CARE: Context Awareness in Residences for Elderly

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Abstract—**In this paper we present a system that is able to monitor activities of people in a domestic environment. The application area is that of ambient assisted living. Because of the increasing number of elderly living at home and the foreseen shortage in the number of caregivers, remote ICT-based applications will have to be developed. One of the tasks of such systems is to monitor elderly in their ability to perform the activities of daily living (ADL). We developed a system consisting of a low-power, low bandwidth wireless sensor network, incorporating simple switch sensors. As a pilot the system was installed in the apartment of an elderly lady. The data were partly annotated by the woman self. We developed a pattern recognition method based on probabilistic models. The detected clusters compare well with the labels of the annotation.**

I. INTRODUCTION

The growing population of elders in our society calls for a new approach in care giving. To avoid rising costs associated with hospitalization, nursing homes or day care centers, it is important that people continue to live in their homes as long as possible. Living independently also contributes to a feeling of well-being. In order for elders to extend their lives at home, some form of automatic health monitoring is required. A good indicator of the health status of elderly, particularly their cognitive status, is the ability to perform activities of daily living (ADL). Examples of such ADL's are bathing, cleaning, and cooking [1].

Usually questionnaires are used to assess the performance of the elder. However, such a method is costly and an assessment of the health status can not be done frequently and completely. By doing this with a telemonitoring system the work can be transferred from the home care professionals to a remote professional. An automated monitoring system would give much more insight and would ease the step from living independently to assisted living. A monitoring system will also be of use to the family and home care workers. For example, if it can be detected that in the morning somebody got out of bed and dressed, the home care worker can visit the elderly at home. This makes the process much more efficient.

Telemonitoring is still not common because of a number

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of reasons. First of all the infrastructure for fast data communication (broadband internet) between the home and a care center was not available until the last years. Only recently some cities decided to connect sustainable homes for elderly to broadband internet. A second obstacle relates to the sensor systems in the homes. Many of the commercial systems need a dedicated communication network, in most cases a special (wired) domotics network, which has to be installed in the home. Thirdly it is important to work with non-obtrusive sensors like switches, movement sensors, pressure mats or sound detectors instead of camera's because of the privacy of the users. Such simple sensor systems require advanced data processing methods to extract the desired information. We developed a system consisting of a wireless network with simple sensors and carried out experiments in the home of an elderly lady.

In this paper we first give an overview on related work. Then we describe our system and the method for intelligent data processing. We describe the experiments in which an unsupervised data analysis was carried out on the data and show that distinctive clusters of activities can be found.

II. RELATED WORK

Human activity recognition is a broad research field. Far out the largest body on activity recognition is carried out using cameras and computer vision techniques, see for example the surveys in [2] and [3]. The application areas for these vision systems are mostly surveillance and safety, but also natural interaction is an application area, for example gesture recognition for control of computers.

Activity recognition is becoming also important in the application area of health care. Changes in activity patterns can be related to many chronic diseases. For example patients with chronic obstructive pulmonary disease (COPD) have a decrease of spontaneous physical activities compared to the healthy control group, and it has been shown that such a decrease relates to a higher risk for hospitalizations [4]. In this particular application accelerometers are used which are worn by the patient.

In our current project we are mainly interested in using the sensor system as an assistive technology for elders with cognitive impairment. Pollack [5] makes a distinction in three forms of assistance: "(1) by proving assurance that the elder is safe and is performing necessary daily activities, and, if not, alerting a caregiver; (2) by helping the elder compensate for her impairment, assisting in the performance of daily activities; and (3) by assessing the elder's cognitive status". The first category aims to ensure safety and wellbeing while there can be a reduction on the caregivers load. The second category provides guidance to people, like giving reminders or notifications what they

need to do and when. The third category attempt to infer how well a person is doing –in the cognitive sense- based on observations of activities of daily living. This is for example important to judge whether an elder has to move from an assisted living home to a care institute. In all three cases it is important that the system is able to measure the activities and classify them, or reason about the performance.

One particular line of research focuses on modeling and recognizing the progression of dementia, mainly by looking at a specific task. In [6] a model is presented that describes a specific task (in this case the 'Kitchen Task assessment') and simulates the progression of dementia using a mathematical model based on symbolic and sub symbolic representations. In [7] another task is used ('Hand washing task') and sensors (in this case a camera system) are used to recognize the execution status and performance of this single pre-established activity and to provide adequate assistance at the right moment.

Our work focuses on the recognition and evaluation of a repertoire of activities with non-intrusive sensors. A comparison of different types of non-intrusive sensing modalities for activity recognition was recently presented in [8]. The results showed that simple static motion detectors outperformed RFID tags and a bracelet that was worn by the patient. Simple sensors distributed in the house were also used by [9], who incorporate state transitions in their model, making it a typical hidden Markov model (HMM). In our approach we also combine a network of simple sensors with advanced processing techniques.

III. FROM SENSORS TO ACTIONS

Figure 1 gives a schematic overview of the system we are building. At the lowest level the various sensor modalities provide the measurements. In the scheme we see not only switch-like or proximity sensors, but also sensors like heart monitoring sensors can be incorporated in the system. On the basis of these measurements an indication of the current activity is given by using the computational approach described in section V.

The current activity is evaluated by comparing its pattern with the standard pattern for that activity, and a trend in time is going to be computed. On the basis of this evaluation a message is generated which falls in one of the four categories: 1) reminder; 2) notification; 3) alert and 4) alarm. For example, a reminder is generated if somebody forgot to take its medicine, or missed a meeting with the daycare centre. A notification is generated if some trends are detected, for example, the person is sleeping less every night, or has a decrease in social activity. An alert is generated if potential dangerous situations may occur, and an alarm is generated if after some notifications and alerts the behavior is still not normal, or if some specific sensors fire (for example CO2 sensor).

On the basis of the type of message (reminder, notification, alert or alarm), the message is sent to a different person. Typically a reminder is sent to the patient, notifications to the patient and maybe family or doctor. This person will take an action as a follow up of the sensor signal.

In a first phase we wanted to test the lower layers: how well can we distinguish different activities based on sensor signals.
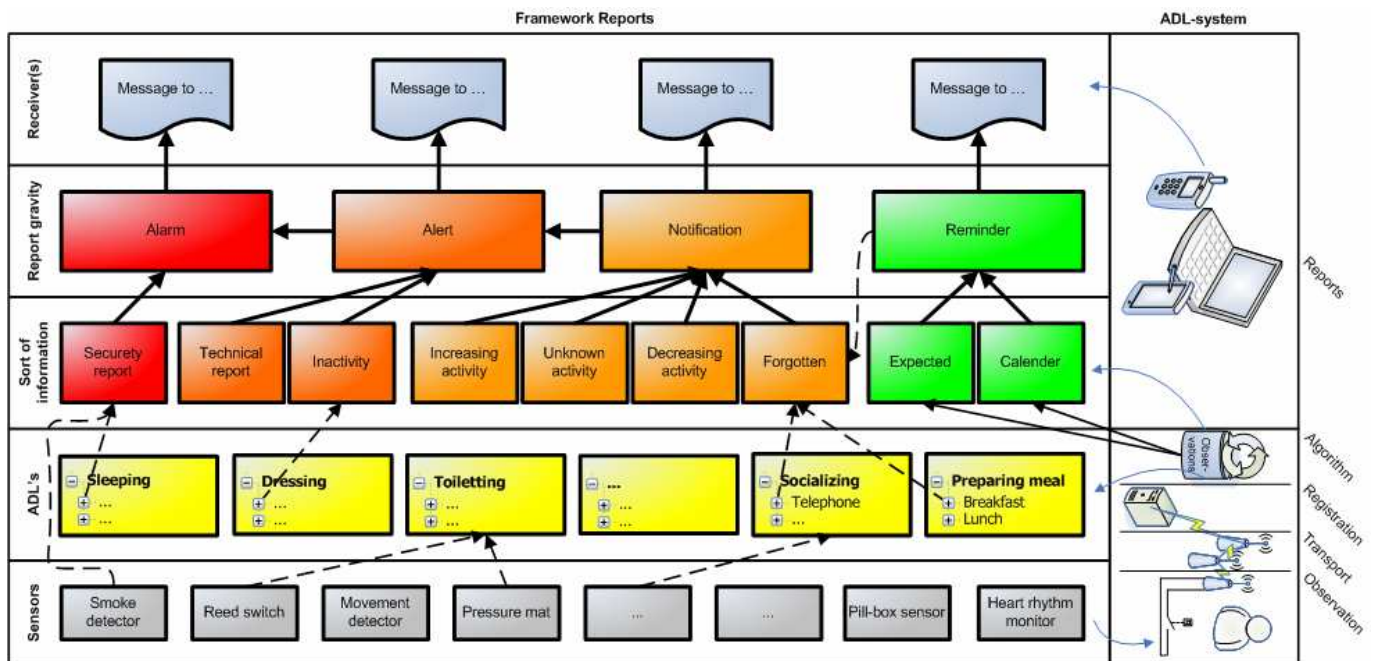

Fig. 1. Global set-up of our monitoring system

IV. IMPLEMENTATION OF THE SENSOR SYSTEM

Our system was built upon two main lines: ease of installation and minimal intrusion. To avoid cables and associated hole-drilling we used a wireless sensor network consisting of a number of small network nodes, to which simple sensors were attached. After considering different commercially available wireless network kits, we selected the RFM DM 1810 The RFM kit comes with a very rich and well documented API and the standard firmware includes an energy efficient network protocol. The kit comes with a base station which is attached to a personal computer using USB connection. A new sensor node can be easily added to the network by a simple pairing procedure, which involves pressing a button on both the base station and the new node.

The node which functions as gateway is connected to a local server. On this server a program is running to read the sensor data together with their time stamps and to store the data in a MySQL database. The database can be accessed via a secure internet connection. The analysis of the data is done off-line. A schematic description is given in figure 2.

V. RECOGNITION SYSTEM

Our goal is to recognize ADLs from sensor readings in a house. Since we use very simple sensors such as switches, the state of each sensor is either '0' or '1'. For the temperature sensor we used a threshold to make it into a binary signal. Since all the sensor states are sent continuously to the server, the system generates a binary multi-dimensional signal $\mathbf{x}(t)$. Our system gives a recognition of the activity at discrete time steps. Therefore the raw input signal is transformed into a time series $\mathbf{x}_k$ by quantizing the time in periods Δt of 300 s. An element of $\mathbf{x}_k$ is 1 if a sensor fired at least once in Δt. The activity could be one of the predefined categories: $\mathbf{a}$={toileting, washing, …}.
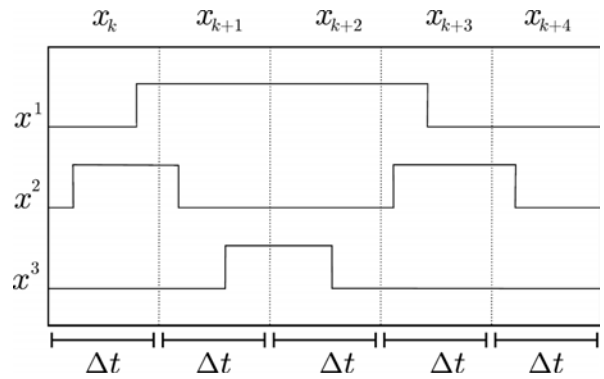

Fig.3. Discretization of the sensor signals

In a first approach we tried to estimate the activity $\mathbf{a}_k$ at time step k directly from the state $\mathbf{x}_k$. For that we used a probabilistic approach, in which we compute the probability of activity a at timestep k given the state $\mathbf{x}_k$ using Bayes rule:

$$p(\mathbf{a}_k \mid \mathbf{x}_k) \propto p(\mathbf{x}_k \mid \mathbf{a}_k)p(\mathbf{a}_k) \qquad (1)$$

The distribution $p(\mathbf{x}_k \mid \mathbf{a}_k)$ can be learned if a training set is available in which we have many examples of a sensor vector $\mathbf{x}_k$ and corresponding activity $\mathbf{a}_k$. Such a training set is only available if we have a large annotated dataset. We used a naïve Bayes model, like [8], to represent this distribution.

The model as described in Eq. 1 is not able to represent temporal dependencies. It is much more intuitive that the probability of a given activity not only depends on the current sensor state, but also on the previous activities. Some sequences of activities are more likely than other sequences of actions. A model which is able to describe such temporal dependencies is a *Hidden Markov Model* [11]. In a special version of this model (first order Markov model) $\mathbf{a}_k$ is conditionally dependent on only $\mathbf{a}_{k-1}$. Figure 4 gives a graphic representation of an HMM.
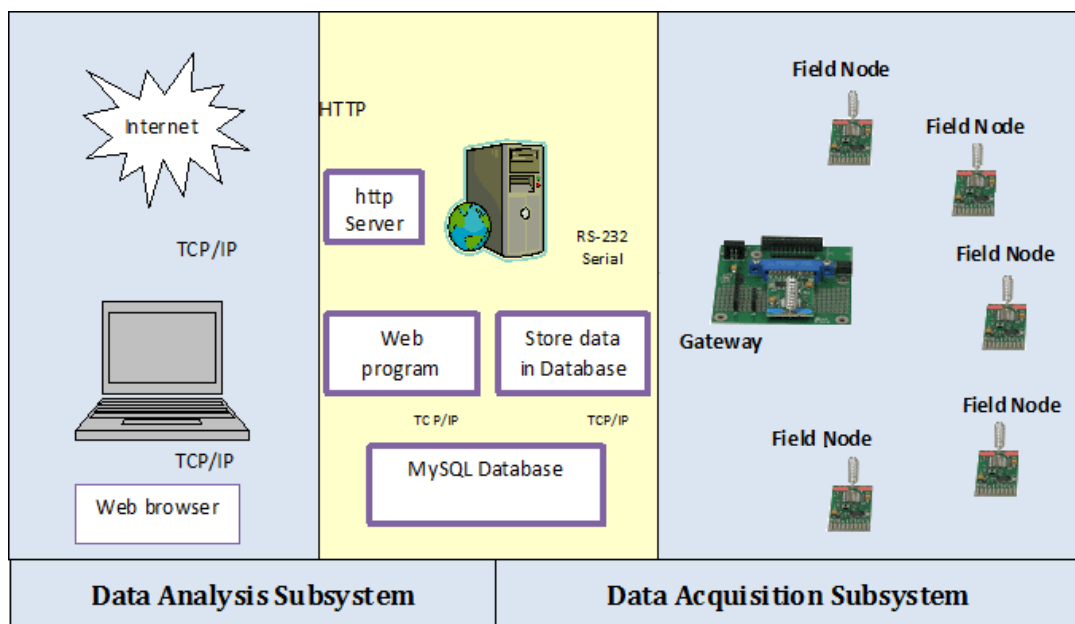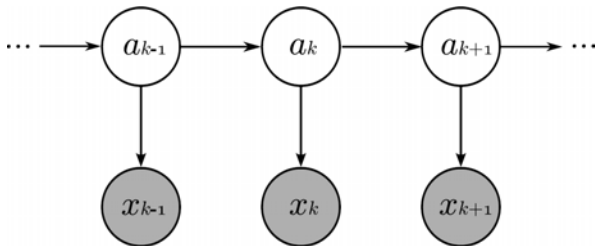

Fig. 2. Implementation of the system

Fig.4. Hidden Markov Model

A HMM can be used to compute the probability of observing a sequence X= x_1 , x_2 , .. x_k but can also be used to find the most likely sequence of activity labels A = a_1, a_2, ... a_k of length K, given the observation sequence X. In previous work we showed that the HMM gives a better result then the Naïve Bayes approach [10].

In case we have no labeled data for the hidden variables an EM method can be used to find the best segmentation into a number of activity clusters given the observations. This is called 'unsupervised learning'. This is the method that is presented in the experiments.

VI. EXPERIMENTS AND RESULTS

With consent of the inhabitant and the patient committee of the care institute, we mounted the sensor network in the home of a 72 year old woman. Sensor data were collected during 6 days. Our network consisted of 18 wireless nodes. To each node a sensor is connected. We used 13 switch sensors, mostly mounted on doors of rooms or cupboards. An immersion sensor was used for placement in the toilet cistern to detect flushing, 2 temperature sensors were places in the cooking area and an humidity sensor was placed in the bathroom. The nodes were fitted in the apartment using double sided sticking tape in order to avoid any damage to the building. An overview of the placement of the sensors is given in figure 5.

We did not want to put up a camera system in the apartment so it was not possible to have a full annotated data set for the six weeks of measurements. The woman was willing to cooperate and offered to maintain a diary of the activities with the times the activities took place. The annotation was done by hand on a form which was handed out to the woman. In this way we were able to have an annotation of the data for one week. An example of the raw sensor signals and the annotation for a full day is given in figure 6.

Since we did not have the annotation for the entire data set we could not use a supervised training method. Instead we used an unsupervised method as described in the previous section. We used an EM procedure in which we segmented the data in a certain number of clusters. After the clustering we calculated the likelihood of the data given this clustering. Then we increased the number of clusters and repeated the procedure. From figure 7 it can be seen that the optimal segmentation is achieved for four clusters. These clusters can be interpreted as toileting, leaving the house, feeding the neighbourhood cat and being idle.

Comparing the recognized clusters with the annotation of one week allows us to calculate a precision and recall score (table 1). Precision is the percentage of correctly recognized activities out of all recognized activities, while recall is the percentage of correctly recognized activities out of all annotated activities. The activities of feeding the cat and being idle are excluded from the table because they were not annotated

Our algorithm successfully recognizes toileting; however, it recognized many more instances of toileting than annotated. This is because our subject did not very accurately label her toileting activity. Leaving the house is also recognized well, although some instances were missed because the subject left the house through the back door, which was not part of this cluster
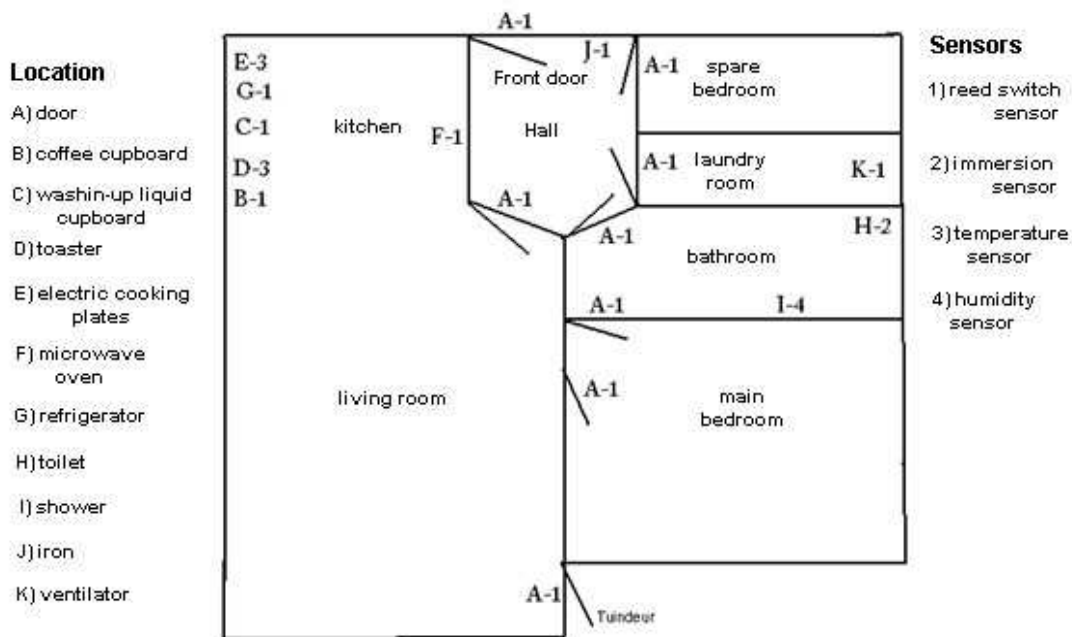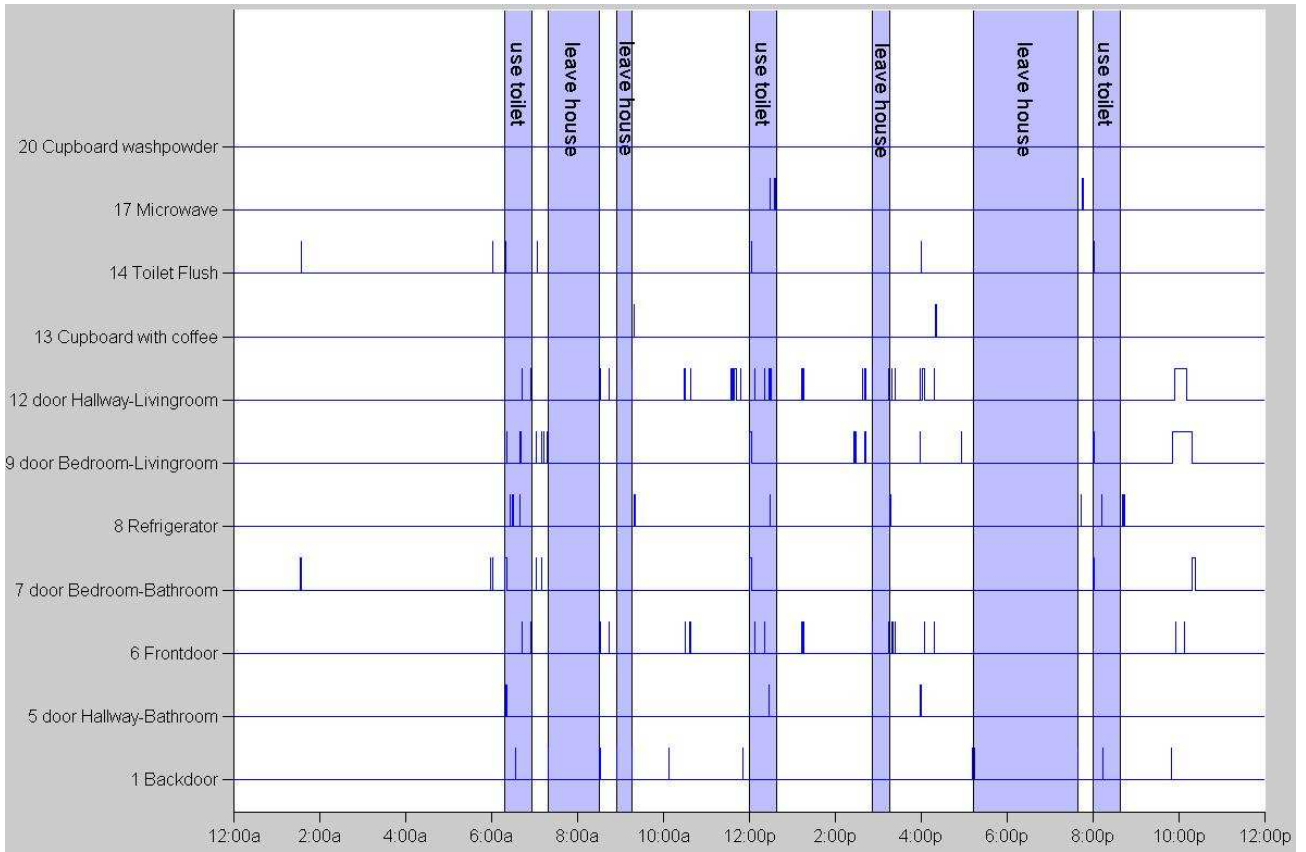

Fig. 5. Locations of the sensors in the home

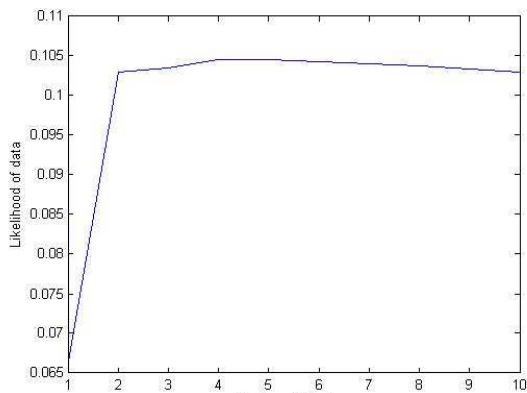Fig.6. Example of sensor firings and annotation added by the user.

Fig.7: The data likelihood as a function of the number of clusters.

Table 1: Results of the data analysis

Activity	Precision	Recall
Toilet	13%	100%
Leave	37%	74%

VII. CONCLUSION

We showed that a low-cost, low-power network with simple sensors can bring information about the activities of an elderly person living independently in a home. We are able to confirm the results of [8] in the sense that simple proximity and switch-like sensors are able to estimate the activities of daily living. Our pattern recognition method based on HMM performs well on these data.

We found that special attention has to given to the annotation. In this project we did not have enough annotated data and used an unsupervised clustering technique. This technique has some advantages but also some disadvantages

One of the advantages is that certain activities that are not annotated will become visible. In this case the clustering method came up with a prominent cluster that combined the sensors of the fridge and the sensors of the back door. None of the annotated activities had this pattern. After a final interview with the patient K. it became clear that she was feeding the stray cats frequently. Since this was not allowed by the housing company, she did not annotate this activity.

A disadvantage of the unsupervised clustering method is that it makes different clusters for an activity that is carried out in a different way. For example, 'Leaving the house' can be done using the front door or the back door.

Our future work will involve ways to have a more reliable annotation scheme and larger data sets to test our methods.

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