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XXIX Ciclo

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A WIRELESS SENSOR NETWORK FOR IOT-BASED AMBIENT ASSISTED LIVING SERVICES

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A WIRELESS SENSOR NETWORK FOR IOT-BASED AMBIENT ASSISTED LIVING SERVICES

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Introduction

The population ageing is one of the most important phenomenon impacting on our society worldwide; many studies underline how this change is unprecedented in the history of mankind, and with few exceptions it touches every economically-advanced country in the world: the aged population is currently at its highest level in human history [1]. The number of people aged 60 years and over has tripled since 1950, reaching 600 million in 2000 and surpassing 700 million in 2006. The causes are to be found in the increase in our life expectancy, thanks to a generally healthier lifestyle and the improvements in healthcare and medicine, and the simultaneous decrease in the birth rate, a trend many governments are trying to face [2]. As a result, nowadays about the 17% of the EU population is over 65 years old and the 4.5% is over 80 years old, and these percentages are respectively expected to increase to 25% and 8% by 2035 [3]. Italy in particular is one of the "oldest" countries in the EU, with 20% of people over 65 years old and the 5.5% over 80 years old, and the region of Liguria (in northwestern Italy) has the highest ratio of elderly to youth in the world [4].

This change is going to have a major impact on the economy of our society; public healthcare will need more and more founding to sustain the increasing demand, not to mention the actual physical space needed in the hospitals for all the people in need, and the medical staff necessary to assist them; furthermore, the public welfare will suffer from the disequilibrium between young workers and retired people: Giuseppe Carone and Declan Costello of the International Monetary Fund projected that the ratio of retirees to workers in Europe will double to 0.54 by 2050 (from four workers per retiree to two workers per retiree) [5].

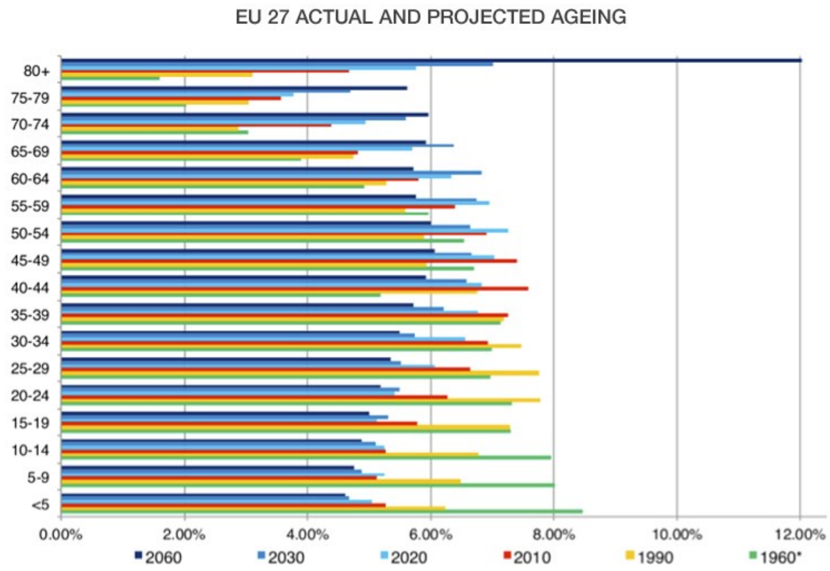

Figure 0.1: a graph showing the actual and projected ageing of the EU population. The 80+ part is foreseen to become by far the bigger one after 2030

The consequences will affect social aspects as well: the "traditional" model, in which the children support their parents and grandparents in their older ages, in already being disrupted by the increase of mobility, reason why parents and children may live in countries far away; moreover, the diminution of the birth rate may cause a single person to sustain all his parents and grandparents, increasing the difficulty to carry on such model. For these reasons the number of requests for nursing homes is increasing, leading to multiple problems for the family: economical, because of the cost related to hospitalize a person, and psychological, because of the trauma caused by being forced to leave their own house, with a sudden loss in the quality of life and happiness.

In the early 2000s, the World's Health Organization set up guidelines to encourage "active ageing" and to help local governments address the challenges of an ageing population (Global Age-Friendly Cities) with regard to urbanization, housing, transportation, social participation, health services, etc...[6].

In this scenario, it will be very important the development of Ambient Assisted Living (AAL), a term used to describe a set of technological solutions aiming at making active, smart and cooperative the environment in which we live.

The importance of this topic has been underlined by the European Union, which created the AAL-Programme, a funding activity aiming at “create better conditions of life for the older adults and to strengthen the industrial opportunities in Europe through the use of information and communication technology (ICT)”. This program founds project aiming at extending the time people can live in their preferred environment, support the preservation of health and functional capabilities of the elderly, promote a better and healthier lifestyle for individuals at risk, enhance security, prevent social isolation and support the preservation of the multifunctional network around the individual.

With AAL-system we may refer to any kind of system that satisfies the definition above, meaning that we could be able to find AAL-systems everywhere, from our bedroom to the local public gardens: in this thesis, for the sake of simplicity, with AAL-system we will refer to a system meant to be installed in a private home.

An AAL-system must help an ageing person, actively cooperating with him in order to reach the goal of a more independent and autonomous life: thanks to a set of actuators and sensors (which may be both fixed and wearable) coordinated by a central unit, the system must be able to elaborate all the data collected, and modulate in a dynamic fashion the conditions of the house to satisfy the user’s needs. Developing such system may be helpful not only to elderly adults, but also to people with disabilities, to reduce their difficulties in everyday tasks.

Moreover, it is of capital importance to monitor the health of the older adults, in order to promptly detect any situations needing immediate assistance even in the absence of a dedicated caregiver.

A system of this kind must satisfy a series of strict requirements. First of all, it must be very easy to use and to interact with, since the average user may have no familiarity with technology, or may have some kind of visual or tactile impairment.

Invasiveness is another key feature: the system must not interfere with the users' everyday life, and they do not have to feel bothered in any way by the presence of the devices around the house.
Related to this is the problem of reliability, in terms of integrity of the devices and tolerance to false positives: the user should not be bothered by frequent maintenance intervention, nor by false alarms that would greatly discourage him from trusting he system.
A high scalability and flexibility is also necessary, since the system must be able to adapt to the user's specific needs, which may be very different from house to house.
Finally, the cost must be contained, since the aim is to be able to offer the system to as many people as possible.
In the last ten years an AAL-system named CARDEA has been developed at the Domotic and Assistive Technology Lab (DoTALab) at the University of Parma, trying to pursue the goals stated above. Using CARDEA it is possible to handle the standard features offered by a home-automation system, like security and safety (intrusions, fire, flood,…), doors and windows automation, lights and heating control.
The main feature of CARDEA is the behavioral analysis (BA): by conveniently installing a series of small devices in the house, it is possible to monitor the daily routine of the residents. This allows to gather a huge amount of information about the habits of the daily living of the users, that, in turn, can be very useful to find information about their health status: for example, if a person suddenly starts spending a lot more time in bed respect to his average, or moves around the house a lot less, it can immediately be deducted that probably there is something wrong going on with that person, and alert the family or the caregiver.
Nonetheless, the greatest potential of this kind of analysis is in the long term: by keeping track the daily habits, it is possible to retrieve some meaningful patterns, and monitor their variations over time. This may be useful not only to the users, for example to notice some unwanted change in their routine, but to the doctors as well: the first manifestations of different diseases may be deducted from combining the measurement of some standard health parameters (like blood pressure or blood oxygenation level) with anomalies

in the daily habits, that usually are disregarded by the people. An automatic detection of such anomalies would instead allow to promptly intervene, before the problem may worsen.
To be able to carry on such analysis, it is indispensable to use wireless devices, to respect the constrain of non-intrusiveness mentioned above. These devices must be able to detect the activities of interests among those carried out by the users during his daily living, like opening the fridge, laying on the bed or using the toilet. The information must then be gathered by a central node and elaborated, to eventually give a feedback to the user and the caregiver.
Therefore, the goal is to create a smart network, in which the devices are connected with each other and controlled by remote. These characteristics outline what in recent times is being defined as Internet of Things (IoT): "the IoT allows objects to be sensed and/or controlled remotely across existing network infrastructure, creating opportunities for more direct integration of the physical world into computer-based systems, and resulting in improved efficiency, accuracy and economic benefit". Storing remotely the data allows the doctors to access them directly, being able to check them in person when an anomaly is detected, and decide if further analysis is necessary.
During the development of the system presented in this thesis, two main topics have been faced: indoor location and user identification.
Within an assisted-living facility, tracking the user's movements can be used to provide accurate alarm information (for instance, fall alarm can include precise location of the fallen person) or to prevent hazards (e.g. wandering of a cognitive-impaired person toward dangerous areas). Besides such primary purposes, the aim is to exploit localization information for behavioral analysis, i.e. enrich the information about the user's habits by considering the movements he makes around the house.
Moreover, in a multi-user scenario proper identification of the user is needed, to correlate the actions detected by the wireless devices to the actual performing person. In principle, this could be accomplished by tracking users' position within the home environment. As will be discussed further in details in the next chapters, an accurate, reliable and low-cost indoor-location solution is a very demanding task, and no technology is yet available to realize

such system. Therefore, a different approach has been developed, aiming at identifying the user when the wireless devices detect a given task of interest. This is the framework in which the research activity has been carried out during the three years of this PhD: consequently, this thesis will space from electronic engineering to healthcare, from wireless-network related issues to the psychological consequences of living alone at home. Therefore, I will do my best to make this work comprehensible for people with different background, and I apologize in advance if I won't be able to do so.
The first chapter will discuss more in the detail the AAL-systems: the different challenges to face when transforming a simple home-automation system into a AAL-solution, and the different solutions available on the market or presented in the literature. Also, the different technologies involved will be discussed, with a particular focus on the one used by the CARDEA system, the ZigBee protocol, and the features of the wireless devices involved. Also CARDEA will be descripted more in details.
The second chapter will focus on the many issues related to the indoor-localization topic and on CARDEAGate, the first technological solution developed during this PhD, designed to solve some of those issues.
In the third chapter, the problem of the user-identification will be discussed in details, and a possible solution will be proposed.
The fourth chapter will discuss about the finalization of the system, that was eventually installed in many pilot sites in the framework of the Helicopter European Project, and the useful feedbacks and information retrieved from this experience, both from the users and the technicians point of view.
The period spent at the Applied Biomedical Signal Processing and Intelligent eHealth Lab at the University of Warwick (UK), under the supervision of Prof. Leandro Pecchia, will be the focus of the fifth chapter. During this experience a preliminary study has been carried on to investigate the relationship between the effects of poor sleep and the human balance: the final aim is to understand how a poor sleep quality may affect the way elderly adults walk, and in particular how this may increase their risk of falling. Falls are the most common cause of injury and/or traumas among people over 65 years old, and the leading cause of accidental death and the 7th leading cause of death in people ≥ 65 [7]. Because of this it is of capital importance not only

being able to detect and promptly treat them, but to prevent them, understanding the situations in which the risk of falling increases, and instruct the person to avoid those kind of risks, or giving him some kind of support to help him.

Finally, the Conclusions and future developments chapter will review the main achieved results and explore the open questions and possibilities for the present work.

Chapter 1

AAL: Services and Technologies

In order to produce systems ensuring high-quality-of-service, it is important to consider different aspects of AAL systems to achieve interoperability, usability, security, and accuracy, which are essential requirements of AAL systems.
This Chapter focuses on introducing the AAL-systems in more depth. In particular, all the principal, relevant concepts for the development of our system will be covered, namely: the evolution from home-automation to AAL system, the techniques and the devices used, the features and potentialities of AAL-services, and their problems as well. A deeper look will also be given to CARDEA and the ZigBee protocol, and to the usage of wireless devices.
This chapter is thought to provide a high-level, introductory view of such topics (far from being exhaustive); the interest reader can gain deeper information, for example, by looking at the references provided. Nonetheless, all these topics will allow us to place the whole presented work into a nicer context.

1.1 From home-automation to AAL

To better understand the evolution of AAL-systems, we have to start from the home-automation: the idea of an “automated house” was born a long time ago, and many AAL-services can be somehow perceived as the evolution of that idea.
First of all, let’s clarify a semantic issue: even if most vocabulary are not including it yet, the word “domotic” (and "domotica" when used as a verb) is widely used and accepted by the scientific and technical community, as a

synonymous of home-automation or “smart-home” (it origins from the contraction of the Latin word for home, *domus*, and the words/fields informatics, telematics and robotics). Therefore, it will be used in this paper with this meaning (sorry Microsoft Word auto-corrector).

1.1.1 A short history of home automation

If we extend the definition of home-automation to any kind of electrical device able to ease our everyday tasks at home, the firsts of this kind are to be dated back to the early 1900s, with the introduction of electrical power distribution and the invention of washing machines, water heaters, refrigerators, sewing machines, dishwashers, and clothes dryers. However, these appliances were very expensive and could only be afforded by the wealthy.

The very first home-automation system, Echo IV, was developed in 1966 by Jim Sutherland: it was able to control temperature and turn appliances on and off, but was never commercialized because of its cost.

The first general purpose domotic network technology, called X10, was created in 1975 in Scotland, and even if a number of higher bandwidth alternatives exist, even nowadays it has remained popular in the home environment, with millions of units in use worldwide, and inexpensive availability of new components. In the first release, X10 included a 16 channel command console, a lamp module, and an appliance module. Soon after came the wall switch module and the first X10 timer [8].

During the 70s and the 80s the potential of domotic started to gain popularity, drawing more and more expectations (see Fig. 1.1), but it was not always perceived as positive: as in the famous short novel “There will come soft rains” by Ray Bradbury, or in “1984” by George Orwell, people started wandering if the development of automation would have led to dramatic consequences on the society. Ironically enough, 1984 is also the year in which the term “Smart Home” was first coined by the American Association of House Builder [9].

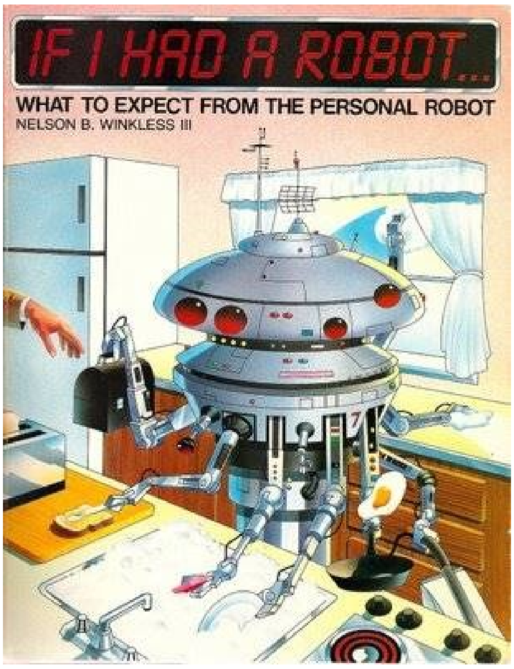

Figure 1.1: I hope that, in a parallel universe, there's another me being helped in the morning by this robot, as in the cover of this book from 1974

In 1998 opened the Integer Millennium House, a demonstration home in Watford showcasing how it was possible to integrate home automation inside the house, controlling heating, security, light, and doors, and including environmental technology such as a green roof and a grey water recycling system.

As technology became more affordable, domotic started gradually to become integrated in our houses: nowadays home automation is everywhere, and we take it for granted or we are not even aware of it. We can control doors, lights, heating, and also appliances and TV via controllers or even our smart phone, making this tasks extremely comfortable and easy: and that's the aim of home-automation indeed.

1.1.2 Telemedicine

The goal of telemedicine is to provide clinical health care from distance, using ICT (Information and Communication Technologies).
Telemedicine is capital in the AAL framework: elderly adults need to check regularly some important health-related parameters like blood pressure or blood saturation, and being able to check them from home is very important for their well-being, avoiding frequent travels to the doctors and queuing time.
These kinds of self-checks would be important also on the doctors and medical-staff side: remote patient monitoring through mobile technology can reduce the need for outpatient visits and enable remote prescription verification and drug administration oversight, potentially significantly reducing the overall cost of medical care [10].
The most common way to use telemedicine is the "store and forward", in which the medical data acquired by the device is temporarily stored and eventually transmitted to a doctor at a convenient; these data can thus be assessed altogether offline, granting the doctor a wider set of information, from which more accurate diagnosis can be deducted.
Modern, wireless devices are available nowadays at a very low cost and are very straightforward to use, making the "self-control" of those parameters a relatively simple task.
The downside of telemedicine is that it relies on the user's sense of responsibility: the user is the one in charge of reminding to take the measurement, of taking it in the correct way, and of maintaining the device operational (e.g. charging or changing the batteries when needed).
As will be discussed in the upcoming Chapters, it would be very useful to integrate telemedicine in a AAL-system, to facilitate the user's task and to act as a reminder to do the measurement and to correctly take care of the devices being used.

1.2 AAL: features and problems

An overview of the main features of a AAL-system has already been given in the introduction. To wrap up, a AAL-system must integrate the standard features of a domotic system:

- Security and safety
- Light, doors and heating control
- Appliances control
- Remote access

With a series of tools and services to actively cooperate with the user, in order to reach the goal of a more independent and autonomous life.
An AAL-system has a different perspective respect to a normal domotic system: to help elderly adults or people with particular needs while they are at home, easing their everyday living and improving their quality of life.

1.2.1 Personal health monitoring

As mentioned in the previous Paragraph, personal health monitoring is becoming more frequent: people are more aware of the importance of keeping their health status somehow under control, and furthermore, they are becoming more familiar with technology, and accept more gladly the idea of using electronical devices for health-related purposes [11].
AAL-systems are therefore used for telehealth and telemedicine facilities, providing remote healthcare services to the users: this can be easily achieved connecting the medical devices with the AAL-system, allowing to send medical data to the health monitoring database. The sensors are thus connected to the Wireless Area Network (WAN), and the information are forwarded to the healthcare application through the home gateway [12]. The home gateways, also known as smart home gateways, often use a wireless router that provides connectivity to enable multiple applications for real-time health monitoring through home networks [13].

Moreover, due to increasing availability of portable, wireless medical devices and wide access to data networks, the usage of medical devices is continuously growing.
Since sensible information are being collected, data security is a critical topic in AAL-systems. Of course, guidelines are provided by the legislation to write suitable authorization policies, to regulate the access to the data and avoid incorrect usage [14]. Moreover, while developing the AAL-system, a strong effort must be directed to make it resistant to any sort of hacking or intrusion.

1.2.2 A helping hand in everyday situations

Easing everyday living can be achieved in many ways and on many different levels. This paragraph is intended to underline some features that an AAL-system may include, to work out as a useful helping hand for the different kind of users.
For example, as the user wakes up at night, the system may automatically turn on some soft lights to guide him outside his room, or maybe to the toilet, and then turn them off as the bed is occupied again: a system of this kind has been developed by several companies (as mylight [15]) and has encountered a good appreciation by the users.
Many elderly encounter some difficulties when carrying the groceries bags around the house: Cavallo et al [16] are developing a series of “house-robots” to solve this issue; these robots can take the bags from outside the entrance of the house, and deliver it to the kitchen table (or wherever the user wants them around the house), even if the house is an apartment and several floors are needed to be climbed (a third robot is able to actually go to the grocery store and pick up the bags from there, but personally I don’t think the world will be ready soon for a robot to safely go to the supermarket).
Some supervision would also be useful in the kitchen: a smart hob has been developed at DoTALab in the framework of the European Project named FOOD [17]: using this technology the hob can be automatically turned on or

off according to some pre-programmed activities and to the data coming from the temperature sensors installed.

Another important device for an elderly adult is the pill reminder [18]: by integrating it in the AAL-system, it would be easier to communicate to the user when to take the pill, and even check that the pill has correctly been taken, for example by attaching a motion sensor to the pill box, or by monitoring with an environmental sensor the opening and closing of the drawer where the pills are stored.

An AAL-system must also be proactive to the user, encouraging him in order to be more active and socially involved, for example by checking his phone calls and suggesting to call some friend or family member in case it's been a while since he last heard from them.

All these examples are related to issues that are not very big deals if taken singularly, but the sum of them can really make a big impact on the quality of life of an elderly adult, and that's what AAL-systems are made for.

1.2.3 Behavioral Analysis

As already mentioned, another important feature in a AAL-system is the possibility to carry on an extensive Behavioral Analysis on the user's health status.

This can be achieved by fusing the data coming from the medical devices to the ones coming from environmental sensors placed around the house. These sensors must of course be completely non-invasive for the user, and must detect when a given action of interest is made.

In order to do so, a list of the actions of interest must be defined: even if this seems a trivial task, it is in fact complicated and multi-faceted. Doctors, engineers and caregivers must cooperate to find the optimal solution:

- At first, the doctors must identify a series of possible diseases that can be monitored
- Then, they have to identify some daily tasks that can lead to diagnostic suspicious on those diseases

- Afterwards, some possible technological solutions must be found to identify those tasks among the daily living of the users
- Eventually, the final devices must be developed in a way that they do not harm or bother the user's daily routine, and are therefore accepted by them.

Putting together all these steps is not as simple as it seems, since very different points of view are to be taken into account, and experts in different fields are needed.

When the proper solution is found, the devices are then installed in the system, and in this way it becomes possible to monitor the daily routine of the users; nevertheless, to close the loop other stages are needed:

- The data coming from the environmental and medical devices must be fused; then they must be analyzed, and an algorithm is needed to find the anomalies and the diagnostic suspicions
- According to the algorithm output, the appropriate person must be alerted, being it the doctor, the caregiver, a family member or the user itself. Every person of this list needs different information and a different way to communicate them, therefore different feedback methods may be needed

The behavioral analysis topic is subject of lively researches nowadays, and is expected to be one of the main research trends in the future [19].

1.2.4 Not only Engineering

Developing a AAL-system is a very complex and multi-faceted task: the technical point of view is not enough at all, because a lot of social and psychological implications have to be taken into account.

We already discussed the main constraints to tackle:

- Easy to use
- Non-invasive
- Reliable
- Flexible

- Low-cost

Moreover, we have to consider that this kind of system must be perceived as useful by the user, that otherwise would look at it just as something trying to spy on him at all the time. Giving feedbacks to the user is therefore something very important: during our older years, the common saying “no news is good news” is more appropriate than ever, because for and elderly adult, being today in the same condition as yesterday is already a positive outcome. For this reason, even if no anomalies or no news are detected by the system, it should still try to interact with the user, giving him positive reinforcement about his daily habits, and telling him that he’s doing fine. Of course this could backfire in case the user feels down or feels sick, so the way this message is given is very important, and so is the reliability of the anomaly detection process.

Finally, the flexibility issue deserves a little bit more of in-depth analysis. Every person can have a different familiarity with technology, can react to technology in a different way, and can think of needing just a very specific help in his daily living, hence perceiving any extra-help as an unwanted interference. Because of this the system may have to adapt to the single user, or will be considered as useless or too intrusive, and therefore the user will not interact with it.

Of course it is not possible to adapt to every specific need of every specific user, but for instance a different set of interfaces can be prepared, from the more advanced to the more basic; in addition, the feedbacks must be programmable, so that any unwanted feedback can be disabled; moreover, the anomaly detection system must be able to work with just a subset of all the available devices, because for a specific user it may not be possible to install them all.

1.2.5 Some examples of AAL-systems

Despite a significant number of research and industry organizations are active within the AAL field, the real world usage appears to be fairly limited and confined to a few devices and standards being applied beyond the pilot-study level. An explanation for this could be the wide gap among the requirements of real world AAL system scenarios and the capabilities of currently available solutions and enabling technologies. Moving from research prototypes and pilot studies is a difficult process that requires more technical, economical, and organizational resources and commitment to succeed. Also, there are large differences in user the population, leading to more complex user-experience and socio-technical requirements, while the requirements to standardization and certification incurs higher efforts and cost of executing the research and development organizations, as compared to traditional system development [12].

Nevertheless, the following is a list of innovative AAL-systems or AAL-related technologies, many of which have already had an impact on the market

- Rosetta

The ROSETTA project [20] has developed an innovative, integrated system aiming at prevention and management of the problems that can occur to elderly persons as a result of chronic progressive diseases (such as Alzheimer). The system consists in a series of environmental and wearable devices to monitor wandering, falls and bed usage of the users, and provides that information to the family members or nurses thanks to an Android app.

- AMICA

AMICA [21] aims to emulate medical consultation at home: auscultation and interview. To achieve this, a series of physiological signals are obtained on a daily basis by means of an ad-hoc sensor. This information is then added to the one provided by the patient interacting with a dedicated mobile device. By combining information coming from sensors and provided by the patient, the system is able to set off medical alarms, modify small aspects of the patients’ treatment program or lifestyle, or even suggest hospitalisation.

- Homer

HOMER [22] is an open and flexible OSGi-based software platform which aims at the integration of various home automation systems and consequential event and situation recognition for smart home (addressing comfort, energy efficiency, etc.) and Ambient Assisted Living applications (addressing safety, autonomy, self-confidence, etc.).
HOMER consists of an extendable graphical user interface which features configuration and design of the home environment including sensors and actuators, logging and monitoring panels. The user interface facilitates creation and maintenance of a floor plan and positioning and assignment of sensors.

- Yoom

The Yoom tablet [23] was developed to support family connections. Goal of this project was to develop a technological answer to the growing problem of loneliness amongst elderly people in Europe.
Yoom enables a real life like view of the other person: seeing more of the body (head, arms and hands) gives a better sense of connection and opens the possibility of engaging in activities together, like drawing, playing games et cetera. It features a large screen and the high quality sound to give an enhanced impression of contact with the other person, and an intuitive control system with built in feedback, to make it easy for elderly to use, even if they have little or no cyber experience.

- Help

The HELP project [24] has designed a system that is able to anticipate when a patient will develop an OFF state or dyskinesia by means of a “Parkinson’s” sensor which sends relevant information to the platform and which automatically establishes a new level of drug administration for the pump to overcome that state. This aims to keep the patient in the ON state most of the time, thus avoiding the debilitating Parkinson’s symptoms. At the same time, a constant level of drug is administered by another sub-system developed through the HELP project, consisting of an intraoral device embedded in the patient’s mouth in the form of a tooth.

- Memas

Memas [25] is a “memory assistant” tablet, that contributes to everyday life and aims to increase user’s independence, by showing a calendar with overview and reminders of the activities that will take place today, providing access to favorite channels on radio, photo album, memos or newspapers, and helping to increase communication between the municipality, the relatives and the user.

1.3 CARDEA

CARDEA [26] is the AAL-system developed at the Domotic and Assisted Technology Laboratory (DoTALab) at the University of Parma. CARDEA is flexible and low-cost, relying on standard and diffused communication protocols, such as IEEE 802.3 (Ethernet) standard for the wired LAN and IEEE 802.15.4/ZigBee protocol (see later paragraph) for the wireless sensor network, because of its low power consumption and low cost, that perfectly fit the needs of an AAL context.
CARDEA handles the usual features of a home automation system like lights, windows and temperature control, deals with safety and security (floods, gas leaks, intrusions…) and features an extended network of devices to monitor daily living: this devices, which have been developed at DoTALab as well, share the same hardware components, and can therefore be configured to monitor different kind of activities, such as bed/chair occupancy, fridge opening, kitchen hob usage, appliance (e.g., TV) usage, toilet flush, etc. This allows for great flexibility and configurability in order to satisfy the needs of the specific user. The devices will be further described in the next paragraph. In addition, since the wireless sensor network is based on the standard ZigBee protocol, any commercial, off-the-shelf device can be exploited as well, like an infrared presence sensor or a plug power meter, leading to even more flexibility and allowing to gather a greater number of information about the users’ daily activities.

Furthermore, a wearable multi-sensor platform, called MuSA (Multi Sensor Assistant), has been designed and introduced, allowing for fall-detection and vital parameters recognition [27].

In this way it is possible to carry on an extended BA, aiming at evaluating a person's health status and behavioral evolution and, in case of particular variation of the parameters, providing information to the doctors and/or the caregivers. Researches about this topic are undergoing at DoTALab and an example of such analysis (using a reduced number of sensors) is presented in [28].

The Domus App has been developed to give at a glance all the information about the status of the devices installed inside the house (see Fig. 1.2): tapping

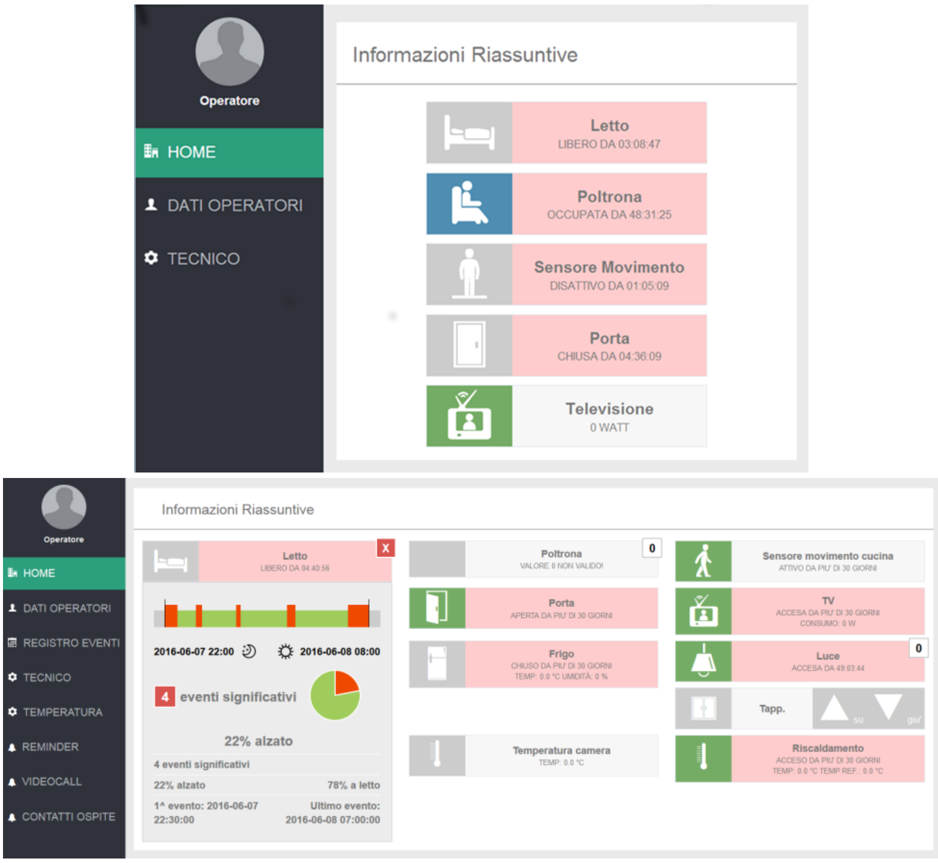

Figure 1.2: the Domus interface. The top version is simpler and with bigger fonts, more suitable for a user not familiar with technology; the bottom version is more detailed

on the single device allows to see in more depth the recent usage of it, the status of the batteries and other useful information. As already underlined, it is important to differentiate the feedbacks according to the needs of the user: the version shown in the bottom part of Fig. 1.1 is thought for a user who is familiar with technology, or for the family members or the caregivers; a simpler and more colorful version is available for those users who are less technology-savvy, shown at the top of Fig. 1.1.
The information gathered by the system are stored in a local server and forwarded in a cloud-based database (usually mysql-based). In this way the information is easily accessible from remote, allowing to an easier analysis of the data for BA purpose.

1.4 Environmental Devices

As mentioned above, CARDEA features an extended network of devices to monitor daily living, that can be commercial off-the-shelf or developed at DoTALab. This paragraph is intended to give a deeper look to the latter ones, since most of the work carried out during this PhD has been related to their development.
First, let’s take a look at the necessary characteristic of wireless devices, and at the main problems that arise when dealing with wireless networks; later on the ZigBee protocol will be further discussed; eventually the environmental devices developed at DoTALab will be described in details.
For the sake of simplicity, in this and in the next Chapters, with Bed, Fridge, Chair, Door, ecc (with the capital letter) we will refer to the environmental devices monitoring the given action of interest, and not to the actual appliances or furniture pieces.

1.4.1 Towards IoT

IoT is a new generation of network service platform that allows everyday objects, including small devices in sensor networks, to be capable of connecting to the internet [29]. It consists of intelligent devices that have a digital entity and are ubiquitously interconnected to a network and to the global Internet. Everyday objects may integrate intelligence and the ability to sense, interpret, and react to their environment, combining the Internet with emerging technologies, such as radio-frequency identification (RFID), real-time location, and embedded sensors [30].

In particular, a lot of attention is being given recently to IoT-based eHealth-services, and the proof can be seen from the success of intelligent medical devices, wearable biomedical sensors and wearable devices for fitness applications. Population aging and the increase of survival chances from disabling illnesses led to an increased demand from the current population, which requires continuous eHealth [31].

As already underlined, wireless devices are nowadays essential to carry on an exhaustive behavioral analysis: the development of microelectronics has pushed the dimension of this kind of devices to very low scales, and in addition they are now affordable to any kind of end user.

We all have a clear idea of the reasons of this success (comfort, low dimensions, low weight, …), but from an Engineering perspective, dealing with wireless devices poses some additional problems respect to their wired counterpart.

First of all, the compromise between power consumption and performance: the more performance it is required from the device, the more power it will drain, meaning that the batteries need to be changed or charged more frequently. This is a very complicated balance to reach, because on one hand being low on battery is the most annoying thing that can happen on the user's experience perspective, but on the other hand what the user wants is a device that is capable of smoothly doing the task that it is expected to do, without delays or high waiting time.

The transmission range is the other big downside of wireless devices: even if radio protocols are becoming more and more reliable, they will never be as reliable as wired-communication; furthermore, the area covered by an antenna is not perfectly stable, and if no redundancies as provided, a device may become isolated from the rest of the network. The Mora postulate [32], that wireless devices are reliable only when there's a sufficiently long cable connecting them, may be a little too extreme, but wireless communication requires a careful planning and development.
The final concern is related to privacy: any radio communication can be easily intercepted and recorded by a specific device operating on the same frequency (usually called *sniffer*); for this reason, it is very important to securely encrypt the information being transmitted, and to adopt a safe protocol.

1.4.2 ZigBee

ZigBee is an IEEE 802.15.4-based specification for a suite of high-level communication protocols used to create personal area networks with small, low-power digital radios, such as for home automation, medical device data collection, and other low-power low-bandwidth needs [33].
ZigBee devices are intended to have less capabilities but to be less expensive than other wireless personal area networks (WPANs), such as Bluetooth or Wi-Fi.
The transmission is not limited to line-of-sight or quasi-optical path like Bluetooth, and the power consumption is much lower than Wi-Fi or Bluetooth devices [34].
ZigBee is typically used in low data rate applications that require long battery life and secure networking (ZigBee networks are secured by 128-bit symmetric encryption keys).

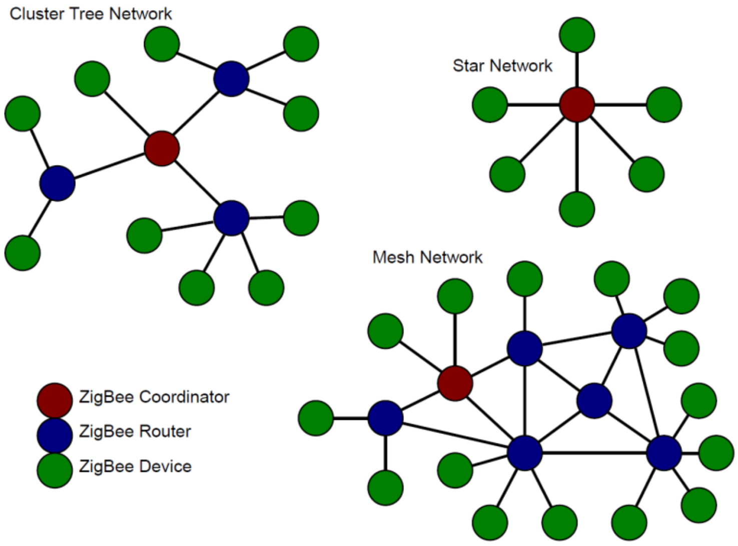

Figure 1.3: tree, star and mesh topology

The downside is the lower data rate: while Bluetooth throughput is up to 1Mbps, and Wi-Fi can easily go beyond that mark, ZigBee is limited to only 250Kbps.

These features make ZigBee on of the best candidate to build a AAL-system: in such networks it is unlikely to have the need of a very high data rate, since the devices must signal only when they are triggered by the user or they detect an action of interest, and these communications are generally limited to a small amount of bytes. Therefore, the focus is to be placed on long-battery life and secure communication, two characteristics in which ZigBee excels.

The ZigBee network layer natively supports both star and tree networks, and more important the mesh networking (Fig. 1.3): in this particular kind of net, there is not a pre-defined path to respect, but every device can be connected to any other, generating redundancies in the path available to go from one device to another one. This increases the fail-safety of the communication, and the probability that if a device stops working, the integrity of the network will not be compromised.

There are three different kind of devices in a ZigBee network:

- *Coordinator*

The Coordinator creates the ZigBee network and gives other devices the permission to join, therefore there can be only one Coordinator for each network. It also stores the ID of every device and the routing tables, containing the information about the path to follow to reach every device in the network. The Coordinator must stay on at all the time, therefore it is usually plugged in a computer (with which it can exchange information using a specific protocol) or a power outlet.

- Router

Routers are used to extend the area covered by the network, and can allow other devices to join; even if a Router can be tasked with context-specific application, it is generally used only for routing purposes. As the Coordinator, Routers as well must be always on.

- End Device

The End Device is the device with lowest network functionality, since it cannot store or route any message, and cannot allow other devices to join. The End Device is usually tasked with a specific application, and undergoes a sleep\awake cycle to reduce battery consumption.
Every End Device is the "Child" to a "Father" device, that can be a Router or the Coordinator itself; every message sent to the Child is first routed to its Father, that temporarily stores it: when the sleep phase is over, the Child asks the Father if there is any pending message for him, and if not it goes back to sleep. With this procedure, the End Device can keep its antenna off for the great majority of time (the on-off time-ratio can easily be in the order of 1 to 1000), allowing for very effective power-saving: the battery duration of an End Device is the order of several months, and if no demanding applications are needed it can be stretched to a few years.

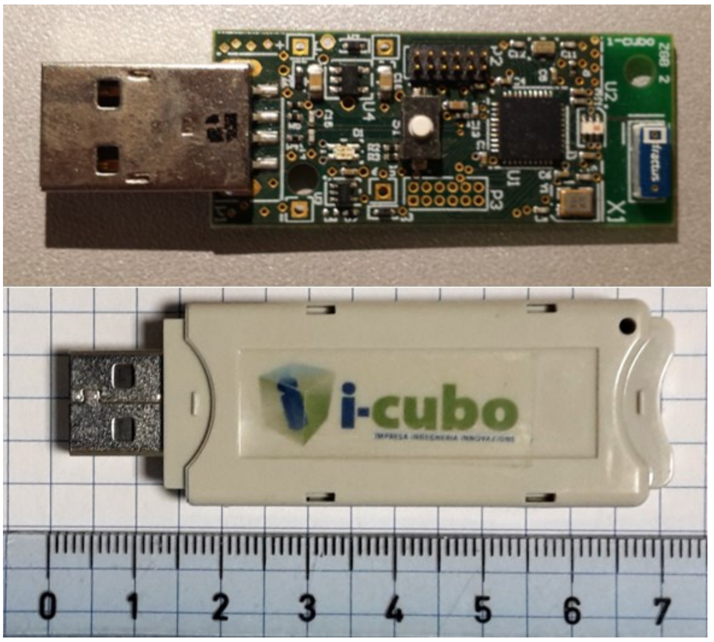

Figure 1.4: the Coordinator and Router Hardware. On the top, the board; on the bottom, the board is enclosed in its case. The USB port is used for both power supply and serial communication

1.4.3 Coordinator and Routers

Coordinator and Routers in CARDEA share the same hardware, completely developed at DoTALab, and shown in Fig. 1.4. The µcontroller is a Texas Instruments CC2531, designed ad-hoc for low-power consumption and implementing the ZigBee Stack. The board features a pushbutton for opening the network (allowing other devices to join) and to reset the device. The USB port is used both as a serial port and for power supply.

The Coordinator is usually plugged-in a computer: communicating via serial port, the Coordinator forwards to the PC the messages it receives from the other devices in the network; the PC then elaborates them and, if necessary, sends a reply to the Coordinator, or shows a notification on the proper interface.

The exchange of information between Coordinator and PC is regulated by a protocol developed ad-hoc, that integrates the different kind of messages included by the ZigBee Stack, and proved to be extremely reliable and safe (though of no easy coding).

The Routers are usually plugged-in a USB power adapter (like the one we normally use for smartphones), and placed around the house in convenient location, i.e. where the ZigBee signal starts being low.

When dealing with Routers, the greatest complications are given by the mobile node MuSA: in fact, the ZigBee protocol was conceived for home automation, thinking of a static condition of every device in the network (i.e. no device moves around the house). In this way, once a device is included in the network, it will keep the same Father throughout all the functioning of the system.

A mobile device instead, while being moved around the house, may reach a place that is not covered by its original Father, being thus forced to change Father, connecting to a closer Router that covers the new location.

This behaviour is not fully supported by the ZigBee protocol, and some tweaking of it has been necessary to solve some connection-problems that arose when making this transition from Router to Router (or to the Coordinator).

1.4.4 Bed, Chair, Drawer, Door and Fridge

These four devices share the same board, also in this case completely developed at DoTALab and show in Fig. 1.5. The only difference between them is the sensor attached, and how this is connected to the board. The top board is the same shown if Fig. 1.4 for the Coordinator and Routers, but without the USB port, since there is no need for that because the devices are battery-powered and are not meant to be connected to a pc.

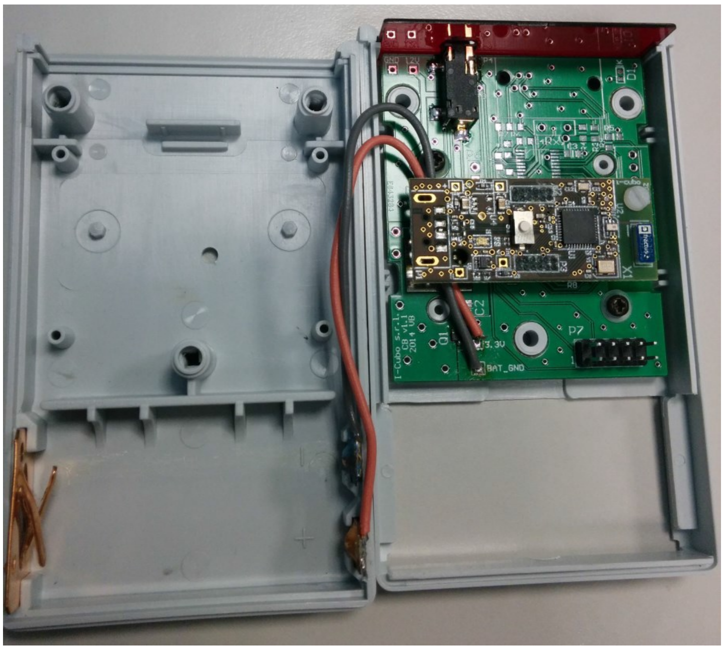

Figure 1.5: the hardware for Bed\Chair, Drawer\Door and Fridge. The only difference between these versions is the connector at the top: in the picture a Drawer\Door is shown, as the 3.5mm aux socket can be clearly seen

The bottom board is used to transfer the power supply to the µcontroller, and to connect the different sensors to the it, connecting the peripheral sockets and pads to the I/O pins of the µcontroller;
They are all programmed as End Device, and they are powered with two AA-batteries that can grant their functioning up to six months, depending on the frequency of the sleep-awake cycle.
As the hardware was already implemented, during the PhD the focus has been on coding the firmware of these devices.

- Bed\Chair

In this case the sensor is a pressure pad, attached with a standard RJ-42 connector. The pad is to be placed under the mattress or on the chair (under a pillow if the chair provides it), and allows to monitor when somebody sits or stops sitting on it. The pad is available on two different sizes, the bigger one being more suitable for the bed, while the smaller one is recommended for chairs. The device itself can be laid on the ground or attached to any part of the bed\chair structure.

- Drawer\Door

This device provides a standard 3.5mm aux socket, that can be used to attach a commercial magnetic sensor: the sensor can then be placed on a door, a drawer, or wherever there is an open\closed situation to be monitored. The Door then signals every time the magnetic contact is opened or closed. The firmware has been developed to avoid multiple-signals at once and false positives\negatives that may be caused by bounces.

- Fridge

The Fridge has an analog luminosity sensor, directly connected to an analog I/O port of the µcontroller; therefore, it is possible to detect when the fridge door is opened or closed, by simply checking the level of luminosity signalled by the sensor. Furthermore, an analog humidity sensor is provided, to check the level of humidity inside the fridge and therefore if the fridge is malfunctioning. For both light and humidity detection, the case of the Fridge has a IR-glass on one side and a series of small holes on the front.

1.4.5 Toilet

The Toilet was developed in order to monitor the access to the toilet area. Originally, a magnetic contact was used, attaching it to the inside of the flushing cabin, so that flushing the toilet (that usually moves a mechanical arm up or down) would have resulted in separating the two magnets; this approach is however not practical, since in some toilets it may be very hard, if not impossible, to properly install the two parts of the magnetic contact in the inside of the flushing mechanism.

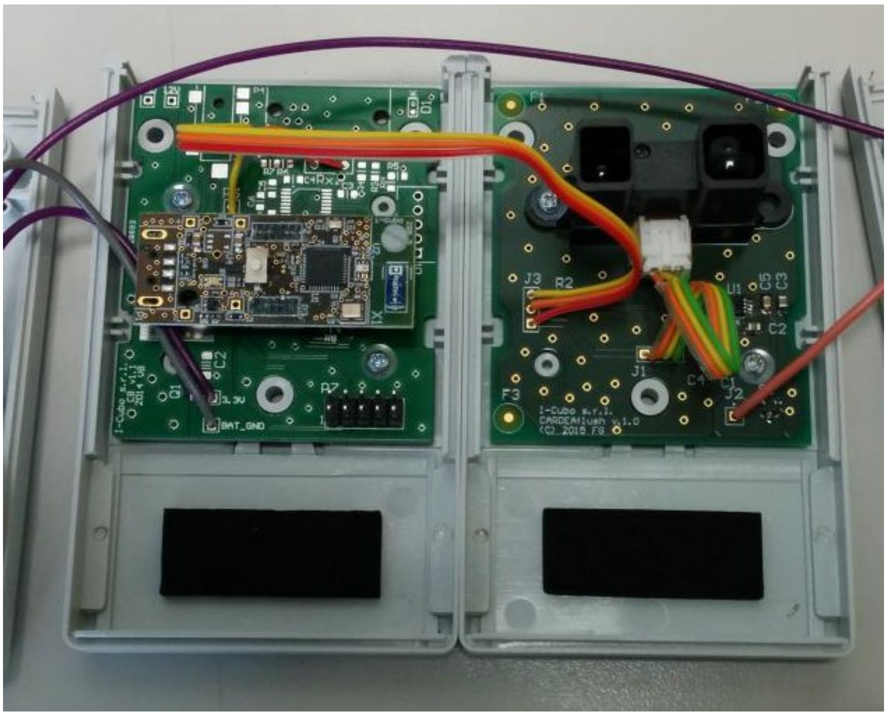

Figure 1.6: the two board composing the Toilet. On the left the same board used for the other devices; on the right the new board, on which the IR sensor is clearly visible. The wires going off-screen are connected to the battery slots on the other part of the boxes.

A different approach has then been followed, connecting an IR-sensor to the board and using it to detect the presence of a person inside the toilet, regardless of him flushing or not the lavatory.

A suitable IR-sensor has been found (SHARP GP2Y0A02YK0F), that however needed a power supply from 4.5 to 5.5 V, whereas the two AA batteries can provide at most 3V. For this reason, a different hardware setup was needed: another board has been designed, to store the IR sensor and a LDO (Low Drop-Out Linear Regulator, Analog Devices ADP3333) needed to stabilise the tension. Then two cases were place one next to the other: one containing the old board and another one containing the new board; both of them were powered by two AA batteries, but they were connected in series, so that, at full charge, the voltage on the new board was 6V (the sum of the four batteries); cables were running from one board to the other, to transfer the input and output signals needed for the correct functioning of the device (Fig. 1.6).

The mode of operation was as following: once decided a sampling interval *t*, every *t* seconds the µcontroller was turning on the LDO and consequently the IR-sensor, which output was then forwarded back to the µcontroller to be read; according to its value the µcontroller had to decide, by making a comparison with a predefined threshold, if there was a person in front of the device, and signal accordingly to the Coordinator; eventually, the IR was turned off, waiting for another *t* seconds before starting over the cycle.

The length of *t* is to be decided as a trade-off between power consumption and resolution of the measurement: the lower is *t*, the higher is the chance to not have a false negative, but the higher is the power consumption as well. For example, if *t* is set to 20, if a person enters and exits the toilet in less than 20s, the device may not be able to detect its presence; however, setting *t* to 10s would halve the battery life.

The value of the threshold can be programmed on-the-go between five pre-programmed distances (50-70-90-110-130 cm), accordingly to the dimension of the toilet and the distance between the device and the walls.

Chapter 2

CARDEAGate

User-localization plays an important role in many AAL functions: knowing the approximate position of the people living inside the house may enable context-sensitive support functions, make emergency calls more effective, etc.

In a multi-user environment, to correctly perform a behavioral analysis we need to attribute data coming from environmental sensors (e.g., opening of the fridge) to a given user: this would be very easy knowing the location of each user, because the one performing the action would most likely be the one being the closest to the device which detected it.

Also, tracking movements may give a lot of information about a person's health state.

In general, indoor location is a complex and multi-faceted issue. A large number of system have been proposed, based on various methods or technologies. It is worth underlining, however, that AAL-oriented applications pose quite different constraints (in terms of required accuracy, system intrusiveness and affordable costs) with respect to main fields localization technologies have been developed for. Reliable, handy and low-cost solution are needed for daily living in home environment, while no extremely high accuracy is needed: for many AAL-applications, a room-level accuracy may already be enough, and in general knowing the user's location with an accuracy of about 1m may be a satisfying result.

2.1 Overview on indoor localization solutions

Indoor localization is a very popular topic among ICT researchers nowadays. A large number of solutions have been proposed in recent years, using different techniques and technologies.
Besides the technologies, there are many different algorithms that can be used for indoor positioning, from triangulation to kNN to fingerprinting: for the sake of simplicity we won't explain in details these procedures since they are not so relevant for the purpose of this Chapter, but an overview can be found here [35].
The following is a short review of some of the most significant studies on indoor positioning, exploiting different technologies and protocols.

2.1.1 Computer vision

Computer vision is based on the elaboration of video images, coming from different cameras placed around the house. The most common approach to detect the presence of the person is to compare an image of the room when no people is present, to the one coming in real-time [36]. In this way, the user does not need to wear any specific device in order to be tracked.
A downside is that the system may suffer from a dynamic-environment (in which furniture is frequently moved) and when multiple users enter simultaneously the same room; also, it may become expensive to install at least one camera in every room of the house (often more than one camera per room is needed).
Anyway, the biggest flaw of this approach is privacy-related: even if the images are not recorded (they are processed in real-time, so no recording is needed) and there is no person watching them (the process is of course automatic), it is common for the user to feel his privacy violated just for the presence of the cameras in every room, and thus refusing to install such system in his house [37].

Computer vision-based system may reach very high accuracy in tracking the user's movements, with errors in the orders of the cm [38].

2.1.2 Infrared (IR)

IR localization system requires the user to wear a tag (i.e. a small wearable device) that periodically emits an IR signal; these signals are received by beacons placed around the house, that calculate the RSSI and send it to a central node (usually a pc) that calculates the tag position from the proximity between the tag itself and the beacons.
IR signals do not penetrate through walls, hence it is possible to confine the reception of each beacon, improving accuracy. Moreover, IR technology is characterized by the absence of radio electromagnetic interference and the power of transmitted IR signal can be easily adjusted to cover only the area of interest.
Nonetheless, IR signals suffer from multi-path influence, that can affect the accuracy. Furthermore, IR requires LoS (Line-of-Sight) visibility between transmitter and receiver: therefore, the signal from the tag may be blocked by clothes, objects, or any kind of material.
IR systems may reach sub-mm accuracy [39][40], but they are very expensive and they require particular conditions to operate: therefore, they are not very suitable for AAL-purposes.

2.1.3 Ultrasound

Ultrasound is generically a wave with a frequency higher than 20kHz (the upper limit of the human-ear hearing capability), and it is usually intended to have a frequency not higher than a few hundreds of kHz. The approach is usually the same as IR systems, with a central unit trying to locate a wearable tag from its interactions with some fixed beacons.

Ultrasound do not require LoS visibility and is a low-cost technology, but their indoor range is usually limited at less than 10m and they may suffer from environmental noise [41]: everyday actions like moving some keys or a metal object may in fact produce some ultrasonic waves, that can interfere with the positioning system.
The Active Bat system by AT&T [42] can reach an accuracy up to 0.5m in a 500m^2 indoor environment, but needs 720 receivers to be placed on the ceiling; the Cricket system [43] may reach an even higher accuracy, but needs a lot of beacons as well, and can be severely affected by environmental noise.

2.1.4 Wi-Fi

Wireless Local Area Network (WLAN) can be used to estimate the location of a mobile device within this network. The great success of Wi-Fi network would suggest a reduction of the costs, since it would be possible to exploit the pre-existing devices: however, an efficient positioning system needs the presence of at least a device in every couple of rooms; therefore, the standard hardware present in every house (a router plus maybe a range extender) would not be enough to implement such system.
Wi-Fi has the advantage of allowing a very high bitrate (up to tenth of Mbps) and a high transmission rate; nonetheless, the power consumption is higher than the other wireless solutions, and the accuracy is limited if no expensive additional hardware is introduced.
The Strongest Base Station (SBS) method is the simplest solution in WLAN RSS-based indoor localization systems [44]: this method has no computational issues and is applicable in most networks. However, the SBS method could not achieve good accuracy because of the complexity of indoor WLAN environments and limitation of the AP coverage; fingerprinting-based methods as [45] are easy to deploy and tolerant to wireless signal noise, then can achieve a higher accuracy (between 2 m to 50 m), but still not sufficient to AAL-purposes.

2.1.5 RFID (Radio Frequency IDentification)

The RFID technology is based on the use of an RFID reader, equipped with one or more antenna, and active or passive transceivers (i.e., tags). Passive RFID tags reflect the signal they receive, adding a few information by modulating it: they are cheap, of small dimensions and don't need any battery, but their range is limited to a little more than 1m; active tags can transmit their ID or any kind of other information and have a wider range, but of course they are more expensive and battery operated.
The Where Net system develop by Zebra Technology [46] is based on small active tags with very efficient power consumption (the charge may last years), but they achieve an accuracy of about 3m; a location estimation method able to guarantee better accuracy in indoor environment localization systems by using angulation techniques and passive tags attached at known locations is presented in [47].

2.1.6 Bluetooth

Bluetooth has a lower bitrate (up to 1 Mbps) and shorter range (up to 10m) compared to Wi-Fi, but is ubiquitous in commercial devices because it is embedded in most devices such as mobile phones, personal digital assistants (PDAs), laptop, desktop, etc. Then, the use of the Bluetooth technology in location sensing permits to reuse the devices already equipped with Bluetooth technology, so adding a new device to such a system does not require any additional hardware.
The drawback is that the accuracy is limited compared to other technologies, and the position can be calculated with a delay of at least 20s, that does not allow for real-time tracking.
In [48] it is proposed a Bluetooth positioning system, exploiting both RSSI and triangulation methods, that reaches an accuracy in the order of 10 cm;

however, it needs 4 beacons in a 6x8 empty room and a calibration procedure, and the presence of human bodies may greatly interfere with the signals.

2.2 CARDEAGate

CARDEAGate is a novel approach to user localization and identification, particularly suited for behavioral analysis purposes: it is a low-cost "gateway" monitoring system composed by a couple of small ZigBee transceivers (named for the sake of simplicity G_a and G_b) of the size of a standard USB flash drive, that allows to detect the crossing of a doorway or a predefined pathway and, interacting with MuSA, the identification of the user.
CARDEAGate is capable of detecting a person crossing a door or any given gateway, and, if he is wearing a MuSA device, to identify him. I.e., CARDEAGate features the basic functionality of any "sight-line" sensor (e.g., infrared barriers), detecting any person crossing the gateway line (i.e. the imaginary line connecting the two transceivers), however posing much less stringent constraints in terms of placement, alignment and maintenance. As a matter of fact, CARDEAGate does not need line-of-sight visibility, so it can easily be embedded into doorframes, home furniture or stand behind curtains and thin (non-metallic) walls. This makes the system also less intrusive, and allows for smooth integration into most home environments. If the user wears a MuSA, further "active" interaction modes with the passing user are enabled, allowing for user's identification. CARDEAGate can be exploited to monitor the access to zones of interest (a room or even the fridge, an armchair, etc.).
CARDEAGate operating principle exploits the absorption of the radio signal power caused by the body of the person crossing the radio link propagation path and is based on the consequent modulation of the Received Signal Strength Index (RSSI), that will be explained in details in the next paragraph. Such an approach lends itself to fairly simple implementation and integration within a ZigBee sensor network, and well fits a wide range of AAL-oriented

services. For example, an elderly adult may need assistance using the toilet, especially if affected by Alzheimer disease or by other kind of dementia, and installing CARDEAGate on the toilet door may alert the caregiver that the person has entered the toilet and needs assistance: in this way the caregiver can take care of other tasks like cleaning the house, cooking, and so forth, without having the constant concern of checking if the person is heading towards the toilet without him noticing.
With CARDEAGate it is also possible to implement a simple room-level localization service: installing CARDEAGate on each door of the house would allow to monitor the movements of the users with room-level accuracy, and to reconstruct how they move around the house during their daily living. Figure 2.1 shows a simple User Interface that allows to load a map and to easily monitor the movements of the MuSAs in the network. The tables and the Logger contain the information about the devices in the network, and the previous detections and the identifications. The dots on the map represent the location of the gateways: once a passage is detected, the corresponding gateway is highlighted.

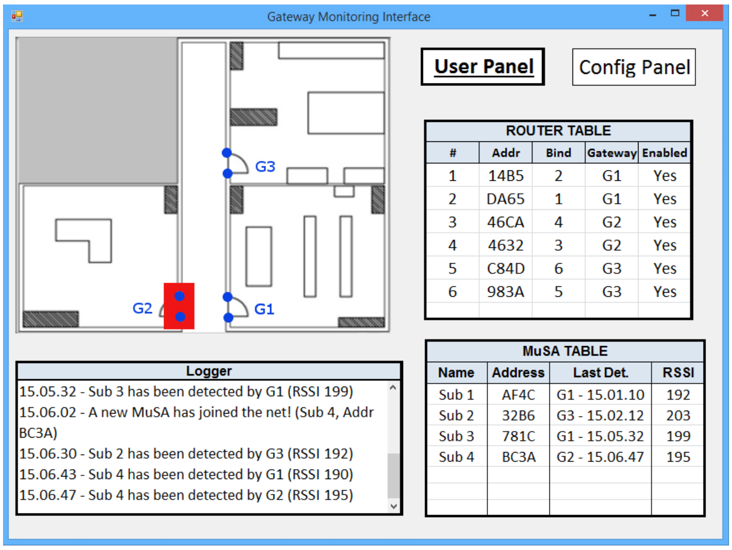

Figure 2.1: a simple User Interface to control the three CARDEAGate deployed

Another possible application is to feedback location information to a wearable sensor that is implementing inertial navigation tracking: based on acceleration data, in fact, relative position can be inferred; stockpiling integration errors, however, yields some drift in the results and progressively affect localization accuracy [49]. CARDEAGate then allows for resetting such a stockpiling error, restoring a reliable reference for inertial tracking. Full integration between MuSA inertial navigation capabilities (exploiting the on-board inertial unit, composed of integrated accelerometer, a gyroscope and compass) and CARDEAGate beaconing is being carried out at DoTALab [50].

2.2.1 Operating principle

CARDEAGate is composed by two small ZigBee transceivers (using the same hardware used for Routers and Coordinator, see Fig. 1.4), to be placed on the two sides of a door or of any point of passage to be monitored. The two devices communicate with each other at a frequency of 5Hz (i.e. sending one message to the other device every 200ms), and calculate the RSSI of each message of this kind they receive.

RSSI is a parameter that any antenna-equipped device calculates when it receives an electro-magnetic signal: the higher the RRSI, the higher the chances that the signal is not corrupted. In addition, RSSI can be related to the distance between transmitter and receiver, using the formula

$$RSSI = A - 10n \log_n d \tag{2.1}$$

Where

A = RSSI at the distance of 1m

n = coefficient of attenuation (given by the environment in which the devices are being used)

d = distance between transmitter and receiver

When a person crosses the imaginary line connecting the antennas of transmitter and receiver, the RSSI experiences a sudden loss, because the human body absorbs a significant part of the power of the signal being transmitted. CARDEAGate exploits this effect, called shadowing [51], to detect the crossing of the person.

During its propagation, an electro-magnetic signals is in part absorbed, reflect and refracted every time it encounters a material with a different propagation coefficient [52]. In an indoor environment, this means that every wall, floor, object and even person causes a series of absorptions, reflections and refractions, that may greatly disrupt the correct propagation of the signal. For this reason, RSSI is a reliable parameter only when considering "short" distances (usually not more than 2m), because as the distance increase, the effects suffered by the signal may have an unpredictable effect on its power.

Nevertheless, this problem has little effect on CARDEAGate, because, for the purposes of monitoring a standard door or hallway, the distances between G_a and G_b are small enough to not be affected by multi-path issues.

2.2.2 Functioning Process

The functioning of CARDEAGate is divided into three stages: training, detection, and identification

- *Training*

The training phase is needed to calculate the RSSI value in "quiet" conditions i.e. when no person passes between the gateway. To do so, the two devices store all the RSSIs of the messages they receive in a 5s time-window; after this short period, they calculate the average of the RSSIs stored. This value is then used as the threshold value during the following phase.

Of course it is necessary that no person crosses the gateway during this phase, because doing so would disrupt the signals and impact on the RSSIs. Usually the threshold is calculated when the system is installed, so that the technicians can guarantee the integrity of the process; however, the two devices can be programmed to recalculate the threshold at a given period of the day, for example late at night when it is very unlikely that someone would be passing through the gateway, or when a given command is received from remote.

- *Detection*

During the detection phase, G_a and G_b send each other a message every 200ms, and compare each RSSI to the threshold calculated earlier: when two consecutive RSSI are below that value, the passage is detected, and the identification phase can start.
It has been chosen to use two consecutive messages to avoid a possible, even if unlikely, multi-path interference in a “quiet” situation, that may cause a sudden loss in one RSSI, and lead to a false positive; it has been chosen not to further increment the number of consecutive messages below the threshold, to still being able to detect a passage even if it lasts less than 500ms, a situation that may happen if the user is walking “fast”.
Since the RSSIs calculated by G_a and G_b may not be the same, it may happen that only one of them detects the passage: to avoid any kind of conflict, as soon as one of the two devices detects the passage, it sends a message to the other one, communicating to start the identification phase.

- *Identification*

In this phase, G_a and G_b try to identify the user that crossed the gateway line, by discovering the MuSA which is the closest to them, because this will likely be the one that caused the detection of the passage.

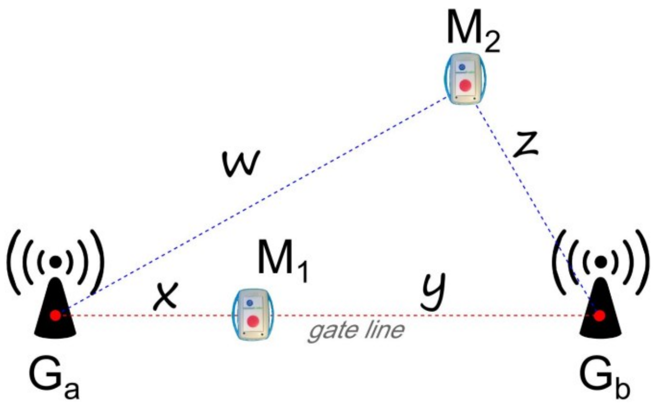

Figure 2.2: a simple drawing showing the geometrical approach used for the identification. G_a and G_b are the two devices composing the CARDEAGate, whereas M_1 is the device crossing the gateway while M_2 acts as an interferer

The two devices send a ping request[1] to each MuSA in the network, and then calculate the RSSI of the replies. The values are then forwarded to another node or to the computer, that is in charge of doing the decision process exploiting a geometric approach explained below.

The device crossing the gateway is the one which features the lowest sum of distances from either gate transceiver: in Fig. 2.2, for instance, M_1 is the device crossing the gate line, whereas M_2 lies nearby. Elementary geometrical reasoning yields

$$x + y < w + z \tag{2.2}$$

where x, y, w, and z are the distances between mobile and fixed nodes, as indicated in figure.

For a given transceiver couple (i, j), after some manipulation starting from Equation 2.2, the distance $d_{i,j}$ can be made explicit

$$d_{i,j} = k * 10^{-RSSI_{i,j}} \tag{2.3}$$

[1] a ping is a message that contains no information, and is used only to inform another device of the presence of the transmitter

Where k is a constant involving signal propagation features and is therefore related to the actual signal path. Thus

$$\begin{aligned} x &= k_{1,A} * 10^{-RSSI_{1,A}} \\ y &= k_{1,B} * 10^{-RSSI_{1,B}} \\ w &= k_{2,A} * 10^{-RSSI_{2,A}} \\ z &= k_{2,B} * 10^{-RSSI_{2,B}} \end{aligned} \tag{2.4}$$

In principle, of course, the propagation constant k is not necessarily uniform along different triangulation legs. Nevertheless, for the sake of simplicity, we can assume a constant value as a worst case scenario: by supposing that propagation along the gate line is better of propagation along longer path (which does not hold true in general, but makes sense for a sensible gate placement) considering a uniform propagation constant k (i.e., $k_{1,A} = k_{1,B} = k_{2,A} = k_{2,B} = k$) may result in relative underestimation of "outer" device distances, thus not harming the selection criteria below.
Hence, from Eq. 2.2, the decision test yields:

$$10^{-RSSI_{1,A}} + 10^{-RSSI_{1,B}} < 10^{-RSSI_{2,A}} + 10^{-RSSI_{2,B}} \tag{2.5}$$

If the inequality holds true, crossing of M_1 is assessed, and M_2 otherwise. More generally speaking, if a multiplicity of MuSA devices is considered, the one crossing the gate line is selected by looking for the minimum value of the distance sum:

$$S_j = d_{j,A} + d_{j,B} = k \ (10^{-RSSI_{1,A}} + 10^{-RSSI_{1,B}}) \tag{2.6}$$

Therefore, the minimum S corresponds to the MuSA which is the closest to the CARDEAGate: this MuSA is thus elected as the one that just crossed the gateway.
A problem may arise in case a person who is not wearing a MuSA crosses the gate and triggers the identification: in this case the system would assign the detection to the closest MuSA, committing an error. To prevent this, a threshold can be set during the identification phase: if the RSSI of the selected MuSA il below this value, the identification is discarded and the crossing is not assigned to a specific user. The threshold can be set by the technicians

during the installation phase by doing some simple trials, checking the typical RSSI values while standing in the proximity of the CARDEAGate.

2.2.3 Detection Tests

The detection performance of the system was tested, and some preliminary evaluations were made, aimed at assessing practicality and reliability of the proposed approach.
At first the gateway was placed in the middle of an empty room in order to minimize interferences caused by furniture or other objects that could interact with the wave propagation, at a height of 1m. Testing patterns are illustrated by Fig. 2.3. Among investigated features were:
a) **Sensitivity to the gate width** (i.e., the distance between G_a and G_b). Gate widths ranging from 0.5 to 3 m were accounted for, with intermediate steps of 0.5 m. Central crossing (Test 1 in Fig. 2.3) and lateral crossing (Test 2) were performed. By repeating each measure 50 times for each width and position, no false negative was actually incurred in (i.e., all 600 passages were correctly detected). In both tests, 100% of actual passages was correctly detected, independently of gate width changes in the given range.
b) **Robustness to false positives:** to this purpose, walking paths close to the gateway but not actually crossing it were tested, both in the parallel (Test 3) and transverse (Test 4) directions. Again, tests were repeated 50 times for each configuration.
The aim of the Test 3 was to find the lower distance from the gateway line that could cause false positives. Walking close to G_a or G_b without crossing the line between them, may in fact perturb the antenna of the devices, causing a false positive if enough power is absorbed.
An accurate measurement of this distance turned out to be unpractical, due to the complex shape of the human body and to the inherent uncertainty in controlling human gait: since even a difference of few centimeters may concur in causing a false positive, to accurately measure it a person should be able to walk of a perfect straight line, without swinging the arms (it is not

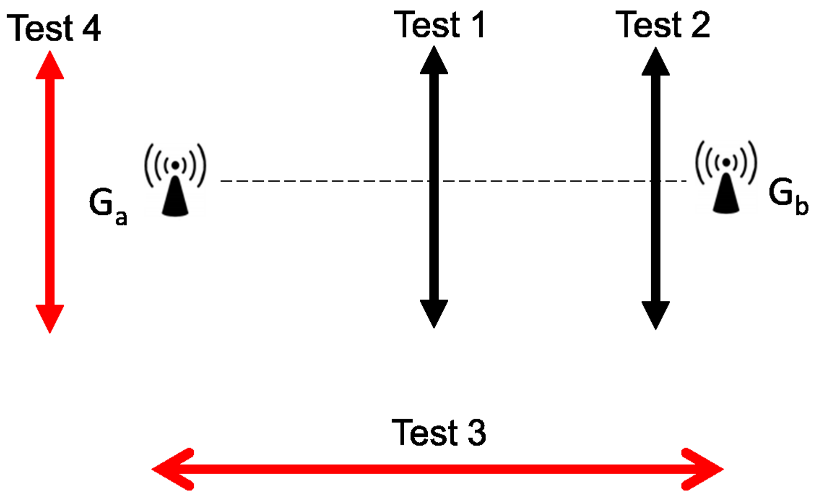

Figure 2.3: a sketch showing the detection tests. The arrows represent the walking direction of the user; the color black represent an actual crossing of the gate, and the color red represent a crossing external to the gate

possible to simulate this by moving a panel along a line, since the absorption of the human body is different from the one of other materials). Nevertheless, it was found that such a figure slightly depends on the gate span, with the "safe" walking distance (i.e., minimum distance from the gate line not causing false positive) ranging from a few centimeters for the narrowest gate span, up to about 60 cm for the widest span tested. This is of course due to the non-selective radiation patterns of used antennas (as mentioned, standard ZigBee transceiver were used, and no critical alignment/calibration procedure was required) and to radio waves reflection/scattering, which are unavoidable in real-world environment. Nevertheless, obtained figures are more than suitable for the aimed purposes.

Test 4, eventually, allowed for evaluating selectivity of the gate when placed in an open space, discriminating passages within the gate opening and outside of it. In this case too, no false positive was detected, regardless of the actual distance from gateway side and of the gate span.

After that, a gateway was installed on an actual door (110cm wide), thus accounting for more realistic boundary conditions: in this case too, 100% of

actual passages was correctly detected, with sensitivity fading to 0 at a 30cm distance from the door line.
These experiments proved that the system is efficiently capable of recognize the crossing of the gateway without generating many false positives, and that the interferences caused by walls and furniture don't impact the detection rate.

2.2.4 Identification Tests

As mentioned before, identification comes from pairing RSSI information coming from the communication between the MuSAs in the network and the fixed gateway devices. Of course, RSSI is meaningful only when a 1-hop messaging path is exploited (i.e., direct communication between the gateway and MuSA device occurs). Since MuSA is a battery-operated device, it relies on a sleep-wake cycle to reduce power consumption (as of ZigBee protocol). Obviously, it can receive messages only when awake, with the ZigBee routing node storing undelivered message until destination node awakens. This makes it impossible to communicate with a MuSA device using a 1-hop message at any time: to cope with this, once a passage is detected by a gateway, G_a and G_b send to each MuSA in the network a message, to which they will reply in 1-hop mode once awaken. RSSIs associated to such replies are then forwarded to the supervisor, which takes care of the decision about identification, according to the strategy depicted in the above paragraph.
A first test has been carried out, in which a person wearing a MuSA (M_1) walked through the gateway (installed on an actual door) and another person, with a second MuSA (M_2), was standing elsewhere. 40 tries were carried out and the results were evaluated.
Fig. 2.4 shows the plot of the RSSI retrieved by G_a (upper plot) and G_b (lower plot). Indices related to M_1 are assumed as the plot abscissa (x axis), whereas the ordinate refer to M_2 (y axis): each dot refers to the same test, as sensed by

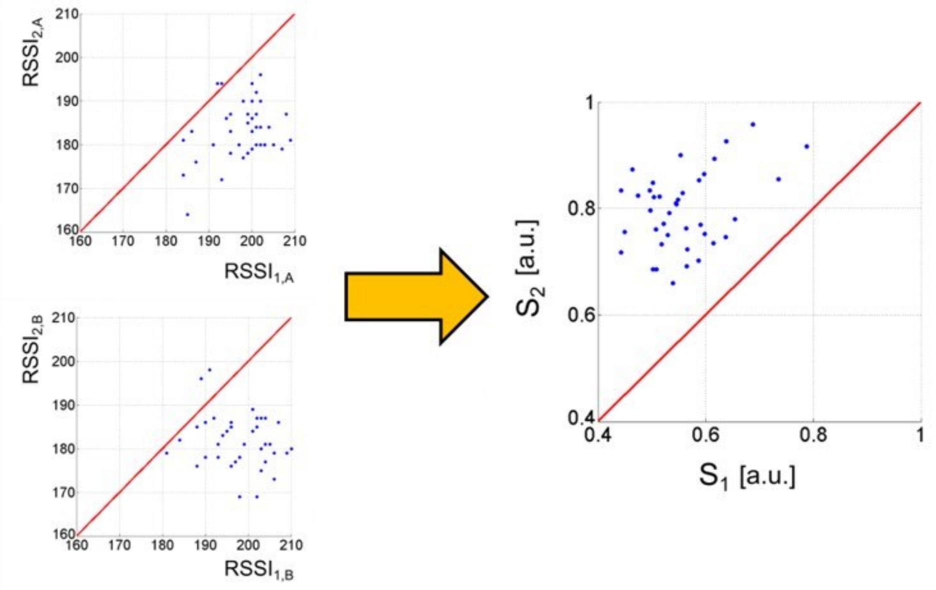

Figure 2.4: on the left, the scatter plot of the RSSI (M_1 vs M_2) retrieved by G_a (top) and G_b (bottom). On the right, the combination using the geometrical approach

either transceiver. Therefore, if the dot lies below the diagonal line (y=x), a greater RSSI was associated to M_1 than to M_2 (i.e., $RSSI_{1,I} > RSSI_{2,i}$, implying (under the aforementioned simplifying assumptions) that M_1 is closer to the given gate edge; if the dot lies above the diagonal, of course, the opposite condition occurs (i.e., $RSSI_{1,I} < RSSI_{2,i}$ indicating M_2 is actually closer.

The test configuration, exploiting a standard door width (so that just a single user is allowed to pass at a time), makes quite likely that the device crossing the gate line is actually closer to both gate edges than other devices. Nevertheless, it is shown that a simple proximity test is not accurate enough: due to both the random device placement and the wave propagation features in a real environment, a few points happen to lay above the diagonal in either plot. This shows that pairing transceiver responses is inherently necessary: accounting for the geometrical algorithm introduced in the paragraph above, ambiguities are solved, as shown in Fig 2.4.

Here, the scatter plot refers to the estimated total distances defined by Eq. 2.6, and shows that all of the events are correctly interpreted: every point lies above the diagonal indeed, yielding $S_2 > S_1$. Also, fair clearance from the diagonal line can be assumed as a confidence indicator for the inferred information.

2.2.5 Multiple Gateways

A test of the system has been conducted in a more realistic and complex situation. Three different gateways (G_1, G_2, G_3) were placed on three actual doors of three different rooms on the same floor, and four subjects were involved, each one of them wearing a different MuSA (M_1, M_2, M_3, M_4): they had to walk through a circular path (starting from the room where G_1 was and arriving in the same room) in which they had to enter and exit from each room where the gateways were placed, so that each person would have crossed each gateway twice, for a total of 6 passages per person and 24 passages in all. In Fig. 2.5 a map with gateway placement and one with the itinerary are shown. While a subject was performing the test, the other three were waiting for their turn inside the room where G_1 was placed (they are indicated with three crosses on the map), at a distance of about 2m from the door: this was set-up

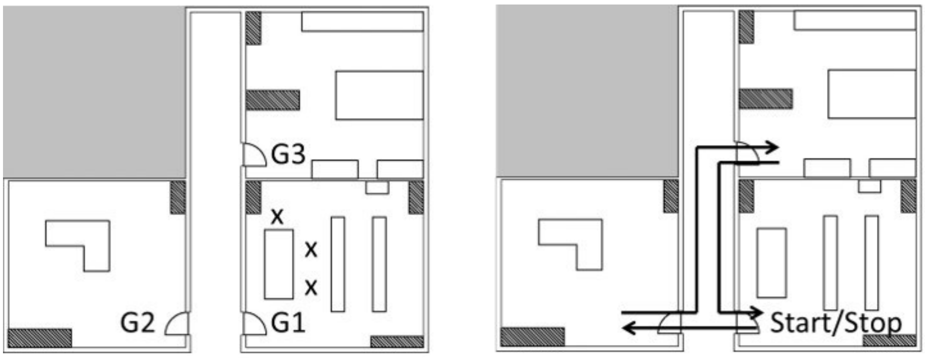

Figure 2.5: the map representing the Multiple Gateway test. On the left, G1-2-3 represent the position of the three CARDEAGates, and the black X represent the position of the users waiting for their turn; on the right, the arrows indicate the path walked bu each user during the try

to monitor the possible interferences between different MuSAs, i.e. to check if, while a user was performing the test, a different user was identified by the system, thus causing an error in the identification procedure.
A 100% success rate was obtained in the detection of the passages, i.e. all of the 24 passages were correctly detected.
A success rate of 91.6% (22 out of 24) was obtained in the identification phase: the two errors were caused by identifying M_2 instead of M_1 during the last passage, and identifying M_3 instead of M_4 when crossing G_3 for the first time.

2.2.6 Considerations

CARDEAGate offers a different and novel approach to the problem of indoor localization. As discussed above, there are many studies focusing on researching a solution suitable for AAL-purpose, but, at least to the best of our knowledge, no other system exploits the shadowing of the human body on the radio signals.
CARDEAGate has the advantage of allowing the detection and the identification of the user using the same technology used by the devices adopted for home automation purposes, without the need of ad-hoc hardware, therefore it's a low-cost solution that maintains high reliability. A gateway system may be very helpful in an assistive context, for example to detect when a not self-sufficient person reaches a place where he needs help or should not go for his safety, or to improve a behavioral analysis system.
CARDEAGate has been successfully installed in four real houses in the framework of the Italian project AALisabeth [53].

Chapter 3

User Identification

As already mentioned, an extremely important feature in a multi-user environment is the capability of identifying which user performed the task detected by the environmental devices.

In this chapter, a different approach to the identification of the user is proposed, based on the communication between the "detector" (the device placed in the environment in a fixed position that detects a given task) and the wearable device MuSA worn by the user. This allows to link the information from the detector to the user who performed the task, and also to track the movements of the user with a sub-room level accuracy, exploiting the different kind of devices deployed in an environment monitored by the CARDEA system. In this way a great number of information about the users' habits are available, allowing for BA and health status monitoring.

A couple of supporting considerations are to be made, however: first, tagging aims at behavioral analysis, which is inherently based on large-scale data collection, over long timeframes. No real-time, instant reaction is triggered by a single event, so that accuracy limitation results in statistical noise in data analysis, which (to a certain extent) can be safely tolerated. Second, at a higher hierarchical level, a reasoning engine is placed, in charge of data fusion and of the inference of behavioral features; at this level, many possible inaccuracies can be ruled out by reasoning (e.g., looking at event sequences or implementing majority polls). In the following, however, only raw response of the physical sensor network is taken into account, as a worst case analysis

3.1 How It works

The identification procedure exploits the communication between the MuSA device, worn by the user, and the devices deployed in the home environment (detectors).
In particular, similar as the procedure seen in Chapter 2 regarding CARDEAGate, the RSSI (Received Signal Strength Index) is used, a parameter of wireless communication giving an indication of the distance between the transmitter and the receiver.
When a detector is triggered (e.g. opening the fridge, sitting on the couch, ...), it sends a message to each MuSA in the network, to which they reply in 1-hop mode (1-hop is essential since the RSSI must be calculated directly between MuSA and the detector, but as mentioned in Chapter 1 the ZigBee network is a mesh network): the detector then calculates the RSSI of the replies and selects the closest user as the tag candidate (of course every MuSA is univocally associated to a single user). Such a simple procedure can thus be embedded into the firmware of each sensor, regardless of its specific role: at no additional cost, we get identification features from the very same network already implemented for sensor communication, leading to a great number of opportunities in terms of BA.

3.2 Hardware and Firmware implementation

To allow a device to correctly carry on the identification procedure, we had to face the limit imposed by the ZigBee protocol.
All the detectors were programmed as End Devices, and as explained in Chapter 1, they undergo a sleep\awake cycle to reduce battery consumption, and they are Child to a Father (being it a Router or the Coordinator itself) that is in charge of routing all the messages where the Child is the recipient: these messages are temporarily stored by the Father, and are then forwarded to the Child when it wakes up from its sleep phase. Therefore, if a message is sent

directly to an End Device from a device which is not its Father, it is very likely that the message will be lost, because the End Device will probably be sleeping (i.e. its antenna is shut down) and it will have no way to receive the message.
As a consequence, it would not be possible to directly send a 1-hop message from the MuSA to the detector: to correctly arrive to its destination, the message should be router by the father, but in this way the RSSI calculated by the detector would be the one between him and its Father, not the one between him and the MuSA that actually sent the message, thus eliminating the identification capability.
A possible solution would have been to keep the detector's antenna on for a few seconds after it detects the action and sends the ping-request to the MuSAs, so that the detector would have been able to correctly receive the replies: unfortunately, this procedure is not allowed by the ZigBee protocol, because an End Device may

- Have the antenna always on
- Turn the antenna on only when it finishes the sleep cycle, and only for the time necessary to know from its Father if there is any pending message for him

And these two behaviors may not be mixed.
It is impossible indeed to keep the End Device always on, because by doing so it would drain the batteries in a few days.
The solution we developed to solve this issue is shown in Fig 3.1, and was found by placing side by side two devices: one in charge of the detection and one in charge of the identification. Once the detector detects a given task, it sends an interrupt to wake up the identifier: at this point the identifier starts the identification procedure and waits a few seconds for the replies by the MuSAs, then forwards the RSSIs to the Coordinators and goes back to sleep. The identifier is therefore programmed to have the antenna always on, but it is turned on and off by the detector, which instead undergoes the classical sleep\awake cycle of the ZigBee End Device.

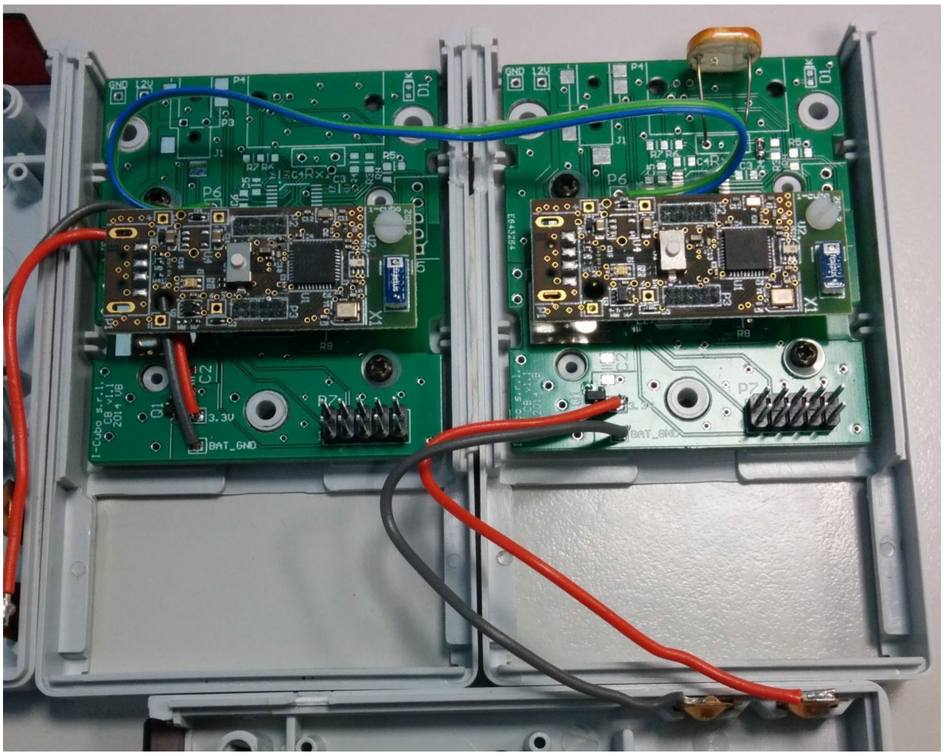

Figure 3.1: the Fridge device (on the right) with the identifier attached to its left. The green and blue wires running from one device to the other are needed to transfer the interrupt signal

The detector needed then a small hardware modification, because two wires were now needed to send the interrupt signal to the identifier.

3.3 Testing

A series of tests has been performed to validate the identification procedure in a multi-user, multi-sensor environment. In each test, a given user (user A) performs an action, while another (user B) acts as an interferer. Both of them were carrying a MuSA device (M_a and M_b, respectively). During each test we aimed at correctly identifying the user performing the task (user A) regardless

Figure 3.2: the living lab environment at DoTALab

of the nearby presence of the user B, using the procedure explained above. The tests were executed in a lab environment simulating a home setting, with furniture, appliances and a variety of different sensors (Fig. 3.2). In particular, sensors were installed to monitor the opening of a fridge and of a drawer, the occupancy of the armchair and the opening of a window.

Three tests were carried out, illustrated in Fig. 3.3. In the first test (1), user A repeatedly opened a sensorized drawer, while the user B stood at a fixed position, 2.5m apart from user A: as shown, three different positions (1_a, 1_b and 1_c) have been tested, changing each time the angle formed by the kitchen furniture and user B; 50 tries were carried out for each position.

Under these conditions, all tests were successful, i.e., 100% accuracy was found in all cases. Table 3.1 reports the number of successes and errors for each one of the three positions, as well as the success rate; also, Table 3.1 reports the mean of the RSSIs and the standard deviation (SD) for each position: it's noticeable how the mean RSSI from M_a is way higher than the one from M_b, leading to a correct identification of the User A; the statistical

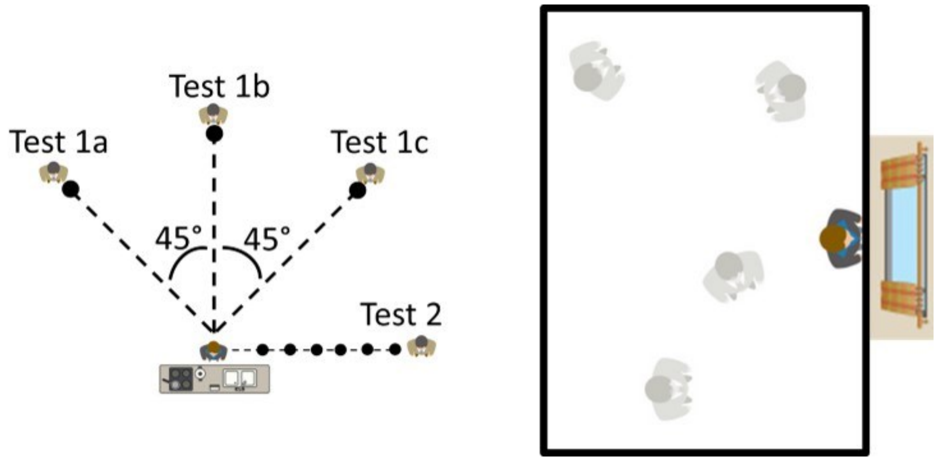

Figure 3.3: on the left, representing tests 1 and 2, the dots represent the positions on which User B was standing during the different tries, while User A stands in front of the drawer; on the right, only the test involving the window is represented: User A is standing in front of the window and keeps opening and closing it, while User B walks randomly in the area behind him

significance of the difference between the two mean values was tested using a pairwise t-test, yielding a value <<0.1.

Seen the very positive results from the first test, we investigated how the accuracy decreased as the two users got closer to each other: starting with a distance of 2m, the test (Test 2 in Fig. 3.3) was repeated reducing each time the distance between users, at 0.25m steps, down to 0.75 m (i.e., with users almost in contact, because 0.75m is the distance between the two devices, and the size of the human body has to be taken into account). 20 tries per step were carried out, for a total of 120 tries. Results are given in Table 3.2: as expected, decreasing the distance below 1.5m implies a lower accuracy. The pairwise t-test signals the low reliability of the measurements at 0.75m, due to the proximity of the two users. Nevertheless, these results show that satisfactory accuracy is retained within the distance range of interest.

A more realistic test (Test 3, illustrated in Fig. 3.3) has been eventually performed. User A interacts with the sensors, with user B freely walking along random patterns, within a 2x2 m2 area next to the position of user A. Namely, 4 different tasks were tested: opening the fridge, opening a drawer, sitting on an armchair and opening a window. 50 tries were made for each

Table 3.1: results from test 1

Position	Succ	Err	Succ (%)	RSSI Mean (SD)		p
				A	B	
1	50	0	100	214 (2.5)	187 (5)	<0.01
2	50	0	100	214(4.4)	184(7)	<0.01
3	50	0	100	210 (4)	176 (6.7)	<0.01
Total	150	0	100			

task, summing up to a total of 200 tries. Random walk of user B was meant for eliciting unexpected propagation issues, possibly reflecting on RSSI. As already explained in Chapter 1, RSSI depends on the propagation of the EM wave between the transmitter and the receiver: any object in the environment may cause a reflection, a refraction and an absorption of the signal that can cause the RSSI to change. Hence, non-deterministic behavior is to be expected, and a statistical approach is needed.
Results from Test 3 are given in Table 3.3, and shows that accurate enough results are obtained even in such a stress condition, for all tested device, with an average accuracy exceeding 90%. Differences among different devices are to be ascribed at different physical features of the environment and of the sensor placement (e.g., within the fridge or embedded in the window fixtures).

Table 3.2: results from test 2

Dist (m)	Succ	Err	Succ (%)	RSSI Mean (SD)		p
				A	B	
2	20	0	100	208 (2.5)	195 (2.6)	<0.01
1.75	20	0	100	210 (3.4)	195 (3.4)	<0.01
1.50	16	4	80	207 (4)	197 (7)	<0.01
1.25	15	5	75	208 (5)	200 (2.5)	<0.01
1	18	2	90	207 (4)	196 (5.3)	<0.01
0.75	14	6	70	206 (3.5)	200 (5)	<0.01
Total	103	17	85.8			

Table 3.3: results from test 3

Task	**Succ**	**Err**	**Succ (%)**	**p**
Drawer	46	4	92	<0.01
Fridge	49	1	98	<0.01
Armchair	44	6	88	0.08
Window	41	9	82	0.1
Total	180	20	90	

The vast majority of the errors occurred when the user B was in the very proximity to the detector (<1m) turned with the MuSA pocket "looking" directly at it: in this case in fact the antenna of Mb had a clear path toward the antenna of the detector, resulting in a high RSSI. If the user B was close to the detector but turned in a different way, the EM wave had to cross part of his body to reach the antenna of the detector, lowering the RSSI and causing the identification process to succeed.

3.4 Considerations

With respect to other localization systems, the proposed approach features low cost and "plug and play" operations: in fact, unlike most systems, no calibration or ambient characterization is needed, resulting in a much lower intrusiveness.
The demonstrated accuracy is largely sufficient for the behavioral analysis purposes it's aimed for, and it is expected to further significantly increase by accounting for more sophisticated decision procedure, involving artificial reasoning.

Chapter 4

A test in the real world: the Helicopter project

This Chapter is about the HELICOPTER ((Healthy lifestyle support through comprehensive tracking of individual and environmental behaviors, [54]) project: a relevant part of the work described in this thesis has in fact been carried on with the aim of actually deploying the proposed solutions in the HELICOPTER framework, hence testing them in a real scenario.
This Chapter will describe the goals of the project, the partner involved, the technological solutions proposed, the problems encountered during the pilot phase and eventually the results retrieved from the analysis of the data.

4.1 Project overview

4.1.1 AAL joint programme

HELICOPTER has been carried out in the framework of the European AAL Joint Programme (AAL JP): this program supports applied research on innovative ICT-enhanced services for ageing well, with a time to market of 1 to 3 years [55]. The overall objective of AAL JP is to enhance the quality of life of older adults while strengthening the industrial base in Europe through the use of ICT.

Since 2008, AAL JP has issued 7 calls for proposals each focusing on different issues and has funded 154 trans-national innovations projects with over 1000 partners.
The aims are:

- Fostering the emergence of innovative ICT-based products, services and systems for ageing well at home, in the community, and at work, thus increasing the quality of life, autonomy, participation in social life, skills and employability of older adults, and reducing the costs of health and social care;
- Creating a critical mass of research, development and innovation at EU level in technologies and services for ageing well in the information society, including the establishment of a favorable environment for participation by small and medium-sized enterprises (SMEs).

The AAL Programme promotes business, technology and social innovation, especially that based on ICT, to ensure that products, systems and services give effective support to older adults in their everyday lives.

4.1.2 Goals

We have already discussed about AAL and the many implications related to developing an AAL-system.
A particular attention has been posed on fusing telemedicine with behavioral analysis, and the issues that may arise. This approach may be adequate when a specific medical condition occurs, whereas, in a prevention-oriented daily routine, may be often perceived as a boring, intrusive task, possibly jeopardized by mild cognitive or memory issues and thus scarcely sustainable. On the other hand, besides objective measurement of clinical parameters, many of the target diseases may reveal themselves through a variety of behavioral "symptoms", which can be assessed by means of indirect indicators, easily detected by means of simple, environmental sensing

devices. Such indirect signs, for instance, include changes in the feeding or sleeping patterns, in the toilet frequency, in physical activity, etc.

Of course, such indirect hints are not reliable enough for actual clinical diagnosis, but may provide a first-level detection of anomalies, addressing the user, or the caregivers, toward more accurate assessment, based on clinical evaluation.

Starting from such consideration, the aim of the HELICOPTER project is to combine in a single, interoperable system different kinds of detectors, ranging from passive, environmental sensors to home clinical instruments, to implement a hierarchical procedure for assessing "diagnostic suspicions" for a set of specific age related diseases.

Such approach is regarded as a form of "automatic triage", in the sense that the system is capable of recognizing conditions which are compatible with actual occurring of such diseases and thus to drive the end-user through a sequence of increasingly accurate assessment procedures, possibly culminating in addressing to professional care.

Thus, the HELICOPTER approach aims at implementing continuous, unobtrusive monitoring of user's habits, which are possibly meaningful to health assessment. This, in turn, may reflect on relieving the user from too demanding self-checking routines (avoiding boredom, discomfort and illness stigma), at the same time providing the caregivers with a new evaluation dimension, based on "low-intensity", long-term behavioral analysis.

The system concept is illustrated by the sketch in Fig. 4.1: end user(s) interact with the system through a heterogeneous layer of sensors; environmental sensors are distributed into the living environment, whereas wearable sensors may provide a more detailed insight about user motion and position; finally, a set of networked clinical sensors are exploited to provide measurement of specific physiological parameters.

Through wireless connections, all sensors feed the system database, providing a detailed, multi-faceted picture of the user's habits and status. Based on such

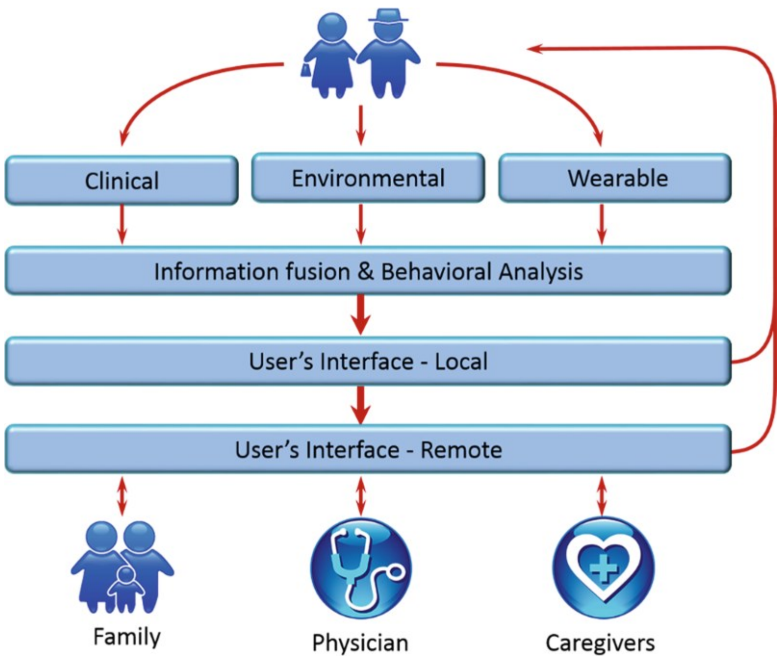

Figure 4.1 the HELICOPTER concept

an information set, an artificial reasoning engine looks for behavioral anomalies, i.e. relative changes in the behavioral patterns (either sudden, abrupt changes or slow drifts). Based on information fusion, the likelihood of some specific medical conditions is evaluated, and suitable feedbacks are addressed to the end-users themselves and to their caregiving network.

In order to illustrate the system aim, we refer here to a simple example, related to the heart failure diagnostic suspicion. Congestive heart failure (CHF) is among the primary causes of hospitalization in elderly population, and regular lifestyle monitoring is recommended to control it and minimize its impact on quality of life [56].

CHF shows up with a set of symptoms which lend themselves to illustrate the HELICOPTER approach quite easily; in fact, people suffering from CHF tend to develop one or more among the following behavioral indicators:

- Increased urinary frequency and/or nocturia[2]

[2] Nocturia is defined by the International Continence Society (ICS) as "the complaint that the individual has to wake at night one or more times for voiding" [57]]

- Sudden changes of body weight1
- Decrease of physical activity, due to tiredness and fatigue
- Discomfort in sleeping lying in bed, due to edema

which can be somehow detected be means of “non-clinical” sensors:

- Toilet sensor
- Bodyweight scale
- Wearable motion sensor
- Bed and chair occupancy sensors

Besides that, main diagnostic instruments, suitable for home use, include the measurement of blood oxygen concentration (oximeter) and of the blood pressure.

Thus, the HELICOPTER system foresees a hierarchical approach to infer a CHF diagnostic suspicion: the user’s behavior is constantly monitored to infer early symptoms of a CHF crisis. To this purpose, a model (currently based on Bayesian Belief Networks (BBN), a detailed description of which goes beyond the scope of this thesis, but more information can be found here [58]) combines outcomes of different home sensors and evaluates the likeliness of the heart failure condition: should the evaluation score exceed a given threshold, the user is (automatically) addressed to the appropriate clinical parameter checks.

Data coming from the oximeter are acquired by the HELICOPTER system: should data coming from the portable, networked oximeter confirm the suspicion, the system alerts the user and his caregiving networks, addressing him to appropriate medical control.

Similarly to the example above, a set of relevant diseases has been selected in the HELICOPTER development stage, developing related behavioral models. The model list includes:

- Hypoglycemia
- Hyperglycemia
- Cystitis
- Heart failure
- Depression
- Reduced physical autonomy

- Prostatic hypertrophy
- Bladder prolapse

Although each model may actually involve a different set of sensors, the overall hierarchy is similar, exploiting the environmental and wearable sensors for inferring potentially troublesome situations, to be confirmed by involving clinical devices into the evaluation. Although conceptually straightforward, the actual system implementation implies several challenging issues, which are discussed in the next Paragraphs.

4.2 HELICOPTER Heterogeneous Sensor Network

Based on the above description, the conceptual scheme in Fig. 4.1 maps over the heterogeneous network depicted in Fig. 4.2. Home sensors pertain to different classes:

- clinical sensors provide the system with accurate data about physiological parameters; their management implies user awareness and action;
- environmental sensors provide data related to the user interaction with the home environment, possibly linked to behavioral meaningful patterns; no user awareness or activation is required; if multiple users are sharing the same environment, criteria for identification of the actual interacting user are needed;
- wearable devices provide information about individual activity, also inherently carrying identification information.

Figure 4.2 the set of heterogeneous devices involved in the HELICOPTER system

All wireless sensors communicate with a home gateway device, consisting of a tiny PC (Lenovo Thinkcentre M53), equipped with suitable radio transceivers. The PC runs a supervision process, which takes care of several functions, besides managing the actual sensor communication. Data coming from the periphery are suitably abstracted, making them independent of actual physical feature of the given sensor, and stored in a system database.

The HELICOPTER database enables communication among different system modules: in particular, behavioral analysis and anomaly detection is carried out by dedicated modules which acts as “virtual sensors”, producing “events” (e.g., anomaly alerts or diagnostic suspicions) which are stored back to the database, in the very same fashion data coming from physical sensors are managed.

Similarly, a variety of interfaces can be implemented (aimed at end-users or caregivers) which query the database for system status. I.e., the database is at the crossroads among different subsystems (sensing, processing, interfaces) and thus supports system modularity; a suitable data structure has been devised and implemented, exploiting a MySQL open-source architecture.

4.2.1 Clinical sensors

Clinical sensors are exploited for the (self) assessment of physiological parameters: all involved sensors need to be easy to use, suitable for being used by the user himself (or by untrained relatives). The HELICOPTER system will provide the user with help and guidance in handling clinical sensors and will automatically manage data logging and transmission over the system infrastructure. I.e., no additional burden (with respect to customary device use) is placed on the user for dealing with system communication.
Clinical sensors are present in a limited number and do not need to be scattered over the whole home area, and thus do not need to cover large transmission paths; we therefore follow the mainstream, commercial approach by using standard Bluetooth communication technology.
The list of currently considered sensors, includes:

- Body Weight scale (A&D Medical UC-321PBT)
- Blood Pressure Monitor (A&D Medical UA-767PBT)
- Pulse Oximeter (SAT 300 BT fingertip device, Contec Medical Devices Co. Ltd)
- Glucometer (FORA G31b, Fora Care Inc.)
- Portable ECG (TD-2202B, TaiDoc Technology Corporation)

It is worth stressing that commercial, off-the-shelf devices have been selected and that the overall system design is making no specific assumption on the specific kind or brand of sensors adopted. I.e., the system is open to communicate with a much wider variety of sensors than that actually planned and will prospectively be able to deal with sensor subsequently made available to the market by third parties, at the expense of properly introducing suitable descriptors in the database structure mentioned above.

4.2.2 Environmental Sensors

The use of sensors of many different kinds and functions is planned, in order to feed the behavioral model; in this case too, we rely either on commercial, off-the-shelf devices or (whenever a more specific function is needed) on purposely designed devices, namely some of the ones implemented for the CARDEA system. In both cases, we adopt the IEEE 802.15.4/ZigBee wireless transmission protocol.

Sensors have been selected based also on user-related features, i.e., the need of actual user awareness in sensor management; installation requirements and intrusiveness were evaluated.

Environmental sensors available for exploitation in the HELICOPTER framework include:

- Door/drawer sensor, exploiting magnetic contact (Reed switches), useful for detecting behavioral patterns related to diagnostic suspicion models mentioned above (e.g., opening the food cabinet, indirectly relating to the food intake frequency and time).
- Fridge sensor, providing information about fridge opening and internal temperature and humidity. It provides information related to feeding habits as well, besides allowing for simple warnings (door left open, temperature too high, …)
- Bed/chair occupancy sensors, based on sensitive pads of different shapes and size, coupled to a wireless transceiver. Provides information about sleep patterns and other daily living habits.
- Toilet sensor, based on proximity sensors, monitoring the toilet usage frequency and time distribution.
- “Clinical” sensor, to signal when the user is going to use any of the clinical devices listed above

Network configuration is carried out automatically, with each sensor registering to the ZigBee network when first turned on, and automatically entering the home ontological description.

Since multi-users pilot were involved, the identification feature explained in Chapter 3 was extensively utilized in those devices accessible by all the users

in the house, namely fridge, toilet, door\drawer and chair sensors; the bed sensor was instead used without the identification feature, since usually both husband and wife sleep on “their own” side of the bed, that remains the same through every night.
Although being initially considered, the CARDEAGate system was instead not included in the final version of the project, to not reach a too high number of devices to install in each pilot, and because it was decided to retrieve trivial information about the users’ movements from the wearable device (described in the next Paragraph).

4.2.3 Wearable Sensor

Wearable sensors were a key component in the HELICOPTER scenario, and for this purpose the wireless sensor platform MuSA [59] was exploted, specifically designed at DoTALab with assistive purposes, and shown in Fig. 4.3. Internal MuSA architecture features a CC2531 SoC [60], which fully manages wireless communication (compliant with ZigBee 2007 PRO protocol, and with the ZigBee “Home automation” standard profile, and thus can be easily integrated in the CARDEA system) and local computing: signal acquisition and processing is carried out by MuSA on-board circuitry.
Radio communication is hence kept at a bare minimum (alarm messages and network management), saving battery energy.
MuSA embeds an Inertial Measurement Unit (IMU, ST device LSM9DS0-iNEMO [61]), featuring a 3D digital linear acceleration sensor, a 3D digital angular rate sensor and a 3D digital magnetic sensor within the same chip. The IMU is exploited to evaluate human body position and orientation information, primarily aimed at fall detection purposes.
Within the HELICOPTER project, fall detection features (although still available) were not in the main focus, and MuSA was involved with two basic aims:

- providing behavioral information

Figure 4.3 MuSA (Multi Sensor Assistant)

- supporting user identification and localization

More specifically, MuSA contributed to the overall behavioral picture with information about user motion.

Although many physiology models [62] assume the walking speed as a meaningful health indicator, inferring such a speed from IMU data is not a trivial task. In fact, velocity can be extracted by integrating acceleration data, projected along the walking average direction. The drift error inherently associated to numerical integration, together with the noise coming from motion components not directly related to the walk, require to introduce complex compensation mechanism [63].

However, wearable devices need to cope with stringent power consumption constraint, to preserve battery lifetime. This limits the available resources, both in terms of computing power and memory, and of radio link usage. To extract accurate motion information, suitable for activity recognition, speed estimation, etc., relatively high IMU sampling rates are needed to fulfill the Nyquist-Shannon criterion. This rules out the possibility of streaming IMU

data in real-time to an external processing units, since it would imply continuous transmission and thus jeopardize battery lifetime. Hence, basic processing need to be carried out on board, limiting activity of the radio link to the transfer of a much lower number of synthesized data. Such real-time processing needs to coexist with other tasks the MuSA device is in charge of (fall detection, management of the tagging procedure described in previous section, emergency button calls, etc.) and, therefore, its computational demand need to be minimized.
In the case at hand, however, we are not interested neither in absolute velocity estimation, nor in navigation path reconstruction, so integration over long time-bases are not needed and we may refer to simpler approaches.
In particular, in the formulation of BBN models, we adopt a differential scheme, according to which we just look for relative changes in the variables, instead of comparing them with fixed thresholds. On the one hand, this allows for minimizing the need of user-specific model calibration; on the other one, common-mode errors are inherently rejected, this in turn relaxing constraints on offset and drift errors. In a more general sense, since the model does not rely on the physical value of the variables, but only on its changes, we may safely select alternative variables, provided they follow a similar change pattern.
Hence we selected, as a meaningful indicator, the Energy Expenditure (EE, [64]), which is a popular choice for assessing the intensity of physical activity. Among many methods to evaluate EE, the use of accelerometers has been often adopted, and many algorithms have been proposed [65]. We adopted the simple formulation suggested by Bouten in [66], which requires to integrate the acceleration vector components over a short time base.
The acceleration components (a_x, a_y, a_z) are sampled at a 60 Hz rate. Then a low-pass filter (Butterworth, 4th order) is applied, to eliminate frequency components at baseband. Acceleration components are then integrated over a time window (whose length is generically noted as TW) and summed:

$$I_{A,tot} = \int_{T_W} a_x dt + \int_{T_W} a_y dt \int_{T_W} a_z dt$$

eventually yielding the following expression for the energy expenditure:

$$EE = k_1 + k_2 I_{A,tot}$$

where k_1 and k_2 are suitable constants.
TW can be tweaked according to the specific need: a lower value means a higher time-resolution and hence a more accurate tracking of the user EE, leading however to an increase in power consumption, since data are needed to be transmitted more frequently.
The algorithm was encoded in the MUSA firmware, coexisting with fall detection and identification tasks, and was first tested in a lab environment. The test involved several subjects of different ages, who were invited to walk on a motorized treadmill: at 1 minute intervals, the treadmill pace was increased by 1 km/h steps.
Test results are summarized in Fig. 4.4: tests were carried out with different subjects of different age classes. Replicable patterns were found, with differences among homogeneous class ages: for instance, at the 5-6 km/h transition, younger subject tended to start running, while middle-agers keep

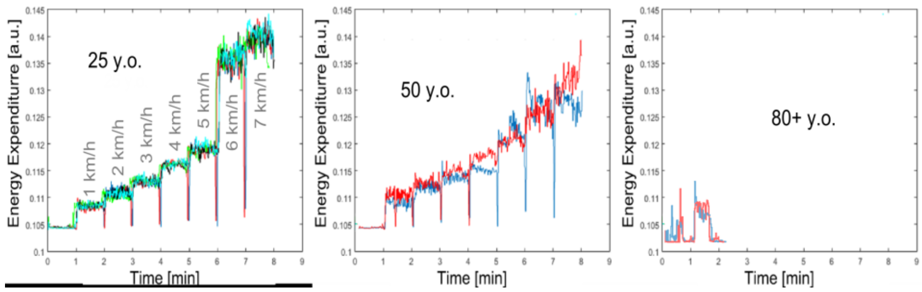

Figure 4.4: the three EE tests involving three different subjects: young (left), middle-age (centre), elderly (right). As can be seen, EE increases regularly as the speed increases

walking. Older subjects, instead, were unable to stand the transition 1-2 km/h, due to fatigue.

In general, such indications were found to be suitable for entering the HELICOPTER BBN models, and the EE estimation algorithm was included in the pilot studies (setting TW at 30s).

A final overview of the devices used in the HELICOPTER pilots is given in Table 4.1.

Table 4.1: overview of the devices used in the HELICOPTER system

Environmental	Wearable	Clinical
Room presence	MuSA:	Body Weight
Door/drawer	- Alarm button	Blood Pressure
Fridge sensor	- Identification	Pulsoxymeter
Bed occupancy	- Energy expenditure	Glucometer
Chair occupancy		
Toilet usage		

4.3 Data processing

Within the HELICOPTER framework, the feedback towards users and caregivers, handling the clinical devices and developing the BBN model were tasks carried on by other partners: hence, in this paragraph we focus on the analysis of the data gathered by the environmental and wearable devices.

4.3.1 Pilot deployment

22 pilot sites were recruited in the Netherlands, named NL_01-22, and 8 in Sweden, named SE_01-08, for a total of 30 pilot sites; among these, 5 in the

Netherlands and 2 in Sweden had two users (husband and wife): in those pilots each person was given his own wearable sensor, while environmental sensors (except for the bed sensors, as mentioned above) were common to both.
The users were elderly adults who were still able to live in their own home with no need of assistance by formal caregivers.
The final setup of the systems deployed in the pilot sites started on the first week of April, and the devices were removed at the beginning of July, allowing data to be gathered continuously for about three months.
Pilots NL_09 and NL_10 withdrew from the project after a short period for personal reasons, and therefore they are not taken into account in the analysis.
Unfortunately, the majority of the users did not remember to wear their MuSA every day while the system was working, nor to charge the battery every night before going to sleep; moreover, some firmware-related or sensor-related issues prevented some environmental device to work continuously. Thus, the data collected were not as regular as expected, but still they were continuous enough to not undermine the analysis explained in the following paragraphs.

4.3.2 A first analysis

A preliminary analysis has been carried out to check the integrity of the data and to perform a first unrefined investigation of the pilot sites, to individuate if the devices in some pilots produced an insufficient amount of data for being correctly processed later on.
Fig. 4.5 shows the data coming from NL_02 during the period from April 25th to May 9th (14 days). The tick on the x-axis signals the start of the day written right below it (i.e. time=00:00). The blue or red ticks signal that the sensor

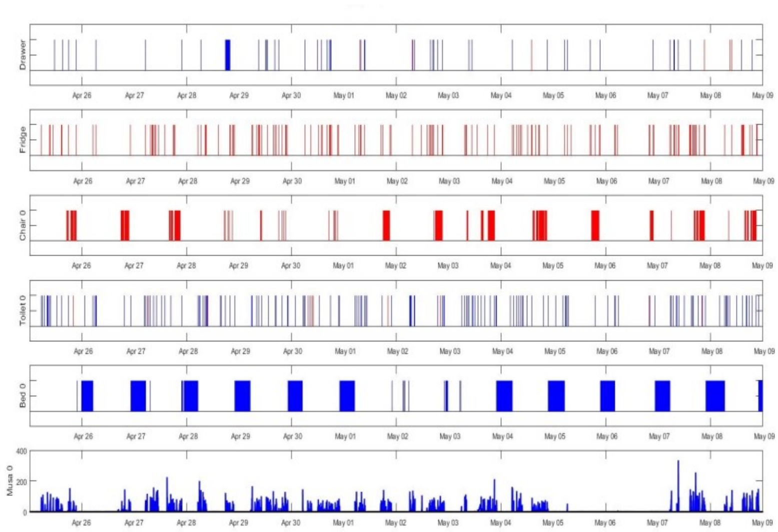

Figure 4.5: some raw data from NL_02. The six plots represent, from top to bottom, Drawer, Fridge, Chair, Toilet, Bed and MuSA. A red or blue line signals the device activity in that moment

detected the given action-of-interest; on the last row the EE coming from MuSA is displayed.

Even at a first glance, the data appear to be well organized and the devices seem to have worked correctly; during the night, the bed signals the presence continuously, while the other sensors are not activated; MuSA was worn correctly throughout the days, except for May 5^{th} and 6^{th}.

It is clearly visible a pattern in which the chair, which was placed in front of the television, is frequently occupied in the evening, right before the bed starts being occupied. Furthermore, even if it is not so visible from the picture, the fridge activity is denser in the period around 12:30 pm and around 19:30 pm respect to the other parts of the day.

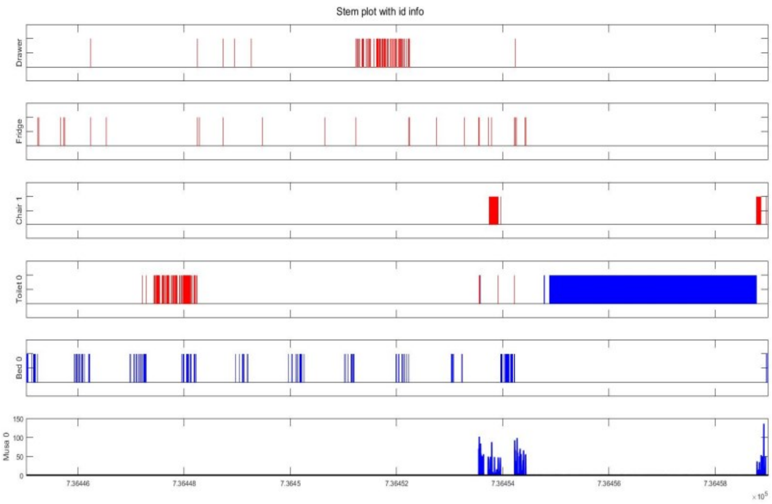

Figure 4.6: some raw data from SE_08

Unfortunately, not all the pilot sites produced data with this regularity. Figure 4.6 shows the data coming from SE_08 during the period from April 25th to May 9th (14 days). The graph has been made in the same way as the one in Fig. 4.5. This time, it can be seen how the bed and chair sensor were not so stable (probably because of bad placement by the technicians), hence the occupancy detection is unreliable; furthermore, the fridge sensor disconnected from the network (probably because of signal issues caused by the shielding of the EM signal by the fridge itself) and stopped signaling completely. Moreover, MuSA is almost never worn by the user.

Under these conditions it is basically impossible to retrieve meaningful information about the user's daily living.

Let's consider now a pilot with two users: Figure 4.7 shows the data coming from NL_01, on a two-days period from April 20th to April 22nd.

The diagram on the left refers to the picture coming from the environmental sensors only, while the diagram on the right shows improvements obtained by introducing MuSA features. In particular, personal energy expenditures appear on the two lowermost rows, and environmental sensors outputs were tagged. The color code is the following: green ticks refer to activity attributed

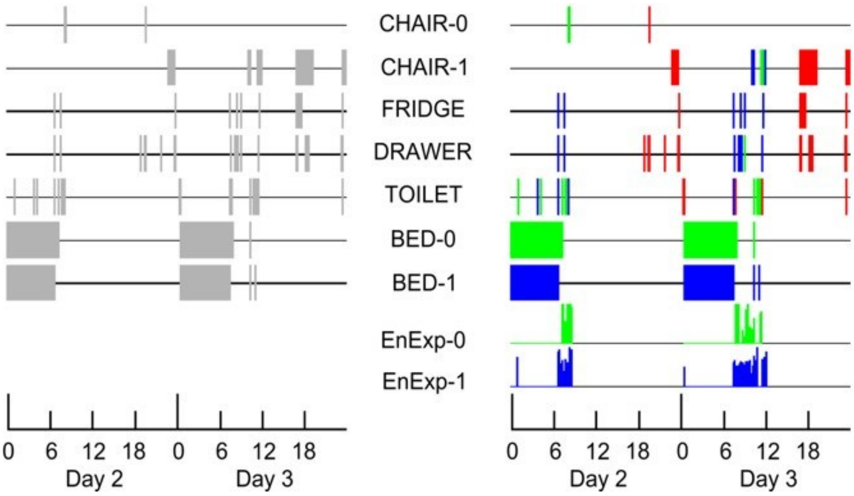

Figure 4.7: raw data from NL_01, where two users are involved. On the right, the situation without identification; on the left, identification is introduced, allowing to distinguish the two users (green and blue)

to "user 0", while blue ticks stand for "user 1" actions. Red ticks instead, stand for actions not tagged (either because performed by a third person, or because the users didn't wear the MUSA device while acting). The overall picture is quite clear and sound: in the experiment, users wore the device during the night and the morning, while they were not wearing it in the afternoon. Consistently, all activities carried out while carrying the wearable device were properly tagged, whereas afternoon activities remained untagged. As expected, the energy expenditure is low while resting in bed, and raises to higher values in the morning.

Some consistency check can be easily done, by comparing different sensors outcomes. In Fig. 4.8, bed sensors and the shared toilet sensors are compared

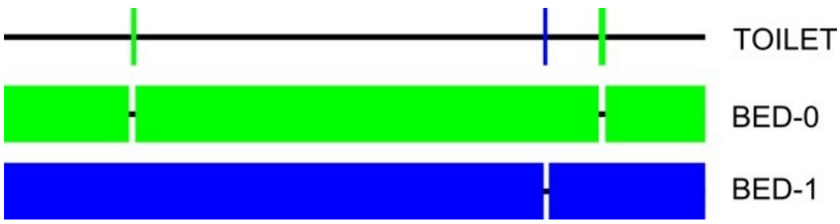

Figure 4.8: a detail from Fig 4.7, showing how the users that gets up from bed is correctly identified by the Toile

in a particular view, related to night time and showing consistent data: whenever the toilet recognizes a specific user, the related bed is shown to be empty.

4.3.3 More in-depth results

The following analysis was carried on the pilots that resulted more reliable after the preliminary assessment. In particular, no pilots with two users were selected, because the lack of commitment by the users in properly wearing MuSA compromised the identification feature too much, resulting in a too noisy dataset since it was not possible to straightforwardly link the detected task to a given user.
To not bore the reader too much, only some significant results are shown in the following figures, but this does not mean that similar conclusions cannot be retrieved from other pilots.
Fig. $4.9_{a\text{-}b}$ shows the daily usage of bed and chair in NL_14, divided by months (April-June-July): every day has been divided in 48 parts of 30 minutes each, and the curves represent the % of time that, on average, the sensor has been active within those 30 minutes; the "shady" part represent the interval of confidence of the prevision (set at 95%).
A similar representation regarding the toilet is given in Fig. 4.9_{c}, but this time the curve represents the chance that, on average, the device is activated at least once within those 30 minutes.
As expected, it is highly probable for the bed to be occupied during the night, whereas the toilet is used with regular frequency throughout the day; furthermore, the user spent time on the chair mostly during the evening, before going to bed. Interestingly, the toilet is never used during the night.

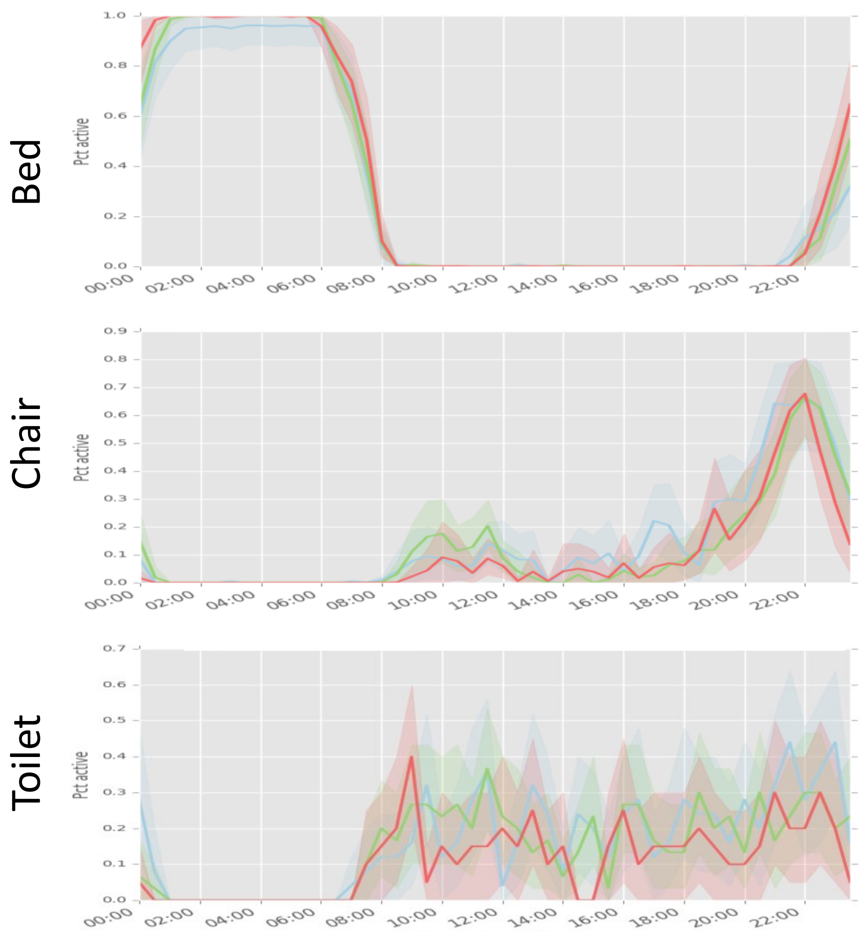

Figure 4.9: daily usage of bed (top), chair (centre) and toilet (bottom) for NL_14. The x-axes represent the time of the day; the y-axes represent the probability of the sensor being activated in the given time slot; the color code is blue for April, Green for May and Red for June

Fig 4.10 shows the same graph for SE_02. A similar pattern as the one spotted for NL_14 is visible for the chair, while the bed is used also in the early afternoon; the toilet is used mainly in particular times of the day, but it is possible to find an activation also overnight.

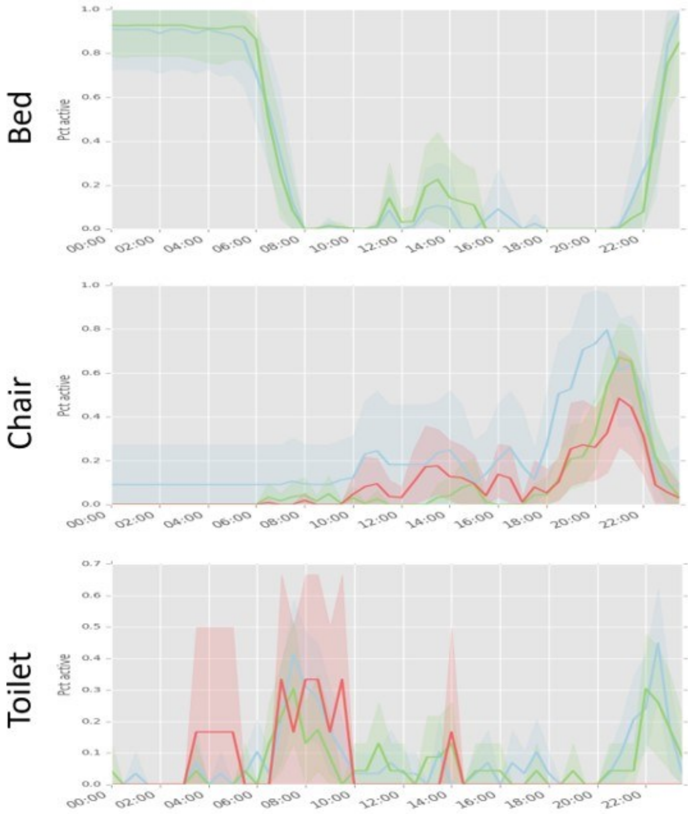

Figure 4.10: daily usage of bed, chair and toilet from SE_02

Starting from the amount of time spent in bed during each day, a predictive approach has been assessed, using the LASSO regression [67]. The expected value of the parameter y can be determined with the formula

$$E\{y|data\} = E_0 + w_1 * f_1 + \cdots + w_n * f_n + N(0, \sigma^2) \qquad (4.1)$$

Where w_i is the weight given to the i-th feature f_i, and N is Gaussian noise. Starting from a list of features, with the LASSO regression it is possible to determine (within a given interval of confidence) which feature is non-significative, and assign to it a null weight.

Two features were considered: week_end (=1 if the considered day was a weekday, =0 if it was a Sunday or Saturday) and lin_trend (to determine if there was a linear trend in the occupancy pattern).
To determine the outliers, a three-steps approach was followed:

1) Eliminate the points outside of the interquartiles[3], i.e. those points which values exceeded $Q_3+(Q_3-Q_1)*1.5$ or were lower than $Q_1-(Q_3-Q_1)*1.5$ (or equal to zero if this number resulted in something <0)
2) Apply the Student's t-distribution on the remaining samples to fit a model, and use that model to estimate a predictor on all the data (included the ones discarded after step 1)
3) Label the ones where 2,5<*t*-value<0,5 as possible outliers, and the ones where *t*-value<0,5 as outliers

Fig. 4.11 shows the regression plot of the bed and chair occupancy on NL_16 and NL_18: the x-axis represents the time (from April to June), while the colored dots represent the amount of time (in hours) that the device has been active during a given day, also showing inliers and outliers with different colors; The black solid line is the regression line; the Figure also reports the weight given to the two features and the intercept value, i.e. the average time spent in bed.
As can be seen, on NL_16 both bed and chair occupancies show no dependency on weekends nor linear trends (all the weights are equal to 0); however, on NL_18 the chair has a linear trend over time, expressed by the linear coefficient equal to -1.832.
To model the toilet usage a similar approach has been followed, this time using a Poisson regression [68], since the dataset was formed by integer numbers (counting the numbers of toilet activation during each days). The Poisson regression exploits the Generalized Linear Model [69], according to which

$$\ln(E\{y\}) = \beta X \rightarrow E\{y\} = e^{\beta X} \tag{4.2}$$

[3] A percentile indicates the value below which a given percentage of observations in a group of observations fall. The 25th percentile is also known as the first quartile (Q_1), the 50th percentile as the median or second quartile (Q_2), and the 75th percentile as the third quartile (Q_3). The interquartile equals to the difference between 75th and 25th percentiles.

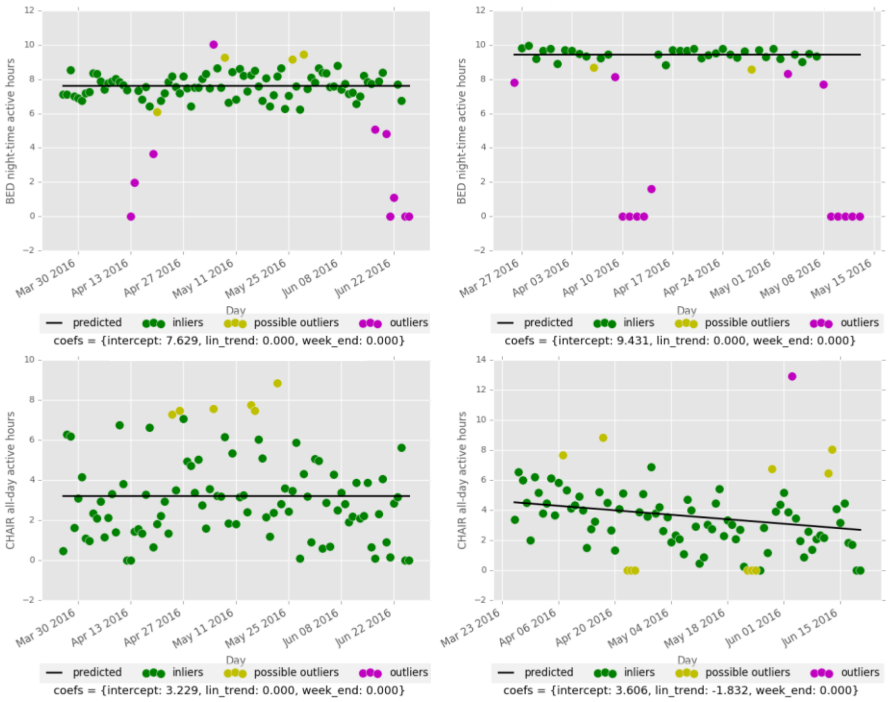

Figure 4.11: regression plot of the bed (top) and chair (bottom) occupancy on NL_16 (left) and NL_18 (right). Green dots are the inliers, whereas yellow dots are possible outliers and purple dots are outliers. At the bottom of each graph are also reported the intercept and the weights given to linear trend and weekend.

Where βX is the linear predictor, a linear combination of unknown parameters β.

In our case, considering the three parameters intercept, week_end and lin_trend (β_0, β_1, β_2) and their three weights (X_0, X_1, X_2), simple mathematical reasoning leads to

$$E\{y\} = e^{\beta_0} * e^{\beta_1 X_1} * e^{\beta_2 X_2} \tag{4.3}$$

Therefore, the parameters β_0 and β_1 have no influence if their weight is equal to 1, not to 0 as in the previous case (X_o has been omitted from the equation 4.3 because its weight is always = 1, hence it has no influence on the multiplication with β_0).

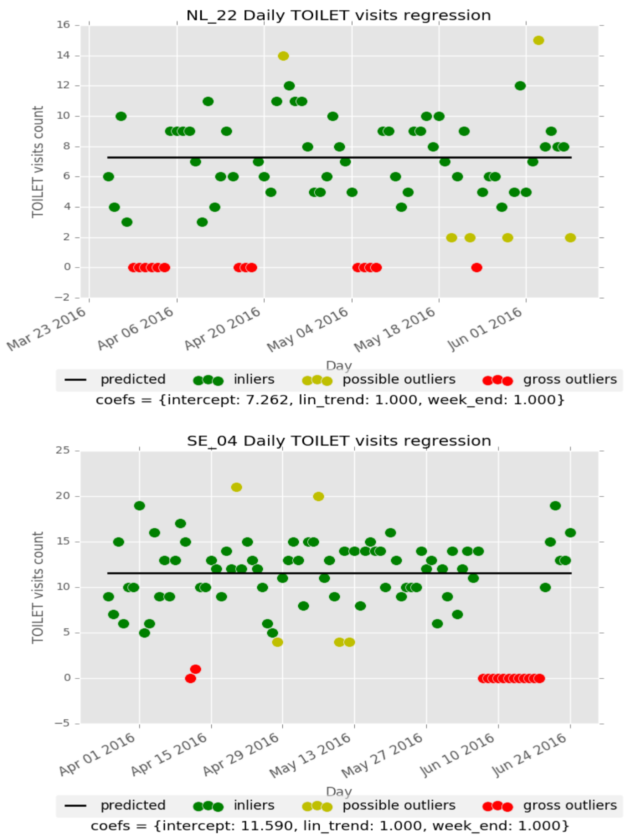

Figure 4.12: regression plot of the Toilet for NL_22 (top) and SE_04 (bottom)

Four different models have been created, taking into account four different combinations of the parameters: β_0, β_0-β_1, β_0-β_2, β_0-β_1-β_2.

The outliers have been determined in a similar way:

1) Create a Poisson distribution based on the predicted values
2) Label the values as possible outliers if the chance of falling outside of the distribution was between 97.5% and 99.5%, and as outliers if the chance was above 99.5%

Figure 4.12 shows the daily toilet visit for NL_22 and SE_04. Even if both of them show no dependencies on the weekend nor a linear trend, a marked difference can be noticed in the intercept value (7.2 against 11.59).

4.4 Considerations

The results showed above are part of the preliminary assessment carried out in the little time between the end of the HELICOPTER project and the writing of this thesis.
Despite some scarceness of integrity in the data and even if considering the devices on their own, it was yet possible to identify some significant patterns. More accurate and meaningful results will emerge from a deeper analysis, taking into account different sets of devices and the combinations of their data.

Chapter 5

Sleep, gait and falls

As already mentioned, within the AAL framework important information can be retrieved from gait assessment: a variation in the parameters determining the “quality” of gait, can signal a deterioration of the cognitive or physical capabilities of the person, as will be further explained later on, and thus can be used as risk-factors for fall prediction.
This chapter focuses on the activity carried on during the period, lasted four months, spent at the Applied Biomedical Signal Processing and Intelligent eHealth Lab at the University of Warwick (UK), under the supervision of Prof. Leandro Pecchia.
During these months, a study has been started to relate the quality of sleep to the possible balance issues that may arise while walking, in the framework of falls prevention in the elderly.

5.1 The problem of falls in the elderly

As mentioned in the introduction, falls are the most common cause of injury and/or traumas among people over 65 years old, and the leading cause of accidental death and the 7th leading cause of death in people over 65 [70].
More than 95% of hip fractures are caused by falling [71], and one out of five falls causes a serious injury such as broken bones or a head injury [72].
Falls have also serious implications on the psychological side: the fear of falling is one of the leading causes in lack of security in elderly movements, jeopardizing their independence and their will to accomplish simple daily tasks, like doing the groceries or the laundry.

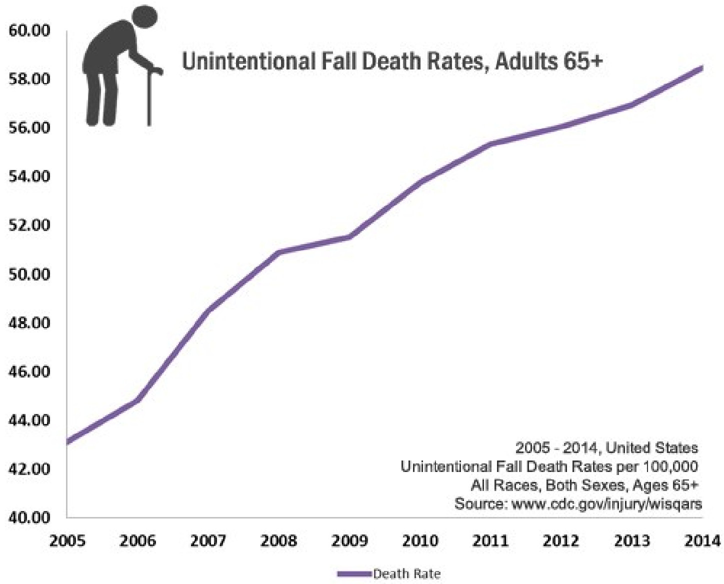

Figure 5.1: the graph above shows as the rate of falls with tragic consequences is increasing over the years. Source: http://www.cdc.gov/homeandrecreationalsafety/falls/adultfalls.html

As a result, more than one out of four older people falls each year, but less than half tell their doctor; furthermore, falling once doubles your chances of falling again, since when a person is less active, he becomes weaker and this increases his chances of falling [73].

Falls are also a serious cost on public health: in the US only, the direct medical costs for fall injuries are $31 billion annually [74]. Furthermore, falls may lead to additional costs for the family, since fractures or other kind of serious injuries may cause the need of further assistance for the elderly.

Therefore, it is important not only promptly detect a fall, but prevent it.

Yoshikawa et al [75] determined the following list of risk factors causing falls:

- Accident, environmental hazard, fall from bed
- Gait disturbance, balance disorders or weakness, pain related to arthritis
- Vertigo
- Medications or alcohol

- Acute illness
- Confusion and cognitive impairment
- Postural hypotension
- Visual disorder
- Central nervous system disorder, syncope, drop attacks, epilepsy

In this Chapter we will focus on the second point, in particular on gait and balance disturbance, and on the factors that may increase its dangerousness.

5.2 Walking and balance problems in the elderly

It is known that our brain learns to coordinate the gait pattern during our early ages, so that this process can then occur automatically, without need of active attention by the person.
Age-related changes, such as decreased muscle strength and decreased sensory input, impair the systems responsible for postural control: when more attention is needed to compensate for deficits in sensory input, less attention is available to be allocated to safe walking; dementia can have a similar impact, increasing the difficulty that our brain has in coordinate the movements, thus causing a more irregular walk [76].
Balance problems are highlighted by walking while dual tasking: as more attentional resources are needed for safe walking during multitask or dual task situations, walking occurs with less automaticity.
Studies by Kressig et al. [77] have underlined how dual-task walking can act as a strong predictor of both dementia and falls in elderly adults.
Other studies have discovered that walking at a speed considered faster, compared to the one used while walking comfortably, can highlight the difficulties that a person can have in correctly coordinating the movements [78].
Balance problems may also arise for other reasons: one of the most common is the lack of sleep, or poor sleep quality; many studies have investigated how

bad and insufficient sleep may affect posture control [79]. Furthermore, other studies discovered how poor sleep quality increases the risk of falling [80], both in elderly and in young subjects.

5.3 Sleep vs Walk tests

Starting from the considerations explained in the paragraphs above, we had the idea to turn the procedure upside down and try to determine if, from gait assessment, it would be possible to evaluate the sleep quality of the subject, thus estimating if his risk of falling was increased, and alerting him to take the correct preventive measures.
Hence, we wanted to assess the walking of several subjects in two different conditions, after a "good" night and after a "bad" night, and try to discover some significant features that changed from one day to the other for all the subjects: in this way, from gait assessment it would be possible to determine the sleep quality, and therefore the risk of falling.
To the best of our knowledge, no study so far has tried to correlate sleep quality and gait assessment: all the studies mentioned above about balance and sleep quality were considering static conditions, where the subjects had to stand still on a force plate or on similar devices [81]; Agmon et al. [82] had the same idea and tried to do the same study explained in this Chapter, but they did not force the subjects to have a bad night of sleep, and eventually their study assessed the impact of dual tasking while walking, without taking into account the sleep quality.

5.3.1 Study Protocol

Ten healthy volunteers were recruited at the Warwick Engineering in Biomedicine (WEB) Laboratory at the University of Warwick. Participant's

general information such as age, weight, health status and use of medications were collected by questionnaire. All subjects signed a written informed consent to participate in the study. The study was approved by the Biomedical and Scientific Research Ethics Committee of the University of Warwick.
The test was conducted for each participant in two consecutive days according to the following procedure: as the subject woke up, he had to compile an in-house adapted version of the Pittsburgh Sleep Quality Index (PSQI) questionnaire, focused on the sleep quality of the previous night rather than the one of the previous month, as the standard PSQI version considers (e.g. the question “During the past month, what time have you usually gone to bed at night?” was changed into “What time did you go to bed yesterday night?”); then the subject had to come at the Gait Lab (at the same time in the morning of both days) at the School of Engineering, University of Warwick, to perform the actual test, in which he had to walk on a treadmill (Sole Fitness F63) for three different sessions of four minutes each: the first at 2.5 Km/h (a speed every subject felt comfortable walking at), the second at 4 Km/h (a speed every subject considered as “fast walking”), and the third one again at 2.5 Km/h, but after 3 minutes of normal walking a second task was introduced (counting backwards out loud, starting from a random number between 120 and 150 and subtracting 7).
The Gait Lab is equipped with a Vicon Motion Capture System XXX consisting in 12 Infra-Red cameras capable of tracking the markers displacement with a sub-cm accuracy, sampling at 200Hz: a total of 39 markers were placed on each subject during each trial (to reproduce the full-body model, as suggested in the manual for dynamic situations), and the markers movements over time were then retrieved using the Vicon Nexus software.
Five subjects were asked to sleep normally during both nights, whereas the other five were asked to sleep normally during the first night, and to voluntarily have a bad night on the second one (e.g. going to bed very late, or setting different alarms during the night).
During both nights, all the subjects wore a Zephyr BioPatch BH3-M1 that recorded the subject’s EEG and movements (using a 3-axial accelerometer).

5.3.2 Data Pre-Processing

The first three minutes of each trial were considered as warm-up sessions to allow the subject to get used to walk on the treadmill, and were thus discarded. The data were retrieved from a 30s time-window starting at a random time between 3:00 and 3:30 for Tests 1 and 2, and starting at 3:00 for Test 3 (the moment in which the dual-task situation was introduced), allowing to process about 46 steps for Tests 1 and 3 and 56 steps for Test 2.
Data were initially low-pass filtered using a fourth-order Butterworth filter with cutoff at 10Hz.
In a single step two main events can be highlighted: heel-strike (HS), when the heel initiates the contact with the ground, and toe-off (TO), when the toe leaves the ground and starts swinging forward. As common for gait assessment on treadmill [83], HS was identified as the moment in which the marked placed on the heel stops moving forwards and starts moving backwards, whereas the TO was identified as the moment in which the marked placed on the toe stops moving backwards and starts moving forwards: with this paradigm TO and HS were extrapolated from the data stream.
A gait cycle is consequently formed by four consecutive events, HS_R, TO_L, HS_L, HS_R (where the subscript R and L indicates the right or left foot): therefore, it was checked that every 30s time-window considered in this test respected correctly this order for every gait cycle.
All the elaboration has been carried out using Matlab.

5.3.3 Gait Assessment

To assess the gait quality, some of the most common gait parameters have been used [84]. In particular, considering

- HS and TO as the vectors containing the instants (in seconds) of each heel strike and toe off, regardless of left or right foot, in chronological order
- $HS_{R/L}$ and $TO_{R/L}$ as the vectors containing the instants (in seconds) of each heel strike and toe off of the Right or Left foot, in chronological order
- $GTC_{R/L}$ as the Gait Cycle Time of Left or Right foot, i.e. the time interval between the HS of a foot to the next HS of the same foot:

$$GCT_{R/L}(k) = HS_{R/L}(k+1) - HS_{R/L}(k)$$

The following parameters were considered for the gait assessment:

- *Pacing Rate (PR)*: the time interval (in seconds) between consecutive HS (of different feet)

$$PR(k) = HS_k - HS_{k-1}$$

- *Double Support (DS)*: the time percentage (relative to the considered gait cycle) during which both feet are in contact with the ground

$$DS = 100 \times (\frac{TO_L(k) - HS_R(k)}{GCT_R(k)} + \frac{TO_R(k) - HS_L(k)}{GCT_R(k)})$$

- *Swing L/R (S_L, S_R)*: the time percentage (relative to the considered gait cycle) during which the left or right foot is not in contact with the ground

$$S_{L/R}(k) = 100 \times \frac{HS_{L/R}(k) - TO_{L/R}(k)}{GCT_{L/R}}$$

- *Step Width (SW)*: the distance (in meters) between the center of left and right foot (assumed as the middle point between the heel and toe markers) between consecutive steps.

No further spatial parameters were calculated (e.g. stride length) because walking on a treadmill correlates them with the time parameters.

5.3.4 Data Processing

The data were divided in two main groups, depending on whether they were from subjects who have slept in a good (GG) or bad (GB) way on the second night. They were also kept separated by day (Day 1 or Day 2) and by test (Test 1-2-3). The above parameters were calculated from every step of every trial, and the ones from the same group, day and test were normalized per-subject and concatenated, creating in total 12 different arrays for every parameter (2 groups for 2 days for 3 tests).
The one-sample Kolmogorov-Smirnov test was executed on each feature to test the null hypothesis that the data in each vector came from a standard normal distribution; according to the result a two-sample t-test or a two-sided Wilcoxon rank sum test was executed on the couple of vectors composed by the same feature taken from the same group and test but from different days (e.g., testing step width from GB on day 1 and test 1 versus step width from GB on day 2 and test 1): in this way the distributions between "good" and "bad" sleepers were tested (features from GB), and also the ones between "good" and "good" sleepers (features from GG) to act as a control group (e.g. checking whether the step width between GB day 1 test 1 and GB day 2 test 1 rejects the null hypothesis, and afterwards checking whether the step width between GG day 1 test 1 and GG day 2 test 1 gives the same result). The resulting p-values were adjusted using the Bonferroni method [85], with a correction index of four (the number of features taken into account).
For every feature, mean, standard deviation (std), coefficient of variation (COV), and the 25, 50 and 75 percentiles were also calculated.

5.4 Results

Table 5.1 shows the comparison of the p-values (after the Bonferroni correction) for each feature divided by test and group, whereas Table 5.2 shows the mean, std and COV (coefficient of variation, obtained as the std divided by the mean) values (divided by day): the following considerations can be derived from both.

5.4.1 Double Support

The t-test revealed a marked difference in the mean of the distribution in GB for Test 2 and Test 3, but not in GG. Moreover, the COV increases from day 1 to day 2 in GB but not in GG. Interestingly none of these conclusions is applicable to Test 1.

Table 5.1: p-values resulting from the comparison of the distributions of the features between day 1 and day 2, divided by group (GG and GB). Cell highlighted in yellow are the ones with a significant p-value (<0.05)

		Test 1		Test 2		Test 3	
		GG	GB	GG	GB	GG	GB
Pacing Rate	sec	0.097	0.067	0.643	0.095	0.267	<0.01
Swing L	%	1.949	0.025	0.064	1.629	0.410	0.745
Swing R	%	0.930	<0.01	0.411	<0.01	1.309	0.011
Step Width	m	0.052	<0.01	0.010	<0.01	0.097	<0.01
Double Support	%	1,844	0,074	2,133	0,020	0,777	0,044

Table 5.2: values of mean, std and COV retrieved from the test, divided by day. The cells highlighted in yellow are the ones mentioned in the analysis

		GG						GB					
		Day 1 - GOOD			Day 2 - GOOD			Day 1 - GOOD			Day 2 - BAD		
		mean	std	COV	mean	std	COV	mean	std	COV	mean	std	COV
DS	Test 1	26,93	2,05	7,62	26,43	2,02	7,64	25,34	1,93	7,62	26,61	3,04	11,44
	Test 2	21,22	1,65	7,78	21,05	1,91	9,06	19,40	1,81	9,31	21,06	3,71	17,61
	Test 3	26,88	2,22	8,25	26,48	2,33	8,80	25,47	2,25	8,82	26,68	3,21	12,03
PR	Test 1	0,63	0,03	4,79	0,65	0,03	4,61	0,63	0,03	3,97	0,66	0,03	4,73
	Test 2	0,53	0,03	5,02	0,53	0,02	4,42	0,54	0,02	4,03	0,53	0,02	4,54
	Test 3	0,62	0,03	4,02	0,64	0,04	6,26	0,67	0,03	4,10	0,65	0,06	9,17
Step Width	Test 1	0,13	0,03	26,48	0,12	0,03	21,75	0,12	0,03	22,07	0,15	0,03	16,71
	Test 2	0,12	0,04	30,08	0,11	0,03	26,91	0,11	0,03	22,98	0,16	0,03	18,49
	Test 3	0,12	0,04	36,20	0,12	0,04	29,81	0,13	0,02	17,27	0,17	0,02	13,21
Swing L	Test 1	36,58	1,28	3,50	36,77	1,74	4,72	37,03	1,72	4,64	37,44	1,58	4,21
	Test 2	39,20	1,15	2,92	39,56	1,25	3,15	40,17	1,49	3,70	40,04	1,60	4,00
	Test 3	36,39	1,68	4,61	36,75	1,42	3,87	37,27	1,50	4,02	37,34	1,46	3,91
Swing R	Test 1	36,51	1,34	3,66	36,77	1,69	4,59	36,90	1,29	3,48	35,97	2,79	7,74
	Test 2	39,58	0,86	2,17	39,39	0,96	2,44	39,70	0,80	2,01	38,89	2,84	7,29
	Test 3	36,69	1,30	3,54	36,79	1,35	3,68	37,27	1,40	3,76	36,00	2,64	7,32

5.4.2 Swing Left and Right

The t-test on Swing Right (test 2 and 3) between day 1 and day 2 revealed a marked difference ($p<0.01$) in GB, but not in GG; this difference is not observed in Swing Left ($p>0.05$). Furthermore, the COV of Swing Right increases in every test from day 1 to day 2 of GB, whereas this behavior is not detected in GG.

5.4.3 Pacing Rate

A significant difference in the distributions was revealed only for test 3 of GB ($p<0.01$). In addiction the COV had a strong increase in this test from day 1 to day 2, and the same did not happen in GG.

5.4.4 Step Width

The distributions of day 1 and day 2 of GB test 3 resulted significantly different, whereas the same was not detected for GG. Moreover, the mean of the width increased from any test of day 1 to any test of day 2 for GB, but this pattern did not repeat for GG. Because of this high increase in the mean value, the COV resulted higher in GG respect to GB.

5.4.5 Comments

The results stated above confirm the hypothesis that sleep quality has an effect on how even young and healthy subjects walk. The increase of the COV of the gait features while walking is considered a meaningful indication of a more chaotic and thus less balanced walking [77]: considering in particular the Double Support feature, the variation of the COV in GB but not in GG in tests 2 and 3 confirms that a more chaotic walking is found in bad sleepers respect to good sleepers. The fact that we did not found evidence of this in test 1 suggests that, at least on healthy people, one night of bad sleep alone is not enough to cause such differences while walking relaxed, but we have found no other study to compare this result to.
It is of particular interest to observe the difference of the results in the Right and Left Swing feature: all the participants in our test were right-handed, so this result suggests that the body may react in a non-symmetric way to a

situation of instability or poor balance. In a recent study [86] on the effects of sleep quality on balance, it was noticed how left and right foot had a different behavior: in particular, the center of pressure related to the left foot had a higher sway respect to the right one, and also in this study all the participants were right handed. Therefore, we suggest that this difference on left and right feature is caused by a different reaction of the dominant side of the body respect to the other one.

The analysis of Pacing Rate and Step Width features are similar to the one made for the Double Support, except that in these cases the differences are meaningful only for the dual-task test (test 3). Furthermore, it is interesting to notice how in every test of GB the mean Step Width increased from day 1 to day 2: since a wider base of support is a manifestation of the fear of a higher instability in our movements [87], this is again a meaningful parameter of how the sleep quality subconsciously affects our balance.

Therefore, at least for healthy subjects, in a normal walking situation it is not possible to detect a meaningful difference in the mean of the distributions caused by the good or bad sleep quality; this difference is noticeable in some features while walking at a higher speed, and arises when a second task is introduced. This task-related difference is not unexpected: as already mentioned, walking while counting backwards causes a high load on our brain, that affects heavily the ability of automatically coordinate the movements as we walk; this study proves that when taking into account the effects sleep quality, the difference between single and dual task is very marked.

A downgrade in the executive functions that control gait and gait variability may be caused by the poor sleep quality [88], and many studies have focused on the relationship between sleep regulation and executive functions [89]. Furthermore, worsening in sleep quality may deteriorate the executive skills through its direct effect on frontal lobe activation, which successively may impact on the executive skills [90]. All this effects may disturb the normal gait, and that’s what we detected with this study

5.5 Final Considerations

As different studies have proven, balance is affected by sleep quality. Just one study so far has tried to link this effect to the walking phase, but all the subjects in that reported a good sleep quality.
In this study, we tried to assess how sleep quality affects the human gait on healthy subjects.
Since gait assessment is greatly influenced by walking while dual-tasking, we studied three different cases: walking at a comfortable speed, walking at a "fast" speed, and walking while counting backwards. The results show how in the first case the differences between the two groups are not very relevant, whereas in the other two cases some noticeable differences arise in the features we considered for gait assessment.
We recognize that the sample size could have been small enough to conduct to misleading results: this is the first study of its kind so we don't have a direct comparison to make with other papers, but the conclusions we drew are in agreement with the literature about gait assessment and with the one about sleep and balance relationship, therefore we feel confident that these results are correct.

Chapter 6

Conclusions and future developments

In this thesis, an AAL-system for personal heath monitoring has been developed. In particular, the features of the CARDEA system have been enhanced, developing a series of devices to carry on a long-term behavioral analysis on the people living inside the house monitored by the system; the devices needed to cope with the main limits posed by the AAL framework: such system must in fact be

- Flexible
- Easy to use
- Low cost
- Reliable
- Un-intrusive
- Perceived as useful by the user

The devices developed allowed to monitor some meaningful actions during the daily living of the users, in particular:

- Sitting on a chair\lying on the bed
- Opening the fridge
- Going to the toilet
- Entering\exiting a room
- Opening\closing a door or a drawer

At first, the firmware and part of the hardware of the devices has been extensively developed, mainly to overcome some limits imposed by the ZigBee standard, tweaking the Stack in order to make the devices work as desired.

Afterwards, a device named CARDEAGate has been developed, allowing to monitor the crossing of a door or the access to any point of interest: CARDEAGate is composed by two ZigBee transceiver that can detect the passage of a person crossing the imaginary line connecting the two antennas. If the user wears a MuSA, further interactions are possible, allowing to identify him.
CARDEAGate has been tested in the laboratory with very positive results both in terms of detection of the passages and identification of the user. The system was then installed in three pilot sites in the framework of the AALsabeth project.
Subsequently, the identification feature was transferred to the other devices, to solve the action-tagging problem that arises in a multi-user scenario: in this case, it is mandatory to identify the user that interacted with the environmental device (e.g. opening the fridge or entering the toilet), in order to insert the action in the behavioral profile of the correct user.
The proposed solution is based on the exchange of a message between the environmental and the wearable devices, evaluating the RSSI to discover the closest user to the device that signaled the action of interest.
This feature was tested in a multi-user, multi-device scenario in a living lab, leading to very positive results.
Many of the solutions developed during this thesis were then used in the HELICOPTER project, installing CARDEA in 30 pilot sites in Sweden and in The Netherlands. The system was then able to run and gather data for several weeks, and a first analysis of those data was presented. From this analysis, it is possible to see how the environmental devices allow to identify some behavioral trends of the users, like the habit of watching the tv for a given time before going to bed, or the amount of time they need to use the toilet over the day.
Finally, the work carried out during the period spent abroad has been presented. During the months spent at the Applied Biomedical Signal Processing and Intelligent eHealth Lab at the University of Warwick (UK), under the supervision of Prof. Leandro Pecchia, a preliminary study has been carried on to investigate the relationship between the effects of poor sleep and

the human balance. The final goal was to understand how bad sleep quality affects the way elderly adults walk, and in particular how this may increase their risk of falling.
The test involved walking in three different ways (at a comfortable speed, at a fast speed, and while dual-tasking) in two consecutive days, once after a good sleep and once after a voluntary bad sleep for the test group, and after another good sleep for the control group.
The test conducted showed as, even on healthy subjects, poor sleep quality decreases the quality of walking, causing some gait parameters to show the same pattern that are usually associated with fallers or with people who are afraid of falling while walking.
Future development of this study may involve increasing the number of subjects to confirm the conclusions hereby stated; afterwards, a test on elderly adult must be carried out, to verify that the same conclusion can be drawn. If this will be the case, important information about the fall-risk of the users could thus be retrieved from monitoring their sleep during the night, further enhancing the features of CARDEA.
The development of CARDEA will continue by enhancing the capabilities of the environmental devices, like some network issues that may arise from time to time and further reducing battery consumption; also, other devices can be developed in the future, to satisfy the need that different situations may impose.
Finally, the analysis of the data will be expanded, taking into account the wearable device and relating the information coming from different sensors, in order to build a more accurate behavioral profile of the user.

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