technology and Health Care*, vol. 17, no. 3, pp. 183-201, 2009.

[21] S. Wang & M. Skubic., "Density map visualization from motion sensors for monitoring activity level," *Proceedings of the IET International Conference on Intelligent Environments*, Seattle, 2008, pp. 64-71.
[22] G. L. Alexander, M. Rantz, M. Skubic, R. J. Koopman, L. Phillips, R. D. Guevara, and S. J. Miller, "Evaluation of an early illness warning system to monitor frail elders in independent living," *Journal of Healthcare Engineering*, to be published.
[23] B. Foxman, "Epidemiology of urinary tract infections: incidence, morbidity, and economic costs," *Disease-a-Month,* 2003, vol. 49, no. 2, pp. 53-70.
[24] R. Asplund, Mortality in the elderly in relation to nocturnal micturition. BJU International, 1999, vol. 84, no. 3, pp. 297–301.
[25] S. Wang, M.Skubic, Y. Zhu, and C. Galambos, "Using Passive Sensing to Estimate Relative Energy Expenditure for Eldercare Monitoring," in *Proceedings, IEEE Intl. Conference on Pervasive Computing and Communications, Workshop on Smart Environments to Enhance Health Care*, March 21-25, 2011, Seattle, WA, pp. 598-604