Assessing Mobility and Cognitive Problems in Elders

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Abstract

Older adults are living longer and more fulfilled lives, and they desire to live as independently as possible. However, independent lifestyles come with risks that are complicated by chronic illness and impairments in mobility, cognition, and the senses. A primary goal of the TigerPlace eldercare facility is to help residents manage illness and impairments and stay as healthy and independent as possible. In this paper, we describe a multidisciplinary project to investigate the use of sensor technology to provide early identification of problems in mobility and cognition. The technology will be evaluated within the TigerPlace facility.

Introduction

In 2004, a unique eldercare facility, called TigerPlace, opened in Columbia, MO. In anticipation of this event, a group of nursing professors at the University of Missouri made their way across campus to the College of Engineering, seeking new solutions to old problems. Their vision has resulted in a collaboration among researchers in Nursing, Computer Science, Electrical and Computer Engineering, Biomedical Engineering, Health Management and Informatics, Social Work, and Physical Therapy. In this paper, we describe TigerPlace and the first project resulting from the collaboration, which now includes researchers from the University of Virginia and the University of Missouri.

TigerPlace is based on a concept called "aging in place": Rather than forcing elders to move as their needs change, TigerPlace will offer varied services as needed. TigerPlace will not only promote the independence of its residents (Rantz, 2003) but will also help residents remain healthier and active longer by providing ongoing assessment, early illness recognition and health promotion activities within well-designed housing. This environment is designed to help residents avoid expensive and debilitating hospitalizations and, for most residents, avoid relocation to a nursing home.

TigerPlace has 32 independent apartments under one roof, which include 2 bedroom, 1 bedroom, alcove, and studio units. Each apartment has kitchen and living areas. In addition, common facilities are included in the form of a dining room (with a gourmet chef), a living area for socializing, a sports bar, a hair salon, an exercise facility, a meeting room, and a family dining room with an attached kitchen for hosting large family dinners. A wellness clinic is staffed by a nurse three mornings a week, and nurses are on call 24 hours a day, 7 days a week. There is also an on-site veterinary clinic that supports residents' pets.

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

A primary goal of TigerPlace is to help the residents manage their illnesses and stay as healthy and independent as possible. To do so, we must help elders maintain functional ability, which is affected by declines in the areas of mobility, cognition and the senses. Mobility and cognitive impairments lead to functional decline (Myres, 1996). Sensory changes -- especially changes in vision, hearing, balance and proprioception -- mediate the nature and extent of mobility and cognitive impairments and the severity of functional decline.

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. Through careful monitoring, deteriorating health conditions can be identified early, such as a shuffling gait (mobility problem), restless sleep (possible medication error), change in activity level (possible heart condition), or a change in one's typical routine (potential cognitive problem).

The focus of our project is to investigate the use of sensor technology to monitor and assess potential problems in mobility and cognition of elders in realistic home settings. We are interested in sensing alert conditions such as falls. We are also looking for changes in daily patterns that may indicate problems. TigerPlace provides the realistic elder resident home environment in a semi-structured facility in which we will develop and test this new sensing and assessment system. In addition, we want to evaluate the usability of the technology for this population of older adults. We have funding to install monitoring equipment in 44 apartments, in anticipation of a planned expansion. Installation of the equipment and inclusion in the study is voluntary.

Project Overview

The integrated monitoring system under development has three main components as shown in Fig. 1: (a) The In-home monitoring system (IMS), 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. Each residence has a PC that is connected to a main server through a wired network connection. Data is monitored and collected at the main server for research purposes. The sensors, including video, transmit data to the residence PC via a wireless connection.

In-Home Monitoring System

The IMS (Alwan, 2003b) consists of a set of wireless infrared proximity sensors to detect motion, as well as pressure switch pads (sensor mats) that can be used to infer specific activities based on the position of the mat. Other sensors include a stove temperature sensor and switches on cabinet doors. The system is augmented with a bed sensor capable of detecting presence, respiration (normal or abnormal), pulse (low, normal or high) and movement in the bed. The Data Manager (Fig. 1a) collects data from the sensors, date-time stamps the data and logs it into a file that is sent to a secure server as binary streams stripped of identifiers, to ensure HIPAA compliance. The system is non-invasive and exploits low-cost X10 technologies coupled with specialized filtering and analysis.

The system also includes a passive gait monitor that relies on a highly sensitive displacement sensor. The sensor can detect small deflections in the floor induced by a person walking ten feet away from the sensor on both carpeted and uncarpeted wooden and concrete floors. The gait monitor processes the raw vibration signal, extracts features of significance, and analyzes the extracted data to provide basic gait characteristics. Preliminary analysis algorithms were able to differentiate between normal gait, limping, and shuffling, and to measure normal gait step count and to calculate cadence (Alwan 2003a).

Event-Driven Anonymized Video Sensor Network

The video sensor network complements the IMS by collecting more detailed information that is not available with motion sensors, sensor mats, and the gait monitor. By providing visual information about human motion for activity analysis, the video sensor helps reduce false alarms generated by the motion sensor or gait monitor.

To preserve the privacy of the residents, two techniques are used in processing video data. One strategy is to use algorithms to identify a person in the image and extract a silhouette (Wang, 2003). The position, orientation, speed, and shape of the silhouette are then used for capturing activity (cooking, sitting, lying down), fall detection and hazard identification. The second technique

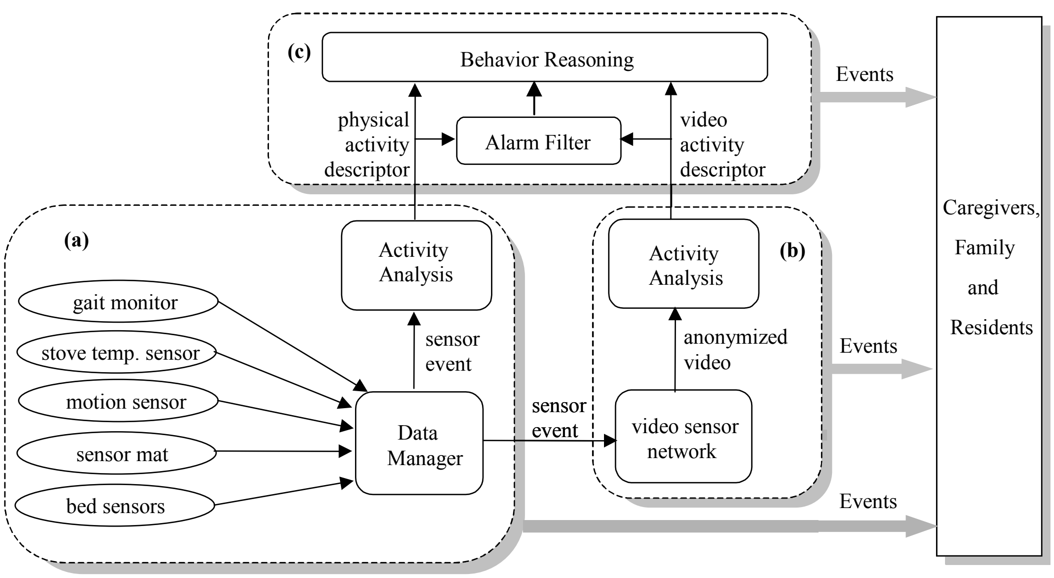

Fig. 1. Components of the integrated monitoring system (a) MARC's In-home monitoring system (b) Event-driven anonymized video sensor network (c) Recognizing and reasoning about behavioral patterns

is to track inanimate objects that are manipulated by the residents. For example, tracking movement of a water bottle can provide indication that the resident is drinking water. The SIFT algorithm is used for vision-based object recognition, and has been shown to work well even in cluttered environments (Lowe, 2004).

Activity Analysis and Behavior Reasoning

In addition to monitoring for urgent conditions and hazards, we are also interested in the analysis of the sensor events captured over time, especially in extracting patterns of activity and then reasoning about behaviors observed over time. To support monitoring, we analyze activities on multiple time scales. Relatively short-term observations of events are used to infer activities such as cooking, getting ready for bed, opening the door to leave, or morning grooming. These short-term observations are made in the **Activity Analysis** components shown in Fig. 1(a) and (b). Likewise, by observing a *sequence of these activities over time*, we can infer, e.g., a typical daytime pattern of behavior, such as getting out of bed, morning grooming, cooking, reading the newspaper, watching television, and so on. This type of longer-term behavior reasoning is represented in the **Behavior Reasoning** component shown in Fig. 1(c).

Although a pattern comprising an activity may be consistent among many people, other patterns may be quite unique to one individual. The value of an intelligent monitoring system is to distinguish a typical pattern for an individual from an abnormal pattern. In our project, we are investigating Hidden Markov Models (HMMs) for learning and recognizing short-term activity patterns. The output of each Activity Analysis process is a descriptor or a set of descriptors that report the likelihood of an activity. This provides a method for fusing data from the two very different types of sensor networks – the IMS sensors and the video sensors.

Fusion is done in the Behavior Reasoning component. There is considerable uncertainty present in this scenario, in part, due to the fact that many behaviors can "look similar" to the sensors. For example, someone who falls down may, for a time, look the same as someone who kneels down to pick something up off the floor. A second source of uncertainty results from the inability of the feature sets to separate different but close behaviors. Additionally, the sensors and feature extractors may, from time to time, produce erroneous results. Such outliers can seriously degrade performance of classifiers if undetected. To produce a robust architecture to classify human behavior observed over time, these forms of uncertainty need to be modeled and managed. To address this, we are exploring fuzzy rule-based systems to model and manage uncertainty for a robust classifier.

While some behavior patterns are common among residents, the definition of "acceptable behaviors" needs to be tailored to individuals. Most statistical classifiers require substantial training data to build generalizable classifiers. Fuzzy rules can also be trained when the data is sufficient, but more importantly, can be modified by the experts (in this case, the nurses) who can insert specific domain knowledge. Events that are highly improbable but nonetheless possible and important to detect are very difficult to "learn" but easy to incorporate in rules. Systems of this type can be tailored to specific residents and easily developed for testing and refinement.

We use learning, when possible, for both the rules and the membership functions that describe the antecedent and consequent conditions. Learning is conducted through probabilistic clustering, such as mixture decomposition (Theodoridis, 2003) and fuzzy/possibilistic clustering (Bezdek, 1999). We also incorporate the nurses' expert domain knowledge to fine-tune and augment the rule base. One advantage of rule-based classifiers is that they can be tailored to particular individuals instead of reflecting only the population statistics. The rule generation can be done by a domain expert (an eldercare nurse), a caregiver, a family member, a spouse, or even the resident. Indeed, we want to explore having the elder residents customize their own rules as part of being an active participant in their own well-being.

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