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A smart home application to eldercare: Current status and lessons learned

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Abstract. To address an aging population, we have been investigating sensor networks for monitoring older adults in their homes. In this paper, we report ongoing work in which passive sensor networks have been installed in 17 apartments in an aging in place eldercare facility. The network under development includes simple motion sensors, video sensors, and a bed sensor that captures sleep restlessness and pulse and respiration levels. 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 such as falls, as well as 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. In doing so, we strive to provide early detection of potential problems which may lead to serious health events if left unattended. We describe the components of the network and show examples of logged sensor data with correlated references to health events. A summary is also included on the challenges encountered and the lessons learned as a result of our experiences in monitoring aging adults in their homes.

Keywords: Sensor networks, passive monitoring, eldercare technology, video sensor network, smart home

1. Introduction

Countries on multiple continents are experiencing an aging population [45]. The number of older adults is growing dramatically. With this demographic shift, there is a desire to keep older adults healthy, functionally able, and living independently, in part because this provides a better quality of life, and in part because the aging population will stress current facilities and resources designed to care for elders. However, significant challenges exist in keeping people healthy and functionally able as they age. A person may fall and sustain injuries that limit mobility or encounter events that may lead to deteriorating health. The continuous assessment of physical and cognitive function can provide an early indication of decline in health and functional ability. Identifying and assessing problems while they are still small can provide a window of opportunity for interventions that will alleviate the problem areas before they become catastrophic.

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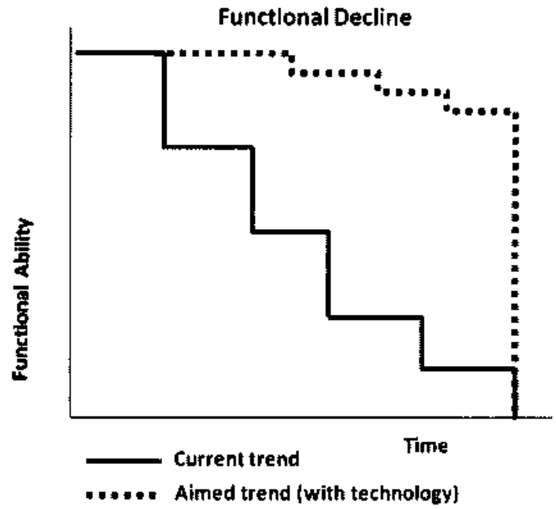


Fig. 1. The trajectory of functional decline. The typical decline without interventions is shown in the solid line. The dotted line shows a targeted change in the trajectory when using the sensor network to identify early signs of health problems.

In this paper, we present our experience with smart home technology designed to address these challenges. To date, 17 sensor networks have been installed in apartments in TigerPlace, an aging-in-place facility located in Columbia, MO. The motivation behind the sensor networks is illustrated in Fig. 1. The solid line shows a typical trajectory of decline in functional ability based on research and practice with older adults [36]. The typical trajectory includes plateaus where no measurable decline occurs and precipitous step-downs illustrating dramatic functional decline, often the result of a significant health event or change in condition. Our goal with technology is to identify the beginning of the change in order to offer an intervention in a timely manner and stop the decline. With technology, the aimed trend (the dotted line) extends the length of the plateaus and reduces the depth of the steps. The result is an increase in functional ability. Thus, the strategy is to identify the problems while they are still small – before they become big problems – and offer timely interventions designed to change the trajectory in functional decline.

The research outlined here is being conducted within the context of an interdisciplinary team of faculty, staff, and students, representing Electrical and Computer Engineering, Computer Science, Nursing, Social Work, Physical Therapy, and Health Informatics [39]. The current work is focused on monitoring older adults through a network of passive 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 [29]. Data collection using motion, stove, and bed sensors has been ongoing for over two years in some apartments. Of the 17 apartments monitored, the average length of time is 15 months, with a range from 3 months to 3 years. This longevity in sensor data collection is allowing us to study the data and develop algorithms for identifying alert conditions such as falls, as well as 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. In doing so, we strive to provide early detection of potential problems which may lead to serious health events if left unattended.

2. Background and related work

Most adults would prefer to remain as active as possible and to live independently in unrestricted environments as they age. However, because chronic illness and declining health affect most people as they get older, placement in more restricted housing environments like assisted living or nursing homes is fairly common. The reason this sort of placement occurs is because health assessments and medical care have traditionally required face to face meetings. This is not necessarily true, though, in the current technological age where there are alternative means for health care providers to reach aging adults with chronic illness to conduct health assessment and suggest medical treatment [30,43]. One alternative consideration for monitoring older adults includes the use of smart sensor technologies which detect activity levels around them, electronically send the activity data to a central repository, and then through web technologies, data can be accessed and viewed by health care providers, families or others interested in the health of the older person being monitored.

There are practical and ethical issues that have to be evaluated before smart sensors should be deployed in any setting. Practical issues that need to be identified include what types of sensors are going to be used and what types of information will be captured. Sensors can be worn on the body, placed so they come in contact with the person, or they can be placed unobtrusively, by being mounted or situated throughout an apartment. In network-based sensor environments with embedded artificial intelligence, various vital signals like blood pressure, electrocardiograms, body temperature, restlessness, falls and gait patterns can be measured using various sensors including vision sensors, electrodes with electrical amplifiers, pressure sensors, light sensors, sound sensors, temperature sensors, etc. [2,9,27,32,34]. Choices made about the types of sensors and information captured raises several ethical considerations about their use.

Privacy and willingness of elders to adopt smart home technology greatly concerns developers and researchers interested in this type of instrumentation. We define privacy as the ability to control access to personal information; in smart homes, this loss of control affects the willingness of people living in these settings to participate in smart home projects as well as the acceptance of certain types of smart home technologies [15]. Perceptions of obtrusiveness in the privacy domain are associated with a perceived invasion of personal information and perceived violations of the physical self and personal space at home; infringement on privacy occurs when health information that users believe should be kept private is shared or when the use of monitoring equipment is not well understood by the elders [16].

Sensor networks for eldercare have been investigated and used for monitoring elders around the world. For example, in Italy, wearable fall detection sensors are being deployed to calibrate acceleration, tilt, trunk sway, staggering and other gait quality parameters which can provide a prompt localization of the fallen person or automatically switch on lights along a walking path [13]. In the Finland, Smart Home Usability and Living Experience, technologies in the eHome include automated/controlled lighting and smart objects such as moving curtains and status aware pots for plants [26]. In Japan, Ogawa et al. continuously monitored two participants for motion activity, sleep time, and appliance use through the use of wattmeters for a year [31]. Honeywell developed an Independent Life Style Assistant (ILSA) to passively monitor elders in 11 homes for mobility and medication compliance over a period of 6 months [20]. Beckwith conducted research in an assisted living facility with 9 residents with dementia [12]. In Beckwith's study, residents and staff wore badges with location tracking systems with motion, door sensors, and load cells on the bed. In work especially relevant to our research, Barnes et al. used motion and door sensors to extract a 24 hour activity profile [11]. An alert could be generated if newly logged data deviated significantly from the stored profile. Majeed and Brown described the "well-being" monitoring of elderly residents with passive sensing from door and motion sensors [14].

Logged sensor data are 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 [25] and MIT's PlaceLab [24]. The PlaceLab has a particularly large array of sensors, including cabinet and door sensors, accelerometers installed on objects, and sensors measuring water flow.

The uniqueness of the study described in this paper is the real life, assisted living setting used to conduct the research and the longitudinal nature of the monitoring. 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, (3) we are also collecting data on medical events and health condition in an effort to correlate the sensor data with the health record, (4) we are exploring novel visualization methods to aid caregivers in understanding the sensor data, and (5) we have continued to involve the participants in focus groups and interviews so that we might understand the impact on this population of frail older adults. In particular, the continued association with an elderly population and the gerontology experts on the team have led us to adopt a passive sensing approach rather than using wearable sensors.

The work described here has been driven by the needs of the frail older adults rather than by the engineering possibilities alone. That is, our solutions are evaluated based on whether they solve the needs of this target population and how they will be accepted. We offer this perspective throughout the paper. To begin, we outline the sensor network under development and the components installed thus far. We describe the actual sensor network installations in TigerPlace and highlight examples of the sensor data collected over time with correlations to medically relevant conditions. Based on three years of experience monitoring frail older adults, we offer a description of the challenges faced and lessons learned. Finally, we describe clinical implications and finish with future directions.

3. Sensor network architecture

The sensor network under development is shown in Fig. 2. The network includes six main components: (1) a passive physiological sensor network with data monitor and motion sensors, stove sensor, and bed sensor (developed by collaborators at the U. of Virginia [3]), (2) an event-driven, video sensor network that hides identifying features of the residents, (3) a reasoning engine that fuses sensor and video data and analyzes patterns of behavioral activity, (4) a flexible alert manager, (5) a component for providing customization of sensor configuration, alert specification, and data access for each resident, and (6) a database server and web interface that provides interactive retrieval and visualization of the sensor data. The physiological sensor network, described in detail below, has been installed in 17 TigerPlace apartments. Collected data is transmitted to the database and can be accessed via the web server. Here, we also report an overview of progress on the video sensor network and the alert manager. Figure 3 illustrates the different types of sensors investigated and installed in TigerPlace apartments; the binary chair pad, the binary floor pad, and the floor vibration sensors have been abandoned because of problems either in implementation or acceptance. More details can be found in Section 4.3.

3.1. Passive physiological sensor network and supporting components

The network currently installed in TigerPlace consists of a set of motion sensors, a stove sensor, and a bed sensor, all passive sensors installed in the environment. Figure 4 shows a typical apartment

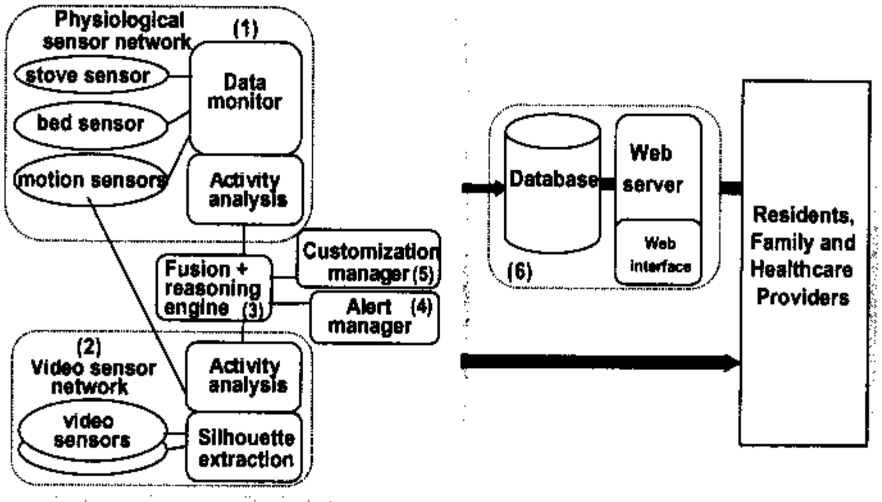


Fig. 2. The integrated sensor network showing the following components: (1) Physiological sensor network, (2) Video sensor network, (3) Fusion and reasoning engine, (4) Alert manager, (5) Customization manager, and (6) Database and web server.

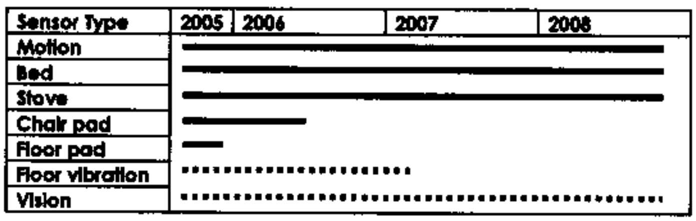


Fig. 3. Sensors investigated for the eldercare sensor network. A solid line indicates the time period for installations in TigerPlace. A dotted line indicates a sensor under development.

configuration. Motion sensors detect presence in a particular room as well as 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. For convenience, a motion sensor is also installed on the ceiling above the apartment door, to detect movement in and out of the doorway (e.g., for apartment exits). The motion sensors used are commercially available passive infrared (PIR) sensors which transmit using the wireless X10 protocol [46]. The sensors detect movement of warm bodies and will transmit an event about every 7 seconds when movement is still detected. This artifact is useful for capturing a general lifestyle pattern; for example, a sedentary pattern will result in a smaller number of sensor events over time compared to a more active "puttering" pattern. Examples are shown in Section 4.2.

The bed sensor is a pneumatic strip (installed under the bed linens) which detects presence in the bed, qualitative pulse and respiration (low, normal, or high), and bed restlessness [29]. 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

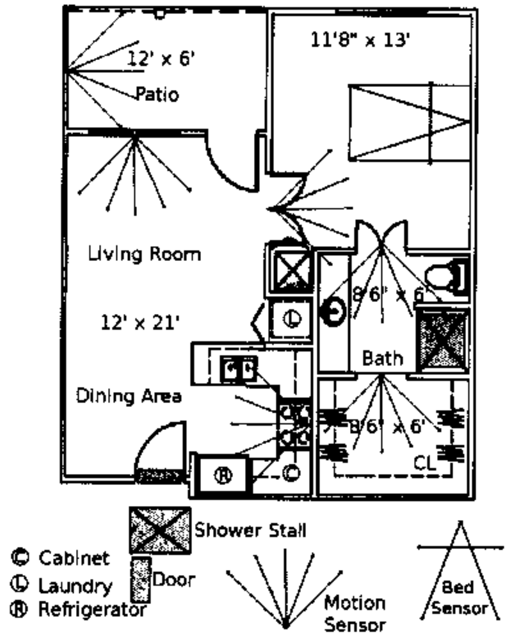


Fig. 4. An example of the physiological sensor network installed in a TigerPlace apartment. Motion sensors are installed in each room and in the laundry closet, the refrigerator, above the front doorway and shower, and in selected cabinets. A stove temperature sensor is installed in the kitchen, and a bed sensor is installed under the bed linens.

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 for 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 restlessness in bed which is used to determine the quality of sleep. All of the output of the bed sensor contributes to the general pattern of the resident.

The stove sensor detects motion in the kitchen as well as the temperature of the stove/oven unit. This is done through a modified X10 PIR motion sensor. When a high temperature is detected, a "stove on" event is generated. When the temperature drops below a threshold again, a "stove off" event is generated. This sensor is included so that an alert could be generated if the stove is left on and there is no indication of someone in the kitchen for a specified period of time. In practice, we have found that TigerPlace residents seldom use their stove or oven, as the facility includes a common dining room. All of the residents eat their evening meal in the dining room and many choose to eat breakfast and lunch in the dining room as well. Nonetheless, we have continued to use this sensor for testing purposes, as it will be applicable in a home setting.

Currently, all of the sensor data is transmitted wirelessly via the X10 protocol to a data monitor PC which is located in each resident's apartment. The data monitor adds a date-time stamp for each sensor event and logs it into a file that is periodically sent to a dedicated central server which stores the data in a relational database. The data monitors are connected to the central server through a dedicated local network, for security purposes. In addition, as a precaution, identifiers are stripped from the data before transmission.

A secure web-based interface is used to display the sensor data for health care providers and other authorized users. The web-interface was refined with input from nursing, health informatics, social work, and residents to ensure it was user friendly and easily interpreted [2]. The interface allows users to select a specific resident and a date range. Sensor data are 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. Screen shot examples of the web interface are shown in Section 4.2, illustrating how sensor readings may change as a result of varying health conditions [10,35]. For more detailed information on the web interface and its evaluation, the reader is referred to [2].

In addition to the web-based visualization, work is also underway to develop automated reasoning techniques for processing the sensor data. Much of the strategy is based on identifying the typical pattern of activity for an individual and then recognizing when the pattern changes. These pattern deviations may take the form of a sudden change as a result of a specific health event, or in the form of a gradual change as a result of a deteriorating condition. One approach for detecting such changes is a new algorithm for temporal clustering [40–42]. A baseline cluster is established for a resident, using 32 features extracted from the motion and bed sensors data, such as time to wake up, time to bed, in bed and out of bed time, and activity density in each room. As more data are added over time, the cluster center may move or new clusters may form, indicating a shift in the resident's pattern.

3.2. Video sensor network

To augment the physiological sensor network, we are also developing a video sensor network. The motivation for using vision sensors is to collect data that cannot be collected through the other sensor suite, including information on gait patterns, walking speed, balance, posture, and detection of falls. In addition, the video sensor network can be used to distinguish between different people in a multi-person setting, e.g., the resident vs. a visitor.

The video sensor network consists of fixed vision sensors and works with the motion sensors to determine possible presence of one or more persons in the room. In the case of possible activity in the room, the imagery is processed to extract silhouettes of the persons present through background subtraction. Silhouettes are used as a means of preserving the privacy of the residents. Studies in focus groups and interviews indicate that elderly residents are willing to consider the use of silhouette imagery even if they reject cameras [18]. In a recent study, elderly volunteers acted out 100 runs of scripted scenarios in TigerPlace while cameras logged their activity. The volunteers were later interviewed and showed silhouette imagery of their own movements. The participants liked the silhouettes and could easily see how this type of imagery could become useful for monitoring mobility parameters and watching for falls. In fact, study participants showed a preference for crisp, realistic silhouettes over "noisy" silhouettes.

Figure 5 shows examples of silhouettes extracted from images using color only and our updated algorithm using color and texture data [28]. This has been shown to yield a more accurate silhouette. A graphics processing unit (GPU) is used to speed up the processing; in some cases, the speed up has been shown to be as fast as two orders of magnitude faster [21]. This facilitates fast processing to deliver expeditious fall detection.

We are investigating different processing strategies for using the silhouettes, including the use of two calibrated vision sensors. Once the silhouettes are extracted from each of the sensors, they are

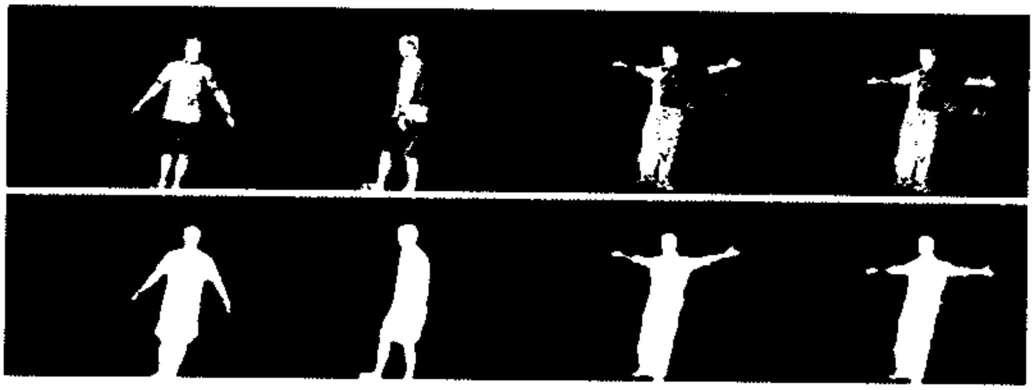


Fig. 5. Robust silhouette extraction. The top row shows examples using RGB color features. The bottom row shows improved results using both color and texture features.

projected into 3D "voxel" space to produce a 3D representation of the person present, which we call voxel person [7]. The advantage of the voxel person representation is that it provides a 3D location of the person, which allows us to distinguish between a person lying on the floor vs. a person lying on a couch. This is important for avoiding potential false alarms of falls.

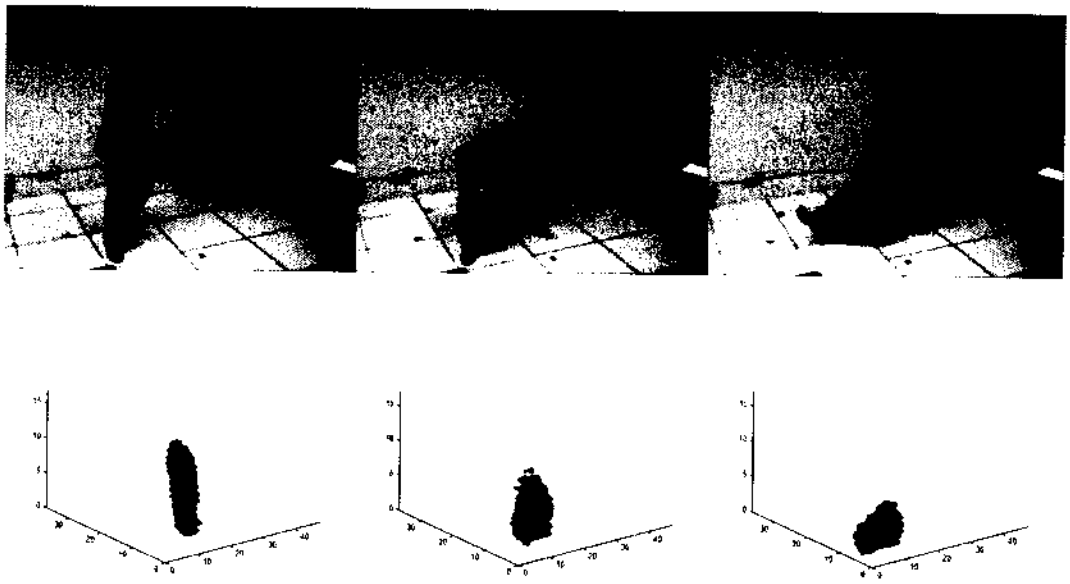
Features from the voxel person moving around over time are used to recognize falls [6,7]. A system of fuzzy rules has been developed to distinguish falls from potential false alarms, using input from the nursing collaborators. To ensure that the rules could recognize falls typical of an elderly population, we collected data using stunt actors. The actors were trained by experienced nurses to fall in 20 different types of falls known to represent typical elderly falls, including falling forward, backward and to each side from a standing position, falling from a sitting position, sliding out of a chair, and rolling out of a bed or couch from a reclining position [34]. The rules have been shown to robustly recognize falls while at the same time avoid false alarms [8]. An example sequence of voxel person falling down is shown in Fig. 6.

Silhouette imagery has also been used to extract gait information while a person walks on a treadmill (Fig. 7). Using two uncalibrated video sensors, with a side view and a rear view, spine movement and shoulder movement are tracked over time to determine posture and gait [1]. The Chamfer distance transform is used to extract a contour of the person's body. A template is then matched to the desired body region using particle swarm optimization. Figure 7 illustrates the linear templates used for tracking spine movement of two study participants [22]. Algorithm development is currently underway to move this technology into the home environment for continuous monitoring.

3.3. Alert manager

An alert manager framework has been developed for generating alert conditions [23]. Figure 8 illustrates the modular design, which uses an extension of the Observer design pattern [38]. Event listeners (the observers) register with an Event Provider to be notified of sensor events (the changes). Here, Event Providers support a filtering operation. That is, a template for the sensor events can be specified so that Event Listeners are only notified if a sensor event matches the template.

The framework provides a cohesive yet flexible mechanism for incorporating different types of alert conditions. State machines are used by Alert Providers to model alert specifications. As sensor events



(a) (b) (c)

Fig. 6. Fall detection using voxel person. The top row shows one image sequence of a fall, and the bottom row shows the corresponding voxel person representations computed from the silhouette imagery, using a cube resolution of 5 inches. The color shows the classification output: (a) red for upright, (b) green for in between, and (c) blue for on the ground.

are observed, an alert model may transition to a new state and, if warranted, will generate an alert condition. Timers may be included for state transitions. The state machine generalization supports simple one-sensor alerts as well as alerts that involve more complex interactions among multiple sensors. The framework easily accepts inputs from multiple sources, including the physiological sensor network and the video sensor network. Sensor events can also be replayed from the database, to facilitate testing of alert algorithms. Alerts may be sent to different output streams, including a pager system for immediate alerts as well as emailed alerts for daily summaries.

Development is currently underway to link the alert framework with the data monitor. Several different types of alerts are supported, including immediate alerts such as falls and the stove left on with no evidence of kitchen activity. In addition, we are working on the automatic linguistic summarization of activity that can be emailed to a family member or healthcare provider through the alert framework, as a means of providing regular updates on a resident's status [5,6].

4. Real world smart home installations

4.1. TigerPlace as a test facility

TigerPlace 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

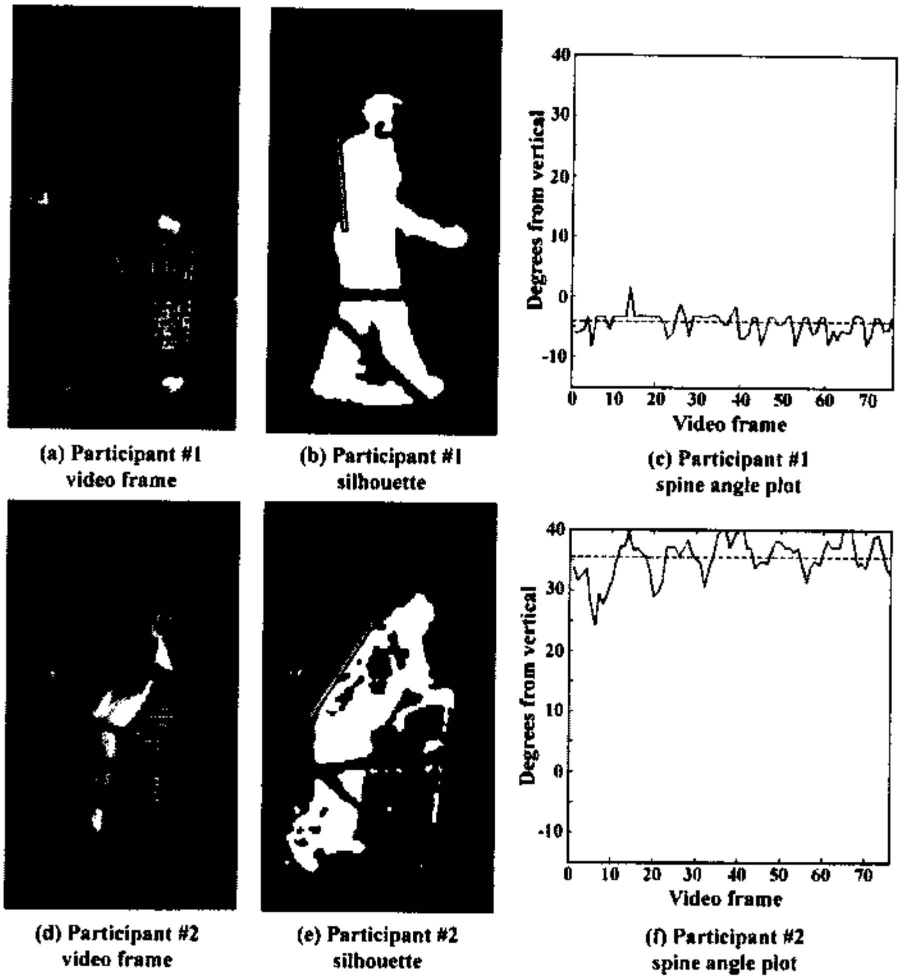


Fig. 7. Tracking spine movement of treadmill exercise. Participant #1 is more upright than participant #2. Also, the signal trace for participant #2 shows a limp.

on the design of TigerPlace to maximize the independence of the residents. The facility includes 31 apartments, a dining room, and common spaces for exercise and recreation. In addition to a friendly, supportive environmental design, TigerPlace helps residents remain active longer by providing 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 95 years. There are 3 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 Alzheimer's. Several of the residents use a walker, a wheelchair, or a cane.

An essential component of TigerPlace is Sinclair Home Care (SHC), a Medicare licensed home health

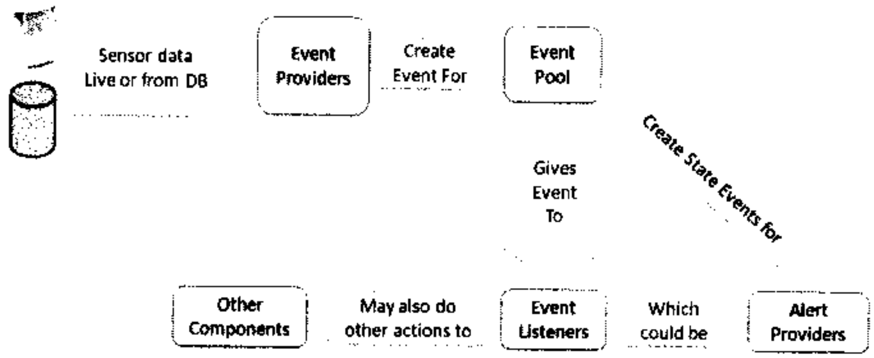


Fig. 8. The alert framework, which supports live sensor data as well as replaying sensor events from the database for testing.

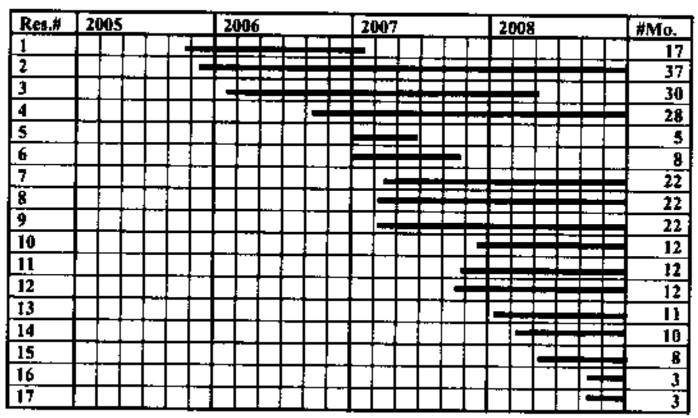


Fig. 9. Enrollment times for the TigerPlace residents participating in the sensor network study.

agency, providing health care, care coordination, and health promotion activities at TigerPlace. SHC provides private pay services to assist clients with personal care, activities of daily living, medication management, and other long-term care needs. The SHC agency also 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, nurses are on call 24 hours a day, 7 days a week.

SHC 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. The IRB-approved access to medical records for the residents being monitored has been a big asset in interpreting sensor data and making connections to medically relevant conditions. Currently, we have been investigating these connections in a retrospective study, i.e., reviewing past sensor data and medical records.

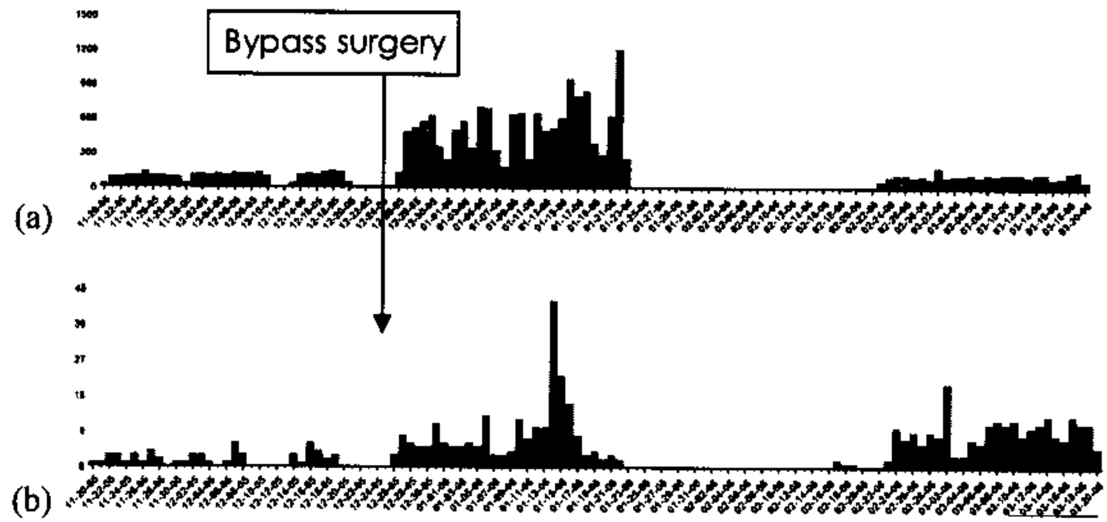


Fig. 10. Sensor firings per day for Resident A. (a) bed restlessness for 120 days, (b) bed tachypnea (breathing rate>30bpm) for the same time period.

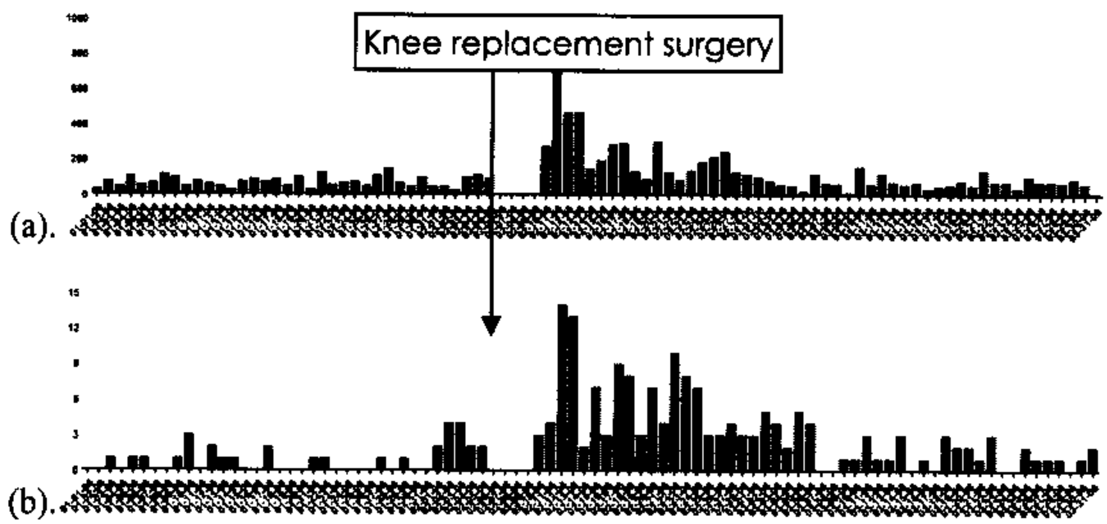


Fig. 11. Sensor firings for Resident B(a) Living room motion for 90 days, and (b) Bed tachypnea for the same time period.

4.2. Examples of sensor data

Data collection with the physiological sensor network began in the first TigerPlace apartment in October, 2005, and we have incrementally added more sensor networks as volunteer residents have been recruited. In total, sensor networks have been installed in 17 TigerPlace apartments. One resident has been continuously monitored for over 3 years. Figure 9 shows the installation times for the 17 participants. Two participants have died in TigerPlace. One participant moved to be closer to a son and then subsequently died. Another participant moved into a skilled nursing home.

We have been examining the sensor data and investigating potential correlations to medical events retrospectively on a case study basis [35,37]. In Figs 10 and 11, we show examples of sensor data for two residents in which abnormal readings are correlated with clinical events. Figure 10 illustrates sensor data for Resident A over a period of 120 days before a cardiac event, treated by bypass surgery and cardiac rehabilitation. Some of the daily sensor readings captured in the resident's apartment (Fig. 10(a): bed restlessness and Fig. 10(b): daily bed tachypnea) displayed an abnormal increase just after the cardiac event and heart bypass surgery, and continued for several weeks. The resident temporarily moved in with a family member while undergoing cardiac rehabilitations and then moved back to TigerPlace. After cardiac rehabilitation, the resident's health improved and his bed restlessness returned to normal, although tachypnea persisted.

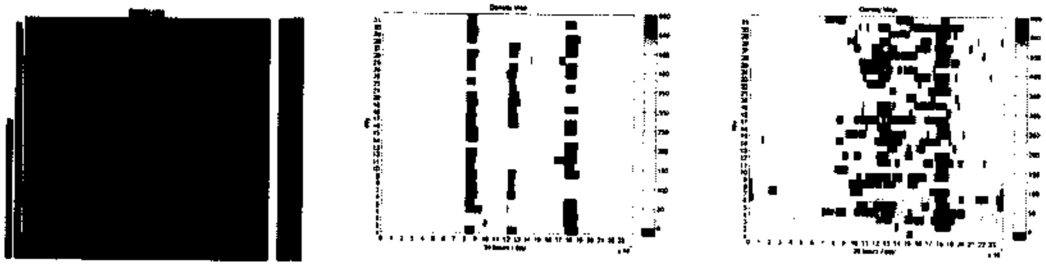
In Fig. 11, we present the total daily living room motion readings and tachypnea firings for Resident B over a period of 90 days, before and after knee replacement surgery. This resident had a very good recovery and, after about three weeks, his motion (Fig. 11(a)) and sleep patterns (Fig. 11(b)) were back to normal.

We have also investigated visualizations of the sensor data, such as the motion density maps shown in Fig. 12. Each of these maps shows computed motion density data over a one-month period [44]. The horizontal axis shows the time of day starting at midnight, and the vertical axis shows the day of the month. Each horizontal line represents one day. The black regions show the times that the resident was away from home, for example, for meals or recreational activities. The different colors correspond to different levels of density as indicated by the color scale. A more colorful map corresponds to a more active resident.

Figure 12 shows the motion density maps for three different residents, illustrating three different patterns of activity [44]. Figure 12(a) shows an active life style in which the resident leaves his home regularly for meals (the vertical black strips present at the 8, 12 and 18 hour marks) and other activities. He consistently goes to bed at about the same time each night and wakes at about the same time each morning. Figure 12(b) shows a sedentary life style. This resident leaves his home only for meal times and sometimes misses meals in the dining room. In contrast to Fig. 12(a), there is less intensity between the meals, indicating that the resident may spend much of his time sitting rather than actively moving around. Figure 12(c) shows an irregular pattern of activity. In contrast, this resident spends less time sleeping and often leaves the home during the day and night. This type of pattern shows possible wandering and/or pacing behavior that may indicate cognitive problems.

By monitoring the motion density maps over time, health care providers can identify a typical pattern of activity for an individual and watch for changes in the pattern. We have observed changes over time for each of the three residents represented in Fig. 12 [44]. Another example is shown in Fig. 13, where part (a) shows the density map for March and part (b) shows the density map of the same resident for September. The changes in the density maps show how the resident's activity is changing. In this case, the resident has become less active in the apartment and also less active in going out of the apartment. Clinical tests indicated an increasing depression; this shows up in the sensor data as reduced activity.

Another example of longitudinal data is shown in Fig. 14. Here, pulse pressure (i.e., the difference in systolic and diastolic blood pressure) is tracked over time. We investigated whether the abnormal pulse pressure events can be predicted based on the sensor values, in order to alert the health care personnel before a possible acute cardio vascular event takes place [33]. A regression is used to compute the tendency of the pulse pressure over time. We see that, except for several periods where depression



(a) (b) (c)

Fig. 12. Motion density maps showing examples of (a) an active life style, (b) a sedentary life style, and (c) an irregular pattern of activity, illustrating potential cognitive problems.

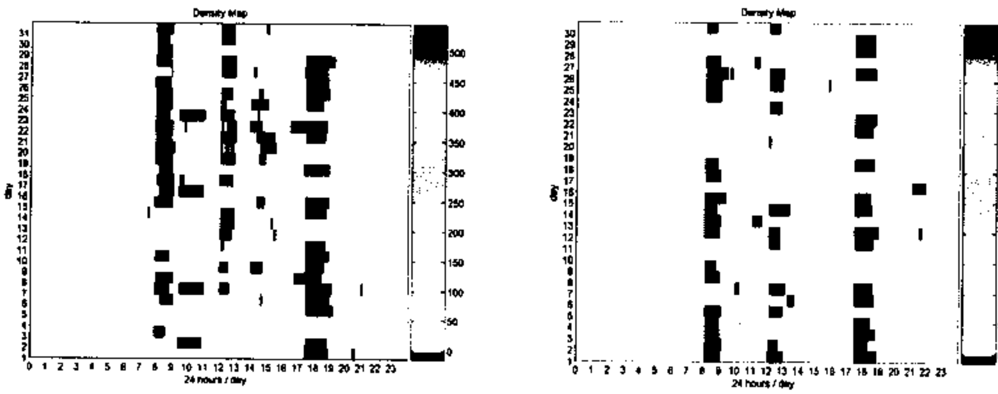


Fig. 13. Motion density maps for a resident showing activity pattern changes over time. (a) March (b) September of the same year.

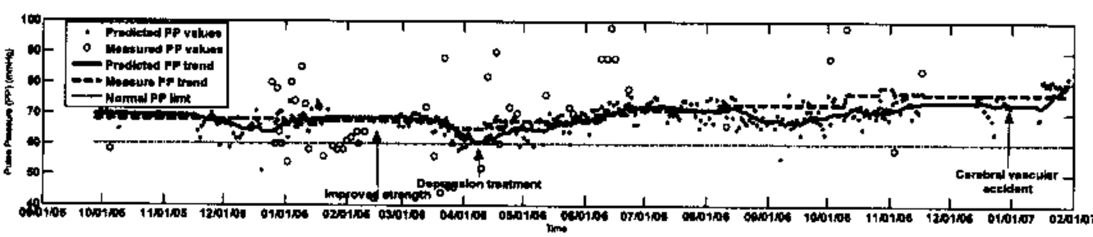


Fig. 14. Predicted pulse pressure from sensor data and measured pulse pressure.

medication was administered to the resident, the predicted pulse pressure trend follows well the measured trend. The continuous increase of the predicted pulse pressure trend from 9/06 to 12/06 in Fig. 14 is consistent with a cerebral vascular accident (CVA) that the resident had in 12/06.

4.3. Challenges and lessons learned

One of the challenges of this project has been that we have moved out of the lab setting and into people's homes. Unlike demonstration smart homes that can be specially configured with numerous sensors and computers, we wanted a system that could be installed in any home with minimal time and effort and especially with minimal wires and cables. In addition, we have observed that people care very much about the looks of their homes, and they do not want extraneous sensors, wires, and computers cluttering up their space. Thus, using small, wireless sensors was an important consideration. In addition, there is the question of how many sensors to use, where to place them, and how to mount them securely. We had to balance the engineering tendency to put sensors everywhere with more practical considerations of installing and maintaining them (e.g., replacing batteries). In addition, we wanted the residents to resume their normal behavior without feeling like they were being watched by sensors everywhere. Our interviews have shown that we have been mostly successful with this goal; residents go through 3 stages in adjustment to the sensors. By the end of the first month, they are already in the third stage and report that they do not consciously think about the sensors [19].

The commercial PIR motion sensors have proven to be practical for this application. They are small, wireless, and lightweight enough to be mounted on the wall or ceiling with double-sided foam adhesive. They can be placed in cabinets, drawers, closets, and the refrigerator to indicate various activities, and they don't show on the outside. A typical configuration is shown in Fig. 4. The apartments at TigerPlace are not all the same size so a custom configuration was necessary. Bigger apartments have more sensors than the smaller apartments.

We have tried other sensors but have discontinued their use (see Fig. 3). Initially, we used a binary floor mat which provided specific location information of the resident, i.e., an event was transmitted when the resident was standing on the mat and another event signaled when the resident left the mat. We discontinued use of the floor mat when it became apparent that this provided a trip hazard for some older adults. In addition, we tried a binary chair pad which signaled when the resident was sitting on a chair. We discontinued use of the chair pad because residents found it awkward to have to continuously readjust the pad for comfort. A floor vibration sensor [4] was also tried in TigerPlace. We had hoped to identify falls from floor vibration signals, as well as qualitative gait patterns, e.g., walking in a limp or a shuffle. However, TigerPlace, like other typical US eldercare facilities, is built on a concrete slab foundation, on the ground floor. Although we could detect floor vibration signals from walking or falling, other activities would also generate similar signals such that classification results were poor. For example, in recognizing falls, it is important that the sensing mechanism detect falls reliably but not generate false alarms. This did not appear feasible using the floor vibration sensor on a concrete slab foundation.

We have also had to consider where to place the computer which provides the data monitor functions. This computer is a small PC with no monitor or keyboard attached. However, for security and reliability considerations, we had decided to use a wired network port, and thus the position of the computer was constrained by the location of the network port. All of the apartments at TigerPlace have a network port in the living/dining area. At first, the computers were simply placed on the floor typically behind a large piece of furniture. While this generally worked fine, there were occasional problems. Sometimes, a resident would unplug the computer because he or she wanted to use the power outlet. Eventually, we decided to dedicate a cabinet to the computer. Cabinets were installed above the refrigerator in each apartment with holes in the cabinet for ventilation. A power outlet and network port to a dedicated local area network were installed inside the cabinet so that all wires and cables are concealed.

Another challenge has been keeping all of the sensors and computers operating continuously. We addressed this challenge by first doing a week-long validation test in the lab with a computer and sensors configured for a specific apartment. This identified some problems and eliminated unnecessary trips to TigerPlace. After the system was installed, there were still instances in which sensors stopped transmitting and computers stopped logging, resulting in gaps in the data. For example, sensors occasionally fell down. A stove sensor failed probably due to excessive heat. Power spikes from thunderstorms caused computers to reboot and sometimes required manual intervention to bring them back on-line. Eventually, we implemented an automated monitoring system which emails the system administrator daily on the status on each network, so that problems can be addressed in a timely manner.

Finally, the biggest challenge has been trying to connect sensor data to medically relevant events. Although we have access to electronic health records, these are not in a form that easily accommodates data mining. Thus, our current studies have necessitated manual extraction of health data and comparison to logged sensor data. In addition, we have found that the sporadic collection of vital signs is not frequent enough to match the continuous collection of sensor data. To address this, we plan to make telemedicine equipment available to the residents and ask that they collect their vital signs using this equipment so the data can be readily captured for retrieval and use in analyses. The data will go into an internal database, which will include other pertinent data on sentinel health events such as hospitalizations and falls.

5. Clinical implications

Sensor system technologies have the potential to enable healthcare providers to detect periods of decline earlier, which result from exacerbations of chronic illnesses. Traditional means of assessing health status require health care providers to be physically present with the patient. Current trends in sensor technology enable health care providers to monitor patients remotely and continuously by transmitting vital information about patient activity levels, physiological parameters such as heart rate and respiratory status, and environmental hazards including stove temperature. Current trends in remote assessment could help the provider to identify sentinel events (falls and periods of bradycardia) which result in other adverse outcomes (increased hospitalizations and emergency room visits) earlier, resulting in improved response rates to the sentinel health events and decreased adverse outcomes. Possible improved outcomes for the patient as a result of earlier intervention are decreased placement in more restrictive and less desirable environments such as skilled nursing homes, fewer emergency room visits and hospitalizations.

Residents who have interacted with the sensor systems have indicated they feel safer having the devices embedded in their apartments. Family members have also indicated they feel better knowing that someone is watching out for their loved ones [2,17–19]. Through these initial interactions we have found that the sensor system functions reasonably well and will continually monitor activity throughout resident apartments. However, a major challenge is annotating the sensor data with medically relevant information such as the timing of sentinel health events, health parameters surrounding the health events, and resident experiences that occurred around the time of the health events. In order to understand how sensors benefit residents during these times it is critical to include them in our evaluation of the sensor system interfaces, to identify when sentinel health events are occurring and to assess the relationship between the occurrence of sentinel health event data and detection of the event by our sensor system. Through retrospective studies and manual annotation using the health records, we have followed case studies such as those presented here; this work will continue with the help of the health care providers and the volunteer residents.

6. Future directions

Although we have made progress in the use of sensor networks in eldercare home settings, there is more to be done. We are especially interested in further investigating connections between sensor data and health events, as noted above. Our intent is to pursue prospective studies in which healthcare providers and residents participate by reviewing the sensor data on an ongoing basis. The sensor network will be used as an intervention that has the potential to influence clinical outcomes by catching declining conditions faster than using traditional healthcare practices. This will also provide a first step toward investigating the predictive capabilities of the sensor data. Adding the silhouette-based vision sensors will provide additional capabilities for capturing falls, gait, and posture.

In addition, we plan to move the sensor networks into other settings, including public housing and private homes. To accommodate these additional environments, easier and more flexible customization capabilities will be required. Elders live in different types of homes and have different types of medical ailments with unique needs to address them. Thus, the sensor network will need to accommodate customization in the sensor configuration as well as individual definitions of what constitutes an alert condition. In addition, we have observed that the residents take ownership of the sensor data. They want to have control over who is allowed to see the data or they may want to view the data first before releasing it to someone else, including a family member. Thus, customization will also be required to specify who has access to the data. We anticipate that this may require a dynamic process, as the access may change according to health conditions of the monitored resident.

In general, we view this ownership feeling towards the sensor data as a positive factor. We hope that providing this information will empower older adults to take an active role in their own health. Perhaps access to this information as feedback will even encourage them to change their behavior in an effort to create a healthier lifestyle.

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