Using Technology to Enhance Aging in Place

M.J. Rantz[1,*], M. Skubic[2], S.J. Miller[1], and J. Krampe[1]

[1] Sinclair School of Nursing
[2] Electrical and Computer Engineering
University of Missouri, Columbia, MO 65211
{RantzM,SkubicM,MillerSt,jakck5}@missouri.edu

Abstract. Integrated sensor networks have been installed in apartments of residents at TigerPlace, a retirement community helping residents age in place. Motion and bed sensor events have been logged continuously for over two years in some apartments. Using data from the sensor network, we have been investigating potential correlations to health events, such as falls, emergency room visits, and hospitalization, to identify patterns in the sensor data which might have offered some clues to predict the events. The long-term goal is to generate alerts that notify care givers of changes in a resident's condition so they could intervene and prevent or delay adverse health events. In this paper, two case studies are presented. In each case, the sensor network detected changes in the resident's condition that were not detected by traditional health care assessment.

1 Introduction

Older adults want to remain as active and independent as possible for as long as possible. They want to age at home, not in institutions like nursing homes [1]. The concept of aging in place is to allow seniors to remain in the environment of their choice with supportive services as needed [2]. With the help of community based services and supportive health care, the dream of aging in place is becoming a reality. Enabling technology, like low cost sensors, computers, and communication systems, has the potential to revolutionize health care services for older adults, promote independence, and enhance aging in place. Our research team is developing and deploying passive sensor networks in apartments of volunteer participants at TigerPlace, a unique retirement community built to help older adults age in place.

A primary goal of TigerPlace is to help the residents manage their illnesses and stay as healthy and independent as possible. To do so, we must help elders maintain functional ability. Interventions to improve function include both evidence-based nursing approaches and innovative technologies. Crucial to successful intervention is early identification of changing conditions that are precursors of declining health status so that interventions can be offered at the earliest indications of need. Through careful monitoring, deteriorating health conditions can be identified early, such as a shuffling gait (mobility problem), restless sleep (possible medication error or pain), change in activity level (possible heart condition), or a change in one's typical routine (potential cognitive problem).

[*] Corresponding author.

S. Helal et al. (Eds.): ICOST 2008, LNCS 5120, pp. 169–176, 2008.

A key focus of our work is to investigate the use of sensor technology to monitor and assess potential problems in mobility and cognition of elders in realistic home settings. We are interested in sensing alert conditions such as falls. We are also looking for changes in daily patterns that may indicate problems. TigerPlace provides the realistic elder resident home environment in an operating senior living facility in which we are developing and testing this new sensing and assessment system.

Sensor networks for eldercare have been investigated previously. Glascock and Kutzik proposed the use of motion sensors to infer activities of daily living [3]. The Independent Life Style Assistant (ILSA) developed by Honeywell was also an early system that incorporated passive monitoring [4]. A field study was conducted in 11 elderly homes for 6 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) continuously for over a year [5]. Beckwith describes a study in an assisted living facility with 9 residents of varying degrees of dementia [6]. Residents and staff each wore a badge for location tracking. The system included motion, door sensors and load cells on the bed. Barger et al. report a monitoring system with 8 passive motion sensors to infer a person's behavioral patterns using probabilistic mixture model analysis [7].

Barnes et al. used motion and door sensors to extract a 24 hour activity profile [8]. 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 [9] [10] Logged sensor data were classified via fuzzy rules into one of 6 activities, such as sleeping, preparing or eating food, and receiving visitors. The system was tested with two elderly participants.

Our work differs from many of the above projects in that (1) sensor networks have been installed in the homes of elderly volunteers with a longevity 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, and (3) we are also collecting data on health and medical events in an effort to correlate sensor data with the health record.

The clinical focus particularly separates this research from other smart home projects [11]. The work builds on existing research by combining sensor technology with individualized clinical nursing assessment to help residents maintain functional independence. Additionally, this project reaches beyond the typical technology used by home health agencies to help collect accurate physiological parameters like weight, blood pressure, pulse, oxygen saturation, blood sugar, etc. [12], [13]. Clinical personnel are using the sensor data coupled with traditional health care assessment to monitor the ongoing health status of residents and help them age in place.

2 The TigerPlace Setting

TigerPlace (www.tigerplace.net) was developed to embody the concept of aging in place. Nurses, physical therapists, occupational therapists, environmental design specialists, and other experts in gerontology were consulted on the design of TigerPlace to maximize the independence of the residents. In addition to a friendly, supportive environmental design, TigerPlace helps residents remain active longer by providing registered nursing care coordination, direct personal care as needed, ongoing nursing assessment (holistic assessment at least every 6 months), social activities, and health promotion activities including exercise classes.

Currently, TigerPlace has 34 residents ranging in age from about 70 to 94 years. There are 4 married couples, and the remaining residents are single. About 90% of the residents have a chronic illness; 60% have multiple chronic illnesses. Common illnesses include arthritis, heart disease, diabetes, and the potential for a stroke. A couple of the residents have early stage Alzheimers. About 15% of the residents use a walker. Several residents use a wheelchair, one wears leg braces, and one is recuperating from a hip replacement and uses a cane. In general, the residents are socially engaged at TigerPlace and are active in the community.

An essential component of TigerPlace is Sinclair Home Care, a Medicare licensed home health agency, providing health care, care coordination, and health promotion activities at TigerPlace. Sinclair Home Care provides private pay services to assist clients with personal care, activities of daily living, medication management, and other long-term care needs. In addition, Medicare services are provided when necessary, for example after a hospitalization to assist with recovery. Sinclair Home Care operates a wellness center at TigerPlace three days per week. Residents may have their vital signs checked, receive assistance with medications, and talk to a nurse regarding health care issues and health promotion activities. Moreover, registered nurses are on call 24 hours a day, 7 days a week.

Sinclair Home Care maintains electronic medical records on the residents of TigerPlace using CareFacts, specialized home health software. Additionally, paper logs of significant health events (hospitalizations, emergency room visits, and falls) are maintained at TigerPlace. A database administrator familiar with the CareFacts software was hired to create de-identified health datasets from the electronic medical records and other health records maintained by Sinclair Home Care.

3 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 U. 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 commercially available X10 motion sensors, as well as a stove temperature sensor and a bed sensor which also use the wireless X10 protocol [16]. 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 measures displacement of the upper body torso to detect presence in the bed, as well as pulse, respiration, and restlessness [15]. A low pulse event is sent if the detected pulse is less than 30 beats per minute; a high pulse event is generated at greater than 100 beats per minute. A normal pulse event is generated for 30-100 beats per minute. Similarly, a low respiration event is sent if the detected breathing rate is less than 6 times per minute, and a high respiration event is sent for rates greater than 30 times per minute. A normal respiration rate is generated for 6-30 times per minute. Four levels of bed restlessness are reported. A level one event is generated for movement up to 3 seconds in duration. A level two event is sent for movement from 3-6 seconds in duration. If movement persists from 6-9 seconds, a level three event is generated, and if continuous movement persists longer than 9 seconds, a level 4 event is sent. Together, these different levels provide a measure of sleep restlessness.

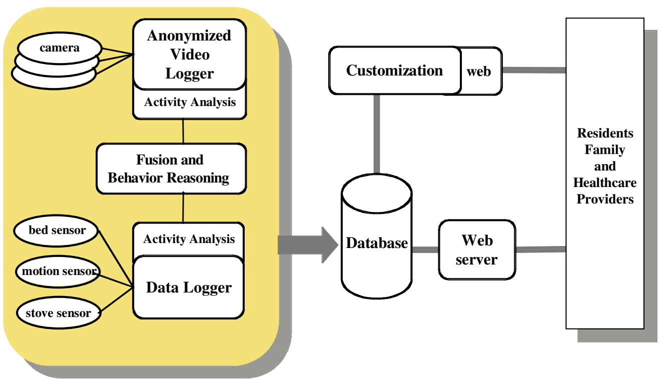

Fig. 1. The integrated sensor network. The data described here are from bed and motion sensors.

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 MySQL 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 [16] 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*.

4 Case Studies

Using the sensor network web interface, sensor data was retrospectively compared to health events including falls, emergency room (ER) visits, and hospitalizations with a goal of detecting predictive patterns and developing methods for tracking ongoing health status. All participants gave informed consent for the use of their medical records as well as sensor data. An exploratory multiple case-study methodology was used because the complex data analysis focused on linkages traced over time, rather than mere frequencies of incidences [17]. Patterns in the data emerged when the data was aggregated to a daily level instead of smaller time frames. Circadian rhythm aggregated data is particularly helpful and has been used in research observing night time restlessness [18].

4.1 Case Study #1

A 96 year old woman living alone in her apartment had a significant cardiac event on June 3, 2007 and was taken to the ER. She was hospitalized on June 5, 2007. She eventually passed away in the hospital. She had a history of heart problems including a diagnosis of congestive heart failure. While frail, she was leading a relatively normal active life with her congestive heart failure managed quite well prior to the cardiac event. In reviewing her sensor data after the health event occurred, a significant increase in bradycardia (slow pulse rate of 1 to 30 beats per minute) was detected, possibly indicating a potential problem. A decrease in bed restlessness at all levels was also noted during this same time.

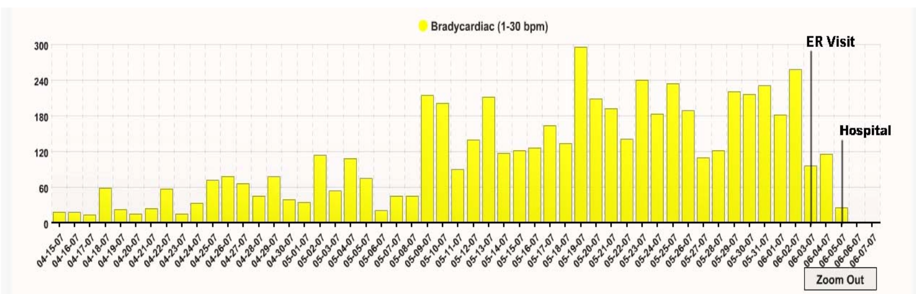

Fig. 2. Screen shot of web-based interface with the addition of marks denoting the ER visit and hospitalization showing sensor data indicating increase in bradycardia (slow pulse rate). The graph represents the total number of bradycardia bed sensor firings aggregated to a daily level for the time frame April 15, 2007 to June 7, 2007.

Unusual signs that would have predicted the impending cardiac event were not detected in traditional physical assessment and observation of the registered nurse care coordinator or other health care providers. Her clinical diagnoses and medication revealed cardiac problems, but could not be used to predict an event. She was receiving assistance daily in the morning to assist with bathing, dressing, and other personal care. Observationally, she seemed to be managing her activities of daily living well and was in relatively good health.

The sensors detected health changes which traditional health care assessment did not. If the sensor data had been detected before the heart attack and the clinical staff alerted, they may have intervened which may have delayed or prevented the cardiac event, thus prolonging the health of the participant.

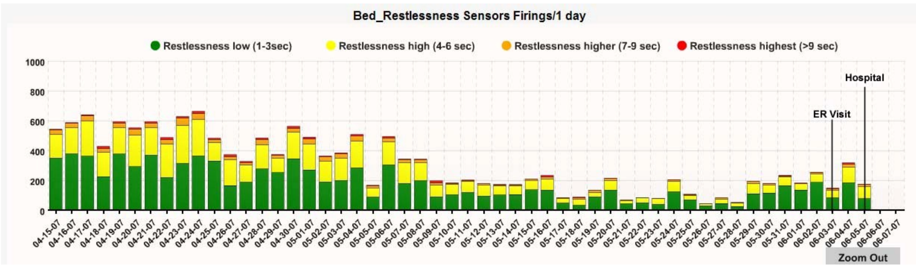

Fig. 3. Screen shot of web-based interface showing bed restlessness sensor firings aggregated to a daily level for the time frame April 15, 2007 to June 7, 2007. All levels of bed restlessness (low, high, higher, and highest) are included.

4.2 Case Study #2

A 79 year old male underwent cardiac rehabilitation, a program of education and exercise following cardiac surgery or other heart problems. He had a heart attack and coronary bypass surgery in December 2005 and underwent cardiac rehabilitation to assist in his recovery.

Following the coronary bypass surgery, he was extremely restlessness while in bed (Fig. 4). This increase in bed restlessness could have been associated with pain while recovering from the surgery, new medications, or other unknown factors such as complications following the surgery. After the rehabilitation program, the bed restlessness returned to normal pre-surgery levels (Fig. 5), which could suggest that the restlessness was related to ongoing issues with his heart that were improved with the exercise and lifestyle changes associated with cardiac rehabilitation.

In this case, the sensor data could have been coupled with traditional health care assessment to provide a clearer picture of his overall health status. The sensor data clearly signified problems, as noted by increased restlessness, immediately following the bypass surgery until the middle of February following the successful completion of the cardiac rehabilitation program.

5 Discussion

The two case studies presented in this paper illustrate the potential of sensor data to augment traditional health assessment by health care providers. In this retrospective analysis, patterns seem obvious that could have been used to prompt health care providers to take a closer look, assess in more detail or depth, and be alert to potential complications or changes in health status. More work is needed to understand the possibilities that sensor data can provide an early "warning" system that a condition needs additional attention. However, in both of these cases such an early "warning" appears to have been possible, as patterns in the sensor data pointed to changes from prior sensor readings.

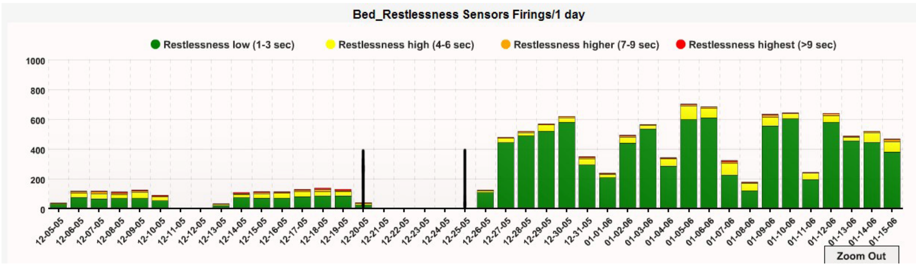

Fig. 4. Increase in restlessness (all levels) following his bypass surgery. The dates of the hospitalization with surgery are marked with solid lines. The graph represents total bed restlessness sensor firings aggregated to a daily level for the time frame December 5 to January 15, 2006.

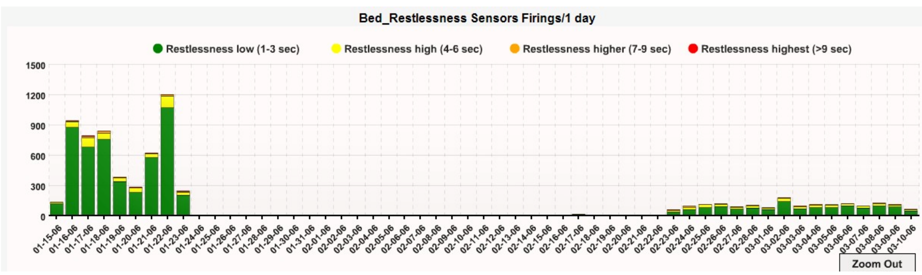

Fig. 5. Return to normal bed restlessness (all levels) following cardiac rehabilitation in January and early February. The graph represents total bed restlessness sensor firings aggregated to a daily level for the time frame January 15 to March 10, 2006. The dates where there are no bed sensor firings are when he did not sleep in his bed; some of these dates he was staying with family while recovering from cardiac procedures.

Using similar retrospective methods, additional case studies have been completed on hospitalizations, falls and other emergent events with the goal of establishing meaningful alerts to notify health care providers of impending problems. Early detection is the key to healthcare interventions which could delay or prevent serious health events and technology provides the means to early detection. With additional case studies, we are optimistic that patterns such as those presented in this paper will be able to be recognized by the sensor network and used as an alert or early "warning" to health care providers. Additional work is underway to establish these health alerts, improve the reliability and accuracy of the sensor network, implement the video sensor network, and refine the web-based interface to make it even more user-friendly and meaningful to health care providers.

Acknowledgements

This research was supported by the U.S. Administration on Aging grant #90AM3013 and the National Science Foundation ITR grant IIS-0428420.

References

1. Rantz, M.J., Marek, K.D., Zwygart-Stauffacher, M.: The future of long term care for the chronically ill. Nurs. Admin. Q. 25, 51–58 (2000)
2. Marek, K.D., Rantz, M.J.: Aging in place: A new model for long term care. Nurs. Admin. Q. 24, 1–11 (2000)
3. Glascock, A.P., Kutzik, D.M.: Behavioral Telemedicine: A new approach to continuous nonintrusive monitoring of activities of daily living. Telemed. J. 6, 33–44 (2000)
4. Haigh, K.Z., Kiff, L.M., Ho, G.: Independent Lifestyle Assistant: Lessons Learned. Assistive Technology 18, 87–106 (2006)
5. Ogawa, M., Suzuki, R., Otake, S., Izutsu, T., Iwaya, T., Togawa, T.: Long-term remote behavioural monitoring of the elderly using sensors installed in domestic houses. In: Proc. of the 2nd Joint EMBS/BMES Conf., pp. 1853–1854. IEEE Press, Houston (2002)
6. Beckwith, R.: Designing for ubiquity: The perception of privacy. Pervasive Computing 2, 40–46 (2003)
7. Barger, T.S., Brown, D.E., Alwan, M.: Health-status monitoring through analysis of behavioral patterns. IEEE Transactions on SMC-A 35, 22–27 (2005)
8. Barnes, N.M., Edwards, N.H., Rose, D.A.D., Garner, P.: Lifestyle Monitoring: Technology for supported independence. Comput. Contr. Eng. 9, 169–174 (1998)
9. Brown, S., Majeed, B., Clarke, N., Lee, B.S.: Developing a well-being monitoring system-Modeling and Data analysis Techniques. In: Mann, W., Helal, A. (eds.) Promoting Independence for Older Persons with Disabilities. IOS Press, Washington (2006)
10. Majeed, B.A., Brown, S.J.: Developing a well-being monitoring system - Modeling and data analysis techniques. Applied Soft Computing 6, 384–393 (2006)
11. Rantz, M.J., Marek, K.D., Aud, M., Tyrer, H., Skubic, M., Demiris, G., Hussam, A.: A technology and nursing collaboration to help older adults age in place. Nurs. Outlook 53, 40–45 (2005)
12. Demiris, G., Speedie, S., Finkelstein, S.: What do patient think of telehomecare? Telemedicine J. and e-Health 7, 241–248 (2001)
13. Rialle, V., Duchene, F., Noury, N., Bajolle, L., Demongeot, J.: Health smart home: Information technology for patients at home. Telemed. J. e Health 8, 395–409 (2002)
14. Alwan, M., Kell, S., Dalal, S., Turner, B., Mack, D., Felder, R.: In-home monitoring system and objective ADL assessment: Validation study. In: Intl. Conf. on Independence, Aging and Disability, p. 161. University of Florida (2003)
15. Mack, D., Alwan, M., Turner, B., Suratt, P., Felder, R.: 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), pp. 51–54. IEEE Press, Arlington (2006)
16. X10. X10 technology transmission theory (2004), `http://www.x10.com/technology1.htm`
17. Yin, R.: Case study research: Design and methods, 3rd edn. Sage, Thousand Oaks (2003)
18. Birath, J.B., Martin, J.L.: Common sleep problems affecting older adults. Ann. Long Term Care: Clinical Care and Aging 15, 20–26 (2007)