Healthcare Decision Support Systems at Home

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Abstract

In this paper we discuss the projects of the AdvISe research lab at KU Leuven that introduce decision support systems into the homes of chronic-diseased patients or older persons. These projects aim to improve the quality of life of the subject, without increasing the health care costs.

Introduction

In this extended abstract we discuss projects of the research group Advanced Integrated Sensing lab (AdvISe) from the Faculty of Engineering Technology of KU Leuven that focus on decision support in tele-care applications.

In Europe, the percentage of population over 65 is expected to reach 29.95% in 2020. This will bring along a huge increase in age related and chronic diseases such as diabetes, heart failure, epilepsy and neuro-degenerative diseases such as Alzheimers. This will not only impact the patients and their families but also the health care budget so it will be an enormous challenge to provide qualitative health care at a sustainable cost for society.

The AdvISe research group contributes to a solution for this problem by implementing healthcare decision support systems that allow a transition in healthcare activities from intramural settings to the home of the patients. A first set of such systems are those that provide early diagnosis such as fall prevention methods or early diagnoses of mild-cognitive decline. A second set of systems allow patients to return sooner to their homes after a hospital admittance. Consider for example systems that allow patients to do their rehabilitation exercises at home. A third and last set of systems are those that allow elderly people to postpone their transfer to a nursing home such as fall detection systems and systems that detect epileptic seizures. In this paper we will focus on the first and third set of systems. An essential aspect in all these projects is that real-life data is collected to build these systems. This gives more guarantees that the developed systems can be applied in practice, although this is an expensive task since i) annotation of data leads to substantial costs; ii) the data is often highly unbalanced due to the relevance of rare events such as falls or epileptic convulsions, requiring a lot of data to be collected; and iii) data is often patient-specific so data needs to be collected from different patients.

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Measuring Fall Risk at Home through Gait Analysis

One third of community-dwelling older adults fall at least once a year. Additionally, patients suffering from neurological diseases such as a stroke, dementia and Parkinsons disease are also reported to have a high fall risk. Important indicators of this elevated fall risk are gait and balance deficits. Gait abnormalities are therefore considered among the most consistent predictors of falls and fall prevention guidelines recommend gait evaluation and gait training to reduce the risk for future falls in both patient groups. We are currently investigating two different sensor modalities for the automatic follow-up of fall risk: video camera's and audio sensors.

In a first study we are using a system consisting of multiple wall-mounted cameras that can automatically measure the time an older adult needs to cross a predefined transfer zone in the home environment. The purpose of this study is the preliminary validation of the algorithm of the camera system through installation and data collection in the homes of three older adults for periods varying from eight to twelve weeks. Trends in the measured transfer times are visualized and subsequently compared with the results of the Timed-up-and-Go tests obtained during the acquisition periods and the clinical observations of a geriatric nurse. The results indicate that it is possible to identify long-term trends in transfer times which can be indicative of adverse health related events (Baldewijns et al. 2013).

A second approach investigates a system able to detect footstep locations through acoustic information retrieved from a wireless sensor network with small and relatively cheap of the shelve microphone arrays. If footsteps can be accurately determined, it is not only possible to determine gait speed but also more detailed gait parameters such as e.g. step length and step time. Results on this dataset show that a median of errors of 31cm per footstep location is achievable, but results heavily depend on the positions of the microphones relative to the footsteps(Van Den Broeck et al. 2013).

Automatic Monitoring of Activities of Daily Living (ADL)

An example of an early diagnosis system is the automatic monitoring of clinically relevant ADL (e.g. eating, personal hygiene, toilet usage, etc.) and the detection of both acute and gradual changes in these ADL patterns. Acute changes are abnormal events that are critical and require an immediate alarm. Examples of such abnormal events include: fall incidents, water that keeps running or a sudden general absence of activity. On the other hand, we also want to detect gradual changes. These changes are important for an early detection of problems such as (early stage) dementia. Examples of such changes are sleeping disorders, ADL decline and behavioural disturbances. The information about these activities and changes in behaviour can then be presented to the caregivers (including family members) to adapt older peoples care plans, and as a consequence, increase their quality of care and quality of life. Hence, allowing them to stay longer at their homes. In the AMACS (Automatic Monitoring of Activities of daily Living using Contactless Sensors) project (Mertens et al. 2011) we investigated the use of video camera's, PIR-sensors and sensors that measure the consumption of public utilities for this purpose.

Wireless Acoustic Sensor Networks (WASN) with audio and ultrasound receivers can also be used for the monitoring of ADL. (Vuegen et al. 2013) describes a baseline approach for ADL classification based on Gaussian mixture models.

Safety and Alarming Systems

As indicated before, falling is one of the most important problems for elderly. Systems that can automatically detect fall incidents are hence very important. To develop a system that works in practice, a good real-life dataset is essential. For our camera-based fall detection system we have installed a camera system at the place of residence of seven older person during the period 2009-2013 and recorded over 21000 hours of video. During this period we registered 29 real fall incidents (Debard et al. 2012). Experiments show that the results of state-of-the-art methods differ significantly between publicly available simulation data and this real life dataset.

Another important alarming system we have been working on for the last couple of years is the automatic detection of epileptic seizures through video camera's and accelerometers. Here, we both use classical machine learning approaches (Cuppens 2012) as well as more novel approaches. An example of the latter is an adaptation of a method used for anomaly detection based on extreme value theory. The advantage of this approach is that no annotation of data and hence expert (neurologist) interaction is required resulting in substantial cost savings. The results of our approach on real data acquired from seven patients with hypermotor seizures are comparable with a state-of-the-art supervised machine learning based approach which requires a labeled dataset (Luca et al. 2014).

Conclusions

In this abstract we presented the research activities of the AdvISe research lab of KU Leuven that are focussed on telecare applications and smart environments targeting older people or patients with a chronic disease. An important aspect of our research group is that we start from datasets collected from real-life situations using different sensor modalities and applying different machine learning methods.

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