
Review on Assisted Living Technologies

ASSISTED LIVING TECHNOLOGIES FOR THE ELDERLY AND
ELDERLY WITH MILD COGNITIVE IMPAIRMENT AND DEMENTIA

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List of Acronyms

ADL:	Activity of Daily Living
ALT:	Assisted Living Technology
ECG:	Electrocardiography
EEG:	Electroencephalography
EMG:	Electromyography
GIS:	Global Information System
GSM:	Global System for Mobile Communications
GPS:	Global Positioning System
IPA:	Intelligent Personal Assistant
MMSE:	Mini-Mental State Examination
PIR:	Passive Infrared Sensor
RFID:	Radio-Frequency Identification

1 Introduction

This report presents an overview of the current status of Assisted Living Technologies (ALTs) with a focus on technologies for the elderly and people with Mild Cognitive Impairment (MCI) or Dementia (D) as well as the use of machine learning for such applications. We present the current state-of-the-art in the research field as well as a short summary of commercial technologies.

The report is organized as follows. Section 2 gives an overview and some examples of the commercial technologies grouped into ALTs for the general public, for the elderly and for the elderly with MCI/D. Section 3 and 4 present the ALTs under research for the elderly and for the elderly with MCI/D, respectively. Section 5 gives a summary of the research work carried out within a number of special projects and research groups that focus on elderly with MCI/D. Section 6 concludes this document with a summary.

2 Commercial Assisted Living Technologies

A considerable amount of assisted technologies are currently (or will be soon) available in the market. In this section, we give an overview with some examples of available technology and systems, grouped into general public, elderly and elderly with MCI/D users.

2.1 General

Assisted living technologies have been progressively incorporated into homes with different objectives: automation and comfort, safety, security, energy consumption reduction, health, etc. Smart sensors and devices have evolved significantly from simple automation systems to more intelligent ones. The combination of several sensors and devices allow the construction of more complex systems such as smart homes. This section gives a short overview of devices found in the market that can be used in a smart home system.

Simple lighting control systems can be very helpful, comfortable for users and energy efficient. There are several commercial solutions in this domain. Light control can be performed via the socket itself, such as the Emberlight socket [Emberlight, 2015] (Figure 1a): it can turn on/off any lamp connected to it via smart phone. It can also be done by smart lamps, as is the case of Philips Hue [Hue, 2012] (Figure 1b) and Cree connected light bulb [Cree, 2015] (Figure 1c). The intensity of the lights can be controlled as well.



Figure 1: Examples of lighting solutions: smart socket and smart bulbs.

In addition to lamps, other devices can be automatically managed. The Belkin WeMo Switch (Figure 2a) can control electronic devices (also remotely) and set specific schedules [WeMo, 2013]. The Logitech Harmony Home Control (Figure 2b) controls home automation devices with dedicated home control buttons [Logitech, 2013].

Other factors regarding the environment at home can be automated. The Ecobee3 Thermostat [Ecobee, 2014] (Figure 5d) controls the ambient temperature. It turns on/off the heating/cooling system taking into account the energy profile in the home and the

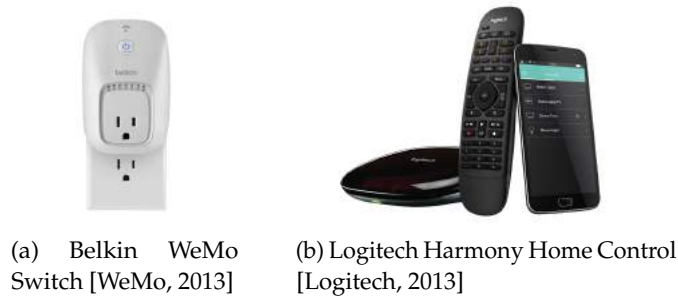


Figure 2: Examples of smart home devices control.



Figure 3: Smart thermostat and smoke and CO detector sensors.

outside weather. Nest Thermostat [Nest, 2011] (Figure 4b) offers the same function, but it is also a learning system, which means the system shall adapt to the users' preferences. Nest also has a Smoke and CO detector [Nest, 2011] (Figure 3c), which can be combined with the Thermostat. The Nest products can send alerts and indicate a path light if they identify people walking in the dark.

Still on ambient features, but from a safety point of view, there exist commercial solutions for detecting water leaks, changes in temperature and humidity, and open doors and windows. An example is the WallyHome [Vitality, 2014] (Figure 4), which send alerts when necessary through audio or via mobile.

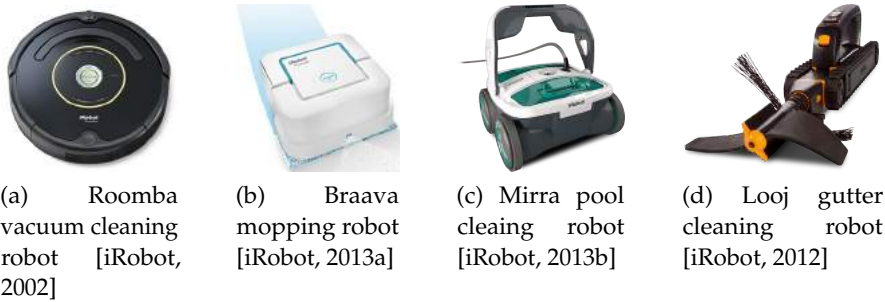
Many technologies address better comfort. Technology can help in housework such as cleaning. There exist several cleaning robots in the market such as Roomba for vacuuming, Scooba for floor scrubbing, Braava for mopping and Mirra and Looj for outdoor maintenance (Figure 5). It also exists devices for cooking assistance. Pioneering Technologies has developed the RangeMinder, which reminds people with sound alerts when the food being prepared in the oven was forgotten. The timer is set based on how much the dial has been turned. Also, a device with same function for the microwave, the Safe T Sensor, and a SmartBurner that do not let food be burned or cook unevenly (Figure 6). Smart fridges are also in the better comfort category. Samsung Family Hub



(a) WallyHome sensor [Vitality, 2014]

(b) WallyHome mobile interface [Vitality, 2014]

Figure 4: WallyHome system.



(a) Roomba vacuum cleaning robot [iRobot, 2002]

(b) Braava mopping robot [iRobot, 2013a]

(c) Mirra pool cleaning robot [iRobot, 2013b]

(d) Looj gutter cleaning robot [iRobot, 2012]

Figure 5: iRobot robots for home.

[Samsung, 2016] is an example of a refrigerator that has a touchscreen similar to a smart phone enabling apps for playing music, displaying pictures and leaving notes; it also allows ordering food from local groceries and takes pictures every time the door closes so the users can be aware of what they have on it (Figure 7).

Regarding home security, there are cameras that can stream the home environment and its video can be watched at smart phones. Nest Cam [Nest, 2016] and Logitech Circle [Logitech, 2015] provide this service and send alerts in case something suspicious happens.

In addition to that, there exist also smart locks. The company August has developed smart solutions for doors. August Doorbell Cam is a camera that stream the video and allows users to see and speak with visitors using their smart phone [August, 2015a]. The camera also records missed visitors and replays conversations. The August Smart Lock



(a) SmartBurner [Technology, 2014c]



(b) Safe T Sensor [Technology, 2014b]



(c) RangeMinder [Technology, 2014a]

Figure 6: Pioneering Technologies devices for cooking assistance.



Figure 7: Samsung Family Hub Refrigerator [Samsung, 2016].



(a) Nest Cam [Nest, 2016]

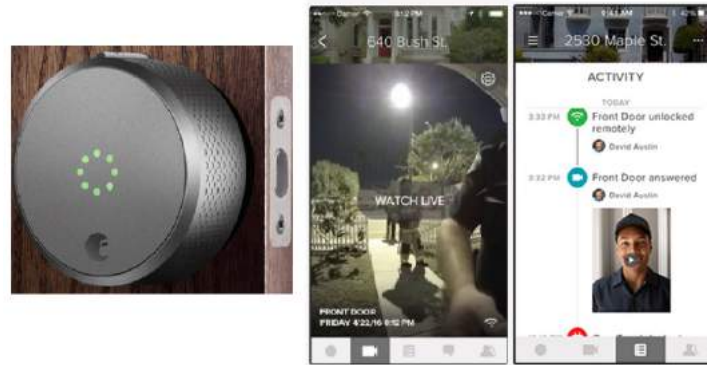


(b) Logitech Circle [Logitech, 2015]

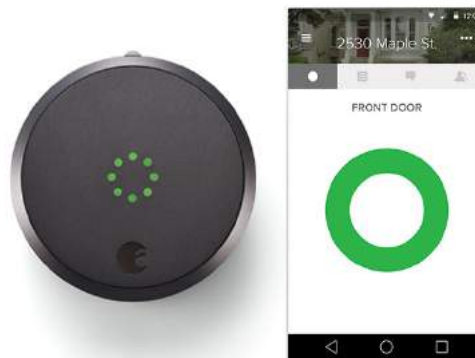
Figure 8: Smart security cameras.

allows the use of a smart phone to lock/unlock doors and keep track of who uses the door [August, 2015b].

When it comes to health, biosignals can be measured and monitored with the great variety of biosensors in the market. For instance, NeuroSky sells EEG and ECG sensors for measuring stress, heart rate, blood pressure, sleep tracking, etc. [NeuroSky, 2004]. Training and exercising is also an important factor in everyday life. To that end, a



(a) August Doorbell Cam [August, 2015a]



(b) August Smart Lock [August, 2015b]

Figure 9: August door security camera and lock.

smart watch is definitely a useful gadget [Sony, 2012, Apple, 2015] (Figure 10). It contains sensors (GPS, accelerometer, gyroscopes, etc.) that are able to provide tracking of activities and movements, record distance, speed and pace when walking, running or cycling for instance. Some can as well monitor vital signs and take physiological measurements. Besides that, they are basically a smart phone on the wrist: they can receive/make calls, install apps with functionalities of weather forecast, music, calendar, maps, and so on.

The many devices and sensors presented here can be combined to make a more complete solution, addressing several functions in the home. In this sense, there exist apps to control and connect several devices, such as Wink [Wink, 2014] (Figure 11).

A more elegant solution is the so-called Intelligent Personal Assistant (IPA). It is a software capable of interacting with its user by voice input, by means of artificial intelligence. In the context of a home solution they are known as smart speakers. These IPAs can be connected to smart sensors and devices and interact with them. They also have access to the web to gather required information, play music, set alarm and



Figure 10: Examples of commercial smart watches.



Figure 11: Smart home app Wink [Wink, 2014].

calendar events, etc., by voice commands. Amazon Echo Alexa [Echo, 2015], Google Home [Google, 2016] and Ives [Ives, 2016] are examples of it (Figure 12). Another IPA that besides voice also uses video camera is under development, Jibo [Google, 2016] (Figure 12d).

In addition to these there are many companies that offer solutions for smart homes. They create a system by using several sensors and devices (such as the ones described e.g. lamps, thermostat, etc.) in which automation is the main utility function.

2.2 For the Elderly

Some ALTs are designed for the elderly people in order to help them with known needs. For instance, forgetting to take medicine is a very common issue. A very usual solution is medicine dispensers. There are simpler ones, which are for example daily pillboxes with a capacity of five alarms [Lifemax] (Figure 13a) or eight [TabTime] (Figure 13b); a bit more automatic ones such as Pivotell Dispenser [Pivotell] (Figure 13c), which supports 28 alarms and makes the correct dose available at the correct time of day or night, locking

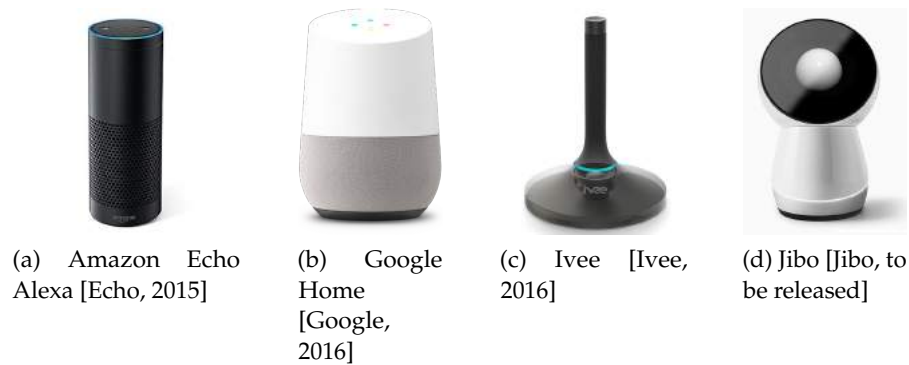


Figure 12: Examples of commercial IPA.



Figure 13: Examples of medication reminders.

out other pills; and more complex and complete ones such as Philips Dispenser [Philips] (Figure 13d) and TabSafe [TabSafe, 2010] (Figure 13e) which generate alarms also to caregivers.

A different commercial solution for medicines is the GlowCap and GlowPack [Vitality, 2011] (Figure 14). The GlowCap (Figure 14a) is a pills bottle with a lid that glows when it is time to take the pill. If in the first hour the medicine is not taken, a song is



Figure 14: Vitality medication reminders [Vitality, 2011].



Figure 15: Examples of fall detectors.

played and, if the bottle is still not opened, an email, text message or phone call will notify the user. The GlowPack (Figure 14b) is a bag with the same procedure, but it can contain other types of medicines rather than pills. Both provide a weekly and monthly report available for the patient, clinician and manufacturer.

Another evident issue in the elderly population is the frequent falls incidence (and consequences). Technical commercial devices in order to detect falls exist in many different solutions, usually containing a help button. Examples are Task fall detector [Task, 2014], Philips GoSafe Alert system [Lifeline, 2013] and the Sense4Care fall detector [Sense, 2016] (Figure 15). The two first ones send an alarm when a fall is detected and if the user does not turn it off the help center provides the necessary support. The latter device calls a person specified by the user.

More complete systems can also be found, such as the Lively Safety Watch [Lively, 2013] (Figure 16). It looks like a smart watch that detects falls as well as inactivity and other situations. It also has a one-push help button, medication reminders, daily activity sharing, step counting, and family alerts.

Falls can also be detected by sensor floor solutions [Shape, 2014] (Figure 17). The SensFloor is a large-area sensor system which detects the location, the number and the movement of people. Besides fall detection which sends an alarm to the nurses, the



(a) Lively Safety Watch and Sensors



(b) Lively interface

Figure 16: Lively safety watch system [Lively, 2013].



(a) SensFloor sensor system



(b) SensFloor sensor mat

Figure 17: SensFloor systems [Shape, 2014].

system also detects presence and wandering behaviour of users. There also exists a sensor mat which sends an alarm as soon as a person is sitting on the bed with their feet over the mat. Other mats are more used specifically in beds and chairs so the carer can be notified if the user were to get out and requires assistance [Lifemax, 2008a] (Figure 18).

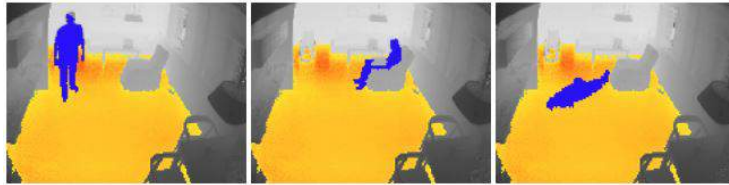
Depth sensors are also emerging in the market for the purpose of fall detection. An example is the XCenter RoomMate, which will be released during 2017 [XCenter] (Figure 19). It can identify falls and alert staff or relatives via SMS and email. There is no need of wearables or any other device. It has other functionalities such as indicating that a person did not come back to bed after leaving for a while and voice call alarm.



Figure 18: Lifemax sensor mats [Shape, 2014].



(a) XCenter device



(b) Depth images

Figure 19: XCenter RoomMate system [XCenter].

A recent device is the Kinesis, which assesses fall risk (Figure 20): it calculates the risk of falling and the reasons or conditions that lead to falling. All the data are accessible through a smart phone app [Kinesis, 2016].

Regarding exercising and rehabilitation for the elderly people, there exists systems such as Jintronix [Jintronix, 2014], VirtualRehab [VirtualRehab, 2014] and Fitness@home [Philips, 2016] that have video for the user to follow the exercises and a camera to detect the user's movements (Figure 21). The monitoring and assessment can be followed by nurses and doctors.

Monitoring systems for the elderly have become an important tool for carers and family. Intel has developed a system called QuietCare to identify deviations from normal daily routines by using several motion sensors and collecting their data (Figure 22)[QuietCare, 2008]. Monitoring the user's trips to the bathroom can alert for a possible urinary tract infection, for example. Reports are then generated and alarms can be sent to the health service. A similar system, GrandCare, also includes medication management and a socialization module which enables video callings and calendar events [GrandCare, 2011].



Figure 20: Kinesis [Shape, 2014].



(a) Jintronix system [Jintronix, 2014]



(b) VirtualRehab system [VirtualRehab, 2014]



(c) Fitness@home by Philips and RespondWell [Philips, 2016]

Figure 21: Examples of exercises and rehabilitation systems.

The trend is that more complete systems will emerge, integrating many functionalities. For instance, the responsive lighting system Stack (Figure 23) serves for monitoring, comfort and safety purposes [Stack, 2014]. It is a lighting system that can be manually controlled with a smart phone, but also provides an automatic light control. In addition, a platform will be released in 2017 to work together with this system, StackCare. It aims to provide useful information about occupancy, activity level and ambient light level through machine learning functions. This can account for safety during the nights especially for the elderly people, for example. It can be used as a patient activity and monitoring module, in which caregivers can receive alerts such as "increase in night bathroom visits".



(a) QuietCare sensors

Resident	#	System Status	Bedroom Exit	Bath Falls	Meds	Meals	Activity	Night Bath
Betty/Robert Clark	102	●	●	●			●	●
Cathy Davis	103	●	●	●	●		●	●
David Edwards	104	●	●	●			●	●
Ella Francis	105	●	●	●		●	●	0
Fran German	106	●	●	●			●	●
Greta Holder	107	●	●	●	●	●	●	●
Hanna Ireland	108	●	●	●			●	●
Irene Jacobs	109	●	09:01AM	●	●	●	●	●
Jessie King	110	●	●	●	●	4	●	●
Anne Brown	150	●	●	●			●	●

Review Alerts/Actions or Motion Through Door or Client Norms/Reports for Group Pine Crest Village

Review Alerts/Actions for Institution Group Pine Crest Village

(b) QuietCare interface

Figure 22: QuietCare system [QuietCare, 2008].



Figure 23: Stack responsive light system [Stack, 2014].

2.3 For the Elderly with Dementia/MCI

Few ALTs are in the market to attend an even more specific group of users, elderly people that have MCI/D.

Regarding the difficulty people with MCI/D often have with managing complex devices, smart phones have been especially designed for them. Doro smart phones are very intuitive to use, have help functions and provide safety features such as the assistance button (Figure 24a)[Doro, 2014].

In order to help on finding objects there exist object finders, such as the FOFA [FOFA, 2008] (Figure 24b), the Loc8tor [Loc8tor, 2008] or the TrackR [TrackR, 2016].

Wandering is a common issue for people with MCI and dementia. There exists a Wander Reminder, which is a system that records personalised messages to help people with dementia maintain their daily routine and reminding them not to leave their homes at inappropriate times of the day (Figure 25a) [Society]. A similar device is the Lifemax voice alert, which can be connected to sensor mats and magnetic clips, easing the alert



Figure 24: Examples of assistive devices for people with dementia and MCI: objects finders.

for the users in case of need (Figure 25b) [Lifemax, 2008b].

Another available solution for wandering is the SmartSoles [SmartSole, 2015]. It consists of a GPS such as a smart phone hidden and sealed in an insole (Figure 25c). The user's location can be tracked through any smart phone, tablet or web browser, and texts and e-mail alerts are sent if they enter/leave a previously defined area.

Besides those, there exists also a watch that contains a wandering detection alarm [Vivago, 2012]. When a wandering behaviour is detected, nurses can be notified and if necessary, door locks can be activated to not let the person leave at inappropriate times.

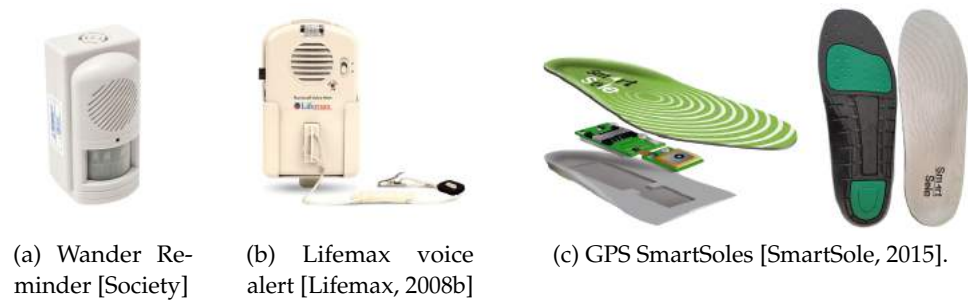


Figure 25: Examples of assistive devices for wandering.

3 ALT for the Elderly

There exists several reviews on technologies for elderly people. Chan et al. [2008] reviews on smart homes, wearable devices and robotics grouping the projects into Europe, United States, Asia and Australia researches. Morris et al. [2012] reviews on smart homes, robotics, virtual reality and gaming, telemedicine and social supports. Rashidi and Mihailidis [2013] group technologies and projects into smart homes, mobile and wearable sensors and robotics, point out algorithms in activity recognition, context modelling, anomaly detection, location and planning, and go over applications in health monitoring tools, wandering prevention and cognitive orthotics. Finally, Ni et al. [2015] provide an extensive review on smart homes, regarding activity recognition activities and all aspects related to it such as sensors, features selection and classification.

In this section 3, we focus on the projects of ALTs for elderly people that we think are relevant to be of our knowledge so we are able to reflect on ongoing studies, limitations and future possibilities. The next section (Section 4) has the same aim, but then the projects are about ALTs for elderly with MCI/D. Both sections present the research projects grouped into functionalities.

3.1 Preventing, Monitoring and Predicting Falls

Fall is one of the clearest issues when it comes to the elderly population. Many reasons can lead to falling, which is the main study pursued by Robinovitch et al. [2013]. They have camera data from 227 falls of 130 individuals from two long-term care facilities. They perform an observational study to identify why (e.g. weight shifting, trip, collapse, etc.) and in which situation (e.g. walking, standing, etc.) the fall has occurred, presenting the results in a statistical analysis. The most frequent cause of falling was incorrect weight shifting (41%) and most of the falls happened while walking forward (24%).

Fall detection can be achieved for instance by using a Kinect, by means of its depth sensor. Several methods were proposed, such as using tracking methods [Mastorakis and Makris, 2012] or geometrical analysis between the person and the floor planes and angles [Yang et al., 2016]. The accuracy for these experiments reaches very good results (some present 100%), but the tests were not made with real-falls dataset. There exists also a floor-vibration sensor developed for fall detection [Alwan et al., 2006]: it uses a piezoelectric sensor coupled to the floor surface (Figure 26). It identifies falls with 100% accuracy by analysing the floor vibration pattern (frequency, amplitude, duration, etc.). Accelerometers can as well be used for that purpose. There are several algorithms based on threshold values (angles, positions, etc.) reaching 97% of accuracy [Bagalà et al., 2012]. Although the accuracy obtained is very good, there is still a considerable number of false alarms, which is very inconvenient for users, and therefore is a current field of study.

Machine learning plays an important role on fall detection by using Kinect depth sensor [Stone and Skubic, 2014] or accelerometers [Özdemir and Barshan, 2014]. In



Figure 26: Floor-vibration sensor for fall detection [Alwan et al., 2006].

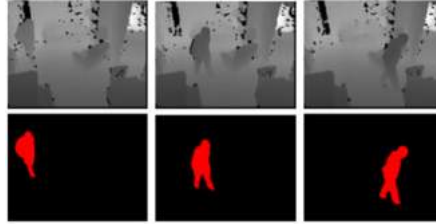


Figure 27: Depth images and extracted foreground from an apartment for fall detection [Stone and Skubic, 2014].

both cases, a dataset needs to be collected, processed and a classifier is trained for fall detection. For instance the depth maps output from the Kinect pass through several processing steps such as background extraction and segmentation (Figure 27) up to features extraction. Stone and Skubic [2014] use 454 acted falls and nine natural ones to train and test their system. They obtained different accuracies results depending on if the person was standing (98%), sitting (70%) or lying down (71%). These results are reduced to 79%, 58%, and 5% when there is some kind of occlusion in the scene. The system gave one false alarm per month. Özdemir and Barshan [2014] reached accuracy above 95%, but with an acted falls dataset and still having false alarms.

There is also research on using more than one sensor for input data. Kepski and Kwolek [2014b] use a ceiling-mounted Kinect depth sensor to detect falls. In addition, an accelerometer is used to trigger the Kinect when a fall is detected. Once activated, the Kinect confirms whether it was a false alarm or not. Kepski and Kwolek [2014a] use the same system, but the Kinect is attached to a pan-tilt head so it can track the user. Again, high accuracy results (98%) but with an acted falls dataset and many false alarms. Zhang et al. [2014a] deploy a Doppler radar for fall detection and a motion sensor network to reduce the number of false alarms. The radar effectively detected the fall by machine learning algorithms applied to the data gathered with 98% accuracy. The motion sensors were used for confirming the fall, reducing the number of false alarms in 63%. The dataset was very small though and not with real falls.

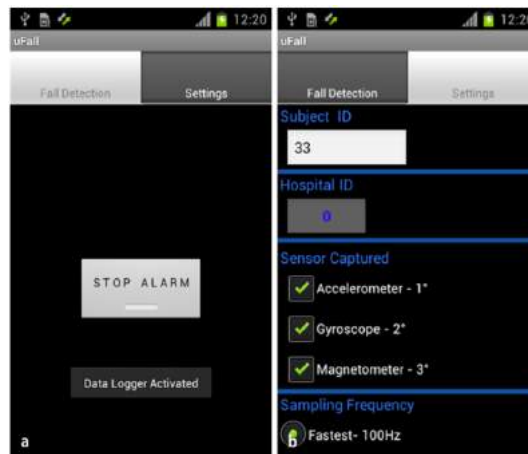
Management and prevention of falls is done by fall risk assessment methods. Kinect was also used in this sense, by means of behaviour monitoring in the bedroom [Liao et al., 2016] and gait analysis [Dubois and Charpillet, 2014, Baldewijns et al., 2014]. In the

former, Liao et al. [2016] detect state transitions in the bed (i.e. sitting, laying, getting out, etc.) through geometric data acquired from depth maps. An alert is sent to caregivers when the state is considered dangerous (e.g. sitting on the bed at midnight). In the latter, the studies track the person's center of mass and calculate characteristics such as the length and the duration of steps and the speed of the gait.

Gait analysis is also possible by using accelerometers [Jiang et al., 2011, Aztiria et al., 2013]. Several variables such as position, angles, angular velocity, linear acceleration, etc., can be acquired through these sensors. Jiang et al. [2011] use the data to assess the gait (normal, attentive and dangerous) and predict falls. Howcroft et al. [2013] list forty studies that use inertial sensors for fall evaluation in the elderly community. The inertial sensors are mostly positioned in the lower back and many variables assessed (position and angle, frequency, linear acceleration, etc.). Falls are classified using fall history, prospective occurrence and clinical assessment. Half of the studies proposed a fall risk prediction, having accuracy results from 62% to 100%. Future research will be on determining best sensor position and connection between falls and reasons.

FARSEEING (FALL Repository for the design of Smart and sELf-adaptive Environments prolonging INdependent livinG) was a European project that took place from 2012 to 2015 [Mellone et al., 2015]. The goal was to provide a better prediction, identification and prevention of falls within the elderly community. The complete project includes smart phones, smart shoes, a smart home system, a dedicated wearable unit for high-risk subjects and a telemedical service model, providing clinical health care at distance. The smart phone is used to collect data from its embedded sensors (accelerometers, gyroscopes and magnetometers) [Mellone et al., 2012a,b]. The users should have it in their lower back by wearing a belt. Two developed apps deliver necessary information for activity monitoring, fall detection and fall risk assessment (Figure 28a).

The smart home system is a wall device with an interface (Figure 28b) accounting for fall risk, fall assessment and exercise guidance, in order to prevent and manage falls [Nawaz et al., 2014]. It also consists of sensors and actuators in the home and a RFID system to track and identify users and objects. Five senior citizens used the system to assess the usability of the system. The reaction was overall positive, but still some issues were pointed out such as difficult readability and inactive screen. The smart shoes (Figure 28c) consist of an insole that combines 3D inertial sensor, a barometer and a force sensing (to measure the load distribution under the foot). It is used for activity recognition, including sitting, standing, walking, stair climbing, ramps and elevators, reaching an accuracy of 93% [Moufawad El Achkar et al., 2016]. A web-based fall risk assessment tool (FRAT-up) was also developed [Palumbo et al., 2015, 2016]. It calculates the probability of a subject falling over a year with a predictive statistical model. The platform proves to be valid for use, although it varies significantly between the tests done in four different datasets, which needs to be highly improved.



(a) Farseeing's smart phone application [Mellone et al., 2012a]



(b) Farseeing's smart home interface [Nawaz et al., 2014]



(c) Farseeing's smart shoes [Nawaz et al., 2014]

Figure 28: Farseeing project results.

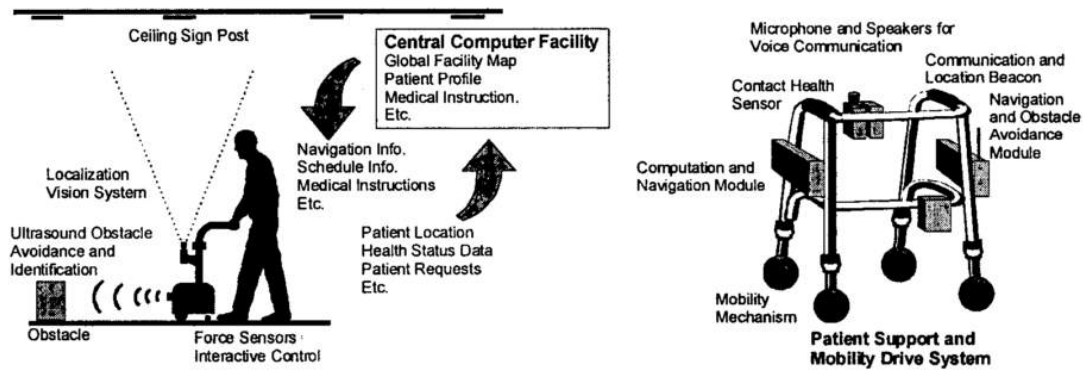


Figure 29: PAMM System Concept. [Dubowsky et al., 2000].

3.2 Mobility, Safety and Monitoring

A Personal Aid for Mobility and Monitoring (PAMM) smart cane was developed for the use of elderly people [Dubowsky et al., 2000]. It provides physical support when walking/standing and guidance, including the right path to be followed and obstacles detection and avoidance (Figure 29). It also allows the monitoring of the user's vital signs. The smart cane is equipped with acoustic sensors to detect obstacles, sensors to measure forces and torques applied to the cane handle in order to identify the user's intent, wireless modem to acquire information on the user's schedule and maps and transmit health parameters to the computer, and a two-way communication system with the carer's computer. The cane had field trials in an elderly living facility, which helped on improving the system and showed a high degree of acceptance. Special improvement would be needed in the control modes, which was difficult for the elderly people in the care assistance to deal with.

In order to help elderly people to use public transport an app was developed in the Assistant project (Aiding SuStainable Independent Senior TrAvellers to Navigate in Towns) [Barham et al., 2015]. It makes use of the GPS in the mobile phone to provide trip planning and guidance over the journey on public transportation. It uses an artificial intelligence based system to detect error (i.e. wrong direction or transport) and communicate with the user. It can also send notifications for someone the user knows in case of assistance or help needed (Figure 30). Besides visual feedback, it also has audible and haptic functions, which makes it useful for blind, partially sighted and deaf people, as well as people that have difficult with oral communication. The project has been developed with involvement of 30 end-users in each stage (concept, pilot and prototype), which means participants over 55 years old. Their insights of public transport and current assistive technologies (specially phones and smart phones) were taken into account from the beginning of the project. The app is to be released in 2017.

Casattenta (Aware home, in Italian) is a smart home designed for elderly people containing several smart sensors in order to track the inhabitant and identify dangerous

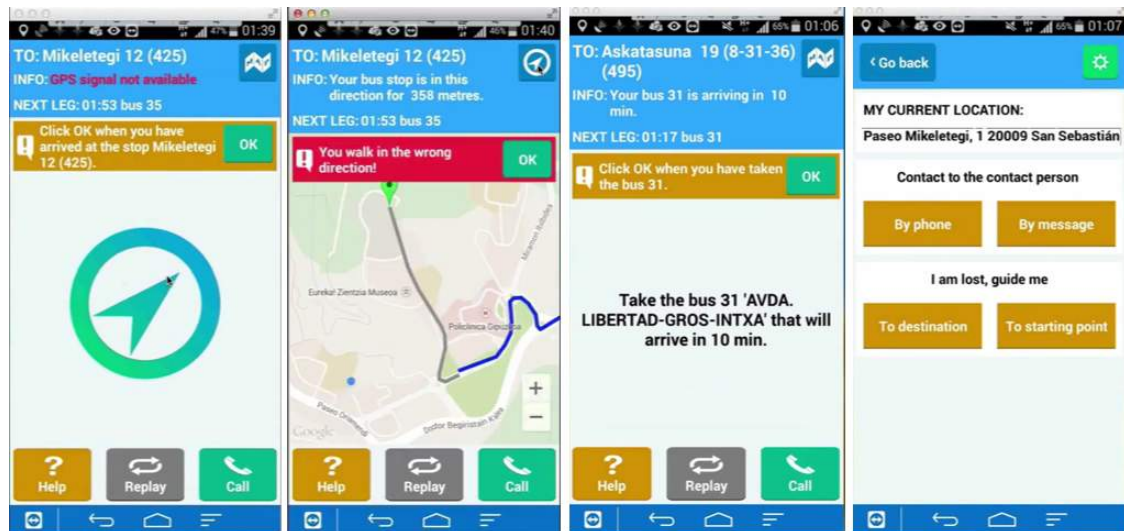
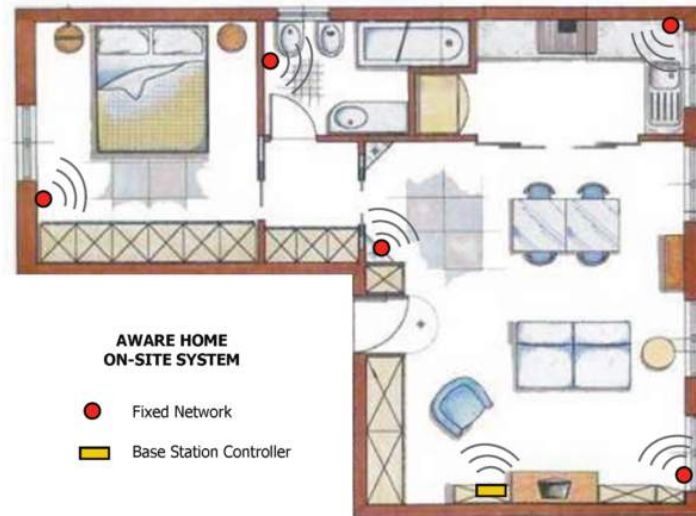


Figure 30: Assistant project app. [Barham et al., 2015].

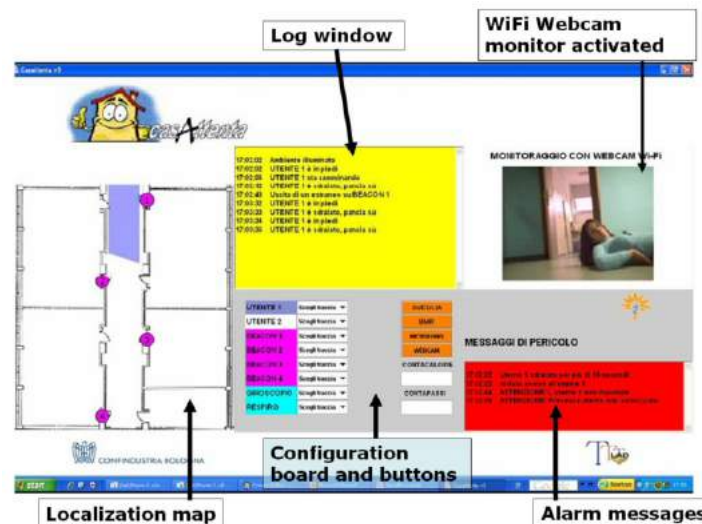
situations (e.g. falls, gas leak) [Farella et al., 2010]. There are wearable sensors and some fixed in the rooms (Figure 31a). The wearable consists of a vibro-motor for alerts, a tri-axes accelerometer for fall recognition and a gyroscope for step counting. In the house there are PIRs for presence detection, microphones for identifying scream for help and unusual sounds and sensors monitoring the temperature, humidity, lighting and opened doors/windows. There is also a graphical feedback enabling functions such as social interaction (video-conference), alarms, reminders, home surveillance and safety (camera in case of fall) (Figure 31b). An example of a situation would be that a fall is detected, the wearable sensor vibrates and if not turned off by the user, the system notifies a call center. The project was developed in two years and tested in labs and regional companies in Italy for improvement. Currently, the system is being installed in collaboration with the company eResult Srl [eResult] and included in the European project ALFA [ALFA].

The ALFA (Active Living for Alzheimer Patients) project combines three solutions for people with dementia at early stage to live independently and to stimulate cognitive functions:

1. Agenda and Fall Detector (Figure 32a): both mobile apps. Agenda is dedicated for planning events and its respective reminders. Fall detection alerts in case of falls. The mobile device should be worn in the waist.
2. Wearable Inertial Sensors (Figure 32b): monitoring of activities, motion and gait analysis.
3. Infrastructure (Figure 32c): system manager that enables the scheduling and synchronization with the other items.



(a) Casattenta's Sensor Network



(b) Casattenta's Graphical Interface

Figure 31: Casattenta Project [Farella et al., 2010].

These solutions will be tested in the nursing houses of the Alzheimer Netherlands Association [Association].

In the Necessity project, Botia et al. [2012] describe their development for an in-home monitoring system for the elderly people. They used PIRs, pressure and magnetic sensors and designed an automation software capable of detecting falls and adapting over time to improve its performance (to reduce number of false alarms). It was tested in a living lab first for adjustments and then there was a pilot experience in 25 houses



(a) Agenda and Fall Detector



(b) Wearable Inertial Sensors



(c) Casattenta's Graphical Interface

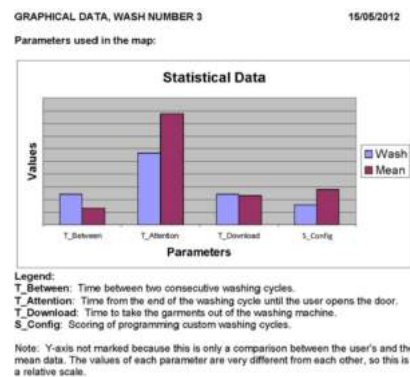
Figure 32: ALFA project solutions [ALFA].

of elderly people for one year. There was one successful case in which the elderly fell down and the system recognized, although many false alarms have happened. The system is now a commercial product and working for elders in the South-East of Spain [Intelligence and ami2].

The European project Easy Line+ built a system to help elderly and disabled people to have more autonomy in the kitchen [Blasco et al., 2013]. The system is called AmI Kitchen and aims at easing the use of household appliances, provides information



(a) User interface



(b) Sample page of a report sent to carers

Figure 33: Easyline+ project [Blasco et al., 2013, Bono-Nuez et al., 2014].

and issues warnings, detects emergency situations and analyses the data gathered to evaluate the user's quality of life. All the information can be accessed by carers and relatives. RFIDs sensors are used in appliances, other sensors such as gas, fire, smoke and flooding were installed for emergency situation detection and magnetic sensors for the doors, light and presence sensors as well. There is a learning system able to detect the user's behaviour, habit changes, loss of abilities and cognitive level [Picking et al., 2014]. It automatically generates a report containing the user's habits of the activities performed in the kitchen [Bono-Nuez et al., 2014] (Figure 33b). There is also a user interface, in which the status of the appliances can be monitored (Figure 33a). The system was assessed by 63 real users and 31 carers in labs in Spain and UK, older people from 59 years old and also younger people with disabilities. Overall, the system was evaluated with good usability (3.85 out of 5 - excellent) and physical, sensory and cognitive accessibility (90%).

Vacher et al. [2013] developed a smart-home based on audio technology and environment sensors, the Sweet-home project. The aim is to provide audio interaction in which the user can easily control their home environment. In the first studies, eight microphones gather data for sound classification including direct information about the user status (e.g. cry, snoring, etc.) and activities being executed (e.g. hair dryer, vacuum cleaner, etc.). Classification machine learning algorithms were used for that end. Their idea is not to do speech recognition itself, but recognize vocal orders, distress sentences and equipment usage. The system was tested by 13 persons (average of 35 years old), in the Domus smart home (Figure 34) [DOMUS]. The participants were asked to perform some ADLs and to make vocal orders. The activity recognition reached an accuracy of 63% (the data that trained the algorithm was not the same for testing). Later, they implemented an on-line activity recognition algorithm by joining the audio data with

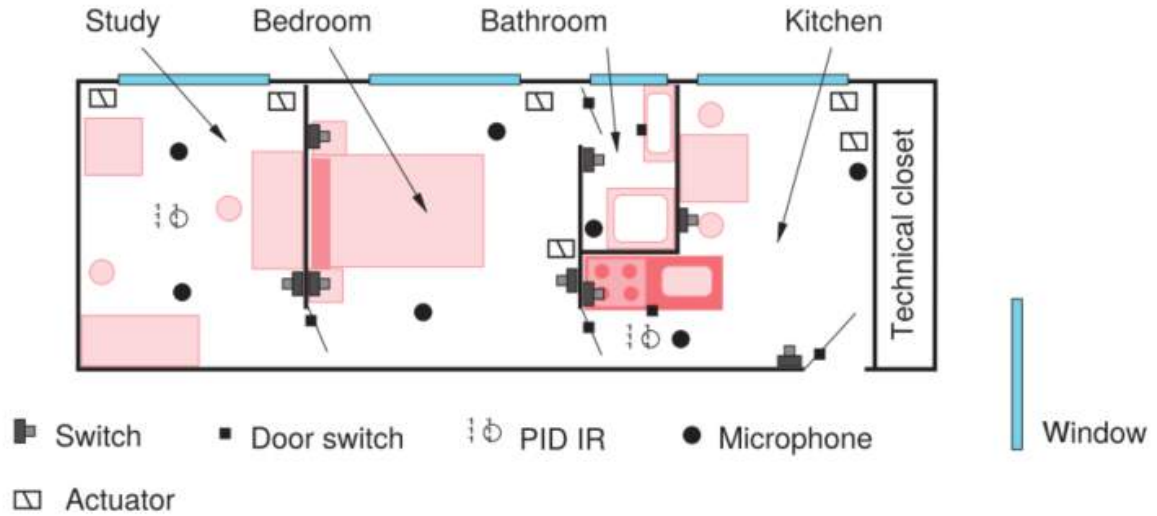


Figure 34: Domus smart home, used for dataset generation and testing of algorithms in the Sweet-home project [Chahuara et al., 2017].

home automation sensors (PIRs, switches, temperature, etc.) [Chahuara et al., 2016]. An algorithm for context-aware decision making was also developed, allowing the system to act under voice commands and unusual situations [Chahuara et al., 2017]. Tests were executed with 31 persons, again asked to perform certain activities, in Domus. The activity recognition algorithm performed with 75% of accuracy.

Domus is a prototype of a smart home part of the Carnot institute LSI, in France. It serves for showcase, dataset collection and testing of home automation techniques. It has a set of sensors and actuators for lighting control (switching and dimming), rolling shutters, motorized curtains, interior blinds, and other equipment plugged into electrical outlets, occupancy and luminosity sensors, opening detectors, energy and water meters, RFID readers and antennas, sound broadcasting equipment and humidity and CO2 sensors. In total, more than 150 sensors and actuators are managed in the flat. Other projects aim at comfort and energy consumption applications.

4 ALT for the Elderly with MCI/D

A few reviews have been done in the past years on ALTs for people with MCI/D. In this section, the ones that are most relevant for us are described, but for further knowledge of different devices, applications and smart homes, please refer to the following reviews. Blackman et al. [2016] reviewed technologies available and under research from 2013 for people with MCI and early Dementia. They group their references into devices and application, physical health systems, mental health systems, user interfaces, safety, and support of daily tasks. Carswell et al. [2009], McCullagh et al. [2009] had reviews on ALTs for assisting people with dementia during night time. Phua et al. [2011] review on technologies for the elderly and for people with dementia regarding smart homes and activity and plan recognition. Lauriks et al. [2010] wrote a review on ICT-based services for people with dementia regarding four needs: personalized information, support of dementia symptoms, social contact and health monitoring .

4.1 Devices

The ENABLE project was designed for people with mild and moderate dementia [ENABLE, 2004, Topo et al., 2004b, Macijauskiene and Budraitiene, 2004, Jones, 2004, Topo et al., 2004a] in which several assistive devices were given to the people involved, to test their acceptance and efficacy (Figure reffig:ENABLEdevices). The studies were carried out in Finland, Lithuania, Norway and UK, having 27, 12, 25 and 32 persons with dementia (plus family carers), respectively. They assessed several devices:

- Day and night calendar (Figure 35a): consists of an LCD display which shows day, date and "Morning", "Afternoon", "Evening" or "Night", as appropriate.
- Locator (Figure 35b): is aimed at enabling people who have mislaid objects in their homes to locate them. It also enables carers to locate objects that have been mislaid by the person they are caring for. The device has a series of touch buttons on the front onto which can be stuck pictures of objects to be located. When the user touches the picture they initiate a noise from a tag attached to the lost object so that it can be found.
- Night light (Figure 35c): it uses a sensor under two bed legs to detect when a person gets out of bed at night. On detection, the Night Light turns ON a bedside light. The light turns ON gradually over about 1 s so as not to startle the user. The sensor continuously measures the weight of the bed and detects large positive or negative changes in weight.
- Gas cooker monitor (Figure 35d): is a monitoring and control system retrofitted to gas cookers. It is designed to detect potentially dangerous situations and intervene to make them safe by automatically turning OFF the cooker knobs. If the initial intervention is unsuccessful, the system informs the primary carer with a text message and isolates the cooker from the gas supply.



Figure 35: ENABLE project devices [ENABLE, 2004].

- Picture gramophone (Figure 35e): it is a computer with touch screen and loud-speakers, showing pictures to be touched. When touching the picture, music will start to play and lyrics are shown on the screen. The content of the programme can be tailored after the person's music preferences.
- Picture phone (Figure 35f): fully functional telephone with big buttons, which can be pre-programmed and show names or pictures of the persons one would like to call.
- Medicine reminder (Figure 35g): it alarms at pre-set times the time for medication. It reminds the person the correct drugs in correct doses.

Fudickar and Schnor [2009] developed a mobile orientation device called KopAL for people with dementia (Figure 36). It has three main functions: orientation assistance which consists in alerting and requesting a caretaker when the user is leaving home, an appointment management that reminds the user of upcoming events by voice through the device and an emergency service that allows two-way voice communication. The usability of the device was evaluated by elderly users and not all could easily use/understand the interface for appointments managements [Fudickar et al., 2011].



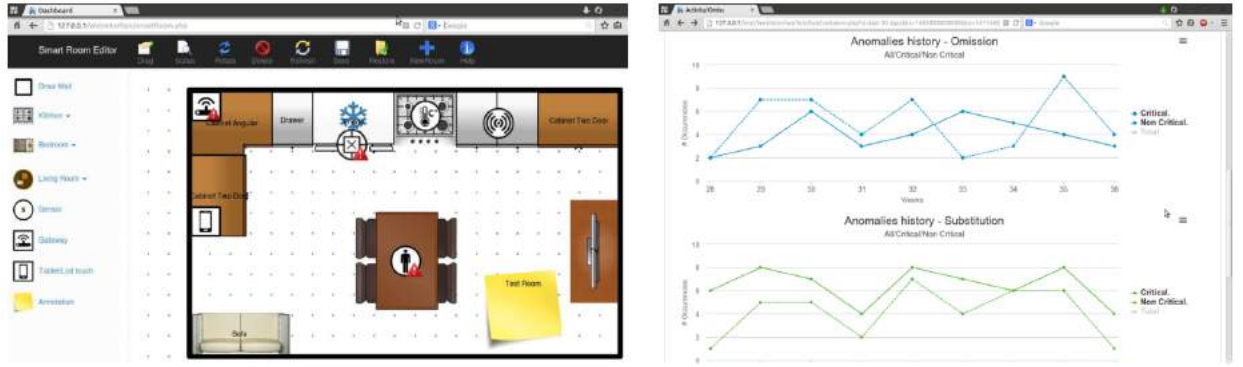
Figure 36: KopAI mobile assistant [Fudickar et al., 2011].

4.2 Diagnosis

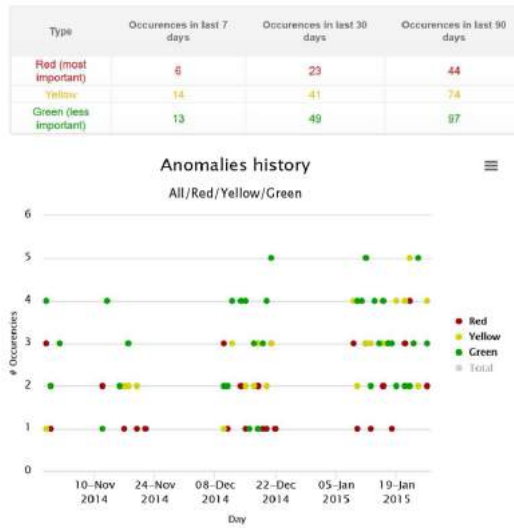
Hayes et al. [2008] evaluated the possibility of detecting the early cognitive impairment in older adults through in-home monitoring. Hence, they have collected data from 14 older adults (healthy people and people with MCI), from 65 years old and older, during 418 days. Walking speed and total movement was computed from the data acquired by PIRs and magnetic sensors. The comparison between the data was done by means of wavelet analysis. The results demonstrated that it is possible to detect the earliest transition to MCI, given the different walking patterns.

The SenTra (Senior-Tracking) project analyses outdoor mobility through the use of tracking technologies by people with MCI and dementia [Oswald et al., 2010]. The main goal was to assess the efficiency of tracking technologies (GPS) for diagnosis of the different kinds of cognitive impairment and the relationship between the mobility behaviour and well-being of the individuals. Pilot data were collected from 19 persons (7 healthy, 6 with MCI and 6 with dementia) between 63 and 80 years old, during one year. The conclusions reached are that healthy participants have higher levels of well-being and smaller network compared to cognitive impaired elderly.

Riboni et al. [2015] developed an algorithm to detect abnormal behaviours for the early detection of MCI (Figure 37). Their idea is to monitor daily living activities, since it was affirmed by previous studies that there are differences in the execution of ADLs between healthy people and people with MCI/D. They proposed the FABER: a novel technique for Fine-grained Abnormal BEhavior Recognition. It is based on medical models that describe abnormal activity routines that people with arising cognitive impairments may show, such as inappropriate timing, unnecessary repetitions and irregularity on eating. The system was improved and renamed as SmartFABER [Riboni et al., 2016], using machine learning techniques. In order to monitor the users, several sensors are deployed in their homes: temperature sensors, PIRs, pressure sensors in chairs, magnetic sensors in doors and RFID readers attached to furnitures and instruments. Two datasets were created. The first (FABER), in a smart home lab in



(a) FABER - Clinicians dashboard



(b) SmartFABER - Clinicians dashboard

Anomaly
NC1: Repository left open
NC2: Medicine not returned
NC3: Food item not cooked
NC4: Meal not prepared
C1: Missed a prescr. medicine
C2: Took a wrong medicine
C3: Repeated medicine intake
C4: Stove burner left on
C5: Had meal with no silverware
C6: Prepared meal not consumed
C7: Burner turned on by mistake
Total

(c) List of anomalies studied

Figure 37: FABER and SmartFABER project.

which actors performed ADLs and anomalies for 21 days of 21 patients, reproducing the behaviour of 7 healthy seniors and 14 seniors with early symptoms of MCI. The second (FABER and SmartFABER), during three months in the home of an elderly person with MCI. In FABER, the data from the sensors was processed and used for statistically infer the actions, reaching results of 0.96 recall in the activity/anomaly recognition. In the SmartFABER, the recall increased to 0.99.

Ashraf and Taati [2016] analysed the feasibility of correlating the activity of hand-washing executed by a person with the MMSE score on diagnosing dementia. The level of dementia is predicted by two features: statistics of occupancy of the regions of the sink and the motion trajectory of the hands while washing. They are extracted from the videos recorded and used to train a regression model. They also used the same features



Figure 38: MAPS prompter and editing tool [Carmien, 2005].

to train classifiers for predicting dementia categories (i.e. aware, mild, moderate, etc.). They had 27 users in which their cognition behaviour was classified by the MMSE test into aware, mild, moderate and severe. Results show that there is a potential in the activity of hand-washing to indicate dementia.

4.3 Memory-aid

Memory-aid devices are quite often under research. The Memory Aiding Prompting System (MAPS) is one of them, mainly designed for adults with cognitive disabilities to help them complete ADLs [Carmien, 2005]. This is accomplished by following instructions from a handheld prompter (Figure 38). There exists an editing tool for the system which should be used by caregivers to write the instructions for activities that should be done over the day, for example, which bus and where to get it to go to a medical appointment. A first usability study was done with seven young adults with cognitive disabilities. Adjusting the prototype with their feedback, a second study was performed with four young adults with cognitive disabilities with positive reactions from the participants.

Autominder is a system developed for people with memory impairment [Pollack et al., 2003]. It consists of a cognitive orthotic system that uses AI methods to provide personalised reminders that are adaptive over time (Figure 39a). The system can model the user's daily activities, check whether the activity was performed or not and decide when is the best time to deliver reminders. Autominder contains three main components: the Plan Manager, which stores the activities of the day; the Client Modeler, that tracks the user's activities; and the Personal Cognitive Orthotic, which is the actual module for

generating reminders, when seen it is necessary. The system was expanded and modified to allow personalization and adaptation to the user over time by using reinforcement learning [Rudary et al., 2004]. The Autominder was deployed on Pearl, a mobile robot [Pollack et al., 2002] (Figure 39b). Pearl is composed by a differential drive system, on-board PCs, wireless Ethernet, laser range finders, sonar sensors, microphones, speakers, touch-sensitive graphical displays, and stereo camera systems. Pearl provides navigation assistance, speech recognition, image capture, face detection and tracking software. They have performed a few experiments with the robot and potential users [Montemerlo et al., 2002]. For three days, the robot's interaction with a large number of elderly users was tested. In two more days, more specific tasks were tested with 6 elderly people. Overall, the robot is easy to manage but few flaws were identified such as difficulty for the robot to follow the person's velocity and some confusion in the speech recognition module.

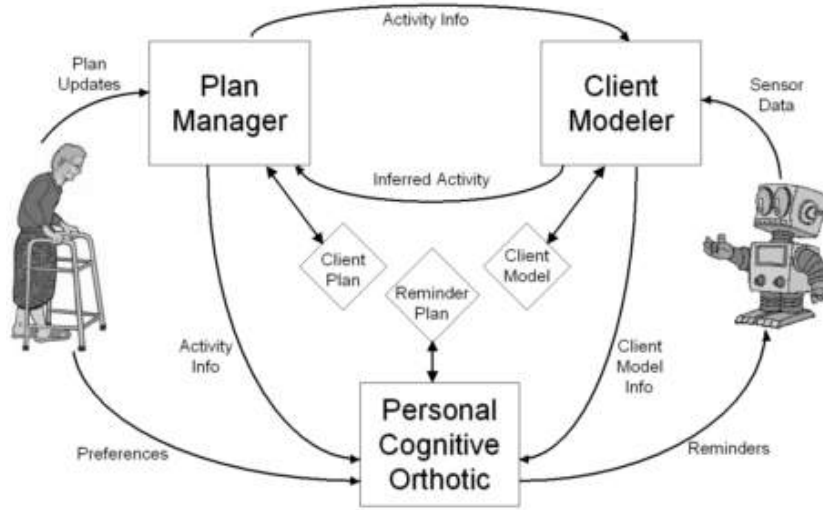
Chaminda et al. [2012] developed a smart reminder system. They use two accelerometers in each wrist to recognize activities through artificial neural networks. Then a algorithm for activity prediction was implemented by having as inputs the current activity, location (acquired through RGB camera input) and past activity patterns. The reminders are sent in case a predicted activity is not being executed. Four subjects participated in the tests and 80% average accuracy was reached.

4.4 Mobility, Safety and Monitoring

Lin et al. [2006] developed a wireless health care service system for elderly with dementia, which includes a motion sensor network and a body-attached rescue locator. They use RFID, GPS, GSM, and GIS to provide indoor, outdoor and remote monitoring and emergency rescue. Family members and caregivers can track the real-time position of the missing elderly people. The performance and reliability of the device was tested by 11 healthy users, in which eight said they are satisfied with the stability of the system and 10 would like to carry it themselves or recommend to a family member.

Chen et al. [2005] designed an acoustics-based system that aims to automatically generate reports on personal hygiene behaviour of people with dementia for their caregivers. Showering, brushing teeth, washing hands, flushing and urination activities are classified in order to produce the report. The deployed system consists of multiple microphones and a PIR to indicate the person entering or leaving the bathroom. From the sounds recorded, several features and classification methods were tested in order to provide the best results. Firstly, the system was trained and tested in a lab. The sound for the activities were recorded by four subjects and they achieved an overall accuracy of sound recognition of 87%. In a second phase, the system was tested in a real trial, again with four healthy subjects, during 10 full days. The mean accuracy in that case was 84%. A user interface shows the monitored activities, as in Figure 40.

Zhang et al. [2014b, 2013] developed the Smarter Safer Home system, which used a wireless sensor network to support older people with mild dementia. They used PIRs



(a) Autominder Architecture



(b) Pearl interacting with elderly people

Figure 39: Autominder [Pollack et al., 2003] and Pearl [Montemerlo et al., 2002].

for indicating movements, accelerometers in mattresses, power sensors in appliances, acoustic sensors for water flows in pipes, temperature and humidity sensors, magnetic sensors for doors and pressure sensors for sofa/couch (Figure 41). By using machine learning techniques, the sensors would provide enough information in order to assess the severity of dementia, detect abnormal behaviours regarding the user's health and intervene when needed. The sensors' output is processed to estimate the activities being executed, allowing for instance the recognition of patterns to identify falls, health decline and critical health situations. The results can be followed by clinicians and health care staff. There is also a video conference module, enabling social inclusion. This system was going to be implemented in a trial platform for 6-9 months and twenty different homes, but to our knowledge no reports exist on that. However, the system is currently

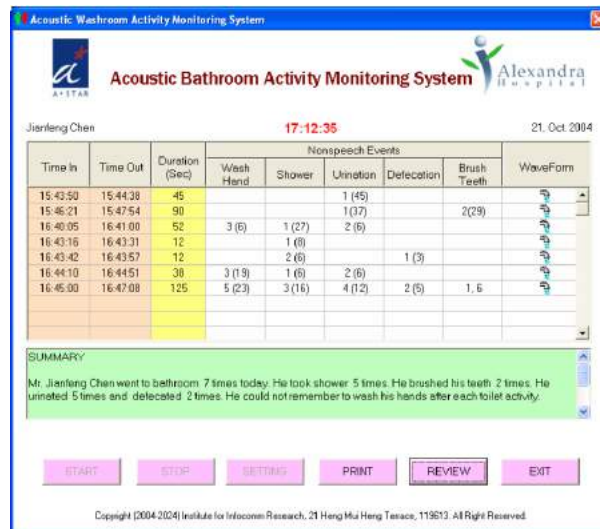


Figure 40: User interface of Acoustic Bathroom Activity Monitoring system [Chen et al., 2005].

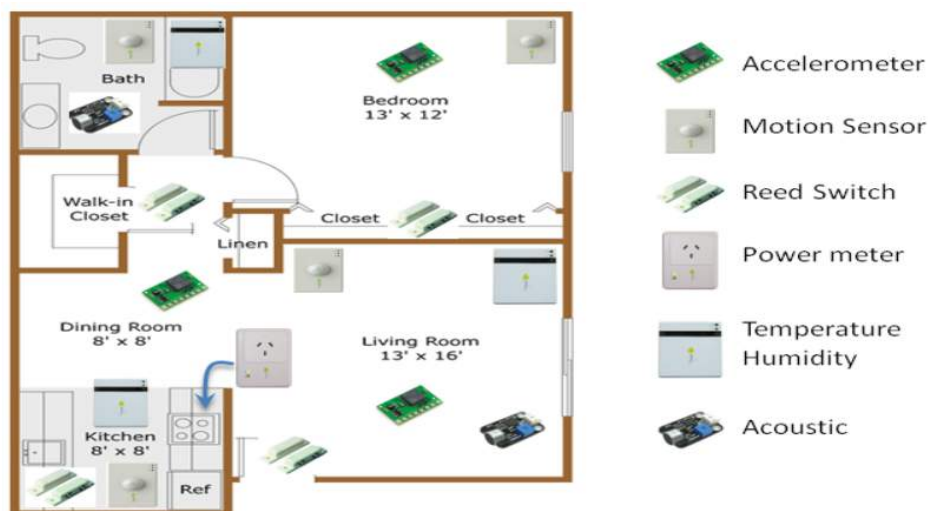


Figure 41: Smarter Safer Home system: sensors deployed in the home [Zhang et al., 2014b].

employed in residences supported by Bromilow Home Support Services [Bromilow, 2015].

Engel et al. [2016] propose a platform for identifying emotions of people with dementia - SenseCare. The idea is that the emotions detected can be monitored by carers and family members to identify negative and positive feelings and act accordingly. They plan to use a camera and wearables (ECG, EMG, etc.) and might also include other

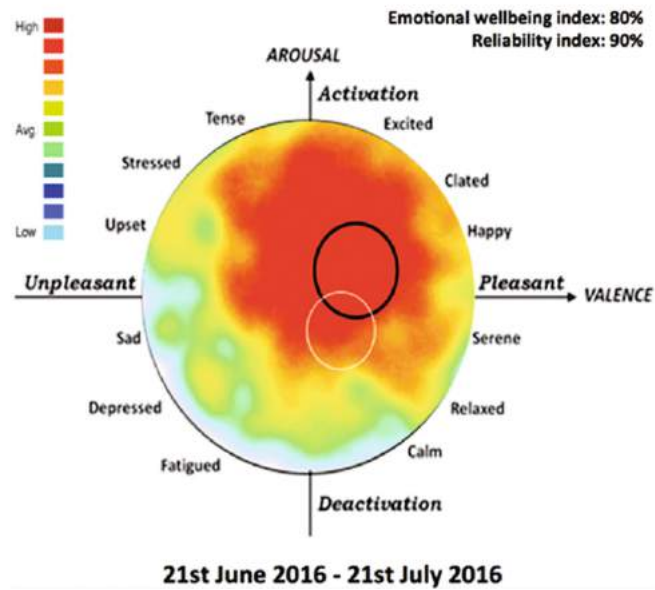


Figure 42: SenseCare platform - proposed output [Engel et al., 2016].

sources such as voice recognition, EEG signal and gait analysis. The project is very new, therefore only the idea and a prototype of an output (Figure 42) of the system were presented. There are no tests or deployment yet.

5 Special Projects and Research Groups with focus on MCI/D

5.1 Intelligent Assistive Technology and Systems Lab - University of Toronto (COACH ++)

The Intelligent Assistive Technology and Systems Lab (IATSL) is a multidisciplinary group (engineering, computer science, occupational therapy, speech-language pathology, and gerontology) in the Department of Occupational Science and Occupational Therapy at the University of Toronto. They have several projects in the topics aging-in-place, ambient health care, older adults with dementia and rehabilitation [IATSL].

In the area of older adults with dementia, one of their very known projects is the COACH (Cognitive Orthosis for Assisting aCTivities in the Home). They use artificial intelligence to support people with dementia by assisting the activity of hand-washing [Mihailidis et al., 2001]. The first prototype consisted on a video camera mounted above a sink that inputs to the software a 2D coordinate of the user's hand, that wears bracelets. An artificial neural network was used for classification of the action and a planning algorithm checked if the tasks were being executed in the right order. In case of an error detected, the program notified the user with pre-recorded cues. As the steps for hand-washing can be done differently, the system also adapted for the user's way of doing it. The later version of the system does not have the bracelets, it uses a colour segmentation on the video to track the hands instead (Figure 43), and the planning algorithm uses a Markov decision process [Mihailidis et al., 2004, Boger et al., 2005, 2006, Hoey et al., 2007, 2010]. The system was tested with simulation and also with seven persons with moderate-to-severe dementia in a ten-weeks trial. The tests were executed in a bathroom in a long-term care facility in Canada, where the system was properly installed. The results showed that the system can very well provide assistance, but there are still challenges to be accomplished such as making the ability to adapt to the users and improvement of the algorithm.

5.2 COGKNOW and Rosetta Project

In order to address many needs of people with mild dementia, Mulvenna et al. [2010], Bengtsson [2007] developed a portable device, called COGKNOW Day Navigator. The system may help users to remember things (e.g. clock, appointments, item locator, etc.), maintain social contact (e.g. picture dialing), perform daily life activities (e.g. radio/lamp control, music player, activity assistance) and provide a feeling of safety (e.g. contact/help icon, safety warnings, night light, outdoor navigation). For some of the functionalities, there are sensors in doors, refrigerators, bed/chairs, and the GPS from mobile phone. Fifteen persons with mild dementia helped in their study by doing interviews and assessing the device developed. They have performed field tests with 42 persons with mild dementia in the UK, Netherlands and Sweden, being judged as useful, user friendly, easy to operate and simple to understand by the users (both carers and

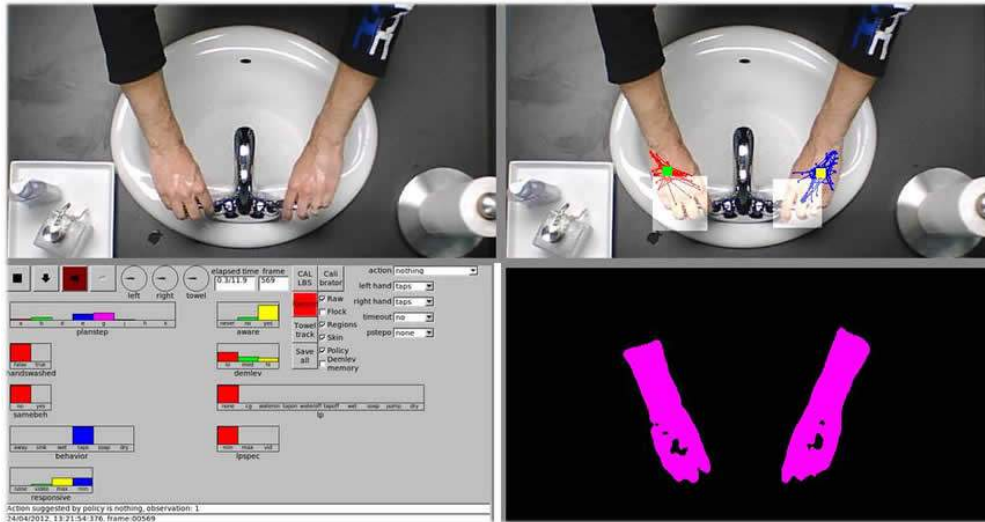


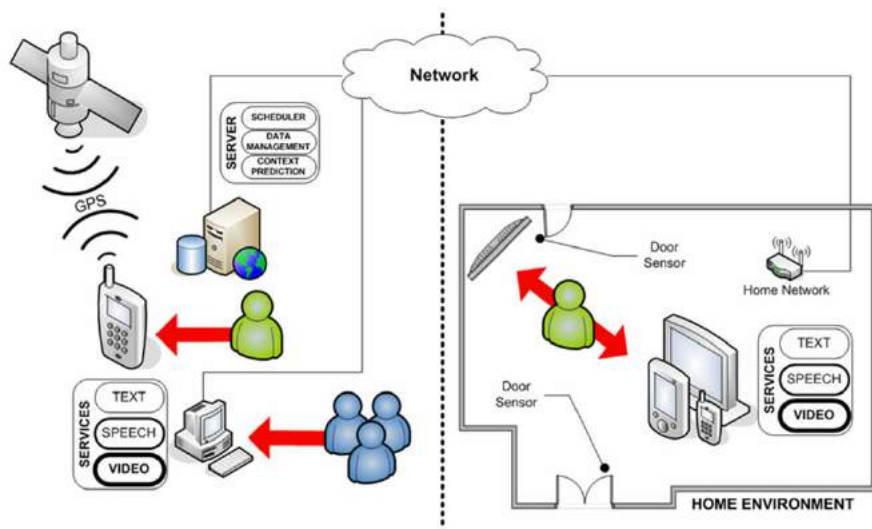
Figure 43: COACH system: video frame with raw image (top left), hand tracking (top right), belief state (bottom left) and skin image (bottom right) [Hoey et al., 2010].

patients). The preferred functionalities were the reminding, picture dialling, appliances control and the mobile. The device was commercially available in 2012 [Cogknow].

COGKNOW was integrated with two more systems to form a complete solution for people with dementia and their carers in the Rosetta project [Hattink et al., 2014]. The two systems were the Early Detection System (EDS) [Storf et al., 2009] and the Unattended Autonomous Surveillance system (UAS-AAPS) [van Hoof and S.M.Kort, 2008]. The former uses sensors in the house (PIRs, reed contacts, pressure mats, blood pressure) to record the pattern of behaviour of people with MCI and dementia so they can analyse sleep-awake rhythm, mobility, meal preparation and personal hygiene. The latter uses movement sensors and cameras to detect emergency situations and send alarms to carers. The final system was used in trials in Netherlands, Germany and Belgium, with pre- and post-test measures, with 42 persons with MCI and/or Dementia and 32 informal carers. The usage of the system varied from half a month to eight months. There were many problems with the installation of the EDS and the UAS-AAPS, which were not available at all times. Rosetta proved to be useful, although not a very friendly device.

5.3 CASAS

CASAS stands for Center for Advanced Studies in Adaptive Systems (CASAS) at Washington State University in the School of Electrical Engineering and Computer Science. CASAS serves to test the technologies using real data through the use of smart homes. Several studies have been done since 2007, and some relevant ones are presented in this



(a) COGKNOW system



(b) COGKNOW fixed device



(c) Mobile device



(d) User interface

Figure 44: COGKNOW system, device and interfaces [Cogknow].

section.

Cook and Krishnan [2014] provided an overview of data mining methods employed in smart homes. Most of them aim to understand the person's daily behaviour and its

impacts in their life. In this sense, the studies make use of several sensors installed in the homes for collecting data and extracting the information from it.

Activity recognition may serve to many purposes, such as activity prediction and behavioural analysis. CASAS has smart apartments test beds (e.g. Figure 45) enabling the collection of data for research on such topics.

For example, Chen et al. [2010] developed an activity recognition algorithm by using the data collected in the test bed of Figure 45. Firstly, they extract features from the data collected by sensors (e.g. time of the day, day of the week, previous/next activity, etc.). Afterwards they select the features by eliminating redundant data and apply classification machine learning algorithms to classify the activities (cook, watch TV, computer, groom, sleep, bed to toilet). They validated the algorithms using real sensor data collected from volunteers living in the apartment test bed during five months, reaching accuracy of 90%. Rashidi et al. [2011] used the same test bed for activity recognition, but by using an unsupervised machine learning approach. They validated the algorithm by running several tests on data acquired from 20 students that performed five different activities (telephone use, hand washing, meal preparations, eating and medication use, and cleaning).

Activity recognition during the data streaming has also been researched with different techniques, such as sliding window [Krishnan and Cook, 2014] and unsupervised algorithms [Rashidi and Cook, 2010b,a]. In another study, both techniques are joined. Therefore, the final algorithm can perform activity recognition via supervised machine learning algorithms and learn new activities by an unsupervised technique, improving the accuracy results [Cook et al., 2013]. A more detailed explanation on activity recognition and activity discovery can be found in [Kim et al., 2010].

Dawadi et al. [2016] introduced an activity curve that represents a person's daily routine. The input for the curve is given by a statistics-based activity recognition algorithm, used to compare those curves over time. This enables the detection of behavioural changes and the assessment on the cognitive and physical health of the person. They have also previously developed an algorithm to predict clinical assessment, which can be used as a tool by health professionals [Nath Dawadi et al., 2015]. Besides that, they have also implemented a change quantification algorithm to confirm that sensor-based methods can predict characteristics of cognitive and physical health [Dawadi et al., 2014]. The activity change detection algorithm was tested for a couple of years and three case studies were presented [Sprint et al., 2016a]. Other change detection algorithms were developed by Sprint et al. [2016b], Sprint and Cook [2016].

Cook et al. [2015] analysed data collected from smart homes sensors in order to determine whether there exists behavioural differences between healthy older adults and older adults with Parkinson Disease (PD) and with MCI when they are executing daily activities. The sensors used include PIRs, magnetic sensors, ambient lights and temperature sensors (Figure 46), vibration sensors in objects (e.g. dustpan, broom, watering can, medicine dispenser, etc.) and wearable inertial sensors (one in the upper

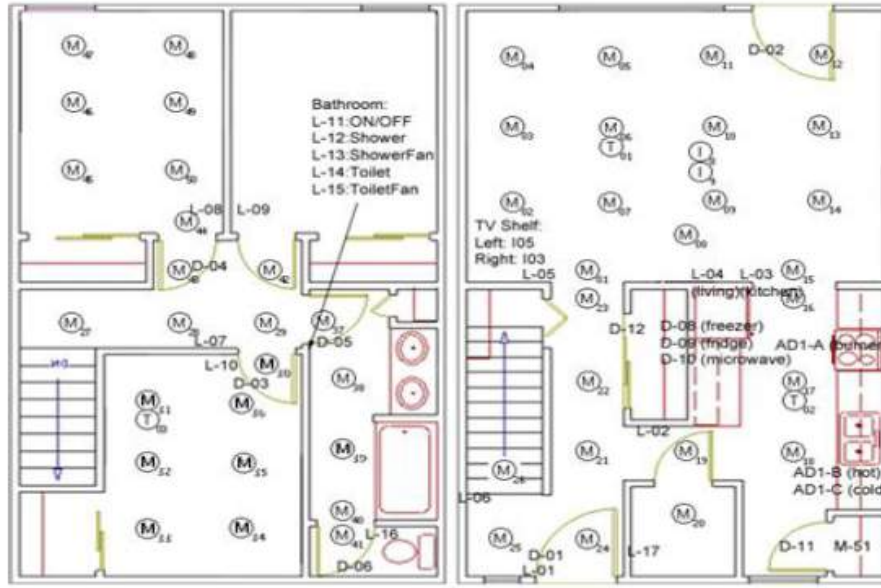


Figure 45: CASAS smart home testbed - floorplan. Three-bedroom apartment with sensors: motion (M), temperature (T), water (W), burner (B), telephone (P), item (I) [Chen et al., 2010].

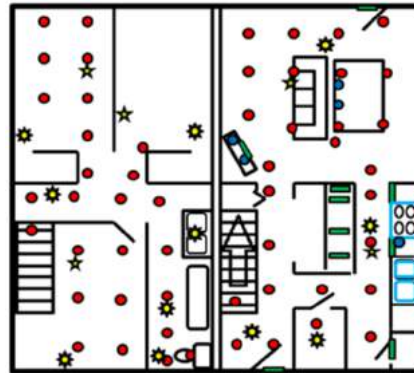


Figure 46: CASAS smart home testbed - floorplan. Motion sensors are the red circles, light sensors are the eight-pointed stars, door sensors are the green rectangles and temperature sensors are the five-pointed stars Cook et al. [2015].

dominant arm and one in the dominant ankle). They have collected data from 84 older adults and achieved 97% accuracy. This proves that sensor-based technologies and wearable sensors, associated with machine learning techniques, can be useful for health monitoring and early detection of functional changes related to PD and MCI.

Predictions of activities can allow automation of the home in terms of energy efficiency, safety and comfort. Besides that, it also enables the implementation of prompting



Figure 47: Three smart home testbeds - floorplan. Red circles and blue triangles represent PIRs and magnetic door sensors respectively [Nazerfard and Cook, 2015].

systems in order to remind users of performing a certain activity. Minor and Cook [2014], Minor et al. [2015], Minor and Cook [2016] developed an algorithm for forecasting the activity and the time activities would be executed. The algorithm is based on current and past sensor events, by means of machine learning algorithms. Regression tree classifier is the main algorithm employed and compared with others. They also compare the performance of different algorithms by training them with two types of features: discrete (on/off and open/close sensors) and what they call sample features (e.g. data from accelerometers). The tests were performed with datasets from 25 smart home test beds (51 sensors in total) with older adults and indicate that by adding sample features the prediction accuracy improves. Nazerfard and Cook [2015, 2013] developed an activity prediction algorithm using Bayesian Networks. In their work, the algorithm predicts the time and place the activity will happen, within the list of ADLs: bathing, bed-toilet transition, eating, entering home, housekeeping, leaving home, preparing meal, personal hygiene, resting on couch, sleeping and taking medication. They had datasets from three different apartments (Figure 47) and the tests achieved accuracy between 60% to 75%.

Williams and Cook [2016] developed an algorithm to model and forecast wake and sleep patterns of people that are recovering from injuries and people with disabilities. Forecasting behaviour can indicate potential sleep problems and help us to understand the relationship between wake and sleep. They also claim that sleep and wake behaviours impact each other. For the study, data from the sensors installed in CASAS

test beds from 20 smart homes were used in a regression analysis, by means of several machine learning algorithms. As input for the algorithms, they used features such as sleep duration, sleep efficiency (ratio of how long the participant slept and the number of hours they person spent in bed), and sleep disturbances (number of interruptions that occurred during a sleep activity, temperature, etc.). They have achieved accuracy results of 99%.

Chen and Dawadi [2011] developed a web-based application for behaviour pattern monitoring in smart environments (Figure 48). The aim is that users will be able to understand and monitor themselves. The app has functionalities such as mobility heat map showing the frequency of sensor events in the home, activity graph and energy usage graph.

Krishnan et al. [2013] used machine learning algorithms to create a hierarchical activity taxonomy by clustering activities from different sources. This allows for example that many datasets can be used for a unique study. They also show how to merge unsupervised activities into a predefined model.

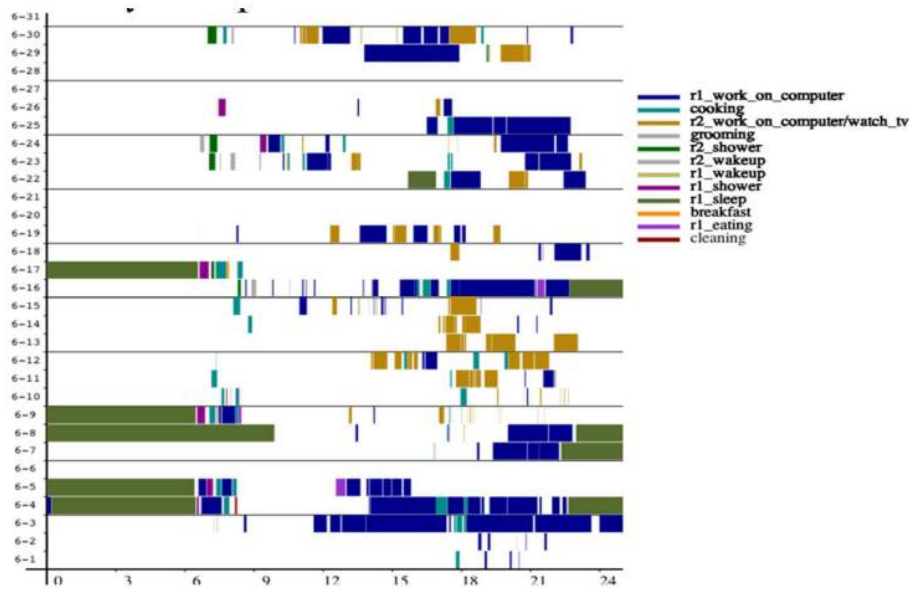
Studies on the minimization of number of sensors preserving the activity recognition accuracy have also been done [Cook and Holder, 2011]. The results show that having too many sensors does not always improve the recognition results. In addition, feature selection and construction techniques can be used to define the optimal placement and number of sensors.

Transfer learning is a technique in which a system would learn from another one. They should be different, but somehow related. For instance, learning within multiple physical spaces [Rashidi, Parisa and Cook, 2010, Rashidi and Cook, 2011] or a sensor-based smart home transferring knowledge to a video-based smart home. It is a technique not very well advanced yet, although many studies are being done in this field. For instance, Feuz and Cook [2015] developed an algorithm for transferring activity knowledge between different sensor platforms.

Seelye et al. [2013] analysed the amount and type of prompts required to assist people with MCI completing daily activities. They had 29 people amnesic multi-domain MCI, 18 people with amnesic single-domain MCI, and 47 healthy older participants executing the activities in a smart home test bed. Eight activities were selected: change light bulb, wash hands, clean kitchen countertops, use telephone and phonebook, sort and fold laundry, cook oatmeal on the stove, file mail into mail organizer and give instructions on how to play a card game. Each of them was depicted into steps and observed through cameras and sensors in the apartment. Prompts would be given through speakers and in graded order, as much as needed. The prompts could be: indirect (e.g., "The oatmeal may burn if the stove is left on"), direct (e.g., "You can turn the stove off now") and multimodal (e.g., "a video clip appears on a computer screen of a person in the apartment turning the knob on the stove to the off position and direct verbal prompt is delivered"). Results showed that the multi-domain MCI people made more errors and needed more prompts than the single-domain MCI and normal ageing groups. Examples of errors



(a) Web-based visualization of behaviour pattern app and heat map



(b) activity graph

Figure 48: Web-based app for behaviour pattern [Chen and Dawadi, 2011].

were: failure to initiate an activity step, incorrect completion of an activity step, activity steps performed in a wrong sequence. Overall, prompting for people that have MCI was considered efficient by the users. This means that receiving prompts helps them on correcting errors and getting back to the activity execution.

Das et al. [2012] developed an automated prompting system. They used sample sensors and defined the timing for prompts from data collected in smart homes. In order to detect when a prompt is required, experimenters were observing the movements of

the people with MCI in the apartment. The idea is that this detection has to be recognized in an automatic way, without compromising the user's privacy. Holder and Cook [2013] also have an algorithm for an automated prompting using machine learning, including an activity-aware module to validate the prompt has worked. They have validated the algorithm with datasets from three smart homes test beds and during 6 months, gathering data of 12 different ADLs.

A digital memory notebook (DMN) serves to provide memory assistance. Its use by people with MCI and dementia can be highly improved by implementing activity recognition and context-aware prompting. It was identified in previous studies that the best time to emit prompts is during the transition between activities [Robertson et al., 2015]. This fact is then used by [Feuz et al., 2015]. The transition period is detected by two machine learning algorithms, one supervised and one unsupervised method. By data from different smart home sensors (PIRs, magnetic, temperature, light and object shake), twelve daily tasks were monitored, as well as their transitions. The supervised technique proved to be more efficient (detects transition faster), although both methods achieve detection with a similar rate.

Dawadi et al. [2013] studied machine learning algorithms for indicating the quality of daily activities based on data from smart home sensors. A number of 179 volunteers performed activities in a smart home test bed, including healthy people (145) and people with dementia (2) and MCI (32). There was a series of eight activities in which they would prepare for a day out and are told to multi-task and perform the steps in any order, as efficient as possible. Results show that machine learning algorithms can be designed to assess the quality of execution of a certain task.

Das et al. [2016] implemented an outlier detection algorithm for recognizing errors in the execution of activities. In this sense, they collected a database including the execution of several activities (e.g. sweeping and dusting, cooking, wandering) in a correct and incorrect way. The machine learning algorithm is trained with the correct data only, extracting features from the activities (e.g. time it started, time from the last time it was performed, etc.). The error is detected whenever the features do not fit the classifier model for a certain activity. Another result from this study was error classification (e.g. omission, substitution, inefficient or irrelevant action, etc.) in the activities recorded, by means of machine learning algorithms applied to smart home sensor data.

Ohgi et al. [2015], Williams et al. [2013] used machine learning algorithms to diagnose people with MCI and dementia. In order to train the algorithms, the used features were the results from different tests people normally have to do for assessing their cognitive health (e.g. language assessment, executive functioning, memory, etc.). Results show that not all the tests usually made to identify MCI and dementia are necessary if machine learning algorithms are used, reducing the work people have to do for their diagnosis.

5.4 DOMUS - Canada

DOMUS stands for DOMotics at the Université de Sherbrook and it is a lab that have studies in the fields of cognitive assistance, medical monitoring and televigilance for people with cognitive disorders (i.e. head trauma, schizophrenia, Alzheimer's disease and cognitive impairment) [DOMUS, 2011]. They have five projects ongoing:

1. COOK - culinary assistant: recent project in which the aim is to design a cognitive orthosis for meal preparation to help people with head trauma [Giroux et al., 2015].
2. Early detection of dementia: automatic measurement of activities' performance and thus AD detection.
3. Amelis calendar (Alzheimer's Memory and Social Links): interactive calendar that displays appointments, temporal orientation, help on maintaining interpersonal contacts and on memory of past events.
4. AGE WELL - DIY-Aide (Do-It-Yourself Adaptable Intelligent Domestic Environment): system that aims to assist elders with cognitive impairments in specific ADLs. Studies in this project include a formulation for affect control theory used for human interactive systems [Hoey et al., 2016], autonomous outdoor mobility [Teipel et al., 2016], plan and activity recognition [Roy et al., 2011, Bouchard et al., 2007].
5. IPADL (Indoor positioning for activity of daily living): indoor positioning through RFID antennas and passive tags, used in classification algorithms [Bergeron et al., 2016]. They are planning to use RFID for activity recognition.

The DOMUS laboratory possesses an apartment/intelligent lab as in Figure 49. It has several sensors and actuators (movement detectors, electromagnetic contacts, tactile carpets, debitmeters, microphones, loudspeakers, readers and RFID tags, etc.), kitchen appliances (cooker, dishwasher, etc.), apartment furniture (table, chairs, cabinets, bed, etc.) and communication objects (wireless screens, touch screens, PDA, cell phones, etc.). In addition, they have a living lab, which consists of sensors (e.g. motion sensors, door and window sensors, microphones, flow meters, water and flood sensors, temperature sensors, humidity sensors, light level sensors, intelligent stove, energy monitoring sensors, light switch sensors), effectors (e.g. touch screens, mobile phones, tablets, interactive table, wireless screens, speakers, lights), and computing resources (servers and industrial-level programmable controllers). In there, prototype software, algorithms and technologies can be deployed for long term evaluation.

5.5 Institute for Infocomm Research - Singapore

Feki et al. [2009] developed a plan recognition algorithm, which detects errors in the execution of activities and may issue cues to people in the initial stage of dementia. The idea is that they recognize activities at a low level or as they call it micro-context (e.g.

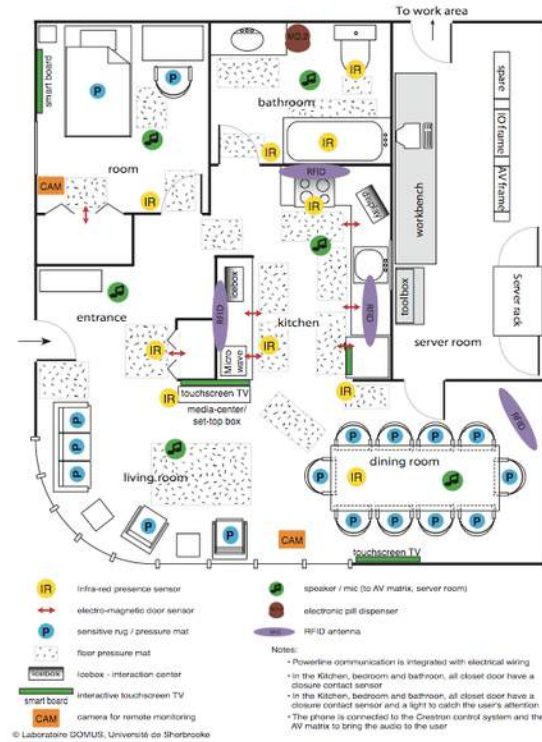


Figure 49: Domus apartment [DOMUS, 2011].

bringing food to the mouth, holding spoon, etc.) and gather them into a high level, an activity detection (e.g eating lunch). The plan would be the execution of activities in a "right" order, according to the different users. For the activities and micro-context detection, they use several sensors in the home: PIRs, ultrasound sensors (for tracking movement), RFID and UWB tags, accelerometers, pressure sensors, magnetic sensors and video and audio sensors when permitted from a privacy standpoint (Figure 50). The data collected by them is applied to machine learning algorithms in order to classify the micro-context and through grammar or graph theoretic techniques the activity recognition is completed. The work proposes a plan recognition algorithm by means of a probabilistic grammar for Dynamic Bayesian Networks and reinforcement Q learning [Feki et al., 2007, Ali et al., 2008] and includes error prediction [Phua et al., 2009] and issue reminders [Biswas et al., 2010a]. They focused in the eating activity, in which they developed a more specific activity recognition algorithm [Tolstikov et al., 2008]. The group also has research works in indoor/outdoor sleep activity pattern monitoring and continence management in nursing homes [Biswas et al., 2007, Wai et al., 2008, Biswas et al., 2010b].

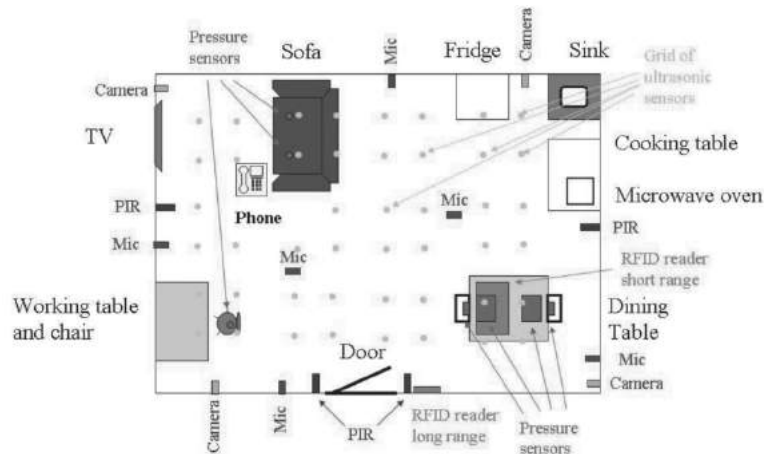


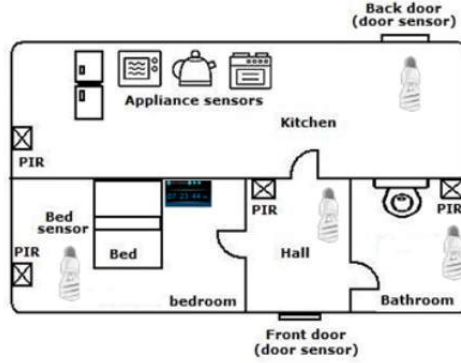
Figure 50: Multi-modal sensors installed in the home [Feki et al., 2009]

5.6 NOCTURNAL

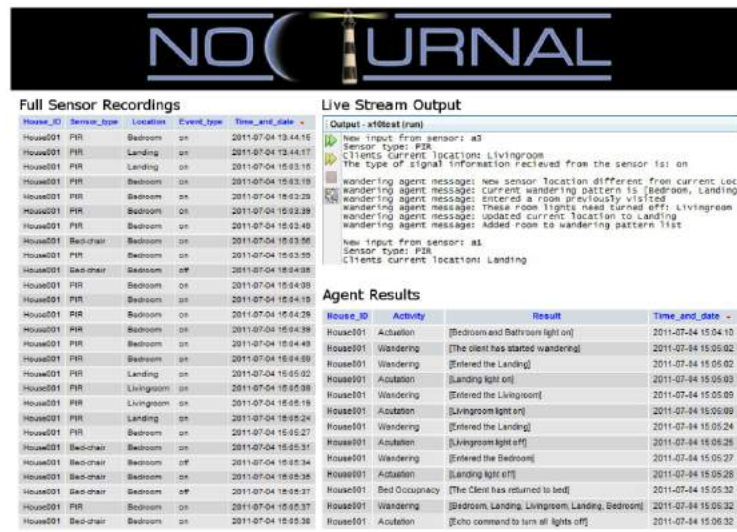
Augusto et al. [2011], McCullagh et al. [2012] developed the NOCTURNAL (Night Optimised Care Technology for UseRs Needing Assisted Lifestyles). The system is mainly designed for people with early dementia, who can often be confused when awakening. The aim is to orientate them during the night time by switching lights on/off automatically (when going to the bathroom), attracting them to bed when a wandering pattern is detected [McCullagh et al., 2011] and using music to help them sleep. Therefore, the system consists of PIR and bed movement sensors, light switches, dimmer and a tablet that provides time, messages, music and pictures. Optional sensors are door and appliances ones. The system is also able to monitor and analyse sleep [Wang et al., 2010, Nikamalfard et al., 2011] and activity patterns [Nikamalfard et al., 2012], which can be accessed by carers and is helpful to identify cognitive impairment levels [Augusto et al., 2014]. The system was assessed and created with the help of stakeholders during the development [Martin et al., 2013]. Eight people with dementia had the system at their homes for a period of three months. The overall reaction was favourable. They also had 12 healthy participants for feedback on the system's functionalities.

5.7 Dem@Care: Multi-Sensing Monitoring for Intelligent Remote Management and Decision Support

Dem@Care stands for Dementia Ambient Care and is a project researching sensor-based techniques on activity recognition, data fusion and mining, knowledge-representation and intelligent decision-making support [Meditkos and Kompatsiaris, 2014, Dem@Care, 2012]. Their research uses multi-parametric monitoring and ontology-based analysis and interpretation of the data collected from sensors. The project is carried out in three environments:



(a) Sensors in the house



(b) Example of the system's screen, clockwise from left to right: gathering information from sensors, a log of events and recording actuations

Figure 51: Nocturnal system [Augusto et al., 2011].

1. Dem@Lab: hospital labs in Nice (France) and Thessaloniki (Greece), with the aim of enhancing early dementia diagnosis.

König et al. [2015] developed a system to diagnose dementia and to assess the autonomy of people in executing activities of daily living by information extracted from video records (Kinect color and depth camera). The data is analysed by the so-called event monitoring system which consists of four modules: people detection, people tracking, gait analysis and event recognition. Afterwards, the extracted features train a machine learning algorithm to classify the user's performance both in autonomy (i.e. good, intermediate, poor) and cognitive status (dementia, MCI, healthy). They have performed tests with 14 healthy people, 23 people with MCI

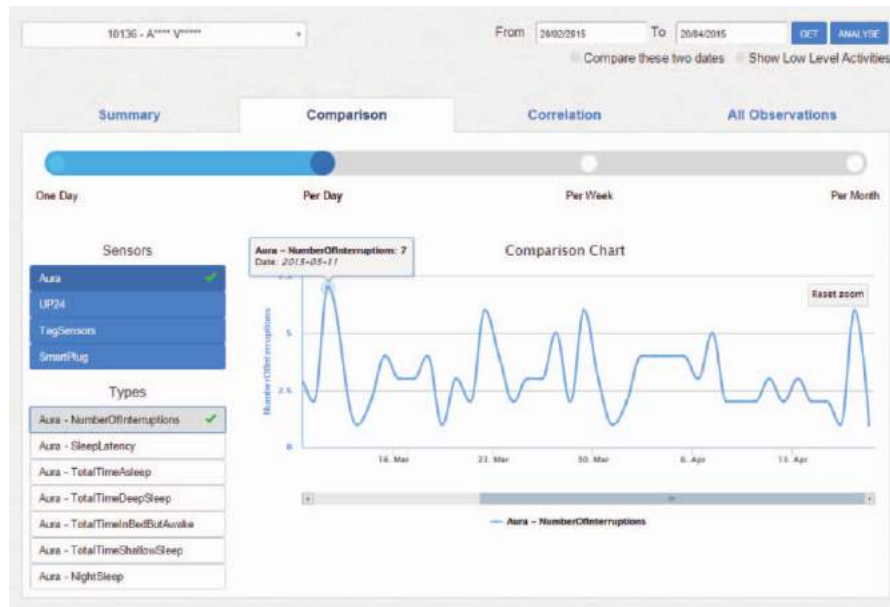
and 12 with Alzheimer, in which they were asked to reproduce certain activities in the lab. The results suggest that it is possible to quantitatively assess IADL execution.

Sacco et al. [2012] use a video monitoring system to quantify the assessment of execution of ADLs by people with AD and MCI. They propose a score called daily activity scenario (DAS) that detects functional impairment. The place in which the ADLs were executed were equipped with two monocular video cameras. The relevant data recorded was first manually extracted and then a mathematical algorithm was developed to assess the DAS score automatically. They had 16 people with Alzheimers, 19 people with MCI and 29 healthy people, who were asked to perform ADLs while being recorded.

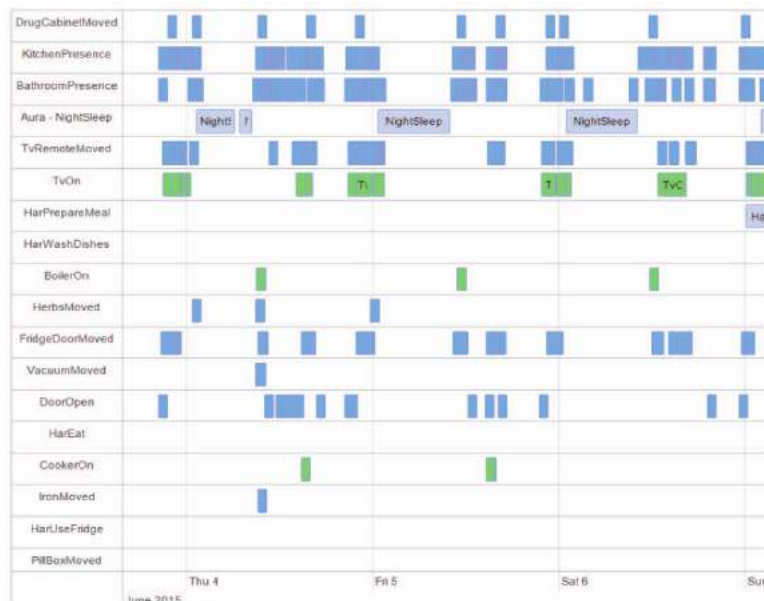
Satt et al. [2013] perform automatic detection and status tracking of MCI and early dementia through speech and voice recordings. In this sense, several vocal features are extracted from the recording of different tasks: speech duration, pauses, number of speech segments per second, etc. The features train a classification machine learning algorithm that diagnosis the person. They had recordings of over 80 diagnosed subjects and the results yields dementia and MCI detection with a rate below 20%.

2. Dem@NursingHome: in Lulea (Sweden), aiming at monitoring daily life for increase safety and lifestyle feedback.
3. Dem@Home: in homes of people with dementia living alone, in Dublin (Ireland) and Thessaloniki (Greece).

Karakostas et al. [2015b,a] implemented a sensor-based home system to support cognitive abilities of people that have Alzheimer disease and dementia. They deploy several sensors to monitor the user: ambient depth cameras (color and depth data), plug sensors (electronic devices), tags (objects of interest such as drug-box, watering can), PIRs, wristwatch (physical activity measurement), microphones and pressure sensors in the bed (sleep duration and interruptions). The data acquired from the sensors is integrated semantically and analysed by means of knowledge-driven interpretation techniques. There is an interface serving two functions: enable the clinicians to follow the monitoring results and support the users through interventions. For instance, the interface provides information on the duration and quality of the user's sleep, allows the clinicians to watch the video records to identify mistakes executed constantly by the person and issue notes when necessary, and displays the use of electrical equipment and correlations (e.g. time spent watching TV and sleep time) (Figure 52). They have tested the system with one person with MCI during a 3-months pilot. The results show that the person has improved in some habits (sleeping hours, TV usage, personal hygiene, etc.). The system was installed in 4 homes and they are proceeding with data collection.



(a) Correlation between activities



(b) Frequency pattern of devices' usage

Figure 52: Examples of interface functions in Dem@care [Karakostas et al., 2015a].

6 Summary

The aim of this report is to provide some detail on the current state-of-the-art in ALTs, including any studies that use Machine Learning, as well as give a short overview of the status of commercial solutions.

Firstly, we have presented an overview of **commercial** technologies for general use. There is a large number of stand-alone devices, however the trend now is to move towards complete systems. This can be accomplished at a small scale by the individual user, for example by installing a hub for smart speakers and using compatible devices. A more technical approach would be to develop a (integrated) system comprising a network of sensors.

Special attention has been given to commercial ALTs for the elderly and elderly with MCI/D. There are by far fewer devices and systems for the latter user group and the overall maturity of the technology is lower. The most common devices and systems in the market are medication dispensers and fall detection/ alarms. In addition, there are some commercial systems for the elderly including MCI/D that claim they do some sort of behaviour pattern monitoring although currently these systems have limited value add. Apart from that, there are several calendar/ socializing apps, some devices/ solutions that address wandering, and some solutions that generate reminders associated to a calendar.

When it comes to **research** work, there is ongoing research activity in automatic fall detection, indicating that commercial technology has not yet reached maturity. False alarms is the main remaining challenge. Machine learning is extensively used here and has been shown to improve results considerably in terms of a reduced number of false alarms as well as applicability to different environments. In general, it is an advantage to achieve automatic fall detection and preferably without the need for wearing any technology. Outside the home it may nevertheless be difficult to eliminate the need for some sort of wearable device and a number of devices exist and keep emerging also in the market. There are no good solutions for predicting falls at the moment.

Besides falls, a lot of research is being carried out on smart homes that address safety, help with indoor orientation (e.g. via illumination), as well as behaviour pattern monitoring as a tool for carers, clinicians and family members. Behaviour pattern monitoring is a particularly important topic for elderly with MCI/D as they have special needs in their daily life, for instance due to memory issues or because of a wandering behavior. Behaviour analysis can shed light to causes, facilitate remedies, and assist with challenges. Hence it is useful both for diagnosis, for activity prediction, and for personalization of the solution.

There is a lot of ongoing research on diagnosis tools for MCI/D (as well as Alzheimer's and Parkinson disease). The idea is that especially with the use of machine learning it is possible to observe relatively small changes in a person's daily patterns and to identify the onset of the disease early. It is also possible to monitor the progress of the disease.

Both these are important in order to provide timely assistance. A number of studies have focused on identifying differences between healthy elderly people, elderly with MCI and elderly with Dementia. This can be done for example using behaviour pattern analysis or execution of activities of daily life (ADLs).

There is a considerable amount of research on activity recognition, and impressive results have been achieved so far. Yet, activity recognition is often realised using simple sensors on absolutely every utilized object and is not always very sophisticated. It usually considers high-level activity recognition, that is activities like watching TV, cooking, sleeping, etc. are often addressed. Very few studies address low-level action recognition. For example, the COACH system decomposed the hand washing activity into actions to be recognized (e.g. put soap, turn on the tap, etc.). This decomposition can potentially facilitate recognition and evaluation of an activity plan, which is a topic that has high relevance for people with MCI/D. It is important to underline here that although activity recognition per se does not have a direct value for the users, it is a prerequisite and a necessary tool for achieving a number of functions in intelligent systems such as prompting systems, diagnosis tools, as well as prediction, anticipation and prevention of hazardous situations, e.g. fires or falls.

Only a few projects have tested their solutions and algorithms in real homes. Testing in real homes and with real users is indeed necessary in order to prove a system's real usefulness and efficacy.

This overview will hopefully facilitate a better understanding of the potential for further work as it emerges from the overall spectrum of activities in the field, and serve as a source of inspiration and a basis for directing the scope of further work.

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