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Smartphone Applications for AAL and Well-being in the Home Environment

Applicazioni Smartphone per l'AAL e il Well-being in Ambiente Domestico

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Abstract

The increasing spread of smartphone devices and their pervasive use open up new opportunities in many fields, such as education, health and marketing. The wide range of sensors and communication interfaces and the portability, make it a versatile and useful tool, suitable for many different purposes.

The objective of this thesis is to investigate how smartphone applications can improve the Quality of Life of both fragile, such as elderly and disabled people, and healthy people, in the home environment. Particularly, the research focuses on two fundamental aspects: the use of the smartphone as an interface towards smart living environments, and the use of the smartphone as a collector of user's behavioural data.

To this aim, a thorough study of the state of the art has been conducted to identify its advantages and weakness. Subsequently, the research has focused on issues and challenges to face during the design phase of smarphone applications aimed at interfacing and collecting data. More in detail, indications and guidelines have been identified in the literature to enable a proper design and to obtain a useful, usable and acceptable system, paying particular attention to the specific needs of elderly and disabled people, suffering from physical or cognitive impairments.

Finally, in order to demonstrate the actual contribution of smartphone applications in incrementing the user's Quality of Life in the home environment, several use cases have been realized and tested.

Abstract

La crescente diffusione dei dispositivi smartphone e il loro uso sempre più pervasivo ha aperto nuovi scenari di utilizzo in diversi ambiti, come ad esempio l'educazione, la salute e il marketing. La portabilità, la vasta gamma di sensori e di interfacce di comunicazione lo rendono uno strumento versatile e utile a numerosi scopi.

L'obiettivo di questa tesi è quello di investigare come le applicazioni smartphone possano incrementare la qualità della vita sia di persone fragili, come anziani e disabili, sia di persone sane in ambiente domestico. In particolare, la ricerca si è focalizzata su due aspetti fondamentali: l'uso dello smartphone come interfaccia di comunicazione verso gli ambienti di vita intelligenti e l'uso dello smartphone come collettore di dati personali dell'utente.

A tale scopo, è stato condotto uno studio approfondito dello stato dell'arte al fine di individuare i vantaggi e i limiti che lo caratterizzano. Successivamente, la ricerca si è focalizzata sui problemi e le sfide da affrontare in fase di progetto sia quando esso viene usato come sistema di interfacciamento, sia quando viene usato come collettore di dati. In particolare, sono state identificate in letterature indicazioni e linee guida per una corretta progettazione al fine di ottenere un sistema effettivamente utile, usabile e accettabile, ponendo particolare attenzione alle esigenze di persone anziane e disabili, affette da limitazioni fisiche o cognitive.

Infine, allo scopo di dimostrare come l'uso dello smartphone possa effettivamente contribuire ad aumentare la qualità della vita in ambiente domestico, diversi casi d'uso sono stati realizzati e testati.

Contents

List of Figures

Chapter 1

Introduction

This thesis addresses the subject of smartphone applications for Ambient Assisted Living (AAL) and wellbeing. The objective of the thesis is described in this Chapter, together with the definition of the research problem, the main contributions, and the thesis organization.

1.1 Research problem

Quality of Life (QoL) has become a critically important concept for healthcare and well-being in recent years. In fact, the perceived QoL may influence a person's mental and physical health. It depends on many factors that can be objective, such as health, work, and financial resources, or subjective, such as self-esteem, sense of security and self-realisation.

When dealing with QoL, we cannot ignore the radical changes that the society is facing in the last few decades. On the one hand, the increasing development of Information and Communication Technology (ICT) led to a spread and pervasive use of technological tools. New paradigms, such as ubiquitous computing and Internet of Things (IoT), are becoming ever more common, integrating systems for the information processing and internet connection inside objects and activities of everyday life. On the other hand, the progressive ageing of the population and increasingly hectic lifestyles are opening up new investigation scenarios for scholars, making it necessary to identify factors and technologies that contribute to the QoL increase.

In this view, investigating technological solutions aimed at improving the living environment, adapting it to the specific user requirements, can be very useful. New domains emerge, such as those of Smart Home (SH) and Ambient Intelligence (AmI). They encompass a huge variety of technologies, applications, and services, aimed at providing intelligence to an environment in which people spend most of their lifetime.

Intelligent capabilities in SH aim at improving the QoL of the resident people, by facilitating routine operations, and anticipating the users' needs, by learning and understanding their behaviours.

Nevertheless, the benefits obtained by these solutions often clash with the inability or reluctance of target individuals, especially elderly, to learn and use them [131]. Acceptability and usability problems emerge, showing the huge gap between the theoretical benefits obtainable from technological resources and those actually perceived in the real life. Studies show that older people have positive attitudes towards everyday devices, such as microwave or television, but not towards most sophisticated ones [47]. In this perspective, among the wide range of available technologies, smartphone devices can be extremely helpful, as they are largely adopted by the general public, and have become integral part of today's society. Their ubiquitous availability and diversified communication interfaces are contributing in making such a technology indispensable in supporting our daily lives, acting as simple communication systems, interaction devices or data collectors. For this reason, the smartphone can represent a key point in the development of easy and low cost solutions, really usable by people, to improve their QoL also in the home environment.

1.2 Outline of objectives

The objective of this thesis is to investigate how smartphone applications can increase the QoL of both fragile and healthy people in the home environment. To this aim, a thorough study of the literature will be presented, identifying advantages, challenges and issues related to the use of such devices both as interfacing system towards the AmI, and as a collector of behavioural data. Furthermore, in order to support this research, several use cases will be presented.

1.3 Main contributions

The contribution to the advancement of knowledge provided by this thesis has been demonstrated by several scientific papers. An in-depth study on smartphone acceptability by elderly or technologically unskilled people, and on guidelines presented in the literature for the implementation of proper user interfaces, is discussed in [150]. Moreover, new applications and systems have been designed and implemented, providing an advancement of knowledge in the Human-Computer Interaction (HCI) field, as described in [165, 127, 126]. Innovative solutions which take advantage of smartphone applications for interfacing smart living environments are also shown in [128, 55, 172, 53]. A further work provides an overview on technological platforms, targeted to elderly people and aimed at prolonging and improve their independence and QoL [169]. In [54, 159, 33] a new wearable sensor that takes advantage of the smartphone to collect behavioural data is presented. Part of the results obtained in the analysis of sleep through commercial smartwatches has been described in [187], while other works are under preparation. Finally, some contributions on related areas are provided in [171, 170].

1.4 Thesis organization

The thesis is organized as follows. Chapter 2 provides a context description, introducing important concepts, such as QoL, AmI and AAL. Moreover, it introduces the smartphone as a pervasive computing device, and presents the related work.

Chapter 3 discusses the use of the smarphone as an interfacing device towards AmI systems, providing a deep study of the state of the art and identifying guidelines for a proper application design. In Chapter 4, the use of the smartphone as a data collector for behavioural analysis is addressed, providing an accurate analysis on related challenges and potentiality.

Such discussions are supported by different use cases developed by the author. In Chapter 5, two smartphone application are described: they exploits Computer Vision (CV) techniques to interface users with the surrounding living environment. Two different touchscreen interfaces are presented in Chapters 6 and 7. The first is addressed to an elderly person living alone at home, while the other one has been developed for formal and informal caregivers.

Wearable systems aimed at acquiring behavioural data are shown in Chapters 8 and 9. The first case describes the system design implications, from the realization of the wearable device, to the development of the smartphone application and the implementation of the transmission protocol. The second case, instead, presents the results of a user study, which exploits a commercial smartwatch for the sleep analysis.

Finally, the main conclusions of the work are drawn in Chapter 10.

Chapter 2

Background

In this chapter some fundamental concepts will be presented: they are essential for understanding the motivation of the thesis and the research work.

First of all, the QoL concept and its domains will be defined and discussed. In fact, the enhancement of target user's QoL through simple, low cost technological solutions is the main objective of the thesis. Among the various domains, it will focus on the home environment. For such a reason, smart living environment and AAL concepts will be introduced: they represent the main context of the research. Finally, a brief excursus on aspects and characteristics which make the smartphone the ideal tool to allow users to benefit from such technologies will be provided.

2.1 QoL domains

The question of what "good life" means has ancient origins, but only recently it has been investigated in a scientific and systematic manner [58]. Many researchers attempted to develop methods to empirically measure the QoL, nevertheless it is still an hard issue to solve. In fact, quality of life is an abstract and personal concept that can be approached at varying levels of generality, from the assessment of societal or community well-being to the evaluation of specific situations of groups or individuals [63]. To define such a concept is inherently complex and involves both objective and subjective factors [21]. The objective factors are quite easy to measure and include aspects such as financial resources, health status and social relations. Conversely, the subjective ones, such as happiness, self-esteem, life satisfaction, are much harder to measure. For this reason there are multiple QoL definitions and each of them reflects the author's point of view. In [112], Liu stated that there are as many QoL definitions as people, pointing out that each individual differs in what he/she considers important.

The best known definition of QoL is probably the one given by the World Health Organization (WHO) [139]. WHO defines it as *the individuals' perception of their position in life in the context of the culture and value systems in which they live and in relation to their goals, expectations, standards and concerns.* Such a definition reflects the point of view according to which QoL is a subjective concept strictly related to a specific social, cultural and environmental context.

According to WHO, this concept involves several facets summarized as four domains: physical and psychological health, social relationship, and environment. These domains and the relative facets are shown in Table 2.1. Investigating the literature,

Table 2.1: The QoL domains according to WHO [139].

QoL domain	**Facets incorporated within QoL domains**
Physical health	Activities of daily living Dependence on medicinal substances and medical aids Energy and fatigue Mobility Pain and discomfort Sleep and rest Work capacity
Psychological	Bodily image and appearance Negative feelings Positive feelings Self-esteem Spirituality / Religion / Personal beliefs Thinking, learning, memory and concentration
Social relationships	Personal relationships Social support Sexual activity
Environment	Financial resources Freedom, physical safety and security Health and social care: accessibility and quality Home environment Opportunities for acquiring new informations and skills Participation in and opportunities for recreation / leisure activities Physical environment (pollution / noise / traffic /climate) Transport

Felce and Perry [63] identified other domains and facets (see Fig. 2.1), focusing on 15 literary sources. Despite some differences, they coincide mostly with those set by WHO.

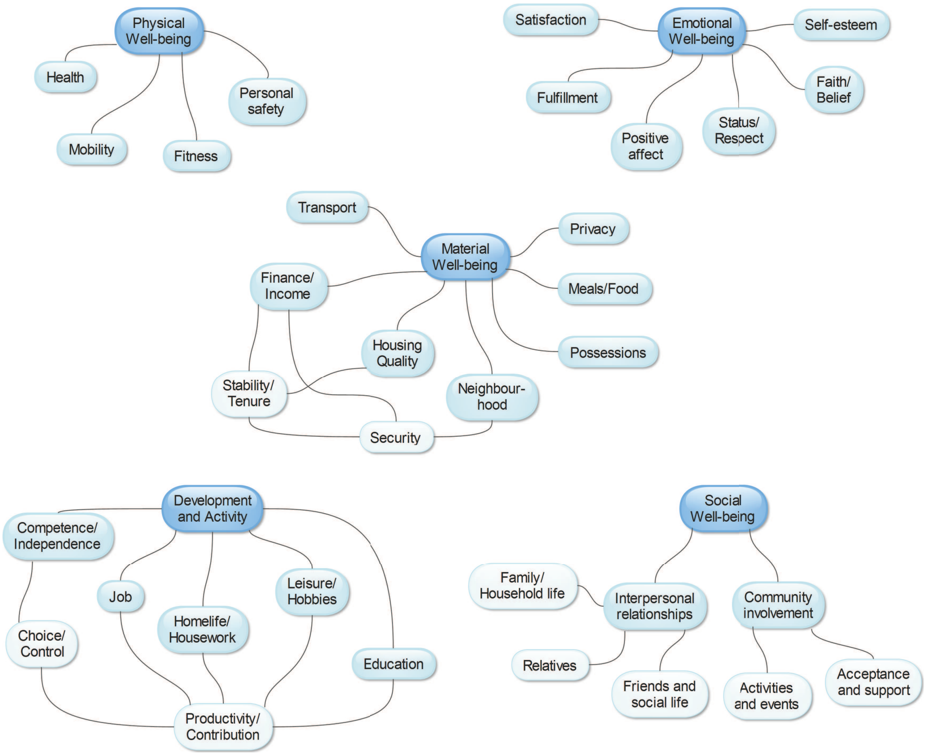


Figure 2.1: Relevant QoL domains identified by Felce and Perry in [63].

Both classifications agree in identifying as fundamental aspects influencing a person's QoL the physical, psychological/emotional, and social well-being. Additional factors concern environment (such as home, neighbourhood, and transport), work context (job, hobbies, education) and material resources (finance, food, possessions). The domains and facets identified highlight the extent of the problem of measuring and improving QoL.

Among the many aspects which define and characterize the QoL, this thesis principally focuses on the home environment. As well known, home is the place where an individual or a family can rest and store personal property. However, this term does not refer only to a physical place, but also to a state of emotional and mental refuge and comfort. This view allows to understand how such an aspect is essential in a person's life. It is so central that, for example, some researchers claim the home is an expression or symbol of the self [116].

When a person is forced to move because of an illness, unexpected event or a simple change due to the normal life evolution, this is often a dramatic moment, especially for elderly. A study conducted by Iwarsson *et al.* demonstrates the importance of the home environment for healthy ageing and more in general its close relationship with well-being [88].

In this context, ICT-based tools can be extremely useful in order to provide additional services and meet the user's needs.

2.2 Smart living environments: a brief introduction

Smart living environment, SH, AmI, and Intelligent Environment (IE) are different terms used in the literature to define the same concept. They refer to a physical space into which ICT and other pervasive computing technology are woven and used to achieve specific goals for the user, the environment or both. AmIs have the ultimate objective of enriching user experience, better manage, and increase user awareness of that environment. As stated by Aarts and Wichert, this approach involves the whole daily context, including each single object, and is strictly associated with HCI [10].

A survey conducted by Acampora at al. defines the characteristics which identify an AmI system [14]:

- context awareness: it exploits the contextual and situational information;
- personalization: it is personalized and tailored to the needs of each individual;
- anticipation: it can anticipate the needs of an individual without the conscious mediation of the individual;
- adaptivity: it adapts to the changing needs of individuals;
- ubiquity: it is embedded and is integrated into our everyday environments;
- transparency: it recedes into the background of our daily life in an unobtrusive way.

AmI, therefore, relies on a wide variety of other fields, like, for example, sensor networks for acquiring contextual data, robotics, to build proper actuators, and HCI to create new and more natural interaction methods.

Cook *et al.* have categorized contributory technologies into five areas: sense, reason, act, secure, and HCI [48]. As regards sensing, different types of sensors were used depending on the specific application. Some examples are presence sensors for indoor localisation, humidity, light, and temperature sensing for context adjustments, physiological sensing to support health monitoring, environmental or wearable sensors for behavioural analysis, and cameras for intrusion detection systems. AmIs are able to execute operations through acting systems. A classic example is to turn on the heating when the temperature goes down below a predefined threshold. Another technology that falls into the acting category is robots. They can perform different types of actions, although they can also carry out all other functions, i.e. sensing, reasoning and interfacing. Reasoning field can be seen as the necessary link connection between sensing and acting. It includes user modelling, activity prediction and recognition, decision making, and spatial-temporal reasoning [48]. Privacy and security are two essential aspects that must be considered when developing technologies for AmI. Benefits obtained from the technology, in fact, are proportional to the perceived sense of security and intimacy. Finally, proper HCI systems are essential to enable interactions between the user and the home environment. A more detailed description of this research field is provided in Chapter 3.

2.3 Ambient Assisted Living

When dealing with home environments, AAL concept cannot be overlooked. Population ageing is a long-term trend in Europe: the share of the people aged over 65 years is increasing in every EU Member State, with a 18.9% share in the EU-28 population estimated at 508.5 million [5]. This trend requires immediate ways to cope with people' needs that are living more years, remaining more active and staying in their home longer than before. According to [3], the objective of AAL is to connect new technologies and environment in order to improve people's QoL in all life stages. More precisely, it applies AmI technologies to enable people with specific demands, elderly or impaired people, to live at home healthy, independent and integrated, and improve the delivery of care where and when needed.

As summarized by Wahl *et al.*, the relation of an ageing individual with the physical context is a crucial contribution for his/her QoL [189]. In fact, the optimization of environmental resources, such as housing, has a great influence on the maintenance of independence/dependence in Activity of Daily Living (ADL) and well-being. A classical example made by authors regards the lift: low mobility capabilities after a stroke can be simply resolved by installing a lift on the building, allowing the user to reach even the higher floors.

Several public institutions, at a national and wider level, are carrying on specific initiatives to promote the flourishing of new products, services and solutions to face the emerging needs of the elderly population. In Europe, many proposals have been presented in the last few years thanks to the Active and Assisted Living programme

[1]. Such a programme is a funding activity that aims to create better conditions of life for the older adults and to strengthen the industrial opportunities in Europe through the use of ICT. According to the programme website, AAL has the purpose of:

- extending the time people can live in their preferred environment by increasing their autonomy, self-confidence and mobility;
- supporting the preservation of health and functional capabilities of the elderly,
- promoting a better and healthier lifestyle for individuals at risk;
- enhancing security, preventing social isolation and supporting the preservation of the multifunctional network around the individual;
- supporting carers, families and care organisations;
- increasing the efficiency and productivity of used resources in the ageing societies.

Other motivations that contribute to the growth of this market, rely on health care costs. In fact, the progressive ageing of the population requires an increasing amount of economic resources to cope with the medical care and necessary assistance.

Thus, the ageing of the population, caregiver burden, and increase of health care costs are some of the reason for the need of assistive technologies. However, as affirmed in [173], despite the huge public and private investments and efforts in research and development, the so called silver market has not been able to grow at the expected pace. This could be due to the fact that the user's needs, expectations and limitations are not accounted for during the design process. A deepen investigation of the state of the art about technology acceptability and usability will be presented in Section 3.2, mainly focusing on the smartphone technology.

2.4 Smartphone as a tool for QoL enhancement

According to a projection published by Ericsson the number of mobile broadband subscriptions will reach 7.7 billion by 2020, while smartphone subscriptions are expected to grow up to 70% of the world's population [39]. In other words, from 2014 to 2020 the number of smartphone subscriptions will be more than doubled. This rapid spread has had, and still has, a great impact in many aspects of the consumer's life. It affects not only the way people communicate, but also other areas, such as marketing, education, culture, relationships, well-being and health. Accordingly, understanding the key factors influencing the adoption of this technology is essential in order to realise products that meet user's expectations.

2.4.1 The evolution of mobile phones

Mobile phones have almost a century of history, considering that back in the 1930s many New York City fire-boats and tugboats were equipped with radio-telephones. Nevertheless, according to Farley, they were just primitive devices; the public mobile phone history began actually in the 1940s, after the World War II [62]. Anyway, the cellular telephony system, as we know it, was born several years later, in 1973, when Motorola filed a patent for its own cellular radio system [49]. A decade later, in 1983, the first commercial cellular service in the United States started: it was the begin of the first generation of mobile telephony.

A revolution in communications occurred with the emergence of the GSM standard: thanks to it, the technology became cheap enough for everyone. Wilcox states that a second great revolution has taken place with SMS [192]. This invention meant that the mobile phone would work even by pager. Again according to Wilcox, this surprising success convinced everyone that other applications could be combined with mobiles. The manufacturers began to launch phones that offered additional functionalities and services, such as web browsing via WAP, MMS, ring tones, wallpapers and music players.

Ceres *et al.* claim the smartphone became a successful commercial product with the introduction of the Blackberry [38], while Mallison indicates 2007 as the market transformation point, due to the release of the Apple's iPhone, and the subsequent launch of Android-based smartphones in 2008 [117]. After that, mobile phones evolved and improved continuously over the time, changing size and aspect, and adding new features.

One study classifies the smartphone's technical innovations in two categories: vertical and horizontal [38]. The vertical innovations refer to the introduction of new or improved technical features which are valued equally by all types of consumers. Conversely, horizontal innovations involve changes that do not attract all users in the same way. The authors studied how the presence of such characteristics has evolved over time in order to determine an emerging dominant design. The vertical features that have been selected for such a study are: weight, WiFi, 3G, multi-touch, micro USB, secondary camera, and 3.5 mm jack [38]. Results show that the proportion of smartphones with touchscreens has quickly grown from 30% in 2007 to about 95% in 2012, while data connection rose from 35% (2006) to 90% (2012). The feature with the fastest increase is the 3.5 mm jack. It has grown from 10% in 2006 to 95% in 2012. The results of this study suggest that a dominant design is gradually emerging in relation to vertical product innovations. As for horizontal features, just width and screen size have been considered in the study. In this case, the product differentiation is still quite high; that means that a dominant design has not emerged yet in the horizontal production innovation.

2.4.2 Characteristics, strengths and limitations

The previous Subsection gave us an idea of how mobile phones have evolved over time. The change rate they have undergone in recent years has been so fast that today's top-end smartphones come with very powerful octa- or even hexa-core processors and a growing set of embedded sensors. Typically, these smartphones are equipped with accelerometer, gyroscope, barometer, temperature, light and proximity sensors. In addiction, many devices integrate optical heart rate sensors, based on the pulse oximetry technique. From the connectivity point of view, they exhibit a wide range of wireless communication interfaces, such as WiFi, data connection, Near Field Communication (NFC), and Bluetooth. Moreover, thanks to the evolution of the mobile operating systems, disparate applications are available in the market at any time, providing the user the ability to populate his device with different and always new functionalities and services.

For all this reasons, "smartphones represent the first truly mobile ubiquitous computing device", as affirmed by Campbell and Choudhury [32]. The aim of ubiquitous or pervasive computing can be summarized with the common slogan "Everywhere at anytime" [79]. Among the factors that make the smartphone particularly suitable to achieve this goal, two fundamental characteristics cannot be forgotten: to be portable and personal.

Portability is probably the most obvious strength of this device. Small size, light weight and the presence of communication interfaces make it a window on the world, always at hand. Being able to have the smartphone always in your pocket means that it becomes also personal. This is an important aspect because it implies that all the information, applications or services contained therein are addressed or referred exclusively to the device owner. Obviously, privacy issues rise: if a smartphone gets lost, a lot of information about the user may be inferred by analysing its content.

Other limitations which should be taken into account are computational power and memory footprint. Although latest mobile phones present characteristics very close to those of PCs, complex or large amounts of data are still not manageable from a smartphone. In this view, the cloud is a very important contribution to the evolution of mobile devices. All information that cannot be handled or processed directly, can be sent remotely. Hence, it follows that without a parallel evolution of the mobile network, the smartphone would not have such a wide spread in different areas of the consumer's life.

Together with computational power and memory footprint, a major concern for the user is the battery life. Since the battery technology is improving only slowly compared to the developments in the digital processing and radio frequency integration [158], there is a clear need to minimize the terminal power consumption.

Despite the limitations, the scientific data show the increase of smartphone usage and foresee its further growth in the coming years. As Verkasalo stated, nowadays "smartphones not only enable new applications and services, but they are also in the heart of customers' digital lives, being ubiquitous, personal mini computers" [185].

2.4.3 Smartphone technologies in AAL and well-being contexts

Up to this point, we discussed how mobile phones have evolved over time and the characteristics which enable their use, not only in the communications, but in many aspects of the user's life. Differently, this Subsection will describe the smartphone technologies proposed and implemented so far in AAL and well-being contexts.

When dealing with such a rich and varied subject, the first step is to divide all the applications and services into categories. Olla and Shimskey wrote a literature survey of mobile health applications, defining an exhaustive taxonomy [136]. From the use case point of view, it divides the applications into 8 categories: diagnosis, monitoring, wellness, behaviour modification, compliance, instruction, efficiency, and environment. Despite being focused mainly on health, it fits perfectly with our field of study. Below, some of the work proposed in the literature will be described exploiting such a taxonomy. Moreover, the different categories will be mapped in the QoL domains (see Section 2.1), in order to highlight the relationship between smartphone application and QoL.

Diagnosis Referring to QoL domains, diagnosis is mainly related to *physical health*, even though it can be applied also to cognitive and burnout conditions, and thus to the *psychological* domain.

Mobile applications used for diagnosis usually exploit sensors, phone attachments or connected devices for medical tests. Typical tests involve heart rate, blood glucose, blood pressure, urine, *etc.* A system for the physiological parameters monitoring has been proposed for example in [26]; it uses wearable sensors for SpO2 and Heart Rate (HR) acquisition, and the smartphone as a central node. In [100], a dongle for the diagnosis of infectious diseases has been presented: such a dongle can be easily connected to the mobile phone, providing performances similar to those obtained in the laboratory. Solutions more focused on elderly patients are, for example, the uHear application, a system for screening hearing loss [13], or the system proposed by McManus *et al.* for the arrhythmia discrimination [121].

Another kind of test that can be made thanks to the smartphone is the assessment of cognitive functions [29]. The data acquired by means of it are often insufficient to enable a diagnosis. However, the system allows to obtain useful information that can contribute to problems identification.

Monitoring Monitoring applications take advantage of environmental or onboard sensors for controlling the user's behaviour, and particularly to detect abnormal or dangerous situations. They typically deal with *physical health*, such as *ADL*, *mobility*, *sleep and rest*, nevertheless, they can be used also to monitor *psychological* and *social* status. A further QoL domain involved is obviously the environmental one, especially *home environment* and *physical safety and security*.

In [76] a taxonomy for fall detection and prevention solutions based on mobile phones with a systematic comparisons of existing studies has been presented. A research study conducted by Abbate *et al.* introduces a smartphone based application for fall detection, exploiting the accelerometers embedded in the device or an external wearable [11]. Also the study presented in [197] uses onboard and wearable sensors for the acquisition of information on movement and to recognize the ADL performed by the user. For the same purpose, Feng *et al.* utilize environmental sensors installed in the smart home and wearables. Events detected by these sensors are sent to the smartphone in order to be stored and processed [64].

Other applications allow to figure out if a user affected by cognitive pathologies left the house and contact the caregiver or provide suggestions to the patient. An attempt of facing the risk of wandering was proposed, for example, with the use of the Android app iWander [174]. The app is targeted to People with Dementia (PwD) and works by using the smartphone's GPS to track the patient at all times.

Wellness The wellness applications are those designed to support the user in conducting a healthy lifestyle. Such applications are increasingly widespread both in market and literature. For example, in [70], a simple Android app for the promotion of physical exercise has been provided to adult subjects for 8 weeks, demonstrating promising results. In this field, one of the most famous app in the stores is Google Fit, that keeps track of physical activities, sets objectives and verify progress. Another equally famous app is Runtastic, available for both Android and iOS devices. As regards weight loss, an app has been presented by Granado-Font *et al.* [72], while Breton *et al.* propose a review on the solutions available in the stores [28]. Other research studies focus on proposals covering various aspects of well-being. As an example, BeWell is a smartphone based system able to track activities such as sleep, physical activities, and social interactions in order to provide a feedback and promote a better heath [102].

This kind of applications focus on different QoL facets, such as *sleep and rest*, *energy and fatigue*, and, more in general, on *physical health*. However, some of them have repercussions in other areas, such as *bodily image and appearance*, *personal relationships*, and *self-esteem*.

Behaviour modification To convince the user to change his behaviour is another possible smartphone application field. The smartphone can be used to help a subject to overcome addictions [75, 120] or promote healthy and secure habits [104]. Also in this case, the QoL domains involved are both the *physical* and *psychological*.

Compliance The compliance category refers to apps aimed at help the user to fulfil his therapy or treatment. From the QoL view, it mainly focuses on *dependence on medicinal substances and medical aids*. Some example regards aids for drug intake management, medical appointment or exercise reminder. As an example, in [19] an iOS based application supporting drug adherence has been evaluated, demonstrating positive outcomes. Also in [123], a medication self-management app has been discussed aimed at improve safe medication use by elderly. A study conducted by Kirwan *et al.* examined, instead, the effectiveness of a smartphone application combined with text-message feedback in order to improve the glycemic control in patients with type 1 diabetes [95].

Instruction Instructional applications are those designed to provide informations or to educate. They can be targeted to user, caregiver or health professional. As an example, a smartphone app, called Strong Heart, was developed taking into account literature contributes with the purpose to provide an educational learning instrument for coronary artery disease patients [42].

Applications providing information on specific operations, can be considered instructional too. For example, in the Alzheimer's Disease (AD) patient case, a smartphone app which provide suggestions on how to complete a task can be extremely useful, as demonstrated in [52].

Also in this case, the benefits provided by such applications fall within the *physical health* and *psychological* QoL domains.

Efficiency Efficiency regards the applications aimed at providing support to caregivers or healthcare professionals for execution of specific tasks. An example is reported in [138], where an intelligent task management platform for the health personnel is presented: it can visualize the assigned tasks through the mobile device. An other efficiency app is the one developed by Lin *et al.* for the coordination of caregivers: it exploits the smartphone technology and is designed for both family and professional operators [111].

Such category contributes to improve the quality of health and social care, for this reason, efficiency applications can be mapped in the *environmental* QoL domain.

Environment Typically, environmental applications refer to location-based systems that provide information on the surrounding context. Some examples concern applications which provide news, instructions and tips in case of emergency situations, for example [195]. As expected, their main contribution falls within the *environment* domain, providing information on *physical environment* and *transport*, ensuring *freedom, physical safety and security.*

Other types of environmental applications are those based on the recognition of objects, places or situations. These solutions can be extremely useful for blind or visually impaired people, as shown in [41]. However, even people with cognitive problems or healthy subjects can benefit from them. For example, the system proposed in [81] is designed to help elderly users during travels by public transportations. It provides relevant information at the right time, and proposes remedies in case of error. The latter, influence also the *physical health*, especially *mobility* and *ADL*, and the *psychologica*l domain.

Applications described so far have been divided in accordance with a taxonomy mainly centred on the use purposes. However, other classifications are feasible. As regards the device functioning, a possible distinction relies on the usage modalities. In fact, the smartphone can be used in different ways: as a simple communication system, as an interaction device or as a data collector. The first mode is the most obvious one. The use of smartphone as an interface, instead, poses a huge number of challenges, especially when dealing with elderly or non-technical people, while the last one is increasingly widespread, since allows to acquire data from different wearable or onboard sensors and store or process them everywhere.

In the AAL and well-being perspective, the last two are probably more significant and interesting than the first one. In the following, we will investigate these aspects, describing the state of the art and the use cases implemented by us.

Chapter 3

Smartphone as a HCI system: a literature survey

HCI is a cross-disciplinary area dealing with theory, design, implementation, and evaluation of the ways that humans use to interact with computing devices. Humans primarily interact with the world through their five major senses of sight, hearing, touch, smell, and taste. In 1996 Blattber and Glinert listed the most relevant sensory modalities in the HCI [22] (see Table 3.1), but additional input modalities are emerging in recent years such as indirect sensing of neural activity, e.g. brain-computer interfaces (BCIs), or implicit interactions such that the interactions are based on the context understanding [160].

Table 3.1: Human sensory modalities relevant to multimodal human computer interaction according to [22].

Modality	**Examples**
Visual	Face location, gaze, facial expression, lip-reading, face-based identity (and other characteristics such as age, sex, race, *etc*), gesture (head/face, hands, body), sign language
Auditory	Speech input, non-speech audio
Touch	Pressure, location and selection, gesture
Other sensors	Sensor-based motion capture

Within the wide field of HCI, this chapter is going to discuss the specific and peculiar aspects related to the interaction between elderly or disabled users and a smart assistive environment. Particularly, the use of commercial mobile devices, such as smartphones and tablets, as interaction tools will be investigated.

3.1 HCI for smart assistive environments

From the technology point of view, AAL and AmI will support new generations of older adults, for a longer and improved QoL. However, in order to make the new technologies really useful for this purpose, it is necessary to first analyse the users' requirements. Specifically, interaction modalities and interfaces should be properly designed to encourage the older user to approach new technologies, and to stimulate user's wish to benefit from the available tools.

As for the AAL field, several projects can be identified in the literature employing different interaction methods [150]. For example, in [74], Grguric *et al.* cite some projects that employ GUIs in platforms for AAL services. For these solutions, a good user interaction design is fundamental, as confirmed by several studies showing that the users' acceptance strongly influences the success of technological innovations. They also propose to apply a gesture-based approach to an existing AAL platform. A study conducted by Dinh *et al.* [60] presents a novel hand gesture interface system which exploits a depth imaging sensor for appliances control in a smart home environments. With such an interface, the user can control smart home appliances such as TV, fan, lighting, and doors. Another gesture-based approach for the interaction with smart environment has been proposed by Kühnel *et al.* in [97]. In such a case, the authors use a smartphone as an input device in order to interpret three-dimensional gestures: movements and rotations of the device correspond to different commands to be sent to the smart home. This solutions does not seem very adequate to elderly subjects, due to their poor motor skills and the need to memorize different gestures.

In [94] the smart home appliances are controlled by a Smart TV based GUI. The use of Smart TV does not require specific technical skills, and the interaction is simple, familiar and intuitive; nevertheless it suffers from a big disadvantage: it is not portable. In order to enable the user to interact with the home environment anywhere, the authors developed also a Web-based interface. However, it is interesting to note that in recent years HCIs are heading towards scenarios that overcome the hitherto predominant model, i.e. the GUI model which foresees the interaction through physical devices like mouse and keyboard. This model, in fact, is not applicable to all users (just think of users with reduced mobility for example), while, vice versa, the need to interact with the technology becomes more and more extensive.

In this view, speech recognition and voice control seem to be a more natural and appropriate solution, even for the older audience. In the market there are several of voice-based devices, enabling the human-environment interaction through a centralized device. The most popular devices are: Amazon Echo [2], Wink Hub [8] e Google Home [6]. The strength of these products is the ability to interface with third-party systems, such as home automation systems, sockets and switches, lights, cameras, audio broadcasting systems, door locks, thermostats and irrigation systems. Even in literature, there are numerous voice-based solutions. As an example, in [87], authors describe a speech recognition system to control intelligent houses, focusing on elderly and disabled people. A study by Portet *et al.* [148] aims at designing and evaluating a voice interface for the smart home, conducting a thorough analysis on the acceptability of this kind of interaction by the elderly. The authors state that voice interfaces are highly preferred by users, compared with tactile systems, since they do not have to be physically available in the place where the command is sent. In this case, the main disadvantage is the sensitivity of the system to noisy environments, for example in the presence of vacuum-cleaner or blaring television. Moreover, in recent years, thanks to the smartphone device's portability, this problem is on the way to be overcome.

As regards people with severe motor disabilities, many solutions have been developed to provide interaction functionalities with the environment. In this context, a rapidly expanding area of research is represented by Brain-Computer Interfaces (BCI)s [106, 129]. Such interfaces are capable of interpreting signals arising from the brain of the subject, such as the electroencephalographic signal, in order to allow the user to control and communicate with external devices. As stated by authors in [108], this solution leads many challenges, such as security and privacy. Reliability, accuracy, and acquisition speed represent further critical issues. However, even addressing these questions, BCIs may be not acceptable by the user, as they require a direct connection between the brain and the external environment.

In [177], a smart home environment platform for assisting people with physical disabilities is presented. 3D cameras are used to capture facial landmarks and expressions in order to map the user intent into a specific action in the smart home environment. Pires *et al.* present an application focused on social interactions, allowing elderly and mobility impaired people to interact with audio-visual Internet-based communication services, both by means of a touchscreen computer and a smartphone [146]. In this project, the key point is the multimodality. The first device supports speech, touch and keyboard/mouse interaction as input modalities, while output is displayed on the GUI or through speech synthesis. The second one supports speech interaction and touch, and simple gesture (e.g. tilt rotations of the device) can be used to scroll up or down on a list.

Some interfacing systems exploit emerging technologies, such as the NFC technology. A paper by Häikiö *et al.* [77] reports the results of a field experiment where a NFC enabled mobile phone was used as user interface element so as to allow home-dwelling elderly people to choose their meals to be delivered by means of a home care service. The experiment showed that a touch-based user interface can provide an easy-to-learn and adoptive user interface paradigm for the elderly. Also Spinsante and Gambi presented a NFC-based interface, named Smart Panel [168]. Such interface is designed to allow elderly and disabled people affected by physical limitations to live safely and comfortably at home, by facilitating the autonomous execution of daily life tasks.

An experimental evaluation of three User Interface (UI) applied to the smart home has been performed in [96]. In such a trial, a PC, a TV remote control and a mobile phone were used to control the home functions by a couple of young users (26 and 27 years old) for six months. The results suggest that different interactions require different interfaces. Indeed, the interaction activities can be classified as pattern control and instant control. According to the users, PCs are more suitable for activity patterns that can be planned and defined in advance, while mobile phones are well suited for instant control. Nevertheless, as can be seen from this study, the subjects are interested in centralized control and have identified the smartphone as the primary centralized remote control. Moreover, thanks to the possibility of customization, its usability can be further increased. As previously mentioned, mobile devices have the advantage of being portable and personal. They are also equipped with multiple wireless communication interfaces, such as data connection, WiFi, Bluetooth, NFC, and GPS. These characteristics make them extremely suitable to be used as interfaces between the user and the surrounding environment.

3.2 Usability and acceptability by elderly and fragile people

The real benefits of technologies rely on the impact of ageing on the technology access. In [50] Czaja states that elderly people are able to successfully use the new solutions insofar problems that may be encountered are identified and resolved. If the design of user interactions plays a key role in the commercial products, this aspect is further emphasized when dealing with older people. In fact, they typically suffer from comorbidity, due to the natural ageing process and may have motor or sensory limitations, thus, to use certain technologies could be difficult or, in some cases, even impossible for them. Therefore, when designing technological solutions addressed to elderly or disabled people, it is very important to select human-system interfaces that can match the user's abilities, and make the user feel secure and at ease [193]. Older adults could have difficulty to learn to use new technologies, or simply reject the idea of introducing new equipment in their home environment and change their habits. In the design phase of the user interface, taking into account the usability related aspects is crucial: if these aspects have been considered, there are more chances the interface is accepted positively by users. Consequently, one of the key requirements for the acceptability of a new technology is the usability.

Several studies analysed the relationship between older people and technology, particularly focusing on acceptability. Although they recognize the benefits of technology, many elderly have never used a computer and consider it difficult to learn. A study [131] conducted by Morris *et al.* on the use of computers and Internet by older users shows that they have positive attitudes mostly towards technologies they really need, showing that the most common reason for not wanting to learn using new technologies is that they are simply not interested. This view is confirmed by Coleman *et al.* in [47], where positive results where detected in the interaction with everyday devices, such as television or microwave, but not with more sophisticated ones. Normally, the elderly do not want to make the effort to learn to use a new technology if it is not strictly necessary. The challenge for AAL framework developers is, therefore, to design a system which is user-friendly, as intuitive as possible, and that delivers a real benefit in older people's lives.

The AAL Association delivered a document [132] in which it summarizes some general advices for the design of services and products targeted to senior citizens:

- to provide additional value: seniors decide to use a specific product or technology depending on the associated perceived advantages [122], for example safety or comfort;
- to provide adaptable support: According to Lawton [105], technical solutions are successful only if they address individual abilities very precisely. A possible solution consists of using modular components which can be added or removed easily and represent a simple and inexpensive solution;

- to keep it simple: the design of clear menus and structures, and the provision of essential functions, reduce the complexity of learning and using the technological tool;

- to enable a joyful experience: in order to encourage the users to use AAL solutions, it is useful to provide an enjoyable experience [156], also because emotionally positive experiences become more important as people grow older.

In addition, many users do not like the idea that someone else might monitor or control their home environment or, more generally, their life. Therefore, the challenge is to develop systems, devices and interfaces that older people can use easily, intuitively and independently in their home environment, without having to face the difficulties related to learning new technologies, and without feeling monitored.

Other aspects to consider during the design phase are the security and privacy issues. From the HCI point of view, the main issue is the prevention of unauthorized users from accessing the information and interfacing with the system. In fact, if a malicious user is able to gain access to the assistive technologies, he might be able not only to collect sensitive information on user habits, but also to interfere practically, by sending commands to the assisted environment through actuators. This represents a clear and considerable threat for the elderly that would be exposed to significant risks, getting damages instead of benefit from the technology.

As for acceptability, the last factor that cannot be ignored is the cost. In [27], Bouwhuis stated that acceptability can be seen as a scale with two extremes: the refusal on the negative side and the attraction in the positive one. It is obvious that rejection due to the cost must not exceed the attraction provided by benefits. Therefore, being able to develop low cost technologies is an important goal also in the HCI context.

Ultimately, key factors influencing acceptability are:

- utility;

- simplicity;

- joyfulness;

- unobtrusiveness;

- safety;

- cheapness.

As regards the usability, ISO 9241 [65] defines it as “The effectiveness, efficiency and satisfaction with which specified users achieve specific goals in particular environments”. More specifically, effectiveness is the accuracy and completeness with which users can achieve specific goals in particular environments, while efficiency refers to the resources spent in relation to the accuracy and completeness of the goal achieved. Differently, satisfaction is a concept related to the users’ feeling and can be defined as the comfort and acceptability of the system according to users and other people affected by its use [7].

The targets addressed by usability rely in saving the user’s cognitive effort, offering products that are easy to understand, learn, use and remember, and that avoid errors or make them recoverable. These features can be accounted for in the following aspects: information architecture and interface design. As stated by Resmini and Rosati in [152], the information architecture can be seen as an information map which enable users to find their route towards the knowledge. It is interesting to note that users become aware of the information architecture of a system only when it is not clear; on the contrary, if not noticed, it means that the information architecture fits perfectly with the users’ concept map and the information is well structured. Instead, the interface design includes aesthetic issues, graphic rules and usability and readability derived by perceptual and cognitive sciences. Referring to GUIs, Jakob Nielsen [133] has provided a list of 10 heuristic principles for the interaction design (see Table 3.2). Such a list does not refer to a specific type of interface, but is quite general and establishes guidelines that must be followed in the design phase in order to provide a tool that is as much easy to use as possible, and has a good impact on the user even at the first sight. Nevertheless, as affirmed by different studies [151, 37] the adoption of new technologies in the AAL field requires their adaptation to the needs of older adults, considering both changes in cognitive and sensory abilities. In the first case, some studies suggest to adopt a practical training rather than a conceptual one, to reach a better result from the learning process. Reduced motor skills, on the other hand, make it difficult to use common input devices such as mouse or keyboards, while visual impairments require for example larger elements on the screen. In Table 3.3, a sum up of guidelines referred to elderly users’ main requirements is provided [132]. These recommendations, like Nielsen’s principles, are not defined for a specific type of interface.

As stated by Hasan and Abdoul-Kareem, the two major types of enabling technologies for HCI are contact- and vision-based devices [80]. Contact-based devices are typically based on the physical interaction of the user with the interfacing device.

As regards smartphones, in most cases they exploit as a detector the multi-touch screen. Acceptability and usability issues for this kind of interaction will be discussed in Subsection 3.2.1. Moreover a brief overview on acceptability of Vision-based Interfaces (VBI) will be provided in Subsection 3.2.2.

3.2.1 Touchscreen technology characteristics

The latest generation smartphones are characterized by different sizes, hardware and software components, however, they are all equipped with a touchscreen. The advantages and disadvantages of using touchscreens over other pointing devices have been listed by Bhalla and Bhalla in [20]. According to the authors, the main advantages are:

- touching a visual display of choices requires little thinking and is easy to learn;
- touchscreens are the fastest pointing devices;
- touchscreens have easier hand-eye coordination than mice or keyboards;
- no extra work space is required as with other pointing devices;
- touchscreens are durable in public access and in high volume usage.

Conversely, the disadvantages are:

- user's hand may obscure the screen;
- screens need to be installed at a lower position and tilted to reduce arm fatigue;
- some reduction in image brightness may occur;
- they cost more than alternative devices;
- screens get very dirty;
- these devices require massive computing power which leads to slow devices and low battery life;
- touchscreen devices usually have no additional keys: when an application crashes, you can't get to the main menu as the whole screen becomes unresponsive.

Despite these drawbacks, however, the technology in question provides a very important advantage which contributes to its widespread use: it is easy to learn and requires little thinking. Moreover, as mentioned by Greenstein and Aranud [73], in touchscreens the input is also the output device. This is a great benefit for the elderly, since they normally suffer from age-related attentional decline. Moreover, they do not require an advanced mental model, so they are considered an easier approach than classical HCI, based on separate input and output devices, such as mice and keyboards.

An interview campaign conducted by Burkhard and Koch [30] over 30 elderly subjects shows that the majority of them accepts touchscreen technology, preferring large screen sizes and lightweight devices. Surely this preference is due to visual and motor limitations, however some studies demonstrates that screen size is an important factor affecting the use of the different applications also for healthy or young people. For example, Fig. 3.1 shows how the dimensions of screens influences the service usage [39].

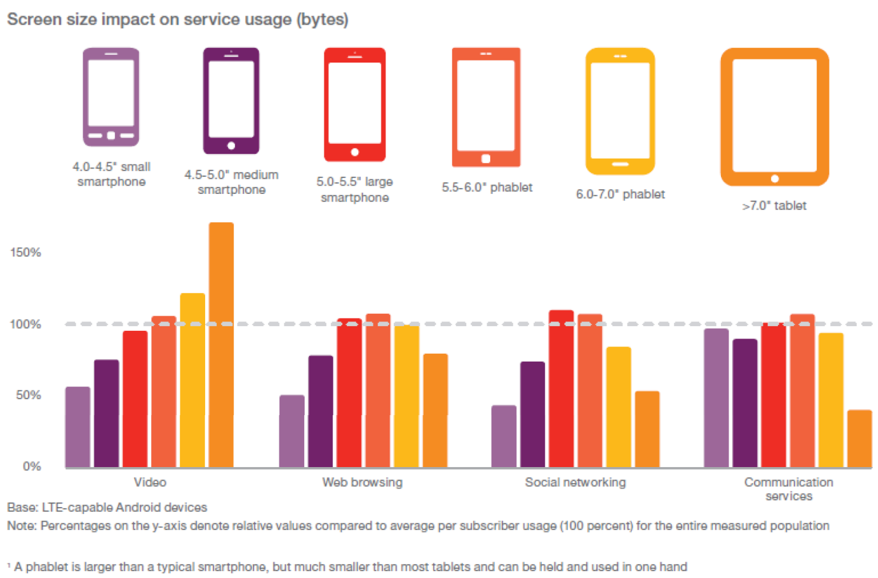


Figure 3.1: Screen size impact on service usage (bytes) [39].

In [125] the authors report on the barriers to smartphone usage among the older adults. The objective of the paper is to understand why the elderly prefer less advanced phones than smartphones. To this purpose, 21 subjects aged 60 and above have been interviewed. The respondents tend to use the mobile device only for calls and they are not interested in more advanced features. Moreover, not all the interviewees were able to read or write text, because of visual impairments. Thus screen dimensions and text sizes are an important aspect to consider in the choice of the interfacing device and in the design phase of the application. Other important consideration can be inferred by such a paper. Some of the respondents defined smartphones as “unnecessary”, while others indicate that to have the possibility to call their families makes them feel safe. From these statements, it can be deduced that the introduction of a new device, never used before, such as touch screen device, can be accepted by elderly only if it provides additional value and suits their physical and cognitive skills.

As regards usability, the Android User Experience Team developed some general design principles [4]. They can be summarized in three theme areas: to enchant, simplify, and give unexpected help. Each of them can then be split in more detailed concepts. Considering the first theme, some of the suggestions provided by the authors are:

- to provide a joyful experience through beautiful backgrounds, carefully placed animations, and well-timed sound effects;
- to use directly touchable objects rather than buttons or menus;
- to allow the customization;
- to learn users’ preferences over the time, in order to provide functionalities or information even before they ask for them.

As for simplification, a few tips are listed below:

- to use short phrases and simple words;
- to prefer pictures over texts;
- to decide for the user in order to avoid too many choices, while guaranteeing the “undo”;
- to break tasks and information into small, digestible chunks, and do not show too much at once;
- to show where the user is located;
- to remember information, settings, and everything requires time to be created;
- to avoid similar views which act differently;

- to interrupt the interaction only if there is something important to communicate.

The last theme for the proper design of smartphone applications consists in making the user feel at ease providing unexpected help. This can be achieved observing the following guidelines:

- to exploit widespread visual patterns in order to reduce the learning efforts;
- to give clear recovery instructions when something goes wrong, avoiding technical details;
- to break complex tasks into smaller ones and provide a feedback;
- to make novices feel like experts, providing shortcuts, which allow the user to perform complex operations in a simple way;
- to make important things easy to find and fast to use.

Among the factors that may influence the effectiveness and quality of touch interaction it is worth mentioning the hand used (if the "preferred" or the other one), if the device is used in static conditions or moving (eg. sitting or walking), and the position of the target area (i.e. the area which, when clicked or interacted, determines a command activation) with respect to each hand. The size of the target area, typically a button, has a great influence on the accuracy of the interaction, no matter which hand is used. In [142], Park *et al.* have shown that the size of the graphic button have a significant influence on the number of errors, success rate and the optimal pressure; that is, applying a normal pressure, the larger the size, the lower the error rate and the higher the rate of success. The results of a study by Pari *et al.* [141] have shown the buttons should be approximately 9.2 mm wide for a mobile device: with these dimensions, the target areas are as small as possible, without decreasing performance. Moreover complex control techniques should be avoided, in fact older people may find it difficult to perform sliding and revolving gestures on touchscreen [196]. While evaluating the use of web-based interfaces by the elderly, Kurniawan and Zaphiris found that they prefer the presence of graphics if it is logically associated with the content, and not only for decorative purposes [98]. Animated elements tend to confuse older users and therefore should be avoided in general, while animated avatars are considered useful. The icons should be simple and meaningful, and large enough to be identified by people with impaired vision [115]. All these studies help us to create an overall picture about the general rules for designing usable touch screen interfaces, which require a minimal effort in understanding by older users.

3.2.2 Vision-based interfaces

In recent years CV techniques have evolved rapidly. Real-time vision algorithms have been applied to HCI in different areas, including face detection and recognition, facial expression analysis, hand tracking and modelling, head and body tracking and pose extraction, gesture recognition, activity analysis, and object recognition [183].

It is interesting to note that, when dealing with VBIs, the interaction can be direct or indirect. In other words, the user can issue commands through hands, head or body movements, i.e. gestures, or the system can obtain information indirectly through facial expression analysis, activity recognition or context understanding. An example of indirect interaction is described in [25]: the authors present a smart home whose ambient light varies according to the user's mood.

Within our area of interest, numerous applications can be deployed using the indirect interaction. For example, there are many solutions for the fall detection based on the Kinect sensor [68, 110, 178]. In [44] the authors propose an algorithm to monitor the food intake, while in [45] the depth sensor is used to recognize the activities carried out throughout the day. In this case, the most critical aspect concerns the privacy. In fact, monitoring applications exploiting video signals, are hardly accepted since they make the user feel observed. For example, in an exploratory study conducted by Steele *et al.* [176], elderly people have been interviewed about perceptions, attitudes and worries about wireless technologies applied to healthcare. A majority of the participants showed no concern about having their health information transmitted wirelessly, but concerns arise when dealing with cameras.

As regards direct interaction, several solutions exploit vision in order to provide a feedback on the user's health status [46], or to enable the correct execution of rehabilitation exercises [35, 43].

There are many applications designed to help blind people to interact with the objects of everyday life or to guide them in indoor environments [163, 181]. Augmented Reality (AR) is another wide field of application. Kurtz *et al.* evaluate through practical field tests whether elderly can deal with AR [99]. Two hand-held applications have been used and evaluated by, respectively, 17 and 8 subjects between 66 and 93 years. The results show that the most critical issue is the necessity to hold the device up. In fact, interfaces typically exploit the back-facing camera in order to capture the scene that should be augmented. This is not appropriate for the elderly because hand-held devices are heavy and their slithery surfaces make it difficult to hold them up for a long time. One possible alternative suggested by the authors is using Google Glass. However, only 3 among the 9 who tried this type of interface claimed to imagine using a head-mounted display in their everyday life.

Further examples of VBIs applied to smart living environments have been presented in Section 3.1. They use gestures as input method. In the VBI context, gestures represent one of the most natural interaction method, but, surprisingly, little research exists on how older adults could benefit from gesture-based interactions. In [153], the authors stated that screen-based gestures have seen a widespread use since they do not change the way the device is held or used. Conversely, gestures away from the screen have not. The authors of the study presented in [194] developed a projection tabletop system targeted to elderly people. The system consists of a projector providing information on the table and a camera which detects the target object touched by the user. During the pilot test, they found that elderly move the hands during thinking while computer literate users move after they decide what to do. This is an important aspect to consider when designing gesture-based interfaces.

Bobeth *et al.* investigated performance and acceptance of freehand gestures for TV menu control [24]. The authors conducted a user study involving 24 older adults. The aim of the trial is to identify which kind of gesture, among direct pointing using hand movement tracking, indirect pointing using static hand positions to control the cursor, directional gestures using hand strokes for a marking menu, and dial plate for a radial menu, is the fastest for selecting tasks and produces fewer errors. Moreover, they investigated if older adults accept gesture-based interactions by asking them about enjoyment, usability and behavioural intention. As a result, the acceptance of the various gesture based menu types was rather high for every tested method, however hand movement tracking performed best and is preferred by the interviewed people.

A survey provided by Manresa *et al.* [119] rely on three attributes listed in the ISO definition already discussed in Section 3.2 to categorize the factors influencing the usability of VBIs. They are: effectiveness, efficiency, and satisfaction. Based on these, further other aspects have been taken into account (see Table 3.4). The first aspect, accuracy and error rate, is strictly related to the CV algorithm's robustness and precision. Thus, a high level of robustness is essential for practical deployment of VBIs and, mostly, for their usability. As stated in [153], in the end robustness can only be determined by thorough testing under a wide range of conditions. As regards duration, gestural commands must be concise, fast and avoid gestures that require a high precision over a long period of time. This is generally true for each user, but it is even more significant for elderly. Also in this case, the aspect is strictly related to effectiveness. In fact, the execution phase sometimes requires maintaining the gesture for a predefined time for robustness. For this reason it is important to make a compromise choice between duration of gesture and robustness of the algorithm. In [147] a Kinect based interface has been developed taking into account the aspects discussed so far: it has been tested by 9 students, aged between 21 and 24 years.

Wigdor *et al.* proposed a multi-modal solution, called LucidTouch, based both on touch and vision [191]. This solution try to overcome those that, according to the authors, are the two main interaction defects of the touchscreens: the occlusion problem, and the fat finger problem. LucidTouch is a mobile device that addresses this limitation by allowing touch interactions on the back of the device. The movement on the back is acquired through a camera attached to the device with a fixed boom. To allow the user to get a feedback on the fingers' position, a projection of the hands is displayed on the screen, giving the impression of handling a semi-transparent tool. In order to evaluate the LucidTouch interaction, 6 participants between the ages of 26 and 43 were given the opportunity to interact with the device. As a result, pseudo-transparency may be useful for some applications, while distracting for some others. Moreover, small lags due to computational tasks are a further distraction source. This highlights another important issue related to interfaces: the computational complexity. In order to be usable, the system should be able to process the input and provide feedback immediately, otherwise it will confuse and frustrate the user. This is a more challenging issue in the VBI context, since CV techniques are often very onerous from the computational point of view.

Table 3.2: 10 usability heuristics for UI design by Jacob Nielsen [133].

Principle	**Description**
Visibility of system status	The system should always keep users informed about what is going on, through appropriate feedback within reasonable time.
Match between system and the real world	The system should speak the users' language, with words, phrases and concepts familiar to the user, rather than system-oriented terms. Follow real-world conventions, making information appear in a natural and logical order.
User control and freedom	Users often choose system functions by mistake and will need a clearly marked "emergency exit" to leave the unwanted state without having to go through an extended dialogue. Support undo and redo.
Consistency and standards	Users should not have to wonder whether different words, situations, or actions mean the same thing. Follow platform conventions in [134].
Error prevention	Even better than good error messages is a careful design which prevents a problem from occurring in the first place. Either eliminate error-prone conditions or check for them and present users with a confirmation option before they commit to the action.
Recognition rather than recall	Minimize the user's memory load by making objects, actions, and options visible. The user should not have to remember information from one part of the dialogue to another. Instructions for use of the system should be visible or easily retrievable whenever appropriate.
Flexibility and efficiency of use	Accelerators – unseen by the novice user – may often speed up the interaction for the expert user such that the system can cater to both inexperienced and experienced users. Allow users to tailor frequent actions.
Aesthetic and minimalist design	Dialogues should not contain information which is irrelevant or rarely needed. Every extra unit of information in a dialogue competes with the relevant units of information and diminishes their relative visibility.
Help users recognize, diagnose, and recover from errors	Error messages should be expressed in plain language (no codes), precisely indicate the problem, and constructively suggest a solution
Help and documentation	Even though it is better if the system can be used without documentation, it may be necessary to provide help and documentation. Any such information should be easy to search, focused on the user's task, list concrete steps to be carried out, and not be too large.

Table 3.3: Recommendations for interaction design targeted to elderly users [132].

Supported dimension	**Recommendation**
Vision	- Offer an adaptable display size with a minimum font of 12 to 14 point - Keep high the contrast between the background and text or buttons - Items can be grouped by colour or, alternatively, by means of size, volume and texture
Hearing	- Use low-range to mid-range frequencies and pulses of sound rather than sustained frequencies - Consider potential background noise - Consider interactions with hearing aids - Avoid computer-generated voices - Use natural speech rhythm, stress and intonation
Mobility	- Allow sufficient time for inputs - Reduce to a minimum motor input for users with motor control problems - Offer auditory, visual or sensory feedback to confirm a motor input - Reduce the number of targets, increase their size and keep sufficient space between them - Use static menus instead of dropdowns
Cognition	- Provide only task-relevant information - Present information in small, screen-sized chunks - Do not provide parallel information at the same time - Indicate the user's current position within the information space - Apply strategies to reduce the users' working memory (e.g. by presenting all available functions instead of showing them only on request) - Use commonly used symbols that are intuitive and known from real life

Table 3.4: Usability aspects characterizing gesture-based interfaces according to [119].

Factor	**Measurement**	**Description**
Effectiveness	Accuracy and Error rate	Correctness in recognizing the gestures
Efficiency	Physical fatigue	Tiredness that appears when interacting with body movements
	Duration	How long the user needs to perform the gesture
	Cognitive load	Total amount of mental activity imposed on working memory
	Learnability and Memorability	Learnability, or time to learn,is the time and effort required reaching a specific level of use performance. Memorability, or retention over time, is the ease of system intermittently for casual users [135].
Satisfaction	Naturalness and Intuitiveness	Naturalness is related with their quality of being real and not involving anything made or done by people. Intuitiveness is the instinctive use of the gestures based on what one feels they should be even without conscious reasoning
	Comfort	Comfort is defined as a pleasant feeling of being relaxed and free from pain
	Ease	Little effort to operate with the system
	User experience and Satisfaction of use	Pragmatic and hedonic aspects of the system
	Social acceptance	Appropriateness of the gesture, by both the user and any observers, in the context in which they are carried out

Chapter 4

Smartphone as a data collector: state of the art

Nowadays, smartphones integrate a wide range of sensors that can be easily managed by the Operative System (OS)'s Application Programming Interface (API)s. In addiction, thanks to different wireless communication interfaces, they can also manage remote resources. According to [154], the smartphone is normally used as a mobile collector of sensor data and is often the most efficient gateway, connecting the Wireless Sensor Network (WSN) and the web.

Systems of all types rely on mobile devices [57], from traffic management [34], to health applications [130]. In the IoT perspective, more and more solutions use the smartphone as a gateway. As an example, Pereira *et al.* propose to use it as a Machine-to-Machine (M2M) gateway for smart cities [144]. Also the AllJoyn interoperability framework [15], one of the most promising frameworks for the IoT system development, uses the smartphone as an intermediary, enabling the communication between different vendors' devices. Likewise, the acquisition of data from the onboard sensors is increasingly becoming an important research field, especially for the user's habits and behaviour detection. For example, a prototype application for personal activity-travel recognition through the use of smartphone sensors has been presented in [12]. The system is able to automatically infer activity type and travel mode. Radhakrishnan *et al.*, instead, use a combination of smartphone and a smartwatch in order to find out the shopper's behaviour inside a retail store [149].

The acquisition of behavioural information, both through wireless and onboard sensors is probably one of the most interesting aspect as regards AAL and well-being. In the following, we will provide a description of the related work about the smartphone use as a behavioural data collector.

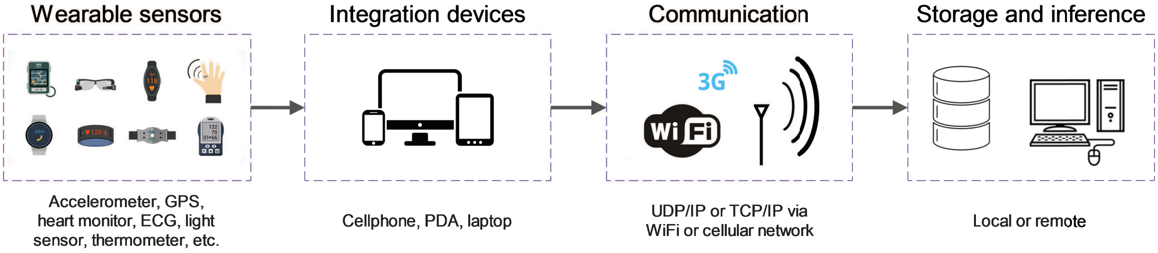


Figure 4.1: Generic data acquisition architecture for behavioural analysis.

4.1 Behavioural analysis through wearables: a survey

The recognition of human activities has been approached in two different ways, namely using external and wearable sensors [103].

Behavioural data can be successfully inferred from environmental sensors. However, they have the disadvantage of being able to monitor the user just as long as he/she is indoor. This shortcoming can be successfully bypassed using wearable devices. Swan affirms that wearable computing as a category is defined by smartwatches and wristband sensors, augmented eyewear such as Google's Project Glass, and wearable textiles [179]. In a sense, also smartphone onboard sensors can be seen as wearable sensors, since the smartphone is generally in the pocket for many hours.

Another device category which is recently entering the market is the monitoring patches. They are low-cost disposable patches that are worn continuously for days at a time and then discarded. An example is the Sano technology [86]. It is aimed at the self awareness of what happens in the own body: the patch monitors the chemistry of the body and an application allows to view information on the smartphone.

A generic data acquisition architecture for behavioural analysis is shown in Fig. 4.1 [103]. Typically, the wearable device is attached to the person's body in order to measure attribute of interest, such as motion, location, temperature, Electrocardiogram (ECG), *etc.* They communicate with an integration device in order to forward the data to a local or remote platform. The integration device is fundamental since wearable device must be small and unobtrusive, and therefore with limited memory footprint and processing capabilities.

According to Lara and Labrador, seven main issues should be addressed when dealing with monitoring systems for human activity recognition through wearables:

selection of attributes and sensors, obtrusiveness, data collection protocol, recognition performances, energy consumption, processing and flexibility.

The attributes and sensors selection depends undoubtedly on the type of activity to recognize. Among many possibilities, the more spread are: environmental attributes, acceleration, location and physiological signals.

Environmental attributes, such as temperature, humidity, or light, are unable to provide sufficient information alone, however they allow to contextualize data obtained by other sensors. Triaxial accelerometers are widely used for ambulation activities [118], but also sleep, eating, working at a computer or brushing teeth recognition. For example, in [56], authors proposes an approach for complex activities detection, e.g. cooking and cleaning, exploiting accelerometers embedded in the smartphone. Obviously, according to the activity to recognize and monitor, accelerometers should be positioned in different ways [16]. Location information are usually obtained with Global Positioning System (GPS) devices. They can be useful to infer activity, for example, if the user is at the supermarket, probably he is shopping. However, GPS devices do not work well in indoor scenarios, for this reason they are often used with accelerometers. Sensor reliability is very important, especially for physiological signals acquisition. For this reason, in the literature several research works attempt to demonstrate the reliability of values acquired through commercial devices [145].

Lara and Labrador affirm that to be successful in practice, such systems should not require the user to wear many sensors, nor interact too often with the application [103]. Unobtrusiveness, is therefore a fundamental requisite for acceptability, together with comfort, non-invasiveness, and low cost. Limiting the obtrusiveness means to reduce size and weight, and consequently to reduce the number of sensors. Also energy consumption, complexity and memory footprint would benefit from minimizing them. On the other hand, more sensors imply more data and, therefore, an increased accuracy.

In order to provide an effective algorithm for activity recognition, it should be tested on a huge number of users with different gender, age, and health conditions. Thus, a proper data collection protocol is crucial for its implementation.

Another aspect to consider regards performance. Likewise any other system, to have good performances is extremely important in order to obtain its actual adoption. They depend on several factors, such as activity set, quality of training data, feature extraction method, and learning algorithm. Once the algorithm has been implemented, it must be widely tested, especially when dealing with monitoring and diagnoses applications, such as applications for sleep, physical activity or HR monitoring.

Energy constraints should be taken into account when designing systems for behavioural analysis. In this context, the most expensive operation is the communication technology. Short range wireless networks should be preferred over long range networks, as the latter require more power. Moreover, data aggregation mechanisms allow to reduce the number of transmissions. In addition, not only the wearable, but also smartphone's battery consumption must be considered.

As regards processing, one of the main concerns regards where the recognition task should be done. The most obvious solution is the local or remote server, which has much higher computing, memory and energy capabilities compared to those of a mobile device. On the other hand the continuous transmission between smartphone and server requires a higher energy consumption and a proper management of privacy issues. For this reason the choice of the processing device has to take into account multiple factors.

The last issue that should be addressed when dealing with monitoring systems for activity recognition is the flexibility. Different people perform activities in different ways, thus the algorithm must work accordingly.

While on the one hand the system implementation poses all of these challenges, on the other hand we wonder what kind of information can be derived from it. As already stated, many wearable devices are currently available on the market. Two examples are Fitbit and Jawbone: they allow to monitor sleep and physical activity. A systematic review of their validity and reliability is provided in [61]. In this case, results indicate higher validity of steps, few studies on distance and physical activity and lower validity of energy expenditure and sleep.

Additional information can be retrieved directly from smartphone applications, using onboard sensors; for example, [137] proposes an overview of smartphone app for sleep analysis.

Frequently the combination of data acquired from wearable and smartphones can provide further information. An example is the system proposed in [66], called Psychlog. It collects physiological, psychological, and activity data for mental health research. The system relies on a wireless electrocardiogram equipped with a three-axial accelerometer and on a self-reported questionnaire on the smartphone. By combining them, the application makes it possible to investigate the relationship between psychological, physiological, and behavioural variables, as well as to monitor their fluctuations over time.

In [182], the authors discuss the design factors for the implementation of a smartphone application, called VITAL-IN. Such an application is able to quantify the objective factors for onset and prevalence of burnout, by means of onboard sensors and wearables. Moreover, through computerized Ecological Momentary Assessment (EMA) [162] also psychological factors are considered.

To support this survey on the use of smartphone as an integration device for behavioural data collection, two use cases will be described in Chapters 8 and 9.

Chapter 5

Vision-based interaction systems aimed at AmI: two use cases

In order to investigate and better understand if a smartphone application can represent a low cost solution for interfacing elderly, disabled or, in general, non-technical people with smart living environments, different use cases have been designed and developed. In the following they will be discussed, starting from VBIs.

5.1 UI based on face detection and tracking

This Section presents a smartphone application exploiting CV techniques and OS's native functionalities, in order to issue commands to the mobile device, by tracking the head and face movements of a subject [127, 126].

This project aims at providing to disable users who cannot move their limbs a suitable communication interface, taking into account their specific needs. Such a solution, allow the disabled person to obtain more autonomy, ensuring him to control the home environment, to communicate with friends and family and, in the future, to access other types of services, such as Internet browsing or leisure activities. For this reason, it has effects in three different QoL domains, as defined by WHO (see Table 2.1): *psychological*, *social relationships* and *environment*.

The mobile app is designed for Android devices and exploits as input the on-board front-facing camera. Thanks to CV techniques, the user can issue commands to the smartphone, through the head movements.

Alternative communication systems, specific for this type of users, are already on the market since several years. Even if CV-based solutions for head tracking are not new, their implementation on mobile Android-based devices, featuring well-known constraints on processing and power consumption, is quite innovative. The most relevant aspect of the proposed application is that, unlike recent works presented in [114, 180], it does not rely on external software libraries to perform CV processing, thus limiting the computational impact on the device performance, and ensuring a timely response to the user's inputs.

In order to avoid the resorting to software libraries other than the native Android OS primitives, a thorough review of functionalities supported by the OS has been performed. The *FaceDetectionListener* API, provided by Android 4.0 framework (API level 14) allows to locate the face of a subject in the YUV video frames captured by the camera sensors.

Using face detection functionalities in an application typically requires several steps:

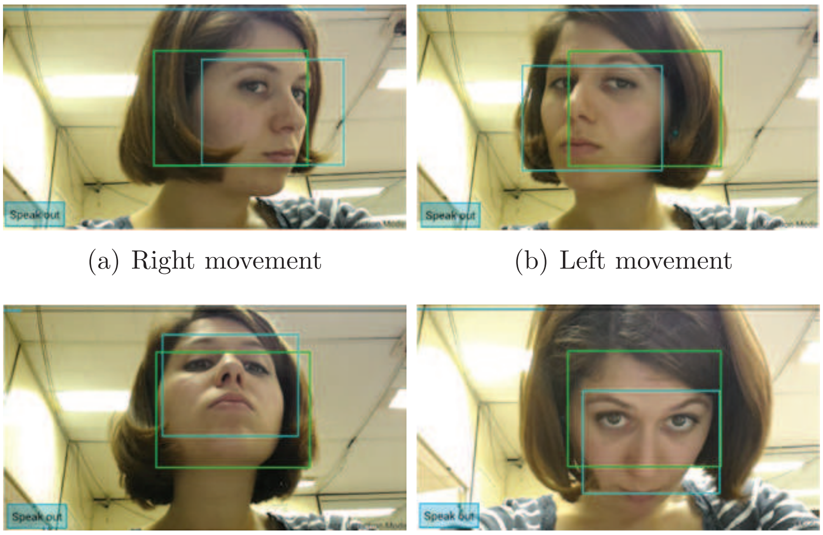
- to verify that the face detection functionality is supported by the device;
- to create a *FaceDetectionListener*;
- to add the *FaceDetectionListener* to the camera instance;
- to run the face detection process, after the camera preview has been started.

For each detected face, a new instance of the *Camera.Face* class is created. It is characterized by the following attributes:

- id: unique identifier of the face, valid as long as the face remains on the scope;
- rect: rectangle that frames the face boundaries;
- leftEye: coordinates of the left eye center point;
- rightEye: coordinates of the right eye center point:
- mouth: coordinates of the mouth center point;
- score: degree of reliability of the detected face.

Some of them, i.e. id, leftEye, rightEye, and mouth, ere optional and may not be implemented in a specific device.

Whit respect to the version of the OS supported by the firmware of the device, it is possible to distinguish between two operational modes: the *face detection mode*, and *eye detection mode*.



(a) Right movement (b) Left movement

(c) Top movement (d) Down movement

Figure 5.1: Available commands in the face detection mode.

5.1.1 Face detection mode

The first working mode does not need to know the position of eyes or mouth and, therefore, can be used by default. It allows to define four commands, which correspond to the movement of the head with respect to a fixed reference position: right, left, up and down, as shown in Figs. 5.1. To such an aim, it is necessary to fix a reference point, through a preliminary calibration phase. This is a fundamental operation, since it affects the precision by which each head movement is recognized.

By assuming that the device is in a fixed position with respect to the user and in uniform brightness conditions, we can simplify the problem, ignoring any device movement and change in brightness. When a person is placed in front of the camera, the application identifies the face and displays a rectangle around it. Obviously, the rectangle size depends on the user's distance from the mobile device: the more he is close, the greater the size.

Once the face is located, if the subject maintains the same position for a given number of frames, such a position is taken as the reference one. Since a still subject is actually affected by involuntary movements, the reference position is corrected by a safety calibration margin, m_c, defined as:

$$m_c = \frac{l_{ref}}{30} \tag{5.1}$$

where l_{ref} is the width of the reference rectangular frame around the face, whereas the factor 30 has been chosen by heuristic approach. Since m_c depends on the individual's

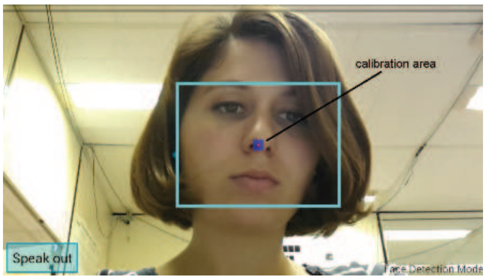


Figure 5.2: Calibration area.

distance from the device, the calibration margin is a fraction of the width of the reference rectangle, which varies according to the distance. Calibration area is then defined as a square centred in the central point of the reference rectangle, with a side length equal to $2 * m_c$ (see Fig. 5.10). To let the user know when the calibration phase is completed, the rectangle changes color, from cyan to magenta.

Once the calibration phase is concluded, the so-called neutral area is defined: it represents the minimum amplitude of the head translation movements needed to issue a command. It can be calculated as following:

$$m_r = \frac{l_{ref}}{10}. \tag{5.2}$$

Also in this case the denominator value has been determined by empirical tests: the larger the denominator, the smaller the neutral area and, consequently, the motion necessary to send the command. As evident from the equations, calibration and neutral areas are not equal, this choice allows the user greater mobility when using the application and greater accuracy in the calibration phase.

The active areas corresponding to different commands are shown in Fig. 5.3. The different sizes of the lateral areas, with respect to upper and lower areas, are clearly visible: they are motivated by the fact that lateral movements are typically broader than vertical ones. If the center of rectangle around the face remains in one of the four regions for a certain number of frames, the respective command is executed. The choice to assign a time for command issuing has two main reasons relative to robustness: the first is to ensure that an accidental user movement is not interpreted as a command, and the second is to let the user return in its initial position, after setting the command.

Obviously area sizes can be easily modified depending on the user's needs. In fact, every disabled person has different needs and motor skills; in particular, for certain types of pathologies the movement capabilities are very reduced: the neutral and the calibration area would be extremely small, to ensure a higher sensitivity. Conversely,

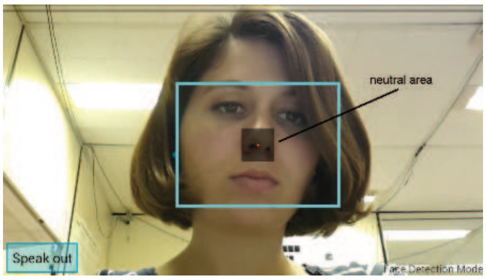


Figure 5.3: Neutral area.

for patients suffering from tremors or difficulty in movement control, the constraints can be relaxed and the two areas enlarged.

5.1.2 Eye detection mode

If the device is able to detect the eyes, it is possible to use an alternative work mode, which does not require calibration: eye detection mode. In this case the command is not associated to the translational motion of the face, but to its inclination with respect to the front position.

The application starts from a default condition, in which the user is not issuing any command, and the virtual straight line connecting the eyes is in a horizontal position. The values of the eyes coordinates are used to identify head rotations, towards left or right directions. Named (x_1, y_1), and (x_2, y_2) the coordinates of the left and right eye position, respectively, the head tilt angle is given by [18]:

$$\vartheta = arctan\left(\frac{y_2 - y_1}{x_2 - x_1}\right) \tag{5.3}$$

In the front position, assumed as a reference, it is $\vartheta = 0$; through a number of experimental tests, the threshold values used to identify the head inclination to the left, or to the right, have been set equal to $-17°$, and $+17°$, respectively. Fig. 5.4 shows the the virtual straight line connecting the eyes, the inclination of which is given by ϑ.

5.1.3 User interaction design

The methods described above allow to send commands to the smartphone in order to perform different operations. In particular, two examples of applications have been implemented. The first one provides a virtual keyboard and a voice synthesizer, in order to enable impaired people to communicate with their families and friends. The

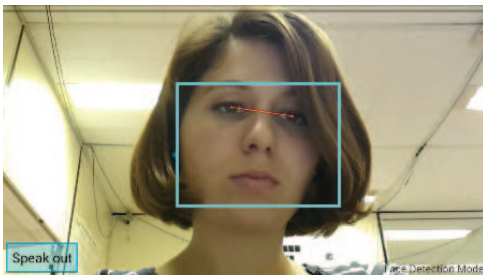


Figure 5.4: Virtual line connecting the eyes position in the *eye detection mode*.

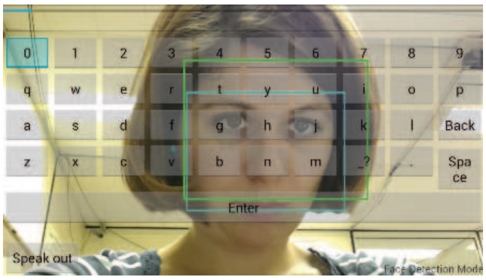


Figure 5.5: An example of user interface: buttons and text area are shown as shaded graphic objects superimposed onto the camera preview.

second one is designed to issue commands to the home automation system, allowing the opening/closing of windows and blinds and turning on/off lights.

The first problem which emerges in the realization of a proper GUI is the contemporary visualization of camera preview, to obtain a feedback on movements, and target elements to control, i.e. buttons and text areas. Since the smartphone display is usually very small, to divide the screen in separated sections would dwindle the text, making it unreadable. For this reason, target elements are shown as shaded graphic objects superimposed onto the video image, as shown in Figs. 5.5.

As for interactions, once detected, a movement shall be translated into a command. The simplest way to issue a command is to push a button. It means that the user must be able to select the desired button and confirm the selection. How to navigate the available buttons is the most critical element in the design of an effective means of interaction. First, it is necessary to decide which command corresponds to confirmation, i.e. the click. In the face detection mode, we chose the top movement, while left has been used in the eye detection mode. The remaining possible movements are used to move the focus over the different keys. In order to make the process of button selection more efficient, the set of buttons is represented by the application as a $N \times M$ matrix. Moreover, in order to make the navigation faster, we use the following technique: if the focus is on the last element of a row, the right movement moves it on the first element of the next row; while, conversely, when the focus is on the first element of a row, the left movement causes the shift of the focus to the last element of the previous row. In both interfaces, the top left button is selected as the starting point, and takes the focus by default.

The fist application's GUI is constituted by a text area and a keyboard containing letters and numbers. Once the message has been composed, the application allows to play it through speech synthesis, simply by pressing the Enter key.

The second application presents instead a smaller number of buttons. Initially, the user can select the object to interact with, i.e. window, lamp, or shutter. Then, for each selected object several options appear: open/close or turn on/off, stop, back. The return button allows to go back to the main menu and choose another object, open/close or turn on/off allows to activate/deactivate actuators, while stop button is used to interrupt the operation that is taking place, in case of mistake or danger.

As already discussed in Section 3.2.2, the time for command acquisition is very important for usability. For this reason, and since one of the most important aspect of a technological aid is the adaptability to the user's specific needs, the calibration and command time can be chosen through a context menu.

5.1.4 Experimental tests

At the current development stage, the interface features a complete engine, i.e. the set of algorithms to perform real-time video analysis, segmentation, and head tracking.

Both applications are available as prototypes. The app for the control of the home automation system communicates through WiFi technology with a panel (see Fig. 5.6) equipped with actuators to turn on/off lights, and open/close shutter and window.

Experimental tests have been executed in order to evaluate the robustness, reliability, effectiveness and usability of the application.

Test on robustness The robustness of the application is evaluated as the capability of performing correctly even in unexpected operational conditions, or in situations different from the default one. As already stated in Section 3.2.2, robustness is essential for the system usability.

First of all, the correct behaviour of the application has been tested over three different commercial devices: a smartphone, and two tablets, featuring different characteristics, as detailed in Table 5.1. The devices are labelled as: *S*, the smartphone, *T1*, and *T2*, the tablets, respectively.

Figure 5.6: Home automation panel.

Table 5.1: Characteristics of the commercial devices used in experimental tests.

Feature	**Smartphone (*S*)**	**Tablet 1 (*T1*)**	**Tablet 2 (*T2*)**
O.S.	Android 4.0.4	Android 4.0.3	Android 4.0.3
Display	4.8" - 1280×720	7" - 600×1024	10.1" - 800×1280
Processor	Quad Core 1,4 GHz	Dual Core 1 GHz	Dual Core 1 GHz
RAM	780 MB	1 GB	1 GB
Front camera	1.9 Mpixel	VGA	VGA
Rear camera	8 Mpixel	3.15 Mpixel	3.15 Mpixel
Avg. frame rate	21 fps	9.5 fps	9.5 fps

a) b) c)

Figure 5.7: Non uniform light distribution in indoor environment: a) front light, limited irregularity, b) back light, limited irregularity, c) strong irregularity.

The application is tested in an indoor scenario, in which the user is at a 40 cm's distance from the device, with uniformly distributed artificial light. The execution of the application is almost perfect on device *S*: the user's face is always located correctly on the video frame, and tracked without errors, even when the user is in a side position with respect to the front camera sensor. The application exhibits some limits when it is executed on device *T2*: the face tracking process becomes slower than in the previous case, and the face detection fails each time the user rotates his head with respect to the camera sensor. The user's face location is lost, if too wide movements of the head are performed. Further, due to the fact that *T2* has a reduced frame rate with respect to *S*, the calibration time and the command execution time are increased. Device *T1* provides almost the same performance of *T2*; however, when its O.S. is updated to Android 4.1.2 version, the application cannot be executed any more, due to the extreme delay exhibited by the face detection process.

When the indoor environment is not uniformly illuminated, as in the case of a room with an open window, the performance attainable depends on how much irregular the luminance distribution on the captured frame is. Looking at Fig. 5.7, conditions shown in a) and b) may be defined as "limited irregularity", whereas condition c) corresponds to a "strong irregularity".

In conditions comparable to Fig. 5.7 a) and b), the different devices show similar performances: the face detection process is correctly executed, whereas the face tracking process often fails, the face is lost, and frequent recalibration is needed. On the other hand, when the ambient light is strongly irregular, as in the case of Fig. 5.7 c), the face detection process fails quite often; no device is able to perform correctly. The last test on the robustness of the application deals with the distance at which the user may effectively interact with the virtual keyboard. When the device *S* is used, the application works correctly up to a distance of 3 m; at shorter distances, the application works well until the user's face falls in the visibility range of the camera sensor. When the application runs on devices *T1* and *T2*, it is more sensitive to

Table 5.2: Comparison of the resource requirements featured by the proposed application, and other two applications base on the OpenCV library.

Feature	**Proposed application**	**App1**	**App2**
Memory usage	696 kB	6.93 MB	14.52 MB
% Battery consumption	2	7	27
CPU time	3m 31s	20m 26s	28m 29s

variations in distance. A common requirement is related to the need of placing the device aligned to the user's head. When running on device S, the application can support the presence of more faces inside the frame, even featuring glasses or beard.

Test on effectiveness The effectiveness of the application is evaluated as the capability of draining as little device resources as possible, with specific reference to: CPU time, battery consumption, and memory usage. In order to test the effectiveness of the proposed application, device S has been selected as the execution platform (being the one that provides better performances); the application is compared to other software applications based on the OpenCV library for head detection and tracking, named *App1* and *App2* [167].

About the memory usage, the application herein presented does not need to import any external library, thus featuring the smallest amount of required memory, as reported in Table 5.2. The same application exhibits the best behaviour even about the percent battery consumption, and the CPU time usage, the latter estimated over about 20 minutes time interval of execution. On average, the Android based application presented in this paper requires the 0.31% amount of battery per minute; this consumption is basically due to the display, that is kept on during the execution of the application. A possible workaround to reduce the battery consumption is to switch off the display until a face is detected by the camera sensor.

Test on reliability The application is reliably executed on any of the devices available for testing purposes, with no crashes or unexpected behaviours, until no external interfering event takes place. As an example, if a timer previously set on the same device expires when the application is running, the user will not be able to control it by means of head movements. Basically, the head movements are correctly identified as commands only by the application that controls the virtual keyboard. In a similar fashion, if an incoming call, or any other system notification occurs when the application is running, it will not be possible for the user to switch the control on the new activity. In fact, the injection of an event from an app to another is limited by the Android OS, for security reasons. This problem can be overcome by implementing a custom version of the OS.

Test on usability Preliminary tests were conducted in the laboratory environment in order to verify the usability and acceptability of the applications. Voluntary health subjects provided positive outcomes, however, a more thorough evaluation of the user's acceptance is foreseen, involving people affected by physical impairments or disabilities.

Referring to Table 3.4, all usability aspects have been considered during the design phase. As already stated, the system is able to correctly recognize the gestures, guaranteeing the effectiveness of the interaction. While, as regards the efficiency, several factors have to be considered: physical fatigue, duration, cognitive load, learnability and memorability. Physical fatigue mainly affects neck, whose effort is particularly noticeable when controlling the virtual keyboard. However, it can be reduced, lessening the size of the neutral area, and, therefore, the motion range necessary to issue a command. The time required to issue the command affects the interaction goodness too. As already mentioned, it can be customized via the context menu and represents a trade-off between robustness and user satisfaction. As for last two aspects, cognitive load and learnability and memorability, the system attempts to make the interaction as natural as possible, associating the head movement to the movement of focus in the same direction. Just the click command is different from others and should be remembered.

Differently from previous factors, satisfaction is very a subjective one. Anyway, all testers have shown an overall positive opinion on intuitiveness, comfort, ease of use, user experience, and social acceptance.

5.2 Access control application based on face recognition and liveness detection

In the domain of SH, technologies for personal safety and security play a prominent role. Among them, the most important concerns the detection of alarming events, such as flooding, gas and smoke leaks, but also intrusion detection systems are becoming gradually more common.

In this Subsection, we address the design of a low-complexity Android-based application for face recognition and liveness detection, based on image processing techniques, to be implemented in embedded Android platforms for video entry-phones.

The main motivation of the work is to provide a low cost solution for access control. It is useful for all type of users, but particularly for elderly people living alone at home, who are often victims of scams and frauds. From the QoL point of view, it provides enhancements mainly in the *environment* domain, involving the facets of *home environment* and *physical safety and security*.

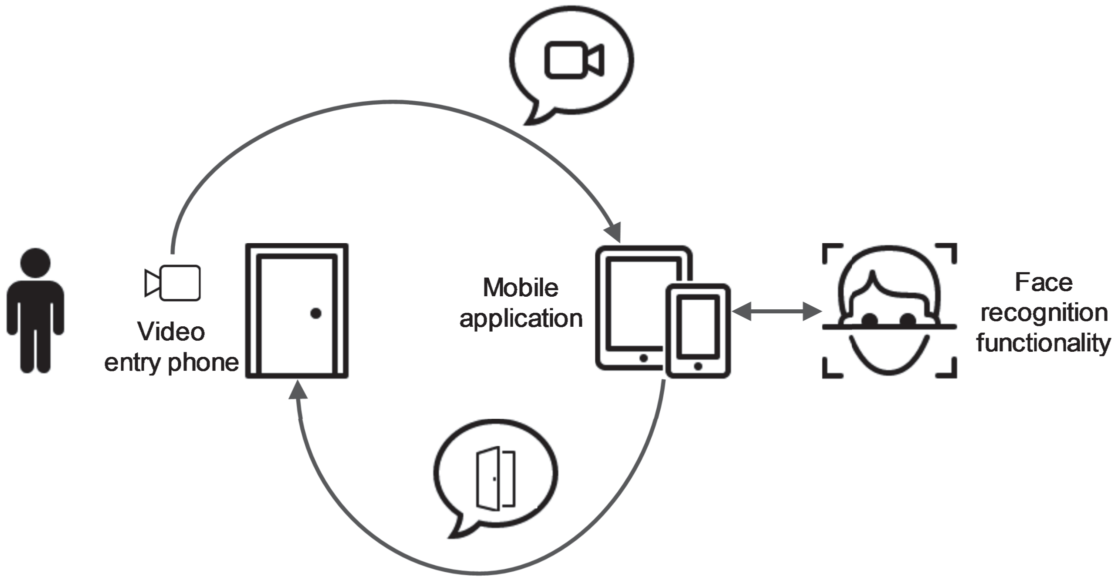


Figure 5.8: Scheme of the system for access control.

The architecture of the proposed system is depicted in Fig. 5.8. When somebody rings the intercom, the image acquired by means of the video entry-phone is sent to the smartphone via Voice over IP (VoIP) technology. The smartphone notifies the user the incoming call, allowing him to answer or hang up. If the user decides to answer, the communication begins and both the video and audio streams are played. Thanks to face recognition features, the smartphone is also able to determine if the photographed subject is in the list of authorized people. In such a case the door opens automatically. Otherwise, a warning message is displayed.

5.2.1 Background

For the human brain, binding an identity to a face is an automated and immediate task, despite its complexity. From a biometric point of view, we must consider that many factors can make it difficult to recognize a face, such as different lighting conditions, facial expressions, rotation of the face, age, physical radical changes, as well as the presence of obstructions, such as glasses, facial hair, or hair, covering part of the face. In spite of these problems, several algorithms have been proposed in the literature, obtaining satisfactory results [190, 188, 109]. Nevertheless, some critical aspects have emerged recently, such as the resistance to external attack and, particularly, to spoofing.

Anti-spoofing, liveness detection and vitality detection are equivalent terms used in the literature to describe the same concept, that is: any technique aimed at verifying if the captured biometric information belongs to a live subject, or to an artificial and synthetic copy of him/her.

In general, the anti-spoofing techniques are divided into: sensor-level, feature-level, and score-level techniques [67]. The first exploits specific sensors in order to identify particular living traits (blood pressure, facial thermogram, *etc*), while the second category refers to those in which the biometric data are acquired via a standard sensor and the distinction between fake and real faces is software-based. The last type of technique is the less common and focuses on the study of biometric systems at a score-level. Obviously, hardware-based techniques have the best performance since they extract information directly from the human body. Nevertheless, they are quite intrusive and expensive. Conversely, the score-level techniques have limited performance, while maintaining low costs and intrusiveness. Among them, a compromise solution is represented by the feature-level group: it combines sufficient performance with low cost and less intrusiveness.

According to Galbally *et al.*, spoofing techniques can be divided in three categories [67]:

- photo attacks: the counterfeiter presents to the recognition system a photo of the authorized user; the picture can be printed on a paper (print attack), or displayed on a digital device (digital-photo attack);

- video attacks: the attacker replays a video of the authorized subject, using a digital device;

- mask attacks: the attack is carried out presenting to the recognition system a 3D mask of the authorized user.

Currently, thanks to the progressive spreading of social networks, to retrieve pictures or videos of an individual is very simple. Conversely, to acquire information on the 3D shape of the face and reproduce it as a mask is more complicated. For this reason, in the proposed application, the liveness detection problem is approximated as a problem of discriminating 2D from 3D objects, i.e. considering just photo and video attacks. In order to reconstruct the 3D structure of the scene acquired by video entry-phone, we chose to use the stereo vision technique, exploiting RGB cameras for low cost reasons.

5.2.2 Stereo Vision

The term stereo computer vision refers to the extraction of 3D information from digital images. By comparing the information captured from two different points of view, the 3D information can be extracted by examining the relative positions of objects in the two shots.

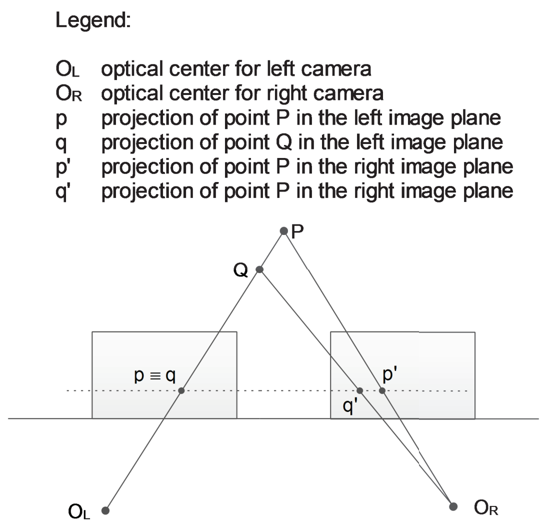
The problem of converting 2D information in 3D can be reduced substantially in two sub-problems: correspondence and reconstruction. Correspondence consists in identifying matched points in the images such that there are no ambiguities. In fact, ambiguous correspondences lead to different interpretations of the scene. With two (or more) cameras, if we are able to find corresponding points, we can infer depth by means of triangulation.

To better understand the concepts behind the stereo vision problem, two simplified model of reality are shown in Fig. 5.9. In Fig. 5.9(a), the projections of the two points, P and Q, in different image planes are shown: p and q on the left, p' and q' on the right. Thanks to epipolar geometry , which describes the relationship between images and real objects, the correspondence issue can be easily addressed. In fact, the epipolar constraint states that the projection of points P and Q in the right image plane must belong to the same line (dotted line) of their projection in the left side. The search in the space of corresponding points can then be narrowed from a 2D to a 1D search.

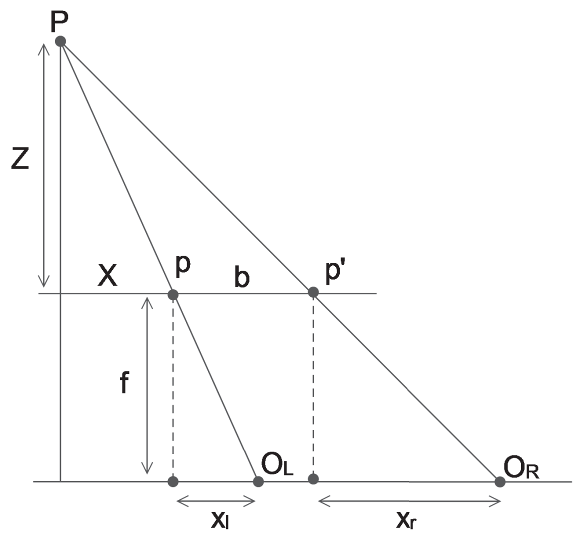
Once the matching points have been identified, it is necessary to calculate their disparity by means of triangulation. Considering Fig. 5.9(b), the disparity can be defined as follows:

$$d = x_r - x_l. \tag{5.4}$$

It represents the difference between the x coordinate of the two corresponding points and allows to calculate the depth. In fact, through some simple steps, it is possible



(a) Epipolar constraint for correspondence: matches for p and q in the right plane must lie on the epipolar line (dotted line)



(b) A simplified model of reality in the top-view perspective

Figure 5.9: Graphic representations of the stereo vision concepts.

to obtain the relationship between the disparity d and the depth Z:

$$\begin{aligned} \tfrac{x_l}{f} = \tfrac{X}{Z} \quad &, \quad \tfrac{x_r}{f} = \tfrac{X+b}{Z} \\ d = x_r - x_l \quad &= \quad \tfrac{f(X+b)}{Z} - \tfrac{fX}{Z}, \end{aligned} \tag{5.5}$$

whence:

$$d = \frac{fb}{Z}. \tag{5.6}$$

Therefore, the disparity of a point is proportional to focal length f and baseline b, and inversely proportional to its depth. Since f and b are constant over the whole image, a disparity map provides a direct encoding of the scene depth.

5.2.3 Design of the Android Mobile Application

Initially the system was implemented for a desktop execution, in order to verify the feasibility of the proposed method. Later, once its proper functioning was verified, the code was ported to Android OS. The mobile application gets as input a couple of images gathered from two different perspectives (left and right) and process them exploiting the *BoofCV* library for stereo vision.

Stereo vision implies a number of pre-requisites the captured images need to satisfy, such as: any image distortion due to the capturing sensor shall be compensated, in order to get pinhole camera - like images; each image in the couple shall be rectified, to be comparable. To this aim, two fundamental operations must be performed before starting the stereo matching and reconstruction processes: camera calibration and image rectification.

Calibration is a process for estimating the camera's intrinsic and extrinsic parameters. The first concern the internal characteristics of the camera, such as focal length or parameters of lenses distortion, while the extrinsic parameters describe the spatial position and orientation of the camera, i.e. the relative translations and rotations between the two images. The knowledge of the intrinsic parameters is an essential first step for the 3D reconstruction, because it enables the derivation of the scene structure in the space and removes the distortion of the lens, which leads to optical errors, degrading the accuracy. The *BoofCV* library provides a calibration feature. To calculate the parameters it is possible to use planar chessboards. Fig. 5.10 shows a sample subset of the chessboard grids used to calibrate the device camera in our experiments.

The image rectification is required when the considered image planes are not coplanar: thanks to this operation the images become coplanar, and the following

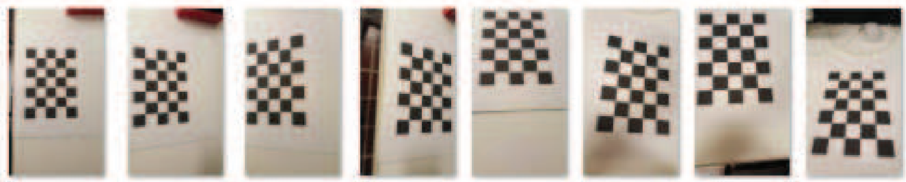


Figure 5.10: Sample subset of calibration chessboards.

procedures (matching and reconstruction) will be faster and more efficient, since they will run on a single dimension, as mentioned in the previous part. Once rectified, the images are processed in order to find associated features, as discussed in the previous paragraph, and the diversity map is calculated. It denotes if a live (3D), or a fake (2D) picture, has been processed.

In summary, four main steps are executed by the application: the camera calibration step ; the rectification of the two images; the stereo matching between features belonging to the captured images, and, finally, the diversity map generation.

The robustness of the process is then increased through a number of intermediate verification steps:

- check if the subject's nose is the element of the face at the shortest distance from the camera;
- check if different areas captured by the sensor (like nose and eyes, or face and background) are located at different distances from it;
- check if expected areas, like the face, the nose or the eyes, can be located in both the captured images;
- check if some kind of involuntary eye movements is detected.

5.2.4 Experimental results

In order to verify the proper functioning of the adopted method, several preliminary tests have been performed using a desktop PC. The objective of such tests is to identify the optimal resolution value which allows to correctly reconstruct the image. In fact, as the resolution increases, computational problems (processing time) increase or calibration inaccuracies appear. Test results show that the best resolution value is 0.3 megapixels. By using this value, the results are obtained in a very short time (about one second) and a correct calibration process is ensured.

Additional factors influencing the results are:

- the subject distance from the camera;
- the relative distance between the two pictures;
- the brightness.

For each of them, three different conditions and every possible combination of them have been considered, as shown in Table 5.3. Results suggest that using as input pictures taken at a great distance produces worst results, at any brightness condition. For minimum and medium distances, the low-light condition does not provide acceptable results in any circumstance, while in the normal light case the face is entirely detected and reconstructed, both for extremely close-up, close-up and half-length photos. For the intense brightness case, acceptable results are obtained only if the two shots are very close together. In summary, in order to obtain a proper 3D reconstruction of the face:

- the scene should be well lit;
- the use of flash should be avoided, unless the two shots are taken at a distance smaller than 5 mm;
- the pair of photos should have a relative distance varying from 3-5 mm to 15 mm;
- within the limits of the considered situations, the distance of the subject from the camera is indifferent for a correct result.

After preliminary tests, the Android application has been tested on different devices (Samsung Galaxy S3, S5 and S6, LG G4, Huawei P8 Lite), equipped with diverse Android OS versions. The app execution runs smooth, if the device has at least 1 GB RAM available.

Despite the not full precision of the acquisition process, the mobile application is able to discriminate faces shown in pictures (spoof) from live ones. Fig. 5.11 summarizes some of the results obtained from experiments conducted in the laboratory.

Future development foresees acceptability and usability tests with target users.

Table 5.3: Summary of the situations envisaged in the test phase, for each analysed factor.

Factor	Possible conditions	Description
Distance between subject and camera	extreme close-up photos	The pictures contain just part of the face and neck
	close-up photos	The pictures contain not only face and neck, but also the shoulders
	half-length photos	The picture is cut at chest level
Distance between the two pictures	minimum distance	The photos are almost coincident and the distance between the two shots is about 3-5 mm
	medium distance	There is a slight shift between the two pictures ($\sim$ 15 mm)
	great distance	The two pictures are far apart more than 30 mm
Brightness	minimum brightness	The subject is illuminated by a low light (for example an abatjour)
	medium brightness	The subject is illuminated by a common warm light bulb
	intense brightness	The subject is illuminated by a common, warm light bulb and in addiction by a flash

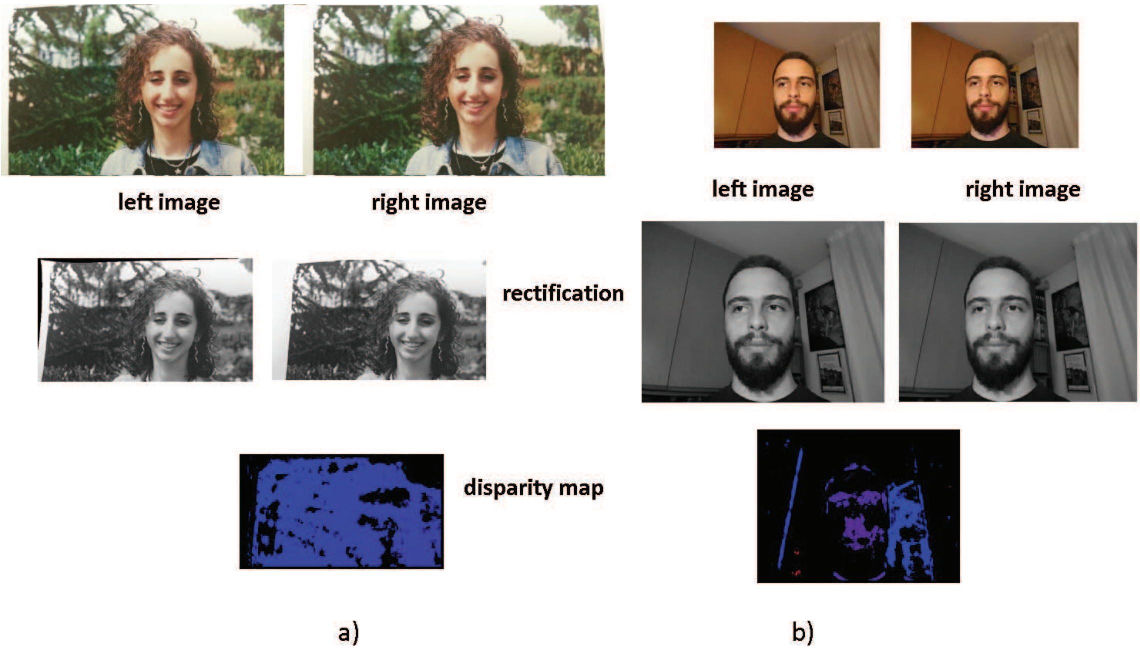


Figure 5.11: Output of the liveness detection mobile app in the case of: a) spoofed face images, b) live and complex face image. The output disparity map in b) clearly features the face profile distinguishable from the background.

Chapter 6

Touchscreen interfaces for users in AAL

The project presented in this Chapter introduces an integrated platform for telecare and AAL aimed at prolonging independent living of the elderly at home [53]. The working hypothesis is to consider a person who normally lives alone. In this scenario my research has focused on the design and development of a touch screen interface tailored to the needs of the elderly person, in order to control the home automation system, monitor the status of some sensors and help the user in the management of drug therapy [166]. For this purpose, the criteria of usability and acceptability of technologies, and more specifically of touch screen technologies, by elderly subjects have been considered in the design phase [150].

Another aspect on which my research has focused is represented by the extraction and processing of the data acquired from environmental heterogeneous sensors to implement server side services necessary for the proper functioning of the user interface. From these data it is also possible to obtain quite detailed information on the user behaviour. Such information allows us to recognize his daily activities and monitor the state of health in the long term, noting for example the vitality level, the sleep duration and the frequency of eating. For this purpose, some simple algorithms, for example presence/absence and wakefulness/sleep recognition, have been implemented.

In this use case, the QoL domains mostly involved are *physical health* and *environment*. The system makes it possible to obtain information on the subject's physical health and timely intervene in case of problems or abnormal situations, without restricting his/her freedom or influencing his/her habits. It also enhances the home environment, facilitating some normal operations and increasing safety and security.

In the following, the design choices and the methodologies used in the development phase will be described. A brief overview on the AAL platform underlying the project is presented first, then the user interface based on touch screen technology is explained in detail, paying close attention to the design choices. Finally, algorithms for the presence and activity recognition are exposed.

6.1 Context: a smart home in AAL

Before discussing the design methodologies used, a quick overview of the underlying AAL framework will be provided. Such a framework covers several aspects of the home living, such as independent living, home security, health monitoring and environmental control. From a general point of view, in the system architecture the information is generated by a multiplicity of subsystems. They implement specific functionalities and, through well defined policies and rules, send the data to a local server (some specific information are delivered remotely), which correlates all the received data, collects information on the status of the system and on the user's habits and behaviour(see Fig. 6.1).

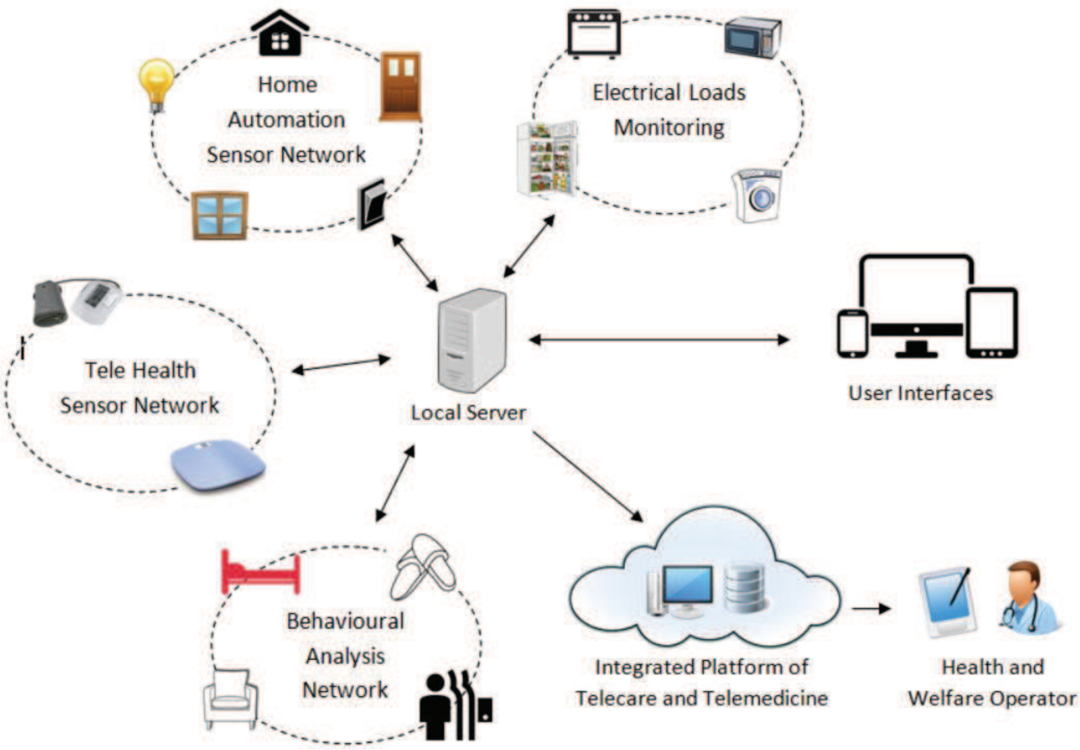


Figure 6.1: Different subsystems in the platform architecture.

The system is able:

- to analyse behavioural data in a unobtrusive way on the long term in order to make a preliminary diagnosis compared to the observed changes in habits;
- to allow the user to interact with the home environment, facilitating certain tasks, such as opening or closing windows and blinds, and turning on or off lights, through the home automation sensor network;
- to monitor the power consumption of the household appliances in order to optimally manage the spending for the electrical energy;
- to collect medical data, such as weight or blood pressure, acquired through electrical devices and transmit the data to a health professional or a doctor for diagnosis.

Each subsystem uses different devices, transmission media (CAN bus, Ethernet, Wi-fi and wireless sub-GHz) and communication protocols. All the acquired data are sent via proper network interfaces to a central server, to store and process information. The server also listens for requests from the user interface to provide adequate information and services.

6.2 User interface design and prototyping

The user interface relies on three different types of touch screen devices: tablets, smartphones and fixed touch screens. Each device has features and offers different advantages, for this reason it is important to choose the right device according to which user is interfacing the system. Smart phones are characterized by a great portability, but due to the small size of the screen, they do not fit with users affected by visual impairments or poor motor skills. Conversely, fixed touch screens allow to display contents even to visual impaired subjects, but cannot be moved from a room to another easily. In this sense, the tablet is a good compromise, ensuring mobility and acceptable screen size. According with the general rules of interface design, previously mentioned, some specific guidelines for the touch screen interaction have been arranged. In particular, they relate to four key aspects:

- *Target elements design*: buttons at least 9.2 mm wide for smartphones, and larger for tablets and fixed screens will be used. Once the target is captured, in order to communicate to the user the success of the operation, a visual or audible feedback is performed.

- *Graphic elements design*: among the elements that influence the effectiveness and the quality of interaction, particularly important are the graphics. To facilitate the understanding of the content, each button has an icon and a text label that specifies its meaning. The used graphics is simple and intuitive, there are no animations.

- *Navigation*: while browsing it is important that the user is always able to know where he or she is; For this reason, each page is characterized by a title that defines its content. Moreover an extra help provides aid during the navigation. One aspect to consider is the navigation hierarchy: it is not recommended to use deep navigation hierarchies that may cause confusion and disorientation to the user.

- *Contents layout design*: having small screens, the use of the text has been limited to the minimum, preferring to use keywords instead of long sentences. The information and graphics are concentrated in the central area of the touch screen; the background and the contents are coloured appropriately.

In addition to these criteria, an initial check on the network connection and popup windows notifying the results of the performed procedures have been implemented. The application final appearance differs automatically according to the screen size, i.e. the interface is optimized for the used device.

The prototype application exploits the Android operating system, from version 3.0 Honeycomb. It allows to check the status of the lights and turn them on or off , activate scenarios and open or close blinds and windows. Through a specific service, the user can obtain the values of the measurements obtained from electro-medical devices and visualize them on the screen. Monitoring functionalities are also available for checking the status of the environmental sensors, of the power consumption and of the activities carried out by the user; an example of graph that summarize the user's daily behaviour is visible in Fig. 6.2. Finally, additional functionalities allow to display notifications to remind the elder to take medicines at the prescribed time. All these services are requested to the local server, according to the classic client-server model, which answers to each request using a string formatted in JSON standard.

6.3 Behavioural analysis

As already widely discussed, the smart home for AAL allows to monitor and assist the daily activities of the elder living alone at home, in order to obtain information on his

Figure 6.2: An example of daily activity graph: a time line representation of sleeping activity displayed by the user interface.

or her behaviour. From the analysis of these information, it is possible to deduce any progressive worsening in the state of health, potential risks and emergency situations. One of the strengths of the project described in the previous Section is the ability to collect a large number of behavioural data without the need for any user action. As already mentioned, this is an essential aspect in the design of systems intended for older users. In order to make the system non-intrusive, environmental sensors have been used, such as:

- PIR;
- magnetic sensors for fridge, doors and windows;
- pressure sensors for beds and chairs;
- power meters for electrical consumption;
- flow meters for water and gas.

The fusion of the data obtained from these sensors allows us to determine the activities carried out by the user. The behavioural data that can be identified are mainly of three types: energy consumption, presence and activities. While the first concerns only the energy consumption and thus may be derived directly from the observation of the data acquired from the power meter, without using more challenging algorithms, the last two types exploit more complex methods of data analysis.

Presence recognition The presence recognition at home is a very important point that allows to identify any abnormal situations or alert. For example the elderly could turn on the stove and, forgetting it on, leave the home. This represents a potentially dangerous situation that should be avoided. To this aim a presence recognition algorithm has been implemented. For the assessment of the state of presence, only some sensors have been considered: PIR, magnetic and pressure sensors. The flow meter and power meter have not been considered at present.

The position of some sensors is essential for the proper functioning of the algorithm. In particular it is necessary to monitor the front door (the working hypothesis is that there is only an entry). For this purpose two PIRs, one inside and one outside the door, and also a magnetic sensor which can detect its opening/closing, have been positioned. The basic concept of the algorithm is that, depending on the user's location, the probability that he exited may be higher or lower; consequently the time needed to determine if he is absent varies according to this consideration. In order to determine where is the user, eight states have been identified:

- Absent;
- User out, door closed: the house is empty and the user is outside; the door is closed;
- User out, door open: the house is empty and the user is outside; the door is open;
- User in, door open: the user is in the house, and the door is open;
- User in, door closed: the user is in the house, and the door is closed;
- Sleeping/resting: the user is in the house, and he is sleeping (night time) or resting (during the day);
- Present (generic): the user is in the house, indoor or outdoor, but we have no more information on what he is doing or where he is;
- Multiple users: the user is in the house, with someone else.

The algorithm consists of a state machine in which events allowing to move from a state to another are those detected by the sensors (such as opening a door or activating a PIR sensor). When a sensor detects an event, the presence reliability is increased by certain percentage value. As time passes, without the occurrence of other events, this value progressively decreases. When reliability reaches zero, the status changes to Absent. The value of decrease depends on the current state. For example, if the user is outdoor and the door is closed, just a few minutes without the occurrence of another event are sufficient to assert that the user is absent; while, when the user is in the house and the door is closed, much more time is necessary before the system can notify the absence. When multiple events occur at the same time in different rooms it is possible to state that there are multiple users. Also in this case, when the timer expires, if no further concurrent event occurs, the system assumes there is only one user. The state diagram of the algorithm for the presence recognition is shown in Fig. 6.3. As obvious, the more refined is the algorithm, the bigger the state diagram becomes.

Activity recognition Through environmental sensors, it is possible to recognize the activities carried out by the user. In this regard, first elementary algorithms have been implemented to understand if the user is cooking, sitting or sleeping. Such information can be obtained using respectively, a fluxometer on the cooker to detect the gas flow, a pressure sensor under the mattress of the bed and a pressure sensor under the cushion of the sofa. Currently, combining the sensor activations and deactivations, it is possible to recognize the individual activity. However, more complex algorithms based on the sensor fusion, are foreseen to detect activities more carefully. About that, for example, the activity of cooking could be recognized by analysing the data from other sensors, such as those indicating the use of microwaves, by means of the power meters or those indicating the opening of the refrigerator, using magnetic sensors. One of the ideas currently under study to understand if the user is sitting or is sleeping consists in implementing truth tables considering the status of multiple sensors, such as PIR and magnetic sensors.

6.4 Outcomes

The assistive home technology described in this Chapter is already available as a Proof of Concept (PoC). Some aspects, such as, infrastructures and data acquisition are more consolidate; other ones, should be improved and more widely investigated, implementing, for example, machine learning algorithms for daily activity recognition.

A first prototype of the user interface is already available. Some screenshots of the application are shown in Figs. 6.4 and 6.5. Respecting the criteria mentioned above, graphics chosen are very simple and easily understandable, there are no animations and the buttons are large sufficiently. Moreover different layouts have been chosen to best fit the size of the screen as you can see in Figs. 6.6 and 6.7. Once the development phase has been concluded, a verification of functions, usability, reliability and effectiveness of the interface prototype for user-system interaction has been realized. The system works correctly in all the different conditions of use. Moreover, in order to obtain an opinion on usability, some volunteers have tested the application and filled out an evaluation form, providing an overall judgement on the interface. It has been also request a personal opinion on the level of usability of the application when used by elderly people. The group of volunteers is composed of 13 subjects, whose average age is 27 years; in Tables 6.1 and 6.2 the evaluations expressed by them are shown.

Table 6.1: Different aspects evaluated by volunteer users voting in a range from 1 to 10 (1: very bad, 10: very well).

Evaluated aspect	**Rate on the prototype**
Visual Appearance: clarity, visual impact, coherence between the different sections	8.7
Intuitive use: easy to learn how to interact with the application	8.4
Immediate detection of functionalities, ease of navigation	8.8
Efficiency: level of user control, reachability of the objectives	8.7
Feedback, notifications, error handling	7.6

Table 6.2: Findings on the use within the AAL evaluated by volunteer users, voting in a range from 1 to 10 (1: very bad, 10: very well).

Evaluated aspect	**Rate on the prototype**
Usability by disabled or elderly users	7.2
Acceptability and impact on users	7.5

Although the tests were not carried out by individuals with characteristics similar to those of the target users, they still provide an initial positive response from people external to the project, considering the first impressions and getting tips for the improvements. Among the various features provided by the touchscreen application, several concern the visualization of daily or weekly charts of the activities performed by the user. Even though more complex or refined algorithms have not been implemented yet, such graphics allow us to determine the actions with a certain degree of reliability. The presence recognition algorithm is currently in the testing phase. From tests carried out so far, it is able to correctly recognize the user's status. Some of the hypothesis made in the design phase have been changed as a result of tests done in the laboratory environment, to better adapt to the real functioning of the system and make it more efficient. The results of the algorithms for the presence and activity recognition are stored in a database and periodically sent to a remote telecare platform which deals with charts. In Figs. 6.8 and 6.9 you can see some graphs of the data collected in the testing phase.

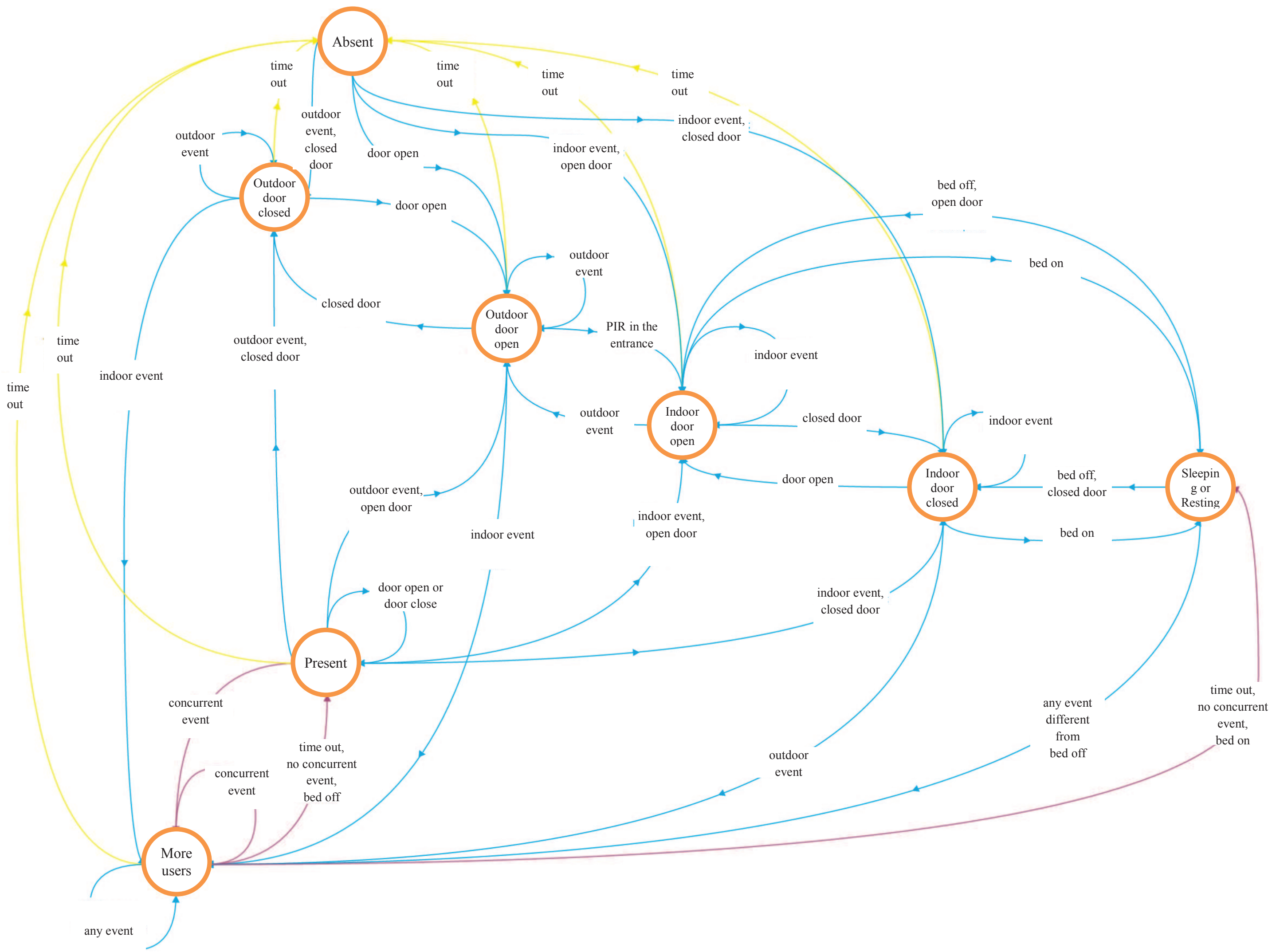


Figure 6.3: The state diagram of presence recognition algorithm.

Figure 6.4: Screenshot of the user interface that monitors the current power consumption of different loads (from left to right: tv, generic load, microwave, generic load and in the bottom the general meter).

Figure 6.5: Screenshots of the user interface that controls the opening/closing of windows and shutters.

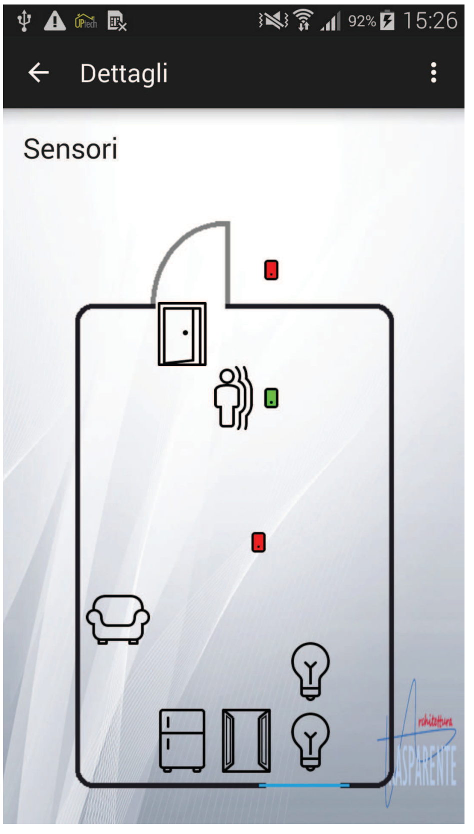


Figure 6.6: Screenshot of the user interface that monitors the state of some sensors: the application can automatically understand the size of the screen and choose the right layout (layout for smartphones).

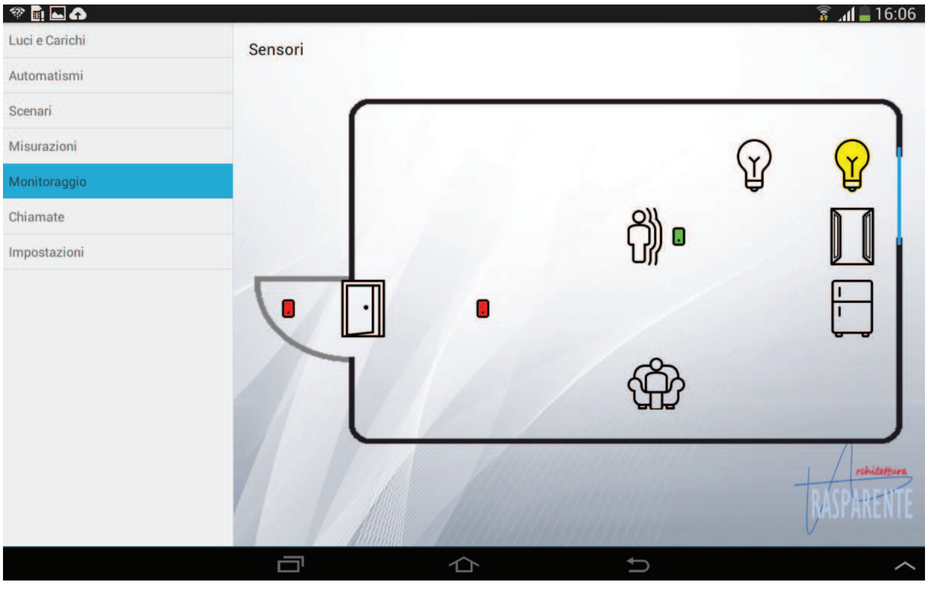


Figure 6.7: Screenshot of the user interface that monitors the state of some sensors: the application can automatically understand the size of the screen and choose the right layout (layout for tablets and fixed screens).

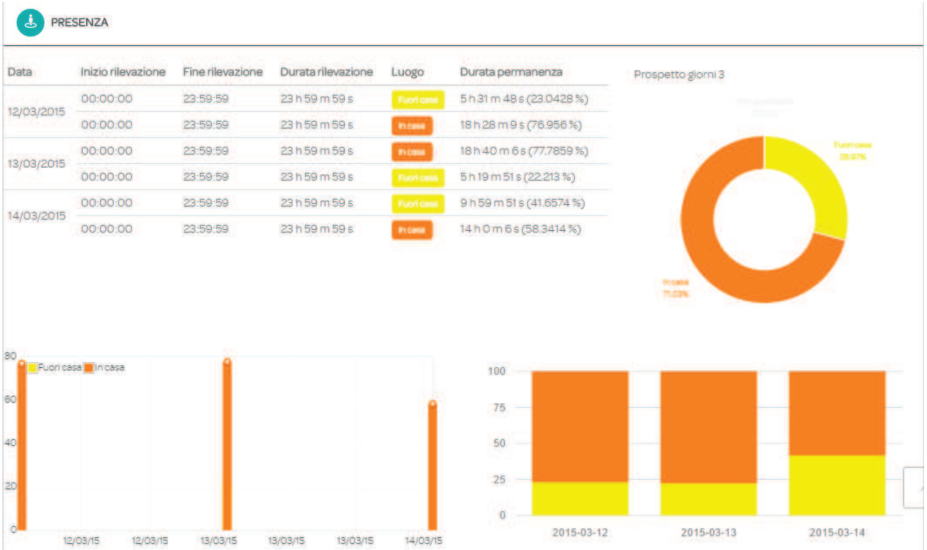


Figure 6.8: Screenshot of the remote platform interface showing presence graphs: yellow and orange portions represent respectively the absence and presence percentage time.

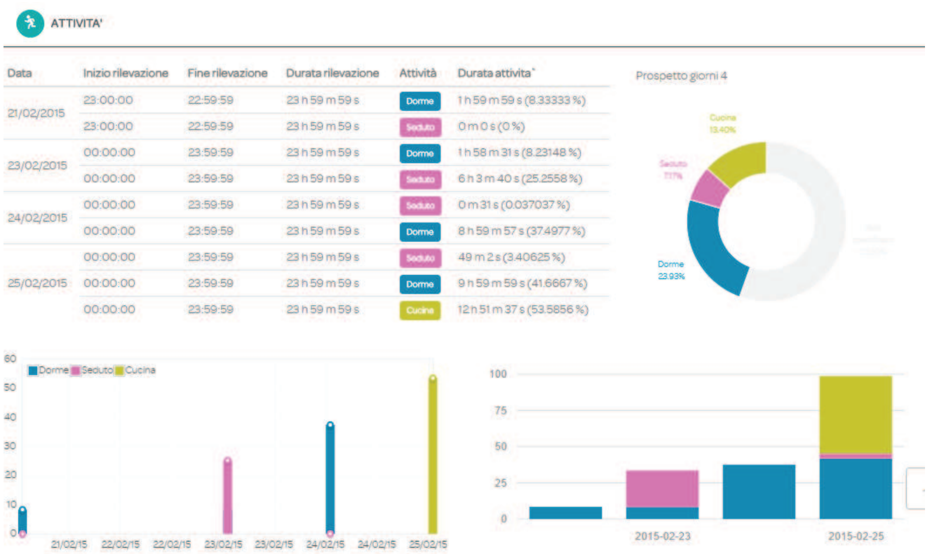


Figure 6.9: Screenshot of the remote platform interface showing presence graphs: each color represents the average time spent for the respective activity (blue for sleeping, green for cooking, magenta for sitting, grey for undefined).

Chapter 7

Touchscreen interfaces for caregivers in AAL

As mentioned in Section 2.3, the purpose of AAL and assistive technologies in general is to increase the QoL not only of elderly and disabled people, but also caregivers. Specifically, this work refers to the case of family members or professional caregivers who look after people with dementia.

Dementia is becoming increasingly prevalent worldwide and is considered as one of the most burdensome disease for the western societies [128]. Among the various types of dementia, AD is the most common. It is a degenerative disease which typically occurs in pre-senile age. A person with dementia can live 20 years or more after diagnosis, during which he/she experience a gradual change of the functional and clinical profile. As consequence of the disease, a progressive loss of cognitive capacity is occurring, eventually leading to disability and to a severe deterioration of quality of life. During the so-called "dementia journey", the disease affects not only the patients but also their informal (e.g. families) and formal (e.g. care staff) caregivers, on whom the bulk of the care burden falls [40].

This Chapter describes a monitoring system which provides alarms to the caregiver in case of dangerous situations or unusual conditions detected in the patient's behaviour. It involves all QoL domains. In fact, if on the one hand it helps to keep the elderly in a good *health* status, ensuring his/her *safety and security*, on the other hand, such a solution relieves the caregiver of the responsibility to continuously monitor him/her. This ensures more free time that can be devoted to *social relationships* or *leisure activities*, increases the *mobility*, since the system is able to operate even at a distance, and reduces the *psychological* and *physical* burden.

The system exploits the user centred design paradigm, since during the design phase the user's needs have been considered. In addiction, thanks to multiple field trials, problems and shortcomings identified were gradually solved. The original system foresaw the installation at home of various sensors for the patient monitoring and an alarm notification system through SMS. However, after a trial of 80 family groups the need of some additional features emerged. Below, we will describe first the original project and then all the evolutions developed over time.

7.1 UpTech Home: a brief description of the original project

The main objectives of the UpTech project were to reduce the burden of the assistance for caregivers, to maintain AD patients at their homes, and to improve the users' QoL. It achieved these objectives mainly in two ways: on the one hand a group of nurses and social health operators performed periodical visits to the patients' houses to provide assistance, while, on the other hand, each family is provided with a technological kit for the continuous monitoring of the patient.

The kit consists of a set of environmental sensors communicating via SubGHz technology with a central unit. It processes the received data according to specific rules and, in case of alarm, sends to the appointed caregivers an SMS which describes the type of event that generated it. The sensor network comprises:

- a sensor to detect the presence in bed of the subject;
- a sensor to detect flooding on the floor;
- a sensor to detect smoke or gas leaks;
- magnetic sensors to detect opening/closing of the door or windows.

In addition, a courtesy light is present, which turns on automatically when the person gets up from bed. Fig. 7.1 shows the architecture of the system.

The choice of the sensors included in the kit was guided by the analysis of the problems related to AD patients, such as cognitive impairment and wandering, and the needs of their caregivers [17]. One of the most important aspects regards unobtrusiveness: sensors chosen do not affect the user's habits. Moreover, since they communicate wirelessly, they can be easily installed at home, without the needing of interventions on the building. This is a crucial factor for the actual adoption of the technology. In fact, it is necessary to complete the set up of the environment in a short time, and to avoid that the patients see the technicians at work in their homes, since it could worry them.

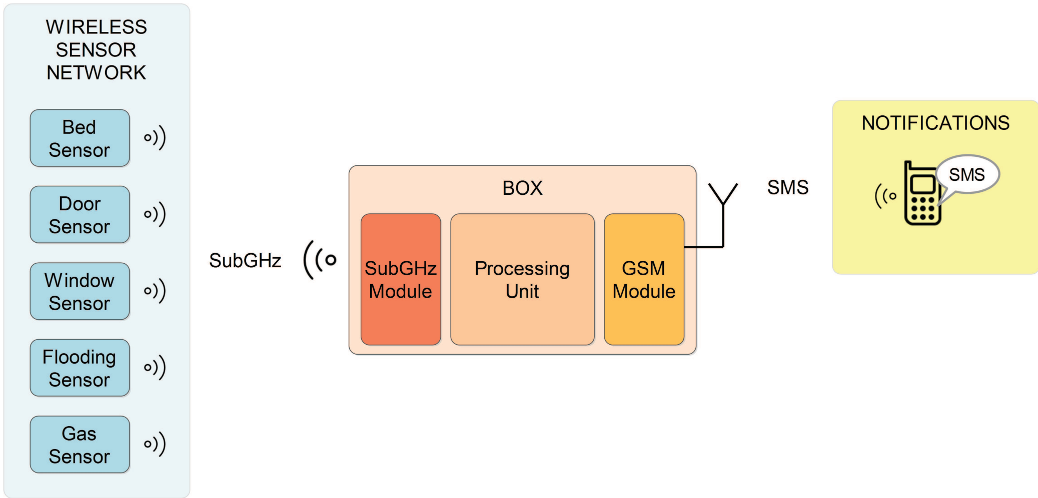


Figure 7.1: UpTech system architecture.

The trial took place in the Marche Region (Italy), it lasted 12 months and involved 450 "dyads", i.e. patient and his/her caregiver, divided into groups. All received three visits by the nurses, a group of them kept periodical phone contacts with the social workers, while the monitoring kits were supplied to a group of around 80 dyads. During the trial, three assessments have been performed using proper questionnaires, distributed by the nurses during the home visits. The questionnaires mainly included: a section oriented to the patient; a section oriented to the caregiver; a section aimed at evaluating the consumption of socio-health resources by the dyads. In addition, an evaluation survey about the technological kit have been conducted.

As a result, a statistical model has been defined for the estimation of the factors related to the Caregiver Burden Inventory (CBI), e.g. the level of caregiver burden [9]. For example, CBI increases proportionally to the hours of assistance, lack of support and inability of the patient to perform ADLs. Moreover, the relationship between patient and caregiver has a great influence on this value, since family members may experience a greater burden, due to the concern for the relative. As regards the technological kit, the overall opinion is positive: challenges identified and suggestions provided by the surveys have led to the realization of a second kit, called Tech@Home. A deeper description of the UpTech project is provided in [40].

7.2 Tech@Home

The Tech@Home system was developed with the aim of filling the gaps detected in the former trial, thanks to feedbacks provided by the caregivers.

The first emerging shortcoming regards the use of SMS as alarming notification. The SMS is a communication technology which does not provide a receipt confirmation mechanism and, therefore, represents a weakness for the whole system. The caregiver may not receive or read the message, leaving the situation unmanaged. The new solution adopted by the Tech@Home system exploits voice call to notify an alarm occurrence. Moreover, it asks for a confirmation of the delivery by pressing a key on the phone. More in detail, the central unit stores a list of caregivers which can contain up to six phone numbers. If an alarm event is detected, a call is directed to the first number in the caregivers' list; in case of no answer, the control unit goes on with the second one, till the end of the list. If none of the caregivers answer, an SMS is sent.

The second issue to solve regards the sensors' reliability. Although the types of sensors have been selected after a careful analysis, some of them were not reliable enough and provided several false positives. This resulted in a distrust on received alarms by the caregiver, less benefit in using the system and a consequent negative opinion on the entire kit. Therefore, Tech@Home foresees the use of new bed presence and water sensors. The new bed sensor provides a calibration that adapts the sensing to the patient's weight, while the sensor for the flooding detection has been replaced because of false alarms due to high humidity rates. In addiction, new sensors have been introduced to enhance the level of monitoring: a presence sensor monitors the user's presence in a room (for example to verify that he/she enters the bathroom periodically), a magnetic sensor placed on the refrigerator door can detect its opening, giving information about eating, and temperature and humidity sensors embedded in the box provide contextual information.

A further problem concerns the reliability of the whole system. When there is a malfunction, if no alarm occurs for a long time, the caregiver may not notice the problem. The remote communication toward a server increases the system reliability, ensuring continuous monitoring, detection of eventual malfunctions and prompt intervention if necessary. Every evening, the processing unit creates a report containing all the information related to the daily activities. It includes events collected by the sensors, configuration changes, and notifications, in addition to status information of the box. The adoption of the server provides additional benefits: the availability of information about a patient enables to perform a long-term analysis of his/her condition, moreover, care providers and medical personnel can access the patient's data for monitoring purpose.

As regards acceptability, a smaller box would make the system less cumbersome and therefore more attractive to the user. Thanks to a more accurate design, the size of the box has been reduced.

The last and most important problem concerns the customization of alarms and, in general, of the whole kit. In fact, each user has different characteristics and habits that need to be taken into account when defining alarms. In order to allow an ongoing dynamic configuration of the kit, two Android applications for smartphone devices have been implemented. A mechanism enabling the configuration of the processing unit was already provided in the previous version of the project. In such a case, by manually connecting the computer to the box, it was possible to access a web page for editing certain parameters and entering the number of the caregiver's phone. Such a solution was designed to be used as a one-off operation, only by installers. The applications presented below are intended to overcome this lack, permitting to dynamically configure the system wherever the caregiver/installer is, in a simple and convenient way.

The two applications have the same structure and graphics, but one of them provides more technical features and is designed for the installer, while the other is targeted to caregivers. Even in this case, like in the Transparent project (see Section 6.2), during the design phase, the usability criteria previously identified have been taken into account. Although in general the users are not elderly, nevertheless, they may be technologically unskilled.

The information is arranged by topic, i.e. *general*, *notification*, and *account*, but in order to avoid deep navigation hierarchies we chose to exploit tab bar located on top of the view (see Fig. 7.2).

In the general tab there are all features referring to the system general functioning. More specifically, they allow the user to:

- set date and time;
- set parameters to access the remote server;
- check the residual credit on the box SIM card;
- set values for the box functioning and request information about its current state;
- request to forward data reports to the remote server;
- request the sensor configuration.

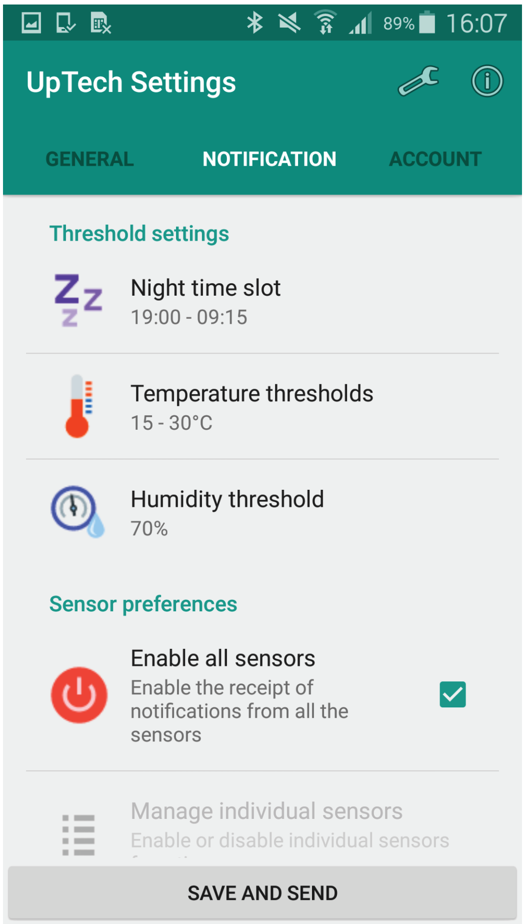


Figure 7.2: Screenshot of the smartphone application: the GUI is the same for installers and care providers.

Naturally, all the features related to the setting of specific operating parameters, and the report or configuration requests can be exploited only by the installer, who has the appropriate skills to manage and use them.

The notification section allows, instead, to modify values concerning the detection of alarms, or to disable notifications from one or more sensors. Specifically, the user can:

- set thresholds (e.g. temperature and humidity limit values);
- enable/disable the receipt of notifications from some or all sensors;
- set timeout values, i.e. the time interval required in particular situations such as getting out of the bed, not opening the fridge or not entering the bathroom.

Finally, the account tab enables to modify the information about the users who interact with the system. Particularly, it is possible to:

- modify the personal password;
- add/remove the caregivers' phone numbers;
- add/remove the installers' phone numbers.

Obviously, the last feature is available only for installers. Once the user has made the desired changes, he or she can save and send them to the box by clicking the "save and send" button in the bottom of the screen. In such a case, it is possible to check the modified settings from a summary window (see Fig. 7.3) and decide whether to transmit or make further changes.

The applications use a simple and intuitive graphics. Each option is accompanied by an image to facilitate understanding, but there are also a title and a more detailed explanation. There are not animations and the inclusion of mandatory information is guided step by step in order to reduce errors. As suggested by Android developers (see Subsection 3.2.1), both applications leverage predefined structures for setting preferences. These structures, in fact, are already known by the user since adopted by the OS.

As regards the communication protocol, applications communicate with the box through SMS. Thus, it is conceived with the aim to reduce the number of characters sent, and consequently the costs.

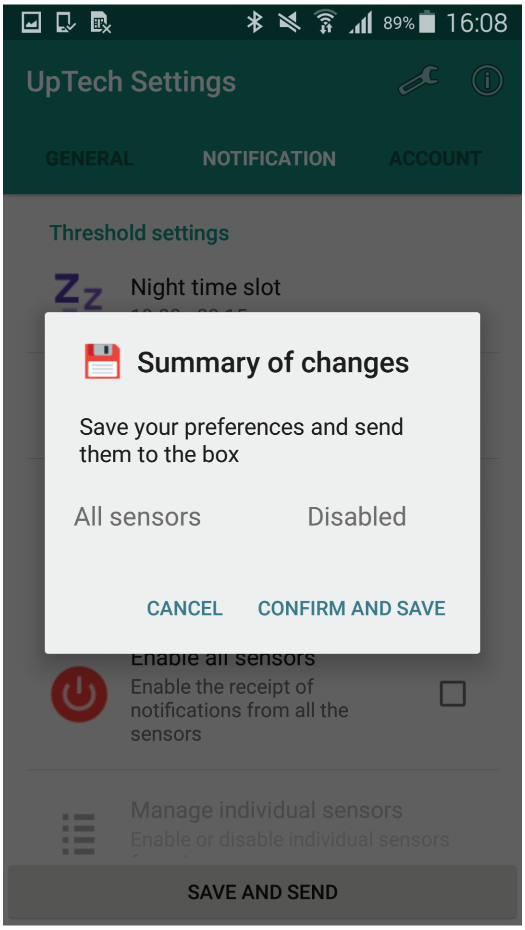


Figure 7.3: Summary window of the changes.

When the caregiver or the installer wants to change a setting or submit a request to the box, the message will be forwarded in the following format: "TECHHOME#FeatureCode#[Parameters]". "TECHHOME" is a keyword which identifies the beginning of all messages. It is followed by an hash character and then by a key-value pair consisting of a numerical feature code and a string with relative parameters. The numerical code establishes the desired functionality, for example "0007" to change temperature thresholds, while the parameter allows to define the new values, e.g. "MAX-30,MIN-15" means the new minimum threshold is 15, while the maximum is 30. To submit multiple commands on the same message, the key-value pairs followed by the hash character must be appended until the number of characters available for a message has finished.

In summary, the new system provides improved features, such as:

- voice calls for the alarm notifications and a mechanism for the delivery confirmation;
- more reliable sensors;
- additional sensors (e.g. flooding, bed, temperature and humidity sensors);
- a small and handy box;
- sending periodic reports to a remote server;
- two mobile applications for the ongoing configuration of the system.

Its architecture is shown in Fig. 7.4.

First functional tests performed in the laboratory environment demonstrate the feasibility and reliability of the improved system. Moreover, the smartphone application and the whole Tech@Home system are currently under test in the houses of a dozen of Swedish families for 12 months, thanks to a collaboration with the Lund University. In addiction, the caregiver application is already available on the Google Play Store, under the name *Tech@Home Caregiver*.

7.3 MQTT-based app

One of the main defects of the system described so far is the use of voice calls and SMSs for notification of alarm events and, especially, for sending configuration data. Hitherto, the choice of these communication channels has been conditioned by the

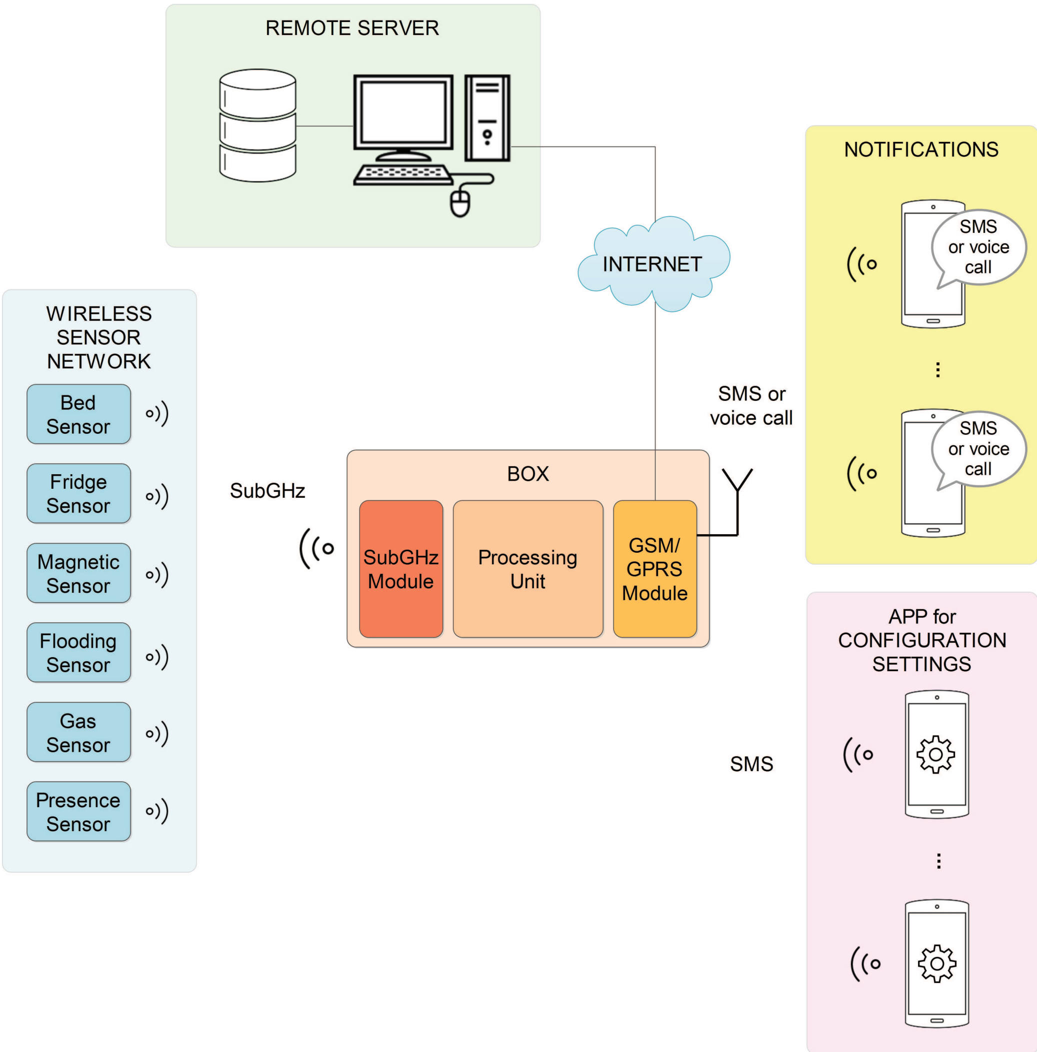


Figure 7.4: Tech@Home system architecture.

fact that, in many countries, elderly users' homes are not equipped with a WiFi coverage. In addition, usually caregivers are not willing to spend money on a data subscription if they do not need it. However, in the IoT perspective, implying a growing technological evolution and pervasive presence of the Internet in users' homes and lives, an alternative version of the system based on the Message Queuing Telemetry Transport (MQTT) protocol has been implemented [55]. Until now, it exploits such a protocol just to send notifications, but we foresee to use it also for settings.

MQTT is an open, simple, easy to implement protocol, defined as the reference standard for IoT. Differently from Hyper-Text Transfer Protocol (HTTP), these features make it more suitable for adoption on devices with limited resources, as in M2M communication scenarios.

MQTT exploits the publish-subscribe paradigm, by means of three types of components: a client that sends messages, called *publisher*, a second client which receives messages, called *subscriber*, and a *broker*, in charge of managing the communication. The broker is responsible for filtering the messages according to the *topic*. Each client subscribed to a topic, receives all messages published on this topic by other clients.

Since the MQTT protocol is based on the Transmission Control Protocol (TCP), clients that wants to initiate a communication need to send a *CONNECT* message to the broker, which responds with a *CONNACK* message. After that, the connection remains open and publisher and subscriber can send and receive messages until they disconnect.

As regards reliability, MQTT offers three levels of Quality of Service (QoS):

- level 0: each message is transmitted at most once;
- level 1: the message can be sent more than once, until the sender gets an acknowledgement from the receiver;
- level 2: the message is transmitted once by following a four steps handshake.

Obviously, each of them has pros and cons. In general, the first one provides the best effort delivery, but is unsafe, while, on the contrary, the level 2 is slower but safer. In our system we use level 1 both for publishing and subscribing because it represents a compromise choice between speed and reliability.

The solution proposed here adopts MQTT only for events notification, even if other configurations are possible [55]. The system architecture is shown in Fig. 7.6. In this case, the remote server acts as a broker, managing all messages, but also as

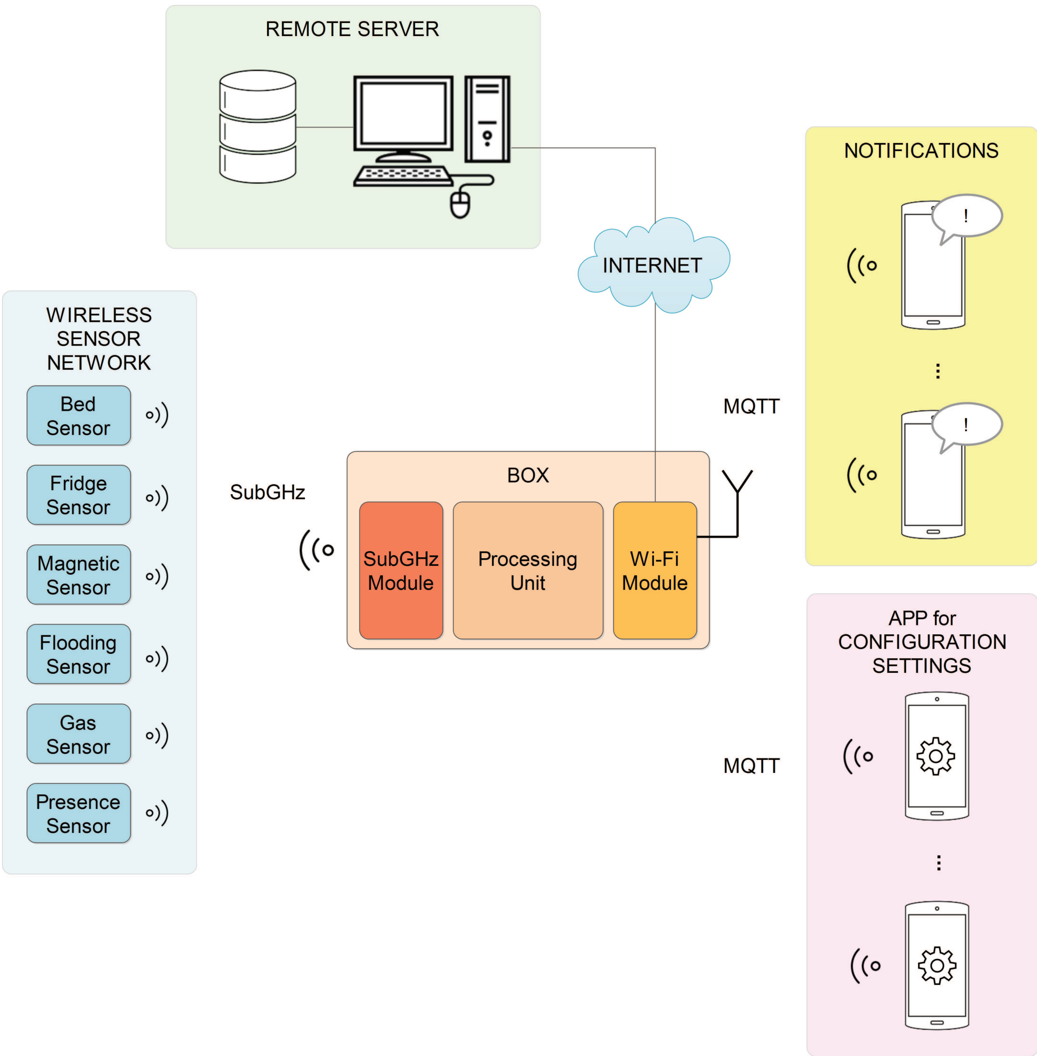


Figure 7.5: MQTT-based system architecture.

a publisher, forwarding the alarm events received from the box to the smartphone interfaces.

At the smartphone booting, the mobile application starts. After checking the availability of WiFi or data connection, it initiates the communication with the broker sending a CONNECT message and subscribes to the proper topic in order to receive notifications.

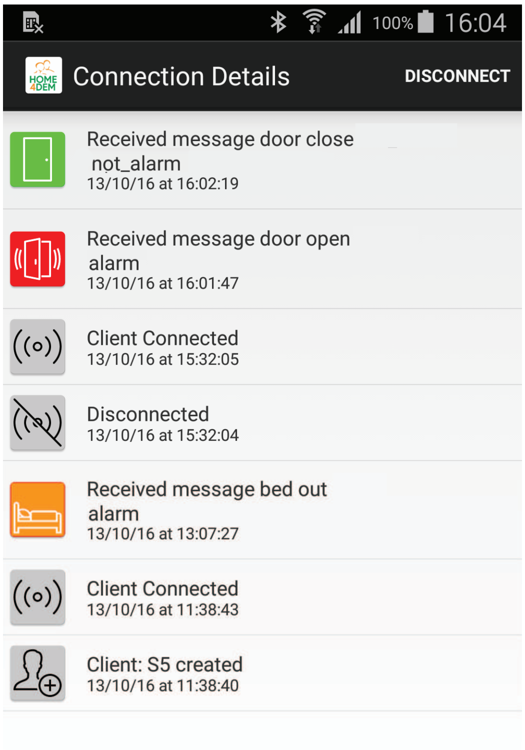


Figure 7.6: MQTT-based smartphone application.

A first prototype of this application is already available for Android devices. It exploits the Paho library which provides an implementation of the MQTT protocol. From the usability point of view, the prototype respects the guidelines identified in the literature and reported in Subsection 3.2.1. The GUI is mainly constituted by a scrollable list of events. Each event is characterized by a title, a description and a small icon in order to identify immediately the type of event occurred. It is possible to set different alarm levels, exploiting colours, sounds and vibration patterns. For example, if the patient wakes up at night and goes out of the bed, this is not a very serious event, thus, the mobile application notifies it with a single short vibration, single sound ring, green flashing led light and green icon. If the patient opens the window, the alarm level rises: it is notified with two longer vibrations and rings, orange led light and icon. But, if the AD patient opens the entry door during the night and goes out, this is definitely a serious event: it is notified with more vibrations, longer rings and red led light and icon. Further improvements foresees the possibility of personalizing alarm levels according to the caregiver's preferences.

Preliminary tests demonstrate the proper functioning of the whole system. The remote server is able to receive and publish the messages in the correct topic. It also manages correctly the communication with the smartphone application, which visualizes the data promptly. The application runs in background, maintaining the connection open. The system operates both indoor and outdoor thanks to data connection.

Future tests will be performed in order to evaluate the efficiency in terms of battery consumption of the proposed solution. Moreover, an usability study on target users will be performed.

7.4 UpTech RSA

A different version of the monitoring system has been developed for nursing homes, called UpTech. Particularly, its purpose is to support the assistance of patients during the night hours, when there is a lack of personnel in the building. Moreover, typically, the night staff is a vulnerable group, receiving less training, supervision and support than day staff, but with a higher level of responsibility [93].

Fig, 7.7 shows the system architecture. As can be seen from the picture, UpTech RSA is characterized by some peculiarities. First of all, in a nursing home, multiple patients are monitored at the same time. For this reason the system has to manage data coming from numerous sensor networks. Moreover, different types of sensors are employed, due to diversity of physical environment. Specifically, the set of sensor installed in each room enables the following functionalities: door, window and French window opening detection, presence in the bed detection and presence in the bathroom detection.

Also in this case, sensors communicate through the SubGHz technology by means of a gateway. A single gateway illuminates multiple rooms. It forwards the event messages to a central server located in the nurses' station, in order to be stored and visualized in a desktop interface. Such an interface provides two visualization modes:

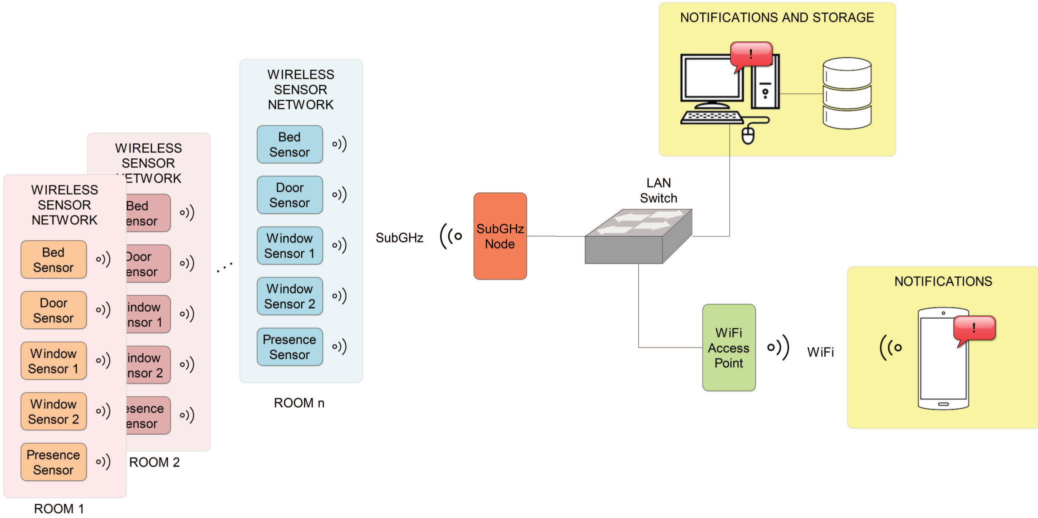


Figure 7.7: UpTech RSA system architecture.

- a two sections version: the interface is divided into two parts. On the right there is a scrollable list of the events acquired by the sensors, while on the left the status of the sensors in each room is shown. There is a top bar which becomes coloured and flashing when an event occurs;
- a multi-user version: the main screen shows all the rooms monitored. When an event occurs in one room, the corresponding frame becomes coloured. By clicking on the box, it is possible to see the details of sensors state.

Nevertheless, if nurses are outside the station for the round check, a fixed interface may not be the best solution. For this reason, a smartphone application has been foreseen. It communicates with the local server through the WiFi connection. The monitoring application starts automatically at 21:00 and stops at 06:00. When it is active, its logo appears in the top-left of the screen, as a fixed notification item. If the WiFi communication stops or the server does not respond, a warning icon is displayed.

From the graphical point of view, the smartphone application is structured as a scrollable list of events identified by the name of the sensor, state, floor and room number, as shown in Fig. 7.8. The associate alert level is indicated as a coloured circle: red for high, yellow for medium, and green for low alert level.

In order to avoid data loss, each event is sent with a progressive unique id. This way, the application can identify the missing message and ask for a retransmission. Missing delivery of a message is a very serious issue, therefore, to be aware of errors and malfunctions is an essential factor for acceptability, but mostly for patients' safety.

Figure 7.8: UpTech RSA smartphone application.

For this reasons, sensors and gateway malfunctioning are notified as grey circles. This way, nurses can intervene promptly.

The system described so far is already available as a PoC. Following the initial development phase in the Laboratory, aimed to better adapt the technology to the emerged operational requirements, the prototype has been installed in the nursing home “Villa Cozza” in Macerata (Italy). Two rooms have been equipped with sensors and monitored for more than three months. In the first room two female patients are housed, only one suffering from AD. The other is a disabled person and cannot move autonomously. In the second room a not independent female patient suffering from AD is housed; she moves through a wheelchair. Each room is equipped with a sensors kit consisting of three magnetic sensors (one applied onto the window, one onto the French window, and one onto the room front door), a PIR sensor in the bathroom, and a force sensor placed in the bed, as shown in Fig. 7.9.

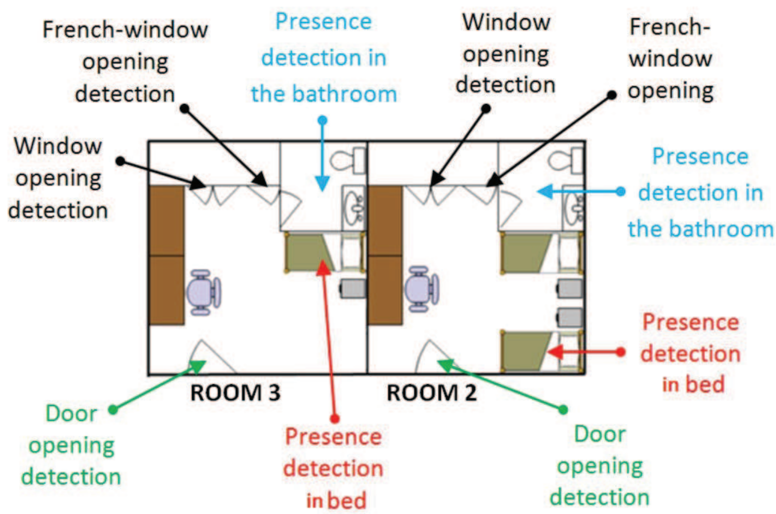


Figure 7.9: Floor plan of the two rooms equipped with the UpTech RSA sensors in the nursing home “Villa Cozza” in Macerata (Italy).

Some weeks after the installation a survey for the evaluation of the system has been conducted over 18 nurses. Although some of them are not very familiar with the technology, the results are highly positive. In the following, some of the most significant questions are listed:

- Is the kit easy to use?
- Do you think that the patients monitored have suffered a stress?
- Do you think that the kit has been a source of stress for nurses?

- Would you recommend the use of this kit in nursing homes?
- Please, give an overall opinion on the technological kit.
- Do you think that the kit can improve the assistance provided in nursing homes?

The 100% of respondents believes the kit is easy to use and recommend it as a monitoring system in nursing homes; 89% of them have an overall positive opinion of it, while only 11% of nurses give it a medium rating. All of them affirm the kit is not stressful for nurses, while just 6% stated it has been stressful for patients. Moreover, during the trial period, two dangerous episodes happened: the opening of a window during the night, and a patient's fall out of the room. In both cases the system detected the alarming situation and the staff was been able to intervene promptly.

In addition to notifying alarm events, UpTech RSA is able to store the data acquired by the sensors. Such data can be very useful because they permit to obtain information about the patient's habits and, consequently, to identify any changes or abnormal behaviours.

The raw data collected by the sensors installed in the rooms are often difficult to interpret. Therefore, in order to carry out the data analysis, it is necessary to find a representation allowing to understand them immediately. The data acquired from each sensor can be seen as a binary signal, in which the value "1" is the activation and the value "0" is the deactivation. In the case of bed sensor, an activation means the patient is on the bed, while a deactivation means he/she is outside. Therefore, we can consider the "10" sequence as a sleep observation.

A sleep observation is characterized by a start-time and an end-time. Fig. 7.10 shows the day-to-day alternation of sleep (green bar) and wakefulness (blue bar) of the AD patient in room 3. From the graph, useful information can be inferred. For example, usually the patient goes to sleep and wakes up at the same hour, respectively 06:00-07:00 and 19:00-20:00. This was expected, since life in a nursing home is bounded by specific time constraint, defined by the daily schedule. Missing nights in the central part of the graph are due to technical problems, which have been notified to the personnel and promptly resolved.

Lotfi *et al.* affirm that, among the various representation methods presented in the literature, the start-time/duration is the most effective one for large data sets [113]. Representing information according to a start-time/duration method means converting the binary signal into two separate sequences of real numbers corresponding to the start-time and duration of each activity, respectively. Fig. 7.11 shows

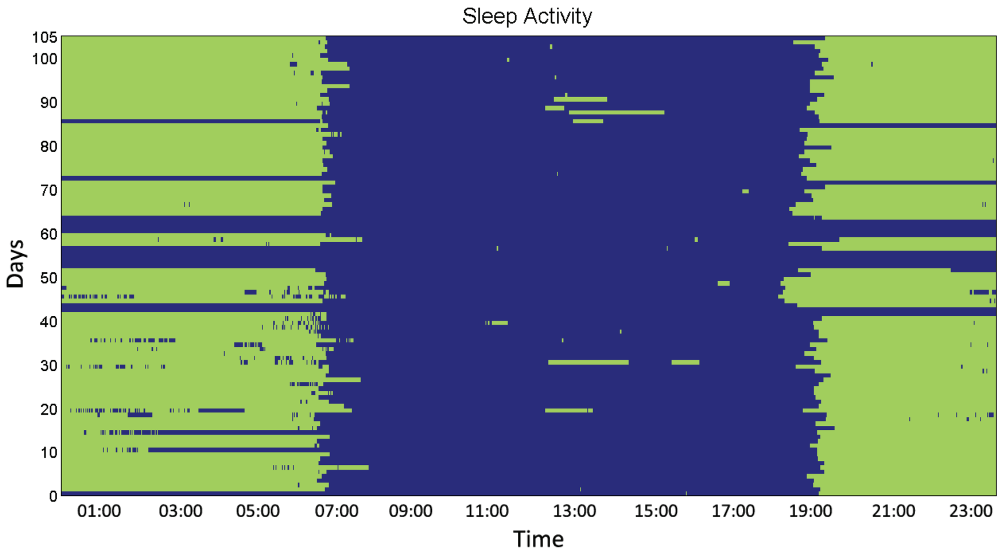


Figure 7.10: Sleep activity representation for the patient in room 3.

the start-time/duration graph of the activity detected by the bed sensor in room 2. Each point on the graph indicates a sleep observation and is characterized by a start-time (on the abscissa) and a duration (on the ordinate). All activities lasting less than 10 minutes have been ignored because they could indicate sensor activations and deactivations due to involuntary movements of the subject while asleep.

Looking at the picture, the presence of two outliers (highlighted by red circles) becomes immediately evident. Another information that can be extrapolated by combining the data obtained from the bed sensor with those detected by other sensors, is the identification of the action carried out after the user came out of bed. This will enable the possibility to calculate the occurrences of predefined patterns of activities, instead of single ones. Such an analysis allows to identify potentially dangerous situations with respect to behaviours commonly exhibited by the subject, and not considered as alarms. The graph depicted in Fig. 7.12 shows the actions executed within 4 minutes after the patient got out of bed, i.e.:

- door opening (marked as a green circle);
- window opening (marked as a black square);
- presence in the bathroom (marked as a blue cross);
- no other activity (marked as a red cross).

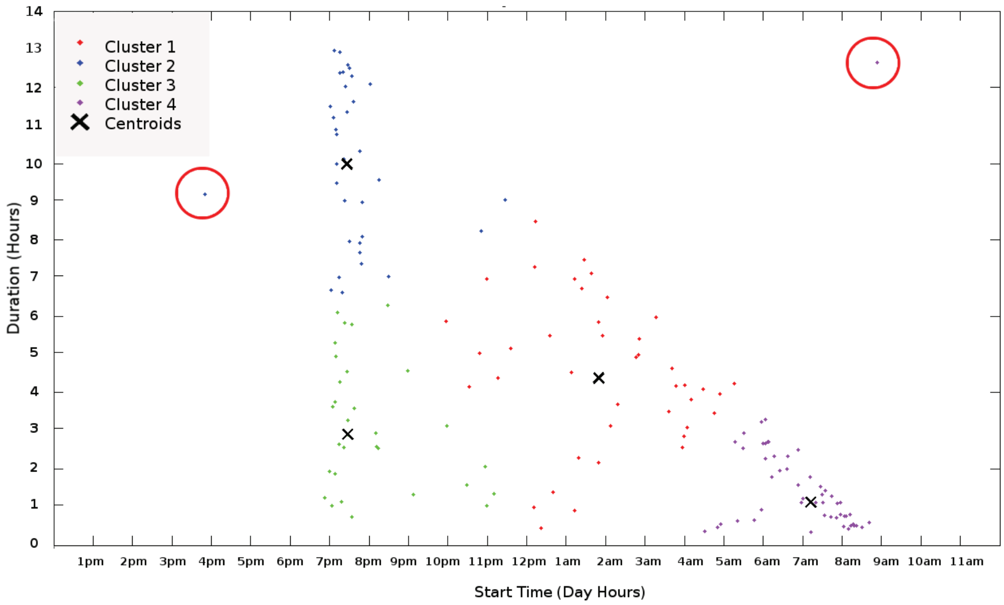


Figure 7.11: Start-time/duration graphs of the sleeping activity detected from May to June 2015 in room 2.

Such charts exploit the start-time/end-time representation. The activity shown is still the sleeping, but, according to the action carried out subsequently, the marker changes. Looking at the picture the observer can notice that the patient very often goes to the bathroom or opens the door immediately after getting up. This agrees with the reports of the nurses concerning the fact that the monitored elder is very lively, and often gets up during the night. In Table 7.1, the percent occurrence rates of each activity described above are given, limited to the night hours.

Table 7.1: Hit rate of the actions that followed the awakenings between 21:00 and 06:00 from May to June 2015.

Event detected after awakening	**Room 2**	**Room 3**
Presence in the bathroom	76%	15%
Door opening	14%	2%
Window opening	0%	0.2%
None	10%	82.8%

The analysis herein discussed is just the very first step for the identification of user's behavioural patterns and abnormal situations. Until now, we focused on the representation and visualization of data, extracting some preliminary information on the habits of two monitored patients.

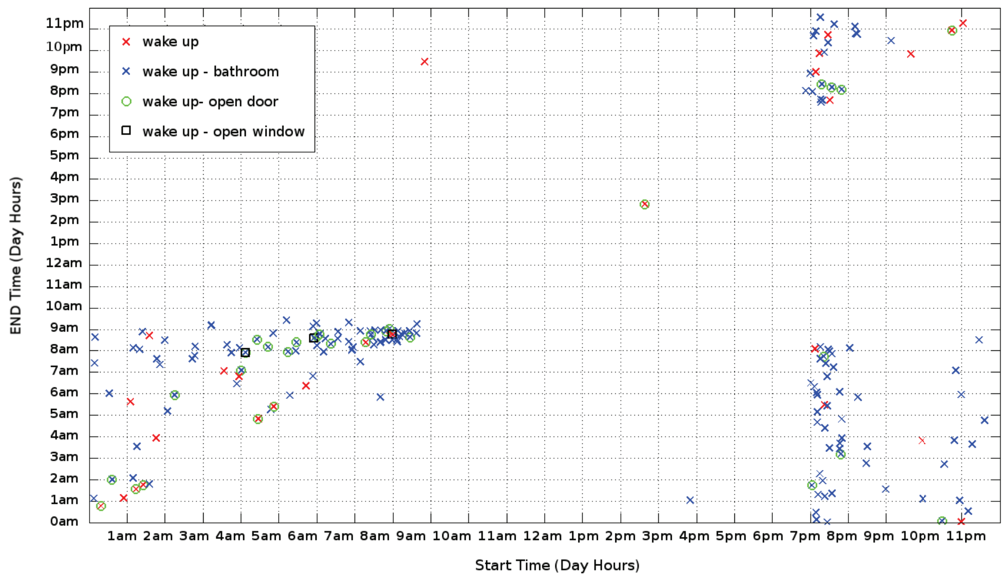


Figure 7.12: Start-time/end-time graphs representing the activities performed after waking up by the patients housed in room 2, from May to June 2015.

Although the behavioural analysis through environmental sensors falls outside the scope of this thesis, nevertheless, it has been useful for the sleep analysis presented in Chapter 9.

7.5 Summary and discussion

Systems presented in this Chapter seek to meet the needs of caregivers, who, taking care of AD patient, suffer from mental and physical burden. Such systems can help to reduce caregivers' workload, monitoring the patient in their place and notifying any potentially dangerous situations. To this end, smartphone applications that allow, on the one hand, to adapt the system to the peculiar subject's needs, and, on the other, to view and receive notifications have been implemented. The interface design has taken into account the guidelines and the criteria identified in the literature, ensuring effective, efficient and satisfactory interactions. Experimental tests demonstrated the proper functioning of the system and first field trials yielded positive outcomes.

Further tests in real contexts are foreseen. Moreover, thanks to the analysis of patients' habits, future developments will be provided, involving the notification of abnormal as well as potentially alarming situations.

Chapter 8

Wearable device data: raw data collection

In the AAL framework, it is very important to monitor the vitality level of elderly users in their daily activities, in order to evaluate, for example, if they are spending too much time in a static condition. In fact, this may point out abnormal trends, possibly related to the physical or cognitive condition deterioration. Therefore, day to day monitoring may be extremely useful in order to perform a long term analysis of the elderly subjects' behaviour.

This Chapter will present a system for the motion data acquisition, based on the Bluetooth Low Energy (BLE) technology [23]. It exploits a smart shoe equipped with a sensorized insole and proper hardware in order to obtain information on the gait. This information is then sent to the smartphone, which acts as a gateway, forwarding it to a server.

A prototype of the system is already available as a PoC. Its architecture is shown

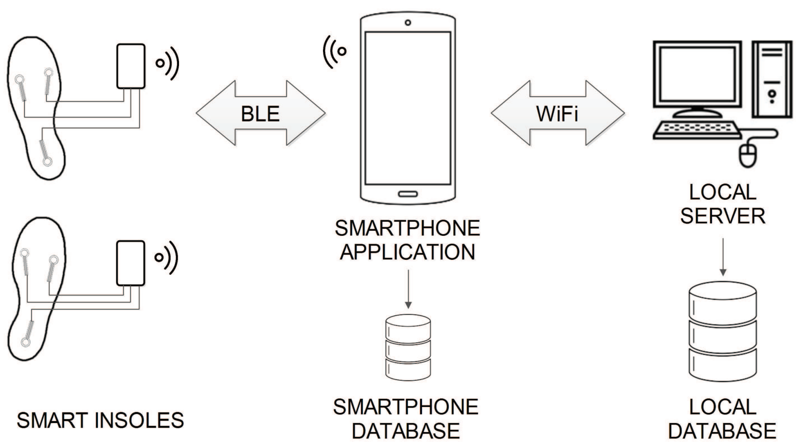


Figure 8.1: Vitality monitoring system architecture.

in Fig. 8.1. This solution is designed to operate both indoor and outdoor. In the first case, the mobile phone sends the collected data periodically to the local server, while in the second, it save all the information in the internal Database (DB), and, when the user arrives at home, it automatically forwards them to the server.

This use case can be mapped in the *physical health* domain of the QoL.

8.1 Design requirements

The main requirements considered during the design phase, are those related to technology acceptability (see Section 3.2) and those discussed in Chapter 4, more specific for wearable devices and behavioural analysis.

When dealing with wearable devices, the first and basic requirement is comfort. Heavy, cumbersome or intrusive equipments should, therefore, be avoided. Moreover, not all people are willing to wear a device that, although useful, does not reflect the current fashion or the own aesthetic taste.

Facilitated maintenance is another requirement to consider: hardware components should be easily accessible, since during their life cycle may deteriorate. Also limited power consumption is important to avoid the need of frequently replacing the battery.

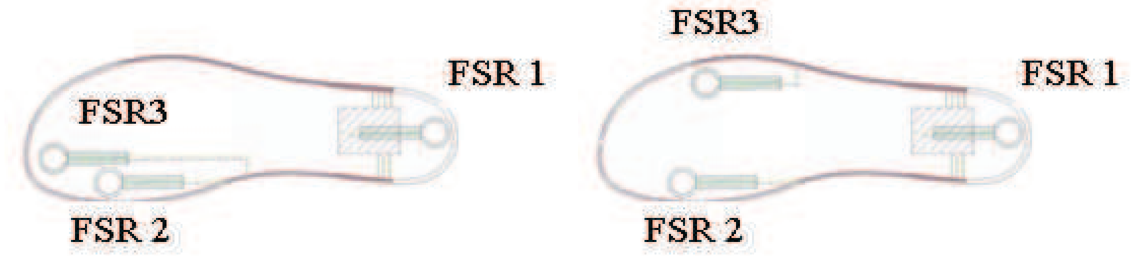
Lastly, an adequate precision and reliability in classifying the detected activity is essential for the user's acceptance, as well as cheap cost, as deeply discussed in Section 3.2.

To fulfil these requirements, hardware and software components have been carefully selected and designed.

8.2 Smart shoes

A first version of the prototype device was presented in [54], followed by a second version described in [159].

The wearable smart shoe collects information on the user's physical activity by exploiting Force Sensing Resistor (FSR) sensors applied to the insole. FSRs are widely used in wearable devices for well-being applications, like sensorized footwear (e.g. [89]). In fact, they enable temporal analysis of the body weight distribution on the foot insole, and of the walking activity, providing an output resistance that varies according to the pressure applied on the active area of the transducer. The specific transducer model employed is the FSR 402 Short, manufactured by Interlink Electronics. The optimal positioning of the transducers on the insole is an important



(a) 1st Configuration (b) 2nd Configuration

Figure 8.2: Configuration sets of the FSRs: a) 1st configuration (FSR1 - heel, FSR2 1st metatarsal head, FSR3 - toe); b) 2nd configuration (FSR1 - heel, FSR2 - 1st metatarsal head, FSR3 - 5th metatarsal head).

aspect to consider, because it affects the decision output by the algorithm on the user's activity. For this reason, several tests have been conducted, considering different amounts of sensors and locating them in different positions on the insole. The outcome of this preliminary investigation suggested the possibility to employ only three FSR sensors, placed in two different configuration sets. In the first one the FSRs are placed in correspondence to the heel, the 1st metatarsal head and the toe, as shown in Fig. 8.2(a), while in the second configuration the FSRs are placed in correspondence to the heel, the 1st and the 5th metatarsal heads, as shown in 8.2(b). The first configuration allows to recognize the user's state, i.e. sitting, standing or walking, while the second one enable the identification of different gait phases, i.e. heel contact (H), flat foot contact (F), push off (or heel off) (P) and limb swing (S). In the definitive prototype, the latter has been chosen, as depicted in Fig. 8.3. Using such a sensor configuration, an example of the time variation of the analogue voltage signal measured at each FSR is shown in Fig. 8.4, where three step cycles are considered in time, along the horizontal axis. In Table 8.1, the association between the combinations of active/non-active transducers, and the step phases is detailed. Moreover, the sequence of step phases corresponding to these voltage outputs is provided in Fig. 8.5.

In order to transmit less information as possible and save power, the step phase recognition is performed by an electronic board. It implements the signal acquisition and data transmission procedures, and has been developed *ad hoc* for our purposes, in order to meet the project requirements: low average power consumption and small form factor. A deeper description of the hardware components can be found in [33].

The shoe prototype has been specifically designed to contain the board. In fact, it can be host in a hole dug in the shoe sole, and covered by a lid. This way, the user walks comfortably, without noticing the presence of the hardware.

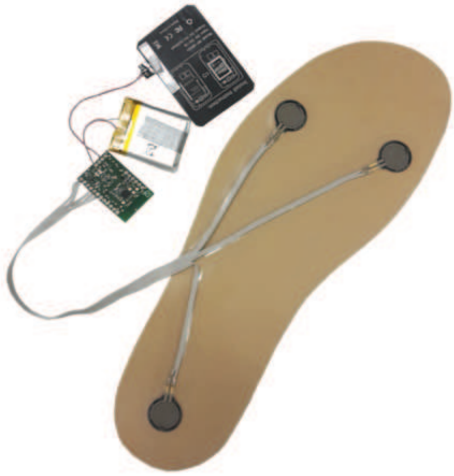


Figure 8.3: Smart insole prototype.

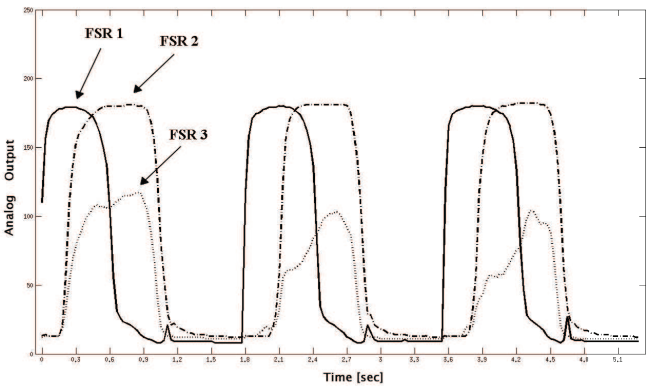


Figure 8.4: Time variation of the analog voltage signal measured at each transducer during the step movement.

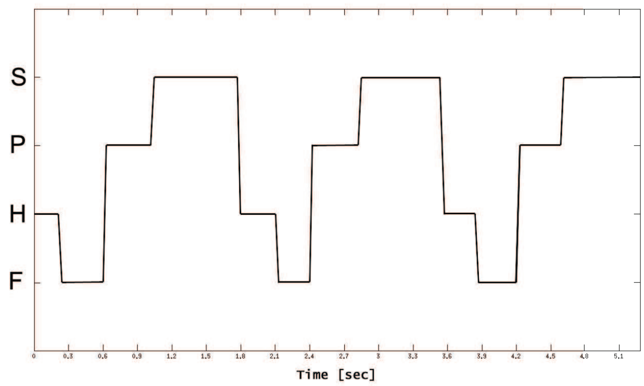


Figure 8.5: Time sequence of the step phases (heel contact (H), flat foot contact (F), push off (or heel off) (P) and limb swing (S)) corresponding to the time variation of the analogue voltage signal measured at each transducer, according to Table 8.1.

Table 8.1: Step phases identification by transducer binary pressure.

FSR1	FSR2	FSR3	Step Phase
1	0	0	Heel Contact (H)
1	0	1	Foot Contact (F)
1	1	0	
1	1	1	
0	0	1	Push Off (P)
0	1	0	
0	1	1	
0	0	0	Limb Swing (S)

To facilitate the battery re-charging operation, a commercial inductive charging system has been implemented. Such solutions allows to facilitate maintenance, since the hardware components are easily accessible.

8.3 Protocol implementation

As already stated, the system exploits the BLE technology in order to transmit the information acquired by the smart shoes to the smartphone.

Differently from Bluetooth, BLE has been designed to be lowest cost, easy to implement, and optimized to transmit small chunks of data. In other words, it is used for applications that do not need to exchange large amounts of data, and can therefore run on battery power for long time at a cheap cost. In our case, it is particularly suitable, since low power consumption and low cost are two design requirements.

The Master role is assigned to the mobile phone, and the Slave role to each shoe (right and left). In order to guarantee adequate efficiency and data reliability, the transfer is realized via the BLE indication mechanism. This way, the Slave send the data and wait for a confirmation, and the maximum payload of 20 bytes is used to exchange data.

In this type of application, it is very important to trade off the duty cycle of data exchange, minimizing it, in order to limit the power consumption, and the needed application throughput, to obtain a sufficient reliability. Since the payload is 20 bytes, the step phases that can be detected are 4, represented by 2 bits, and the efficient analysis of gait requires a sampling every 10 ms, the packet can be sent every 800 ms. During this period, however, the system can exploit the channel to resend lost packets, making the communication more robust. A detailed description of the protocol implemented by the board and the design choices is reported in [33].

8.4 Smartphone application

The smartphone application prototype relies on the Android APIs supporting the BLE stack, available since the Jelly Bean 4.3 version. It acts as a gateway interfacing, on one side, the smart insoles via BLE, and, on the other, the local server, by means of WiFi connection.

As regards the communication with the shoes, the application flow chart is shown in Fig. 8.6. The app aims at creating a BLE star topology network, where it acts as a master, while low consumption devices play as slaves. After the mobile device booting, the application starts automatically, looking for the slave nodes available for the communication. This process is repeated periodically to allow the smartphone to connect to the electronic boards as soon as they are within the BLE reach.

When the slaves were detected, the master tries to connect to them and, if successful, enables the GATT notification for each one. By enabling the notification feature, it remains in a waiting state, listening for data sent from the smart insoles.

As soon as the shoes send a data packet, it is stored in an internal DB, together with a unique identifier number, the identifier code of the device who has sent it, and the arrival timestamp. When the user is indoor, periodically, i.e. every 5 minutes, all the information stored in this time period are sent to the local server, as a Comma-Separated Values (CSV) text.

In order to use the system even outdoor, it was necessary to implement a method to recognize when the user is at home. The smartphone, indeed, continuously stores the data in the internal DB and sends them to the local server once back at home. The system is capable to recognize it, simply by checking the SSID of the WiFi network to which the phone is connected. By means of a broadcast receiver, i.e. a feature provided by Android APIs, the mobile phone keeps listening the connection changes, waking up when the home network is identified.

Assuming that the user leaves the house and come back after several hours, the memory footprint of all data acquired in such a period would be considerable. Therefore, the use of the CSV format is very important, since it reduces the redundancy of the information and makes the message light. As reliability is a design requirement, the throughput chosen for the BLE communication is quite high, and the amount of stored data rises quickly. Choosing a data format characterized by a greater redundancy, such as JSON, causes a significant growth of DB's memory footprint, slowing down the communication and decreasing the application efficiency.

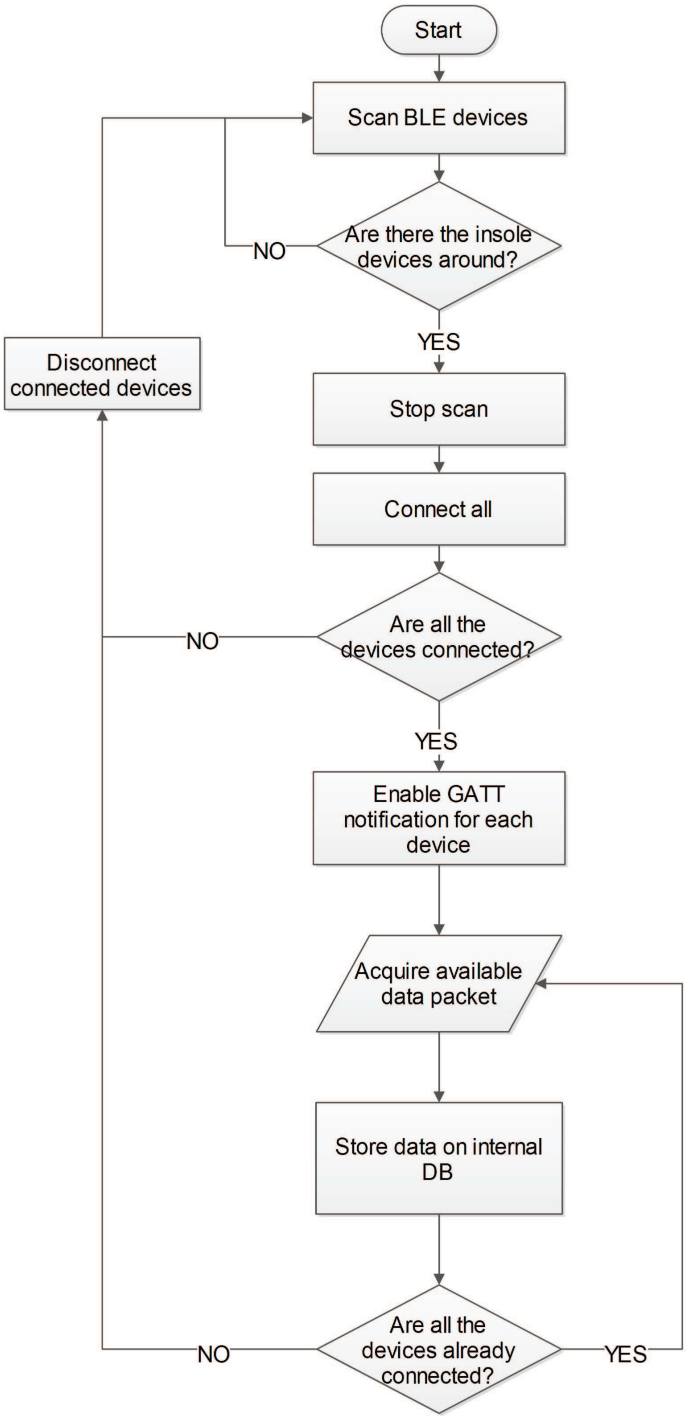


Figure 8.6: Application flow chart: it starts after the device booting and ends when the latter is shouted down.

Furthermore, in order to ensure system reliability, it is essential to avoid data loss. To this aim, a check functionality has been implemented in the communication between smartphone and local server. In fact, the WiFi communication is much slower than the BLE one. Thus, during data transfer, other records will be added to the DB, making it necessary to remind which ones have been already sent. Thus, when the information are send to the server, it answers the first and the last identifier number of the events reported in the CSV text, both as reminder and confirmation of receipt. Once the response has been received, the smartphone can delete the data already sent from the internal DB.

8.5 Local server

The local server is a classic Rest server, communicating with clients through the HTTP protocol. Its task is to permanently store the data coming from the shoes, writing them on a relational DB. Such data are raw data, since they have not undergone any intermediate processing by the smartphone device. The server saves temporarily such information as files, and, subsequently, at the end of the day, it elaborates and stores them in the DB. For each received data set, it answers to the mobile device the "IDs" of the first and last event; this way, the smartphone can easily delete such data, without risking to lose useful information, since it is sure that they are properly arrived at their destination.

At the current stage of development, the server performs only the storage task, but it is foreseen the use of the acquired data to carry out a long time analysis of the user's gait, in order to detect worsening on the walking or abnormal behaviours.

8.6 Discussion

The system described so far is already available as a prototype. Its realization involved several aspects: requirements analysis, hardware selection, design of the communication protocol, shoe manufacture, implementation of firmware and smartphone application.

In all these phases, the requirements identified at the beginning have been fulfilled, enabling the realization of a non-intrusive, low cost, low power, and especially reliable system. In addition, it does not require any user interaction, since the smartphone application automatically starts after booting and the communication begins as soon as the BLE devices are reachable.

The periodic battery recharging can take place at night, when the user is asleep and is not wearing the shoes. The use of the inductive charger allows the wireless recharging, simply by approaching the shoe to the charging pad.

From the aesthetic point of view, the shoe does not undergone any noticeable changes, since the small sizes of board and battery allow to embed them on the bottom of the shoe.

Balancing low battery consumption and sufficient reliability has been the more challenging aspect. The use of the indication transfer mechanism and the optimization of the connection parameters represent a good solution for energy consumption efficiency. Moreover, the choice of sending the processed information (i.e., step phases) allows to reduce the number of transmitted bits and consequently the number of transmissions. In addition, two scenarios must be considered in the testing phase. Considering the outdoor scenario, in which the user wears the smart shoes and typically carries the smartphone inside his pants pocket, the mean value of RSSI is approximately -60 dBm. In indoor scenario, instead, the user might not have the smartphone with him; accordingly, the variable distance of connected devices, the complex multipath channels and non line-of-sight conditions bring to lower values of RSSI and higher probability of packet loss. For this reason a retransmission mechanism has been implemented, balancing throughput and reliability. A further mechanism to avoid data loss has been implemented in the communication between smart phones and servers.

Functional tests demonstrated the proper functioning of the system, both indoor and outdoor, enabling the correct acquisition of behavioural data. Future developments foresee the implementation of algorithms for data processing and gait analysis.

From the smartphone use perspective, this project allows to understand how such a device is essential for the development of this type of solutions. First implementations, presented in [54, 159], exploited SubGHz technology for data transmission and fixed gateways installed at home. For this reason smart shoes could be used only indoors. The smartphone, acting as a portable gateway, guarantees the service also outdoor, with a significant benefit for the user.

Chapter 9

Wearable device data for sleep analysis

Among factors influencing the QoL reported in Section 2.1, WHO mentions sleep and rest. As well known, sleep is essential for well-being, health, and performances. Humans need 7-8 hours of consolidated sleep, preferably overnight. However, in many countries, people sleep one or two hours less. A study found that sleep duration of students decreased from about 7.5 hours per night in 1969 to 6.5 hours per night in 1989 [82]. Moreover, according to [155], sleep pathologies affect about 70 million people in United States alone, approaching epidemic levels.

Sleep research has led to discover a huge number of adverse health conditions associated with poor sleep, such as hypertension, [90], type 2 diabetes [161], stroke risk [69], *etc.* Even the physical appearance is affected by bad sleep habits. A study by Oyetakin-White *et al.* indicates that chronic poor sleep quality is associated with increased signs of intrinsic ageing, diminished skin barrier function and lower satisfaction with appearance [140]. Further negative consequences concern mood. For example, reduced sleep duration implies increased reactive aggression. A survey among 2499 African American individuals reported that who sleeps on average less than 5 hours per night is nearly three times more likely to loose his temper and engage in a physical fight [184]. Although sleep is an essential factor for the human being, it is still not clear how sleep quality can be measured and predicted, what is the role of genetic and environmental factors in determining ideal sleeping patterns and how much sleep is optimal. According to Roenneberg, one of the reasons for this lack of understanding stems from the fact that most of what we know about sleep comes from laboratory studies and not from real life [155].

The goal of this Chapter is to present the results of an experimental study conducted in a real life scenario, in collaboration with the University of Copenhagen

Table 9.1: Some representative measures of the sleep domains according to [157].

Sleep Quantity	Sleep Quality	Sleep Architecture	Sleep Schedule
- Sleep duration - Daytime sleep duration - Night-time sleep duration - True sleep time (excluding wakefulness during sleep period)	- Awakenings during sleep - Sleep efficiency - Events of disordered breathing during sleep (e.g. snoring, apnea) - Unique expressions during sleep (parasomnias)	- Amount or proportion of slow-wave sleep stages - Amount or proportion of REM sleep stages - Spectral distribution of EEG during sleep	- Sleep onset time - Morning rise time - Distribution of naps - Estimates for circadian (24h) rhythmicity

(Denmark) [1]. Such a study has been approved by a relevant ethic committee [85] and involves 16 healthy users: 10 students and 6 working women, wearing Basis Peak. The data acquired during the trial have been processed in order to perform a first behavioural analysis and to identify the sleep habits of the monitored users in the long term. Moreover, some parameters have been detected in the literature in order to assign a first "naive" score and, in the future, determine the sleep quality.

9.1 Sleep quality parameters: literature survey

Currently, one of the most used method for the sleep quality evaluation is the Pittsburgh Sleep Quality Index (PSQI), a questionnaire containing 19 self-rated questions and 5 questions rated by the room-mate or partner. They refer to several aspects, such as sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleep drugs, daytime dysfunction and subjective sleep quality [31].

Although its spreading, PSQI is based on subjective data, that may be influenced by biases. For this reason, our purpose is to identify objective parameters. From an objective point of view, Sadeh affirms that the sleep is characterized by five domains: duration, quality, brain activity patterns, sleep architecture, schedule or circadian aspects [157]. Excluding brain activity patterns, that exploit sophisticated clinical instrumentation, some measures representing the remaining domains are listed in Table 9.1.

[1]Department of Computer Science (DIKU), Human-Centred Computing (HCC) section.

In order to understand objective parameters which describe sleep quality, it is necessary to understand the characteristics of normal sleep. According to Carskadon and Dement, the sleep of a normal human adult is structured as follows [36]: it enters through Non-Rapid Eye Movement (NREM) sleep, in particular stage 1 sleep persists for only 1-7 minutes, followed by stage 2 which continues for approximately 10 to 25 minutes. After that, stages 3 and 4 last respectively for few minutes and 20-40 minutes. A series of body movements usually signals an ascent to lighter sleep stages, i.e. stages 3 and 2, and precedes the first Rapid Eye Movement (REM) episode. During the night NREM and REM sleep continue to alternate every 90 minutes in a cyclic fashion. The 90-min cycle is repeated 5-6 times at night [198].

It is important to point out that sleep stages 1 and 2 are also called with the term *light sleep*, while stages 3 and 4 are are called *deep sleep* or *slow-wave sleep*.

Despite numerous studies in progress, sleep medicine has not defined a standard for the evaluation of sleep quality. Some non clinical solutions attempted to address such an issue, investigating just a part of the domains. For example, a solution based on an upper harm strap exploits only the slow-wave sleep stages to assess sleep quality [124]. The authors affirm that the deep sleep is the most important sleep stage and, therefore, its percentage is considered as the main parameter. Further aspects, such as sleep fragmentation, efficiency and duration have been considered by Glenn *et al.* for older adults [101]. In such a case, the sleep quality has been evaluated by averaging the scores of each parameter; in particular, the fragmentation score has been multiplied by -1 so as higher scores represent better sleep quality. Participants have been classified as having:

- good sleep quality based on fragmentation ≤ 25, efficiency ≥ 85, and duration ≥ 420 min;
- poor sleep quality based on fragmentation ≥ 40 and efficiency ≤ 75, or duration ≤ 360 min;
- average sleep score the remaining individuals.

This study compares the measures of sleep quality obtained through the PSQI and by means of a smartwatch. The results suggest that perceived sleep quality is quite different from objective reality, at least for adults older than 55.

Dafna *et al.* presented a contact-less method based on audio record analysis for sleep quality assessment, considering five parameters [51]:

- Total Sleep Time (TST): overall duration of sleep stages;

- Sleep Latency (SL): time that elapses between going to bed and falling asleep;
- Sleep Efficiency (SE): ratio between TST and total time in bed;
- Wake Time After Sleep Onset (WASO): overall duration of awakenings during sleep;
- Awakening Index (AI): average number of awakenings per hour.

These parameters are not combined to obtain a single sleep score value, but evaluated separately.

Additional parameters have been considered in [78]:

- SE;
- SL;
- Number of Awakenings (NA);
- WASO;
- Periodic Limb Movement Index (PLMI);
- Stage 1 percentage (S1);
- Stage 2 percentage (S2);
- Stage 3 and 4 percentage (S34);
- REM Percentage (RP);
- REM Latency (RL);
- Respiration Disturbance Index (RDI);
- Snoring Index (SI).

In this case, authors use different sensors to obtain the desired information, for example: ECG sensor, actimeter, oximeter and microphone. The value generated by combining these 12 parameters is called Total Sleep Index (TSI), however, the formula used to calculate it is not explicitly reported in the paper.

Table 9.2: Fields characterizing each minute of data acquisition.

Field title	**Type**	**Description**
datetime	string	date and time in the *yyyy-mm-dd HH:MM:SS* format
skin_temp	double	skin temperature in ^oF
air_temp	double	air temperature in ^oF
hertrate	double	heart rate in *bpm*
steps	integer	number of steps
gsr	double	galvanic skin response in $\mu S/cm$
calories	double	calories burned
act_type	string	physical activity type (walk, run, bike or an empty string)
sleep_type	string	sleep type (light, deep, rem, interruption, unknown or an empty string)
toss_turn	string	"toss_and_turn" or an empty string

9.2 Experimental study description

Sleep analysis rely on a commercial wearable device: Basis Peak. Basis Peak is a smartwach able to minute-basis measure:

- physiological data, such as HR, Galvanic Skin Response (GSR), and skin temperature;
- environmental data, i.e. air temperature;
- steps and calories.

It can also monitor and classify physical and sleep activities.

Such information are periodically sent to the associated smartphone through the Bluetooth technology to be processed and stored. Moreover, a web platform and a smartphone interface are provided in order to access personal information. Data can be exported as CSV files. Particularly, there is a file for each participation day, and a row for each minute of acquisition. A row is characterized by 10 fields, as shown in Table 9.2.

As regards reliability, Basis claims to have validated its sleep staging technology through polysomnography data [143]. A comparative evaluation performed by Jovanov [91] involving three different devices, i.e. Basis Peak, Zephyr Bioharness 3, and SOMNOscreen+, indicates that it provides sufficient performance in physiological monitoring, while a study conducted by Stahl *et al.* demonstrates its accurate measurement of HR during walking and running activities [175].

The trial was held in Copenhagen from mid November 2015 to mid July 2016. It involves 10 students, 8 males and 2 females, between 18 and 30 years old, and 6 working women, of which only one has no children. A summary of the information available for each subject is shown in Table 9.3. Some people have a smaller number of days since they left the trial before its end for different reasons; for example, subject 18 (S18) left on January because of technical problems, while S19 experienced an allergic reaction to the smartwatch's materials.

Data collection is achieved by means of qualitative and quantitative methods. Qualitative methods comprise an entry survey at the pilot beginning, and Day Reconstruction Method (DRM) [92] once per week. Quantitative data collection involves, instead, Basis Peak data and data obtained by means of a smartphone application, called mQoL-log. It is a measurement-based tool for the minute-based collection of user's geographical location, network connectivity details, phone/SMS usage patterns, running and used applications, and user touches of the screen [186]. In this context, my research focuses mainly on the analysis of sleep activity, exploiting the information acquired by the smartwatch.

9.3 Data analysis

Raw data have been analysed, obtaining different graphs and statistics in order to better understand the information acquired so far. Specifically, a first analysis concerns the calculation of the average values for each field of interest, subsequently a study on sleep habits has been done, identifying usual bedtime and wake time, sleep duration and distribution. Finally, by means of a thorough analysis of the literature, some sleep quality parameters have been identified and calculated for each night.

Physical activities Basis Peak can detect and classify physical activities. Specifically, it can recognize walking, running and biking. The average minutes spent in each activity by all subjects are summarized in Fig. 9.1. It is interesting to note that the monitored subjects are not used to run, but some of them usually go biking, especially in weekdays. As well known, Copenhagen is the City of Cyclists [71], so it is not unusual for its inhabitants to move by a bicycle.

Table 9.3: Summary of information available for each subject.

Subject	**Dataset**	**Additional info**	**Participation days**	**Percentage of data collected**
2	working woman	1 children, lives with a partner, pregnant	249	79%
3	working woman	2 children, lives with a partner	239	92%
4	working woman	2 children, lives alone	212	28%
5	working woman	4 children, 2 away from home, lives with a partner	52	96%
8	working woman	childless, lives with a partner	213	59%
10	working woman	2 children, lives alone	183	41%
11	student	master's student in Physics, age between 25-30	241	95%
12	student	undergraduate in Computer Science, age between 18-24	249	84%
13	student	undergraduate in Computer Science, age between 18-24	250	86%
14	student	master's student in Games, age between 25-30	245	96%
15	student	undergraduate in Computer Science, age between 18-24	249	84%
16	student	undergraduate in Computer Science, age between 18-24	215	72%
17	student	undergraduate in Computer Science, age between 18-24	251	78%
18	student	undergraduate in Computer Science, age between 18-24	90	91%
19	student	undergraduate in Computer Science, age between 18-24	51	78%
20	student	master's student in Pharmacy, age between 18-24	250	96%

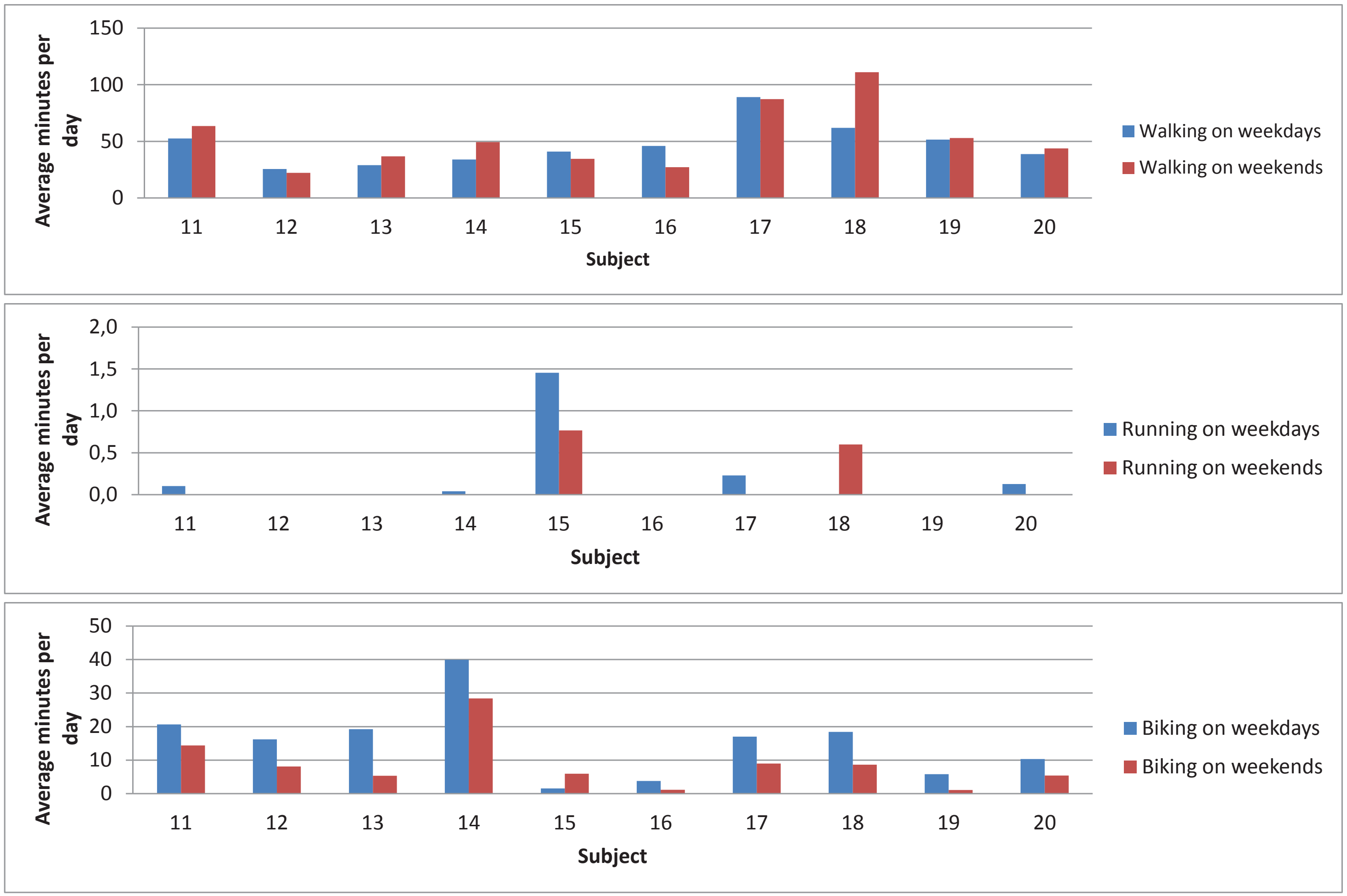


Figure 9.1: Daily average minutes spent in each activity by subjects on weekends and weekdays.

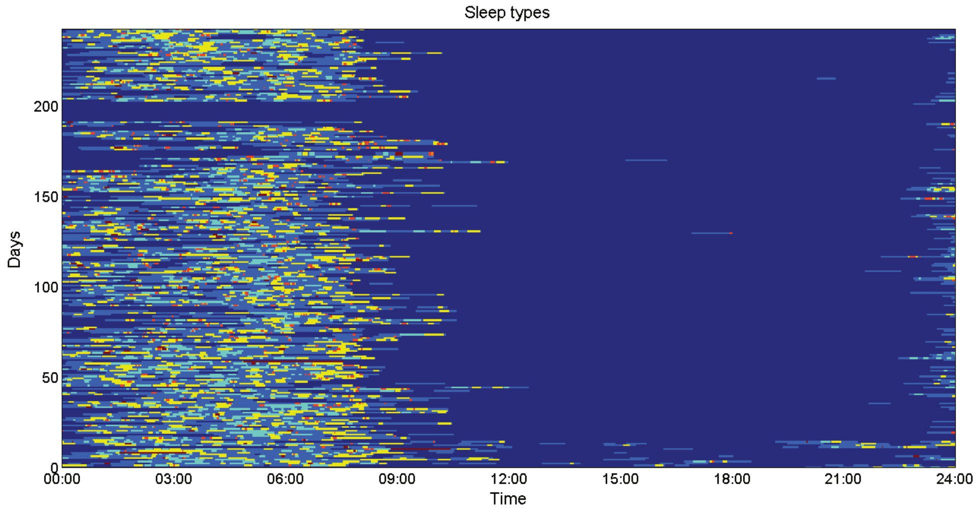


Figure 9.2: Sleep activity representation of S11; the sleep phases are represented with a different colour: light sleep is light blue, deep sleep is cyan, REM sleep is yellow, interruption is orange and unknown is dark red.

Sleep types As shown in Table 9.2, Basis Peak is able to classify sleep types. As an example, Fig. 9.2 presents for each acquisition day the sleep activity of subject 11 (S11): it shows also the information on the sleep types, colouring them differently. In Table 9.4, the percentage of light, deep and REM sleep, compared with the total sleep, is reported. The latter has been obtained as the sum of these three sleep types. The interrupted sleep occurs when a subject wakes up for few minutes and, for example, goes to the bathroom, and then goes back to sleep. Thus it has not been considered as sleep time. Also unknown sleep has not been considered in this calculation. In fact, the unknown values represent the cases in which the Basis Peak's onboard algorithm is unable to interpret the physiological measures and to classify the type of sleep.

In Table 9.5, the overall sleep duration on weekends and on weekdays is summarized for each user. The latter, provides also the p-values resulting from the ANalysis Of VAriance (ANOVA) test. They show that just two individuals present a statistically significant difference ($p - value < 0.05$) between hours of sleep on weekends and on weekdays. This means that the major part of monitored subjects sleeps on weekdays as much as on weekends. Moreover, most of them sleep less than recommended (7-9 hours for adults and young adults [84]), more specifically: 62% on weekdays and 56% on weekends.

Heart rate For each user, the average HR both while awake and asleep have been calculated. As an example, Fig. 9.3 presents the graph of S11. The blue line repre-

Table 9.4: Percentage of light, deep and REM sleep respect the total sleep both on weekdays and on weekends.

Subject	Weekdays			Weekends		
	Percentage of light sleep	**Percentage of deep sleep**	**Percentage of REM sleep**	**Percentage of light sleep**	**Percentage of deep sleep**	**Percentage of REM sleep**
2	59%	19%	23%	60%	17%	22%
3	58%	19%	23%	59%	19%	22%
4	49%	25%	26%	53%	25%	23%
5	61%	18%	21%	61%	17%	22%
8	58%	19%	22%	61%	18%	22%
10	56%	19%	24%	56%	19%	24%
11	64%	15%	21%	64%	15%	21%
12	51%	24%	25%	54%	22%	24%
13	63%	17%	20%	63%	16%	21%
14	60%	18%	22%	62%	17%	21%
15	61%	17%	23%	62%	16%	22%
16	58%	18%	23%	57%	19%	24%
17	62%	16%	22%	61%	17%	22%
18	56%	20%	24%	55%	22%	23%
19	59%	18%	24%	57%	20%	22%
20	58%	20%	23%	59%	18%	23%

Table 9.5: Average sleep duration for each subject on weekends and weekdays.

Subject	**Average sleep duration on weekdays**	**Average sleep duration on weekends**	**p-value**
2	6 h 33 m	6 h 47 m	0.463
3	6 h 50 m	7 h 4 m	0.389
4	7 h 22 m	5 h 48 m	0.058
5	5 h 58 m	8 h 16 m	**0.00004**
8	6 h 46 m	6 h 38 m	0.902
10	6 h 9 m	6 h 13 m	0.907
11	6 h 37 m	6 h 17 m	0.257
12	7 h 24 m	7 h 28 m	0.834
13	5 h 48 m	6 h 15 m	0.850
14	7 h 15 m	7 h 58 m	0.300
15	7 h 29 m	7 h	0.231
16	6 h 4 m	6 h 12 m	0.737
17	6 h 14 m	5 h 40 m	**0.041**
18	7 h 28 m	7 h 39 m	0.731
19	7 h 7 m	6 h 7 m	0.534
20	6 h 48 m	7 h 5 m	0.233

sents the average HR while he is asleep, conversely the red line represents the average HR rate while awake. Comparing this values with the corresponding periods, and with weekdays and weekends, a clear relationship appears, as shown in Fig. 9.4.

The total average heart rates for each subject, considering all days and excluding the empty ones, are shown in Table 9.6. Observing the table, it is evident that during the sleep the heart rate is lower than during the wakefulness, as expected [107]. Furthermore, in this table, the results of ANOVA test between weekdays and weekends values is provided: statistic differences ($p-value < 0.05$) between weekdays and weekends are highlighted in bold. Few subjects have statistically significant differences while awake, and, in most cases (i.e. S5, S12, and S16), they indicates a lower HR on weekdays, probably due to more relaxing activities. On the contrary, during the sleep, the average HR values are significantly different for many users, and for all of them the weekend values are higher than weekday ones. Despite not knowing exactly what users do on weekends, it is easy to assume that the average HR's increase is due to alcohol consumption. In fact, Spaak *et al.* show the dose-related effects of alcohol consumption on the heart rate, through a trial of 13 volunteers. While the aftermaths of a single drink are negligible, two drinks causes an heart rate increase of 5.7 ± 1.6 bpm [164]. Even smoking or be exposed to second-hand smoke may cause

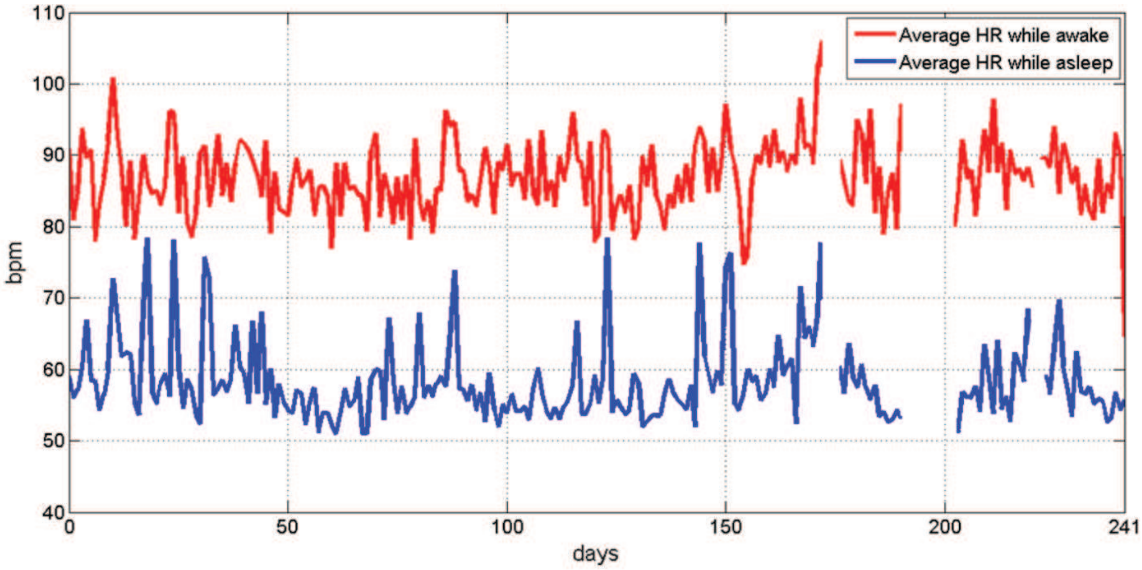


Figure 9.3: Daily average HR of S11, while asleep (blue line) and awake (red line).

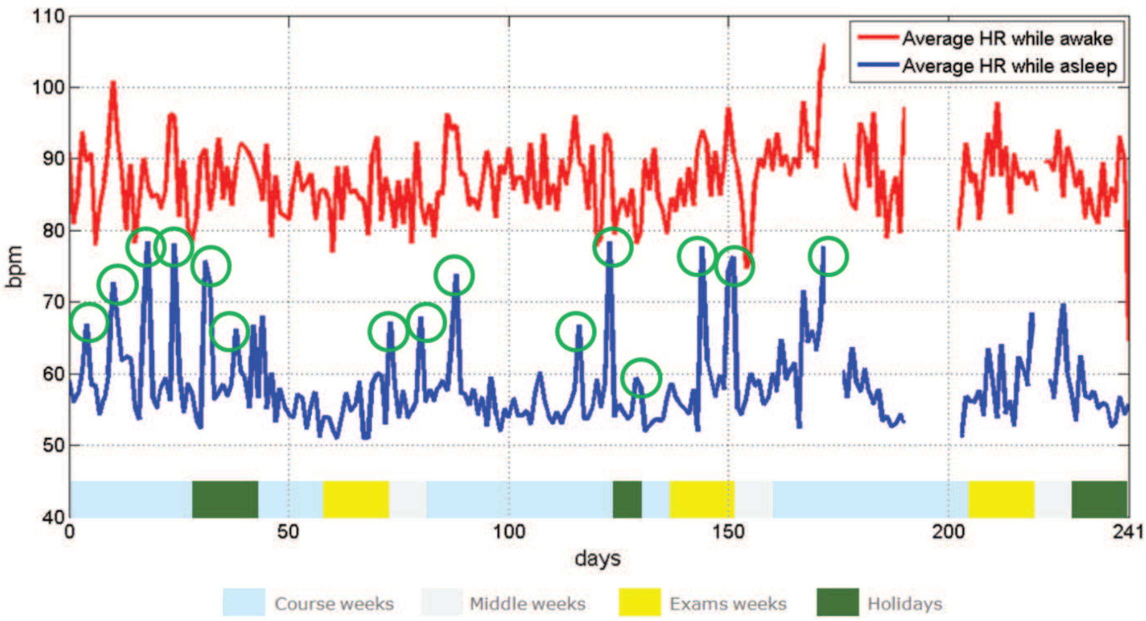


Figure 9.4: Daily average HR of S11: the clear relationship between nocturnal peaks and weekends is highlighted with green circles.

Table 9.6: Average HR for each subject while asleep and awake, differentiated by weekends and weekdays.

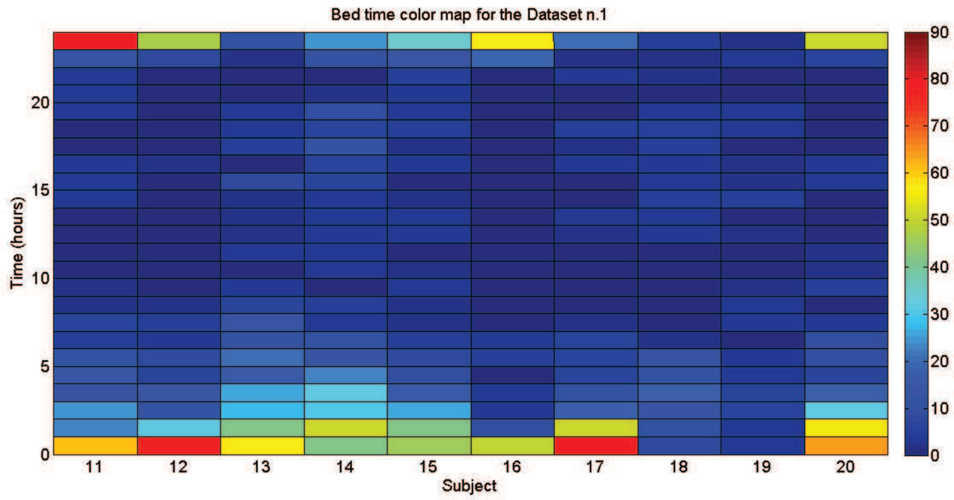
Subject	Weekdays		Weekends		ANOVA test results	
	HR while awake	HR while asleep	HR while awake	HR while asleep	p-value of HR while awake	p-value of HR while asleep
2	92,88	73,39	93,13	74,47	0,678	0,324
3	91,25	71,39	91,70	72,51	0,405	0,060
4	85,43	56,55	83,67	57,44	0,505	0,480
5	73,67	60,65	70,63	61,74	**0,012**	0,420
8	79,51	56,88	80,01	60,71	0,741	**0,002**
10	84,03	59,50	83,34	59,40	0,728	0,941
11	86,55	56,91	87,82	62,03	0,091	**0,000000003**
12	80,70	57,35	78,32	61,72	**0,008**	**0,00000003**
13	79,23	54,90	80,33	62,09	0,852	**0,0000003**
14	84,16	57,35	89,20	64,21	**0,000001**	**0,000000000005**
15	80,21	62,52	81,92	66,93	0,161	**0,0002**
16	81,61	63,47	78,46	62,02	**0,002**	0,215
17	83,14	60,73	82,80	63,75	0,729	**0,021**
18	93,26	57,90	98,28	69,07	**0,010**	**0,00003**
19	90,37	74,09	91,83	75,08	0,447	0,745
20	86,93	53,84	85,36	57,50	0,115	**0,00003**

an HR increase [59].

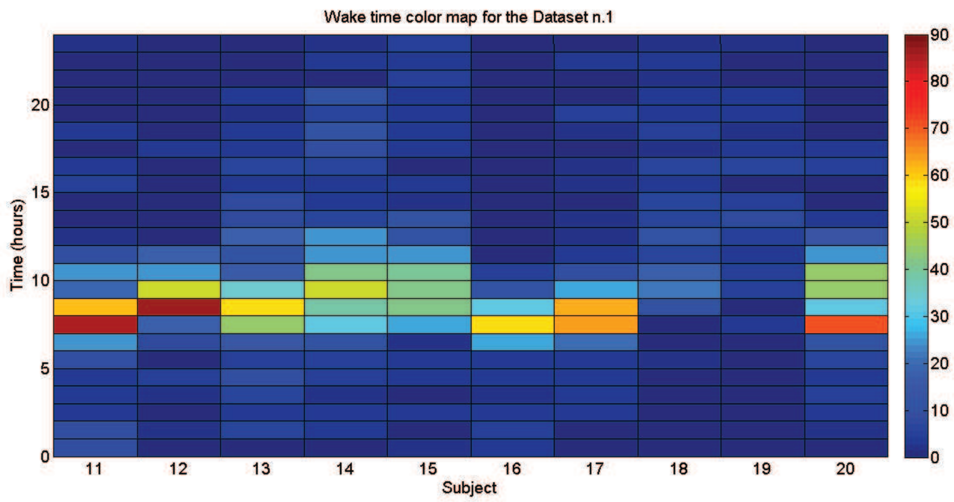
Bedtime and Wake-time The sleep type data provided by the Basis Peak can be seen as a binary signal, in which the value "0" corresponds to the absence of a label in the "sleep_type" field and the value "1" corresponds to its presence. Differently from the sleep analysis performed in Section 7.4 through a pressure sensing mat, in this case, a sleep observation is represented by a sequence composed by at least a 1 and followed by a 0. It is characterized by a start-time and an end-time, which correspond respectively to bedtime and wake-time.

As depicted in Fig. 9.2, night sleep is usually fragmented into several chunks. For this reason and in order to consider just one bedtime per night, the data have been filtered unifying the near sleep observations, i.e. whose distance is less than 90 minutes. Such a gap has been classified as unknown sleep.

Figs. 9.5 show for each hour the number of bedtime and wake time instances for students, while Figs. 9.6 show similar graphs for working women. The graphs point out that some people tend to wake up and to go to sleep every morning at the same



(a) Bedtime

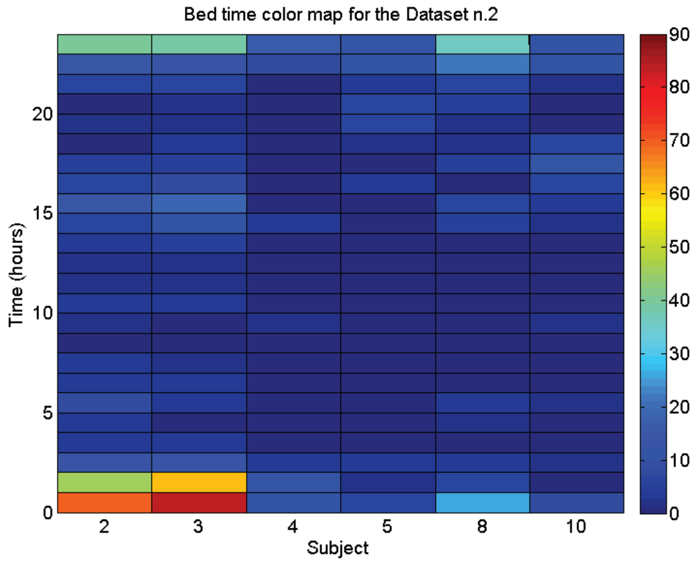


(b) Wake-time

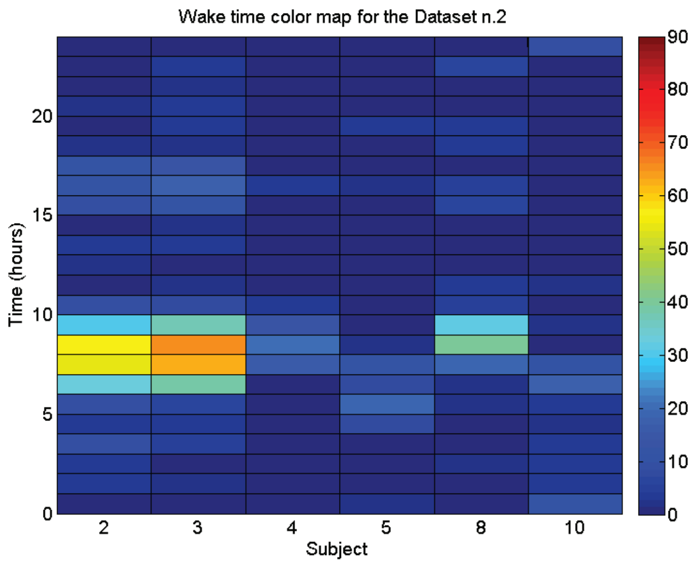
Figure 9.5: Bedtime and wake time for students: the color indicates the number of bedtime and wake time instances in the relative time slot.

time (e.g., subject 11 and 12), while others have a less regular life (e.g., subject 14 and 15). However, in general, the women use to go to sleep and wake up slightly before than students.

Sleep distribution In order to obtain the sleep probability, all the rows of the original files in which the "sleep type" field is equal to "light", "deep", "REM" or "unknown" string have been considered. For each minute of the day, the sleep instances have been summed and then divided by the total number of days. Figs. 9.7 shows respectively the results for students and working women. Moreover, two differ-



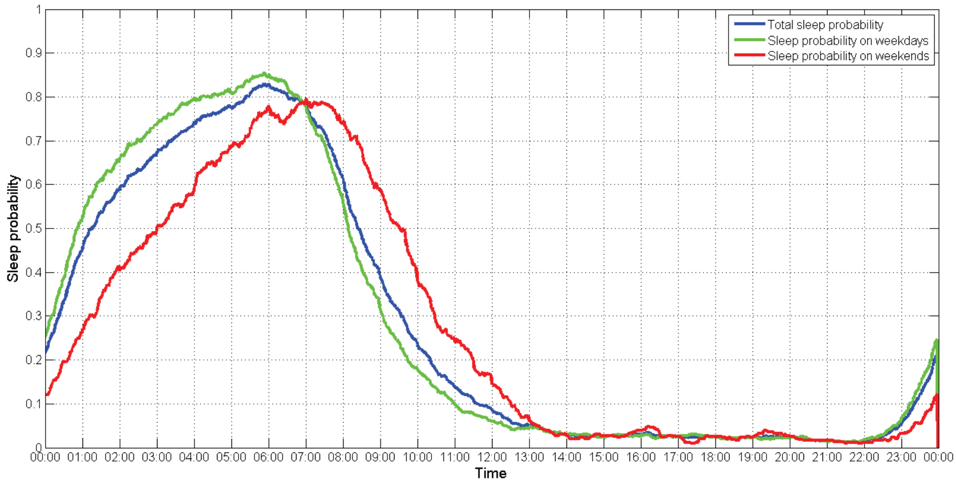
(a) Bedtime



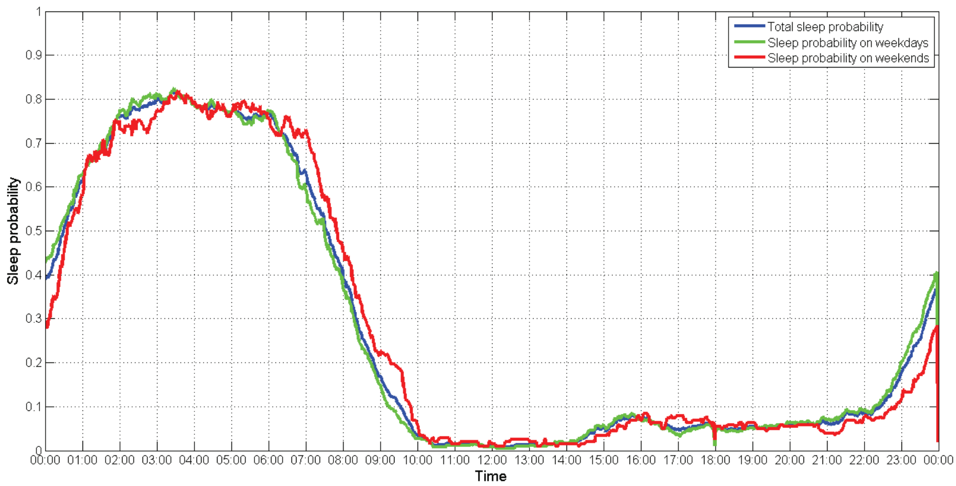
(b) Wake-time

Figure 9.6: Bedtime and wake time for working women: the color indicates the number of bedtime and wake time instances in the relative time slot.

ent probability distributions have been traced for weekends (red line) and weekdays (green line), showing a significant horizontal translation of the resulting curves, especially for students. That means that students use to go to bed and wake up about one or two hours later on weekends, while working women just half an hour.



(a) Students



(b) Working women

Figure 9.7: Probability distribution of sleep per minute: total sleep (blue line), sleep on weekdays (green) and weekends (red line).

Sleep quality assessment Even though a standard for the sleep quality assessment has not been defined yet, some parameters were selected from the literature, in order to understand if the sleep of the monitored subjects corresponds to the optimal sleep.

Since in this case information on breathing and movement of the limbs are not available, just some parameters listed in Section 9.1 have been considered. The chosen parameters and their optimum values are reported in Table 9.7.

Basis Peak is able to distinguish just light, deep and REM sleep, thus S1 and S2 are merged together. In the following we will refer to them as S12.

Table 9.7: Sleep quality parameters and corresponding optimum values chosen from the literature.

Parameter	**Optimal Value**	**Description**	**Reference**
TST	$7-9$ hours	The amount of actual sleep time	[198]
NA	< 10	Number of awakenings during night	[78]
WASO	< 15	Total time spent awake during the sleep period time	[78]
S1	$1-5\%$	Percentage of the stage 1, based on total sleep time (TST)	[83]
S2	$\sim 50\%$	Percentage of the stage 2, based on total sleep time (TST)	[83]
S34	$10-20\%$	Percentage of the stages 3 and 4, based on total sleep time (TST)	[78]
RP	$20-25\%$	Percentage of the stage REM, based on total sleep time (TST)	[83]
RL	$\sim$ 90 minutes	The interval from sleep onset to the first appearance of stage REM sleep	[78]
Num of Cycles	$5-6$	Number of NREM-REM cycles alternating through the night in cyclic fashion	[198]
Avg Duration of Cycle	$90-120$ minutes	Average time duration of a NREM-REM cycle through the night	[83]

For each night, the values of selected parameters have been calculated and a first "naive" score has been assigned to it. We considered only the sleep observations whose total duration is more than 120 minutes. The TST value has been obtained by summing the durations of the three types of sleep, excluding interruptions and unknown sleep; while WASO and NA have been obtained calculating duration and number of interruptions. S12, S34, RP are respectively percentages of light, deep and REM sleep whit respect to TST. REM latency represents, instead, the time interval between the start time of the sleep observation and the first REM sleep record. Lastly, NREM-REM cycles have been identified by looking for deep-REM sleep sequences, except for the last cycle that could not contain the deep sleep. Their average duration is the ratio between the total sleep duration and number of cycles.

The "naive" score indicates how many values correspond to the optimal, and can be calculated by summing a "1" for each fulfilled condition. The evolution over the

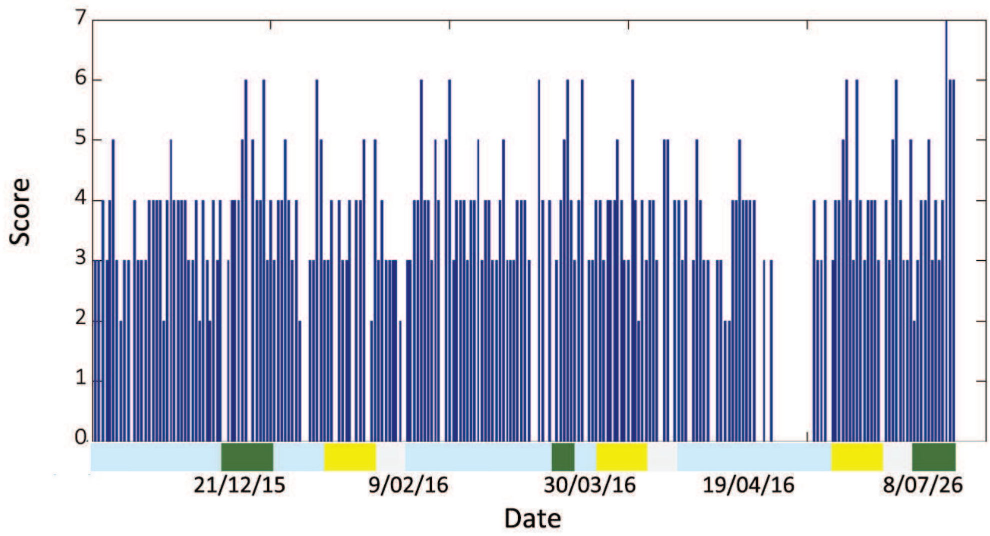


Figure 9.8: Naive score for each night of S11.

time of the S11's sleep scores is shown in Fig. 9.8 for each acquisition day (labeled as in Fig. 9.3), while a summary of fulfilment percentages is provided in Table 9.8 for all subjects.

The table shows that some parameters are fulfilled rarely, for example RL, while others, such as WASO and NA present higher percentages. This is due to the fact that many subject presents high percentages of light sleep at the beginning, moving forward in time the REM sleep.Furthermore, they wake up at most a couple of times during the night, so NA and WASO fulfilments are quite high.

Looking at the graph it is evident that the score never reaches the maximum value, i.e. 9, but it is mostly about 3 or 4. This may be due to the fact that some of these parameters are related. For example, deep, REM and light sleep percentages are linked together with the following formula:

$$S12 + S34 + RP = 100 \tag{9.1}$$

Thus, we can consider just two of them. Likewise, the average duration of a cycle (adc) is related to total sleep time and number of cycles (nc),:

$$adc = \frac{TST}{nc}. \tag{9.2}$$

In Fig. 9.15, a different score has been obtained excluding Stage 1 and 2 percentage (S12) and average duration of cycles for subject 11. In this case, the average score on weekends is 4.26, while on weekdays is 4.42.

Table 9.8: Percentage of fulfilment for each selected parameter and for each subject.

	TST	**S34**	**S12**	**RP**	**RL**	**WASO**	**NA**	**Num of cycles**	**Avg duration of cycle (min)**
S2	38%	87%	78%	92%	13%	94%	100%	20%	23%
S3	40%	86%	77%	94%	13%	92%	100%	23%	24%
S4	40%	53%	53%	86%	12%	91%	100%	35%	33%
S5	24%	85%	82%	94%	9%	91%	100%	6%	6%
S8	52%	88%	84%	97%	17%	86%	100%	34%	19%
S10	46%	85%	79%	90%	10%	100%	100%	33%	31%
S11	38%	88%	69%	83%	14%	94%	100%	21%	23%
S12	65%	56%	47%	85%	9%	83%	100%	45%	31%
S13	31%	85%	78%	84%	21%	96%	100%	5%	18%
S14	36%	84%	76%	90%	24%	86%	100%	22%	22%
S15	42%	86%	80%	87%	9%	87%	100%	17%	12%
S16	54%	86%	73%	82%	14%	100%	100%	21%	18%
S17	31%	86%	72%	88%	24%	94%	100%	9%	18%
S18	35%	67%	67%	97%	22%	94%	100%	14%	28%
S19	33%	83%	81%	89%	3%	97%	100%	8%	17%
S20	42%	77%	63%	87%	17%	98%	100%	26%	24%

Figs. 9.9-9.24 show the sleep score calculated with a subset of parameters for all subjects (the acquisition days are labeled as in Fig. 9.3). While Table 9.9 reports the average sleep scores for all subjects both on weekends and on weekdays.

Even though such a score gives us an indication on the number of parameters corresponding to optimal, it does not represent a quality score. To evaluate the quality of sleep we must understand which of these parameters has a higher weight. Unfortunately this topic is still much debated and, as already mentioned, there is no standard for the evaluation of objective parameters able to establish the quality of sleep. Further researches are foreseen in order to achieve a more efficient scoring method and thus to assess the sleep quality score.

9.4 Discussion

The study presented in this Chapter demonstrates how to acquire data through wearable devices could be extremely useful in order to recognize habits and behaviours. In this case, the wearable is a commercial smartwatch able to collect physiological and contextual information and to recognize and classify sleep and physical activities.

Table 9.9: Average score (in percentage) for all subjects in weekends and weekdays.

Subject	**Average score on weekdays**	**Average score on weekends**	**p-value**
2	63.6	63.7	0.9566
3	63.5	65.2	0.4109
4	60.7	55.8	0.4598
5	57.7	61.9	0.4234
8	68.1	67.0	0.7336
10	65.0	70.0	0.3763
11	63.2	60.9	0.3194
12	64.1	62.2	0.4077
13	61.1	58.3	0.1937
14	64.0	60.9	0.1942
15	61.6	59.8	0.411
16	64.7	66.8	0.4794
17	63.0	57.8	**0.0205**
18	62.1	58.6	0.2787
19	57.7	63.5	0.1888
20	63.7	63.6	0.9772

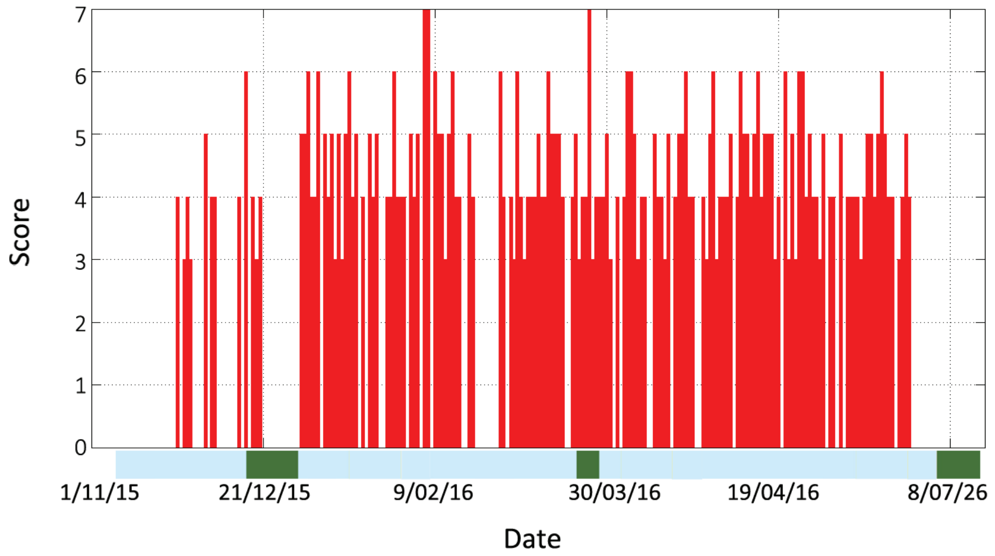


Figure 9.9: Naive score for S2 calculated considering a subset of parameters for each night.

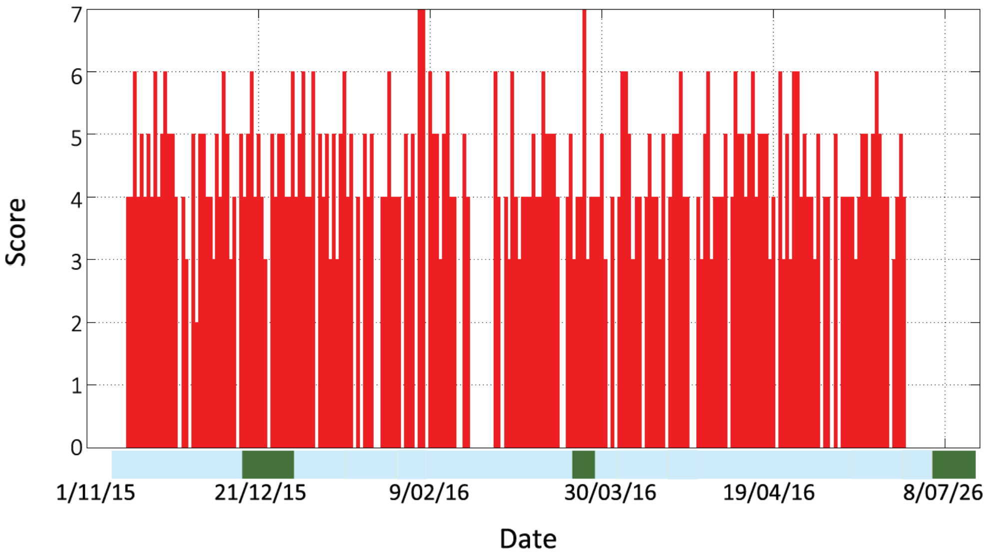


Figure 9.10: Naive score for S3 calculated considering a subset of parameters for each night.

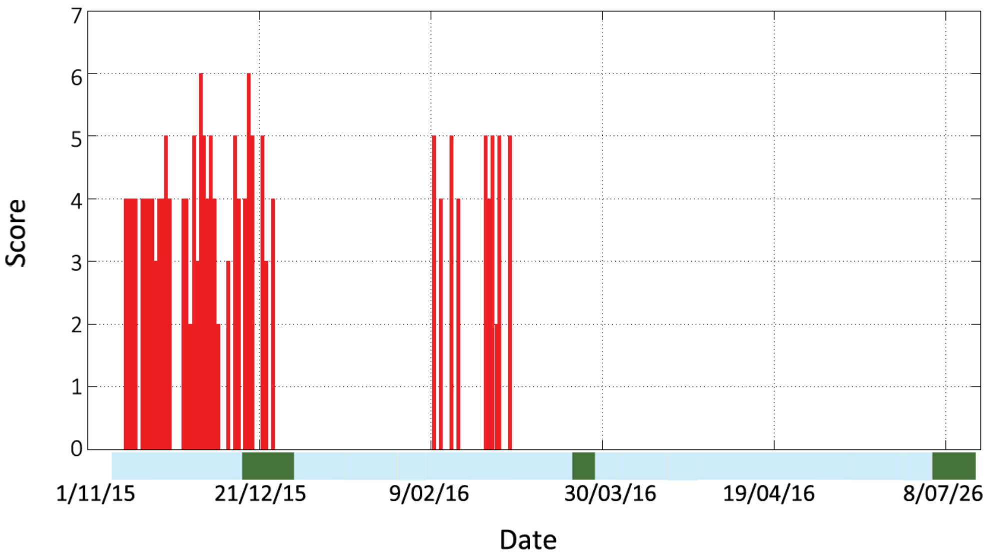


Figure 9.11: Naive score for S4 calculated considering a subset of parameters for each night.

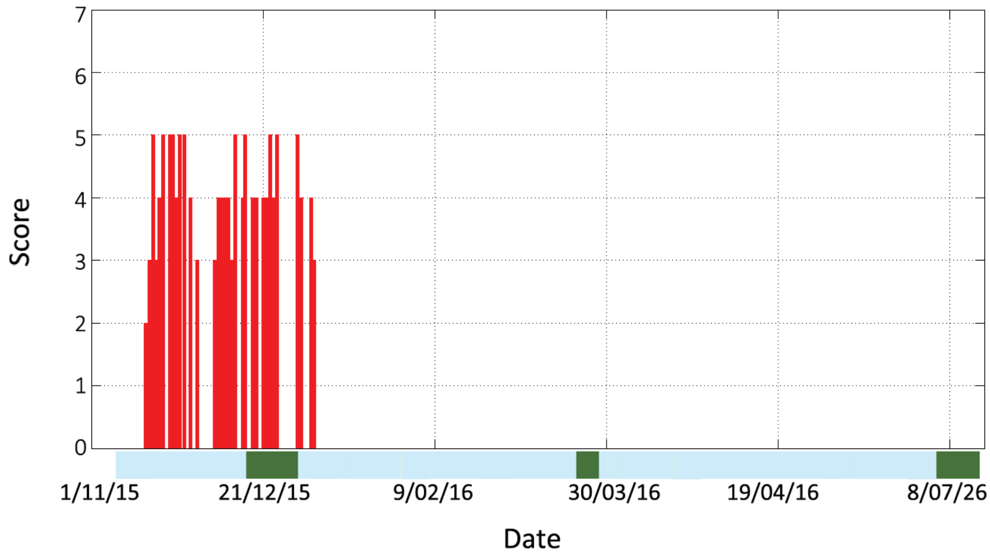


Figure 9.12: Naive score for S5 calculated considering a subset of parameters for each night.

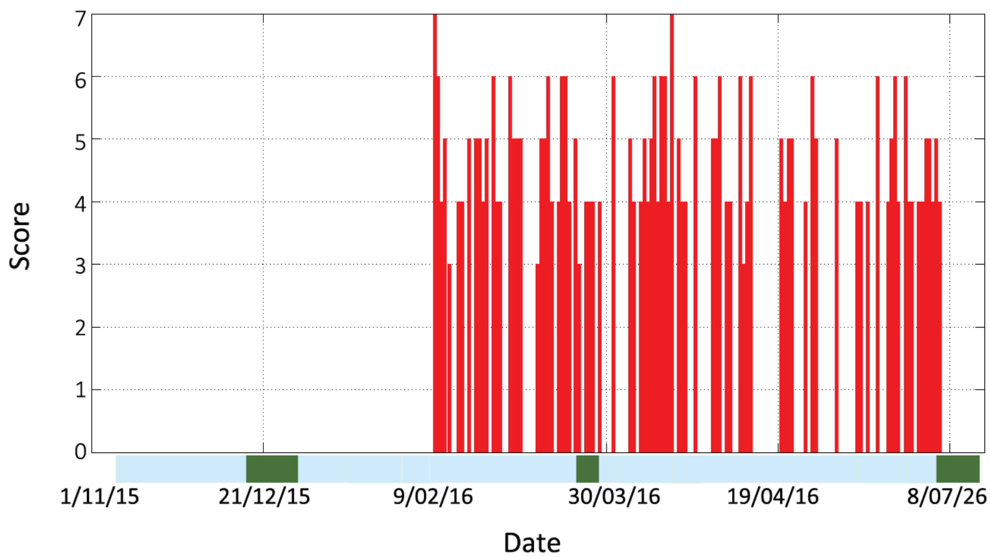


Figure 9.13: Naive score for S8 calculated considering a subset of parameters for each night.

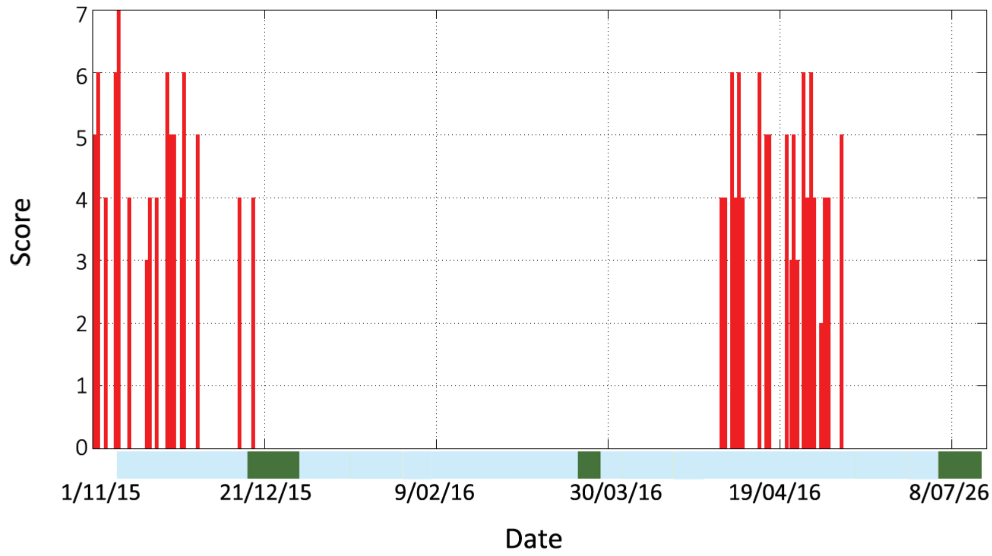


Figure 9.14: Naive score for S10 calculated considering a subset of parameters for each night.

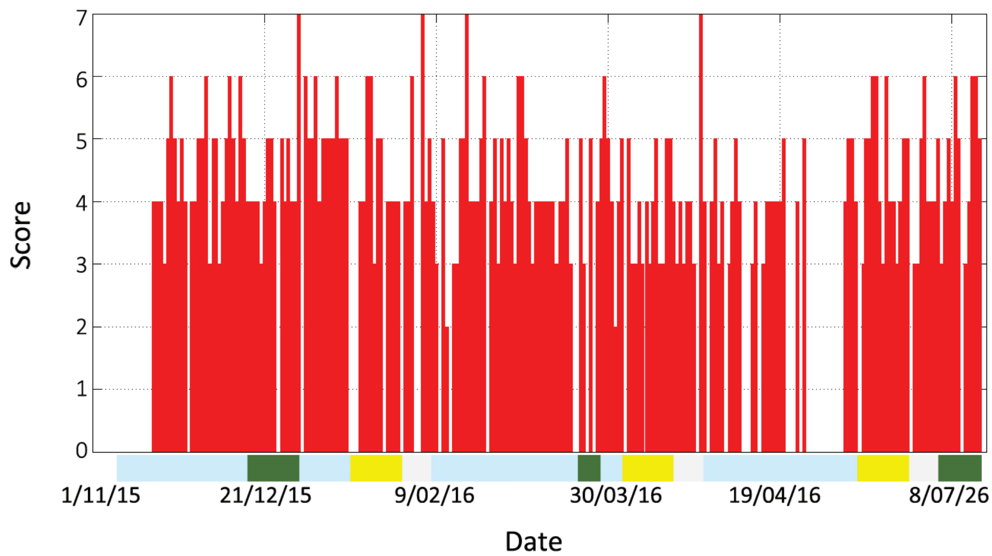


Figure 9.15: Naive score for S11 calculated considering a subset of parameters for each night.

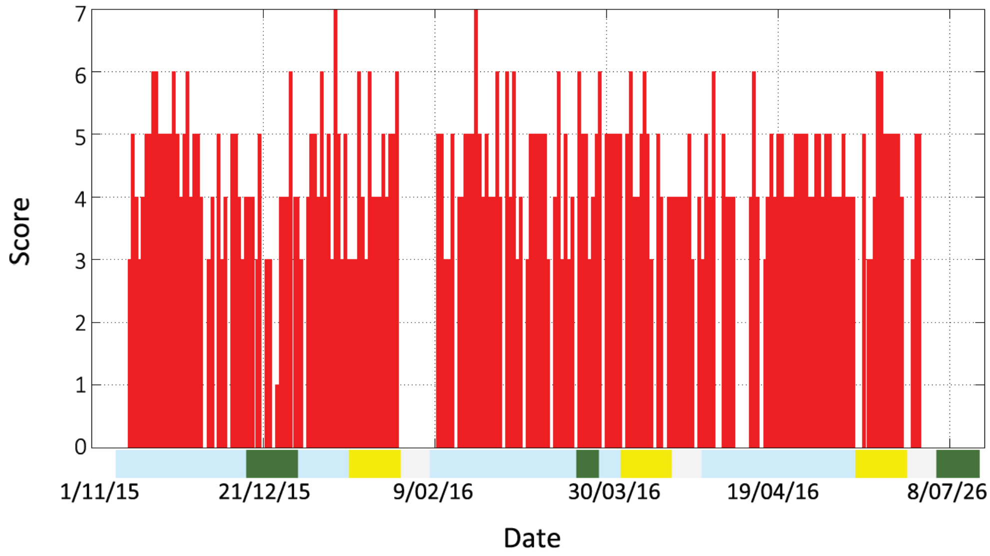


Figure 9.16: Naive score for S12 calculated considering a subset of parameters for each night.

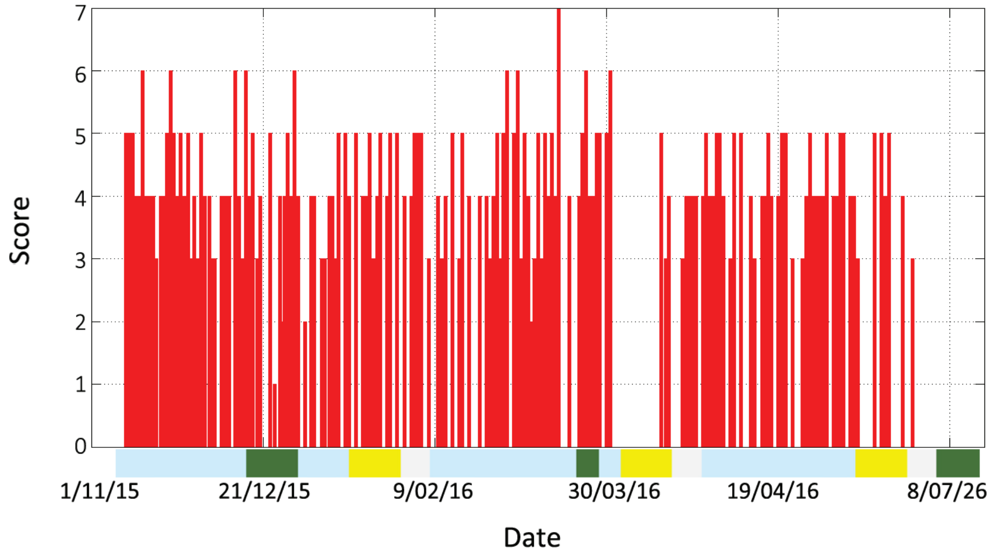


Figure 9.17: Naive score for S13 calculated considering a subset of parameters for each night.

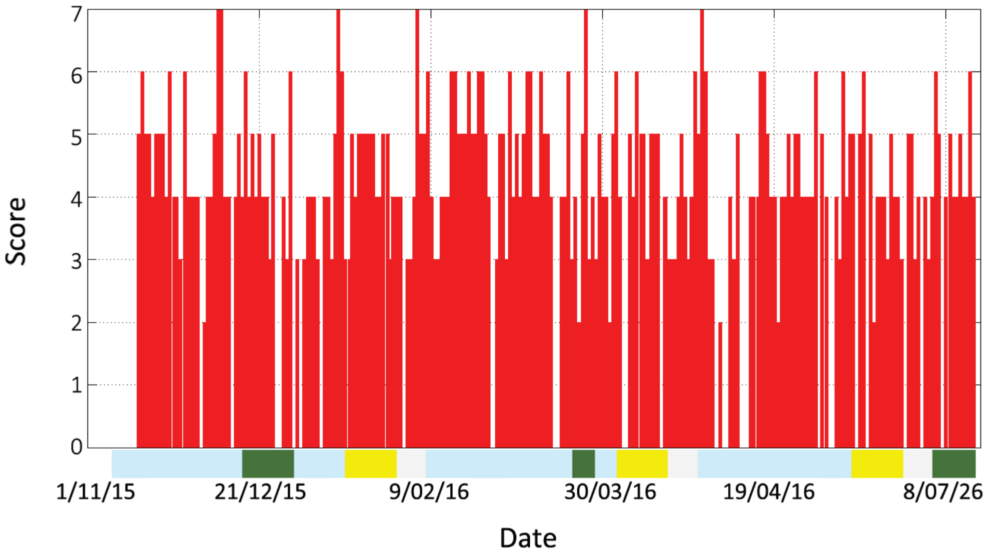


Figure 9.18: Naive score for S14 calculated considering a subset of parameters for each night.

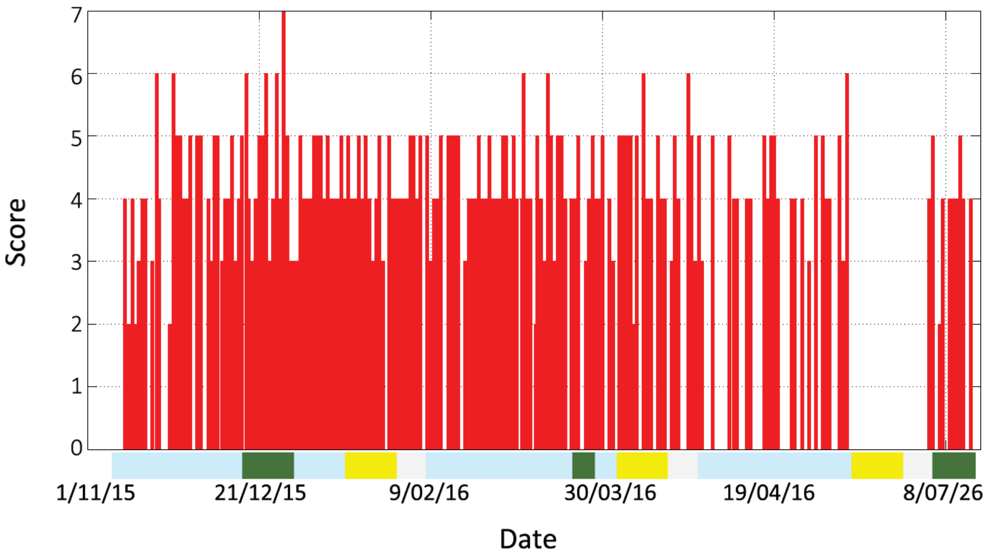


Figure 9.19: Naive score for S15 calculated considering a subset of parameters for each night.

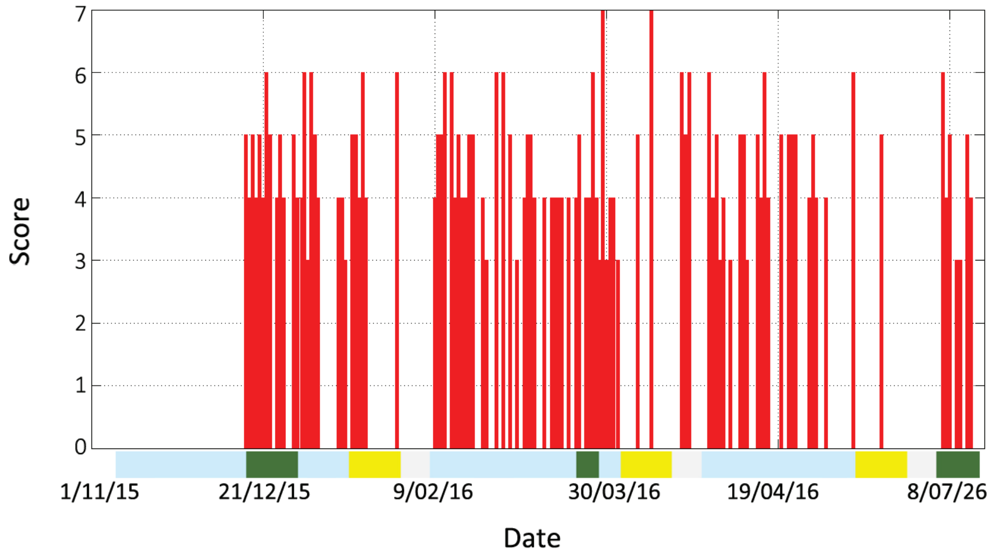


Figure 9.20: Naive score for S16 calculated considering a subset of parameters for each night.

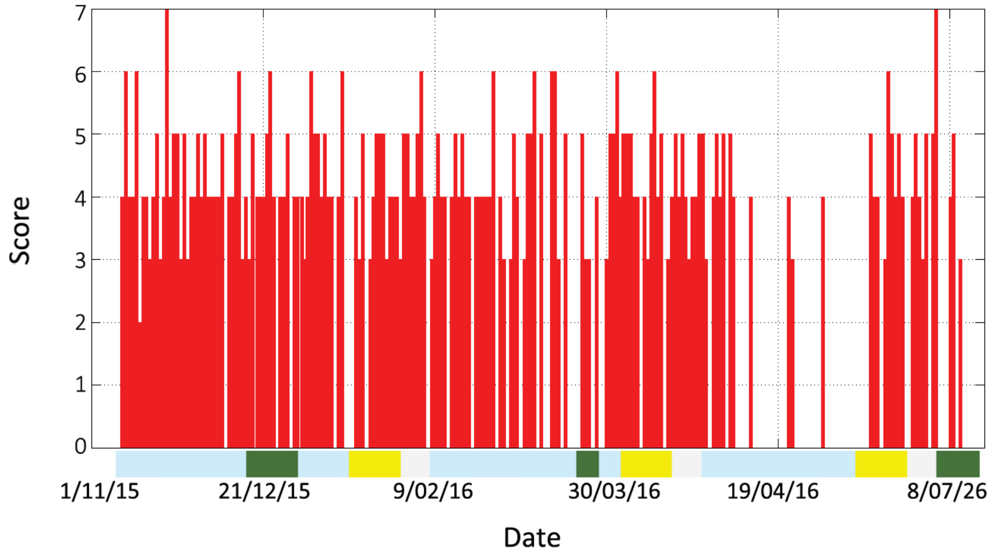


Figure 9.21: Naive score for S17 calculated considering a subset of parameters for each night.

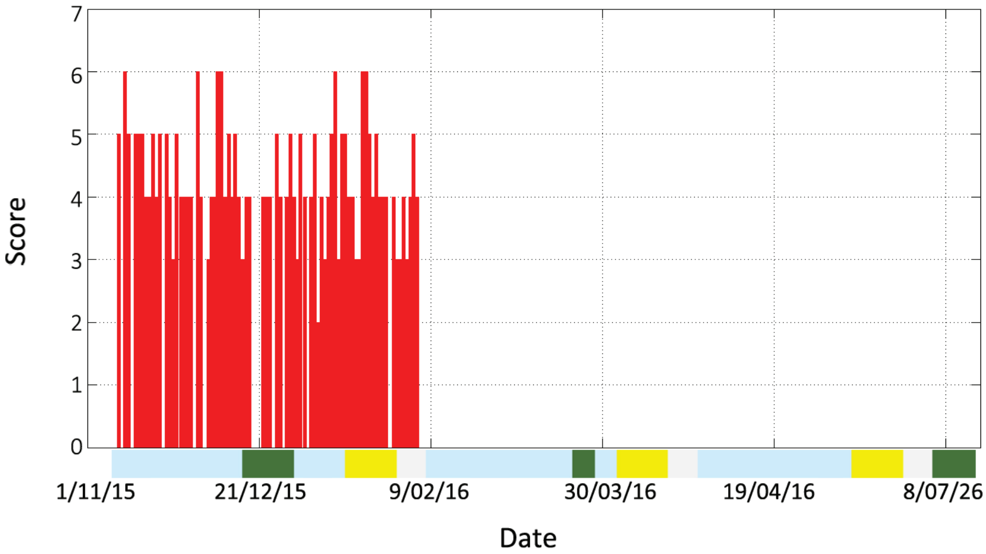


Figure 9.22: Naive score for S18 calculated considering a subset of parameters for each night.

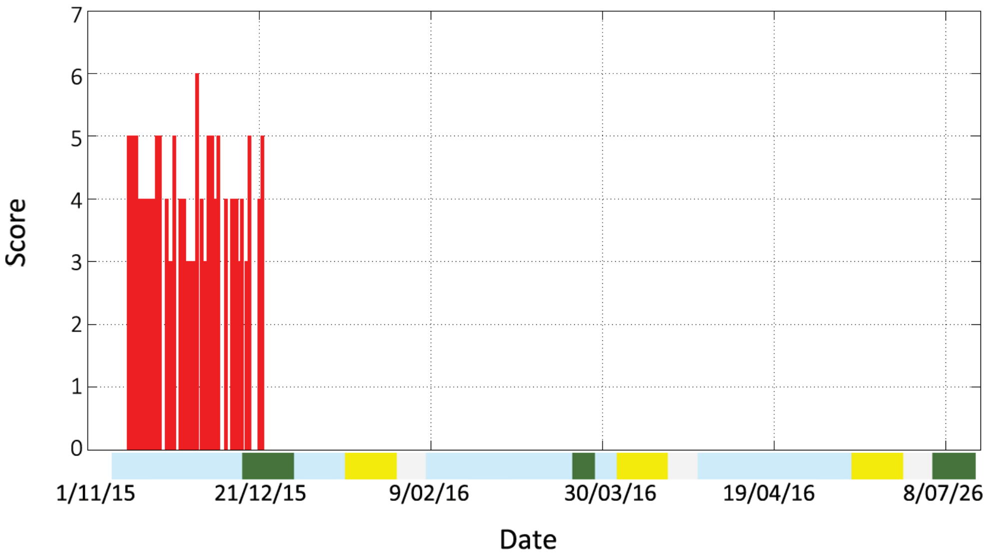


Figure 9.23: Naive score for S19 calculated considering a subset of parameters for each night.

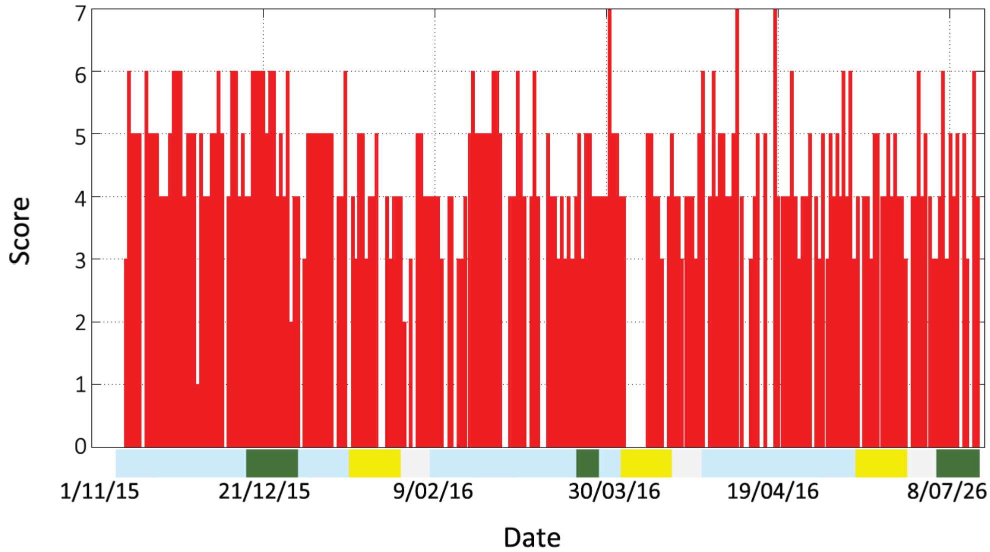


Figure 9.24: Naive score for S20 calculated considering a subset of parameters for each night.

In order to understand which information can be retrieved by such a device, 16 healthy subjects, divided in students and working women, have been monitored for 8 months. One of the main results of the trial is the identification of the sleep habits of both types of users. Usual bedtime, wake time, and hours of sleep have been calculated. Students usually go to sleep between 23:00 and 02:00 and wake up at 07:00-10:00. Similarly, working women fall asleep between 23:00-02:00 and wake up at 08:00-09:00. Anyway, both types of users sleep in general less than recommended. Nevertheless, the most interesting aspect that emerged from the study is that the major part of subjects usually have alcohol, smoke or other exciting substances before sleep on weekends. It can be easily deduced just by observing the HR during sleep in the long term. Specifically, the 56% of monitored subjects, that is the 80% of students and 17% of women, usually have alcohol on weekends, before sleep. Moreover, students use to go to sleep few hours later on weekends compared to weekdays, differently from working mothers.

In order to classify good and bad sleep, a first "naive" score has been assigned to each night. However, future developments foresee a more detailed study of the state of the art, further investigation on sleep quality assessment, and more refined classification and machine learning algorithms.

Chapter 10

Conclusions

10.1 Summary and discussion

The home environment is decisive for active ageing and, more in general, for users' well-being. Technologies supporting their living environment can be very useful, especially for frail, disabled and elderly people, allowing them to continue to live comfortably in their own homes. However, without a careful selection of devices and a proper system design, the benefits may not meet the real user needs. In fact, learning the functioning of a new system can be stressful and undesirable for those who are not technologically skilled. The aim of this thesis is to show how, through a careful analysis of requirements and a proper design, simple smartphone applications can contribute to make user-accessible the AmI, increasing its QoL.

Mobile devices, thanks to their inherent attributes, such as portability, richness of sensors and wireless communications interfaces, represent key tools for both interfacing the underlying system, and acquire data. To this aim, the research has mainly divided into two parts: the first part concerns the study of the state of the art, requirements analysis and identification of guidelines, while the second part presents the use cases designed and developed by the author.

As regards the use of the smartphone as a interfacing system towards smart living environments, the criteria of acceptability and usability identified in the literature have been deeply described and discussed, both for vision-based and touch-based interfaces. To support this study, different use cases, designed and developed during the PhD course, have been described in Chapters 5, 6, and 7. They were realized taking into account the target users' needs and respecting the guidelines identified in the literature. In particular, a CV-based application for interfacing disabled people with the external environment is presented in Section 5.1. It is a low cost and low complexity solution aimed at facilitating social relations, via virtual keyboard and speech synthesizer, and controlling the house, interacting with the home automation system. Section5.2 describes a system for access control which exploits face recognition techniques. More specifically, liveness detection issue have been faced for anti-spoofing purposes. Chapter 6 discusses the TRASPARENTE project, an integrated platform for telecare and AAL aimed at prolonging independent living of the elderly at home. In this scenario, research work focuses on the design and development of a touch screen interface tailored to the needs of the elderly person, in order to control the home automation system, monitor the status of some sensors and help the user in the management of drug therapy. As regards HCIs, the last use case is the UpTech project and its evolutions (see Chapter 7). It consists in a kit for the monitoring of PwD and AD patients at home. Such a system allows the caregiver to receive alarm notifications, limiting the care burden and improving its QoL.

A further research field concerns the development of applications for behavioural data collection through wearable devices. The behavioural analysis can be very useful in well-being and AAL contexts, since it allows to conduct an analysis in the long term, and to identify improvements or deteriorations in health status. First, an analysis of requirements and challenges has been discussed in Chapter 8, referring to the existing literature, then two different use cases has been presented. The former relies on an architecture for the acquisition of motion data by means of intelligent shoes. The system uses the smartphone as a gateway to connect the shoes with the local server. Design choices and challenges have been discussed, from the requirements analysis to the prototype realization.

The last case study, presented in Chapter 9, regards the sleep monitoring through a commercial smartwatch device. A pilot study has been conducted for 8 months, involving 16 healthy subjects, 10 students and 6 working women. First analysis provide promising results: through a statistical approach we have been able to identify sleep habits, such as usual bedtime, wake time, hours of sleep, and parties on weekends. Furthermore a "naive" score has been assigned to each sleep observation in order to evaluate how much it is close to optimum.

Although not all use cases are effectively tested in a real life scenario, however, the obtained positive results demonstrate that smartphone applications, supported by proper architectures, can be very helpful in the home environment, on the one hand interfacing the user with the AmI technologies, and on the other hand, enabling the acquisition of behavioural data by means of wearable devices.

10.2 Impact

The research work conducted in this doctoral thesis deals with real problems, concerning the applicability of existing technologies in everyday life. In particular, it focuses on the use of a widely spread low-cost device that offers countless possibilities: the smartphone.

A thorough survey of the literature shows that a proper design of the technological solution can positively influence its real adoption, especially when dealing with elderly or disabled people. Applications and systems developed by the author have confirmed the theory, showing that the smartphone can actually provide considerable benefits, making the technology more user-friendly in the various use cases presented.

The criteria identified and the methods adopted are applicable to real practical problems and can be used by anyone who wishes to create a system in the AAL and wellbeing fields, both from academy and industry.

10.3 Future work

As previously discussed, first experimental results have delivered positive results, even if field tests has not been provided for all projects. Future development foresees to verify functions and systems presented so far, in realistic scenarios, involving target subjects. Additionally, usability and acceptability test campaign should be set for some applications, in order to demonstrate that the requirements identified in the literature are sufficient and appropriate to users' needs.

As regards the behavioural analysis, a major improvement would be obtained by integrating the information obtained from the wearable devices with those derived by the onboard sensors and from the analysis of interactions with the smartphone. Such analysis, however, does not fit to all types of users, but only to those which have a significant number of interactions with the mobile device over the day.

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Acronyms

AAL Ambient Assisted Living

AD Alzheimer's Disease

ADL Activity of Daily Living

AI Awakening Index

AmI Ambient Intelligence

ANOVA ANalysis Of VAriance

API Application Programming Interface

AR Augmented Reality

BCI Brain-Computer Interfaces

BLE Bluetooth Low Energy

CBI Caregiver Burden Inventory

CSV Comma-Separated Values

CV Computer Vision

DB Database

DRM Day Reconstruction Method

ECG Electrocardiogram

EMA Ecological Momentary Assessment

FSR Force Sensing Resistor

GPS Global Positioning System

GSR Galvanic Skin Response

GUI Graphical User Interface

HCI Human-Computer Interaction

HR Heart Rate

HTTP Hyper-Text Transfer Protocol

ICT Information and Communication Technology

IE Intelligent Environment

IoT Internet of Things

M2M Machine-to-Machine

MQTT Message Queuing Telemetry Transport

NA Number of Awakenings

NFC Near Field Communication

NREM Non-Rapid Eye Movement

OS Operative System

PLMI Periodic Limb Movement Index

PoC Proof of Concept

PSQI Pittsburgh Sleep Quality Index

PwD People with Dementia

QoL Quality of Life

QoS Quality of Service

RDI Respiration Disturbance Index

REM Rapid Eye Movement

RL REM Latency

RP REM Percentage

S1 Stage 1 percentage

S2 Stage 2 percentage

S12 Stage 1 and 2 percentage

S34 Stage 3 and 4 percentage

SE Sleep Efficiency

SH Smart Home

SI Snoring Index

SL Sleep Latency

TCP Transmission Control Protocol

TSI Total Sleep Index

TST Total Sleep Time

UI User Interface

VBI Vision-based Interfaces

VoIP Voice over IP

WASO Wake Time After Sleep Onset

WHO World Health Organization

WSN Wireless Sensor Network

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