Exploring Patterns of Activities of Daily Living in the Home Environment

Thijs M. Tönis [1], Harm op den Akker [1], Simone T. Boerema[1], Freek van Polen[2], Hermie J. Hermens[1,3]

[1] Roessingh Research and Development, Enschede, The Netherlands
[2] Almende, Rotterdam, The Netherlands
[3] University of Twente, Enschede, The Netherlands

Background

Senior citizens tend to live longer and longer independently. Judging whether a senior person is still capable of living on his own is often based on the occurrence of incidents, with all consequences thereof. In the specific case of early dementia, the symptoms are not immediately apparent and the occurrence and severity of incidents progress gradually over time. In this case, the children or grandchildren are burdened by the question whether or not the elderly adult can still live safely and independently in his or her own home. This decision is only based on input obtained through incidental visits. We believe that the capability of independent living can only be objectively judged, by a health professional, if long term objective information on the elderly person's daily activities of living (ADL) is available.

The progress in the field of miniaturised wireless sensors makes it possible to obtain real-time, objective information on a user's activities in his home environment in a way that is unobtrusive and respects the user's privacy, to ultimately be able to automatically, and unobtrusively detect slow changes in the behaviour of elderly people living in their own homes. A system, comparable to [1] is needed, one that is able to recognize a broad spectrum of ADL (e.g. cooking, eating, and sleeping) from the output of various types of miniaturised wireless sensors.

Goal

In this work we describe the first step in the development of the system aforementioned: the setup of an experiment in a house fully equipped with miniaturised wireless sensors, capable of detecting ADL performed by a single user. The goal of the experiment was to capture real-time sensor data and simultaneously obtain the gold standard on the subject's current activities in the house. From an enormous and redundant sensor-set we want to identify the minimal set of sensors needed to accurately recognise ADL.

Methods

Five subjects have been living solitary in a fully sensor-equipped house, for five days each, as part of the experimental validation of the wireless sensor network platform developed within the ALwEN project [2]. Figure 1 shows the floor plan of our experimental setup in a normal house, including the installed equipment. The various coloured squares in the figure indicate the placement of the various types of sensors that were used. 1) Pressure sensors were placed under chairs, couches and the bed, to detect the use of this furniture. 2) Magnetic switch sensors were placed on doors, kitchen cupboards and kitchen appliances to detect the state of the doors (open or closed). 3) As the kitchen and stairs don't have doors, their use was detected by light gates, placed at the kitchen pass through and up- and downstairs. 4) Passive infrared sensors were placed in each of the rooms to detect the subject's movement through the house. 5) Temperature and humidity sensors were placed in the kitchen and bathroom to sense environmental changes, indicating cooking and showering. 6) All electrical appliances (e.g. the television, washing machine, and vacuum cleaner) and all the lights were equipped with AC current sensors to detect electrical currents flowing through them, indicating their use. 7) Additionally the washing machine, iron and vacuum cleaner were equipped with a 3D-accelerometer, to detect its usage. 8) Finally, the subject was wearing a 3D-accelerometer and a heart-rate sensor.

A gold standard is needed to define the truly performed ADL. To this end, seven cameras were placed, covering most of the living spaces, excluding the toilet and bathroom because of privacy. Video images will be annotated by two independent researchers, making it possible to retrospectively identify all ADL performed by the subject. From this we can validate the activities recognised based on the sensor dataset using clustering techniques. The large corpus of sensor data also gives the opportunity to study the minimal sensor set needed to detect ADL with an acceptable accuracy.

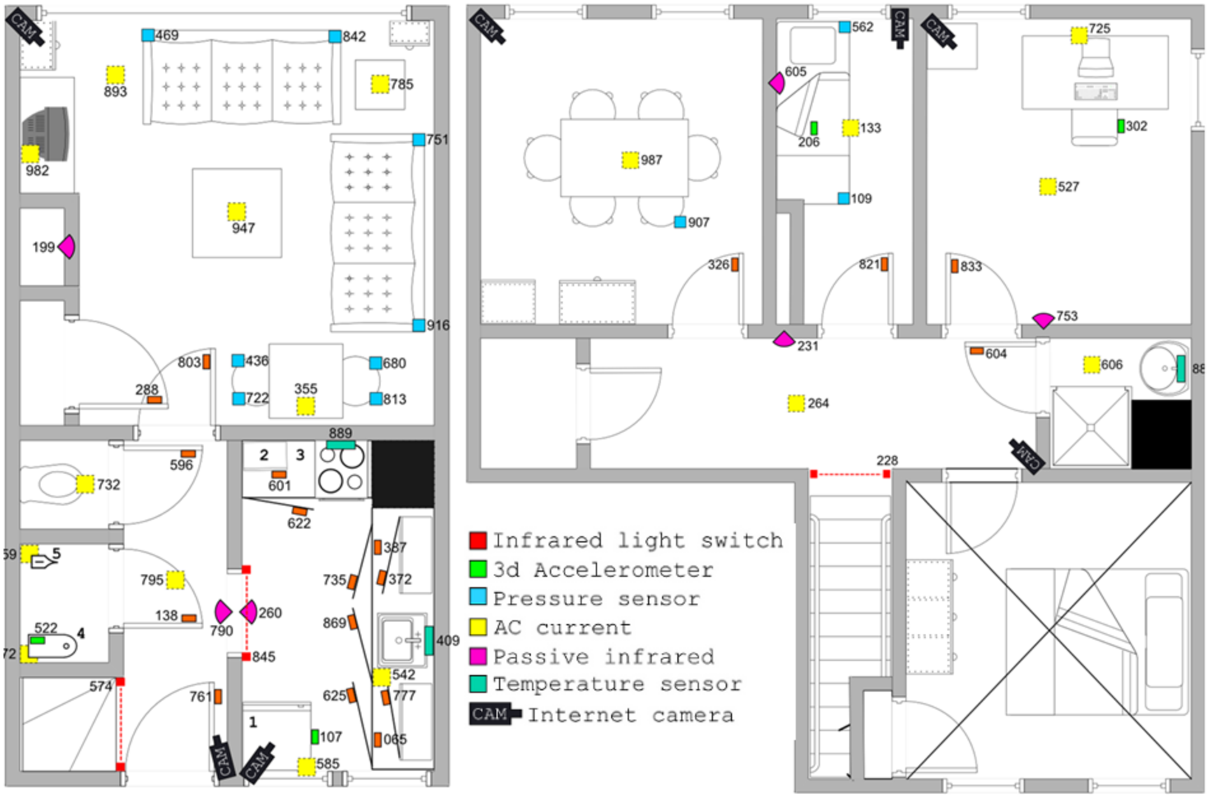

Figure 1: Floor plans of the ground floor (left) and upper floor (right) of the experiment house, including sensors and cameras.

Results and Discussion

The experiment took place from March 2011 till June 2011. In this period we have created a large corpus of sensor data from five healthy subjects living in the equipped home environment. In total we gathered sensor and video data of 36 days (576 hours). All 63 sensors send each minute their state of the previous minute, which was stored in the database. Although no results based on the dataset are available yet, we have shown that wireless sensor technology has great potential to be applied in home monitoring environments. In our opinion the use of a gold standard (camera system) is essential during this early stage of research towards an ADL monitoring system. We believe a monitoring system like this should be wireless in order to be easily applicable in any home environment. The wireless nature of the system makes it vulnerable to data loss. Data analysis will show whether our redundant sensor setup is sufficiently resistant against these errors.

The next step will be to create the gold standard ADL data set by hand-annotating the video data on all relevant events, ranging from “door open”, “television on”, to more complex compound events such as “cooking” or “cleaning”. Using the gold standard data we can experiment with machine learning techniques that have already proven their merit in earlier studies such as Support Vector Machines [3] in order to find the best method of training classifiers for the various events and evaluate them properly. From the recognized activities, “activity-patterns” (such as daily or weekly patterns) must be extracted, and compared to some definition of a healthy lifestyle for a particular user. The final step of automated extraction would be to automatically detect slow changes in the recognized activity patterns in order to be used in the detection of early stage dementia.

References

[1] Intille, S. S., Larson, K., Tapia, E. M., Beaudin, J., Kaushik, P., Nawyn, J., & Rockinson, R. (2006). Using a Live-In Laboratory for Ubiquitous Computing Research. *Pervasive Computing*, *3968*, 349-365.

[2] ALwEN project website. www.alwen.nl

[3] Zhao, L., Wang, X., & Sukthankar, G. (2010). Recognizing household activities from human motion data using active learning and feature selection. *Technology and Disability*, *22*(1-2), 17-26.