Aging in Place and Eldertech Research at the University of Missouri

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The Aging in Place research and practice team in the MU Sinclair School of Nursing, initiated in 1996, has successfully developed and tested the aging in place model of care and conducted research on the cost and clinical outcomes. The Eldertech research team, initiated in 2003 and now led by the Center for Eldercare and Rehabilitation Technology in the College of Engineering, works with researchers from the Schools of Nursing, Medicine, Social Work, Health Management & Informatics, Health Professions, and others at MU. The Eldertech team is nationally and internationally recognized for their cutting edge interdisciplinary research on technological solutions for the complex problems facing elders as they want to age in place[8-23].

Background

Many senior citizens and their families, preferring to remain at home, want to postpone or even avoid nursing home care. The Aging in Place (AIP) project vision was developed in 1996 in the Sinclair School of Nursing with an interdisciplinary team to provide more and higher-quality services at home, allowing people to "age in place."

Fig. 1. The TigerPlace Aging in Place Facility

People get services when they need them, regain independence, and then services are limited or withdrawn so costs are controlled. State legislation in 1999 and 2001 enabled the construction of TigerPlace, built by Americare Systems, Inc. in 2004 and expanded in 2008: a state of the art independent living facility, built to nursing home standards, licensed as intermediate care so people can use long term care insurances, and operated as independent housing with services in Columbia, MO. Americare operates the housing, housekeeping, and dining operations at TigerPlace. Sinclair Home Care, under the MU Sinclair School of Nursing, runs the clinical operations, including the wellness clinic, clinical care coordination, and the exercise program.

Grants for Aging in Place and Eldercare Technology, led by principal investigators from the interdisciplinary Eldertech Team, totaling over $12 million, include funding from the National Institutes of Health, the National Science Foundation, the Agency for Health Care Research and Quality, the Administration on Aging, the Alzheimer's Association, RAND Health, the Gerontological Nursing Interventions Research Center, and the Centers for Medicare and Medicaid[24-25].

Early Interventions through Nursing Care Coordination AIP Research

The impact of AIP through clinical care coordination has been validated showing a cost savings to Medicare and Medicaid in the community with Aging in Place evaluations ($1,591 per month for the nursing home comparison group, $483 per month for the home and community based comparison group). In both the community and TigerPlace evaluations, RN nurse care coordination reduces adverse health events, improves care outcomes, reduces nursing home utilization, and is cost-effective. Costs for any TigerPlace nursing home eligible participant has never approached or exceeded nursing home care (average annual care cost for 2008 was $7,331 plus the housing cost). For those not eligible for nursing homes, the annual average care cost was $2,591. These cost savings represent nearly $9 billion for those in the community and over $3 billion in nursing homes if RN care coordination were implemented for only 10% of our nation's elders.

About 10 million people need long term care in the US[2]. Of these, about 4.6 million are older than 65 and live in the community. These 4.5 million represent a potential $89 billion in cost savings if everyone had access and participated in the RN nurse care coordinator intervention that has been tested at MU[3-7]. This is more than 40% of all dollars spent on people with long-term health needs in the US. Nurse care coordination, coupled with technology, has huge potential to help older people stay at home, where they want to be, safely and more cost-effectively. Technology can aid in the early detection of health problems so that they can be addressed early while health problems are more manageable and can be treated with less cost, and health outcomes are better (Figure 2).

By 2030, one in every five Americans will be 65 or older, growing from 35 million in 2010 to 71.5 million in 2030 [1]. Most older adults also have one or more chronic health conditions that require self-management or assistance in managing, and more than 40% need assistance with one or more activities of daily living.[1] RN care coordination, health promotion, and early illness recognition and interventions through the use of technological innovations can address these needs while reducing costs.

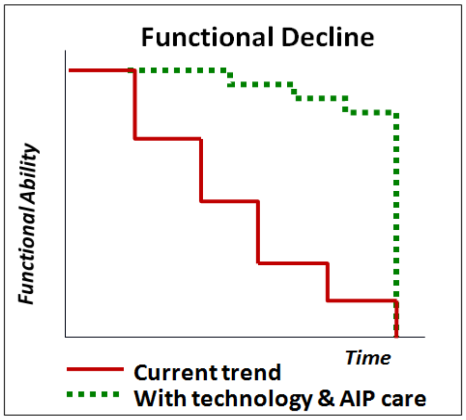

Fig. 2. Squaring the Life Curve with Detection of Early Illness and Functional Decline

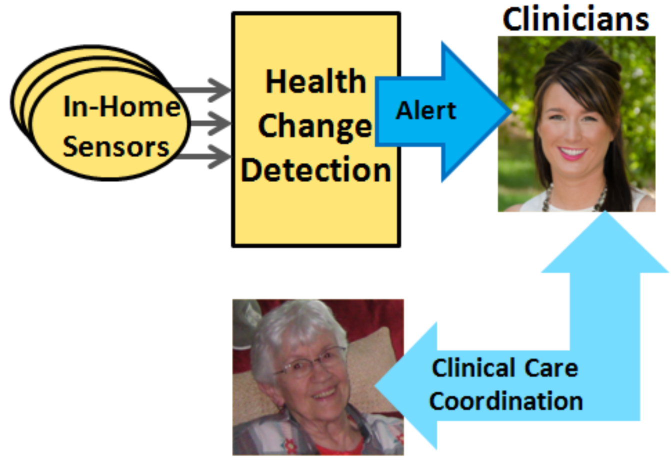

Fig. 3. The in-home sensor system with health change detection functions as a clinical decision support system. Early health change alerts are sent so that early interventions can be offered.

Clinical Decision Support: In-Home Sensor Networks for Detection of Early Illness and Functional Decline

Sensor networks have been installed in TigerPlace apartments since Fall, 2005. The initial suite of sensors included motion sensors, chair pads, a stove sensor, and a bed sensor capturing restlessness, and low, normal, and high pulse and respiration rates. We have developed an integrated intelligent monitoring system that functions as a clinical decision support system (Figure 3), reliably capturing data about the residents and their environment in a noninvasive manner while balancing the needs of health, safety and privacy. We have developed algorithms to extract patterns of activity from the collected sensor data and generate alerts that indicate a potential health change, evaluated the usability of the interfaces, and investigated the acceptability of the technology by seniors. Figures 4 show an example of a sensor data display that illustrates changes in sensor data patterns due to health changes.

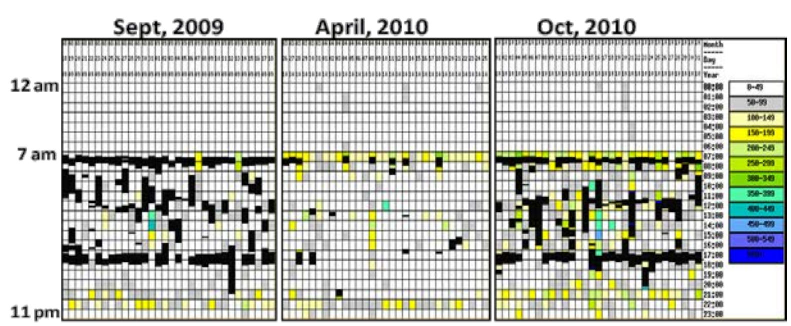

Fig. 4. Motion density maps showing a changing lifestyle due to decline and then improvement after an intervention[12]

In a recent NIH study, we showed statistically significant differences in health outcomes between a control group and an intervention group in which health alerts (based on sensor data) were automatically sent to nurses[11]. Nurses rated the clinical relevance of the alerts and their potential in aiding early interventions; this information has been captured in a database for refinement of the health alert algorithms[13]. We are now conducting a large randomized clinical trial for people living with the sensors and nursing staff receiving automated health alerts based on in-home sensor data.

Passive Fall Detection and Gait Analysis for Fall Risk Assessment

One in every three people age 65 or older falls each year, making falls the most common cause of injuries and hospitalizations for trauma in older adults and the leading cause of death due to injury. Our approach to fall detection does not require the client to wear anything, push any buttons, or charge any batteries. Rather, we have been investigating sensing that can be embedded in the environment, including vision, depth images (e.g., from the Kinect), acoustic arrays, and radar[14-17]. Likewise, fall risk assessment is accomplished through daily monitoring in the home, also using sensing installed in the environment [18-21], to capture gait changes that may indicate problems in physical or cognitive health. Figure 5 shows a Kinect sensor installed in a TigerPlace apartment and an example of the 3D model constructed from the Kinect depth data. Gait parameters are extracted from the Kinect model to capture in-home walking speed, stride time, and stride length [19-20]. Gait parameters are captured automatically as residents walk around the home in their normal, daily activities. Changes in gait are then tracked to observe trends and used for health alerts.

Sensing systems are rigorously studied in the lab with a motion capture system for validation before deployment in senior housing. Volunteers aged 20 to 90 have participated in validation studies. Fall detection systems have been developed using stunt actors, who are trained to fall in 21 different falls typical of older adults and then act out the falls for data collection. Figure 6 shows an example of an actual elderly fall captured in the home using the Kinect system.

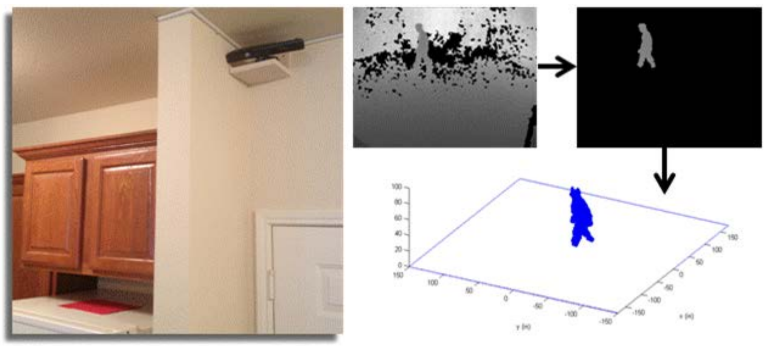

Fig. 5. A Kinect sensor installation with a 3D model constructed from the Kinect depth data

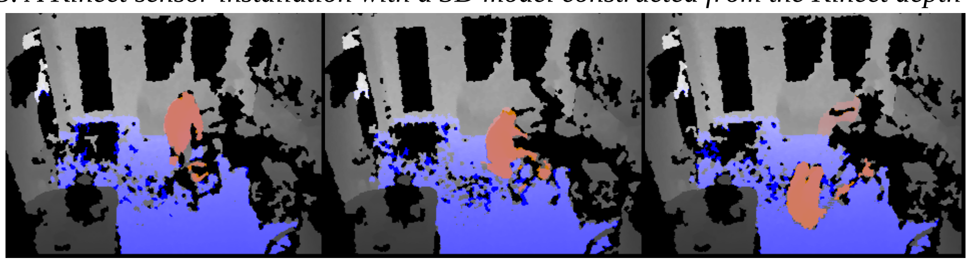

Fig. 6. A fall detected in a TigerPlace apartment. Blue shows the floor plane.

Physiological Monitoring with a Passive Hydraulic Bed Sensor

The MU eldertech team has developed a new hydraulic bed sensor that captures quantitative pulse and respiration rates as well as bed restlessness[22-23]. Figure 7 shows the sensor with data collected while positioned under the bed mattress. Algorithms automatically separate the ballistocardiogram heart signal from the respiration signal to compute pulse and respiration rates. This bed sensor is now part of the health alert system. The hydraulic bed sensor provides more detailed information for detecting changes in sleep patterns and physiological signals that may indicate changing health.

Fig. 7. The hydraulic bed sensor with 10 seconds of data. The high amplitude, low frequency signal is breathing. The high frequency component is the ballistocardiogram of the heart.

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