PREDICTION OF CLINICAL EVENTS IN ELDERLY USING SENSOR DATA: A CASE STUDY ON PULSE PRESSURE

A Thesis presented to
the Faculty of the Graduate School
at the University of Missouri – Columbia

In Partial Fulfillment
of the Requirements of the Degree

Master of Science

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by

ELENA FLOREA

Dr. Mihail Popescu, Thesis Supervisor

MAY 2009

The undersigned, appointed by the dean of the Graduate School, have examined the thesis entitled

PREDICTION OF CLINICAL EVENTS IN ELDERLY USING SENSOR DATA: A CASE STUDY ON PULSE PRESSURE

presented by Elena Florea,

a candidate for the degree of master of science,

and hereby certify that, in their opinion, it is worthy of acceptance.

Assistant Professor Mihail Popescu

Professor Marilyn Rantz

Assistant Professor Yang Gong

ACKNOWLEDGEMENTS

I would like to thank my academic supervisor, Assistant Professor Mihail Popescu for his help and support during my Master's program. He was very open to new ideas and a good listener. His encouragement and guidance increased my self confidence up to the point of being able to successfully finish this thesis.

I would also like to thank my internship mentors, Professor Marilyn Rantz and Professor Marjorie Skubic, for their help and advices while I worked on the TigerPlace projects. Without them and TigerPlace this thesis would not have been possible as the research idea was the result of the two year collaboration with them.

Last, but not least, I thank Assistant Professor Yang Gong for his insightful comments, encouragement, and advice during my program of study.

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PREDICTION OF MEDICAL EVENTS IN ELDERLY USING SENSOR DATA: A CASE STUDY ON PULSE PRESSURE

Elena Florea

Dr. Mihail Popescu, Thesis Supervisor

ABSTRACT

The use of technology can help older people who experience deteriorating health to live independently. Supporting the idea of early identification of changing conditions, the primary goal of this research was to find a link between abnormal levels of daily activities, captured by a unobtrusive sensor monitoring system, and vital signs, especially pulse pressure, using data mining algorithms. A widened pulse pressure is associated with cardiovascular risk factors such as diabetes, hypertension, and smoking. It also predicts a higher risk of subsequent cardiovascular events, coronary heart disease, renal disease, heart failure, and mortality, particularly in the elderly. Furthermore, after identifying if this relationship exists, it seemed reasonable trying to predict the pulse pressure and compare the predicted pulse pressure trend with the measured pulse pressure trend. Different classification algorithms including neural network, robust regression, and SVM have been applied to two data sets corresponding to a male and female living at TigerPlace. The results suggest that the bed restlessness and motion levels may be used to predict high pulse pressure in elderly and also by taking into consideration the low heart rate led to an improved prediction rate. The robust regression proved to be the best

algorithm. Keeping the robust regression as the choice of the algorithm and choosing the day and night motion as features for the pulse pressure trend calculation, we were able to obtain the predicted pulse pressure trend. We think that differences between the two might be able to provide a hint about the possibility of upcoming abnormal clinical events. Surprisingly, the medication influencing the motion and sleep pattern did not alter the pulse pressure prediction but the predicted pulse pressure trend was able to capture the influence of hyper- and hypotension medication, such as Lopressor and Lasix.

CHAPTER 1

INTRODUCTION

Technology has had a tremendous impact on our daily lives. Recently, technology and its impact on aging has become an expanding field of inquiry. A major reason for this interest is that the use of technology can help older people who experience deteriorating health to live independently. Today, 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 impairments so that interventions can be offered at the earliest indications of need.

Aging in Place program is designed to help its participants to live independently and therefore, stay in the home of their choice as long as possible. Participants receive care to prevent or postpone the need to move to a more restrictive living environment like a nursing home. One of the two facilities implementing this program in Columbia, Missouri, is TigerPlace. A primary goal of TigerPlace is to help the residents not only manage their illnesses but also stay as healthy and independent as possible. The use of sensor technology to provide early identification of problems in mobility and cognition is currently under development and investigation.

1.1. STATEMENT OF THE PROBLEM

The aim of this research is to identify the existence of a relationship between the change in health status and sensor data produced by the In-Home Monitoring System currently implemented at TigerPlace. The primary goal is to find a link between abnormal levels of daily activities and vital signs like pulse pressure of residents using data mining algorithms. For example, an abnormal sleep pattern and/or low level of motion may be related to an elevated blood pressure or to a heart attack. Furthermore, if a relationship is identified the next logic step will be trying to continuously predict the pulse pressure and by comparison with the measured trend to be able to identify health events before their occurrence. The algorithms will be validated using the clinical records along with diary notes of the participants connected to the In-Home Monitoring System.

The thesis includes eight chapters. An extensive literature review is presented in Chapter 2 together with the literature review method, literature review themes, limitations and recommendations. Chapter 3 describes the Aging in Place concept and its implementation at TigerPlace using sensor technology. The components of the integrated monitoring system in place at this facility are explained in more depth. Chapter 4 gives details about the web-based visualization interface designed for exploring and visually analyzing the sensor data produced by the In-Home Monitoring System. An internal database required not only by the business processes at TigerPlace but also by the necessity of storing the health related incidents and vital signs of the residents in a format that is easy to access by the researchers is presented in Chapter 5. As any other research, this thesis includes a methodology section which is detailed in Chapter 6, followed by the results explained in Chapter 7, and lastly the conclusions and future work that wrap up the thesis in Chapter 8.

CHAPTER 2

LITERATURE REVIEW

2.1. LITERATURE REVIEW METHOD

The literature review section is largely composed of eight parts: aging population trend and issues, predictors of functional decline, cardiovascular diseases and mortality, role of technology in supporting independent living, sensor technology used in previous research, data mining algorithms used in previous research, sensor-based systems for supporting independent life style of elders, systems' limitations, and recommendations.

After analyzing the content and coverage of the numerous bibliographic databases and library catalogues dealing with technology use in supporting independent living of elders, predictors of decline and cardiovascular diseases in elders, data mining algorithms, and wireless sensors, the most appropriate databases for this research topic are MEDLINE, CINAHL, Compendex, and ACM Digital Library. Keywords used when searching Compendex and ACM Digital Library include "smart homes", "elders", "older people", "elderly", "seniors", "data mining", "sensors", and "independent living". Combination of the above keywords led to 172 articles when ACM Digital Library was used. The same combination gave only 15 articles using Compendex. CINAHL and MEDLINE searches included combination of the following terms: "community living", "assisted living", "aged", "aged", "80 and over", "frail elderly"," technology", "assistive technology". Less than 20 articles resulted after searching those two databases. After analyzing all results mentioned above, 35 articles were selected and classified in eight major categories, which constitute the parts of the literature review section.

2.2. AGING POPULATION TREND AND ISSUES

The average life expectancy in the United States has increased from 47.3 years in 1900 to 68.2 years in 1950, to 77.3 years in 2002 according to Teaw et al. (2005). It is predicted that the US population over age 65 will grow from the 1999 level of 34.6 million persons to approximately 82 million in 2050. The most rapid increase in the US senior population will take place between 2011 and 2030. During this time interval, seniors will expand from 13% of the population to 22% of the population (Teaw et al., 2005). The proportion of people age 60 and over worldwide is growing faster than any other age group (Ruyter & Pelgrim, 2007). Hence, there will also be a reduction in the number of people who can provide care to those seniors. A 1997 study found that almost one-third of US adults, most of whom also held full-time jobs, were serving as informal caregivers—mostly to an elderly parent (Dishman, 2004).

The proportion of elderly in the population is growing at a rapid rate in countries around the world, not only in the United States. Many of these seniors prefer to live independently for as long as they are able, despite the onset of conditions such as frailty and dementia (Cuddihy, Weisenberg, Graichen, & Ganesh, 2007). It is well known that the major cause for placement of elderly people in an institution is loss of autonomy due to physical or cognitive impairment (Chan, Campo & Esteve, 2005). With such a high and continued increasing average life expectancy rate, followed by the dramatic change in trend of the proportion of elderly in the total population, medical care for senior citizens, age 60 and over, is becoming progressively more important. Solutions are needed to enable independent living while enhancing seniors' safety and their families' peace of mind (Cuddihy et al., 2007; Rowan & Mynatt, 2005).

Aging adults are often stereotyped as purposefully masking any decline in abilities to avoid outside intervention and this fact leads to the concern held by adult children about their aging parents: knowing if there are subtle declines in capabilities or behavior of their parents (Rowan & Mynatt, 2005). Elderly patients are particularly at-risk for late assessment of cognitive changes due to many factors: their impression that such changes are simply a normal part of aging, their reluctance to admit to a problem, their fear of being institutionalized and even the failure of physicians to fully assess their cognitive function due to the belief that no intervention is possible (Hayes, Pavel & Kaye, 2004). Even ongoing or post-treatment monitoring of patients through periodic but infrequent office visits has many limitations. Relying on self-report by the patient or their family is also unreliable. Current clinical monitoring approaches may miss important fluctuations in behavior and health state (Hayes et al., 2004). This problem still remains in nursing homes. Physicians might visit their patients for only a short period of time, usually once a week. Assessment of a patient's progress is thus based mainly on reports from staff (nurses and nurse assistants). The reports may be incomplete, or even biased due to schedule shift and the fact that each staff person has to care for many patients (Chen,Yang, Malkin, & Wactlar, 2007). This may result in insufficient observation for monitoring either progressive change, or brief and infrequent occurrences of aberrant activity that might lead to diagnosis of some diseases.

2.3. PREDICTORS OF FUNCTIONAL DECLINE, CARDIOVASCULAR DISEASES, AND MORTALITY

Clinical observation shows that human beings' functions follow periodical variations regulated by the internal biological rhythms. When the period of the cycle approximates 24 hours, it is qualified as circadian and as nycthemeral when it lasts exactly 24 hour (Virone, Noury, & Demongeot, 2002). Our body temperature, weight, muscular force, and arterial pressure follow these biological rhythms. Consequently, the essential information revealed by the biological rhythms cannot be ignored when making a medical diagnosis. Human beings' daily activities also periodically fluctuate (and are, therefore, predictable) according to imperative schedules (sleep, wake-up, meals, leisure, etc.). These activities are influenced by society, education, and culture, and, therefore, can be qualified as "social" rhythms. These cycles cannot be ignored in the medical monitoring follow-up of a patient because biological and social circadian rhythms are interdependent (Virone et al., 2002).

It is well known that even subtle changes in behavior of the elderly or patients with chronic disorders can provide telltale signs of the onset or progression of the disease. In the elderly population, prostatism, degenerative joint disease, bursitis, and gastroesophageal reflux are common causes of frequent awakening episodes and disturbed sleep, along with congestive heart failure, coronary artery disease, and chronic obstructive pulmonary disease (Yang et al., 2004). Distress from acute symptoms of a psychiatric disorder may also promote disturbed sleep, and certain restless limb movement during sleep may be associated with renal failure and iron deficiency (Yang et al., 2004).

Physical activity (PA) in older adults is critically important in the prevention of disease, maintenance of independence and improved quality of life. Increasing PA in this group will also help minimize the burden on health and social care costs. Low to moderate intensity PA significantly reduces risk for all-cause mortality, cardiovascular disease and type-2 diabetes in older adults (Davis & Fox, 2007). Higher levels of PA are associated with reduced risk of depression, cognitive impairment, dementia, and attainment of higher levels of mental well-being (Davis & Fox, 2007).

Medical professionals believe that one of the best ways to detect emerging medical conditions before they become critical is to look for changes in the activities of daily living (ADLs), instrumental ADLs (IADLs) and enhanced ADLs (EADLs) (Tapia, Intille, & Larson, 2004). These activities include eating, getting in and out of bed, using the toilet, bathing or showering, dressing, using the telephone, shopping, preparing meals, housekeeping, doing laundry, and managing medications. A study by Atkinson et al. (2005) found IADL impairement among the predictors of functional decline. The main goal of this study was to determine predictors of combined physical and cognitive decline in elderly women. To assess the cognitive and physical decline the authors used clinical tools of assessment, Mini-Mental State Examination (MMSE) questionnaire for cognitive decline and walking speed for physical decline. Cognitive decline was defined as a MMSE score less than 24 and physical decline as a walking speed of 0.4 m/s or less in at least one of the three annual follow-up visits. 558 women participating in this study were stratified into groups based on cognitive or physical decline or both. Group characteristics were compared, and results were adjusted for age, race, education, and significant covariates. Physical decline was associated with age, nonwhite race, former smoking, baseline walking speed, and instrumental activities of daily living (IADL) impairment. Cognitive decline was associated with age and baseline MMSE scores. Combined, physical and cognitive decline was associated with age, baseline walking speed, MMSE score, IADL impairment, as well as current smoking and hemoglobin level. Some limitations worth mentioning are: all participants were women, use of MMSE to define cognitive decline and definition of physical decline. Due to the nature of the sample, these findings are limited to older functionally impaired women. The use of the MMSE is not a sensitive means of detecting subtle declines in cognitive function in community- dwelling, cognitively intact persons. Similarly, the definition of physical decline as falling to below a specific cutoff may have limited the detection of more subtle declines in physical performance. No direction of causality can be determined to explain combined cognitive and physical decline, and future studies are needed to examine this question (Atkinson et al., 2005).

Schultz-Larsen and Avlund (2007), tried to determine whether the responses to questions about tiredness in daily activities is an early subjective sign of frailty indicating older community-living adults at increased risk for disability and mortality. Tiredness in daily activities as measured by the Mob-T Scale, maximal power in sustained work, and comorbid diseases were assessed together with sociodemographic variables in a sample of 705 non-disabled, 70-year old men and women surveyed in 1984. Vital status of members was determined prospectively over the next 15 years. Onset of disability was measured at 5-, 10-, and 15-year follow-up. Onset of disability among non-disabled 70-year old men and women was strongly related to tiredness in daily activities at 5- and 10-year follow-up. Scores on the Mob-T Scale were significantly associated with mortality during the aggregate 15-year follow-up period. The results of this study not only indicated that tiredness in daily activities is a strong independent predictor of both disability and mortality, but also that tiredness mediates the effects of comorbidity and maximal power in sustained work on disability/mortality. The main drawback of this study is self-reported tiredness in daily activities, which was the basis for identifying vulnerable frail subsets of older adults.

Hypertension and its treatment is of particular relevance to the elderly and very elderly (Peters, Marero, Pinto, & Beckett, 2007). As systolic blood pressure (BP) tends to rise with age, at least in most populations, relatively high percentages of elderly population are classified as hypertensive. More specifically, it is systolic BP that rises more linearly with age, although it may plateau slightly at approximately 80 years, whereas diastolic BP rises until approximately 60 years and falls thereafter (Peters et al., 2007). This is of particular interest when it is remembered that those aged over 80 years are among the fastest growing sector of the population, and are likely to be hypertensive and to have an isolated systolic hypertension with larger pulse pressure (PP) values.

The majority of individuals older than 70 years have a widened pulse pressure resulting from age-related stiffening of the central elastic arteries and systolic hypertension. A widened pulse pressure is associated with cardiovascular risk factors such as diabetes, hypertension, and smoking. It also predicts a higher risk of subsequent cardiovascular events (Peters et al., 2007); Blacher et al., 2000), coronary heart disease (Franklin et al., 2001)., renal disease, heart failure (Swaminathan & Alexander, 2006), and mortality (Safar, Lajemi, Rudnichi, Asmar, & Benetos, 2004; Mitchell et al., 2007; Glynn, Chae, Guralnik, Taylor, & Hennekens, 2000; Lee, Rosner, & Weiss, 1999), particularly in the elderly. According to Safar et al. (2004), PP of 60 mm Hg is a strong mechanical factor predicting cardiovascular mortality. Based on epidemiological studies, it is well accepted that PP above the critical levels of 60 mm Hg, cause particular risk in patients. Such cutting point, has been established for PP on the basis of epidemiological studies indicating the lower level of PP at which renal, cerebral, and most ischemic cardiopathies (myocardial infarctions) occur (Safar et al., 2004). In contrast, according to Peters et al. (2007) and Swaminathan and Alexander (2006) no practical cut-off value exists for differentiating normal pulse pressure from abnormal pulse pressure. Swaminathan and Alexander (2006) stated that most patients with systolic hypertension have elevated pp (>60) and by age 75, the majority of individuals have elevated PPs. In addition, PP seems to increase with age (figure 1) (Safar et al., 2004) and for any given age, men have a 5%-10% higher PP than women (Swaminathan & Alexander, 2006).

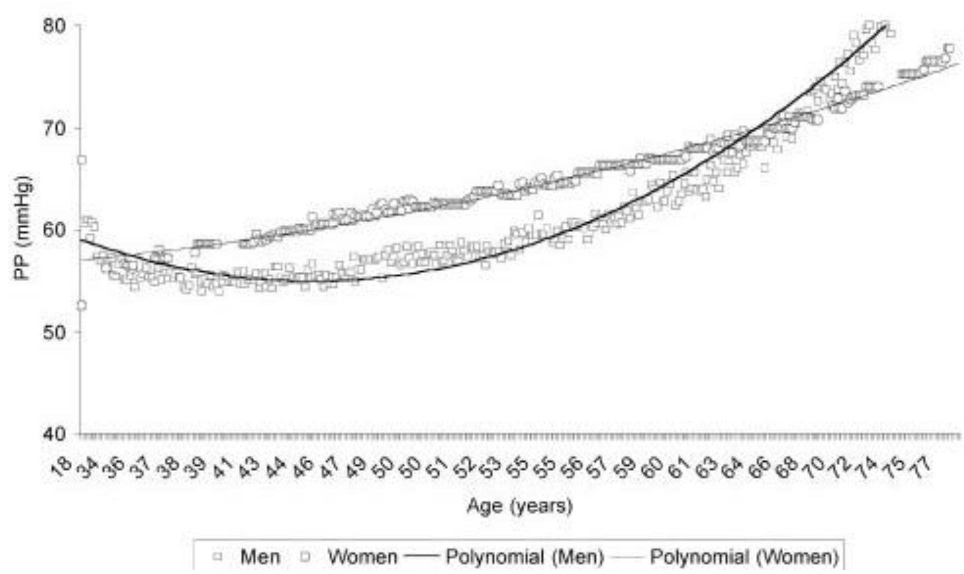

Figure 1: PP increase with age in men and women (from Safar et al., 2004)

2.4. ROLE OF TECHNOLOGY IN SUPPORTING INDEPENDENT LIVING OF ELDERLY

Technology has the potential to help address common problems encountered by older adults related to functional decline by offering creative options that mainstream healthcare often fails to consider (Rantz et al., 2005). Williams, Ganesan, and Hanson (2007) affirmed that the ultimate goal is to “consumerize” these technologies and make it practical and affordable to incorporate them into existing homes and lifestyles.

In addition to warning of an immediate change in status, there are potential long-term benefits from continuously monitoring the condition of people with chronic and potentially progressive conditions. Existing research has shown that changes in behaviour or gait can be associated with early signs of neurologic abnormalities or chronic heart failure due to reduced muscle strength and endurance, the rate of motor deterioration through continuous monitoring, however, has not been investigated. With continuous monitoring of the movement, gait, and resting posture combined with body sensing, the progressive changes in patient’s motor performance can be detected and complementary physiotherapy can be introduced accordingly (Yang et al., 2004).

New terms have emerged along with the use of technology in helping elders’ independent lifestyle. Ruyter and Pelgrim (2007) define Ambient Assisted Living as electronic environments that are sensitive and responsive to the presence of people and provide assistive propositions for maintaining an independent lifestyle. Also they refer to Ambient Intelligence concepts and technologies that should address user needs by focusing on the safety and protection of the personal environment and the simulation and enabling of elderly people to maintain an active lifestyle. Social connectedness is also very important in elders' lives. Technology can be used in this area by implementing awareness systems, which are a class of computer-mediated communication systems that help individuals or groups build and maintain a peripheral awareness of each other. Awareness systems can help individuals stay in touch with dear friends or family and provide affective benefits to their users (Ruyter & Pelgrim, 2007).

Yang et al. (2004) mentioned in their study the concept of ambient sensing, which relates to using unobtrusive sensors that are placed around the person's home to form a wirelessly connected network. These devices provide the basic information that can be used to build a holistic profile of the occupant's well-being in terms of physical, mental, social and environmental factors. Varshney (2007) defines pervasive healthcare as "healthcare to anyone, anytime, and anywhere by removing location, time and other restraints while increasing both the coverage and the quality of healthcare". This includes prevention, healthcare maintenance and checkups; short-term monitoring (home healthcare monitoring), long-term monitoring (nursing home), and personalized healthcare monitoring; and incidence detection and management, emergency intervention, and, transportation and treatment. According to Varshney (2007), comprehensive health monitoring services would allow patients to be monitored at anytime in any location. Using their medical history and current conditions, one or more actions can be taken including sending an alert message to the nearest ambulance or a healthcare professional. Some intelligence in the form of context awareness can be built in pervasive services to avoid "false-positive" alerts. These services could reduce the time between the occurrence of an emergency and the arrival of needed help (Varshney, 2007).

Subjective methods as questionnaires and interviews can monitor human behavior but correct and precise records are difficult to obtain, especially from the elderly (Shieh, Chuang, Wang & Kuo, 2006). Also, daily behavior patterns are often non-quantifiable. As opposed to subjective methods of behavior monitoring, continuous monitoring uses prior assessments as the norm or "control" for later changes in an individual's behavior (Hayes et al., 2004). The development of ambient sensing technology can allow detailed level of activity information for the identification of both temporally and spatially daily living activities such as eating, drinking, reading, resting or sleeping out of bed. Furthermore, activity states related to emotion can be identified such as agitation, restlessness or pacing up and down. Abnormal individual events or trends in the spatial or temporal distribution of these activities are extremely valuable in the context of maintaining independent living for the frail and elderly by health and social care monitoring since they can be used to indicate either the start of slow onset symptoms of chronic degenerative or mental illness or the mismatch of the state of illness to the currently prescribed intervention (Yang et al., 2004).

One of the foremost worries on the part of seniors and their families is that of a senior being immobilized due to a fall, and not being able to get up or summon assistance (Cuddihy et al., 2007). Fear of falls and not receiving help quickly were among the top concerns expressed by surveyed residents, as revealed by the pre-monitoring survey results in the study of Alwan et al.(2006). Rantz et al. (2005) identified among the most common situations encountered in care of elders falls (or fear of falling), urinary incontinence, sight and hearing loss, reduced mobility and strength, social isolation, cognitive impairment, and difficulty managing medications.

Advances in sensor, communication, and information technologies in the recent past have created opportunities to develop novel tools enabling remote management and monitoring of chronic disease, emergency conditions, and the delivery of health care (Alwan et al., 2006). The evolution of wireless technology is also extremely fast-paced. Wireless communications technology has become readily available for the general public, with 7.5 million households in the U.S. using some form of a wireless network in 2004 (Teaw et al., 2005). The benefits of wireless technology are obvious: portability, convenience, ease of installation, and low cost. According to Alwan et al. (2006), in-home monitoring may be one of the key solutions to the problem of care delivery to the world's growing elder population.

A considerable potential market exists for automatic fall detection (Sixsmith & Johnson, 2004) by using sensor technology. However, according to Sixsmith and Johnson (2004) the current and emerging technologies have key limitations: simple sensors, such as single- or dual-element passive infrared sensors, provide fairly crude data that is difficult to interpret; wearable devices such as wrist communicators and motion detectors have potential but rely on a person's ability and willingness to wear them; cameras might appear intrusive and require considerable human resources to monitor activity. Machine interpretation of camera images is complex and might be difficult in this application area. Participants in a study by Sixsmith and Johnson (2004) expressed concerns about cost, intrusiveness, reliability, and replacement of human services by technology. The authors noticed a lack of understanding of how the technology works: for example, someone might consider the “blob” images an invasion of privacy, even though their system does not reconstruct an image for viewing.

A primary technological challenge in the prevention domain is automatic data input. Software agents are another technology that can provide various kinds of assistance for home-based care, but its effectiveness depends on the right balance of “assistance” versus “nuisance” as well as appropriate interfaces, devices, and media (Dishman, 2004). Mobile, embedded, wearable, and even implantable technologies can help to establish personal baselines—typical sleep patterns, eating habits, body temperature, and blood pressure. Home-based sensor and diagnostic technologies could help establish “disease signatures” that show up physiologically and behaviorally before more severe symptoms become readily apparent. Research must address not only medical science and engineering issues but also questions of storing and analyzing data collected perhaps over decades (Dishman, 2004). Trust and privacy also pose critical policy and technological challenges in this area. Home-based systems that allow personalization and customization of everything from the device to the application and interface offer hope for improving human compliance with the care plans the medical community has studied and sanctioned. Personal wellness systems are not meant to replace the mainframe system of hospitals, clinics, and physicians but rather to put seniors and the activities of daily living more squarely into the healthcare mix. Professional caregivers need access to remote, real-time diagnostic data through telemedicine technologies that help them conduct remote checkups on their elderly patients to detect troubling trends such as increased blood pressure or loss of appetite (Dishman, 2004).

2.5. SENSOR TECHNOLOGY USED IN PREVIOUS RESEARCH

With the maturity of sensing and pervasive computing techniques, extensive research is being carried out in using sensor networks for home care environments. For the elderly, home-based healthcare encourages the maintenance of physical fitness, social activity and cognitive engagement to function independently in their own homes (Yang et al., 2004). Health monitoring in home environments can be accomplished by 1) ambulatory monitors that utilize wearable sensors and devices to record physiological signals; 2) sensors embedded in the home environment and furnishings to unobtrusively collect behavioral and physiological data; or 3) a combination of the two (Alwan et al., 2006).

Sensors in the first category include accelerometers (Davis & Fox, 2007), cell phones (Eagle & Pentland, 2006), and wireless body area network (WBAN) that monitor the user's heart rate and locomotive activity (Otto, Jovanov, & Milenkovic 2006). Sensors in the second category include field sensors (Hayes et al., 2004), contact sensors (Hayes et al., 2004; Gil et al., 2007; Cuddihy et al., 2007), motion, location or infrared sensors (Hayes et al., 2004; Chan, Campo, & Esteve, 2005; Shieh et al., 2006; Gil et al., 2007; Virone et al., 2002; Alwan et al., 2006; Cuddihy et al., 2007), strain sensors (Rowan & Mynatt, 2005), low power smart cameras (Williams et al., 2007), microphones (Fogarty, Au, & Hudson, 2006), thermal imaging sensors (Sixsmith & Johnson, 2004), switch sensors (Tapia et al., 2004), pressure sensors (Gil et al., 2007), and electrical sensors (Gil et al., 2007). A study by Virone et al. (2006) is an example of health monitoring in home environments accomplished by using a combination of wearable devices and sensors embedded in the home environment. The authors of this study used unobtrusive area and environmental sensors deployed in the assisted living environment (rooms, hallways, units, furniture) including: motion, video camera, temperature, humidity, acoustic, smoke, dust, gas, etc. combined with wearable interactive devices equipped with a variety of sensors (such as heart-rate, heart-rhythm, temperature, oximeter, accelerometer). Similarly, Teaw et al. (2005) combined wireless sensor networks, existing RFID (Radio Frequency Identification) and Vital Sign Monitoring technology to simultaneously monitor vital signs while keeping track of the users' location.

Many researchers have explored the area of wearable sensors for their advantages in the area of continuous monitoring. They provide more precise tracking methodologies as long as the subject wears the devices at all times (Hayes et al., 2004). Accelerometers offer a feasible tool for the assessment of several aspects of PA in older people. They provide valuable data for the assessment of volumes, intensity and patterns of PA across the daily and weekly patterns (Davis & Fox, 2007). Eagle & Pentland (2006) used cell phones as wearable devices for their ability to measure information access and use in different contexts, recognize social patterns in daily user activity, infer relationships, and identify socially significant locations.

Sensors embedded in the home environment and furnishing proved to have many advantages in the area of health monitoring in home environments. They are non-intrusive and easily accepted by elders in their residences (Alwan et al., 2006; Rowan & Mynatt, 2005; Demiris et al., 2004), inexpensive (Shieh et al., 2006), do not require the occupant to push any buttons or wear any devices (Rowan & Mynatt , 2005), and are user-friendly, familiar fixtures in home security systems (Cuddihy et al., 2007; Demiris et al., 2004). Wireless sensors provide flexibility of installation of additional sensors in a very short time and minimally disruptive to the subject (Hayes et al., 2004). Non contact sensors are considered more practical than wearable sensors. For example, a switch sensor in the bed can strongly suggest sleeping, and pressure mat sensors can be used for tracking the movement and position of people (Tapia et al., 2004). Also, data provided by switches and motion sensors is reliable and very easy to process (Chen et al., 2007) while strain sensors provide relatively clean and reliable signals (Rowan & Mynatt, 2005). Generally, wireless sensors have a low power consumption and low production cost, can be embedded in different places or objects at home or they can become wearable by integrating them into clothing or small apparel items like watches or jewelry (Shieh et al., 2006). Particularly, thermal imaging sensors have the advantage that sensing of a subject's motion can occur locally, within the detector, using only a modest processor (Sixsmith & Johnson, 2004). This is due to the relative ease, with which data from the sensor can be interpreted. They are cost-effective, and because the low-level data lacks detail and there is no need to transmit data outside the detector, the system composed of thermal imaging sensors will seem less intrusive to users. A sensor of this type can reliably locate and track a thermal target in the sensor's field of view, providing size, location, and velocity information. The participants generally view thermal imaging more positively than cameras (Sixsmith & Johnson, 2004).

Assistive technology should be very carefully designed because it may be rejected if it detracts from the aesthetics of the home (Rantz et al., 2008), leads an elder to feel spied upon, or creates a feeling of embarrassment over the need for assistance (Hayes et al., 2004). Hayes et al. (2004) identified many negative reactions to the intrusion of sensors into the living space, including objections to the potential for damage caused by the adhesive used for installation, concern that sensors were placed in locations accessible by children or pets, and objections to the placement of cameras and microphones in the home. Rantz et al. (2008) found 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. Elderly individuals are frequently unwilling to adapt even to small changes in their environment, including wearable sensors in their clothing (Chen et al., 2007). Requiring the subject to wear a device at all times is obtrusive and can result in non-compliance (Hayes et al., 2004). For example, among challenges posed by cell phones as wearable devices for continuous monitoring are human-induced errors by the phone being off or left on but separated from the user (Eagle & Pentland, 2006).

Even simple, not wearable sensors, can impact behavior and have other disadvantages. One of the two participants in a study by Tapia et al. (2004), explained that being sensed did cause her to alter some behaviors as she always made sure to wash her hands after using the bathroom. On the other hand, Demiris, Parker-Oliver, Dickey, Skubic & Rantz (2008) found that by the end of the first month, participants in their study do not consciously think about the sensors. As opposed to wearable sensors, the data provided by switches and motion sensors cannot provide detailed information. For example, a motion sensor can only tell that there is a person in the monitored area, but cannot tell the exact location (Chen et al., 2007). In general, installation of the non wearable sensors is not always easy. Sensors requiring installation by the end users cause significant issues: end-users can make a variety of errors, often due to the directional requirements of sensors or uncertainty over exactly where a sensor needs to be positioned. Even if the sensors are not required to be installed by the end users, sometimes their installation creates real challenges. For example, installation of strain sensors requires access to the underside of the floor, making it impossible to use these sensors on the second floor of an existing home. This fact led to the idea of using wireless motion sensors in future deployable version of an awareness system instead of the strain sensors used in early versions (Rowan & Mynatt, 2005).

More complex systems based on cameras or microphones are not challenge free. One of the major challenges of vision-based systems is the apparent intrusion of privacy because of the way that the image data is transmitted and analyzed (Yang et al., 2004). Existing systems are mainly based on central processing units where multiple video streams are received and processed. Due to the complexity of the computational tasks, data buffering and storage is often required, giving rise to major concerns over practicality and the potential intrusion of privacy (Yang et al., 2004). Furthermore, Tapia et al. (2004) affirmed that in the case of complex sensors such as cameras or microphones, the recognition inference problem is often seriously underconstrained. Computer vision sensing, for example, often works in the laboratory but fails in real home settings due to clutter, variable lighting, and highly varied activities that take place in natural environments. Little of the work with video and audio processing in the lab has been extensively tested in the field (Tapia et al., 2004). Perhaps just as importantly, because sensors such as microphones and cameras are so general and most commonly used as recording devices, they can be perceived as invasive and threatening by some people. The acclimation period to more invasive sensors such as cameras would be substantially longer. Some people would not agree to studies involving video observations or others would agree to those studies restricting cameras from the bathroom. (Tapia et al., 2004).

The deployment of sensor networks in a home environment, however, requires careful consideration of user compliance and privacy issues. The choice of sensing technology that does not identify the person reduces the privacy concerns. Older adults are concerned about maintaining a careful balance between privacy and autonomy (Rowan & Mynatt, 2005). While both are important, aging often necessitates some compromise. Giving up some privacy in order to maintain autonomy is a valid choice. There is, however, a limit to how much and what type of sensor technology provides the correct balance (Rowan & Mynatt, 2005). Referring to awareness systems Romero et al. (2007), affirmed that achieving awareness is how to achieve a balance between what information people would like to know about others or, conversely, to make known to others. There is a tradeoff between trying to address the need to communicate and the need for privacy, which gets reflected in the level of detail/abstraction of information displayed (Romero et al., 2007).

Whatever the practical benefits might be, users might not accept the technology if they believe it impinges on their privacy and lifestyle. The ethical aspects of implementing such technology are also important. In particular, these technologies should be used only where end users or their caregivers understand the technology and can provide informed consent. According to Sixsmith and Johnson (2004) technology solutions should be one of a range of care options available to people. Ensuring that implementation does not lead to a technological “fix” for all the problems facing the elderly should be central to good practice.

It is essential to create end user acceptance of the assistive technology in their homes. One way is by providing the elderly a sense of control over Ambient Intelligence concepts and technologies (Ruyter & Pelgrim, 2007). In a case of an awareness system tested by Rowan and Mynatt (2005), the authors concluded that older adults accept a sort of sensing in their home and a visualization of that data for the adult child, and more importantly, they welcome and rely on the sensing or they circumvent and game the system. Another way to create user acceptance of the systems in their homes is to design systems that are unobtrusive and do not require the users to adjust their daily routine. To achieve this, the sensor nodes need to be small enough to be placed discreetly in appropriate locations (Rantz et al., 2008). Ideally the sensor nodes would scavenge power from their surroundings, enabling an autonomous sensor network to be installed easily and to operate for extended periods of time with little or no outside intervention (Yang et al., 2004).

2.6. DATA MINING ALGORITHMS USED IN PREVIOUS RESEARCH

The use of data mining and on-line analytical processing (OLAP) is potentially interesting in this context of continuous monitoring because of the possibility of exploring, detecting and predicting changes in the level of activity of people's movement that may reflect change in well-being. The measure of activity, presence in locations and interaction with objects might provide information to assist understanding of patterns in people's behavior (Gil et al., 2007). If there are regular patterns in the life of a person, changes to such patterns could suggest a change that should be followed up in a dialogue between a care provider and that person.

Most of the research in the area of continuous monitoring is related to identification of activities of daily living, which is an important predictor of cognitive and physical decline of elders (Tapia et al., 2004; Atkinson et al., 2005). For intelligent analyses the sensors are grouped together according to the domain knowledge and specific activities of interest. Thus each activity of daily living will have an associated group, which fuses data from all the sensors that are related to that activity. Yang et al. (2004) suggested that rather than gathering data from all sensors and carrying out an overall data-mining algorithm, a focused and more efficient algorithm can be applied to each of the activities according to the available knowledge and the data collected by the corresponding sensor group.

Usually three types of activities are included in the analysis phase: long-term trends, significant patterns, and associations among patterns (Yang et al., 2004). The analysis of well-being is challenging, as abnormal patterns of behavior are difficult to identify. Additionally, what is considered to be normal for one person can be abnormal for someone else. Moreover, people have a tendency to change the way they do things without necessarily being affected by deterioration in their physical or mental abilities. For example, the same person can behave in quite a different manner depending on the weather conditions. Therefore, interactive and adaptive algorithms are necessary to handle such analysis with the particularities of each individual in mind. One of the limitations of ambient sensing with simple sensors is that it is difficult to infer detailed changes in activity and those physiological changes related to the progression of disease.

In fact, even for the detection of simple activities such as leaving and returning home, the analysis steps involved can be complex (Yang et al., 2004).

From the computational aspect, various data analysis techniques have been used including classification algorithms, as decision trees (Chen et al., 2007; Gil et al., 2007),SVM (Chen et al., 2007; Williams et al., 2007), logiboot (Chen et al., 2007), rule based approach (Alwan et al., 2006),mixture models as Gaussian mixture (Eagle & Pentland, 2006), pattern recognition algorithms (Fogarty et al., 2006), sophisticated data mining techniques and machine learning algorithms like Markov chain (Eagle & Pentland, 2006), artificial neural networks (Sixsmith & Johnson, 2004), and Bayesian models (Tapia et al., 2004). Another approach recently used to discriminate patterns generated from healthy and pathological states as well as aging is based on frequency and rank order statistics of symbolic sequences because complex physiological signals may carry unique dynamic signatures related to their underlying mechanisms (Shieh et al., 2006). In order to produce a better estimation of the activity, health status or autonomy, heterogeneous data coming from multi-sensor acquisitions might be combined, a procedure called data fusion, using different techniques based on evidence or probabilistic theories (Virone et al., 2006).

2.7. SENSOR-BASED SYSTEMS FOR SUPPORTING INDEPENDENT LIFE STYLE OF ELDERS

With the maturity of sensing and pervasive computing techniques, extensive research is being carried out in using sensor networks for home care environments. A vast body of research studied the human behavior during the daily life to diagnose possible health problems through changes in living patterns. Otto et al. (2006) developed a system consisting of an unobtrusive wireless body area network (WBAN) that monitor user's heart rate and locomotive activity and a home health server, which stores the time-stamped information uploaded from the network. They suggested good potential for ambulatory monitoring of patients undergoing cardiac rehabilitation or for monitoring of elderly at home by informal caregivers. They also reported high user and patient compliance. As opposed to other researchers referring to wearable sensors, they mentioned that even if the sensors are wearable, they are wireless, unobtrusive and well accepted by the users.

The system Health Tracker 2000 developed by Teaw et al. (2005), combines wireless sensor networks, existing RFID (Radio Frequency Identification) and Vital Sign Monitoring technology to simultaneously monitor vital signs while keeping track of the users' location. The device that can remotely monitor vital signs of users is wearable and is designed to measure temperature, pulse rate, breath rate, and blood oxygen level. The information from this device is sent to a base station which is connected to a computer. Several patients may be monitored from a single base station and medical personnel and/or family members can use the information obtained from the wireless devices.

The pilot study of an In-Home Monitoring System evaluated by Alwan et al. (2006) and involving 22 participants recruited from an assisted living facility is composed of wireless motion sensors installed in every room, including the bathroom, a motion sensor dedicated to the shower area, a stovetop temperature sensor, and a bed sensor system. Sensors transmit their data wirelessly to a personal computer. Each system was enhanced with the ability to notify caregivers automatically upon the detection of conditions consistent with possible emergency situations. The system was in use for three months.

Measures of interest in a study by Hayes et al. (2004) include total activity levels, average walking speed, and patterns of activity through rooms in the home. They monitored 3 elderly subjects (83.9 +/- 2.6 years) in their homes and data have been collected for 8 weeks. Processing of data to identify errors and remove redundancy reduced the data to about 11% of the raw data collected initially. Subjects had normal cognitive process for their age as determined by standard clinical testing at their time of enrollment in the study. The restricted-field sensors were used to estimate the average walking speed. To approximate the distribution of walking times they used kernel density estimation and for estimation of walking speed over time they used moving week-long window (1 day overlap). They used robust estimation by excluding the top 10% of walking times from further analysis.

Chan et al. (2005) were interested to assess parameters as getting up, going to bed, going out, visiting the toilet, and in-bed restlessness. The monitoring system consists of 10 infrared sensors mounted on the ceiling of elderly housing in an institution and connected to a PC by means of wire version of communication network. Four participants took part in the study (94, 76, 86, 81 years). A trial was carried out during an 8-month period but the monitoring period was only from 9:00 PM to 7:00 AM. The nursing staff was involved in this study as they regularly called on the participants and recorded ratings about them and their night-time visits. System results were compared with nursing staff ratings. The researchers discovered a significant relationship between restlessness in bed and leaving the room or going to the toilet. Thus, in-bed restlessness may be indicative of the participant getting up, getting away, visiting the toilet or even falling in the toilet.

Shieh et al. (2006) demonstrated that monitoring human behavior to detect changes in living patterns can be achieved by using infrared positioning sensors. Data was gathered from a number of sensor points within two different houses, a nursing home room and a research home, respectively, linked using the main wiring and then automatically transmitted signals using wireless protocol or TCP/IP interface to the internet into a monitoring and supervisory center. They introduced a quantitative metric to define distances among symbolic sequences. Average distances and change distances were determined by using tools from frequency and rank order statistics and proved to be an important index for diagnosis of subjects' living patterns and possible health problems.

A similar approach of monitoring patient's successive activity within the patient's home environment was used by Virone et al. (2002) in their "Health Integrated Smart Home Information System" based on location sensors placed in each room of the system. Data analysis was performed each hour, with a comparison between the actual hourly cycle and the usual hourly cycle according to thresholds based on the result of statistical calculations. Differences between both actual and usual cycles show deviations in the patient's behavior. For each room, the hourly successive mean values follow an hourly biological rhythm. They calculated the information carried by each event because an unexpected or rare event will carry a strong information rate, whereas regular events will transmit a weak information rate. They proceeded with a sampling in an hourly schedule to detect weak rhythmic variations. Based on numerous measurements, they established a mean value with confidence limits. This allows them to define a zone within which the patient's activity is qualified to be "predictable." Alerts are set off if the patient's activity deviates from that zone.

Activities in a home can be detected not only by monitoring the people living in the home but also monitoring changes in states of objects and devices existent within the home. This approach was used by Tapia et al. (2004). Two studies were conducted in 2 homes (2 women in their 30s and 80s) for 14 days. Seventy-seven state-change sensors and 84 respectively were installed in the homes. They chose naïve Bayesian classifiers. Two versions have been implemented: (1) multi-class naive classifier and (2) multiple binary naive Bayes classifiers. In the first case the class node represents all the activities to recognize with the assumption that they are mutually-exclusive. Each child node consists of one of the two attribute types, exist or before. In the second case, each classifier represents an activity to recognize. This version does not enforce mutual exclusivity. Maximum likelihood was used to learn the parameters of the networks. In order to label the subjects' activities the participants were required to use a PDA running the Experience Sampling Method software. The number of labels was not sufficient for training the machine learning algorithms. For this reason indirect observation was used with a lot of assumptions and using the subject feedback. Leave-one-out cross-validation was used in each evaluation method in order to calculate the confusion matrix and measure the classification accuracy. Overall, the exist attribute showed the best discrimination power. Preliminary results show that adding the attributes using the type of object in which the sensor was installed and location information such as the before type and before location features to the exist attribute did not represent a significant improvement in accuracy. Since activities such as “going out to work” and “doing laundry” are represented by sensor firings from a single sensor (door and washing machine respectively), it was expected that they would show higher detection accuracies than other activities. However, the sensors were also activated during other activities which decreased their discrimination power. On their dataset, the multi class and multiple binary classifiers (one per activity) performed with approximately the same accuracy.

As privacy is a major concern in continuous monitoring, Gil et al. (2007) processed the data generated by a monitoring system using the concept of busyness. Busyness as a concept is a measure of overall movement and activity within a house, and of interactions with objects. This potentially preserves the privacy of the occupant to a greater degree than would be the case if specific activities were being identified, measured or inferred. The measure of activity, presence in locations and interaction with objects in a private house, without attempting to infer specific activities, might provide information to characterize an individual’s lifestyle. The nature of the busyness, the count of movements or interactions, builds a busyness model of a person’s life. This research used data from a previous pilot study at a residential care home for 9 months using passive infrared sensors, pressure sensors, door contacts and electrical sensors. The methodological approach includes the following activities: construction of a data warehouse, preparation of data, visualization of data with OnLine Analytical Processing (OLAP) technology to explore a person’s busyness at different levels of granularity, and building of a data mining model to seek patterns and unexpected features in the data sets. Data that showed a normal pattern of busyness was used in the classification algorithms. Different training and testing data sets were used for several times, until the results produced an understandable and simple set of rules. In addition, the set of rules was selected by choosing the model with the highest accuracy percentage on the test data. The pruned C4.5 decision tree algorithm was selected because it produced the most accurate and simple rules.

An interesting approach to inferring activities in the home was used in a system developed by Fogarty et al. (2006). The authors deployed a small number of low-cost microphone-based sensors, in a real home for six weeks, at the locations where wastewater leaves the home. Attached to the outside of existing pipes, these sensors listen for the flow of water. Based on water usage patterns, activities in the home can be inferred. The authors of this research used pattern recognition algorithm to identify cloths washing, shower taking, toilet usage, usage of bathroom sink meaning preparation of breakfast, lunch, or dinner depending on the time of day of data generated by the sensors, and usage of kitchen sink. Among their findings, they shown that a model built on microphone-based sensors that are placed away from systematic noise sources can identify 100% of clothes washer usage, 95% of dishwasher usage, 94% of showers, 88% of toilet flushes, 73% of bathroom sink activity lasting ten seconds or longer, and 81% of kitchen sink activity lasting ten seconds or longer.

Physical activity (PA) in older adults is critically important in the prevention of disease, maintenance of independence and improved quality of life (Davis & Fox, 2007). The study by Davis and Fox (2007) is believed to be the first study to feature detailed objectively measured PA on a large sample of healthy European adults aged 70 and over using accelerometers. They used 163 older adults (mean age 76.1 ± 3.9 years) and 45 young adults (mean age 26.9 ± 4.1 years). Data collected from the young adults was used to provide comparison data. Older adults were less active than young adults at most times of the day but differences were most marked in the evening with younger adults maintaining or increasing activity and older adults achieving very little. Older adults were at their most active in mid to late morning. The difference in diurnal patterning between older and young adults is likely to reflect contrasts between working and retirement routines and different social patterns. Diurnal patterning raises questions about the optimal time of day for PA interventions for older adults. On the one hand, it may be most effective to encourage activity at times of the day when they are naturally more active. On the other hand, it may be important to stimulate activity during long periods of lower activity such as early evenings.

One of the foremost worries on the part of seniors and their families is that of a senior being immobilized due to a fall, and not being able to get up or summon assistance (Cuddihy et al., 2007). Cuddihy et al. (2007) focus on a system to detect unusually long periods of inactivity associated with a possible fall, consisting of a small number of wireless motion sensors and door sensors deployed in the home, collecting data to model the resident's normal activity. Raw data is collected from the sensors and is used to draw conclusions about the resident's activities on a daily basis. This information is then made available to their caregivers via a secure website along with alerts when a potentially troublesome situation occurs. With the same goal of fall detection, Sixsmith & Johnson (2004) developed an intelligent fall detector (SIMBAD) based on a low-cost array of infrared sensors. The system is composed of IRISYS (InfraRed Integrated Systems) thermal imaging sensors, wall mounted. First, SIMBAD analyzes target motion to detect falls' characteristic dynamics. Second, it monitors target inactivity and compares it with a map of acceptable periods of inactivity in different locations in the field of view. The combined fall detection and inactivity monitoring is potentially powerful, avoiding many false alarms by observing the activity after what looks like a fall. They used neural network to classify falls using vertical-velocity estimates derived either directly from IRISYS sensor data or from the tracking system. SIMBAD generates two classes of alarm—those triggered by excessive periods of inactivity (according to the risk map) and those triggered by the detection of a fall.

Low-power smart cameras have proved to be a good choice of sensors in automatic detection and localization of falls. Williams et al. (2007) evaluated such a system by an experimental setup of 6 cameras in a small room where an individual walked about the room for about 10 minutes (approx. 150 samples per camera). In addition 40 images were collected from two different rooms each containing one of four individuals in normal positions or pretending to have fallen for evaluation of fall detection procedure. Classification algorithms have been used including the SVM and since SVM requires training data, leave-one-out testing was used in order to maximize the useful number of training examples per test.

Technology can be used not only to detect activities of daily living patterns, falls or in-bed restlessness, but also social interaction patterns of elderly people. Chen et al. (2007) conducted both a "Wizard of Oz" style study and an experimental study of various sensors and detection models for detecting and summarizing social interactions among aging patients and caregivers. They first simulated plausible sensors using human labeling on top of audio and visual data collected from a skilled nursing facility. The most useful sensors and robust detection models were determined using the simulated sensors. Decision tree model achieved more than 99% accuracy with only 3 types of sensors: talking, walking and leaving, plus temporal information under noise-free conditions. When noise is present, the SVM and the logitboost models proved to be more robust against noise than other models.

Social interaction can be detected using various sensors including cell phones. Eagle and Pentland (2006) demonstrated the ability to use mobile telephones to measure information access and use in different contexts, recognize social patterns in daily user activity, infer relationships, and identify socially significant locations. Data was collected from 100 mobile telephones over the course of 9 months. Their ultimate goal was to create a predictive classifier that can perceive aspects of a user's life more accurately than a human observer. They quantified the amount of predictable structure in an individual's life using information entropy metric. Also, they developed a simple Hidden Markov Model conditioned on both the hour of day as well as on weekday or weekend. After training the model with one month of data from several subjects a good separation of clusters with greater than 95% accuracy was obtained.

Social connectedness, so important in the independent elders' life, is possible today regardless of the distance between the elderly and loved ones, by ingenious use of technology. Awareness systems deliver and are targeted to attaining the feeling of being connected with other people, of not being alone (Romero et al, 2007). Digital Family Portrait (Rowan & Mynatt, 2005) was intended primarily to offer piece of mind to distant family members. Initial work on the Digital Family Portrait used Wizard of Oz techniques to simulate activity detection. In this study, Rowan and Mynatt (2005) installed strain sensors on the underside of the first floor of an elder's home. By detecting the weight of a person standing on the floor, these sensors allow the Digital Family Portrait to show the activity based on movement throughout the first floor of the home. The field trial was conducted over a period of one year involving an aging parent living alone in her own home and her adult child living 50 miles distant. Rowan and Mynatt (2005) based their calculations on the fact that certain days of the week will have a regular pattern. One of the simplest ways to characterize a day is to ignore which sensors have fired and accumulate the number of sensor firings over a particular time period. Doing this calculation for the current day and displaying it against the background of previous similar days of the week provides a simple means of comparison.

As described above, research in the area of continuous monitoring ranges from simple systems involving few sensors to complex systems composed of various types of sensors, from wearable interactive devices to unobtrusive area and environmental sensors deployed in the living environment. An example of such a system was developed by Virone et al. (2006). Among the sensors used are motion, temperature, humidity, acoustic, smoke, dust, gas sensors and wearable devices equipped with sensors for measuring heart-rate, heart rhythm and body temperature, and oximeters and accelerometers. The authors tested reliability, accuracy and robustness of the system by performing a one week experiment in a simulation lab (simulating a nursing home room). The testing results demonstrated a good performance of the system.

2.8. SYSTEMS' LIMITATIONS

A common limitation to all systems analyzed in this paper is the small number of subjects participating in implementation or validation phases. This fact makes it hard to extrapolate the results. Another common problem is the reduced number of representative samples (Davis & Fox, 2007) or very short series of testing (Shieh et al., 2006; Fogarty et al., 2006). Some of the studies are even based on simulated data of different behaviors on long or short periods (Virone et al., 2002).

Monitored activities are dependent on the type of sensors used. For example, the microphone-based sensors used by Fogarty et al. (2006) allow detection of what sink is in use and cannot recognize more specific activities at sinks. Other sensors have the potential to capture more activities in a home but the activities captured depend on the places the sensors are installed. While the ability to install a contact switch nearly anywhere in the home, most of the sensors in a study by Tapia et al. (2004) were installed in the kitchen or bathroom, with success in detecting activities such as meal preparation and toileting. Also, it should be a balance between the engineering tendency to put sensors everywhere and the more practical considerations of installing and maintaining those (Rantz et al., 2008).

When subjects involved in the study are required to interact with the new technology, new challenges arise and impact the study result. This was the case of the study by Tapia et al. (2004), which required the two participants to use PDAs running software especially designed to label the subject’s activities. The participants needed to answer to several questions regarding their activities every 15 minutes for 14 days. According to Tapia et al. (2004), subjects had a difficult time adjusting to the experience sampling device and did not enjoy having to tell the computer about doing the same activities repetitively. However, the number of labels was not sufficient for training the machine learning algorithms.

Even if the studies are intended to support independent living, some of the subjects were recruited from assisted living facilities (Chan, 2005; Alwan et al., 2006) and others were the researchers and their families (Fogarty et al., 2006) or friends (Shieh et al., 2006). I suspect the reasons for that is either, to increase the number of prospective participants or convenience, and to have a way to validate the research questions by using additional resources, like nurses or family members of the participants, or the researchers themselves.

Some articles mentioned as a major limitation low sensitivity of the algorithms, which can be increased by adding more sensors to the existing system (Cuddihy et al., 2007; Alwan et al., 2006), or by careful refinement to reduce the rate of false alerts (Alwan et al., 2006). The major limitation of all studies is that they assume single persons present in the homes or rooms under investigation. When multiple people are present in a home the number of sensor firings will increase dramatically making possible wrong inferences from the data. Hayes et al. (2004) excluded the data when the subject of their study had visitors.

The majority of studies were experimental or exploratory and some of them even used Wizard of Oz technique. Chen et al. (2007) used both, Wizard of Oz and experimental study of various sensors and models for detecting and summarizing social interaction among aging parents and caregivers. Rowan and Mynatt (2005) also used Wizard of Oz technique before their pilot study of Digital Family Portrait for enhancing peace of mind of an adult child living 50 miles away of his elderly parent.

2.9. RECOMMENDATIONS

Several recommendations surfaced from the systems presented above. Hayes et al. (2004) identified as an unanswered question in their research how the total activity levels, average walking speed, and patterns of activity through rooms in the home vary across different clinical populations, from those showing normal cognitive processing on standard clinical tests, to those who show minimal cognitive impairment or early cognitive losses. The majority of studies have as a future aim solving the problem of multiple people present in the home instead of ignoring it or even discarding that data (Rowan & Mynatt, 2005; Sixsmith & Johnson, 2004; Virone et al., 2006).

In order to increase the accuracy of the models used in processing sensor data, some of the authors proposed some solutions of improvement, as using more powerful techniques like Support Vector Machine (Eagle & Pentland, 2006), a finer granularity of data (Fogarty et al., 2006), fusion of data coming from several sensors (Virone et al., 2002; Virone et al., 2006) or identifying and using an optimal size of data sets (Gil et al., 2007). Still, in most cases, the correlation between the information produced by the systems and the clinical reality will have to be performed by a physician (Virone et al., 2002), and this requires building of interfaces to show this information in ways that communicate most intuitively (Gil et al., 2007).

All studies presented in this paper tried to validate their algorithms or research questions by using different approaches and instruments involving the participants, family members or care providers. According to Rowan and Mynatt (2005), in the literature there is an absence of research data on a person’s movement in his or her own house that is not biased by self-report or by third party observation and all articles follow this observation. None of them used the approach of trying to connect clinical data of the subjects, which is not biased in any way, to their sensor data. My research attempts to make this connection by trying to find a link between abnormal levels of daily activities (expressed by the levels of motion within the house, restlessness, and possible pulse and breathing) and change in health status (for example, subtle declines in capabilities or behavior caused by elevated pulse pressure) and validate them with real clinical data.

CHAPTER 3

AGING IN PLACE IMPLEMENTATION AT TIGERPLACE

3.1. BACKGROUND

“Aging in Place” project started in Columbia, Missouri according to Rantz et al. (2005) from the fear of elders participating in research projects about aging, of moving to a nursing home. They stated their wish to stay at home as long as possible. The faculty involved in those projects believed that with the right supportive and restorative services it would be possible to help older adults improve their health and well-being, avoiding the need for traditional nursing home care. The Aging in Place model includes an environmental component as well as health and supportive services (Rantz et al., 2005). Thus, the Aging in Place project has two major complementary parts: Senior Care, providing health and supportive services and TigerPlace, providing the environmental component.

Key to the concept of Aging in Place is creating an environment that supports independence in older adults. Rantz et al., (2005) developed a diagram depicted in figure 2, intended to compare the typical trend of functional decline in older adults (solid line) based on research and practice and the aimed trend using technology (dotted line) which should extend the periods where no measurable decline occurs and reduce the depth of the functional decline.

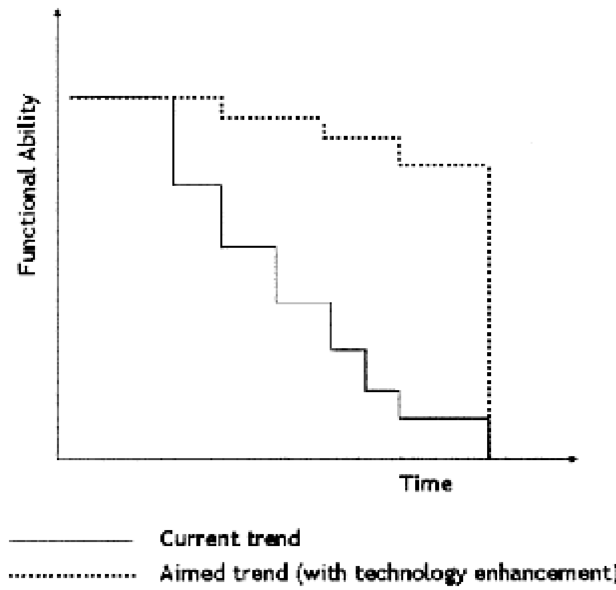

Figure 2: Trajectory of functional decline and goal for the use of technology (from Rantz et al., 2005)

Due to its clinical focus, the TigerPlace project encompasses a broader approach to individualized technology than that of the “smart home” concept which is an emerging trend in health informatics. Smart home features usually include motion-sensing devices for automatic lighting control, motorized locks, door and window openers, motorized blinds and curtains, smoke and gas detectors, and temperature control devices. The TigerPlace initiative builds on the smart home technology and moves beyond it with individualized clinical nursing assessment for risks of functional decline and alerting mechanisms of the need for intervention (Demiris et al., 2006).

3.2. THE IN-HOME MONITORING SYSTEM

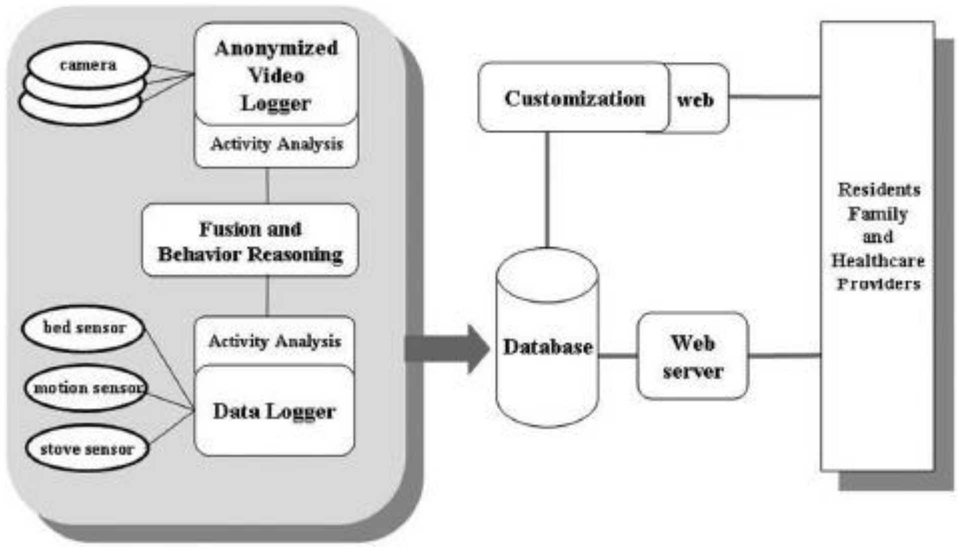

Figure 3: The integrated monitoring system (from Rantz et al., 2008)

The integrated monitoring system under development at TigerPlace and illustrated in figure 3 has three main components: (a) The In-Home Monitoring System, developed by collaborators at the Medical Automation Research Center - MARC, University of Virginia, (b) An event-driven, video sensor network that hides identifying features of the residents, (c) A reasoning component that fuses sensor and video data and analyzes patterns of behavioral activity (Rantz et al., 2008). Data from sensors is transmitted wirelessly via the X10 protocol to a data monitor PC located in each resident's apartment connected to the network, date-time stamped and logged in into a file that is sent to a secure server as binary streams stripped of identifiers, to ensure HIPAA compliance (Rantz et al., 2008).

The In-Home Monitoring System implementation started in 2005 when the first resident was connected to the system. Currently, the system is installed in 17 of the TigerPlace apartments. It consists of a set of commercially available wireless passive infrared sensors to detect motion or specific activities, stove temperature sensor, and a pneumatic bed sensor capable of detecting presence, breathing (low, normal or high), pulse (low, normal or high) and movement in the bed (four levels of restlessness). The motion sensors are placed in various places, such as bathroom, bedroom, kitchen, living room, etc. They are capable of capturing resident motion through his/her apartment or indicating specific activities by emitting a signal (firing) as often as there is movement around them. For example, a motion detector installed above the shower indicates bathing activity. A signal is emitted every seven seconds when motion is detected from about 12 feet or less, and every eight seconds when motion is detected from further than 12 feet. After 20 feet, motion detection is at a bare minimum. The stove temperature sensor, as expected, is attached to the stove and detects cooking activity. It also can be used to send a safety alert if the stove has been on for too long. Consequently, it has two levels of severity – low temperature, when the stove is turned off, and high temperature, when the stove is turned on. The bed sensor is a pneumatic strip able to keep track of the resident's presence in the bed, movement in the bed, namely restlessness, pulse and breathing, as long as the resident is in the bed. Unlike the motion sensors, the pneumatic strip captures qualitative pulse and respiration, and bed restlessness, which are structured on three or four levels of severity. 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 six 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 sent for movement up to three 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 nine seconds, a level four event is sent (Rantz et al., 2008). Together, these different levels provide a measure of the restlessness in bed which is used to determine the quality of sleep. All of the outputs of the bed sensor contribute to the general pattern of the resident. Some residents might have a second bed sensor attached to their recliner chair. Data generated by this sensor is captured separately from the data generated by the sensor attached to the bed.

Several methods for displaying the data including a web-based interface and motion density maps have been investigated in an effort to interpret the data and explore possible correlations to the health data provided by Sinclair Home Care. The web-based interface is presented in Chapter 4.

3.3. THE EVENT-DRIVEN ANONYMIZED VIDEO SENSOR NETWORK

The second component of the integrated system under development is an event driven anonymized video sensor network for tracking relevant data on gait and range of motion and to detect falls (Rantz et al., 2008). The system is designed to complement the In-Home Monitoring System by reducing false alarms generated by the motion sensors. To preserve the privacy of the residents, algorithms are being developed to find a moving person in the image and generate a silhouette (Chen et al., 2006; Wang et al., 2003). Important features are then extracted from the silhouette and a hidden Markov model (HMM) is trained to recognize known activities (Anderson et al., 2006). While the use of video camera is promising, the computational requirements for processing present a challenge. Therefore, other options for fall detection have been investigated and an acoustic fall detection system (FADE) developed based on an array of off-the-shelf acoustic sensors (Popescu et al., 2008). The false alarms are removed using the height of the signal and falls performed by stunt actors trained by nursing collaborators were 100% detected with a rate of five false alarms per hour.

3.4. THE BEHAVIORAL REASONING SYSTEM

The final component of the integrated system is a behavioral reasoning system that uses the motion sensor data to establish normal patterns of activity and recognizes deviations from the established patterns. Much of the strategy is based on identifying the typical pattern changes. These pattern deviations may take form of a sudden change as a result of a specific health event, or in the form of a gradual event as a result of a deteriorating condition. Several methods of behavioral reasoning using fuzzy logic rules (Wang et. al., 2006) and a hierarchical HMM are being investigated. Another approach for detecting such changes is a new algorithm for temporal clustering (Sledge et al., 2008, Sledge & Keller, 2008). Monthly activity density maps have also been created to track activity levels over time (Wang & Skubic, 2008).

The biggest challenge of the research conducted at TigerPlace is trying to connect sensor data to medically relevant events. The electronic health records of the residents are in a format that does not allow for easy access and data mining. Therefore, extraction and comparison of health data to logged sensor data is performed manually (Rantz, Skubic, Miller & Krampe, 2008). In addition, collection of vital signs is not frequent enough to match the continuous sensor monitoring of the residents. One option to address this issue is to provide telemedicine equipment and ask the residents to collect their vital signs daily (Rantz et al. 2008). Data collected by this equipment will go into an internal database along with other pertinent data on sentinel health events such as hospitalization, falls, and ER visits. The initial design and implementation is described in Chapter 5.

CHAPTER 4

A WEB-BASED VISUALIZATION INTERFACE FOR SENSOR DATA

Sensor data stored on the server is available from any computer with remote access to the server through a web-based visualization interface refined with input from nursing, health informatics, social work, and residents to ensure it is user friendly, easy to use, and clinically meaningful. The interface allows care providers to select a specific participant (figure 4) while residents are allowed to view only their own data (figure 5).

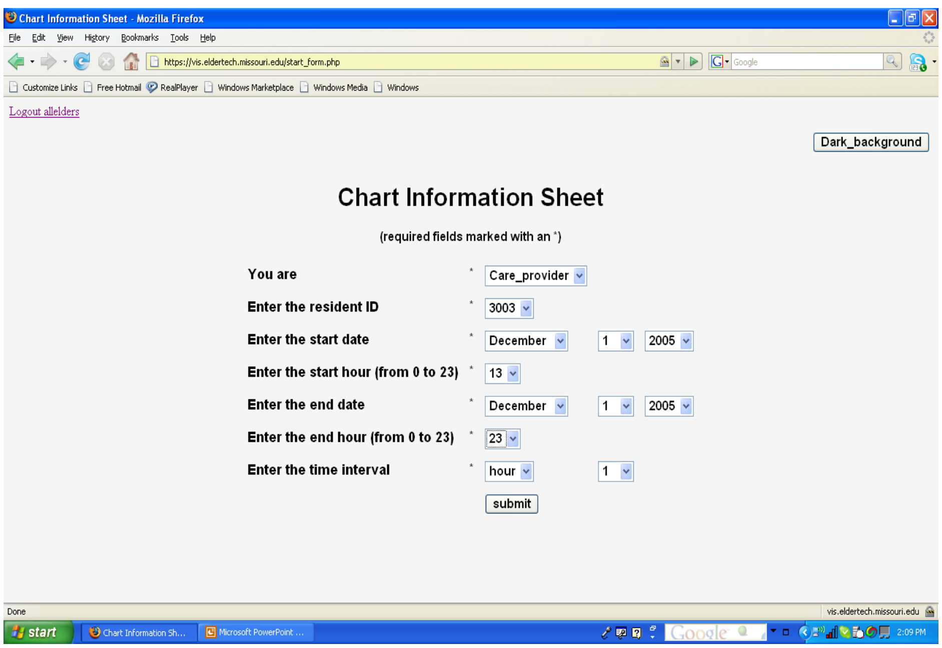

Figure 4: Chart information sheet for care providers

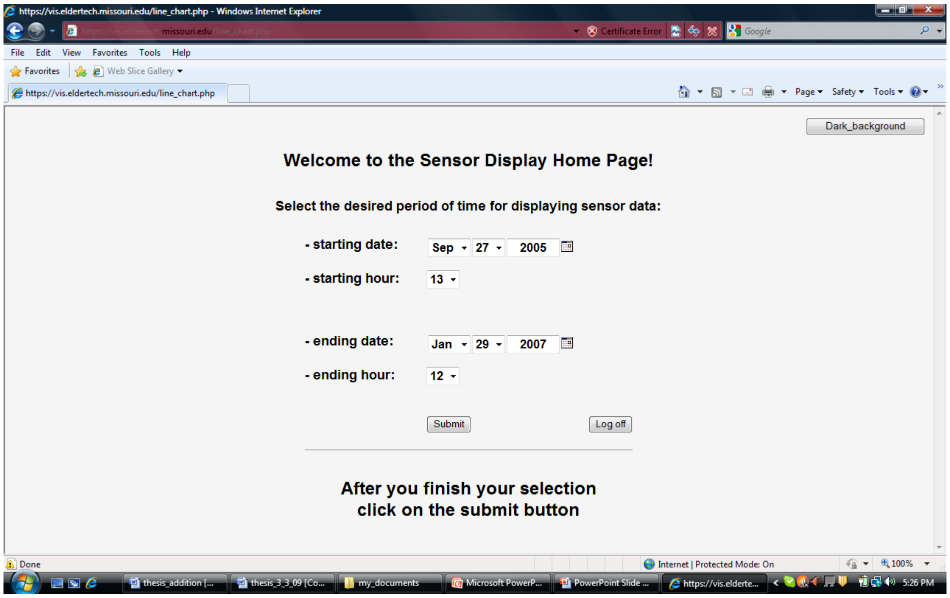

Figure 5: Chart information sheet for residents

Date range is also selected by the users. Therefore, data available for visualization is grouped by resident and can be displayed for a particular period of time day by day, for longer intervals, such as weeks or months, or in one, two, up to 12 hour increments for intervals up to two weeks. Several chart options and types are available to the user. Chart options include events that are monitored by the sensors: motion, restlessness, breathing, pulse, and stove temperature. Chart types include line (figure 6), histogram (figure 7), or pie (figure 8).

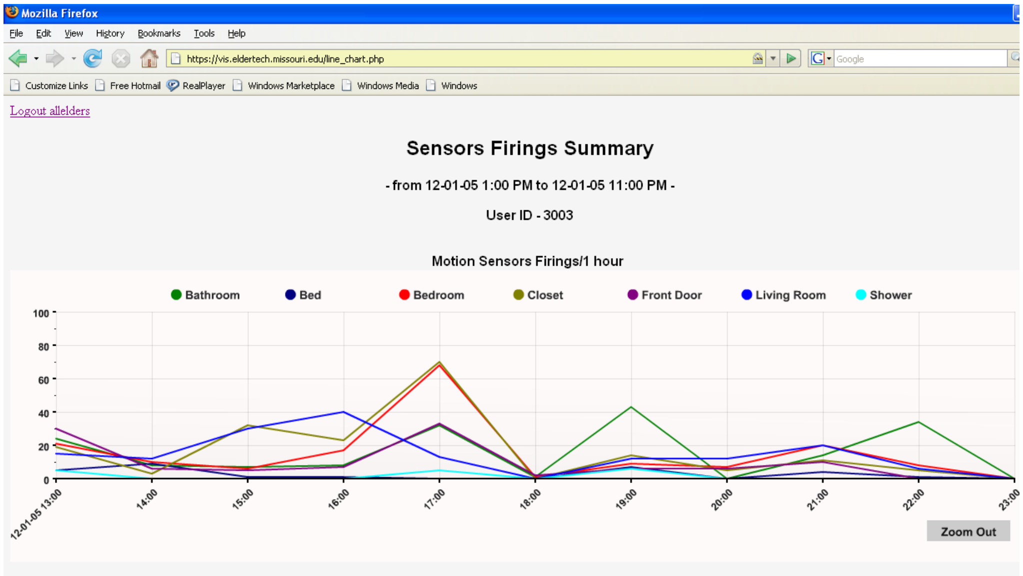

Figure 6: Motion line chart

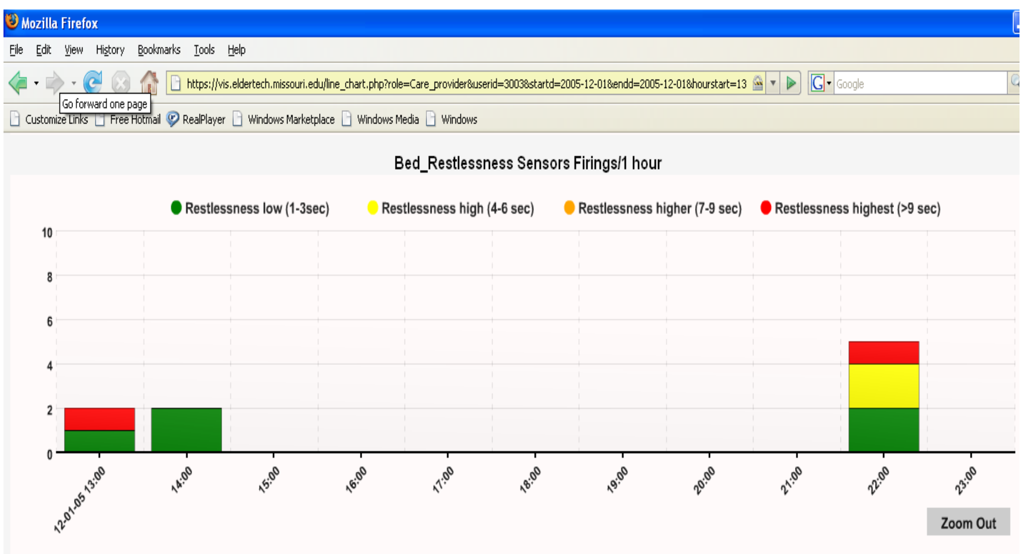

Figure 7: Restlessness histogram chart

The line and histogram charts share the same characteristics: the horizontal axis (X-axis) represents time (days or hours) and the vertical axis (Y-axis) represents hits of the sensors (number of sensor firings) corresponding to days or hours represented on the X-axis. The pie chart is cumulative and it shows the total number of sensors firings corresponding to a particular activity during the desired time period (the time increment is ignored in this case).

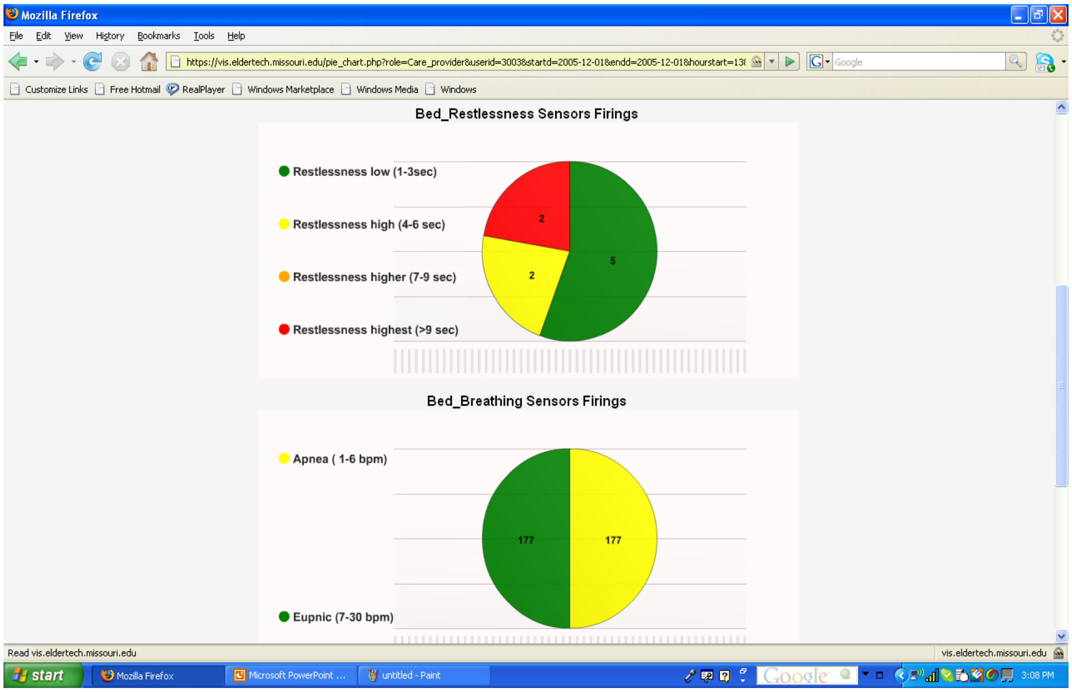

Figure 8: Restlessness and breathing pie charts

Users can drill down in the interface to see data from individual sensors (figure 9) or with a time granularity of 15 minutes (figure 10).

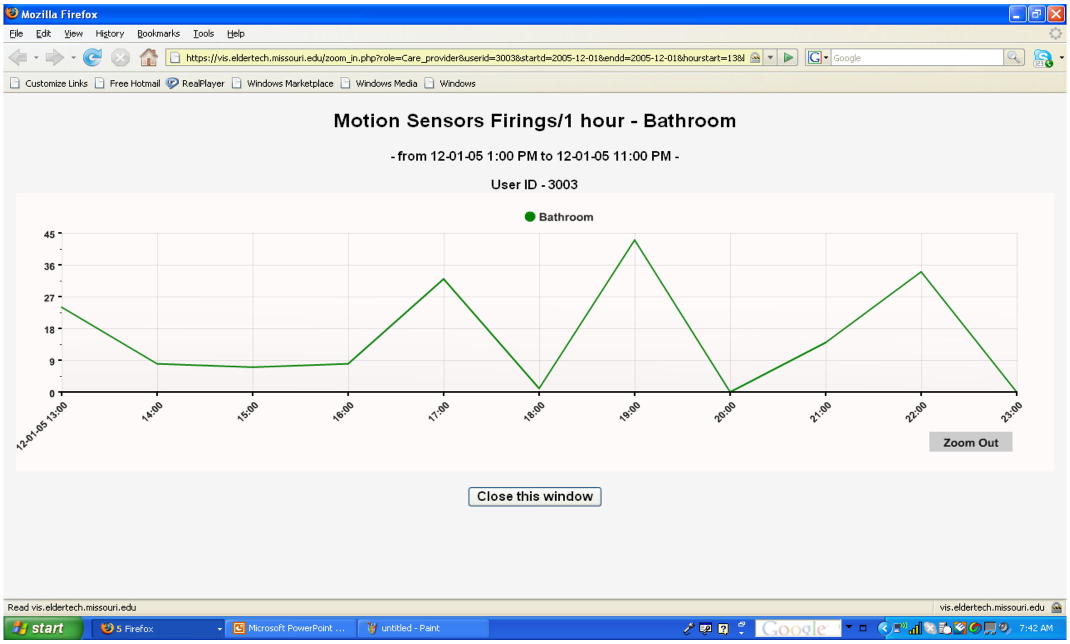

Figure 9: Motion sensor activity in the bathroom only

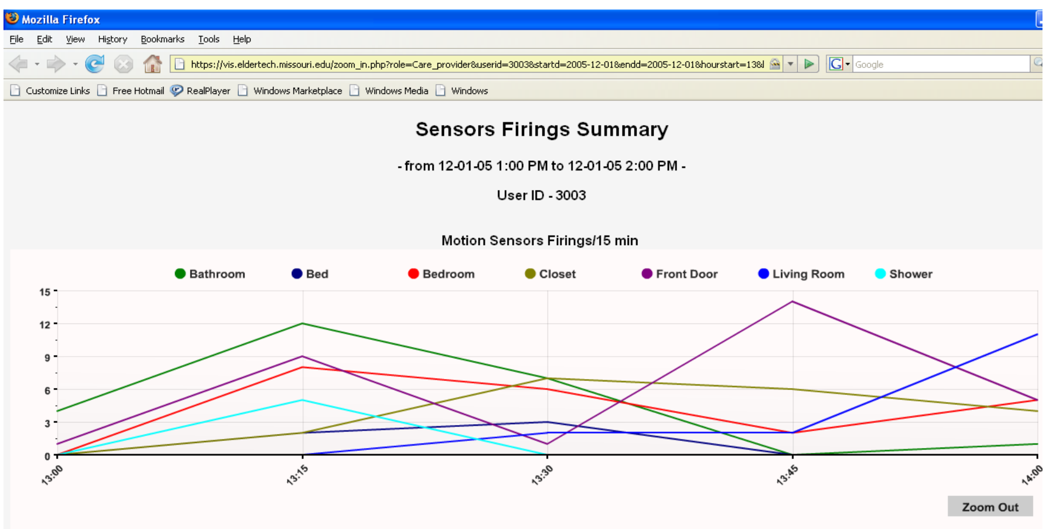

Figure 10: Drill-down in a full motion sensor chart

Along with the drill-down feature, the interface has a zoom out feature which can be activated by clicking on the “Zoom Out” button at the bottom of each chart. This feature is designed to display sensor data one week before and one week after the time interval that a particular chart is showing and whose “Zoom Out” button was clicked on.

CHAPTER 5

THE TIGERPLACE INTERNAL DATABASE

The TigerPlace internal database started as a project for a database class and is still in a refining stage as a result of the benefits and advantages that it brings not only to the TigerPlace administration but also to the multidisciplinary research team. The initial ER diagram is illustrated in figure 11.

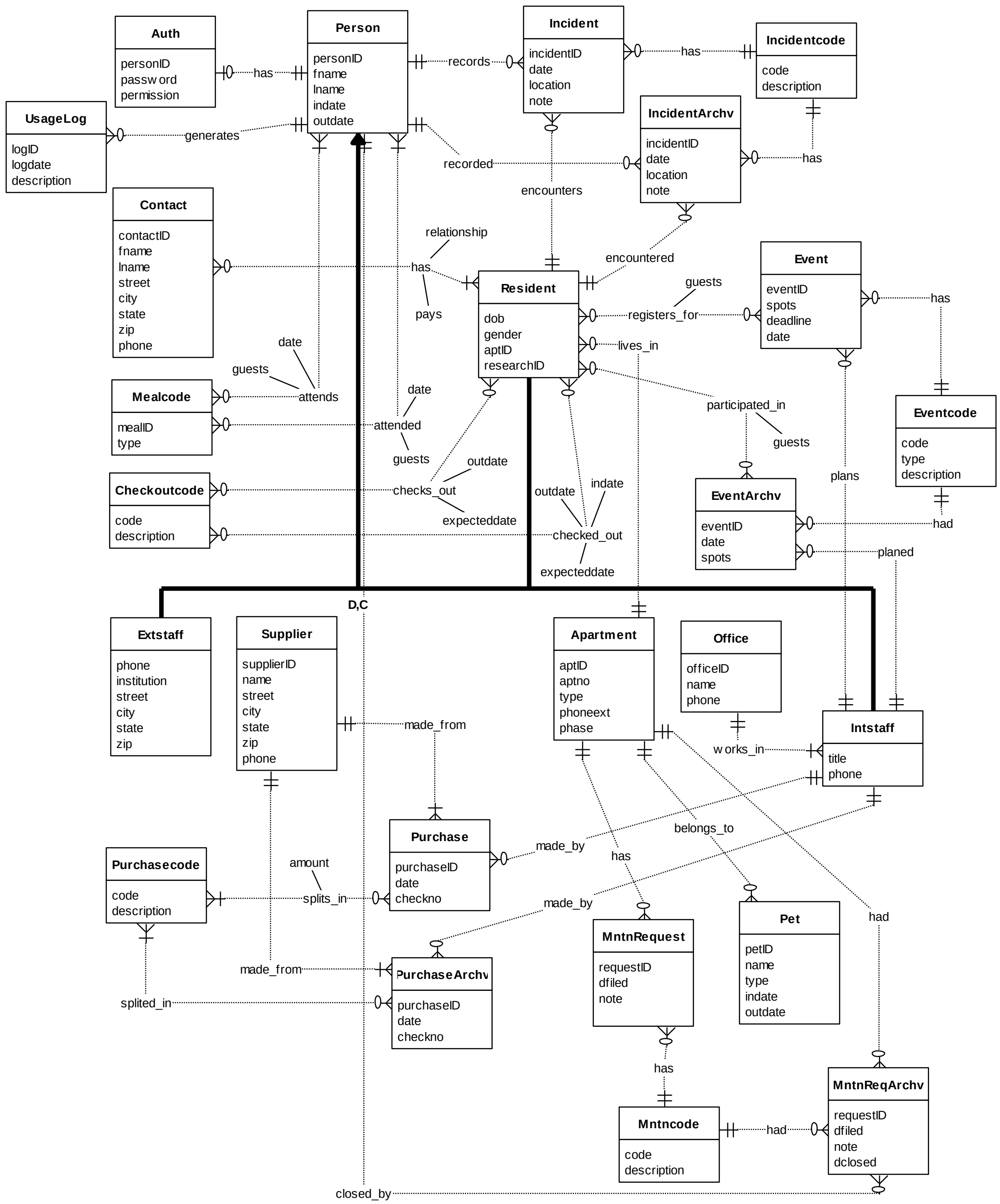

Figure 11: ER diagram of the TigerPlace internal database

As we can see from the diagram the database was not only designed to store the "business" data of the facility but also the sentinel health events, called "Incidents". Currently, the feature of storing the vital signs of the residents is in a developing stage.

There are five database user categories including the administrator, resident, staff which refers to employees excluding maintenance and cleaning staff, maintenance staff, and nurse. Any of the users mentioned above can connect to the database using a username and password, through an interface and can perform different activities ranging from visualization the data up to creating new data, based on their roles and privileges. The administrator is the only one who has full access to all the database features. His navigation menu is illustrated in figure 12.

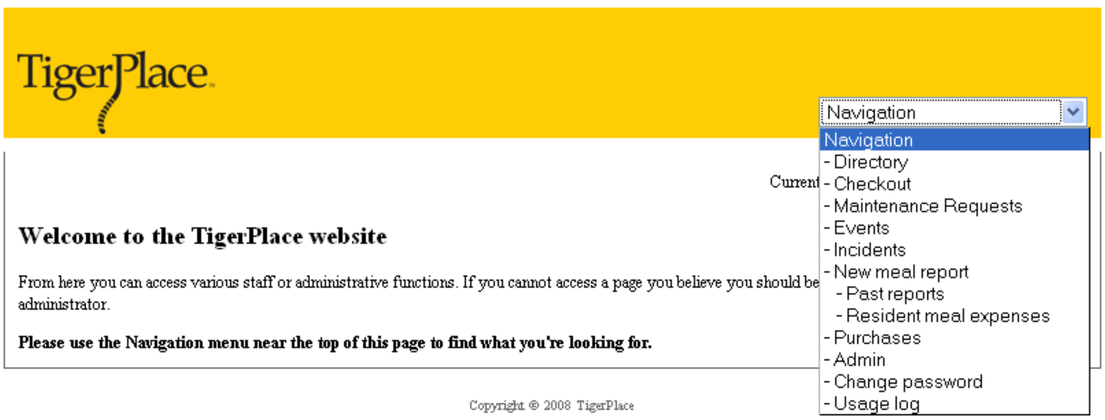

Figure 12: Administrator's navigation menu

As the navigation menu shows, the administrator can see the TigerPlace directory, check out and check in residents leaving or coming back to the facility, create, update or cancel events, incidents, meal reports, and purchases. He also is able to see the usage log of the database and can access a special admin page where he can add/update a residents, employee, pet, contact information, etc. The feature that is in direct relationship with the research conducted at TigerPlace is the possibility to collect and store data related to sentinel health events. The "Incidents" page is shown below.

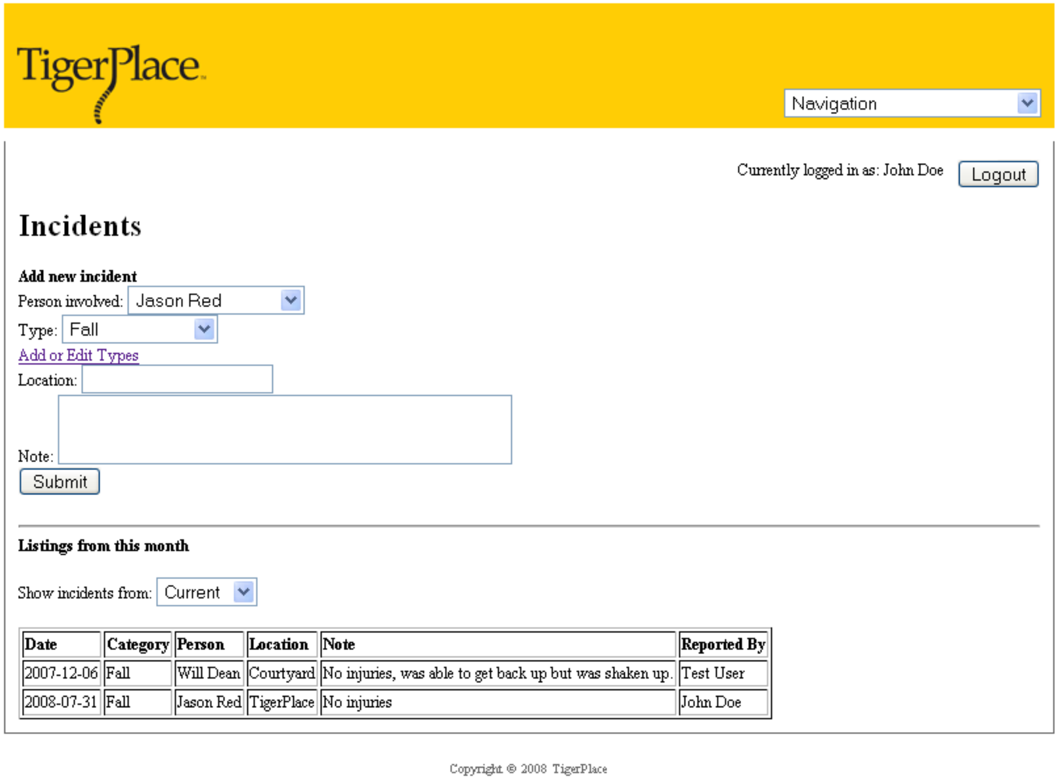

Figure 13: The incidents page

The administrator, nurses or other staff have access to this page and they are able to fully document an incident such as a fall, hospitalization or ER visit by specifying the type, resident involved, location where the incident occurred, and additional details and comments. The association between the medical incidents and sensor data is extremely helpful to students and faculty conducting research at TigerPlace. This is doable by the built-in link between the two databases based on the resident id.

CHAPTER 6

METHODOLOGY

Among the predictors of functional decline are mentioned activities of daily living which is measured in the medical field by using clinical tools of assessment. Usually, they are based on patients self-reporting or third party observations, as family members or nurses, procedures that bias the results. Even continuous monitoring using wireless sensor technology poses many challenges, and validation process is also based on self-reporting or third party observation. Another predictor of multiple diseases characteristic in elderly people is the pulse pressure. Although pulse pressure is calculated from blood pressure assessment, as the difference between systolic and diastolic BP, it often fades into the background of vital signs. For example, few clinicians would be alarmed by a BP of 135/55 mm Hg obtained during a routine visit in a 75-year old patient (Swaminathan & Alexander, 2006).

In certain groups of patients, precautionary warning can be set to signal sudden changing in blood pressure (Yang et al., 2004). Transient abnormalities cannot always be captured during a doctor visit. For example, many cardiac diseases are associated with episodic rather than continuous abnormalities such as transient surges in blood pressure, paroxysmal arrhythmias or induced or spontaneous episodes of myocardial ischaemia (Yang et al., 2004). These abnormalities are important but their timing cannot be predicted and much time and effort is wasted in trying to capture an "episode" with controlled monitoring. Important and even-life threatening disorders can go undetected because they occur only infrequently and may never be recorded objectively (Yang et al., 2004). High risk patients such as those with end-stage ischaemic heart disease or end-stage myocardial failure often develop life threatening episodes of myocardial ischaemia or ventricular arrhythmia. These episodes, if reliably detected would lead to better targeting of potentially life saving (Yang et al., 2004).

There are biological differences in older people, so that usual symptoms are often not present and there may be a reduction in sensitivity and specificity of any one traditional symptom (Shieh et al., 2006). The result of these factors is that an older person may show the presence of disease in total body responses and changes in overall levels of functioning. Traditional methods of diagnosis fail to demonstrate this transition, and there is a need for methodologies that will provide objective and continuous assessments of an individual function that can be used for a person in their own home. It is important to obtain information for detecting conditions in their early stages and/or for maintaining health care in daily life. For this purpose it is desirable to measure physiological and vital signs without attaching any biological sensors to the body or making a burden of the measurement (Shieh et al., 2006).

The facts mentioned above shaped the methodology used in this research, which is based on data mining techniques, namely, classification algorithms. The study will be considered successful if the results can prove that the level of motion and restlessness can predict a low or high level of pulse pressure. Thus, four features will be used in the classification algorithms, motion level during the day and night and restlessness level during the day and night, 24 hours prior to the day of measuring the blood pressures. This choice of the features is based more on intuition than on previous research given that this approach of linking sensor data to pulse pressure was never used before. Intuition tells us that a normal pattern or daily life supposes high level of activity, i.e. motion, during the day with short or absent periods spent in the bed, while during the night the opposite holds, i.e. long period spent in the bed with low level of restlessness and low level of activity throughout the apartment. The class considered here will be pulse pressure with two labels, low (PP<= 60 mm Hg) and high (PP > 60 mm Hg).

Vital signs of residents at TigerPlaces, including the blood pressures, are not checked daily but more on a need basis or at the regular 6-months check up. Even if the blood pressure would be measured daily, this would not increase the chances of capturing transient abnormalities. Transient abnormalities cannot always be captured during a doctor visit (Yang et al., 2004). For example, many cardiac diseases are associated with episodic rather than continuous abnormalities such as transient surges in blood pressure, paroxysmal arrhythmias or induced or spontaneous episodes of myocardial ischaemia (Yang et al., 2004). These abnormalities are important but their timing cannot be predicted and much time and effort is wasted in trying to capture an “episode” with controlled monitoring. Important and even-life threatening disorders can go undetected because they occur only infrequently and may never be recorded objectively (Yang et al., 2004). High risk patients such as those with end-stage ischaemic heart disease or end-stage myocardial failure often develop life threatening episodes of myocardial ischaemia or ventricular arrhythmia. These episodes, if reliably detected would lead to better targeting of potentially lifesaving (Yang et al., 2004).

The gap in detecting a disease in an early stage of development can be filled by using data generated by the In-Home Monitoring System and processed using data mining techniques.

The data mining approach will follow the subsequent steps:

- Data selection
- Data preparation
- Algorithm selection
- Data classification and validation

6.1. DATA SELECTION

The visualization interface described in Chapter 4 was used to select the data sets that ensure reliable and complete data. The sensor data for 24 hours before each date with blood pressure measurements available was visually analyzed and dates with missing data for more than three hours (e.g. the resident was out of the apartment) or uncorrelated sensors firings (e.g. restlessness firings present but no pulse and/or breathing firings during the same hours and vice versa) were not included in the data set. The results of the data selection dictate the size of the data sets and implicitly, the number of subjects because the sensor data is grouped by resident. The larger the data set, the better, and therefore, extremely small data sets will not be considered. In conclusion, the corresponding subject was not included in the study.

6.2. DATA PREPARATION

This step implies aggregation of motion and restlessness data by day (7:00 AM to 9:00 PM) and night (9:00 PM to 7:00 AM), 24 hours and 48 hours respectively, before each day when blood pressures were measured. Therefore, for each 24 hours there are four features considered: the total number of motion sensor firings from 7:00 AM-9:00 PM, the total number of motion sensor firings from 9:00 PM-7:00 AM, and the total number of restlessness level one firings for the same two time intervals. For this task a small piece of software was developed that is able to connect to the database, perform the aggregation and write the results in a data file. The content of this file was imported in a spread sheet and the pulse pressure values transformed in low (0) or high (1) will be added to each resulting row. The data was further imported in the MATLAB workspace. At some nurse collaborators' suggestion, low heart rate was also aggregated following the same procedure as for the motion and restlessness, but only for 24 hours before each day when blood pressures were measured.

6.3. ALGORITHM SELECTION

Since this research was an exploratory study, robust regression (MATLAB function "robustfit", Stats package), SVM (MATLAB Bioinformatics package), and neural network algorithms (4-4-1, MATLAB Neural Net package) have been used. In the robust regression, the independent variables considered were the features identified above, i.e. total motion, restlessness, and low heart rate per day and night, and the dependent variable was the pulse pressure level. Robust regression was one of the options given the fact that the robustfit function uses an iteratively reweighted least squares algorithm, with the weights at each iteration calculated by applying the bisquare function to the residuals from the previous iteration. This algorithm gives lower weight to points that do not fit well. The results are less sensitive to outliers in the data as compared with ordinary least squares regression (Holland & Welsch, 1977). SVM technique is based on the linear regression concept but ensures model accuracy. Neural network is usually used for unknown relationships between dependent and independent variables.

6.4. DATA CLASSIFICATION AND VALIDATION

For the purpose of this research the value of 60 mmHg was used for PP but further analysis requires different threshold levels of PP given the controversy existent in literature regarding the abnormal levels of PP. Leave-one-out cross-validation was used in each case in order to evaluate the classification accuracy. ROC curves were used for comparing the classification models.

The following algorithm for calculation of the ROC curves points has been used:

1. Train each algorithm with N-1 data points and use the one not included in the training set for testing.
2. Let Y_p be the vector output of the neural network or regression algorithms, i = 1, …, N, with values between 0 and 1. Let $Y_t(i)$ be the ground truth labels, where $Y_t(i) = 0$ if $PP < 60$ and $Y_t(i) = 1$ if $PP \geq 60$. Consider a set of output thresholds $\{T_k\} = \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, \ldots\}$
3. For each threshold T_k
    a. For i = 1, …, N calculate the predicted output Y_p (between 0 and 1) and threshold it such that $Y_{pt}(i) = 1$ if $Y_p > T_k$ and $Y_{pt}(i) = 0$ if $Y_p \leq T_k$
    b. Calculate the false positive rate, x(k) and the true positive rate, y(k):

x(k) = normal PPs identified as abnormal / total normal PPs

y(k) = abnormal PPs correctly identified / total abnormal PPs

using the formulas code below:

$$x(k)=1 - sum((1-Y_t(i))*(1-Y_{pt}(i)))/sum(1-Y_t)$$

$$y(k)=sum(Y_t(i)*Y_{pt}(i))/sum(Y_t)$$

(where i = 1, …, N)

Going even further, after identifying the existence of a relationship between the sensor data and PP of the participants, the idea of trying to predict PP and comparing the predicted PP trend with the measured PP trend seemed the right way to go. The algorithm used for calculating the PP trend has the following steps:

1. Use N_{start} PP measurements $\{y_i\}$ and the related sensor vectors $\{x_i\}$, i=1,N_{start}, to compute the first set of regression coefficients, β;
2. For each new sensor input $i \in [N_{start+1}, N]$

   - Use β to compute the PP estimate $\hat{y}_i$

   - if there is a measurement in that day y_i, update the regression coefficients, β'

   - set $\beta = \beta'$

   End For.
3. Compute the trend of the predicted and measured values as the average of the previous week (7 previous values, if some days are missing).

The choice of the sensors used for this algorithm was made based on the average relative error (ARE) of different combinations of sensor data including motion, restlessness, and low heart rate. The number of training samples, N_{start}, and algorithm weight threshold that improves the ARE by excluding from the regression calculation points with weights less than a given threshold were decided by trial and error. Clinical records including medication, nursing visits, hospitalization, etc. and personal diaries of the participants have also been used to determine the influence of these factors on the predicted PP trend. IRB approval was obtained for all studies conducted at TigerPlace including this research.

CHAPTER 7

RESULTS

After performing the first step of the data mining approach, only two residents have met the inclusion requirements in this study. The table below summarizes the results of the data selection.

Table 1: Results of data selection

	Total clinical records	Missing BP measurements (records)	Missing or incomplete sensor data (records)	Total data set (records)
3003 (male)	93	5	47	41 (33 PP≥60)
3007 (female)	139	2	47	90 (35 PP≥60)

7.1. PULSE PRESSURE PREDICTION

The classification algorithms mentioned above were performed using those two sets of data. Resident 3003 has a relatively simple configuration of the sensor network, without an additional bed sensor attached to a recliner chair as is the case of resident 3007. For consistency reasons, the recliner chair data generated by the bed sensor attached to it was ignored. The figure below illustrates the ROC curves for resident 3003 obtained with the robust regression algorithm using the features mentioned previously.

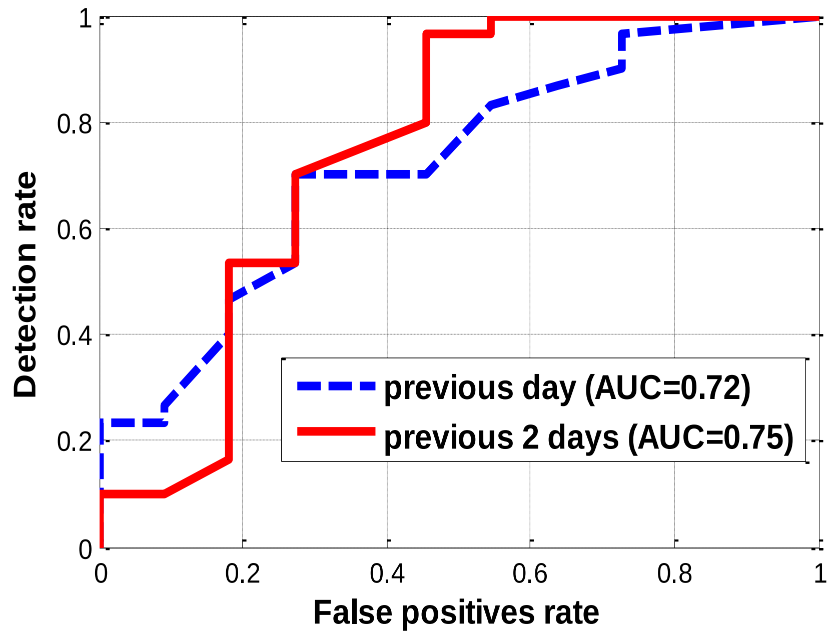

Figure 14: ROC curves for resident 3003 for previous 24 and 48 hours – robust regression

The further away of the ROC curves from the imaginary diagonal line the better the performance of the algorithm. ROC curves relatively closed to the imaginary diagonal line represents the fact that for every true positive of any of the models we are as likely to encounter a false positive. The closer the ROC curves to this imaginary line, the less accurate the model (Han & Kamber, 2006). Another interpretation of the ROC curves is given by the area under the curve (AUC). Thus, the larger the AUC, the better. Using the features for 48 hours the performance of the prediction the AUC increased from 0.72 to 0.75. The same approach is depicted by the figure below but this time user 3007.

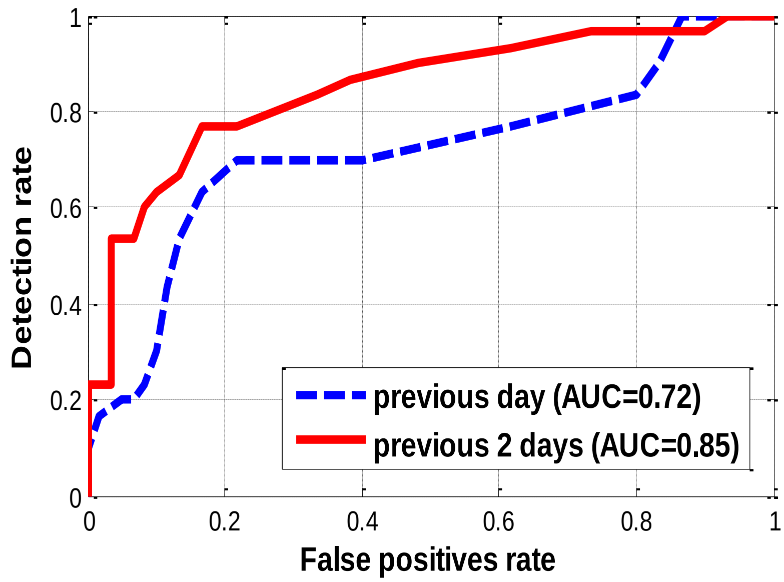

Figure 15: ROC curves for resident 3007 for previous 24 and 48 hours – robust regression

The performance of the prediction when using the features for 48 hours shows an improvement higher than in case of the resident 3003 going from an AUC = 0.72 to an AUC = 0.85. This better performance could be a result of the larger dataset of the resident 3007 as opposed to resident 3003.

For comparing the three algorithms, robust regression, SVM, and neural network, only the features for 48 hours which proved to increase the performance of the regression have been used. The ROC curves for resident 3003 are depicted in the figure below.

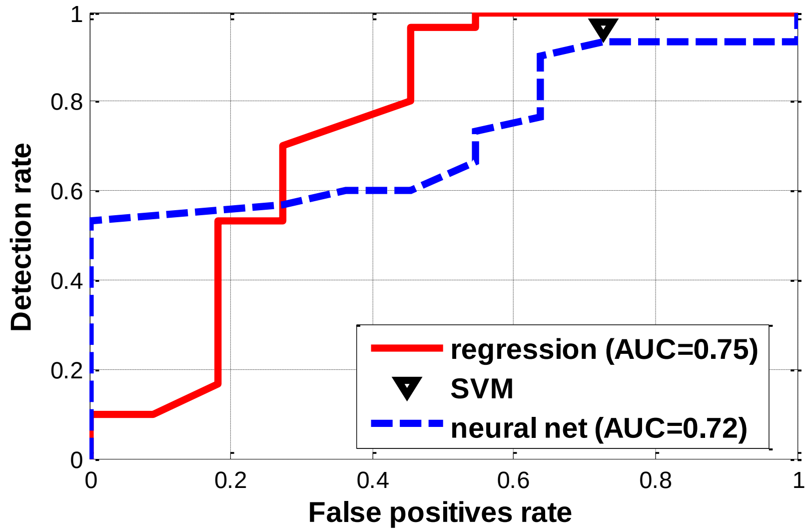

Figure 16: ROC curves of the 3 algorithms for resident 3003 with features for 48 hours

As we can observe from those curves the neural net algorithm performed relatively well for detection rates lower than 55% but for higher detection rated it was outperformed by the robust regression algorithm. Even the SVM algorithm performed poorly in this case being able to detect 96% of the abnormal PP but with a 72% false alarm rate. Overall, the robust regression performed the best, with an AUC = 0.75. The ROC curves of the three algorithms for resident 3007 are shown below.

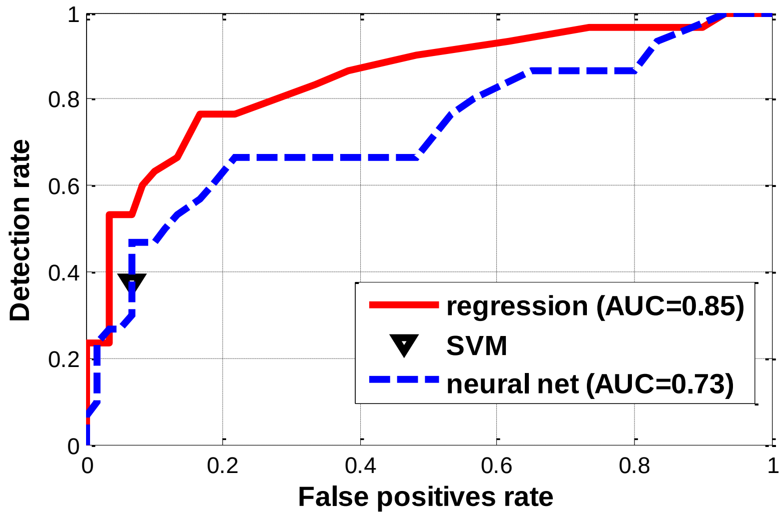

Figure 17: ROC curves of the 3 algorithms for resident 3007 with features for 48 hours

Surprisingly, the SVM performed poorly in this scenario. However, the robust regression performed better than the neural net, as the area under the ROC curve of the regression is larger than the area delimited by the neural net ROC curve (0.85 vs. 0.73). Once again, the robust regression seemed to be the best choice for this scenario, too.

By inspecting the collected data using the data visualization interface for several patients, our nursing collaborators suggested that the daily total of low pulse hits acquired by the bed sensor may be a predictor of clinical events. To validate these statements, we added two more features (low pulse during previous day from 7:00 AM to 9:00 PM, and during previous night from 9:00 PM-7:00 AM) to the four features for the previous day case (motion and bed restlessness during the same time intervals). The related robust regression ROC curves for resident 3003 are given in figure 18.

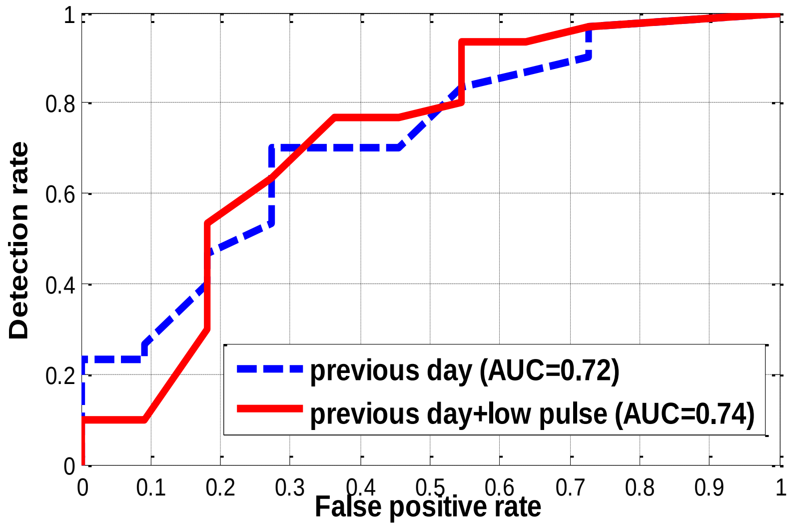

Figure 18: ROC curves for resident 3003 with and without low pulse data

Adding the low hearth rate features to the motion and restlessness features proved to increase the prediction accuracy from an AUC of 0.72 to 0.74. An increase in prediction accuracy with the addition of the low pulse data can also be observed for the resident 3007 in the figure below.

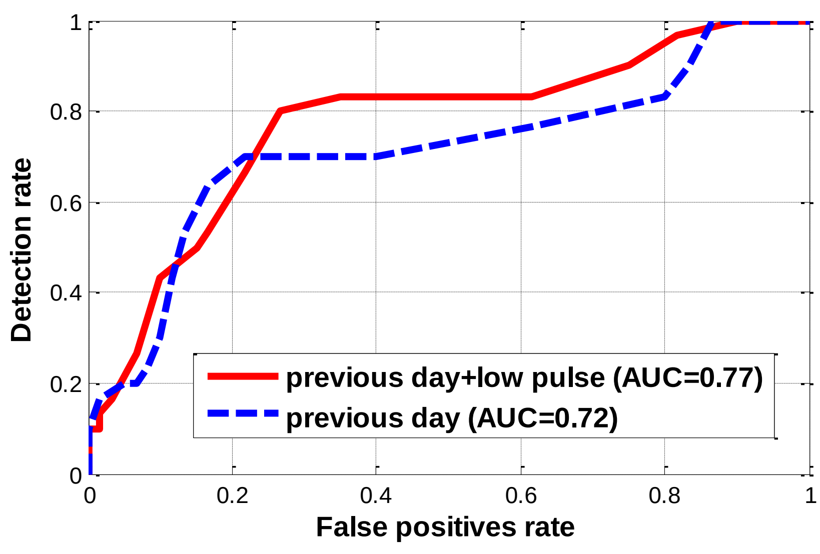

Figure 19: ROC curves for resident 3007 with and without low pulse data

The increase in this case is higher than for resident 3003, from an AUC of 0.72 to 0.77, due probably to the larger data set used for 3007. In conclusion, the low heart rate increases the pulse pressure prediction accuracy, validating the observation that our nursing collaborators made.

7.2. PULSE PRESSURE TREND

From the previous subsection we have concluded that the robust regression was the best choice in any of the scenarios analyzed. Adding the low heart rate data as features of the algorithm increased the prediction rate of the PP, thus making it a good candidate for sensor data selection. The average relative errors for the tested combinations for the two participants are given in table 2.

Table 2: ARE for various combinations of sensor data

No.	Sensor type	Resident 3003 [%]	Resident 3007 [%]
1	motion	3.1	8.5
2	motion + restlessness	3.8	9.8
3	motion + restlessness + heart rate	10.5	11.5
4	motion + heart rate	7.4	10.7
5	Restlessness + heart rate	4.2	15.5
6	day motion + day restlessness	3.7	9.2

An ARE below 10% denotes that the PP trend can be predicted reasonably well. Thus, motion is by far the best choice of sensor data with a value of 3.1% for resident 3003 and

8.5% for resident 3007. The PP trend for resident 3003 obtained using a robust regression with the day motion and night motion as features is illustrated in figure 20.

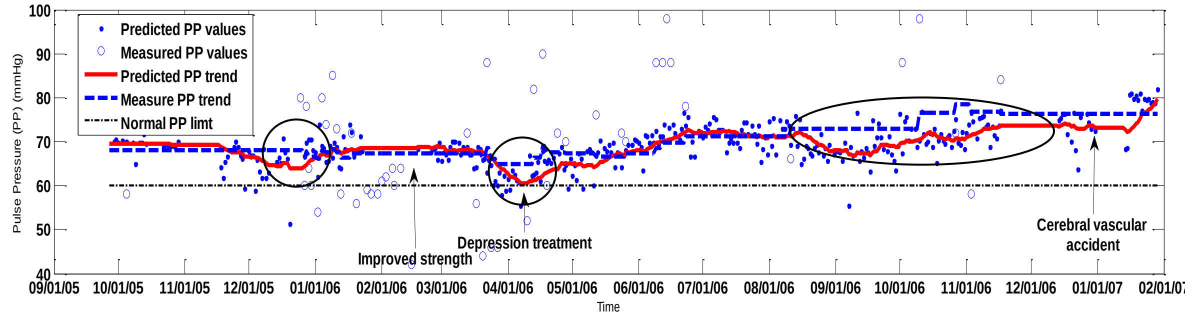

Figure 20: PP trends for resident 3003

This resident had a decreasing functional status during the period under observation: his PP was all the time over the normal limit, with a continuous increasing trend. In fact, he passed away one month after the observation period ended. A different trend resulted for resident 3007 which is depicted in figure 21.

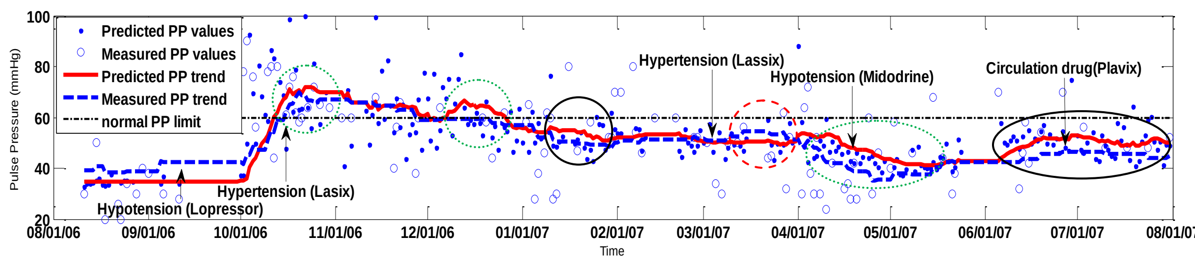

Figure 21: PP trends for resident 3007

The resident 3007 (figure 21) had an episode of high blood pressure (October 2006) after which she recovered and remained in relatively stable condition with the help of medication. The predicted PP trend was able to capture the influence of hyper- and hypotension medication. In figure 21, we see that the predicted PP trend increased when Lopressor (drug that increases blood pressure) was administered (Aug 20, 2006) and decreased when Lasix (drug that lowers blood pressure) was taken.

In both figures there are certain difference between the two PP trends (circled) that could not be explained by the influence of medication that alter motion and sleep. However, given the fact that elderly persons try to hide and negate their deteriorating health status and functional decline, we suspect that those changes are related to this aspect of elderly behavior. Therefore, subtle changes in the sleep and motion pattern were not reported by the residents. For example, resident 3003 was identified with depression in April, 2006, and had a cerebral vascular accident in January, 2007. In both cases the predicted PP trend underestimated the measured PP trend previous and during the time the resident had these health issues. Interestingly, the resident's diary did not mention any change in the way he felt that time. The PP trends for resident 3007 depicted in figure 21 show alternating differences, i.e. underestimation and overestimation of the measured PP trend. Similarly to resident 3003 case, when she felt worse having pneumonia (dashed circle), we can see an underestimation of the measured PP trend. On the other hand, when she felt better an overestimation of the measured PP trend (square doted circles) can be observed.

As mentioned in the methodology chapter, the constants of the algorithm were calculated by trial and error. A value of the algorithm threshold of 0.8 improved ARE by about 10% for both residents, for all choices of features. For the second constant which is the number of initial samples needed for calculating the starting regression coefficients, a value of about 30 samples proved to minimize the error as shown in table 3.

Table 3: ARE for various numbers of initial samples (resident 3007)

N_{start}	7	12	26	33	40	46
ARE[%] Resident 3007	9.1	7.7	7.4	6.7	6.9	7.1

CHAPTER 8

CONCLUSIONS AND FUTURE WORK

The main purpose of this project was to find a link between the sensor data generated by the In-Home monitoring system in place at TigerPlace and vital signs, i.e. PP, of participants connected to the sensor network. Furthermore, after identifying if this relationship exists, it seemed reasonable trying to predict the PP and compare the predicted PP trend with the measured PP trend. In order to achieve the main goal, different classification algorithms including neural network, robust regression, and SVM have been applied to two data sets corresponding to a male and female living at TigerPlace. The results suggest that the bed restlessness and motion levels may be used to predict high PP in elderly and also by taking into consideration the low heart rate led to an improved prediction rate. The robust regression proved to be the best algorithm.
We did not limit our investigation to these findings and therefore, tried to predict the PP trend and compare it with the measured PP trend. Keeping the robust regression as the choice of the algorithm and choosing the day and night motion as features for PP trend calculation, we were able to obtain the predicted PP trend. We think that differences between the two might be able to provide a hint about the possibility of upcoming abnormal clinical events. Surprisingly, the medication influencing the motion and sleep pattern did not alter the PP prediction but the predicted PP trend was able to capture the influence of hyper- and hypotension medication, such as Lopressor and Lasix.

However, more data and more subjects are necessary in order to support the superiority of any of the previous algorithms and truly validate our supposition. One suggestion is that blood pressure of several residents connected to the In-home monitoring system should be measured daily, for a longer period of time (our proposal is for two to four months). In addition, a result fusion (ex. using a 2-out-of 3 voting scheme) might substantially reduce the false alarm rate. Also, other machine learning algorithms such as AdaBoost can be used in conjunction with the SVM and neural network algorithms to improve their performances.

This study demonstrated that other possible improvements or more relevant clinical results can be obtained. They include using sensor data for more than a day before the day the BP measurements were recorded or incorporating more features, such as presence of visitors, time out of the apartment and sleep duration. Right now, with the data that is available, we cannot try the additional experiments varying the number of days because "x days before BP measurement" will eliminate some of the data points of the data sets that are already too small. The elimination will be necessary because those data points will overlap with part of the existing data points and we need to ensure as much as possible that the data points used in the algorithms are independent of each other. On the other hand, based on a conversation with one of the research nurses that we work with, we are not sure that "x days before BP measurement" will provide more relevant clinical results. She explicitly explained that they do not know how many days in advance can signal a potential health problem but intuitively, according to her, “a day is a very good starting point”. It is also known that sensor readings are influenced by factors such as the presence of visitors, time out of the apartment and sleep duration that we only partially accounted for. TigerPlace researchers are currently working on algorithms to detect these features in order to correctly integrate them in future work.

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