Ambient Assisted Living for an Ageing Society: a Technological Overview

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Abstract. The rise in the average age and the decrease in the rate of births, cause the phenomenon called *population ageing*, which rises a number of issues. The oncoming shortage of caregivers and the strong desire of the older adults to live in their own homes originated an increasing interest in Ambient Assisted Living (AAL). AAL encompasses technical systems to support people in their daily routines. The paper focuses on the technological aspects of AAL systems describing the capabilities they require and how they are being addressed.

Keywords: Population Ageing, Ambient Assisted Living, Sensing, Acting, Reasoning, Interacting

1 Introduction

The rise in life expectancy is one of the great achievements of the twentieth century. This is a still running trend, as life expectancy is projected to reach 83 years in the more developed regions and 75 years in less developed ones by 2045-2050 [65]. Moreover, the most developed countries are experiencing a long-term downtrend in fertility. As a result, natural population growth rates are in decline or even decrease. The rise in the average age and the decrease in the rate of births, cause *population ageing*, which rises a number of issues:

- The decrease of the working-age population results in decline in human capital, which could reduce productivity.
- Pension and social insurance systems can become heavily burdened.
- A growing number of elderly will require long-term health care services. Considering constant the current use rates, the number of people requiring such services will double by 2040 [6], increasing the related public spending.
- Population in need of care services will increase much faster then the working age population, this could result in the impossibility of providing the needed services even in the case of financial stability.

From a technological point of view, the oncoming shortage of caregivers and the strong desire of the great majority of older adults to live in their own homes and communities originated a still increasing interest in what has been defined as *Ambient Assisted Living* (AAL) [22]. AAL encompasses technical systems to support people in their daily routines to allow an independent and safe lifestyle as long as possible. Often AAL solutions focus on the needs of special interest groups other than elderly, such as people with disabilities or people with temporarily need of assistance [26]. The main goal of AAL has been defined as the application of Ambient Intelligence (AmI) technology [55] to enable people with specific demands [36]. The paper aims at providing an overview of the technological aspects related to AAL systems providing a description of the anatomy of current AAL systems. Moreover, the paper provides an overview of some of the available AAL systems.

2 Anatomy of AAL systems

AAL systems usually rely on the *sense-act/interact* loop depicted in Figure 1.

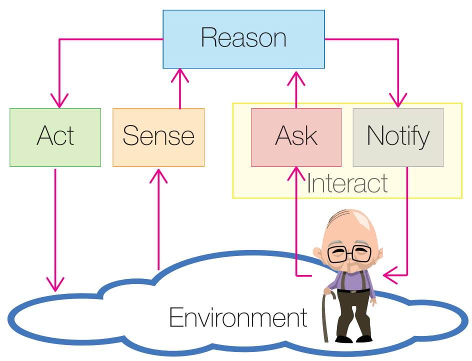

Fig. 1. Capabilities in AAL systems.

The *Sensing* and the *Asking* activities capture respectively information from the environment and wanted from the users. *Reasoning* is in charge of interpreting captured data to act on the environment and on the user respectively through the *Acting* and the *Notifing* capabilities. The user can be considered as part of the environment itself: information about him can be obtained through Q&A or observation capabilities. Finally, in order to cooperate, each activity relies on *Communicating* technologies depicted as pink arrows in Figure 1.

2.1 Sensing

Sensing is the fundamental capability of an AAL system because sensors capture information about the environments and the people who inhabit it. Sensors are usually enriched with processing and communication capabilities. Such sensors are commonly called *smart sensors*, which can be seen as a special case of *smart objects*, that is, autonomous cyber-physical objects augmented with sensing (or actuating), processing, storing, and networking capabilities [24]. In AAL systems sensors are generally divided in two main categories: *wearable* and *environmental*.

Wearable Sensors. Wearable sensors are positioned directly or indirectly on the human body. They usually monitor the physiological state of a person and her/his position and body movements. Concerning the person's physical state, a wide range of parameters can be obtained from different sensors, for example:

- *Tympanic, skin, oral, and rectal temperatures* are obtained by thermistors.
- *Blood pressure* is sensed through sphygmomanometer cuff [50].
- *Carbon dioxide* is commonly measured by a capnograph.
- *Oxygen saturation* is acquired by devices that rely on pulse oximetry.
- *Heart's electrical activity* is measured with a electrocardiography.
- *Blood chemistry* is usually sensed by means of chemical sensors.

Person's position and movements are commonly exploited in order to perform ADLs (Activities of Daily Living) recognition and classification [41] and, more recently, fall detection [43, 38]. The most common monitored parameters are:

- *Outdoor position* is generally acquired via GPS (Global Positioning System) devices by the resection process using the distances measured to satellites.
- *Detection and identification of a person* are generally obtained by Frequency IDentification (RFID).
- *Body position and movement* are normally obtained by tri-axial accelerometers, magnetometers, and angular rate sensors.

Environmental Sensors. Environmental sensors are embedded into the environment. They typically detect conditions that are descriptive of the environment or interactions between users and the environment. Research in this specific field is usually divided between *video-based* and *non-video-based* solutions.

Video-Based AAL Solutions. Vision-based solutions for AAL applications (VAAL) is a trending topic mainly due to the high versatility of cameras. The most explored areas are activity recognition in the rehabilitation and health care [13], and fall detection [57, 47]. A noteworthy innovative approach is in exploiting video technology to recognise and monitor physiological data. The main concern over the adoption of VAAL is the loss of privacy [13]. Moreover, those solutions must be accepted by potential users and their families, who may have concerns even in applications that claim to ensure privacy [68].

Non-Video-Based AAL Solutions. Sensors in this category usually have only a few parameters they can monitor, reason for which they are often combined together. Some examples of sensed parameters are:

- *Ambient light* is usually measured with sensors based on photodiodes.
- *Room temperature* is acquired as body temperature, thus using thermistors.
- *Humidity* is usually sensed by a Relative Humidity (RH) sensor.
- *Movement* and *presence* are usually sensed by Passive Infrared Sensors (PIR).
- *Door/window/cabinet open/closed* is usually obtained by a magnetic proximity switch based on reed elements.

– *Pressure*, intended as the force applied toward a surface, is obtained by force-sensing resistors that can be easily attached to flat surfaces such as chairs.
– *Environmental sounds* are sensed through microphones. The more widely adopted are Electret, which are specific kind of capacitor microphones that do not need a constant source of electrical charge to operate. Microphones can be used as presence sensor (like PIRs) or to achieve acoustic source localisation [51, 34]. Localising the source of a sound can be used to perform a more precise indoor positioning or for fall detection [52, 53, 38].
– *Odours* provide a lot of information about the surrounding environment. In recent years, many researchers have focused on developing olfactory sensors, able to capture and distinguish odours [19].

Environmental sensors overcome the main issue of wearable sensors by not requiring the users to always wear them. However, they have their own issues (apart privacy and acceptability problems): their price is higher, their require installation (and, thus, related cost), and they are fixed on their location, thus operating as long as the user is at home.

Trends in Sensor Technology. Since wearable sensors loose their functionalities if not worn, the research trends are toward size and weight reduction, durability, and waterproofing. *Microelectromechanical Systems* (MEMS, but it is also known as micro-machines in Japan or Micro Systems Technology (MST) in Europe) is an innovative technology consisting in miniaturising mechanical and electromechanical elements using micro-fabrication techniques. Miniaturisation has also enabled *ingestible sensors* and *implantable sensors*, mostly used in professional medical environments. Ingestible sensors are systems integrated into ingested devices such pills. They are conceived to be powered by the body and communicate through the tissue. These sensors can monitor ingested food, weight, and various physiological parameters, but also body position and activity, thus favouring users sustaining healthy habits and clinicians providing more effective healthcare services [54]. Implantable sensors are used in post-surgery: once implanted they can monitor and transmit data about the load, strain, pressure, and temperature of the healing site of surgery.

2.2 Reasoning

Reasoning is the process of converting data acquired from the field to meaningful information, which may have different meaning at multiple levels of interpretation (e.g., 12 oclock (noon) may mean 12:00, mid-day, day time and so on), depending on the personal context of the user. *Personal Context* is defined as user specific context information: parts of the environment (e.g. things, services, and other persons) accessed by the user; the physiological state (e.g. pulse, blood pressure, weight) and psychological state (e.g. mood and stress); the tasks that are being performed; the social aspects of the current user (e.g. friends, neutrals, co-workers, relatives); the spatio-temporal aspects of the other context components from the user point of view [48]. The main properties related to reasoning are: *data collection and processing*; *activity recognition, modelling, and prediction*; *decision support*; *spatio-temporal reasoning*. Different reasoning modules exploiting different properties can be combined in a single application. Artificial Intelligence (AI) can help in obtaining better performing modules and thus to be able to produce more useful applications.

Data collection and processing. Data acquired via the sense activity is usually easy to collect and process, however the amount of such data is a challenge especially if audio and visual information is included. Being able to obtain and integrate information from different kinds of sensors and sources is crucial to make AAL systems able to recognise events and conditions and, thus, to identify contexts and status. This skill is called *sensor data fusion* and is defined as the process of combining data to refine state estimates and predictions [61].

Activity recognition, modelling, and prediction. Reasoning technologies in AAL should be able to understand the contexts and the current status not only by using static rules and patters, but also dynamic and reactive models that take into consideration complex information (e.g., behaviour models of users). Moreover, they should be able to extract relevant information (data mining) and update the same models (learning machine). Specifically, AAL systems need to have capabilities such as: reinforcement learning (i.e., learning from the world observations), learning to learn (i.e., learning from previous experiences), developmental learning (i.e., learning from the world exploration), and e-Learning (i.e., learning from the Web and information technology) [1].

One of the main contribution that reasoning algorithms offer is the ability to recognise user activities. Different methods are available to recognise activities [4]: *template matching techniques* [9], *generative approaches* [12, 63, 67], *decision trees* [42], *discriminative approaches* [39, 23, 43].

Models of the user behaviours and the recognition of activities are fundamental for predicting probable statuses and context outcomes. This property is necessary both for anticipating possible negative events and conditions, thus acting in order to avoid them, and for predicting desires of the users, thus increasing their satisfaction.

Although recognising normal activities has a key role in health applications, abnormal events are very important too, as they usually indicate a crisis or an abrupt change in regimen that is associated with health issues. Likewise normal activities, abnormal activities can be recognised by classifiers, which usually require to be trained with datasets containing examples of the activities to be recognised. However, datasets containing activities related to critical situations (such as heart disfunction or falls) are rarely available. For these reasons, anomaly detection in AAL is receiving an increasing interest [53, 14, 43].

Decision support. Decision Support System (DSS) is a general term for any computer application that supports enhanced decision making. DSSs have been widely adopted in healthcare, assisting physicians and professionals in general by analysing patients data [35].

Spatio-temporal reasoning. Being able to reason on spatial and temporal dimensions is a key element for understanding the current situation. For example, a smart house system is able to recognise if someone turns on a cooker and leaves it unattended for more than 10 minutes; if this happens the system takes action by autonomously turning off the cooker and/or warning the user [16]. Thus, a number of proposal have been made in order to enable spatio-temporal reasoning in AAL contexts [7, 25, 44].

2.3 Interacting

Interaction is a well studied area under the umbrella of the Human Computer Interactions (HCI) and it encompasses all kinds of tool, both software and hardware, that allow the interaction process between the user and the system [3]. When designing an AAL system, attention must be put in the interacting activity because it has been pointed out that AAL systems will go unused if they are difficult or unnatural to use for the residents, especially the elderly.

The HCI may be *explicit* or *implicit*. Explicit HCI (eHCI) is used explicitly by the user who ask the system for something. This kind of interaction is in direct contrast with the idea of invisible computing, disappearing interfaces, and ambient intelligence in general. eHCI always require some sort of dialog between a user and the system and this dialog brings the computer to the centre of the user's activity.

Implicit HCI (iHCI) tries to reduce the gap between natural interaction and HCI by including implicit elements into the communication: the system acquires *implicit input* (i.e., human actions and behaviours done to achieve a goal, not primarily regarded as interaction with a computer) and may present *implicit output* (i.e., output from a computer that is not directly related to an explicit input and that is seamlessly integrated with the environment and the task of the user) [58]. The basic idea is that the system can perceive users' interaction with the physical environment, and, thus, can anticipate the goals of the user.

Towards a Natural Interaction. The analysis of the key issues in interaction and communication between humans offers a starting point toward new forms of HCIs. Three concepts have been identified as crucial toward better interactions:

- *Shared knowledge.* In interactions between humans a common knowledge base is essential; it is usually extensive but not explicitly mentioned. Any communication between humans takes some sort of common knowledge for granted and it usually includes a complete world and language model, which is obvious for humans but very hard to grasp formally.
- *Communication errors and recovery.* Communication is almost never error free. Conversations may include small misunderstandings and ambiguities,

however in a normal dialog these issues are solved by the speakers through reiteration. In human conversations is therefore normal to relay on the ability of recognise and resolve communication errors. However, in interactive computer systems that are invisible, such abilities are less trivial.

- *Situation and context.* The meaning of the words as well as the way the human communication is carried out are heavily influenced by the context (i.e., the environment and the situation that lead to communication), which provides a common ground that generates implicit conventions.

Comparing the way in which people interact to the way people interact with machines, it becomes clear that HCIs are still at their early stages. What humans expect from interactions is dependent on the situation, which is one of the concepts on which the field of Context Awareness Computing is based [2].

Interaction in the AAL domain. As mentioned at the beginning of this section, one of the key aspects in the success of any technological solution is its usability and acceptability according to end-user perspectives [1].

This is particularly true in AAL because most of the current and near future end-users of any AAL system are individuals with low to none affinity for technology. In order to develop successful interfaces for AAL services, designers should act accordingly to usability and acceptability criteria. Among all the theories, the most important are the Technology Acceptance Model [20], the Unified Theory of Acceptance and Use of Technology [66], and the Usability Theory [29].

2.4 Acting

Adding acting capabilities to an AAL system can be seen as obtaining the equivalent of a Closed Loop Control System in Control Theory, although the parameters affected by the actuation may not always be monitored by sensors and not every sensed parameter may be influenced by the actuations.

While sensors are required to understand and monitor the physical world, *actuators* are those mechanical objects that act on the physical world as a consequence of a software system action.

The number of different available sensors greatly outnumbers the number of actuators. However a few key actuators are sufficient to build a large number of complex smart objects.

The most common and simple actuators are already present in most of the homes, but almost always they are standalone systems. For example, indoor illumination and air conditioning (AC) systems. First attempts into making illumination systems more context aware have been achieved by coupling lightbulbs with motion sensors (PIRs): this way the lights do not require any explicit interaction in order to be switched on or off, but the movement of the user is an implicit input that cause the lights switching.

Actuators. As mentioned, there is a small set of common actuators that are used as building blocks in AAL systems. Some examples are:

- *Relays* are usually electromechanical devices acting as remote switches that can be activated by a software system through a low-power signal.
- *MOSFETs* (Metal-Oxide-Semiconductor Field-Effect Transistors) are transistors and serve as switches. Compared to relays, MOSFETs are usually very small and some of them can switch almost 10 orders of magnitude faster then relays. However, magnetic fields, static electricity, and heat can easily broke them. They are usually employed to operate in low amperage situations (e.g., to switch on/off led lights or motors and servos).
- *Lights* have been among the first actuators included in AmI system. Modern lights for AAL usually support dimmer facilities, provide different light colours, and include a small micro controller handling communication. Most of the modern lightning solutions are based on Light Emitting Diodes (LEDs) that can come to full brightness without need for a warm-up time.
- *Motors* commonly used are the DC (Direct Current) ones. Their are used in garage doors, curtains, or wheel chairs. A DC motor is a device that converts electrical energy into mechanical energy. In order to increase precision, stepper motors are usually adopted. Another highly used class of electric motors are servo motors, which are electric motors that can push or rotate an object with great precision. Servo motors are commonly adopted for precise, small movements that may require high torque.
- *Screens and speakers* provide feedback or information by transforming electrical data into physical phenomenons, light emissions, and sound waves respectively.
- *Haptic feedback engines* date back to 1968 [62], but only in recent studies they have been consistently considered in AmI solutions. Haptic Interfaces are used to provide tactile feedback (skin perception of temperature and pressure). It is a technology that complements visual and audio channels [1]. Force and positional feedback is considered as the next step of haptic interfaces for Virtual Reality, as they can also provide information on strength, weight, force, and shape.

2.5 Communication

Communicating capabilities are key aspects of AALs, since they are usually made up of distributed devices cooperating to provide the desired services. Three different types of networks are considered in AAL systems:

- *WANs* are employed whenever an AAL system needs to transmit information outside the system. Today solutions usually exploit an Internet connection obtained through one of the different providers available. With the increasing number of devices connected to the Internet, identification and addressing have been the most studied issues, which resulted in IPv6.

– *LANs* are used within home systems. They count different classes of technologies, such as cabled connections, powerline communications or wireless LAN (WLAN). Home automation often exploits dedicated buses, which means that gateways must be considered in order to put home automation systems in communication with the rest of the AAL structure.
– *BANs* derives from the widespread use of wearable devices [4, 33]. In a BAN sensors and actuators (mostly haptic, sound, or visual) are attached on clothes or directly on the body and less frequently implanted under the skin. BANs are characterised by three communication layers: intra-BAN (communication within the BAN), inter-BAN (connection between body sensors and Access Points), and beyond-BAN (streaming body sensor data to metropolitan areas, for example, to remote database where the users' profiles and medical histories are stored and made accessible to professional caregivers.)

3 Examples of AAL Solutions

3.1 Evolution of AAL Technology

There are three generations of technologies supporting AAL [27, 10].

First generation solutions requires users to wear a device, generally equipped with a button that the user can press in order to alert call centers, informal caregivers (family members), or emergency services. A reduction of the stress levels among the users and the caregivers, the reduction of hospital admissions, and the delayed transfers to long-term care facilities are some of the benefits achieved [59]. The limitations are mainly related to the responsive-only nature of the systems: if the user is physically harmed or mentally incapacitated, she/he may not be able to trigger the alarm. Moreover, highly risk situations such as night wandering may occur without the device being worn.

Second generation solutions usually feature a proactive behaviour. They are able to autonomously detect emergency situations, such as falls [47], or environmental hazards, such as gas leaks [49]. As they do not require an interaction with the user, these systems are especially suitable for older adults with normal cognitive ageing or mild cognitive impairment [49, 10]. The main drawback is the obtrusiveness of the employed devices.

Third generation solutions are the most advanced and exploit recent ICT advancements. Third generation solutions are not only able to detect and report problems, but proactively try to prevent problems and emergency situations. Prevention can be achieved by two different activities: the first is the monitoring of the user's vital signs, and of any eventual change in his mobility and activity patterns, thus predicting ongoing changes in health status; the second activity is aimed at limiting the exposure of the user to high risk situations on the basis of actions performed and by using actuators.

Fall detection systems represents a good example of three stages of evolution of AAL systems: early proposals were passive and relied on the user actions; contemporary solutions are autonomous and proactively detect falls; finally, most innovative approaches are going toward falls prediction and avoidance.

Falls represent a major health risk that impacts the quality of life of elderly. Roughly 30% of the over 65 population falls at least once per year, the rate rapidly increases with age and among people affected by Alzheimer's disease. Fallers not able to get up by themselves and that lay for an extended period will more likely require hospitalisation and face higher dying risks [43].

The factors that impact the risk of falls have been classified in two categories: *intrinsic* and *extrinsic* risk factors. Intrinsic risk factors include age, low mobility, bone fragility, poor balance, chronic diseases, cognitive and dementia problems, Parkinson disease, sight problems, use of drugs that can affect the mind, incorrect lifestyle (inactivity, use of alcohol, and obesity), and previous falls. Extrinsic risk factors are usually related to incorrect use of shoes and clothes as well as drugs cocktails. Finally some environmental risk factors related to indoor falls have been identified as slipping floors, stairs, and the need to reach high objects. Only 8% of people without any of the risk factors fell, compared to 19% of people with one risk factors, 32% of people with two, 60% of people with three, and 78% with four or more risk factors [64]. In order to promptly detect and notify falls, most common technological solutions exploit wearables accelerometers embedded in smartphones [43, 60, 18] or ad-hoc devices [38, 31]. Most of the proposals use domain knowledge algorithms, usually based on empirically defined thresholds. More advanced solutions exploit machine learning techniques, with most of them requiring fall data in order to properly train the classifiers. Since real fall data are quite difficult to achieve, those solutions rely on simulated falls. However, simulated falls are not truly representative of actual falls [37]. Thus, Micucci et al. [43] evaluate the efficacy of anomaly detectors trained on ADL data only. Their findings suggest that prior understanding of fall patterns is not required.

3.2 Existing AAL Platforms

A number of platforms have been proposed in the literature, one of the first and more general purpose AAL projects was *CASAS*, that stands for Center for Advanced Studies in Adaptive Systems. Its goal is to design a smart home kit that is lightweight, extendable, and with a set of key capabilities [17]. In CASAS environments as intelligent agents, whose status (and of their residents) is perceived using several environmental sensors. Actions are taken using controllers with the aim of improving comfort, safety, and/or productivity of the residents. A three layered architecture characterizes CASAS: the Physical layer deals with sense and act activities, the Middleware layer manages communication exploiting the publish/subscribe paradigm, and the Application layer hosts applications that reason on the data provided by the middleware.

Other solutions are more directly focused toward the phenomenon of the ageing population and therefore to the elderly.

As an example, the iNtelligent Integrated Network For Aged people (NINFA) is a project focused on the users wellness. The aim is to build a service platform suited for elder people whose user interface allows to deliver at home different services, such as user supervision, communication and interaction among users for social inclusion, exergame delivering [56], and general monitoring of the wellness [46]. To allow an early diagnose, discourse and conversation analysis is applied to monitor verbal behaviour of people affected by different types of disorders (e.g., aphasia, traumatic brain injury, dementia). Moreover, to perform motor/cognitive analysis, the system deliveries a set of custom designed exergames via HCIs suitable for elderly or motor impaired patients. Another solution focused on prevention of age-related issues is *ROBOCARE*. The ROBOCARE approach comprises sensors, robots, and other intelligent agents that collaborate to support users. ROBOCARE is an example of a branch of AAL solutions that are exploring the advantages and challenges of integrating assistive and social robots within the systems. Specifically, it is based on a mobile robot unit, an environmental stereo-camera, and a wearable activity monitoring module. Based on the observations obtained by the camera and the wearable unit, the system applies automated reasoning to determine if the user activities fall within predefined and valid patterns. Such patterns are defined by caregivers also considering the user's medical state [15].

There are also other solutions, that aim to support users with specific needs, regardless of their age. As an example, the BackHome project is focused on designing, implementing, and validating person centred solutions to end users with functional diversity. The project aims at studying how brain-neural computer interfaces and other assistive technologies can help professionals, users, and their families in the transition from hospitalisation to home care. BackHome main goal is to help end users to accomplish goals that are otherwise impossible, difficult, or create dependence on a carer [8]. The outcome of the project is a tele-monitoring and home support system [45].

Nefti et al. propose a multi agent system for monitoring dementia sufferers. Besides classical sensors (such as, temperature sensor and infrared motion sensors), the system uses specific sensors, such as natural gas and monoxide sensors, smart cup in order to measure regular fluid intakes, flood sensors near sinks, and magnetic contact switches for monitoring doors and windows [49].

Jeet et al. propose a system in which verbal and nonverbal interfaces are used to obtain an intuitive and efficient hands-free control of home appliances [30].

Alesii et al. propose a solution targeted to people affected by the Down Syndrome. The system provides a presence and identification system for domestic safety, a dedicated time management system to help organise and schedule daily actions, and remote monitoring, control, and communication to allow caregivers and educators sending messages and monitoring the user situation [5].

Lind et al. propose a solution targeted to people with severe heart failure, taking into consideration how an heart monitoring system should work in a contest where users are used to heart monitoring but not accustomed to technology [40].

Innovative Platforms for Wearable Technologies. Current measures related to health and disease are often insensitive, episodic, subjective, and usually not designed to provide meaningful feedback to individuals [11]. Current research in wearable devices and smartphones opens new opportunities in the collection of those data. A great opportunity comes form Apple that in March 2015 announced Research Kit (RK), an open source framework for medical research that enables researchers that develop iOS applications to access relevant data for their studies coming from all the people that use RK-based applications. Moreover, information will be available with more regularity as people use and interact with their devices. In the following, some example of applications and studies based on RK will be provided.

mPower. The mPower is an app is a clinical observational study about Parkinson disease conducted through an app interface. The app collect information through surveys and frequent sensor-based recordings from participants with and without Parkinson disease. The ultimate goal is to exploit these real-world data toward the quantification of the ebbs-and-flows of Parkinson symptoms [11].

Autism & Beyond. Autism & Beyond aims to test new video technology able to analyse child's emotion and behaviour. The app shows four short video clips while using the front facing camera to record the child's reactions to the videos, which are designed to make him/her smile, laugh, and be surprised. After the acquisition, the analysis module marks key landmarks on the child's face and assesses him/her emotional responses. The goal is not to provide at-home diagnosis, but to see whether this approach works well enough to gather useful data [21].

EpiWatch. EpiWatch helps users to manage their epilepsy by tracking the seizures and possible triggers, medications, and side effects. Data are collected from sensors and from surveys that investigate the activities performed and the user's state before and after the attacks, and notes about medical adherence [32].

Cardiogram. Cardiogram applies deep learning techniques to cardiology in order to detect anomalous patterns of heart-rate variability, and to study atrial fibrillation, which is the most common heart arrhythmia. Data is collected from people suffering from heart diseases as well from normal one using an app on the Apple Watch [28].

4 Conclusion

The paper presented an overview of the current state of AAL from a technological point of view. Enabling technologies for both the *Sensing* and the *Acting* activities are nowadays available. Moreover, both sensors and actuators are going to be embedded in more and more items, which will allow to obtain more and diversified data and control different aspects of the physical world respectively. Finally, a lot of interest is currently put toward further miniaturization, cost reduction, and precision of both sensors and actuators.

For what concerns the *Reasoning* activity, the community is very active: context modelling and understanding is fundamental in order to make meaningful inferences on the sensed data. As the acquisition of the data improves in quality and quantity, new inference engines can be designed and with them new AAL systems. Finally, more detailed context and user understanding, allow the *Interacting* activity to move toward the concept of custom tailored implicit interaction between users and systems.

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