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Monitoring indoor human activities for Ambient Assisted Living

by

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Contents

Abstract

At the end of the 20th century, Ubiquitous Computing and Ambient Intelligence were introduced as a vision of the future society. In this context, the paradigm of Ambient Assisted Living (AAL) has allowed the evolution of methods, techniques and systems to improve everyday life, by supporting people in both physical and cognitive aspects, especially in case of the so-called "fragile people". The state-of-the-art research develops means for vital data measurements, for recognizing activities and inferring whether a self-care task has been performed. These results are obtained through the simultaneous presence of different technologies deployed into physical environments in which people live.

The monitoring of human activities is fundamental to enable the AAL paradigm. For instance, people spend sleeping several hours a day, thus monitoring this activity is fundamental in understanding and characterizing a person's sleep habits. On the other hand, at daytime, several indoor activities can be inferred by knowing the exact position of a subject. In this view, the main goal of this thesis is the proposal of advancements in the field of both daytime and night-time monitoring of human activities, focusing on indoor localisation and sleep-monitoring as key enablers for AAL.

Regarding Indoor Positioning Systems (IPSs), the lack of a standardized benchmarking tool and of a common and public dataset to test and to compare results of IPSs is still a challenging open issue. Advancements in this direction can lead to improve the performance evaluation of heterogeneous systems, and, consequently, to obtain improvements of the IPSs. Some steps have been made towards introducing benchmarking tools, for example, through the introduction of the EvAAL framework, that defines tool and metrics usable

for comparing both real-time and offline methods. This thesis contributes by proposing (i) some improvements to the EvAAL benchmarking framework, especially considering real-time smartphone-based positioning systems; (ii) presenting a common, public, multisource and multivariate dataset, gathered using both a smartwatch and a smartphone, to allow researchers to test their own results. Then, this thesis focuses on both single-device and multiple-device localisation. Concerning single-device positioning strategies, several smartphone-based systems have been recently presented, based on data gathered from smartphone built-in sensors, though with performances not completely satisfactory. In this view, the thesis proposes a novel approach based on deep convolutional neural networks, in order to improve the use of the pedometer (one of the main smartphone built-in sensors used in IPSs) e consequently the Pedestrian Dead Reckoning algorithm performances. Finally, we extend the concept of a single-device localisation to several devices in indoor environments. Localising multiple devices into the same environment can lead to detect, for example, social behaviour and interaction. Several systems try to reach the goal in AAL scenarios, but using an intrusive and expensive ad-hoc infrastructure. Instead, we propose a novel approach for finding the presence of people in indoor locations, through a cheap technology as Wi-Fi probes, demonstrating the feasibility of this approach.

Regarding the sleep monitoring problem, recent findings show that sleep plays a critical role in reducing the risk of dementia and preserving the cognitive function in old adults. However, state-of-the-art techniques for understanding the sleep characteristics are generally difficult to deploy in an AAL scenario. This suggest that more effort should be spent to find sleep monitoring systems able to detect objective sleep patterns and, at the same time, easy to use in a home setting. In this thesis we propose a system able to perform the human sleep monitoring in an unobstrusive way, using force-sensing resistor sensors placed in a rectangular grid pattern on the slats, below the mattress; it can also detect human bed postures during sleep sessions and to identify patient movements and sleep stages, an information particularly useful, for instance, to assure the pressure ulcer prevention.

The proposed advancements have been thoroughly evaluated in the laboratory and in real-world scenarios, demonstrating their effectiveness.

Acronyms

Acronym	**Meaning**
AAL	Ambient Assisted Living
ADLs	Activities of Daily Living
AI	Ambient Intelligence
CSD	Consensus Sleep Diary
DTW	Dynamic Time Warping
FSR	Force Sensing Resistor
ICT	Information and Communications Technology
ILSs	Indoor Localization Systems
IMU	Inertial Measurement Unit
IoT	Internet Of Things
IPS	Indoor Positioning System
KSQ	Karolinska Sleep Diary
LBS	Location-based services
LoS	Line-of-Sight
NIOM	Non-Intrusive Occupancy Monitoring

Acronym	**Meaning**
PDR	Pedestrian Dead Reckoning
PIR	Passive Infrared Motion Sensor
PSG	Polysomnography
PSQI	Pittsburgh Sleep Quality Index
RCSQ	Richards-Campbell Sleep Questionnaire
REM	Rapid Eye Movement
RFID	Radio Frequency Identification
RSSI	Received Signal Strength Indication
SE	Sleep Efficiency
SOL	Sleep Onset Latency
SWS	Slow Wave Sleep
TST	Total Sleep Time
UWB	Ultra Wide Band
WASO	Wake After Sleep Onset
WSN	Wireless Sensor Networks

Chapter 1

Introduction to Ambient Assisted Living

Ubiquitous Computing and Ambient Intelligence (AI) were introduced in 1991 as a vision of the future society [1]. Simultaneously to the introduction of ubiquitous computing, the technological evolution has been more effective and pervasive.

Nowadays, according to the dominant role of computers in people's lives, we can benefit of intelligent interfaces displaced in every human context, (for instance, furniture, devices, or clothes), and supported by networking technologies. As a consequence, many services have been introduced, in order to try to make these objects able to react with people and environments. Furthermore, in the last decade, efforts were spent to create unobtrusive solution able to interact with people in a transparent manner. The interaction between smart devices, environment, and people are often defined into a Smart Environment. Nowadays, Smart Environment paradigm is applied on several and different scenarios and contexts (i.e. smart city, smart industry, smart health, smart home). Basically, the idea behind these scenarios is the same: applying advanced technology and computing resources to support individuals in their daily routines, tasks and operations. This wide range of possibilities has attracted a huge participation and interest of researchers and industries.

A typical scenario, called Ambient Assisted Living (AAL), is composed of both the Smart Home and the Smart Health scenarios. On one hand,

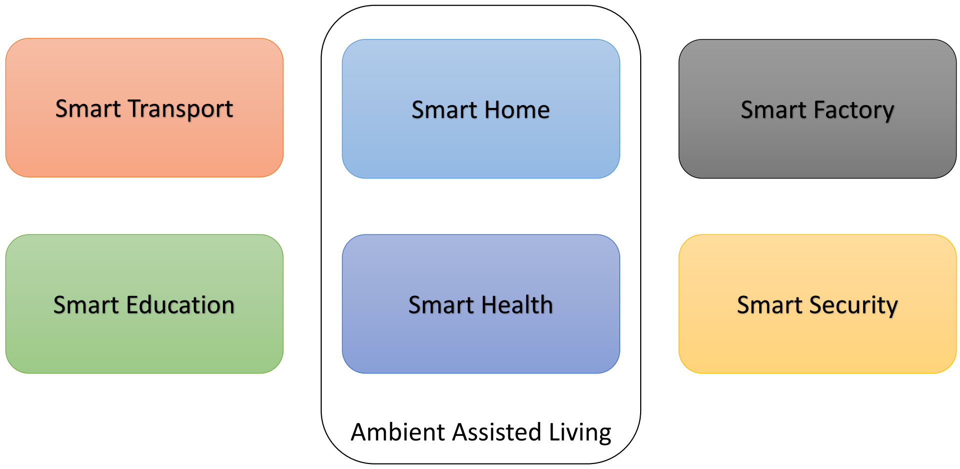


Figure 1.1: Ambient Assisted Living and typical smart scenarios.

Ambient Intelligence into a Smart home scenario, may be seen as a layer on the top of domotics. The purpose of Ambient Intelligence is to create integration between isolated devices, based on network protocols, and to make interoperability capabilities. Figure 1.1 shows a graphical representation of AAL and typical smart scenarios.

The presence of intelligent systems that support long-term monitoring of selected behaviours and, more generally, human well-being, can prevent the emergence of illnesses or pathological situations related to unhealthy buildings or bad user's habits like sedentariness, absence of socialization, and nutritional issues. Wireless Sensor Networks (WSN) Intelligent systems can be used to complement or replace human observers altogether, and while they may convey a slight sense of surveillance, this perception is likely reduced as sensors get smaller and smaller, and consequently less obtrusive.

On the other hand, Ambient Intelligence into the Smart Health context provides solutions to improve the health management, especially of the elderly or chronically sick people, providing short and long term monitoring. In fact, with a continuously increasing percentage of old population, interventions to preserve health, and tools to assist people, are urgently needed. Such needs require to identify old people at greatest risk of adverse health events.

In fact, old adults are often the ones who experience frailty and vulnerability.) subset [2]. Many old people experience age-related losses in different domains of functioning (i.e., loss of mobility, vision, cognitive abilities, or social contacts), which can lead to a complex mixture of problems. Mobility issues and losses in the user's social network can result in social isolation; furthermore, several chronic conditions can cause low physical fitness and a depressed mood. Such issues increase the risk of adverse outcomes, such as unsuccessful ageing, inadequate use of health care, hospitalization, decrease in social activities, dependence on others, caregiver burden, lower levels of well-being, and, ultimately, death [3]. To this regard, in September 2011 [1], the European Commission has published an interesting book, titled "e-Health Projects. Research and Innovation in the field of ICT for Health and Well-Being: an overview", containing a collection of European projects focused on various approaches on this research field. Furthermore, the European research program H2020 Societal Challenge 1 (Health, demographic change and well-being) contains many calls for the study and the development of ICT tools for Health technologies, with the clear objective of promoting an easy technology transfer to the people, especially to the elderly. Consequently, nowadays it is common to denote this trend using the "Active and Healthy Aging" label and, in this field, the European commission has set the goal to reach increasing life expectancy and to allow a more independent life for older adults.

In conclusion, AAL can be described as the collection of concepts, products and services that combine new technologies and social environment to improve the quality of life for people in all the phases of life. AAL is an important component for addressing the challenges of the demographic evolution performed by the so-called "aging society". In fact, by using assistive technologies, people can reach and maintain good level of Productivity and health, both at home and at work. Essentially, AAL uses new technologies combined with social services to extend the part of life when people are productive (at work) and independent (at home), and also to improve the quality of life for people in need of care (e. g. with chronic diseases). Figure 1.2 shows an partial overview of existing and future application fields involving the AAL

[1]http://ec.europa.eu/digital-agenda/en/news/ehealth-projects-research-and-innovation-field-ict-health-and-wellbeing-overview

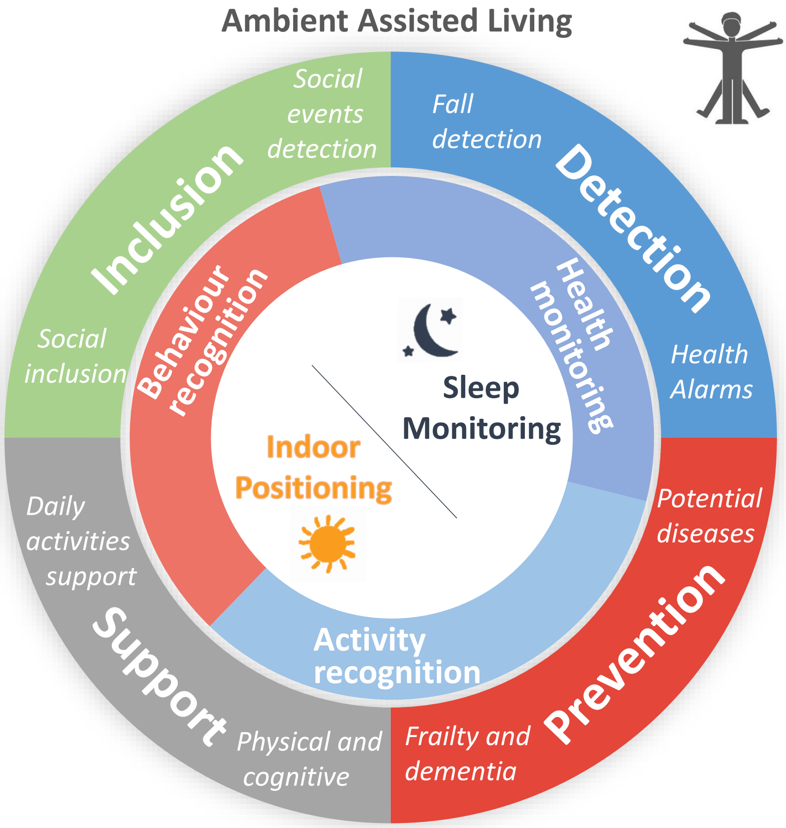


Figure 1.2: An overview of the application and services in AAL paradigm

paradigm, visualizing how almost all the services in this scenario can become interconnected, and highlighting the approach proposed in this thesis.

AAL systems are particularly useful for old people but, in general, the AAL vision can be extended to all people with special needs. The Ambient Assisted Living Association categorises users into primary, secondary and tertiary users:

- Primary end-users are old adults who are using AAL solutions.
- Secondary end-users are families, friends, organisations that are related to the primary end-users. Also in this case, people benefits directly and

Factors influencing technology acceptance	Factors influencing the need for technology
Costs	User generation / cohort
Compliance with individual needs	Housekeeping style
Personal experience with technology usage	Number and type (partner, children) of inhabitants in household
Accessibility barriers (physiological, cognitive)	Personal attitude towards technology

Table 1.1: Factors promoting technology use

indirectly from AAL products and services.

- Tertiary end-users are mainly public organisations and institutions that play a role in providing or enabling AAL services.

An important aspect to consider, regarding the primary end-users, is that despite younger people's perceptions, seniors' use of technology is the rule rather than the exception. As reported in [4], seniors (age 65 to 75) report an average of 19 to 31 interactions per day with their daily appliance, including computers and devices. In general, elderly users are considered less inclined to accept new technology than younger people. Typically, the reason is the motivation. In fact, if they are motivated to use new technological solutions – because the benefits are clearly perceived – this inclination changes. Table 1.1 shows factors that can promote acceptance of new technologies or not. The most important predictor in terms of technology acceptance is the interest in innovation. Instead, rejection of technology arises from: a lack of trust in particular technological capabilities [5] and the feeling to be unable to handle technology.

Seniors of 65 and more are still far less experienced with ICT than younger users, but they are rapidly catching up, as the following statistics from Germany prove [2]:

- 59% of seniors use computers;
- 26% of seniors surf the Internet regularly;
- 12% of seniors surf the Internet daily;
- 3% of seniors are members of social online communities;

[2] Generali Altersstudie (2013): Wie ältere Menschen leben, denken und sich engagieren.

- 55% of seniors own a mobile phone.

Furthermore, the actual levels of technology use by users between 50 and 64 years are often much higher.

According to aal-europe[3], Table 1.2 lists the usual arguments in favour of and against the purchase of an AAL solution from the primary end-users' perspective.

Factors for AAL solutions	**Factors against AAL solutions**
Enhanced quality of life and comfort	Unclear personal benefit (e.g. compared to classical emergency systems)
Detection of an emergency	Fear of stigmatisation
Enhanced security	Disturbance of daily routine owing to the system
Enhanced autonomy and independence	Fear of not being able to control or use the system
Improved contact with family/friends	Unclear follow-up costs
Support in cases of helplessness	Number and type (partner, children) of inhabitants in household
Living alone, having health problems	Living with others, healthy

Table 1.2: Factors that promote or inhibit the purchase of an AAL system from the end-user perspective

Turning these findings into design recommendations, including security or comfort functions (instead of only focusing on compensating for deficits), offer an opportunity to make AAL solutions more appealing to senior end-users (especially to healthy seniors living with others). It is important to ensure that application scenarios fit in the daily routines, otherwise they will not be used. Finally, it is worth noting that users prefer does not allow others to draw inferences about recorded data, protecting their privacy. Installing AAL solutions in familiar surroundings is preferred over relocating elsewhere. Avoid using cameras or microphones (except for communication) may represent a solution.

Furthermore, it is relevant to adduce the fact that the AAL research community is recently focused on AAL Packages and integrated solutions. Basically, the future research in this field is to support innovative, transnational and multi-disciplinary collaborative projects, highlighting a clear route to the market and producing added-value products specifically designed for different types of end-users. In fact, many solutions have been founded to address to

[3]http://www.aal-europe.eu/

specific needs, but those have not yet been integrated and incorporated into everyday life, and, furthermore, they have not yet been evaluated sufficiently.

Which kind of activities and daily routines can be considered in AAL scenario? The answer to this question is not simple, and, in general, it depends on the level of details is to be considered. For example, entailing the knowledge of the exact position of a people, a system can infer about the part of the house that is occupied by an user and, consequently, about the kind of activities the user is performing. A higher level of generalization can lead to Activities of daily living (ADLs) recognition. This term generally refers to people's daily self-care activities recognition, such as: dressing, personal hygiene, self-feeding, ability to walk, get in and out of bed. On such a wide range of research questions, this thesis focuses on two different aspects of people's daily life: first, on indoor localisation and positioning as a key component for monitoring and inferring activities, especially at daytime, and then, on human sleep activities for night-time monitoring activities. The following section will show how both of these aspects are particularly useful into an ambient assisted living scenario and it will convey. Some more details about the context behind this thesis and the contributions presented to the research community.

1.1 Research perspectives

The paradigm of AAL has recently moved from mere research to practical use products, as the western population gets older. But even more feasible solutions must be developed in order to allow elderly people to live at home longer and to remain independent. Research develops the means for the measurement of vital data, to recognise or even prevent emergencies, and develop better mobile healthcare systems and home care systems. At the same time, elderly people still in good health can be supported by systems and services that offer both security at home and "lifestyle functionalities". These systems need ambient and vital context to react properly.

Take, for example, the scenario of people affected by dementia. It is desirable to detect this disease as soon as possible before accidents happen, such as a forgotten cooking pot on the stove, or a lit cigarette in an ash tray. If in the house an object finder has been installed, the person can find important and tagged items, like keys, a cell phone, a wallet, and the first hint of an abnormality may be detected when the object finder is often called. Additionally, the warning systems in the house reacts better if the position of the person is known. For instance, the warning information that the stove is still running is useless if the person stands next to it, but it becomes more effective if it is known that the user has not been in the kitchen in the last 10 minutes. However, dementia patients in hospitals present a different scenario: It might only be necessary to know whether they are inside the area they are allowed to be, or if they have left it. Activities based on positions or position shifts can include information like walking, sitting, lying, falling, leaving a room, or no movement at all. Another example of areas where Smart Devices can be used is the healthcare of people affected with Alzheimer: they suffer from a reduction of flexibility and mobility, and they might need the same warning information that have been proved to be useful with people affected with dementia.

Symptoms of dementia or Alzheimer can then be detected by examining a change in movement pattern, or in the general reduction of the movement activity. The goal here is to detect anomalies as soon as possible, so that precautions can be installed in the patience's home, and a caretaker can be found or the person can be quickly moved into a nursing home. After Alzheimer is diagnosed, monitoring the movement behaviour represents a way to follow the disease's progress. Furthermore, devices help the patience, even if non-affected by particular disease progress, navigate through a large, unknown building, which, especially for elderly people, can be very hard and most likely stressful.

From a technological point of view, as a matter of fact, the last decade have been characterised by a vibrant proliferation of embedded sensing technologies in mobile devices, and several wearable devices have been presented to the market, equipped with several and different technologies and sensors, such as accelerometers as well as biological parameters transducers. The main drawbacks of this kind of approaches are related to the user experience and comfort. In literature, the need of semi or completely unobtrusive solutions has been managed using video cameras, although this approach leads to issues from the end user perspective. Indeed, privacy aspects and the feeling of being watched are the key concerns involved with this approach. Besides, these solutions present some technical hurdles, mainly due to low resolution, poor light condition, fields-blind, especially in indoor environments, and a general computational complexity demand, which is a big issue in real-time scenarios.

Indeed, thanks to an accurate indoor positioning detection, it is possible to infer more complex activities. It is well known that outdoor localization is well performed through the Global Positioning System (GPS) technology. In general, GPS is not available to indoor positioning scenarios, due to the fact that the signal received from the satellites is not strong enough to reach indoor places through the walls. In literature, several works have been presented in order to reach the ambitious goal of having a stable indoor standard de-facto as the GPS solution, but it is still an open issue with a trade-off between performance and costs. In indoor scenarios, like hospitals and nursing homes, some hardware and technology deployment may not be allowed. Considering the reference AAL scenario, systems have, in general, to deal with low cost and unobtrusive constraints.

On the other hand, smartphones and, in general, other mobile devices, are by their own nature ubiquitous, and applications that are able to leverage contextual information, such as location, have become increasingly powerful. Furthermore, many time critical emergency scenarios are based on location information about a person, which makes the position a key context information. In general, Indoor Positioning System (IPS) have proved to be essential in AAL scenarios [6, 7, 8]. In fact, in recent years, the development of IPS has been under constant improvement, especially with the availability of new, small and inexpensive sensors. Some modern IPS are based on the use of a variety of sensors and devices that are embedded in smartphones (e.g., accelerometer, gyroscope, magnetometer) since they does not require a dedicated infrastructure or higher processing capabilities. Considering the reasons already discussed, the focus of this dissertation will mainly be on indoor localization and positioning system, in particular on the smartphone-based one. However, even smartphone-based solutions present some drawbacks. Mainly, they require a little interaction human-machine, in terms of maintenance. For this purpose, in this thesis other approaches will be discussed, based on a completely different points of view. In particular, a discussion on infrastructure based solution is presented and two different technologies are implemented and discussed.

The idea behind this thesis is to guarantee the life quality, especially for elderly and sick people, in its totality. Consequently, a key aspect in the daily life is related to night-time, and in particular to sleep issues and sleep monitoring. Sleep assessment and the related evaluation research has grown steadily [9]. In this field, a hard task to reach is related to obtaining a sleep dataset and, in the last years, many researchers have tried to address this problem [10]. These works demonstrate how to gather sleep features through accurate sleep session logs, particularly developing systems able to capture the sleeping behaviour in terms of regularity, length of bed time, number of night awakenings, sleep on set and sleep disorders.[11]. These disorders are summarised in two different, secondary and primary, grades.

The main primary sleep problems identified are related to the Sleep Disordered Breath (SDB), the Rapid eye movement Sleep Behaviour Disorder (RBD), Restless Leg Syndrome (RLS) and to the Periodic Limb Movement in Sleep (PLMS). Research also identifies secondary sleep disorders, caused by discomfort, protracted pains, dysponea, and medical treatments which can interfere with the sleep quality. Several subjects might suffer from coexisting sleep disorders. This aspect can lead to situations of psychiatric disorders, especially in the case of a persistent insomnia. Furthermore, the human sleep behaviour can change as a consequence of life–style modifications (i.e. bereavement, retirement, environmental changes). Information and Communications Technology (ICT) solutions can help to better manage patients with chronic diseases and to overcome these different challenges. In particular, in [12, 13], the impact of "Humans and ICT interaction" has been deepened demonstrating that such technologies can efficiently support researchers in this field, leading to the development of artificial devices able to understand cognitive processes and consequently improving both human well-being and human-machine interactions.

1.2 Contributions of the thesis

As a summary of this dissertation, it is possible to affirm that this work addresses the monitoring indoor human activities, focusing on activities at daytime, indoor positioning and related research questions, and at night-time in terms of sleep monitoring system.

Daytime monitoring - Indoor localisation systems

This thesis contributes to addressing the need for context-awareness in AAL by:

- Overcoming the lack of a common evaluation benchmarking framework - this dissertation introduces improvements within the EvAAL benchmarking framework, which aims at fairly comparing indoor positioning systems through a challenging competition under complex, realistic conditions. Although there are many papers in literature trying to solve the indoor localisation issue, the lack of a common dataset and standardised frameworks to compare and evaluate solutions is the main drawback in this field. Each approach presents algorithms and results using its own dataset. Under these conditions, it is not possible to compare different solutions since experiments are impossible to be reproduced [14].

- Addressing the lack of a common dataset for Indoor Localization Systems (ILSs) - the main contribution of this work is the creation and the release of a publicly available dataset, that can be used to validate different systems proposed in this field using a common dataset [15]

- Overcoming a common problem of the pedometer, the main sensor used in smartphone-based solutions, by proposing a novel deep learning approach to improve indoor positioning smartphone-based solution performances [16].

- Creating an open-source smartphone-based indoor localisation application - this work tackles the latter problem by proposing a free software framework enabling the development of indoor localization applications on the Android platform [17].

Details of these contribution are given in Chapter 3. Finally, this dissertation try to address the indoor activity recognition issue, extending the concept of a single device and/ or a single person to many. In particular:

- Performing crowd localisation through cheap and common technologies - this dissertation demonstrate the feasibility of using Wi-Fi probes to identify frequented regions by experimenting in three different indoor environments with sniffing devices [18]. Details of this contribution are given in Section 3.3.

Night-time monitoring - Sleep monitoring systems

This thesis contributes to addressing the night-time monitoring of human sleep by:

- Proposing a novel system able to perform human sleep monitoring in an unobstrusive way, using forty–eight Force Sensing Resistor (FSR) placed in a rectangular grid pattern on the slats and below the mattress. FSRs are connected to a single–board Raspberry responsible for gathering and sending data collected to a central unit using a middleware layer. Our proposal overcomes classical problems of the sleep monitoring solutions. In fact, these technologies use wrist and/ or wearable devices (actigraphy-based), particularly complicated to use in a real test bed scenario. Instead, our work is based on cheap technology and does not require active interactions between the users and the system [19, 20, 21].

- Proposing a system able to detect human bed postures during sleep sessions, involving several machine learning techniques in order to extract a global model for different users [19, 20, 21].

- Proposing a system able to identify patient movements and sleep stages. This information is particularly useful, for example, in order to assure pressure ulcer prevention. Regarding this illness, especially elderly people deal with the inability of repositioning or to reach desirable positions, promoting blood circulation problems and, indeed, ulcers [19, 20, 21].

Details of these contribution are given in Chapter 4.

1.3 Organisation of the Thesis

The structure of this Ph.D. Thesis is the following: Chapter 2 introduces the human indoor activity recognition system in active and assisted living scenarios. Furthermore, the challenge posed by indoor positioning and sleep monitoring are highlighted, especially providing the state of the art of these research fields, which represent a fundamental part of the overall scenario under consideration in this work.

Chapter 3 studies the activities at daytime, mainly considering indoor positioning issues and the relative research open question. It also contains some innovative contributions to indoor positioning field provided by this work as well as some experiments. All the considered cases present qualitative and quantitative evaluation metrics. Moreover, an extension from one person to many is considered and discussed, realizing a crowd sensing approach. The results presented in this chapter have been published in [14, 16, 15, 17, 22, 23]

Chapter 4 studies the activities at night-time. It provides the description of a sleep monitoring unobstrusive system able to infer about sleep positions and to estimate sleep information. The results presented in this chapter have been published in [19, 20, 21]

Finally, the Chapter 5 resumes the main contributions of this Ph.D. Thesis, as well as the planned future works.

1.4 Publications

In the course of this Ph.D. thesis, the results of my research have been published as follows:

1. Potortì F., Park S., Jiménez Ruiz A. R., Barsocchi P., Girolami M., Crivello A., Lee S. Y., Lim J. H., Torres-Sospedra J., Seco F., Montoliu R., Mendoza-Silva G. M., Pérez Rubio M. D. C., Losada-Gutiérrez C., Espinosa F., Macias-Guarasa J., *Comparing the performance of indoor localization systems through the EvAAL framework*, Sensors, vol. 17 (10), article n. 2327, 2017. MDPI.

2. Crivello A., Palumbo F., Potortì F., *The EvAAL evaluation framework and the IPIN competitions*, Using Geographical and Fingerprinting Data

to create Systems for Indoor Positioning and indoor/outdoor Navigation: Challenges, Experiences and Technology Roadmap, 2018, Elsevier.

3. Crivello A., Mavilia F., Barsocchi P., Ferro E., Palumbo F., *Detecting occupancy and social interaction via energy and environmental monitoring*, International Journal of Sensor Networks, 2017

4. Barsocchi P., Bianchini M., Crivello A., La Rosa D., Palumbo F., Scarselli F., *An unobtrusive sleep monitoring system for the human sleep behaviour understanding*, IEEE 7th International Conference on Cognitive Infocommunications, Wroclaw, Poland, 16-18 October, 2016. Proceedings, pp. 91–96. IEEE.

5. Crivello A., Palumbo F., Barsocchi P., La Rosa D., Scarselli F., Bianchini M., *Understanding human sleep behaviour by machine learning*, Cognitive Infocommunications, theory and applications, Topics in Intelligent Engineering and Informatics, Springer. Accepted for publication

6. Barsocchi P., Crivello A., Mavilia F., Palumbo F., *Energy and environmental long-term monitoring system for inhabitants' well-being*, State of the Art in AI Applied to Ambient Intelligence, Frontiers in Artificial Intelligence and Applications, vol. 298, pp. 91–108, 2017. Amsterdam, IOS Press.

7. Barsocchi P., Crivello A., La Rosa D., Palumbo F., *A multisource and multivariate dataset for indoor localization methods based on WLAN and geo-magnetic field fingerprinting*, International Conference on Indoor Positioning and Indoor Navigation (IPIN), Madrid, Spain, 4-7 October, 2016. Proceedings, article n. 7743678. IEEE.

8. Barsocchi P., Crivello A., Girolami M., Mavilia F., Ferro E., *Are you in or out? Monitoring the human behavior through an occupancy strategy*, IEEE Symposium on Computers and Communication (ISCC), Messina, Italy, 27-30 June, 2016. Proceedings, pp. 159–162. IEEE.

9. Barsocchi P., Crivello A., Girolami M., Mavilia F., Palumbo F., *Occupancy Detection by Multi-Power Bluetooth Low Energy Beaconing*, International Conference on Indoor Positioning and Indoor Navigation (IPIN), Sapporo, Japan, 18-21 September, 2017. IEEE.

10. Potortì F., Crivello A., Girolami M., Traficante E., Barsocchi P., *Wi-Fi probes as digital crumbs for crowd localisation*, International Conference on Indoor Positioning and Indoor Navigation (IPIN), Madrid, Spain, 4-7 October, 2016. Proceedings, article n. 7743599. IEEE.
11. Crivello A., Agostini M., Palumbo F., Potortì F., *An Open-source Framework for Smartphone-based Indoor Localization*, AI*AAL Third Italian Workshop On Artificial Intelligence For Ambient Assisted Living, Bari, Italy, 14-17 Novembre, 2017.
12. Barcaro U., Barsocchi P., Crivello A., Delmastro F., Di Martino F., Distefano E., Dolciotti C., La Rosa D., Magrini M., Palumbo F., *INTESA: An integrated ICT solution for promoting wellbeing in older people*, AI*AAL Third Italian Workshop On Artificial Intelligence For Ambient Assisted Living, Bari, Italy, 14-17 Novembre, 2017.
13. Shao W., Luo H., Zhao F., Wang C., Crivello A., Tunio M.Z., *DePedo: Robust Smartphone pedometer with deep convolution neural networks*, IEEE International Conference on Communications (ICC), 20-24 May, 2018. Accepted for publication
14. Shao W., Luo H., Zhao F., Wang C., Crivello A., Tunio M.Z., *Mass-Centered Weight Update Scheme for Particle Filter Based Indoor Pedestrian Positioning*, IEEE Wireless Communications and Networking Conference, 15-18 April, 2018. Accepted for publication
15. Potortì F., Crivello A., Girolami M., Traficante E., Barsocchi P., *Sensing the Crowd: Localizing Devices through Wi-Fi passive Probes*, Ad Hoc Networks, Elsevier. *under revision*
16. Shao W., Luo H., Zhao F., Wang C., Crivello A., Tunio M.Z., *Towards Improving Indoor Magnetic Field Based Positioning System Using Pedestrian Motion Models*, IEEE Access, IEEE, *under revision*

Chapter 2

Background and related work

This Chapter introduces the background concepts and related works for the research topics described in Chapter 1, namely daytime and night-time monitoring for AAL.

In this thesis, the daytime monitoring regards mainly indoor localisation systems and the related research questions. In particular, a general discussion about common evaluation frameworks and datasets is provided and, for this purpose, we consider the EvAAL scenario, an annual international competition that addresses the challenge of evaluation and comparison of AAL systems and platforms. Then we focus both on the indoor localisation of a single device, in particular considering smartphone-based approaches, and on the indoor localisation of multiple devices, in particular via Wi-Fi probes. Finally, the issue posed by multiple devices localisation and positioning leads us to deal with room occupancy and social interaction detection, as a natural consequence of the need for developing services and applications for well-being in AAL scenario.

Concerning the night-time monitoring, this chapter first describes the state-of-the-art of sleep monitoring approaches and actigraphy-based solution. Secondly, the main goals and strategies related to sleep monitoring issues are discussed. Then, we focus on actigraphy-based solution and finally we present a general purpose sleep monitoring system able to infer sleep stages, sleep patterns and to detect postures in bed. These information may be used for the pressure ulcer risk assessment, to monitor bed exits, and to observe the influence of medication on the sleep behaviour. Our proposal is based on cheap technology and does not require active interactions between the users and the system.

2.1 Daytime monitoring of indoor human activities

One of the main basic mechanisms of AAL systems is the recognition of human activities. This possibility optimises the prevention of emergencies, which can have important effects on public and private healthcare services. Also age related chronic diseases, such as dementia, depression, cardiac insufficiency, or arthritis, can be faced in a proactive and preventive way in order to let patients take advantage of more adequate assistance services [24, 25].

In the literature of behavioural monitoring and health state assessment, a great standardisation effort has been done by means of the so called Activities of Daily Living (ADLs). ADLs are daily activities carried out by individuals, such as feeding, dressing, sleeping, walking, watching TV, etc. [26, 27], which act as a basis to represent habits of healthy people. Health professionals can thus refer to the ability or inability to perform ADLs as a measurement of the functional status of people with disabilities. Most AAL research is currently carried out with the purpose of allowing software systems/agents to detect ADLs on the basis of suitable processing, reasoning and manipulation of sensors data. There are many settings in which Ambient Intelligence can greatly impact on our lives, enriching environments to create "smart homes". Several artefacts and items in a house can be enriched with sensors to gather information about their use and in some cases even to independently act without human intervention [28]. The main expected benefit of this technology is the increasing safety of people with specific demands and of elders. By monitoring lifestyle patterns or everyday activities and providing assistance when a possibly harmful situation it is going to happen, a smart home realises the so called Ambient Assisted Living paradigm [29].

With the maturity of sensing and pervasive computing techniques, extensive research has been carried out aimed at using different types of sensors for understanding human behaviour [30]. Behaviour modelling can be realised through different approaches. Probabilistic models are the most common. Discriminative approaches, as well as approaches based on behaviour pattern clustering and variability, are also used. The main distinction among these techniques is the modality of inferring the context and identifying an emergency or a significant event in the user's behaviour; i.e. by data-driven sensors or knowledge-based methods [31]. The former approach faces the problem of recognition of human activities and the detection of anomalies during their occurrence by using the information provided by sensors, in order to build, infer, or calibrate a behaviour model [32]. Machine learning techniques have been extensively used with this purpose, and, more specifically, probabilistic models [33, 34], data mining [35, 36], and inductive learning [37, 38].

The research results presented in this thesis focuses on the data-driven approach, with particular emphasis on smartphone-based systems, as kinds of context sources that can be exploited in pervasive environments. Sensory data sources typically deployed in smart homes are related to positioning sensors, home automation systems, and energy monitoring devices. Several research works have been conducted in the indoor context inference in order to offer solutions in elderly care facilities. These solutions are based on dedicated positioning sensors, like passive infrared detectors (PIR) and magnetic sensors [39], fall sensors [40], wireless sensor networks and radio frequency identification (RFID) sensors [41], and off-the-shelf conventional home automation sensors [42]. The idea behind this thesis is to investigate the efficiency of smartphone-based and range-based systems as potential sources of information, and to propose several advancements in this field.

2.1.1 Indoor localisation

Localisation of people and devices is a key component of context aware systems [43, 44]. The user position represents the core information for detecting user's activities, to discover devices activation, to implement proximity-based services, to perform people short or long term monitoring [7, 45, 46].

It is well known that outdoor localisation is well performed through Global Positioning System (GPS) technology. In general, GPS is not available to indoor positioning scenarios, due to the fact that the signal received from the satellites is not strong enough to reach indoor places through the walls. In literature, several works have been presented in order to reach the ambitious goal of having a stable indoor standard as the GPS solution, but it is still an open issue [8, 23] with a trade-off between performance and costs.

The state-of-the-art of the indoor localisation systems is mainly represented by range-based systems. In detail, these systems work using radio characteristics, such as: received signal strength intensity (RSSI), time of arrival (TOA), angle of arrival (AOA) and time difference of arrival (TDOA) [47]. All these features can be extracted by knowing the exact positions of the station and anchors involved into the communication protocol. Consequently, they require an ad-hoc and accurate hardware deployment. In this thesis a novel range-based system is shown in order to evaluate the indoor positions of single/ multiple devices using Wi-Fi probe request packets gathered by APs or sniffing devices. However, especially in AAL scenarios, an ad-hoc hardware deployment can be not allowed. As a consequence, several advancements for infrastructure-free indoor positioning systems are shown, in order to offer reliable and efficient solutions in our scenario.

2.1.2 Comparing Indoor Localisation systems

Some criteria to evaluate Indoor Positioning Systems (IPSs) for personal networks were proposed in [48], as for example: privacy, cost, performance and robustness. In [48], it is observed that the two main performance parameters are the accuracy and the precision, where the former is related to the geometric error and the latter was defined as the success of the position estimations with respect to a predefined accuracy (e.g., the space-based location or the percentage of error in positioning below a threshold). In general, the choice of an evaluation metric is implementation-dependent.

RADAR [49], the first Wi-Fi based indoor positioning system, used the quartile values of the error (defined as the Euclidean distance between the actual and the estimated positions) in order to compare the proposed method to other (naïve) solutions in a basic analysis. The experimental testbed was located on the second floor of a 3-storey building, with an area of 43.5x22.5 $/\mathrm{m}^2$, more than 50 rooms and 3 Wi-Fi APs. HORUS, another well-known IPS developed in 2003 [50], provided the median error in positioning and it was tested in two environments: an area of 68x26 $/\mathrm{m}^2$ with 172 locations and 21

APs, and an area of 36x12 /m^2 with 110 locations and 6 APs. The two testing approaches are quite different because the density of APs was 0.003 APs/m^2 in RADAR, whereas HORUS provided two scenarios with densities of 0.012 APs/m^2 and 0.14 APs/m^2 respectively, i.e. the scenarios where HORUS was tested had approximately four times the AP density of the evaluation testbed of RADAR. Therefore, comparing the results provided in the original references might not be fair.

In order to provide a fair comparison between RADAR (the deterministic method developed by Microsoft) and HORUS (the probabilistic technique developed by the University of Maryland), they were both implemented and evaluated using the same testbeds in [50, 51]. According to the data provided in [52, 50, 51], the density of access points in the testbed used in [50], a university department corridor, was higher than in [52, 51]. This change might be due to an improvement of the WiFi network. Despite this minor change in one of the evaluation testbeds, the work done in [50, 51] showed that a fair comparison requires to use the same testbed, or testbeds, rather than reusing the results provided in the literature.

Apart from the diversity of environments, there is also a certain variability both in the hardware used for localisation and in the metrics employed to evaluate an IPS. In fact, each research work uses specific hardware even when they use the same base technology for positioning. A Huawei Mate smartphone was used in [53], 6 different devices where used in [54], and a simulation was carried out in [55]. Using multiple devices in the set-up might be more challenging than using a single device or simulated data. Therefore comparing the results of those works might not be easy at all.

Although the vast majority of papers agree that the error in positioning is defined as the shortest distance between the estimate and current position, consensus in using a particular metric to evaluate the IPS has not been reached yet. This conclusion is in line to a study where 195 papers of the first edition of the Indoor Positioning and Indoor Navigation (IPIN 2010) Conference were analyzed [56].

The in-deep literature review previously shown opens two research questions: how to evaluate results produced by different indoor localisation systems? How to evaluate different data-fusion strategies and algorithms of a single indoor localisation system?

2.1.3 How to evaluate indoor localisation systems

As in any mature technology field, common evaluation criteria are fundamental in order to add transparency to the market, by defining a common performance language and eventually to build and nurture stakeholders' trust.

The problem with indoor localisation systems is that they are generally complex. While in the laboratory the base techniques are individually analysed and optimised, real working systems use many techniques that work synergically, thanks to the use of data fusion methods. At the base of these techniques, a wide spectrum of sensors work together to provide raw data. On the top of these techniques, applications are dedicated to a wide variety of use cases. It is therefore not straightforward to devise ways to evaluate indoor localisation systems through a series of parameters. It is not even easy to simply compare two of them, because a comparison is possible and meaningful on many dimensions, depending on the particular use case.

In 2010, the EU FP7 universAAL project started its work towards creating a universal framework for developing applications for AAL and, more generally, for smart homes and smart environments, building on advances in ubiquitous computing, distributed middleware and pervasive computing and communication [57]. The universAAL framework is intended to support an ecosystem of independent applications, so that the problem of comparing and evaluating their performance naturally came forward.

As an answer to this demand, the universAAL project started EvAAL, with the purpose of evaluating AAL systems through competitive benchmarking [58]. The idea was to gather together working systems, both prototypal and mature, and independently compare their performance in one or several specific areas, with the long-term objective of creating a set of evaluation benchmarks for indoor pervasive systems. In fact, two areas were considered during EvAAL competitions, starting in 2011 in Valencia (ES): indoor localisation and indoor activity recognition.

EvAAL competitions were organised yearly during the lifespan of the universAAL project, until 2013. In 2014, the IPIN conference decided to start an indoor competition on its own, building on EvAAL's experience, and the first IPIN competition was born.

In the same year, the Microsoft Indoor Localisation Competition was launched, in association with the International Conference on Information Processing in Sensor Networks (IPSN) [59]. Rather than focusing on rigorous evaluation of working systems as the EvAAL and IPIN competition did, such a competition focused on simplicity and comparison of basic functionality, even for very prototypal systems, with the result of attracting a higher number of contestants with respect to EvAAL and IPIN.

The EvAAL indoor localisation competition

When EvAAL was born, its long-term goal was to build one or more frameworks for evaluating entire AAL systems, a huge task which was tackled step by step by considering single system modules. The first module was in fact indoor localisation. In 2012, a second track was added, namely Activity Recognition for AAL. Both tracks were present in the 2013 edition too.

During the years 2011-2013, the Indoor Localisation and Tracking competition has been based on the same idea: inside a living lab, that was a small house instrumented with various sensors, a path, unknown to competitors, was drawn in advance; competing systems were given a fixed time for installing their devices in the smart home and estimating in real time the position of an *actor* walking the path. The basic criteria used for the setup are listed below.

Accommodating any technology – Competitors were free to use any technology that could be installed in the living lab and on the *actor*'s body in one hour's time.

Natural movements and environment – Measurements were done in real time on an *actor* moving in a natural way, in a natural environment: heshe walked around the house, sit on the bed or the coach, looked for a book in a bookshelf, turned on the TV set or the shower tap.

Reproducible path, equal for all competitors – The path followed by the *actor* was precisely known (in fact, drawn step by step on the floor) and travelled at a precisely known speed following a chime marking each step. This arrangement allowed for an estimated path reproducibility with 10 cm error in space and 100 ms error in time, well below the accuracy required for human indoor localisation.

Secret path – Competitors got to know the path shape only after their own installation was complete and the measurement was going to begin, because the markers on the floor were hidden by carpets before the measurement phase and only one competitor at a time was admitted to the area.

Independent measurements – Competing systems had to send location estimates in real time to a central database, twice per second.

Accurately controlled timing – Each competitor had one hour for installing their hardware in the living lab and checking the communication with the measurement system provided by the organisers.

Different scenarios – Three scenarios were used; first, a person was located as being inside one of several Areas of Interest (AoI) or outside any AoI; second, a person was located with absolute coordinates inside the living lab; the third situation was like the previous one but with a second *D*isturbing actor moving on a predefined path different from the main path.

The evaluation was based on a set of predefined metrics, both objective and subjective, the latter based on scores given by a small committee after an interview to the competitors. The final score was a weighted average of the metric scores listed below.

Accuracy (objective, weight 0.35) – The third quartile of the point localisation error, where the error is defined as the distance from the ground truth position (the mark on the floor) and the position estimated by the competing system, computed through linear time interpolation.

Availability(objective, weight 0.20) – The rate of real-time samples, produced by the competing system, that were at a distance of 500 ms from each other.

Installation complexity (objective, weight 0.10) – The time taken by the competitors to install their system, with a min time of 10 minutes and maximum of one hour.

User acceptance (subjective, weight 0.2) – Interview scoring based on characteristics like battery duration, possibility of hiding the installation in a house, need of cabling, need of periodic recalibration, and so on.

Interoperability (subjective, weight 0.15) – Interview scoring based on characteristics like presence of documented API, use of a free software license, use of standard protocols and libraries, operating systems supported and so on.

The score with the highest weight was the accuracy performance, as should be expected for evaluation metrics of a positioning and tracking system. The choice of the third quartile favors result stability and credibility [58], and was a prominent distinguishing characteristic of the EvAAL competitions.

The setup and the evaluation criteria made EvAAL a rigorous and difficult competition, and, in fact, the number of attendants for the localisation track was seven or eight in all the three editions. Competing systems not only had to show good performance, but they had to be installed from scratch in an unknown environment in one hour, they had to interact with an external logging system, and to work without interruption for the ten minutes or so of the longest path walked by the actor. All these requirements were hard to meet for prototypal or unstable systems.

The major advantage was that EvAAL competitions were realistic. The actor moved in a realistic way in a real domestic environment and the results were gathered and displayed in real time. As a consequence, the accuracy performance was significantly lower than that reported in academic papers, as it reflected real-life situations. From this point of view, the EvAAL competitions were a breakthrough, as for the first time they provided realistic performance measurements of indoor localisation systems.

In this thesis, improvements of the EvAAL benchmarking framework are shown in Section 3.1. This contribution has been accepted as state-of-the-art of benchmarking tools for indoor localisation systems by the Indoor Positioning Indoor Navigation (IPIN) conference.

2.1.4 Strenghts and weakness of common datasets for evaluating indoor positioning systems

In the literature, many papers deal with geo-magnetic field- and RSS-based fingerprinting methods for indoor localisation solutions. In this section, we focus on the datasets used for testing such solutions and we also survey whether they are publicly available or not.

A state-of-the-art analysis of both available and not available datasets for IPS purpose is shown as follows, highlighting strengths and weakness, with the purpose to demonstrate which kind of information are considered useful by the researchers in this area.

In [60], geo-magnetic field data authors collected in different environments, like corridors, intersections of two squares, and rooms. Only geo-magnetic field values were gathered, although the authors stated that WiFi may be used to avoid errors in the proposed localisation solution. In [61], an environment of 67x12 /m^2 is considered, composed by a corridor, a lab, an office, and a library. Data are statically collected with 45 cm intervals and 10 seconds spent in each location. The created database consists of 350 samples from a 3-axes magnetometer. However, how the information has been collected is not described.

In [62], all the samples were taken in a 260 /m^2 laboratory, which is composed by 8 corridors, at the Universitat Jaume I. The 8 corridors and the 19 intersections were mapped in two different directions with a Google's Nexus 4 and Android 5.0.1. As a result, there were 54 different alternative paths. Sampling on every path was repeated 5 times, so that the database designed for training purposes is composed of a total of 270 different continuous samples. Data from magnetometer, accelerometer and orientation sensors are included in a public database [1].

Besides differences of environments, number of points and samples, it is important to analyse which kind of information are considered useful by researchers in this field. This aspect is related to which kind of algorithms is implemented, or better, which kind of sources information is used as input of different algorithms and strategies.

Many papers, in the literature, deal with RSS-based methods for indoor

[1] http://archive.ics.uci.edu/ml/datasets/UJIIndoorLoc-Mag

Table 2.1: Comparing the datasets in the literature.

Paper	Infrastructure	Spaces	# of features	# of samples	# of reference points	source	available
[60]	N.A.	1D and 2D	magnetic	125	-	smartphone	no
[61]	N.A.	1D	magnetic	350	-	smartphone	no
[67]	N.A.	2D	magnetic	-	-	smartphone	no
[68]	N.A.	2D	magnetic	29	-	smartphone	no
[69]	N.A.	2D	magnetic	78000	-	smartphone	no
[62]	N.A.	1D	magnetic, accelerometer, orientation	40159	270	smartphone	yes
[49]	based	2D	RSS	-	280	smartphone	no
[63]	free	2D	RSS	10000	167	smartphone	no
[64]	free	2D	RSS	-	96	smartphone	no
[65]	free	2D	RSS	9358	1176	smartphone	no
[66]	based	2D	RSS	-	320	smartphone	no
[70]	free	2D	RSS	21049	933	smartphone	yes

localisation [49, 63, 64, 65, 66]. In [49], the impact of the number of fingerprinting points, number of samples, user orientation, and the issue of tracking a mobile user have been investigated.

Although we presented several state-of-the-art works, the related datasets are not completely available or detailed regarding the use cases and the environments analysed.

Table 2.1 shows a comparison of the surveyed datasets available in the literature. In this thesis we propose a new dataset, shown in detail in Chapter 3, as the only one able to provide information derived from both a smartphone and a smartwatch and, at the same time, to present a higher number of samples. The simultaneous presence of two different sources of information can be particularly useful in order to validate or to propose new IPS.

2.1.5 Indoor positioning of a single-device: multiple information sources and smartphone-based approaches

Researchers have developed various indoor positioning techniques to satisfy indoor Location-based services (LBS) requirements. In general, these systems utilise position signals, including Ultra Wide Band (UWB), Radio Frequency Identification (RFID), echo, Wi-Fi, and magnetic field. UWB and RFID based schemes allow to reach high positioning accuracy, but they need to deploy dedicated infrastructures [71, 72]. Also echo schemes allow good results in terms of accuracy, but dense sampling prevents it from continuous positioning in large scale [73]. Wi-Fi signals almost exist in every modern building, but using Wi-Fi based approaches lead to achieve low accuracy, due to the fluctuation of this signal [74, 75]. The indoor magnetic field is also ubiquitous due to the pervasiveness of magnetic field, but magnetic schemes allow to achieve high precision only in local areas [76].

Both Wi-Fi and magnetic field signals are pervasive and complementary, so researchers have tried to combine them to implement an accurate and reliable indoor positioning system. In [77], RADAR [49] and a magnetic field approach combined, using particle filter, achieving good accuracy. However, this method needs to restrict the phone attitude, aligning it with the user moving direction, which is not often detectable. Another drawback is caused by the need of sampling Wi-Fi and magnetic field training data separately, because of their different positioning principles. This aspect increases sampling and environment survey workloads.

Considering the wide range of sensors generally available into a single-device, or more specifically into a smartphone, accelerometers can be used as a pedometer and magnetometer as a compass heading provider [78], and they can be used as well to supplement other positioning and navigation methods. Pedestrian Dead Reckoning (PDR) allows to reach high accuracy, in particular when the Inertial Measurement Unit (IMU) which gathers inertial signals is mounted on the shoes. In this way, the user moving distance can be calculated through the double integral of acceleration [79].

Unfortunately, smartphones have little chances to be mounted on shoes. The positioning research community proposed to utilise pedometers, in order to detect a step event and, consequently, to estimate an average step length as the moving distance [80]. Step detection techniques mainly belong to two classes: foot mounted and hand-held like methods. For the foot-mounted case, it is relatively easy to implement step detection due to the fact that a step must contain a phase in which the foot makes contact with the floor for few seconds, which is also known as zero velocity update (ZUPT) [81]. Therefore, researchers can use acceleration variance, acceleration-magnitude, or angular rate energy detectors to detect a step event [79].

For the hand-held like case, users tend to hold the phone in their swing hand, in the bag, or in a phone call posture. When users walk, phones at these positions have no zero velocity phenomena, so the detection method cannot be used in the foot-mounted case. In order to detect steps, researchers take advantage of the low frequency of steps, that is, step acceleration signal contains low frequency peaks for each period [80], and hence step detectors detect these peaks as steps.

In order to reduce false alarm rates, step detectors further remove false step peaks by comparing the similarity of several continuous step periods [82, 83]. This method reduces the false positive rate, but the initial multi-period comparison causes a lag for the pedometer first response. On the other hand, steps apart, many human movements are periodic and occur at low frequency, like shaking hands or legs. Therefore, the above mentioned multi-period comparison has little effect on these periodic movements. Traditional step detectors tend to be error-prone with respect to periodic negative-step movements. Definitely, for a PDR based positioning system, these two drawbacks will cause the system to be unfriendly to users. For instance, the initial lag problem makes the system seem stutter, especially when the users stop frequently. On the other hand, the problem of periodic movements causes inexact position results when a static user shakes hands.

Besides the discussion about different types of signals and hardware components, it is worth considering that the user location tracking is challenging because it is a mathematical high dimensional problem. The particle filter approach is a good choice of processing these issues [84]. Consequently, current works or indoor positioning problems combine particle filter and magnetic fingerprint maps by updating particle weights with the map matching results. In general, matching is evaluated using similarity measures, but it is difficult to establish the similarity metric between two warping fingerprints. Therefore, researchers use a well-known algorithm coming from the time series analysis domain, the Dynamic Time Warping (DTW) algorithm, to measure the likeness between training and positioning fingerprints [76]. In detail, without assuming Line-of-Sight (LoS) measurement, Wi-Fi fingerprinting is a process of signal collection and association with indoor locations. A position is characterised by its detected signal patterns (e.g., a vector of Received Signal Strength Indication (RSSI) from different Wi-Fi access points (APs)). Thus, without knowing exact AP locations, fingerprinting requires neither distance nor angle measurements, leading to its high feasibility in indoor deployment.

Unfortunately, DTW based positioning algorithms are computationally hungry, especially when they are applied to large amounts of particles. Considering also the limited battery capacity of the smartphone, in order to reduce power consumption and guarantee strong performances, indoor positioning providers tend to adopt a client/server scheme. The client, composed by the smartphone, only collects environment signals. Then using an external server, sophisticated positioning algorithms are able to evaluate user and/ or device positions. Using the traditional algorithm, in order to serve mass user, companies and industries should spend more hardware cost for realising efficient indoor positioning services.

2.1.6 Indoor positioning of multiple devices: localising crowds through Wi-Fi probes

Few works concentrate on sniffing Wi-Fi probes with the aim of localising people.

The main technical difficulty is that probes are sent only occasionally, as discussed in [85], with an experimental study of several factors that influence the number and the frequency of the probes sent by the popular smartphones. There are two major factors determining the behaviour of such devices, namely the Operating System (OS) and the existence of known Wi-Fi networks. As an example, devices based on Android 5.0.1 are observed to emit about 1500 probes per hour in general, while for iOS devices (iOS 8.1.3) the number drops to 120 per hour. Devices usually send bursts of probes, the frequency of bursts strongly depending on the existence of known networks. The observed frequency of bursts ranges from one every 66 s (Android 5.0.1) to one every 330 s (iOS 8.1.3).

As a consequence, it is only possible to get sparse samples of people's positions. In [86], Wi-Fi probes are used to estimate the trajectory of devices, which is a tracking task. This is made possible by equipping an arterial road, 2.8 km long, with 7 Wi-Fi monitors. The authors manage to track some individual devices with a median error of about 50 m with monitors placed at a distance of 460 m. They use a Hidden Markov Model of possible trajectories and make the final estimate using the Viterbi algorithm. They do not only sniff for Wi-Fi probes spontaneously sent by mobile devices, but use several additional techniques to elicit response packets from devices and increase the length of packet bursts sent by each device, thus improving the tracking performance once the device radio is on. Anyway, they can do nothing when the device turns off the radio or decides not to transmit. Accuracy performance of this approach is very good, considered how much far are the monitors, but it is only achievable in an environment where two requirements are simultaneously satisfied: few well-defined possible trajectories and device tracking. Our work instead is aimed at being applicable in wide unstructured indoor areas, such as a mall, where a great number of trajectories are possible and configuring a Markov model would be a complex and long task, which contradicts our aim of a simple setup.

To the best of our knowledge, the only other paper that exploits Wi-Fi probe messages for localisation purposes is [87], where pedestrians are tracked in an outdoor environment using triangulation. A 1 m average positioning error is reported, based on a single experiment without any details on the number of samples taken. While it is possible to observe this high accuracy in a small outdoor environment with few obstacles, the adopted triangulation method is not generally usable in an indoor environment, where reflections from ceiling and floors are strong and no line of sight from the device to the monitor exists, leading to a generally weak relationship between received signal strength and distance, which makes triangulation unreliable. Moreover, many modern devices' operating system use some form of probe anonymisation which prevents tracking, unless the device is associated with a Wi-Fi network, which is generally not true.

In this thesis, our goal is to study whether Wi-Fi probes are usable to identify the presence of unspecified people in a given indoor area, without any attempt to track or identify specific devices. Specifically, our contribution, explained in detail in Section 3.3, focuses on the accuracy of the position samples through experimentation in a static environment. To the best of our knowledge, no measurement campaigns, whether extensive or not, have yet been published on the positioning accuracy obtained by eavesdropping Wi-Fi probe request packets using APs or sniffing devices.

2.2 Night-time monitoring of indoor human activities

People experience changes, especially, both in mental and physical aspects, especially as they grow old. As a consequence, people deal with life-changing problems. One of this problem generally affects the characteristics of the sleep habits: changes in pattern, sleep duration, and quality [88]. Elderly people with ageing deals exhibit difficulty of falling asleep, sleep fragmentation and maintaining sleep. According to [89], sleep disturbances increases of 50% for people over 65 years old. Many factors can influence these phenomena in old adults: heart failure, allergies, depression, Alzheimer's disease, social isolation, loneliness, and drug use. Health-care professionals should be aware that the sleep problems of the elderly people are an integral part of life. An accurate sleep monitoring is fundamental in order to detect early signs of sleep deprivation and insomnia, evaluating their sleeping habits, and consequentially implementing mechanisms and systems for preventing and overcoming these problems [90]. As a conclusion, a better quality of life in elderly people may be achieved by increasing sleep quality as well as promoting good sleep [91].

Recent findings show that sleep quality plays a critical role in reducing the risk of dementia and preserving cognitive function in old adults [92]. Understanding changes in sleep quality may help in detecting cognitive decline, and becomes a research imperative [93]. In literature, sleep quality has been assessed using different techniques, including subjective and self-reported measures (e.g., the Pittsburgh Sleep Quality Index, the Consensus Sleep Diary, the Richards-Campbell Sleep Questionnaire, the Karolinska Sleep Diary) and objective measures (e.g., polysomnography and actigraphy). Current research efforts focus on the methods used to quantify some parameters of the sleep quality [94]. It is worth noticing that, unfortunately, sleep quality is a complex construct, making it challenging to define and to evaluate. The following part introduces the importance of the objective measures of sleep quality using both subjective and objective measures. Lastly, to conclude, actigraphy-based and unobtrusive systems are shown. In fact, the advancements proposed in this thesis, and explained in details in Chapter 4, are not made to answer what sleep quality is but, rather, they offer a reliable method in AAL to understand characteristics of sleep and human behaviours during bed rest.

2.2.1 The importance of objective measures for the sleep quality

The term sleep quality is generally used in the sleep medicine research community, but there is no exact definition widely accepted. Sometimes, it is used to signify a series of sleep measures, including Sleep Onset Latency (SOL), Sleep Efficiency (SE), Total Sleep Time (TST), Wake After Sleep Onset (WASO), arousals and frequencies of apnea events [95].

The term quality may be not referred to the amount of sleep and awakenings, but it signifies how the experience of sleep changes. Sleep quantity variables (e.g., TST, SOL, WASO, number of awakenings) may not reflect people's total sleep experiences. This aspect have to be taken into account in order to better characterise people's sleep experiences. Sleep quality represents some sleep experience's characteristics that are not gathered from other subjective indices. As a result, further study of objective indices may lead to a better understanding of user's sleep experience.

It is important to explore how sleep quality estimation differs for subjective vs. objective measures, in particular for old adults.

2.2.2 Potential measures of sleep quality through invasive systems

Sleep quality may characterise some aspects of sleep experience not currently understood, and the development of objective correlates for these ratings has the potential to allow an improved characterisation of the experience of sleep. Whereas there are many potential correlates, traditional Polysomnography (PSG) measures, NREM sleep EEG spectral indices, CAP rate, and actigraphy all should be considered for further study.

The following discussion highlights the limitations of traditional PSG and considers these alternate methodologies, exploring other invasive analysis methods, self-report diaries, actigraphy-based and unobstrusive systems.

Among these are scoring methods for characterizing the cycling alternating pattern (CAP), sleep EEG spectral analysis, self-report diaries and actigraphy-based systems.

Traditional polysomnography

PSG is considered the gold standard methodology for detecting the sleep pattern by analysing epoch by epoch sleep records [96].

Furthermore, PSG provides measures strictly related to sleep architecture such as Rapid Eye Movement (REM) sleep, Slow Wave Sleep (SWS), stage 1 sleep, and stage 2 sleep. These sleep characteristics cannot be self-reported, but they have been also involved as a part of some indices of sleep quality. In [97, 98, 99] authors show, that for some time, individuals show sleep complaints while SOL, WASO, TST, and number of awakenings that are close to those seen in non-complaining individuals.

These parameters, considered together, provide indices of:

- the relative distribution and amount of each of the sleep stages
- the time and quantity of occurrence of sleep
- the quantity of pathological events as indicators of periodic limb movement disorder (PLMD) and sleep disordered breathing (SDB)

Sleep quantity variables may be particularly useful in different context, such as in insomnia treatment studies [95]. PLMD and SDB have become the standard for both diagnosis and treatment of these conditions. Unfortunately, the nature of sleep is a continuous process and the traditional PSG-derived sleep stage scoring, is a crude indicator able to provide only four categories for a sleep session (stage 1, stage 2, slow wave sleep, EMEM). A night record using the PSG methodology (generally performed using a resolutions of 24 bit, 12 channels at 500 Mhz) is simplified to four categories. Consequently, the deep nature of sleep, provided using this information, may be useful for individuals who meet diagnostic indices which differ from normal sleepers [97, 98, 99], but the sleep quality may in general be not correctly addressed.

Non-REM EEG frequency spectral analysis

Non-REM (NREM) spectral analysis allows the identification of the frequency content of electroencephalography (EEG) signals gathered during NREM sleep events. These signals are generally elaborate applying Fast-Fourier trasforms (FFTs) in order to obtain measures of the activity considering a set of classic frequency bands in EEG data analysis (from 0.5 Hz to 45 Hz). Consequently, this method generates a continuous analysis of the nature of sleep, using a sleep stage categorisation. The main weakness of this analysis is that the identification of clinically important aspects might be not guaranteed. More specifically, it has been hypothesised that a greater high-to-low EEG frequency ratio during sleep is an indicator of bad sleep in that it is similar to the EEG signal during waking. Furthermore, the EEG pattern has been found to correlate with the cortical activity, as measured with positron emission tomography during sleep [99, 100, 101].

In terms of the relationship of NREM EEG spectral measures and self-reported sleep, NREM EEG activity has been found in patients with insomnia who show no sleep pathology (relative to normal sleepers) on traditional PSG [101]. In [99], authors found no overall relationship of any PSG measure with subjective sleep quality in a group of 30 primary insomnia patients and 20 normal sleepers.

However, the sleep quality is related to greater high frequency activity during NREM sleep among a subgroup of insomnia patients whose traditional PSG indices (SOL, WASO, TST, etc.) are comparable to normal sleepers. These findings suggest the possibility that NREM EEG spectral indices may have some potential as objective indices of sleep quality ratings. However, relatively little research has been carried out with this technique, and the methods are still not standardised.

The Cyclic Alternating Pattern (CAP)

CAP is a manualized measure of NREM sleep state instability which derives from PSG data. It quantifies the presence of particular types of NREM sleep EEG patterns and the degree to which shifts occur between these patterns over time [102]. Because CAP rate is an analysis of data occurring during identified sleep periods, it is, like NREM EEG spectral analysis, a potential measure of the nature/depth of sleep rather than an index of the quantity and timing of sleep. It therefore may be of interest as a measure of sleep quality. In this regard, CAP rate has been hypothesised to reflect the mechanisms that control arousal level during sleep. Consistent with this hypothesis, increased CAP rate has been observed in individuals who experience continuous acoustic perturbation [103] and it is significantly more common in individuals with insomnia or sleep apnea [103] compared with normal sleepers. Of particular note, CAP rate was found to be the strongest correlate of sleep quality ratings, having a stronger relationship with these ratings than any of the traditional PSG measures [104].

In summary, CAP rate has sown promising as a potential measure of the sleep quality because it provides a possible indicator of aspects of sleep beyond what is provided by traditional PSG indices. Like NREM EEG spectral indices, the major limitation of CAP is that relatively little work has been carried out to date and its intrusive approach form a user point of view.

Self-report diaries

The effort for understanding humans' sleep has traditionally utilised self-report methodology to gather data on sleep behaviour. As previously described, a discrepancy between objective PSG measures of sleep and subjectively collected information is expected. However, the debate on what exactly is important to measure in order to better characterise sleep is ongoing. Self-report questions on the sleep behaviour have used several different formats. Despite the lack of a standardised format, the sleep diary has been regarded as the gold standard for subjective sleep assessment, and several efforts have been made to understand the validity of self-reported sleep indices. This process may facilitate interpretation and understanding of sleep data. The following discussion focuses on four different self-report diaries Pittsburgh Sleep Quality Index (PSQI),Consensus Sleep Diary (CSD), Karolinska Sleep Diary (KSQ), Richards-Campbell Sleep Questionnaire (RCSQ)), exploring their strengths and weaknesses.

Sometimes, sleep quality is inferred through the evaluation of objectives indices performed from PSG. These objective parameters are measures such as TST, SOL, WASO, SE, and number of awakenings that, in general, correspond to measures taken from self-report methods (e.g., PSQI, sleep diaries) [105]. Self-report indication present a good level of validity and reliability and these data have to take in consideration but, especially in elderly, age related cognitive changes in memory and/ or executive capabilities may lead to errors in reporting.

Pittsburgh Sleep Quality Index

The widely adopted PSQI evaluates the sleep quality variable based on user's evaluation, generally calculated in the previous month, and it includes a series of sleep measures, including sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, the use of sleeping medication, and daytime dysfunction [106].

The PSQI was originally developed to provide clinicians with a valid, standardised measure of sleep quality that could reliably categorise individuals as either good or poor sleepers. This 19-item questionnaire assesses sleep quality using subjective ratings for 7 different components (i.e., sleep duration, sleep quality, sleep efficiency, sleep latency, use of sleeping medication, sleep disturbance, daytime dysfunction).

Respondents are asked to answer the questionnaire retrospectively, surveying sleep components spanning the previous month. Since its introduction the PSQI has emerged as the de facto gold standard subjective measure of sleep quality. However, as [106] explained, the PSQI does not correlate well with PSG. PSG, as already described, is the gold standard objective measure of sleep [107]. In [106], it is suggested that the retrospective nature of the PSQI (a global sleep quality estimate spanning the previous month), could explain its limited agreement with single night PSQI recordings. Perhaps PSG recordings averaged over the same period queried by the PSQI would be correlated, but this assertion needs to be confirmed empirically. However, the invasive nature of PSG usually requiring an overnight stay in a sleep laboratory or clinic—makes long-term multi-night recordings impractical.

PSQI requires respondents to express answers that are suitable to reflect their sleep during the previous month. This task requires the capacity to accurately remember one's recent past due to the fact that the response accuracy depends at least in part on the cognitive capacity to reflect on the past month [108]. As a consequence, discrepancies between PSQI-based sleep quality evaluation and actigraphy-based systems may be observed, especially in elderly.

Basically, PSQI estimation may discriminate between poor and good sleepers. However, this methodology might not identify important clinical changes in users' sleep quality, due to disease and interventions, and to age.

Consensus Sleep Diary

The CSD [109] is the product of collaborations with insomnia experts and potential users. This workgroup designed, tested, and refined a consensus based standardised sleep diary to be used primarily for the purposes of insomnia research, but also for clinical and research applications for both good and poor sleepers. CSD contains 9 questions about: the time of getting into bed, the time at which the individual attempted to fall asleep, sleep onset latency, number of awakenings, duration of awakenings, time of final awakening, final rise time, perceived sleep quality, and an additional space for open-ended comments from the respondent.

However, in [109], authors observe that users express limitation about the diary format, and in particular about its ability to address efficiently the sleep experience. They advocated for additional questions or items in order to describe these experiences. The CSD, and other diaries, should be seen as a good source of information for some aspects, but not good enough for all the aspects of sleep. This aspect is also caused by the fact that sleep is a highly variable phenomenon across different nights [110]. Sleep diaries must be used together with other patient monitoring tools or clinical instruments where a broader assessment of sleep is needed.

The main point of interest is the verification of sleep parameters gathered using CSD, to prove if they match those of the actigraphy-based data, and to investigate their accuracy. Regarding the consensus sleep diary, as observed in [111], participants tend to under- and overestimate these respective parameters compared to activity tracker data.

In [94] authors suggest, especially for older adults, subjective measures of sleep quality (i.e., the PSQI and CSD) survey different aspects of sleep quality, when compared with objective measures (i.e., actigraphy). As a conclusion, an older adult's perception of their sleep quality is quite different from objective reality.

Richards-Campbell Sleep Questionnaire

RCSQ [112] is a brief five-item questionnaire, used to measure: perceived sleep depth, sleep latency (time to fall asleep), number of awakenings, efficiency (percentage of time awake), and sleep quality. Each RCSQ item is gathered on a 100-mm visual-analogue scale, with higher scores representing better sleep and the mean score of these 5 items, known as the total score, representing the overall subjective perception of sleep.

In a psychometric evaluation of the RCSQ [113], researchers found an internal consistency of .90 (Cronbach's alpha) and demonstrated that scores on the scale have a correlation of 0.58 ($P < .001$) as a correlation among the PSG sleep characteristic, sleep efficiency index, and the total RCSQ score. As a consequence of the difficult to interpret and implement polysomnography on a large-scale basis, in [114], sleep is evaluated using the RCSQ instead of PSG, showing a similar clinical validation reported in [113].

A recent work [2] investigates quality and quantity of patient sleep in the Hospital, trying to compare RCSQ indices and actigraphy-based system. Authors show no difference between patients' perceived quality and quantity of sleep, and wrist actigraphy. However, they notice that patients perceived that they were awake more frequently than as measured by wrist actigraphy. Furthermore, no statistical relationship are found between the subject patient perception of sleep (RCSQ overall) and sleep efficiency, and between the subject patient perception of sleep quality (RCSQ item 5) and sleep quality as measured by wrist actigraphy system.

Karolinska Sleep Diary

The KSQ [115] contains 12 items. Most of them asks a response graded from 5 to 1. In detail the diary is composed as follow:

- Bedtime (h.)

[2] `https://digitalcommons.centracare.com/cgi/viewcontent.cgi?article=1074&context=nursing_posters`

- Time of awakening (hr.)
- Subjective sleep length (hours and minutes)
- Subjective sleep efficiency (derived from sleep length/time in bed)
- Subjective sleep latency (hours and minutes)
- Sleep quality-phrased as "how did you sleep?" [very well (5) - very poorly (1)]
- Feeling refreshed after awakening [completely (5) - not at all (1)]
- Calm sleep [very calm (5) - very restless (1)]
- Slept throughout the time allotted [yes (5) - woke up much too early (1)]
- Ease of waking up [very easy (5) - very difficult (1)]
- Ease of falling asleep [very easy (5) - very difficult (1)]
- Amount of dreaming [much (5) - none (1)]
- Number of awakenings
- Number of awakenings/hour of sleep (derived from previous item/sleep length)

The diary has been used in several studies [115, 116, 117] in order to address the encountered sleep disturbances of initiating and maintaining sleep as well as a users' appreciation of sleep. The diary contains also sleep quality and feeling refreshed items that are used as global indicators of sleep. Instead, other items cover specific aspects of sleep.

In [115], the authors derived that a sleep was rated very good if it contained only 4% or less of waking, whereas very poor sleep corresponded to 24% or more of waking. Very difficult response corresponds to more than 100 minute of sleep latency. Calmness of sleep appears maximal at 0.1 awakenings per hour or less and minimal at 0.5 awakenings per hour or more. According to the reported results, it seems that a subjectively good sleep evaluation has mainly effected by calmness and efficiency of sleep indices.

In [117], the correlation between KSQ ratings and PSG sleep examined in individuals without clinical sleep complaints. Their results show how subjective sleep quality and restoration from sleep reported are strictly correlated with sleep stages rather than time spent awake or number of awakenings as indicated by PSG. According to [118], TST and SE are associated with a better sleep quality. Instead, latency seems to be correlated with worse sleep quality (higher global PSQI scores).

In [119], the authors observed a low overall and mostly non-significant correlation between actigraphy measured sleep and subjective sleep quality, presenting a study of different week nights including weekends. During week nights sleep percent was to correlate better than TST evaluated with subjectively reported sleep quality. TST was to correlate more with subjective sleep quality during weekend.

2.2.3 Sleep monitoring via actigraphy and unobstrusive systems

The variation of findings across different studies and methodologies previously discussed can be partly explained by the different subjective sleep quality measuring systems used (diary and questionnaire ratings), several and non-standard definitions of sleep quality, and the difference between a sleep recording session performed at home or in laboratory. In fact, recording several human sleep nights, considering an extended period, in a home setting with no restrictions, presumably better reflects habitual sleep than a highly controlled laboratory study conducted over a few consecutive nights.

This suggest that more efforts should be spent to find reliable sleep monitoring system able to detect objective sleep quality characteristics strong correlated with findings of invasive clinical methods, self-report diaries, and actigraphy-based systems. It is worth noting that, especially in elderly and AAL, self-report diary approaches may be difficult to be used.

Fortunately, technological advances have allowed the development of non-invasive, long-life, battery powered, wearable devices equipped with tri-axial accelerometers (i.e., actigraphy) able to monitor and collect data generated by movements. Some devices exploit a piezo–electric mechanism to detect movements, along two or three axes, and to digitally count the accumulated movements across pre–designed epoch intervals (e.g. 1 min), storing them in an internal memory.

In 1995, the Standards of Practice Committee of the American Sleep Disorders Association (ASDA) commissioned a task force to evaluate the role of actigraphy in sleep medicine. ASDA's effort on actigraphy led to a review paper on the topic [120] and a set of guidelines [121]. The acknowledge for actigraphy as a valid tool by ASDA was an important landmark in its acceptance by sleep–related researchers and clinicians. The use of actigraphy is continuously rising in sleep research and medicine, as demonstrated by the increasing number of publications over the years [122].

Wearable devices for actigraphy, and in particular wrist-worn actigraphy devices, measuring sleep parameters have been validated through the comparison with PSG [123, 124]. In [107], the authors recommend the usage of actigraphy-based system concurrently with CSD methodologies, in order to identify period during which users are attempting to sleep. This combination of CSD and actigraphy is currently accepted as an alternative to the PSG methodology [125]. Actigraphy devices may be used to gather objective sleep quality measurements in a natural environment allowing a comparison with the PSQI, using some recommendations. In fact, the PSQI has been compared previously to actigraphy in a non-clinical scenario. In [126], the authors compared PSQI scores during 7 days (and less than 7 days in some cases) of actigraphy and concurrent sleep diary entries in 53 young and 59 old adults. They showed global PSQI scores did not correlate significantly with actigraphy in younger or older adults; but did correlate with sleep diary entries. These findings suggest that subjective measures differ from actigraphic measures of sleep quality. In [127], the authors recommend to improve actigraphy-based system using 14 days recordings in order to take into account day-to-day and week-to-week variability. In general, longer actigraphy-based monitoring may correlate better with PSQI.

Strengths of actigraphy-based systems are the low impact on the user daily life and their low cost. However, the major weakness of this method is the limitation in distinguishing activity from motionless while users are awake or being asleep. This phenomenon lead to, for example, SOL delay or to an overestimation of the number of night-time awakenings (which are seen as the primary features of insomnia) [128, 129]. Despite the main strength of actigraphy lies in the ability of monitoring sleep behaviour and inferring sleep wake patterns over long periods of time at home, actigraphy also has several weaknesses. In [130], the authors report that up to 28% of weekly recordings of children and adolescents were insufficient for the sleep analysis. The main reasons for data loss included patient non-compliance to the pre-defined protocol (inability to complete the diary or log and misplacement of the wearable actigraph device), illness, and technical problems. Indeed, detailed patient logs are essential for accurate scoring of records. Showers (with the actigraph off), just before bedtime or after rise time, can be easily confused with sleep activity. Conversely, activity of co–sleeping of bed partners or sleep during car rides may be scored as waking.

For these reasons, the log should contain information about bedtimes, rise times, time when the actigraph is not worn, and time of external motion or unusual events. When the actigraph data are retrieved, patients should be queried about moments when the log and the actigraph records are incoherent. Moreover, children and adolescents are remarkably capable of bending metal parts, dislodging event buttons and otherwise damaging the instruments. Data loss may also occur when curious wearers of any age remove the battery cover to "see what's inside". Finally, instruments may lose calibration and fail in many other ways. Unlike laboratory studies, where technical problems and artefacts are recognised quickly and either resolved or thoroughly documented, problems occurring over long periods of home recording often lead to a complete loss of data.

In [131, 132], the use of wearable general purpose sensor technologies to monitor the bed posture of patients is proposed. In [133], an unobtrusive system able to infer the bed posture and the breathing signal is presented. The system is based on an expensive technology which employs a sensor, called Kinotex, that was developed by the Canadian Space Agency for tactile robotic sensing. Finally, in [134], an inexpensive system based on placing above the mattress a capacity textile sensing technology is described. However, the authors noticed problems on the reproducibility of the experiments, due to the movement of the textile system, which necessitates a new calibration phase each time.

Vice versa, the proposed system is able to merge the inexpensive feature of [133] and the unobtrusive feature of [134], just placing, under the mattress, several FSR, able to report the force pressure generated by the patient over the mattress.

Chapter 3

Daytime monitoring - Advancements in Indoor localisation systems

Indoor localization systems during the last years have been the object of significant research activity and of growing interest for their great expected social impact and their impressive business potential. Application areas include tracking and navigation, activity monitoring, personalized advertising, Active and Assisted Living (AAL), traceability, IoT networks, and Home-land Security.

The present Chapter collects the contributions of this Ph.D. thesis to daytime monitoring, and particularly to indoor localisation systems.

In particular, Section 3.1 describes the general lines of the EvAAL benchmarking framework, which is aimed at fairly comparing indoor positioning systems through a challenging competition under complex, realistic conditions. In fact, in spite of the numerous research advances and the great industrial interest, no canned solutions have been defined yet. The diversity and heterogeneity of applications, scenarios, sensors and user requirements, make it difficult to create uniform solutions. From that diversified reality, a main problem is derived which consists in the lack of a consensus both in the metrics and in the procedures used to measure the performance of the different indoor localization and navigation proposals. To evaluate the framework capabilities, we show how it was used in the 2016 Indoor Positioning and Indoor Navigation (IPIN) Competition. The results reported in this Chapter, regarding the EvAAL framework have been published in [14].

Section 3.2 describes the improvements obtained for single smartphone based indoor localisation. As a consequence of the results of Section 3.1, this section shows a common dataset useful to compare different indoor localisation systems and, successively, describes a novel approach based on Deep Convolutional Neural Networks to improve the robustness of the main source of information used by these system, the pedometer. To evaluate these proposal, real-world indoor scenarios are considered; the results of this Section have been published in [16]. Finally, a proof-of-concept of a smartphone-based framework for AAL is described. This proposal arises from the IPS context but, considering its modular architecture may be extended as a general framework for both daytime and night-time monitoring services for AAL. Partial results of this work have been published in [17].

Finally, Section 3.3 describes the feasibility of using Wi-Fi probes to identify frequented regions by experimenting in three different indoor environments with sniffing devices produced by Cloud4Wi. Using our proposed approach, single and/or multiple devices may be detected and furthermore it is possible to identify frequented regions in indoor environments. The same process can be carried out using the Wi-Fi access points already installed in the environment, allowing for operation free of installation, calibration and maintenance. To evaluate our proposal we consider three different indoor scenarios. The results described in this Section have been published in [14].

3.1 Comparing the performance of Indoor localisation systems: improving the Evaal Benchmarking Framework

In Chapter 2.1.1, we have already shown that no standard methods for evaluating indoor localization systems are generally accepted and used by researchers and industry. As a consequence, the lack of common test beds is a problem when evaluating the relative performance of different systems.

In this thesis, we describe the EvAAL evaluation framework. It defines tools and metrics usable for comparing both real-time systems and off-line methods based on recorded data. In this section, the EvAAL framework is discussed together with a discussion on the performance and technologies used by the competing systems. As a result of the experience gained from the authors as software chair and real-time smartphone-based track chair of EvAAL competitions, a focus is dedicate to smartphone-based solutions.

3.1.1 Characteristics of the EvAAL benchmarking framework

The EvAAL framework is characterized by several *core* (the distinguishing features of the EvAAL framework) and *extended* (all adopted by the EvAAL competitions) criteria. The *core* criteria are the following:

1. Natural movement of an actor – The agent testing a localization system walks with a regular pace along a predefined path. The actor can rest in a few points and walk again until the end of the path.

2. Realistic environment – The path the actor walks is defined in a realistic setting.

3. Realistic measurement resolution – The minimum time and space error considered are relative to people's movement. The space resolution for a person is defined by the diameter of the body projection on the ground, which is set to 50 cm. The time resolution is defined by the time a person takes to walk a distance equal to the space resolution. In an indoor environment, considering a maximum speed of 1 m/s, the time resolution is 0.5 s.

4. Third quartile of point Euclidean error – The accuracy score is based on the third quartile of the error, which is defined as the 2-D Euclidean distance between the measurement points and the estimated points. A deeper discussion on this point can be found in [14].

The *extended* criteria additionally introduced are the following:

5. Secret path – The final path is disclosed immediately before the test starts, and only to the competitor whose system is under test. This prevents competitors from designing systems exploiting specific features of the path.

6. Independent actor – The actor is an agent not trained to use the localization system.

7. Independent logging system –The competitor system estimates the position (at a rate) of twice per second, and sends the estimates to a logging application provided by the EvAAL committee. This prevents any malicious actions from the competitors. The source code of the logging system is publicly available[1].

8. Identical path and timing: the actor walks along the same identical path with the same identical timing for all competitors, with time and space errors within the above defined resolutions.

As a result of the experience gained from the EvAAL competitions and the feedback obtained from the organizers and competitors, the EvAAL committee has formalized this evaluation framework [14] to be applied to indoor localization competitions in order to measure and compare the performance obtained by the competing systems.

3.1.2 A test case: applying EvAAL criteria to the IPIN 2016 competition

During IPIN 2016, four competition tracks were run in parallel: Smartphone-based (track 1), Pedestrian dead reckoning positioning (track 2), Off-site Smartphone-based (track 3), Indoor mobile robot positioning (track 4).

The competitors of each track were evaluated according to the third quartile of the positioning error. This error is measured based on (x, y) coordinates (longitude and latitude). Also, a *penalty* $P = 15$ m is added for each floor error. For example, if the (x, y) error is 4 m and the estimated floor is 2 while it should be 0, the computed error for that estimate will be $4 + 2P = 34$ m.

[1]http://evaal.aaloa.org/2017/software-for-on-site-tracks

This reflects the real user point of view, because some movements in the environment are restricted by physics and architectural elements [135].

As far as the *core* criteria of the EvAAL framework are concerned, the IPIN competition 2016 follows them as close as possible for a given scenario.

- The two first *core* EvAAL criteria are followed closely: in Tracks 1-3 the actor moves naturally in a realistic and complex environment spanning several floors of one (for Tracks 1&2) or few (Track 3) big buildings; in Track 4 the robot moves at the best of its capabilities in a complex single-floor track.

- The same holds for the third core criterium: the space-time error resolution for Tracks 1-3, where the agent is a person, are 0.5 m and 0.5 s, while the space-time resolution for Track 4, where the agent is a robot, are $\approx$1 mm and 0.1 s. In Track 4, only the adherence to the trajectory is considered, given the overwhelming importance of space accuracy with respect to time accuracy as far as robots are concerned.

- The last core criterium of the EvAAL framework is followed as well, as the third quartile of the point error is used as the final score. The reason behind using a point error, as opposed to comparing trajectories using for example the Fréchet distance [136, 137], is that the latter is less adequate to navigation purposes, for which the real-time identification of the position is more important than the path followed.

As far as the *extended* criteria of the EvAAL framework are concerned, the IPIN competition also similarly follows them.

- In tracks 1&2, the path is kept secret only until one hour before the competition begins, because it would be impractical to keep it hidden from the competitors after the first one in a public environment. However, competitors could not add this knowledge to their systems. In Track 3, the competitors work with blind datasets (logfiles) so that the path can be kept secret. In Track 4, a black cover is used to avoid any visual reference of the path and other visual markers.

- The agent is independent for all tracks apart from Track 2, where the technical difficulties suggested that the actor was allowed to be one of the members of the competing team.

- The logging system is independent only in Track 1. An exception was added in Track 2 for the logging system, which was done by the competitors themselves rather than by an independent application. In Track 3, competitors submitted the results via email before a deadline. In Track 4, the competitors had to submit the results via email within a 2-minute window after finishing the evaluation track.

- The path and timing was identical for all competitors in Track 3 and Track 4. The paths are slightly different in Tracks 1 and 2, which involved positioning people in real-time, because the path was so long that it would have been impossible to force the actors to follow exactly the same path with the same timing many times.

In order to see the potential power of the EvAAL framework for evaluating different and diverse locating scenarios and systems, we now give some details about the three different competition scenarios used in the past 2016 IPIN competition.

Smartphone-based track: Positioning of people in real-time

This subsection details the rules for real-time Smartphone-based track of the IPIN 2016 Competition. The competing systems had to be engineered or prototyped so that an external actor could use them without impairing his movements.

In Track 1, actors were not trained to use the competing systems. Generally actors are people from the conference audience or people from the organizing committee willing to support the competition. Competitors had to use standard smartphones, with the possibility of using any sensor available on the device: GPS, accelerometer, gyroscope, compass, Wi-Fi radio and barometer. Competitors were allowed to only exploit the existing Wi-Fi access points available on the competition area. Teams in Track 1 were allowed to perform two runs each during the competition day, and consider only the best result. During each run, the actor tested one competing application by using a measurement application developed by the organizers, called StepLogger.

The detailed competition rules are published at the IPIN web page [138, 139].

Surveying the area

Competitors of both tracks received detailed geo-referenced maps of the competing area and were able to survey the area the days before the competition. They used the survey time to check how their system performed in the area and were able to perform the algorithm tune-up.

During the survey, competitors in Track 1 were mostly interested in taking Wi-Fi measurements, both fingerprints in various locations (a long and tedious task) and checks on the position of access points in the area. Most access points were in fact indicated on the maps, but some were not, and up-to-date ids (MAC, SSID) were not provided to competitors. After the competition, many competitors in Track 1 informally said their system would have performed much better if they had spent more time in taking Wi-Fi measurements during the survey, because the area was so big and the hours they dedicated to the task were not enough. Most notably, the winning Track 1 team needed very little survey time. To the amazement of bystanders, including some other competitors, after slightly more than half an hour spent in a specific small area of the building they claimed that they had collected all the data required by their system.

Evaluation path

A reference path is necessary to measure the accuracy of the competing systems, and was used as the ground truth. In practice, some dozen markers (keypoints) were stuck on the floor and their coordinates were measured in advance. The actor followed the markers sequentially stepping over them. For Track 1, the synchronization between the real position of the actor and the estimated position was guaranteed by the StepLogger app, running on the same smartphone where the competing app was running. When the actor steps over a mark on the floor, he pushes a button on the smartphone screen, and the app records the time. Since the markers are walked in a predefined order, the time stamps are easily associated with the corresponding mark and logged to persistent memory. The log produced is then compared with the log of the continuously estimated positions provided by the competitor.

In Tracks 1, the organisers provided an application for producing the results from the time-stamp log and the log of the competitor estimates. The applications read the space-time logs and computed the errors as (x, y) distance plus the floor penalty. The third quartile of error is then computed and presented as the final score. A dedicated application, available on the EvAAL web site, produces a graphical representation of the map including the ground truth and the estimated path.

The path was defined with the goal of realistically reproducing the way people move within wide indoor environments. In fact, the path complexity is a distinguishing feature of the IPIN competition. To this purpose the following rules were considered:

- stairs and a lift are used to move between floors;
- the path traverses 4 floors and includes the patio, for a total of 56 key points marked on the floor, 6000 m^2 indoor and 1000 m^2 outdoor;
- actors stay still for few seconds in 6 locations and for about 1 minute in 3 locations; this cadence is intended to reproduce the natural behaviour of humans while moving in an indoor environment;
- actors move at a natural pace, typically at a speed of around 1 m/s;
- total length and duration are 600 m, 15'$\pm$2', which allows to stress the competing apps in realistic conditions.

As mentioned before, the setting was the Polytechnic School of the University of Alcalá (EPS-UAH). EPS-UAH is hosted in a square building composed of four floors connected with stairs and lifts. Floors have all a similar layout, with a side of about 140 m. The central big and open round hall gives access to four wings where medium sized rooms are located. The structure is mostly made of concrete with many pillars in the central hall. Glass walls separate the patio from the ground floor indoor areas. Wi-Fi is available inside and immediately outside the building.

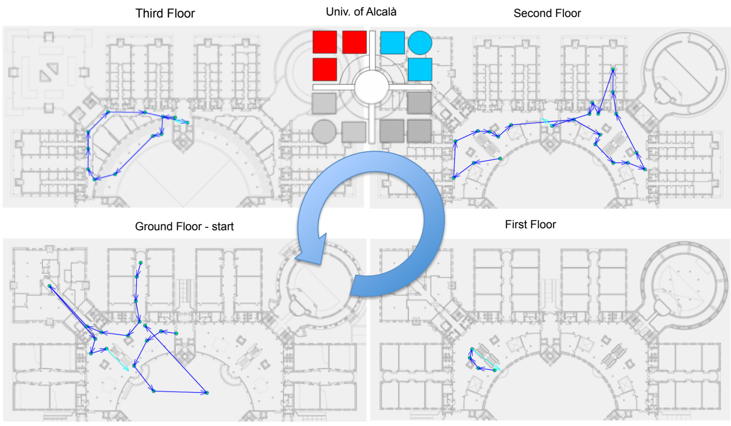


Figure 3.1: The IPIN competition path for the on-site tracks.

The path is shown in Fig. 3.1. It is composed of 56 key points, 5 of which placed in the patio. The path starts from the ground level, up to floors 1, 2 and 3 by means of stairs, then goes to a terrace about 50 m long and proceeds to the ground level, goes to the patio and indoor again. When going to lower floors, the lift is used for Track 1.

Key points were labelled with a tag `[buildingID,floor,markerID]`[2]. They were placed on the floor following these criteria:

- the key points were placed in easily accessible places where people usually step over;
- the distance between key points ranged from about 3 to 35 m, with an average of 8 m;
- each key point was visible from the previous one, to ease the movement of the actor and reduce random paths between two consecutive key points.

[2]Key point labels were written on the button displayed by the StepLogger app, to reduce errors on the actor's part which would require him to restart the path from the beginning.

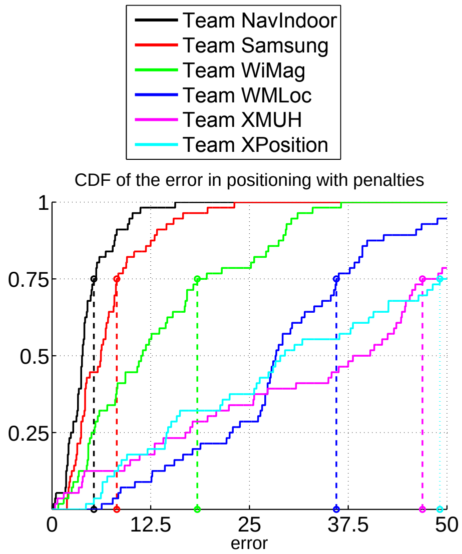


Figure 3.2: Cumulative distributions of the localization error in metres for the first competing tracks.

Track 1 Results

In the first track, 6 teams were admitted [140, 141, 142, 143, 144, 145]: NavIndoor, Samsung, WiMag, WMLoc, XMUH and XPosition. Each competitor had two chances to run the path, considering only its best performance.

NavIndoor and Samsung teams obtained the best results, respectively with a third quartile score of 5.4 m and 8.2 m, while the remaining teams had scores higher than 15 m, as shown in Figure 3.2. Note that the localization errors are in the order of a few metres, which is acceptable for navigating an indoor environment and it is consistent with the EvAAL criteria. Again, we stress that we tested real working systems in a realistic environment with a realistic usage pattern and rigorous criteria: no simulations, no small or controlled environments, and no simplifying assumptions.

Lessons learned from the IPIN Competition track

We observed that tests done on a realistic and long path stress the competing applications, which are required to have a good degree of maturity to run regularly for long time periods. The independent actor may behave in a way different from what the competitors had anticipated. We think that these are key features for assessing the performance in realistic conditions. As far as performance is concerned, we noted that accuracy, speed and scope of site surveying, especially for Wi-Fi measurements, was the key to success for all competitors.

Different environments, different test areas, different sensor technology, etc. have a significant impact on how location results are processed and evaluated, which makes it difficult to directly compare performance. One additional road to comparing algorithms in controlled conditions has been to set up measurement databases, however differences in formats, recording procedure and range of sensor used again makes this road not straightforward.

Our claim is that applying the EvAAL rigorous criteria makes it possible to directly compare the performance of heterogeneous systems in a more significant way than with other existing methods.

3.2 Improvements in smartphone-based indoor localisation

The market of mobile devices is moving toward a new era. As a matter of fact, the last decade have been characterized by a vibrant proliferation of embedded sensing technologies in mobile devices. Moreover, smartphones and in general mobile devices are, by their own nature ubiquitous, and applications able to leverage contextual information, such as location, become increasingly powerful. This constitutes the main motivation of many works in literature that address smartphone-based indoor localisation issues, as described in Section 2.1.5.

Moreover, Section 3.1 contents led us to deal with other open questions: how much would a IPS be advantaged by using a common dataset and by sharing a common evaluation framework? Is it possible to build a viable localization system that uses other mathematical approaches never applied in this context?

We think that investigating the above questions is in fact significant to further the state-of-the-art in indoor localization for AAL systems, This Section is meant to answer these questions.

Finally, this Section contains a proof-of-concept of a smartphone based framework for AAL. In fact, as a consequence of a work specifically presented for the IPS context, we believe that many services and applications for AAL should be packaged together in order to integrate different solutions to support healthy and independent living of old adults. At this regard, the AAL Call 2017[3], a part of the Active & Assisted Living Programme approved in May 2014 by the European Parliament and the Council of the European Union, launched a new Challenge-led Call for Proposals: "AAL packages/Integrated solutions". Many solutions for AAL address only a specific need, have not yet been integrated and incorporated into everyday life and have not been evaluated sufficiently. Our proposal try to answer to this question, proposing a modular architecture that can be exploited to easily develop further strategies and to integrate many specific information as, for example, daytime and nighttime monitoring services.

3.2.1 A common and public dataset for indoor localisation systems

The lack of a common dataset or framework to compare and evaluate solutions represent a big barrier to be overcome in the field. The unavailability and uncertainty of public datasets hinders the possibility to compare different indoor localization algorithms. This constitutes the main motivation of the proposed dataset described herein. We collected Wi-Fi and geo-magnetic field fingerprints, together with inertial sensor data during two campaigns performed in the same environment. Retrieving sincronized data from a smartwatch and a smartphone, worn by users, for creating and presenting a public available dataset is the goal of this contribution.

[3] http://www.aal-europe.eu/get-involvedcall-challenge-2017/

Data acquisition

The data acquisition process involved two campaigns performed at the first floor of the Institute of Information Science and Technologies (ISTI), inside the Italian National Research Council (CNR) building. The data acquisition campaign has been performed by wearing two devices simultaneously: a smartphone and a smartwatch. The smartphone model is the Sony Xperia M2, while the smartwatch is the LG W110G Watch R. Both devices were running the Android OS with dedicated apps developed to collect the data [146]. Data gathered during the study comprises both physical parameters and Wi-Fi access points information. In details, the devices log data regarding:

- force applied to a device on all the three physical axes (x, y, z) expressed in m/s^2, including the gravity;
- ambient geo-magnetic field for all the three physical axes (x, y, z) expressed in μT;
- orientation or degrees of rotation that a device makes around all the three physical axes (x or pitch, y or roll, z or azimuth) expressed in degrees $^\circ$;
- device rate of rotation around each of the three physical axes (x, y, and z), expressed in *rad/s*.

The axes orientation on every Android based device is shown in Figure 3.3.

During the acquisition, the smartphone was kept at the chest level with the screen facing up. Every time the user was on a predefined location, the device recorded the following additional data concerning the detected Wi-Fi access points (APs):

- WiFi network name;
- AP MAC address;
- AP Received Signal Strength Indication (RSSI) expressed in *dB*.

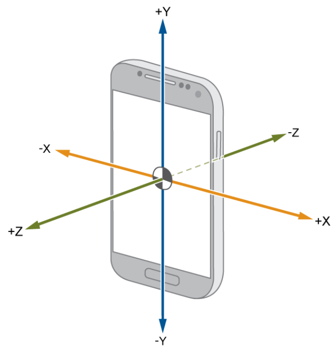


Figure 3.3: Axes orientation on Android based smartphones.

Table 3.1: Parameters collected for each device

	Phone	**Watch**
WiFi APs	X	-
Accelerometer	X	X
Geomagnetic	X	X
Gyroscope	-	X
Orientation	X	X

The reference time used by the smartwatch is synchronized with the smartphone before starting each data acquisition session. Every time sensors or Wi-Fi data are recorded, an entry is written in a file together with the acquisition timestamp. Sensor output is sampled with a frequency of 10 Hz.

Table 3.1 shows the data collected for each type of device used in the experiments. The place in which the data collection was carried out is an indoor office environment composed of two rooms, two corridors and one small entrance hall. Both datasets collected cover a surface of 185.12 m^2.The overall map is shown in Figure 3.4.

Each dot in the map corresponds to a detection point and for each of them, two samples of each parameter were collected. The points were equally spaced by 60 cm in both directions in order to uniformly cover the interested area.

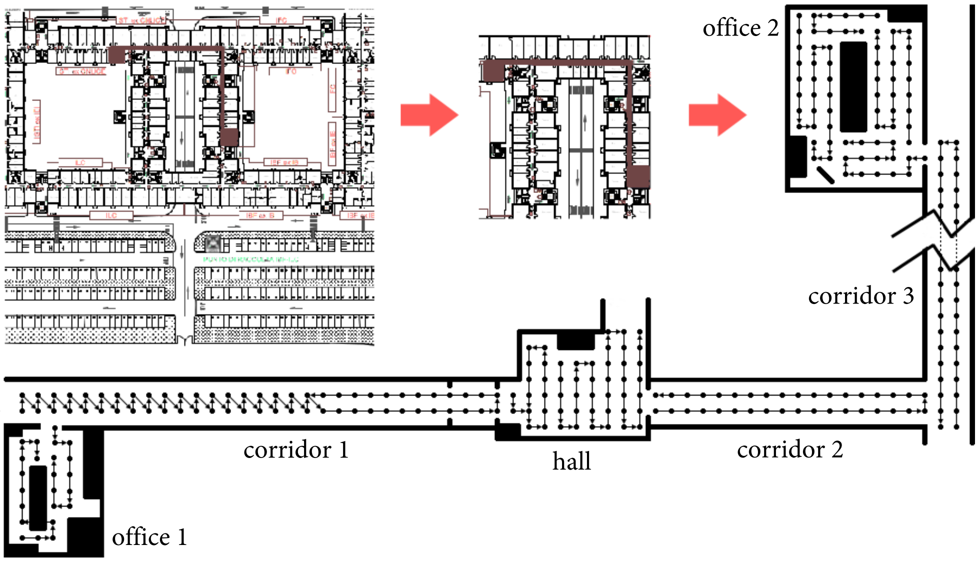


Figure 3.4: Map of the data collection environment.

Table 3.2: Main characteristics of proposed dataset: Number of Campaign (N), Number of buildings (N_B), Surface, Number of floors, Number of places, Number of WLAN Samples, Number of WAPs, Number of Geomagnetic Samples, Number of devices

N	N_{Bu}	N_{Fl}	N_{Su}	N_{Pl}	N_{Ws}	N_{Wa}	N_{Ge}	N_{De}
1	1	1	185 m^2	325	10850	127	7500	2
2	1	1	185 m^2	325	10945	132	7500	2

Dataset description

The records of both datasets have been captured on 325 different places. These places are shown as bullets in Figure 3.4. Local coordinates are given considering the X-Y axis origin on the bottom-left corner. By this point, each bullet is 0.6 meters far from its neighbours since each tile is $0.6m * 0.6m$. Table 3.2 shows the main characteristics of the proposed datasets.

Each dataset contains the following elements:

- Place ID;

Table 3.3: Mapping table - First campaign

Place ID	**X Axis**	**Y Axis**
25	20.4	4.8

- AccX, AccY, AccZ;
- MagneticFieldX, MagneticFieldY, MagneticFieldZ;
- Z-Axis Angle (Azimuth), X-Axis Angle (Pitch), Y-Axis Angle (Roll);
- GyroscopeX, GyroscopeY, GyroscopeZ;
- Timestamp.

Regarding the Wi-Fi dataset, it also contains:

- Place ID;
- RSSIs collected from the different SSIDs observed.

The database also collects the mapping between the coordinates of the reference points used during the campaigns, identified by the relative Place ID, and local Cartesian coordinates - according to Figure 3.4. As an example, Table 3.3 shows the coordinates of the 25th Place ID.

The dataset proposed can be used for developing and testing novel approaches to the indoor localization problem. The multisource characteristic is supported by the presence of two different devices collecting, simultaneously, data from the surrounding environment: a smartphone and a smartwatch, respectively. Each device collects multivariate data represented by their inertial parameters (i.e. acceleration, orientation, and gyroscope), geo-magnetic field, and received signal strengths from Wi-Fi access points. Finally, it can be easily exploited by ILSs fusing different data. Several examples are available in literature focusing on hybrid methods [147, 148] and information fusion frameworks [149, 150]; these systems can now be tested on real world data, publicly available to researchers.

The presence of Wi-Fi RSSs and geo-magnetic field values, together with the map of the monitored environment, opens various fingerprinting-based possibilities for ILSs, helping researchers in the off-line collection phase.

On the other hand, the geo-magnetic field can be used to lower the effort in rebuilding the off-line Wi-Fi RSSs map, since it does not differ between different campaigns. Further technical details are available in [151].

3.2.2 A deep convolutional neural network approach

The development of smartphones has opened up many new application fields, where traditionally the use of IMU has been too costly, or the sensors too bulky. One important application is the pedometer, which counts the steps that a person takes and it is usually employed in sport or health management softwares.

A pedometer is also an indispensable module for smartphone-based PDR, that is an important positioning strategy. PDR can reach a high accuracy, if the IMU is mounted on the shoes, because the user moving distance can be easily calculated through the double integral of acceleration. However, smartphones have little chances to be mounted on shoes. Therefore, researchers first utilize pedometers to detect a step event and then estimate an average step length as the moving distance.

Step detection techniques mainly belong to two classes: foot-mounted and hand-held like method. Considering the foot-mounted case, it is relatively easy to implement step detection. In fact, a step must contain a phase, also known as zero velocity update (ZUPT), in which a foot touches the floor for a few seconds. Then, researchers can use acceleration-variance, acceleration-magnitude, or angular rate energy detectors to detect a step event.

For the hand-held like case, users tend to hold the phone in their swinging hand, bag, or in a phone call posture. When users walk, phones at these positions display no zero-velocity, so the detection method cannot be used as foot-mounted case. In order to detect steps, researchers take the advantage of the low frequency of steps. Step acceleration signal contains low-frequency peaks for each period, and hence step detectors count these peaks as steps. In order to reduce false alarm rates, step detectors further remove false step peaks by comparing the similarity of several continuous step periods. This method reduces the false positive rate for true negative steps, however, the initial multi-period comparison injects several seconds of lag for the pedometer first response.

Apart for steps, many human movements are periodic and have a low frequency, like shaking hands or legs. Therefore, the above-mentioned multi-period comparison has little effect on these periodic movements. Traditional step detectors tend to be error-prone also in conjunction with periodic negative-step movements. Definitely, for a PDR based positioning system, these two drawbacks will make the system unfriendly to users. For example, the initial lag problem makes the system seem stutter, especially when users frequently stop. On the other hand, the drawback of being error-prone to periodic movements is that the output of the systems in terms of position floats when a static user shakes hands.

So, the main aim of this contribution is to improve the robustness of pedometer measurements reducing false negative-step detection, especially during periodic movements, and to decrease the initial response time.

Creating a robust pedometer is challenging, because the step-like features change depending on the way a user holds the smartphone. Thus, it is necessary to utilize many step features to improve the pedometer anti-interference ability and decrease the dependency on periodicity. With this purpose, we propose a deep convolutional neural network (CNN) approach. In fact, the CNN is supposed to learn automatically more of these step features, rather than designing a sophisticated artificial step detection logic.

Another challenge is how to design and to train a CNN for the pedometer application. Based on the feature analysis of steps, we adopt the acceleration strength as an input feature, and then design a five-layer pedometer CNN. In order to train the network parameters, the learning process needs a consistent amount of labelled training data. Therefore, we present a step-data automatic extraction and labelling method for the network training.

The third challenge lies in the real-time step detection. The proposed pedometer leverages a sliding window to extract real-time input features from smartphone sensors. The proposed system leaves aside the traditional peak detection method, and shows more flexibility. However, this operation, also causes multiple positive step outputs when a true step event occurs, because

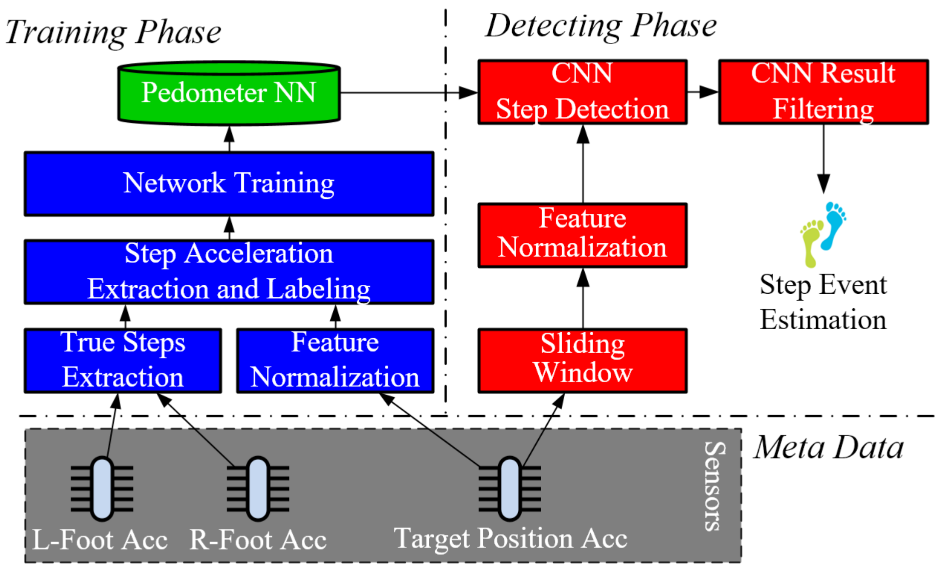


Figure 3.5: Step detection system architecture. In the sensors module, Acc means a triaxial accelerometer. L-Foot stands for the left foot. R-Foot stands for the right foot. NN means neural networks. And CNN means convolution neural networks.

acceleration features around true step-events are similar. Therefore, we consider a filtering method to improve the prediction.

System architecture

As Figure 3.5 shows, the smartphone-based pedometer system consists of seven modules: step feature extraction, the feature normalization, the acceleration extraction and labelling, the network training, the sliding window, the CNN step detection, and the resulting filtering module (used in the online detecting phase). In addition, a sensor module provides basic acceleration signals of the left foot, right foot, and the target position to upper modules.

During learning, users collect acceleration signals from the two feet and target positions, thus training the pedometer CNN. A target position is where the system should be able to detect steps, for example, a swinging hand, a phone call posture, or putting the smartphone into a bag case. The training-data collection system is shown in Figure 3.6, including the one target-sampling

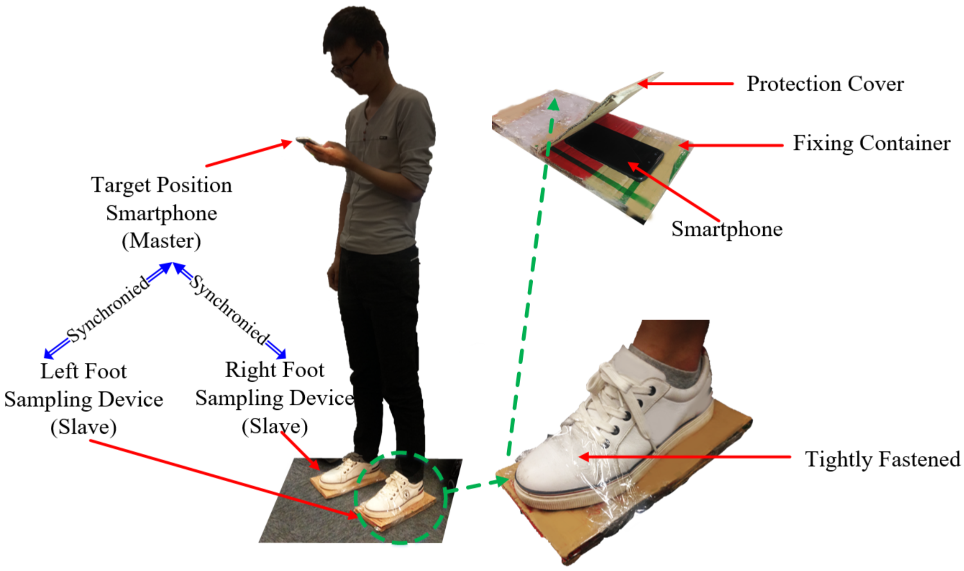


Figure 3.6: Training data collection system. The figure enlarges a foot sampling device to clarify its working process. In this figure, the target position is a texting hand.

smartphone and two foot-sampling devices. The foot-sampling device consists of one smartphone and a container. The smartphone is fixed into the container, and then the container is tightly fastened to the bottom of the shoes, since this place provides the most similar acceleration signal of the foot. When data collection starts, the target position smartphone opens a Wi-Fi access point connection, working as a master. Then the two foot-sampling devices connect to the master, synchronizing with it, using the smallest round trip time (RTT). Based on our experiments, the synchronization accuracy is under 2.5ms, less than the data collection period (5ms). After the data collection phase, the system extracts true steps from the foot-sampling data, then it labels acceleration data of the target position. Because the foot-sampling data and the target-sampling data are synchronous, the acceleration signal segment of one-step in the target position can be confirmed by the step scope of the foot data. Then, this signal segment is extracted and labelled, generating a pattern for training. Successively, the network training module trains the pedometer neural network using these labelled data.

It is worth noticing that here it is assumed that a user performs only a limited set of extra actions when heshe is running (e.g., swinging hand, phone call posture, putting the phone in a bag case). Such an assumption is called "closed world" in machine learning [152]. Actually, we expect the causes of misclassification when the pedometer runs (i.e., an action performed by the user and detected as a step) are few, so that such an assumption, even if it is not always true, it is reasonable in real life cases.

In the online detecting phase, users only collect acceleration signals from target positions. Unlike traditional step detecting methods that select candidate steps by the peak detection technique, the proposed system utilizes a sliding window. The window length is equal to the length of training step segments. The detecting frequency is 20 Hz. Then the CNN step detection module detects the input features and output raw predictions.

Finally, a result-filtering module processes the raw predictions and generate the final output.

True Step Scope Extraction

As Figure 2 reveals, the acceleration of a walking foot consists of flat and fluctuation areas, corresponding to the stance and moving phase in the gait cycle. Take the left foot for example: when it contacts the ground at the sample index one, the foot is in a static state, so the acceleration closes to zero.

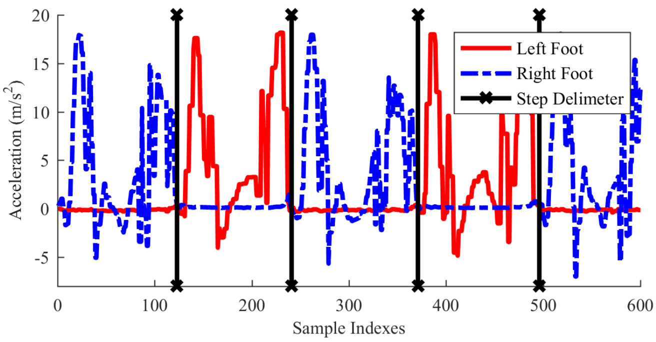


Figure 3.7: The variation of accelerations for the left and right foot of a pedestrian.

When the following step two starts, left leg swings the left foot, therefore the left foot acceleration changes violently in step two. Noticing that for a pedestrian, his two feet can keep in stance phase simultaneously, but it is impossible to keep both of them in swing phase.

The proposed system extracts true step scopes from the two foot-sampling devices. Since a foot acceleration consists of flat and fluctuation areas and, to detect the scope of a step, the system has to identify the end of flat acceleration area as the step start index and the start of the next flat acceleration area as the step stop index. Our proposal first calculates the moving standard deviations of accelerations, detecting flat areas with small standard deviations, and then it finds edges as possible steps. The method further removes too short steps in case of outliers.

Convolutional Neural Network for the Pedometer

As Figure 3.8 shows, the proposed deep pedometer CNN has four stacked layers: a convolution layer, a batch normalization (BNorm) layer, a rectified linear unit (ReLu) layer, and a fully connected multi-layer perceptron (MLP).

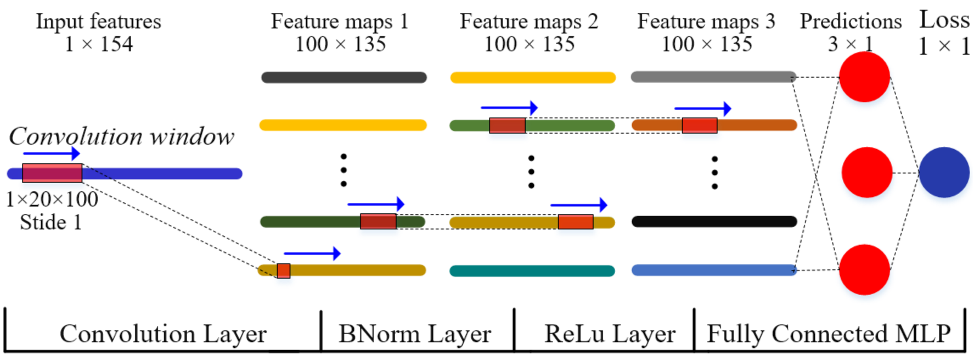


Figure 3.8: Deep pedometer neural network. BNorm stands for batch normalization. ReLu means rectified linear unit. MLP stands for multi-layer perceptron.

In detail, the convolution layer slides a convolution window along the input acceleration features, generating a new feature map. In the proposed system, this layer has 100 convolution windows, so that the layer generates 100 feature maps in the feature maps 1.

Then, the BNorm layer normalizes the activations of the previous layer at each batch by applying a transformation that maintains the average activation close to zero and its standard deviation close to one, in order to accelerate the network convergence. The next module, the ReLu layer adds non-linearity to the network. It helps in accelerating the network convergence and improves the network performance. Finally, the fully connected MLP calculates prediction values of all labels. The CNN scheme uses a softmax loss function at the end of the stack, to evaluate the error of predictions.

The input feature to the CNN is an acceleration strength vector with 154 elements equal to the mean sample data count of one-step, with a sampling frequency of 200Hz, and with the mean time of one-step of 770ms. The convolution window has 20 randomly-initialized parameters. It slides along the input features, computing convolution values within the window at a stride interval of one. Therefore, the convolution layer outputs feature maps 1 with feature-length of 135.

The training data consist of three labels: left step, right step, and negative step. The training data for left and right steps are acquired through the above-mentioned method, and then they are resampled according to the length of the input features. For the negative-step case, we first ask a user to use the smartphone without walking, collecting negative-step acceleration signals. Then, the system utilizes a fixed-length sliding window to extract negative-step training data. The window length is also the same as the input features.

The proposed pedometer CNN has more than 2,000 parameters. These parameters are randomly initialized and the backpropagation algorithm is used for training.

Online step detection and output filtering

In the online detecting phase, the proposed system utilizes the trained neural network to predict steps through the retrieved real-time acceleration signals. To this purpose, a sliding window is implemented to extract input features from real-time signals. Therefore, as Figure 3.9 shows, the system generates prediction results each time the window slides.

When a true step event occurs, the CNN produces a preliminary output as a series of discontinuous positive step predictions. Being this preliminary

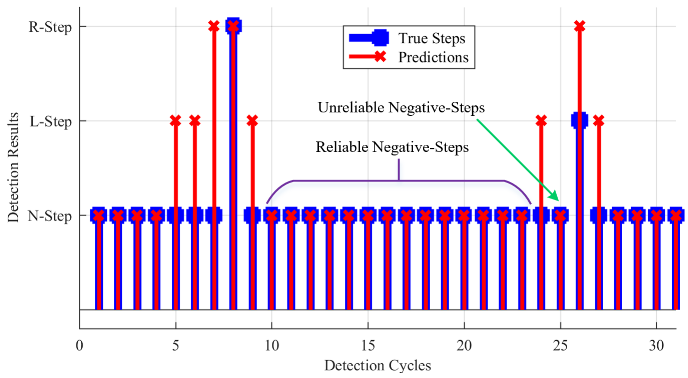


Figure 3.9: The real-time prediction results. The true step event is defined as the time that a foot contacts the ground from a swing phase. L-Step means left step event. R-Step stands for right step event. N-Step means negative-step event. The time between detection cycles is 50 ms.

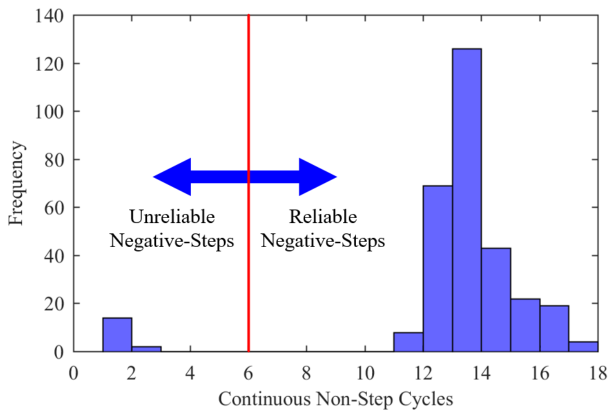


Figure 3.10: Continuous negative-step cycle count statistics.

CNN predictions confusing to users, the system filters the predictions before produce the final output. In fact, the system filters the original pedometer CNN predictions based on the fact that the number of reliable negative-step cycles is much larger than the unreliable near step events, as Figure 3.10 shows.

In our experiment, we use a threshold value equal to six to distinguish the two type of cycles. On the other hand, since the features of the left step

Brand	HTC	Samsung		Huawei	
Series	One X	S4	S5	Mate-8	P9
CPU	1.5G 4 cores	1.6/1.2G 8 cores	2.5G 4 cores	2.3/1.8G 8 core	1.4/1.6G 4 cores
RAM	1 GB	2 GB	2GB	4 GB	4 GB
Function	L-Foot Sampling	R-Foot Sampling	Compare	Target/ Compare	Compare

Figure 3.11: Experiment Smartphones

and the right step are similar, the system usually confuses the detection of these steps. Therefore, the filtering system merges the two types of events into a single one. The system outputs the step events as soon as the pedometer outputs a positive step prediction. Then, the system keeps outputting negative-step events until it passes a long enough continuous negative-step period.

Experiments and Performances

In our experiments, we collect acceleration signals using five commercially available smartphones. Specifications are shown in Table 3.11. We utilize the One X and S4 to collect the left and right foot data, and the Mate-8 to collect the target position data. The S5, P9, and Mate-8 have inherited the pedometer software, so we compare our algorithm with them. The smartphones send the collected data to a PC server to train the pedometer neural network. Then, each smartphone runs the trained neural network to detect real-time steps. Our system trains the network with MatConvNet Matlab software and then runs online step detection on Android devices with Deeplearning4j, a java open source software. The step count of the training data, and the testing data at each target positions are all 200. Before the experiment, we had trained the pedometer CNN with data from different target positions.

In order to examine the influence of user's height and gait, the experiment involves six users, who walk for 200 steps naturally, wearing the foot-sampling device. Then the system counts the detected steps and calculates the correct detection ratio using the number of true step divided by the absolute value of

Users	#1	#2	#3	#4	#5	#6
Gender	F	M	M	M	M	M
Height	1.61m	1.95m	1.74m	1.67m	1.76m	1.69m
Ratio	99%	99.5%	99%	98%	100%	99.5%

Figure 3.12: Correct Ratios of Different Users on Normal Speed

Users	#1	#2	#3	#4	#5	#6
Gender	F	M	M	M	M	M
Height	1.61m	1.95m	1.74m	1.67m	1.76m	1.69m
TP Ratio	97.5%	99.5%	99.5%	98.5%	98.5%	98%

Figure 3.13: True Positive Ratios on New Users

the difference between the true step and the detected step counts. As Table 3.12 shows, the true step extraction method achieves high accuracies.

This part evaluates the performances of the proposed CNN pedometer from various aspects, comparing it with the three algorithms available in three different smartphones. Pedometers in the smartphones need to acquire data from seven steps before they can count the initial step. The proposed method has no such limitations.

True Positive-Step Evaluation of Different Users: users have different walking speeds and gaits, so the experiment involves six users walking for 200 steps, to calculate the correct step ratio. As Table 3.13 shows, although users are different in gender and height, the true step ratios are approximately the same. Therefore, the height and the gender have little influence on the system performance.

True Positive-Step Evaluation of Different Target Positions: this experiment requires the user to put the phone in different target positions, including a swinging hand, assuming the phone call posture, and in a bag. Figure 3.14 shows that the proposed method performs well in the calling and bag case, but weakly in the swinging hand scenario, comparing to the other three algorithms. Since the step patterns of a swinging hand are more random than the relatively static calling and bag case, and considering that we only use 200 piece of training data to train the network for each case, more training data of swinging hands are needed to improve its performance.

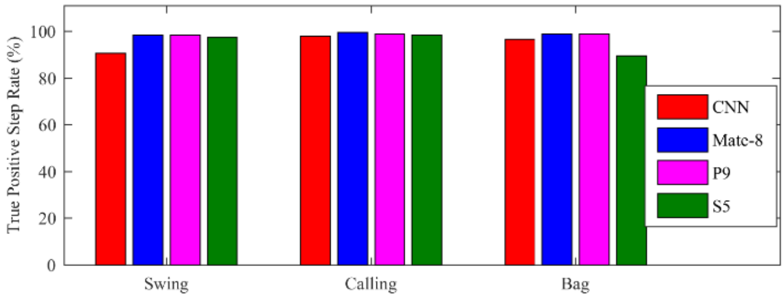


Figure 3.14: True positive step ratios of different target positions.

False Negative-Step Evaluation: periodic motion is difficult to be inferred for periodicity-based pedometers. This experiment simulates periodic motion in four manners, horizontal shaking, vertical shaking, mild shaking, and violent shaking. The tester sustains the periodic motions for three minutes, then counts the false positive steps. Figure 3.15 shows that the proposed CNN pedometer performs rather better than the other methods. Its false positive step count is 10% smaller with reference to the other pedometers, revealing its strong ability to overcome the problem of negative-step periodic motions.

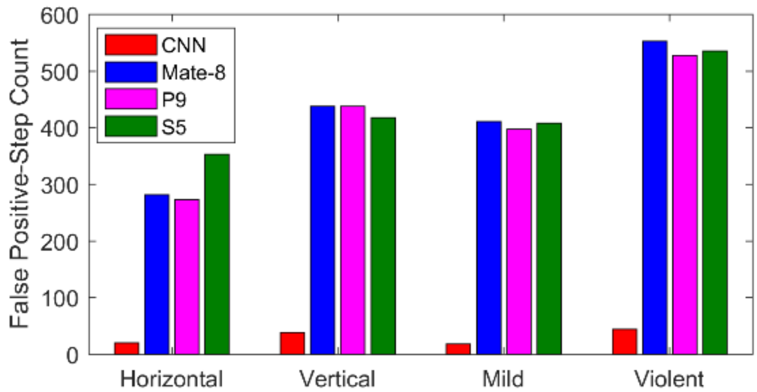


Figure 3.15: False positive step counts of different negative-step movements.

3.2.3 A proof-of-concept of a smartphone-based framework for AAL

In this contribution we present a proof-of-concept of a smartphone-based framework for AAL scenario. The idea behind this application, proposed as an advancement in this thesis, arose from IPS context. We believe that, as a positive side effect, this smartphone application can be exploited in AAL due to its modular architecture. The proposed software allows to extend its functionalities to other services, by implementing new raw-data reader interfaces (e.g., creating connections to embedded and general purpose devices, such us Raspberry, Arduino) and front-end interfaces in order to present the processed data to an end-user. Performances and results of these applications are presented only for indoor localisation purpose.

The proposed system is composed of two applications, namely PrettyIndoor and FingerFood. The former is the position engine, which implements all the algorithms and incorporates the data structures required. It comes with a front-end interface, thought for researchers' testing operations with many possible strategies, already existing or coming in the near future. The latter is an utility application that allows the user to capture Wi-Fi and magnetic fingerprints, save them into a file, and make a textual fingerprint map that can be used through other applications. Both PrettyIndoor and FingerFood access the phone sensors through a library, which extends the Android native methods for sensor access.

Using PrettyIndoor

The positioning application is composed by an Android service, implementing the back-end, and an essential graphical user interface shown in Figure 3.17. These two main components provide all the utilities for testing indoor navigation solutions. Currently, the user can choose among PDR-driven, fingerprint-driven or mixed strategies, but many more techniques are planned to be implemented.

PrettyIndoor requires a starting position, to be specified in the text box. After that, the localization service can be started by pressing the *Play* button. This action switches the front-end to the *online* mode: the bottom floating

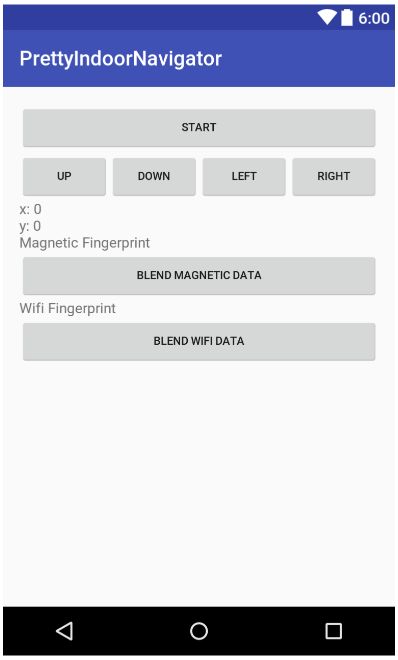


Figure 3.16: FingerFood activity

action buttons change and the toggle buttons, corresponding to sensors used by the chosen strategy, are switched on. These buttons allow to enable and disable any data source during run-time, which is a useful function for a deeper testing. The indoor positioning service runs in the background, updating its saved *current position* in real-time, using the user-selected method. The current position can be saved into a log file, which is automatically created by the application, by pressing the bottom-right button in the online-mode GUI. The format of the position log is simple: `timestamp`,x, y, z, where `timestamp` is the time when the button is pressed, x, y is the 2D position on a floor, while z is an integer value representing the floor, where 0 is the ground floor. Lines are newline-terminated, so the log is a standard CSV text file, where every row contains a different time-position relation. To save the current position, the *flag* button must be pressed, and the separation of the back-end logic into an Android service allows to easily expose this function to a future extension of the application and even to third-party applications.

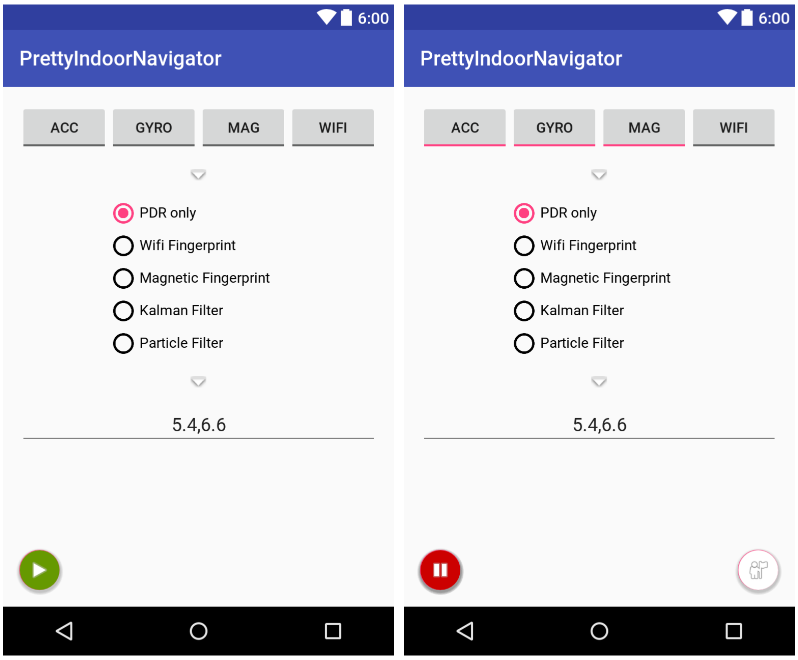


Figure 3.17: Left: the screen during positioning hasn't started. Right: screen while positioning is active.

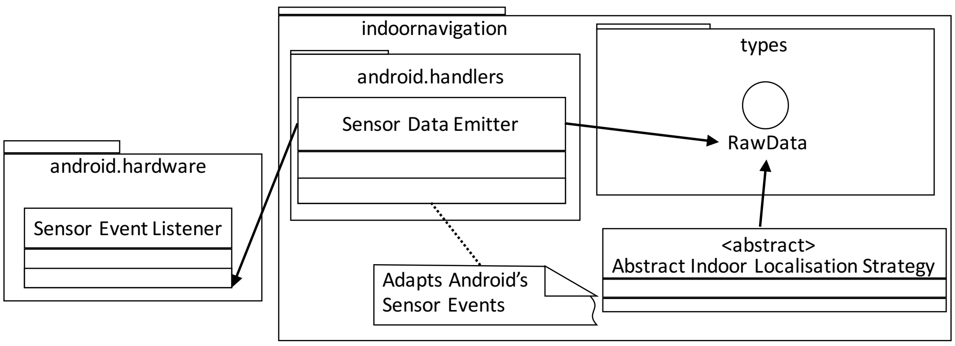


Figure 3.18: Adapter pattern workflow

The architecture of PrettyIndoor

Figure 3.20 shows the architectural concept of PrettyIndoor. The main goal is to develop a three-tier architecture with a logical separation between the

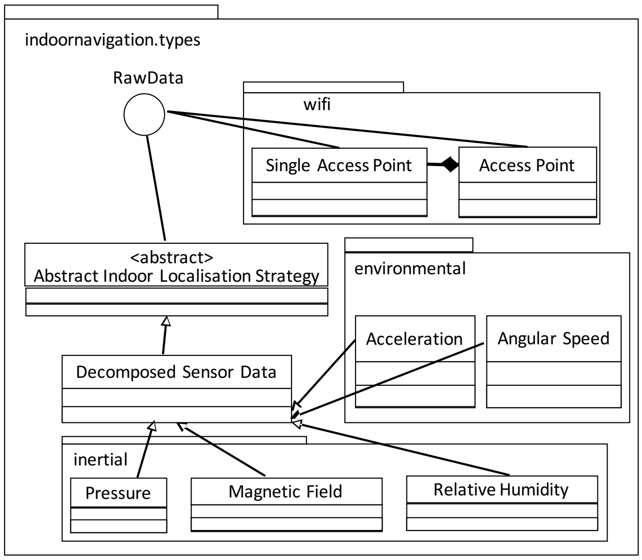


Figure 3.19: Data encapsulation layer.

native raw data, the data abstraction layer and the core logic layer. The strength of this model is the easy implementation of further modules and strategies into the core logic layer and, more specifically, inside the localization strategy sub-layer. In fact, handlers which manage the native raw data, coming from the built-in sensors the smartphone board, are offered using an adapter. PrettyIndoor allows to implement new algorithms, or to enhance the implemented one, without a priori knowledge on how the operating system manages the sensor data. The final output is a local coordinate triple x, y, z useful for rendering, navigation, and mapping.

As shown in Figure 3.21, the current version of the PrettyIndoor service implements five different strategies for solving the indoor location problem. These strategies have been chosen and implemented after a state-of-the-art analysis of the papers presented to the real-time smartphone-based track of the IPIN 2016 competition [140, 141, 142, 143, 144, 145].

The first strategy is based on PDR (Pedestrian Dead Reckoning) techniques. This technique relies only on the accelerometer, the gyroscope and the magnetometer, using sensors for determining orientation and step events.

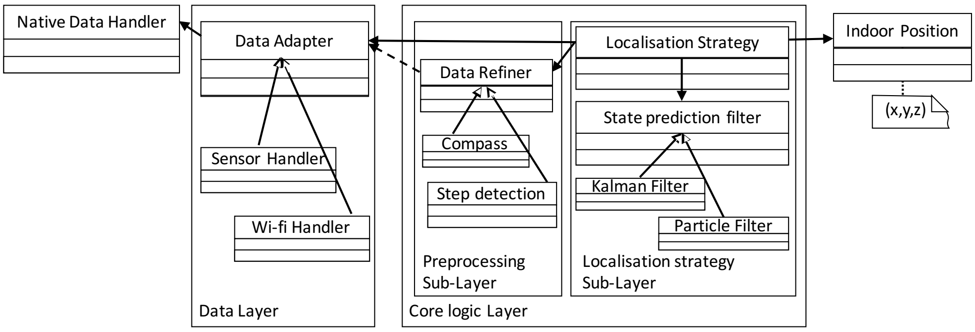


Figure 3.20: Architecture of PrettyIndoor application.

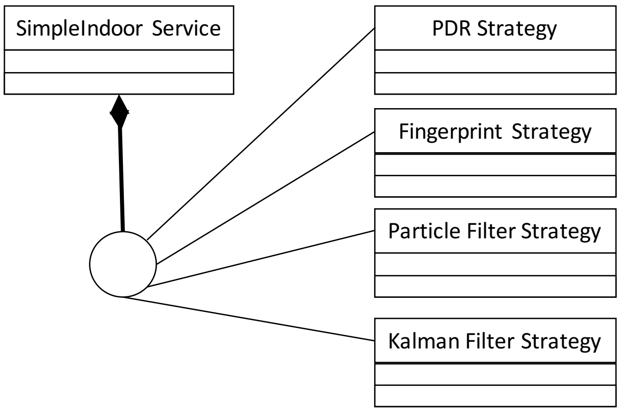


Figure 3.21: Scheme of the implemented strategies.

The conceptual workflow is shown in Figure 3.22. This implementation considers an average step length of 0.6 m and simply elaborates the variation on the x, y coordinates and adds it to the previous saved position.

The strategy that uses a fingerprint map compares either the measured Wi-Fi RSSI or the magnetic field with the values in the database. The position is then found by operating on the results of the k-Nearest Neighbours (k-NNs). A lot of solutions present in literature are not limited by the usage of a single technique, instead they usually combine many of them. In order reach this goal, one of the location strategies within the application uses a Kalman filter. It always keeps the positions found by both PDR and fingerprint, whose

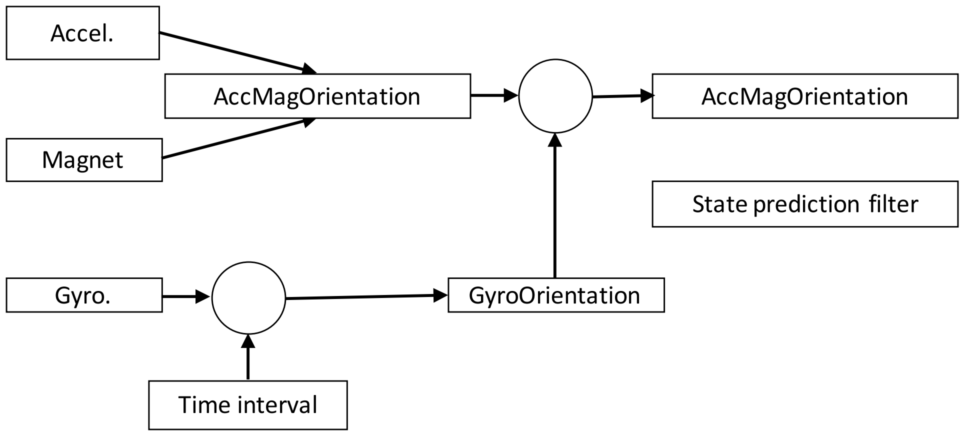


Figure 3.22: Orientation algorithm workflow

difference is then corrected combining it with a predefined covariance. This refined variation is then added to the position and the output is assumed as the new coordinates.

Another strategy that uses a state estimation filter is based on a particle filter. In contrast with the Kalman filter, this filter directly operates on the position. In fact, during the initialization, a number of particles representing the possible positions are generated on the starting point. When a step is detected, the particles are moved by the variation detected by the PDR plus a random error. This error comes from a model represented by a zero-mean Gaussian distribution with σ set to 0.15 m. For each particle, the algorithm then calculates a distance $d_{particle} = \sum_{i=1}^{n} \frac{d_i}{r_{i,particle}}$ and constraints the particles to lie inside the map. Picking a random number from 0 to an experimentally tunable maximum, if it lies between zero and $d_{particle}$, the particle is removed. Eventually, a number of particles is resampled in order to restore their original number.

All these strategies take into account the map topology in order to assure the correctness of the found positions.

Portability through data encapsulation

Since portability is an ubiquitous requirement in recent software production, even PrettyIndoor, FingerFood and their libraries accomplish this aim by encapsulating data in a proper type for each kind of source.

Figure 3.18 represents how the listener and the adapter are organized and work. For example, when an Android *SensorEvent* is sent to the listener, the array containing its floating point values is made ready by the adapter for making an *Acceleration* object, which is then sent to the classes that are waiting for it.

The current data type hierarchy is represented in Figure 3.19. For this, the Android service that implements the navigation creates a new data object when an Android sensor event arrives through an adapter class.

Experimental Evaluation

Experiments were performed at the Italian National Research Council (CNR), located in Pisa. The map of the experimental region is characterized by two straight corridor with offices located on both sides, a small hall between the two corridors and two offices of 10 m^2, as shown in Figure 3.23. Dots in the map are reference points. Using FingerFoood, Wi-Fi and magnetic fingerprints were acquired by standing still for 5 s, in order to create two fingerprint maps. The points are equally spaced by 60 cm in both directions in order to uniformly cover the interested area.

Figures 3.23 and Figure 3.24 show the two different paths used in the experimental campaign, represented as green lines. Paths are composed by 13 and 8 points, respectively. Points were placed on the floor, using circle markers, used as ground truth. An actor, who held the smartphone in his right hand, used the PrettyIndoor application as explained in Section 3.2.3. We tested the application using two different smartphones: a Xiaomi Mi3w with Android 4.3, and an Lg G3 with Android 6.4. For each path and for each smartphone, different runs were performed using the different algorithms and strategies currently implemented on PrettyIndoor.

In order to test the proposed framework, we evaluated the results of different paths calculating min error, max error, mean error, and third quartile

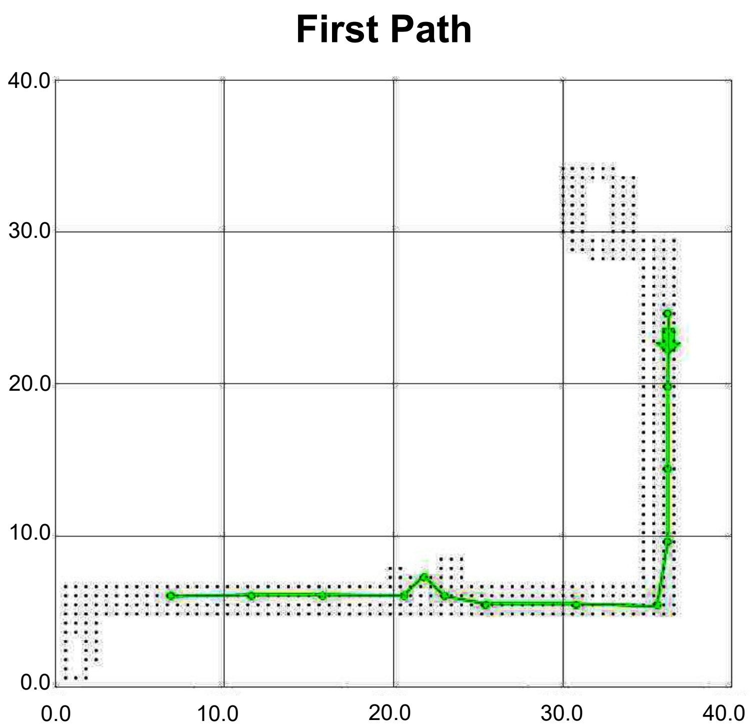


Figure 3.23: Map of the experimental region (dots) and first evaluation path (green line).

error, the latter according to the EvAAL competition metric. Table 3.4 shows the results obtained using the Xiaomi Mi3w smartphone, while Table 3.5 is obtained using the LG smartphone.

The overall localisation performance was measured on two paths for five different strategies:

- PDR - only using the inertial sensors;
- Wi-Fi - only using the Wi-Fi fingerprint database;
- GeoMag - only using the magnetic database;
- P.F. - using the first three fused in a particle filter;
- K.F. - using the first three fused in a Kalman filter.

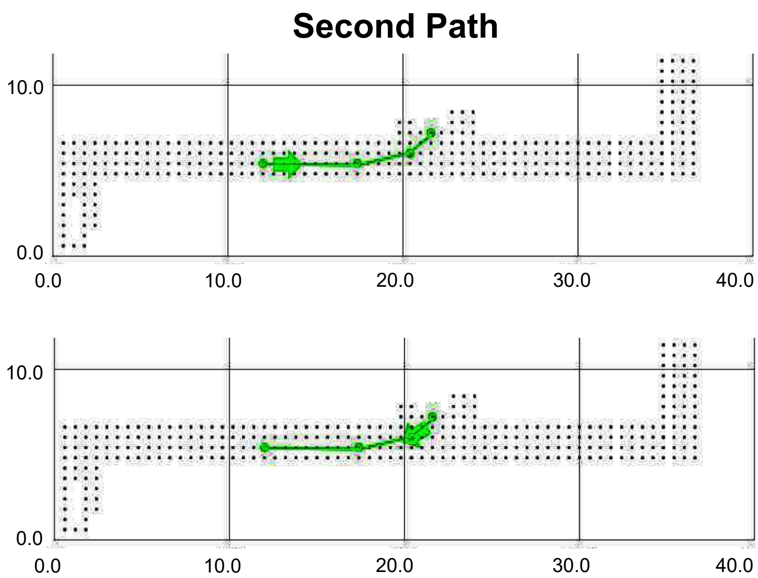


Figure 3.24: Second evaluation path.

Table 3.4: Xiaomi Mi3w - Android 4.3

	$P.F.$	$K.F.$	PDR	$Wi-Fi$	$GeoMag$
First Path					
ϵ_{min}	3.7	6.7	4.8	0.9	1.1
ϵ_{max}	31.9	41.0	36.5	24.1	21.0
ϵ_{mean}	20.4	26.4	23.2	11.8	10.4
ϵ_{thq}	22.9	36.0	27.1	20.5	16.1
Second Path					
ϵ_{min}	0.4	16.6	0.6	1.4	5.3
ϵ_{max}	7.3	34.3	9.8	7.9	13.9
ϵ_{mean}	5.0	21.7	6.9	4.0	7.8
ϵ_{thq}	6.6	23.6	9.4	5.0	9.0

The performance is generally better for the second path. By looking at the results for the first three simple strategies, we can observe that a significant

Table 3.5: LG G3 - Android 6.4

	$P.F.$	$K.F.$	PDR	$Wi-Fi$	$GeoMag$
First Path					
ϵ_{min}	2.0	11.2	4.2	0.5	2.1
ϵ_{max}	24.5	38.9	32.8	20.8	17.1
ϵ_{mean}	13.6	27.0	23.0	11.1	8.3
ϵ_{thq}	16.1	35.1	25.8	19.4	13.1
Second Path					
ϵ_{min}	0.6	17.4	0.9	1.6	6.2
ϵ_{max}	6.3	31.1	8.7	7.7	11.9
ϵ_{mean}	6.0	19.4	8.0	4.3	7.5
ϵ_{thq}	4.6	20.1	8.2	4.5	8.7

part of path 1 has a bad Wi-Fi performance in a specific area, which probably means that the fingerprint database should be improved in that location. Similar observations can be done for the magnetic fingerprint database. Additionally, one can notice that the step detection implementation is far from being perfect, and works reasonably well only if there are bends along the path. Oppositely, steps are lost in long rectilinear paths. These problems are all concentrated in the first path, which explains why particle filter performance is much better for the second path. It is worth noticing that the above analysis is simplified by the modular nature of the tools, which allows to enable, disable and fuse modules together.

The results obtained in the second path suggest that the framework can produce good results once the algorithms are optimised. Therefore, we could say that its purpose, which was to create a flexible, extensible and modular software architecture, is accomplished. Moreover, this implementation can also be useful for researchers in AAL, thanks to the free software license used for distribution.

3.3 Localising crowds through Wi-Fi probes

Mobile devices, that we carry with us routinely, disseminate radio messages, as it is the case with Wi-Fi scanning and Bluetooth beaconing. Is it possible to examine these digital crumbs to obtain useful insight on the presence of people in indoor locations? The literature lacks of answers to this question. We demonstrate the feasibility of using Wi-Fi probes to identify frequented areas by experimenting in three different indoor environments with sniffing devices.

3.3.1 The probe sensing architecture

Devices with an enabled Wi-Fi network periodically emit Wi-Fi probe requests. Their purpose is to actively scan the network searching for available Wi-Fi access points or for a previously accessed access point. This discovery phase usually prepares an association phase through which a device establishes a connection to a specific network. Devices send probes with a frequency depending on several factors, including the Wi-Fi device driver and decisions made by the operating system. For example, some devices do not perform any Wi-Fi scanning when they are connected to a wired network, while other devices still emit Wi-Fi probes even if they are connected.

Probes are sensed by all APs in the area as a part of their normal activity, as the IEEE 802.11 standard mandates. Using them for different purposes can be done internally to the APs or externally by a server to which the APs send the collected probes. For simplicity of the experimental set-up, we collect the probes emitted by Wi-Fi-enabled devices by means of a network of sniffing devices, namely FogSense devices distributed by Cloud4Wi. FogSenses are plug-and-play Wi-Fi sensors provided with a USB port as well as a mini-USB port for configuration (figure 3.25). The Wi-Fi module is a Broadcom WICEDTM from USI, supporting IEEE 802.11 b/g/n Wi-Fi standards. A FogSense logs Wi-Fi probes emitted by nearby Wi-Fi-enabled devices and sends the logs to a server at intervals of 15 s.

The data stored by the server include information extracted from the captured probes: (i) the reception time stamp, (ii) the MAC address of the sending device, (iii) the ID of the receiving FogSense and (iv) the RSS (dBm)

Figure 3.25: A FogSense Wi-Fi sensor used in the measurement campaign.

measured by the FogSense.

3.3.2 Experimental setting

We perform our experiments in three scenarios characterised by different layouts, sizes and number of sniffers needed to cover the area. Analyses of probes presented in this work are based on anonymised data. Maps of the three scenarios are shown in figure 3.26.

In a real deployment scenario probes are normally gathered by already installed APs, and FogSenses are only deployed if the number and positions of APs is not sufficient to obtain a good accuracy performance. In our experiments, however, we only work with FogSenses, for simplicity.

The CNR area in Pisa (from now on CNR) covers about 350 m^2 and it is characterised by a straight corridor with offices located on both sides. The sensing region includes 12 offices where we deployed 4 FogSenses, as shown in figure 3.26a. The Cloud4Wi Italian office (from now on C4WIT) covers about 250 m^2 and is located in an old historical building with 9 offices of irregular shape, where we deployed 8 FogSenses (figure 3.26b). Finally, the Cloud4Wi San Francisco headquarter (from now on C4WUS) is an open office covering about 500 m^2, with 3 small offices and a meeting area (on the right and on the top left side of figure 3.26c) where we deployed 5 FogSenses.

It is evident from the maps that the three scenarios are quite different. C4WUS is an open space, with no obstructions. This is not very dissimilar from CNR, where some of the walls are gasbeton and others are drywalls, both of which are not a serious obstacle to Wi-Fi signals. On the other hand, C4WIT is quite different: this is an ancient building with many brick and stone walls up to 60 cm thick. We expect this scenario to produce more accurate results, because different FogSenses generally receive well differentiated signal strengths from devices.

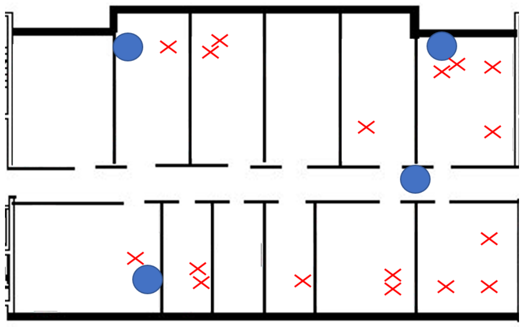
We installed different number of FogSenses in the three areas, specifically a higher number is needed in the C4WIT location, because the effect of the walls is similar to significantly increasing the distances.

To evaluate the performance of the proposed methods, we considered the position of some *known* stationary devices, e.g. workstations, laptops, smartphones and other Wi-Fi-equipped devices in each location.

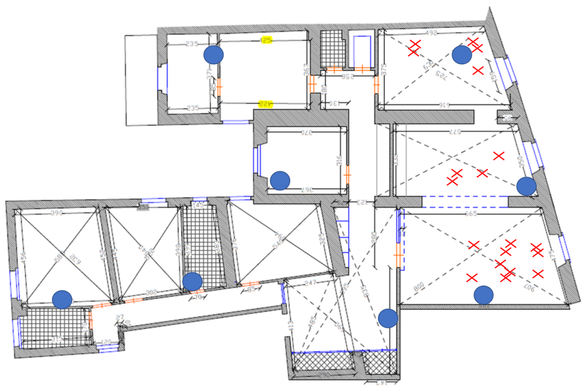
The position of known devices is the ground truth of our experiment: the accuracy is measured by comparing their real position with the one estimated by different localisation methods. All devices are stationary: this is strictly true for workstations and laptops, and almost always true for the smartphones. Given the office working habits, we estimate that each smartphone, during the whole experiment, is located into its known position for about 90% of the time, being inside the measurement area.

Note that experimenting with stationary devices, as we did, implies no generality loss with respect to experimenting with moving devices. The localisation procedure, in fact, relies on fixed sniffers to receive a packet sent by the device, at moving speeds that have no influence on the radio propagation. Additionally, the goal of the methods described in this contribution is to gather samples of people's position, rather than tracking them, so that the movement patterns of probe-emitting devices are largely irrelevant for this scope.

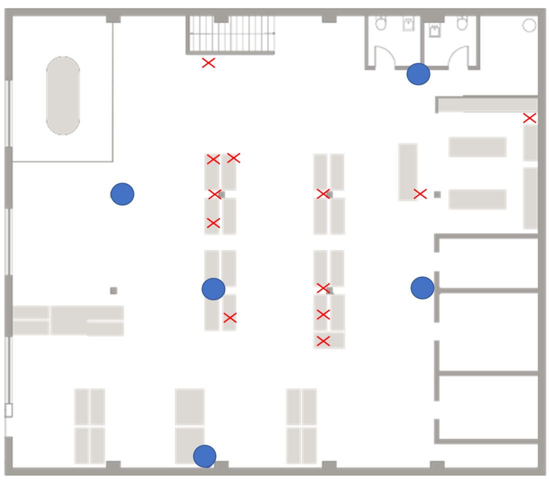
Among the known devices we could not include those using MAC randomisation techniques, for instance based on recent iOS operating systems, because randomisation makes it impossible to identify which device is sending the Wi-Fi probe. While this is a limitation, as far as our experiment is



(a) Map of site CNR. Map width is 22 m.



(b) Map of site C4WIT. Map width is 25 m.



(c) Map of site C4WUS. Map width is 24 m.

Figure 3.26: Maps of the scenarios selected for the experiments. Blue dots show the FogSense positions, red crosses indicate the reference devices.

Table 3.6: Scenario characteristics

Scenario	FogSenses	Unique MACs	Duration	Known devices	Probes	Size
CNR	4	24000	70 days	16	2.2e6	350 m^2
C4WIT	8	130000	60 days	18	2.3e6	250 m^2
C4WUS	5	34000	30 days	12	1.6e6	500 m^2

concerned, it does not impose any constraints for the intended usage of our technique which, as already mentioned, does not involve tracking.

The data gathering campaigns have different duration, ranging from 30 days at C4WUS to 70 days at CNR, and different number of FogSenses installed in each scenario. The different numbers of unique MACs observed are due to the proximity of offices to roads. Table 3.6 summarises the features of the three scenarios.

Since this contribution is concerned with assessing whether Wi-Fi probes can be used for the purpose of localisation, and since no other measurement campaign of this kind is available, we try here to give an idea of the numbers we are working with.

Figure 3.27 shows the number of the probes gathered by the most talkative known devices. Note how the number of probes produced can vary considerably between devices, as already discussed. We account for this difference in number of collected probes when measuring performance, in order to avoid weighting one device more than others.

Figure 3.28 illustrates the RSS distribution for the known devices. The three distribution have different width, as highlighted by their standard deviation (shown in the figure). This is consistent with our previous observations on the difference of the three scenarios and it represents a confirmation that C4WIT is the scenario where the FogSenses gather most of the information.

Future work will investigate the usage of this information to assist the deployment in different environments, especially for deciding whether the already-installed APs are sufficient as sniffing devices to gather probe requests. In principle, adding FogSenses in the area to improve the localisation accuracy could make sense unless this addition makes the standard deviation

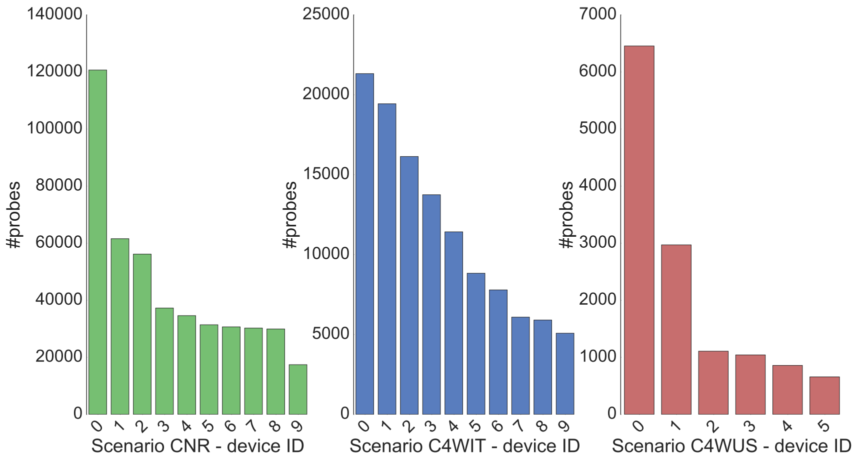


Figure 3.27: Top 10 known devices by number of probes.

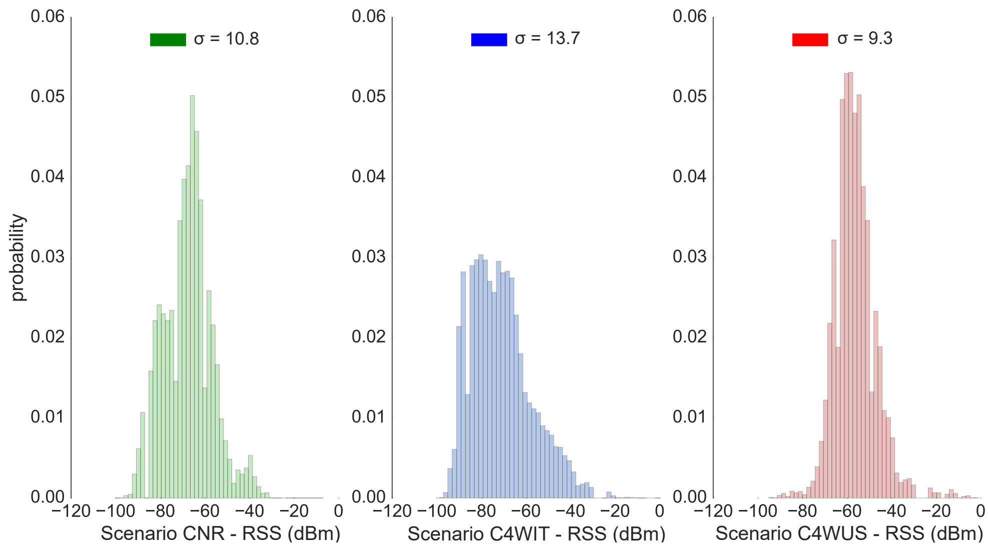


Figure 3.28: Probability distribution of RSS values of known devices.

too narrow.

Finally, Figure 3.29 shows the number of probes received in 25-minute intervals as time series covering one week. It is evident that, in CNR and

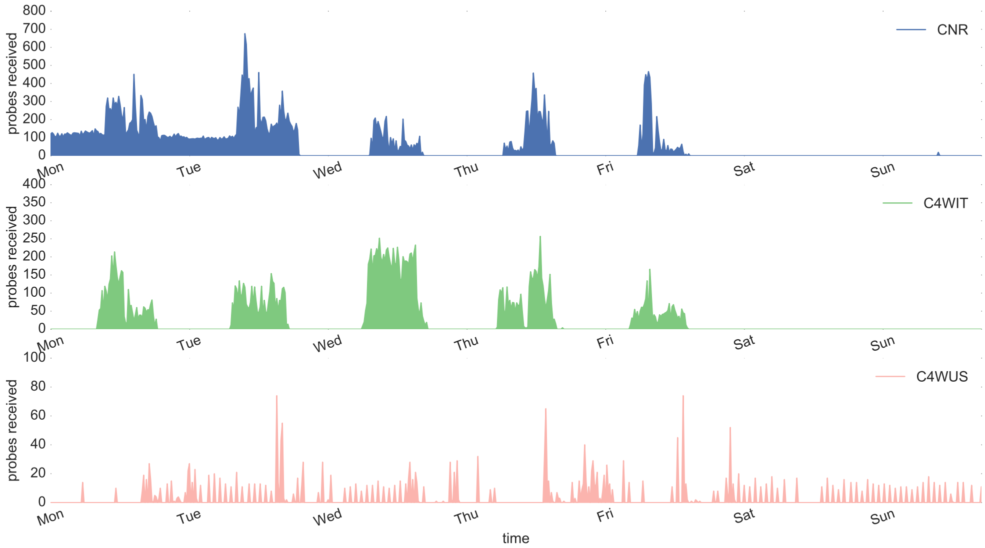


Figure 3.29: Time series of captured probes in a week's time, 25-minute intervals.

C4WIT, the number of captured probes increases during the working hours and it drops down during off-work hours and weekends. In fact, being the known devices laptops and smartphones owned by the employees at the three locations, the probes they emit well reproduce their working rhythms. At C4WUS such pattern is less clear for two reasons. First, most of the known devices are static and always connected to a local stable Wi-Fi network, which reduces the number of probes sent. Second, they are not owned by the employees, and are therefore working also during off-hours and weekends.

3.3.3 Performance of localisation algorithms with Wi-Fi probes

We experimented with some localisation algorithms, in order to find the best one in terms of accuracy and robustness to changing environmental conditions. Our purpose was that of investigating whether we can find an algorithm with sufficient performance to be used as a basis for the crowd localisation problem.

Generally speaking, RSS-based localisation techniques can be divided into *range-based* and *range-free* methods. Range-based techniques estimate the user position by considering the received signal strength of that user device and exploiting a Wi-Fi signal propagation model. They are prone to errors due to reflection of waves over the walls, floor and ceiling, especially in presence of obstacles obstructing line of sight between the transmitter and the receiver. On the other hand, range-free techniques do not rely on the radio propagation properties of the environment. We only considered range-free algorithms.

Each *algorithm* we used has several parameters to be tuned. Choosing an algorithm and a set of parameters gives rise to a different localisation *method*. All algorithms are based on k-NN classification, so each algorithm gives rise to different methods based on the value of k which, in our experiments, varies from 1 to 3. Given the target application, we expected that each device is seen by a low number of FogSenses, so we have not experimented with high values of k. The final estimate is the $k - th$ centroid.

The simplest algorithm, which we call *strongest*, predicts that the observed device is in the same location of the FogSense which has observed the strongest RSS (Received Signal Strength). When k is greater than 1, we considered the k-th strongest RSSes instead of only one. Since we used k from 1 to 3, the *strongest* algorithm gives rise to 3 methods.

All the other algorithms are based on *fingerprinting*. Fingerprinting is a technique commonly used for indoor localisation, which is composed of an installation *off-line* phase, followed by a run-time *on-line* phase. During the *off-line phase*, one takes measurements of the RSS of Wi-Fi packets received from the APs (Wi-Fi Access Points), as observed at a number of reference points. These reference observations are collected into a *fingerprint database*. During the *on-line phase*, an agent makes a new observation, by measuring the RSS received from the visible APs at the location. This new observation is compared with those in the fingerprint database. The entry in the database that is closest to the new observation is selected, and the agent's estimated position is set to that of the closest entry in the database, or to the centroid of the k closest entries, when k-NN is used. Fingerprint methods have been first proposed many years ago [153] and are still being actively investigated [154], since they are at the base of most indoor localisation systems. For example, all competitors in the EvAAL-ETRI off-site competition at IPIN 2015 used some form of fingerprinting [155].

Fingerprints observed during the on-line phase are variable in length, because the number of FogSenses receiving a given probe from a device is variable: in fact probes are lost for a variety of reasons, including collisions, interference and insufficient transmitting power. Generally speaking, the higher the number of FogSenses receiving a probe, the higher the localisation accuracy, but the lower the number of probes we can consider as valid samples. The trade-off between accuracy and number of usable probes depends on the FogSense positioning, the number of devices expected in the area, the presence of other Wi-Fi networks and, the expected accuracy of the results, and should be decided for each scenario, on a case-by-case basis.

In this work, we use a threshold of 3 for all scenarios; in other words, we only consider probes which have been received by at least 3 FogSenses.

Interpolating the fingerprint database

Usually, building a fingerprint database starts with selecting several calibration points. The purpose is to measure, at each point, what is the RSS observed from each of a number of APs in the area. In our case, we need the converse provedure: we should measure the RSS observed by the FogSense when a probe is sent by a device located at the calibration points. From a conceptual and practical point of view, this change of perspective is unimportant, and all the procedures commonly used for fingerprinting remain the same.

The RSS values associated with each access point are collected at the calibration points over a certain period of time and then stored in fingerprint database together with the location coordinates. During the on-line phase, the person or object of interest is localised by comparing the observed fingerprint to those stored in the database, looking for the most similar ones. Building a fingerprint database is a time-consuming task, especially for large areas that may contain thousands of calibration samples.

In order to be commercially viable, the proposed method should require very little or no installation and maintenance measurements. To this aim, we take advantage of the probes sent by the FogSenses themselves, which are connected to a server via Wi-Fi, and occasionally send probe requests collected by the other FogSenses. This is enough to build a self-updating database composed of fingerprints relative to the positions of the FogSenses. When using APs instead of FogSenses, we can profit from the probes sent by APs during the routine neighbourhood scanning.

A database obtained with this unsupervised procedure, however, is too sparse for assuring a satisfying accuracy, because the typical density of FogSenses in the environment should be low. In order to get a denser database, we resort to apply interpolation on a square grid, an idea already proposed in the indoor localisation literature [156, 157]. In particular, we further refine the solution proposed in [23] by exploiting several 2-D interpolation strategies.

Off-line phase: building the fingerprint database

The fingerprint database is automatically built without human intervention thanks to interpolation, which in real deployment scenarios guarantees an installation-free systems when the number and position of APs allows it, and for automatic fingerprint update when additional FogSenses are needed to improve the positioning accuracy.

The first interpolation strategy we used is based on the *linear interpolation over Delaunay triangulation* [158] whose vertices are the known points, that is the FogSense positions. Note that this strategy does not provide extrapolation, which means that it provides no estimates for unknown points that lie outside of the convex hull of the known points.

The second interpolation strategy was *inverse distance* [159]. At each unknown point, the estimate is the average of the values at the known points, each weighted by the inverse of their distance from the unknown. The third interpolation strategy was based on Kriging [157]. Kriging is an interpolation strategy originally adopted in the mining industry. Suppose that one can draw scalar samples from an unknown function of points belonging to a given domain. In our case, the samples are RSS measurements and the points in the domain are the locations in the area where we take measurements. Kriging interpolation is based on the assumption that the variance of the difference of the samples taken at two different points is only dependent on the distance of the two points. The function that relates the variance to the distance is called *variogram*. In *simple Kriging*, the mean of the samples is a known constant. *Ordinary Kriging* can work with unknown constant means. If we

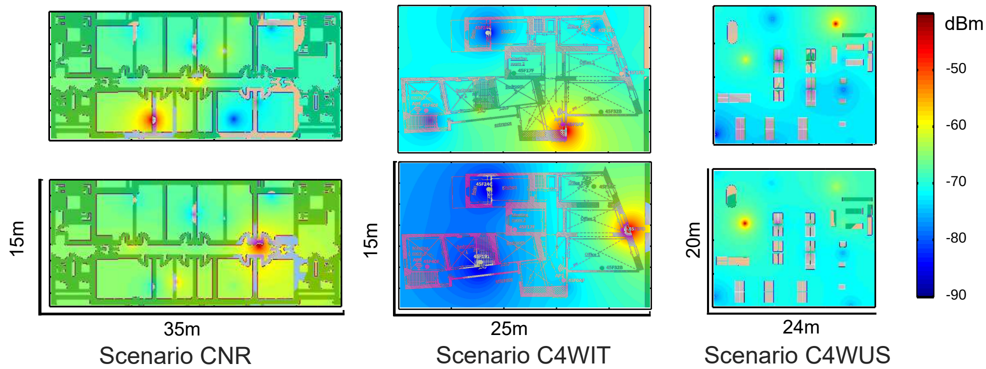


Figure 3.30: Examples of fingerprint maps generated with *inverse distance* interpolation.

need to drop the constraint that the mean is constant, we resort to *universal Kriging*, where one can impose a trend on the mean of samples as a function of distance.

This is our case, because the RSS expressed in dB can be modelled, at a first approximation, as a linearly decreasing function of the distance. In our experiments, we used the same parameters adopted by [156]: *spherical model* with a *range* of 6 m, *sill* set to 31 dBm^2 and nugget set to 9 dBm^2 and linear trend. Our experiments have shown that these choices are in fact good enough in our scenarios.

By interpolating the measured cross-FogSense fingerprints over a regular grid, we obtain an interpolated set of fingerprints, that is, our final fingerprint database. Figure 3.30 shows some interpolated RSS radio maps. For illustration purposes, the maps are computed on a very small grid width of 10 cm. Each map is seen from the point of view of one FogSense, whose position on the map is the point where the RSS value is the highest (the red point).

On-line phase: using the fingerprint database

During the on-line localisation phase, the fingerprint of the probe request sent by a mobile phone is compared with the RSS fingerprints stored in the database, an operation which requires a *measure of distance* to be defined. Fingerprints are N-D arrays, where N is the number of probes that are received. As stated above, we worked with $N \geq 3$. We experimented with several measures of distance: 1- and 2-norm distances, differential 1- and 2-norm distances, cosine distance and FreeLoc distance.

Given two fingerprints A and B of dimension N, the most usual distance is the Euclidean distance:

$$\|x\|_2 = (\sum_{i=1}^{n} x_i^2)^{\frac{1}{2}}. \tag{3.1}$$

Generalising the Euclidean distance brings us to the p-norm distance:

$$||x||_p = (\sum_{i=1}^{n} x_i^p)^{\frac{1}{p}}. \tag{3.2}$$

Setting $p = 2$ produces the Euclidean distance, while $p = 1$ produces the Manhattan distance. A variation on the p-dist is the differential p-dist, where only the differences between the measured values of each vector are considered. Specifically, the ND vector A is converted into an$(N-1)$D vector A_d:

$$A = x_1, x_2, \cdots, x_N, A_d = x_2 - x_1, x_3 - x_2, \cdots, x_N - x_{N-1} \tag{3.3}$$

We call the *differential* p-norm distance of vectors A and B the p-norm distance of vectors A_d and B_d. The purpose of differential p-norm distances is to remove the bias given by different devices possibly sending probes with different transmitting power.

The *cosine similarity* between two vectors A and B is a value in the interval $[-1, 1]$ defined as:

$$\frac{A \cdot B}{||A|| \times ||B||}. \tag{3.4}$$

Since we need a measure of dissimilarity, we (improperly) define the *cosine distance* as the complement to 1 of the cosine similarity.

The FreeLoc distance is inspired by [160]. The idea is that one should not rely on exact RSS values when comparing two fingerprints, but the only significant information comes from deciding whether the signal received by one FogSense is significantly higher, significantly lower or about the same as

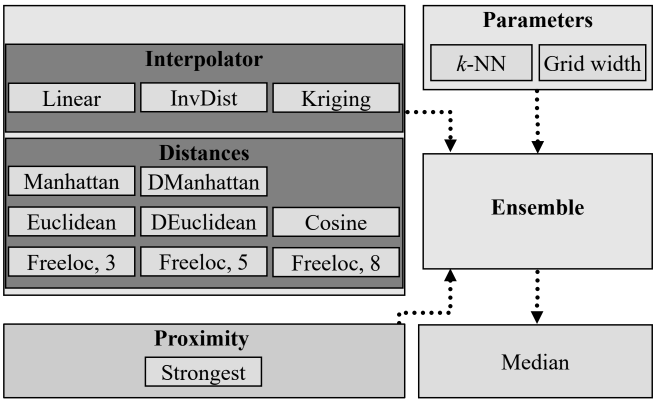


Figure 3.31: Generation of localisation algorithms.

the signal received by another FogSense. This information is ternary, and coded by -1, 0 and +1 values. A threshold p is used to decide whether two signals are nearly equal ($|x - y| < p$), giving rise to a 0. In our computations, we used for p one of the three values 3 dB, 5 dB, 8 dB (the latter being the value used in [160]).

Each fingerprinting vector A of length N is thus converted into a new A_f ternary vector of length $N \times (N-1)/2$, which is the number of pairs of the N dimensions. Comparing the ternary vectors is just a matter of obtaining their scalar product. Similarly to the previous case, the similarity is obtained using the complement to 1:

$$1 - (A_f \cdot B_f)/\frac{N \times (N-1)}{2} \tag{3.5}$$

3.3.4 Creating ensemble estimators

Using the above-described building blocks, we defined some parametric algorithms for localisation, and for all of them we evaluated the performances. Then, we turned our attention to the performance in terms of robustness across varying scenarios. We start with the definitions, we proceed by illustrating accuracy performance, and then we consider trading some accuracy for robustness.

An *algorithm* is either the *strongest* algorithm or a fingeprinting algorithm. Fingerprinting algorithms are defined by the choice of an interpolator and a measure of distance. The choice of the interpolator, used in the off-line phase, affects the creation of the fingerprint database, while the distance is used in the on-line phase to identify the k fingerprints in the database which are closest to the measured fingerprint. Each algorithm is associated with several parameters to produce a set of *methods*.

For each algorithm, the parameters we consider are the interpolation grid size (not significant for *strongest*, which is not based on interpolation) and the k value. By varying the parameters, as shown in Figure 3.31, we produce a spectrum of alternative methods. In summary, we have used 3 different interpolators and 8 different distances, which give rise to 144 methods based on fingerprinting, to be added to 3 more methods based on the *strongest* algorithm.

In order to compare the 147 methods, we choose the error median as an accuracy performance measure. We obtain an error median for each method applied to each of the three scenarios. Given a method and a scenario, the error median is computed by first obtaining the error distribution for each device of that scenario, and then merging together those distributions. In this way the results are not dependent on the number of samples per device, which in fact are quite different, as shown in Figure 3.27.

Table 3.7 shows the performance of the 25 best methods for each scenario. Some methods that are used in the following discussion are marked with a letter id, whose meaning is listed in Table 3.9.

We do not want to choose the best method for each scenario. Rather, we want to find a way to select methods that have good performance overall. To this end, we resort to the concept of *ensemble estimator*, which is employed in [161] for a similar case. Ensemble estimators (ensembles for short) are useful when dealing with optimisation on many discrete parameters. For example, in our case, varying the parameters creates a total of 147 methods. Just choosing the method having the best performance would lead to overfitting.

Overfitting, which means tuning the parameters to the specific case that is being analysed, can produce brittle methods, that is, methods that perform well only in a specific situation. In order to increase the robustness of the choice, and possibly the performance too, we select a set (an ensemble) of methods. Once the set is chosen, the position estimated by the ensemble estimator is defined as the centroid of the positions estimated by each method in the ensemble. To define an ensemble estimator, a criterion is needed to select the methods composing the ensemble. For example, a simple criterion would be to just choose the N best accuracy performers among all the considered methods and use those as elements of the ensemble. More complex criteria are possible to select the methods that are part of an ensemble, see [162, 161] for more in-depth discussion.

The criterion we choose in the following is quite simple: we select the methods that appear among the best performers in all three scenarios, that is, a set of methods which is the intersection of the three sets whose accuracy performance is listed in Table 3.7. The selected methods compose the *intersection ensemble*; they are marked with upper-case letters, defined in Table 3.9.

In order to better evaluate the performance of the intersection ensemble, we compare it against three additional *reference* ensembles, each tuned on a different scenario. We create the CNR ensemble using the 4 methods having the best accuracy performance in the CNR scenario, and similarly for C4WIT and C4WUS. The methods composing these 3 scenarios are marked with lower-case letters in Table 3.7. Note that the top performer methods are different in each scenario. For example method a is the best for the CNR scenario and the second best for the C4WIT, but it is not even among the top 25 methods for C4WUS. Similar considerations apply for method b, which is the best in the CNR scenario, but not in the top 25 methods for C4WIT and C4WUS.

3.3.5 Experimental results

Table 3.8 shows the accuracy performance of the three *reference* ensemble methods, each specialised for a different scenario; on the diagonal we show the median localisation error of ensemble CNR, ensemble C4WIT and ensemble

C4WUS applied respectively to CNR, C4WIT and C4WUS scenarios. As expected, the results shown on the diagonal are not worse than the top method for each scenario that are listed in Table 3.7. This confirms the effectiveness of the ensemble approach measured by the accuracy. For example, the error of ensemble the CNR ensemble applied to the ad-hoc scenario is 4.3 m, while the best method in the CNR scenario has error 5.1 m, and similarly for C4WIT and C4WUS.

However, when we apply the reference ensembles to scenarios in which they are not specialised, performance drops significantly. Taking the CNR scenario as an example, the error grows from 4.3 m when using the specialised ensemble, to 5.3 m and 5.6 m when using the other reference ensembles, as shown in Table 3.8. We take this as indication that the reference ensembles are not robust across scenarios.

We finally analyse the performance of the ensemble of choice, the *intersection ensemble*, which is built with the purpose of being robust across scenarios. The *intersection ensemble* is the intersection of the three sets of the 25 best-performing methods in each scenario. Its member methods are marked with upper-case letters A–D in Table 3.7. The last row of Table 3.8 shows the performance of the intersection ensemble applied to the three scenarios CNR, C4WIT and C4WUS. We observe that, as expected, while the results of the ensemble interpolation (in bold) are worse than those of each reference ensemble for its own specialised scenario (underlined), they are generally good.

Moreover, and most importantly, the performance of the intersection ensemble can be considered satisfactory for the intended purpose of this work, meaning that it is indeed feasible to use the experimented strategy for crowd localisation. In fact, median errors ranging from 3.7 m to 5.5 m are acceptable for crowded areas such as a shop inside a mall, the space in front of a shop window, a waiting room, a bathroom area, a reception desk.

A more detailed overview of the numeric results in Table 3.8 is given in Figure 3.32, where the cumulative density distribution of the error is depicted for all ensembles applied to all scenarios.

Results are consistent with the characteristics of the three scenarios: as expected, accuracy is higher for C4WIT. This can be explained by looking at Figure 3.30: RSS varies a lot between different areas in the C4WIT map,

Table 3.7: Median errors of the best 25 methods for each scenario [m]

Best CNR	Id	Best C4WIT	Id	Best C4WUS	Id
5.1	a	2.9	e	4.8	C
5.1	b	3.0	a	4.9	B
5.1	c	3.2	f	5.0	h
5.2	d	3.2	g	5.0	i
5.3		3.3		5.1	
5.3		3.4	B	5.2	
5.3		3.5		5.2	
5.4		3.5		5.2	
5.4		3.5		5.3	
5.4		3.6	A	5.4	D
5.4	e	3.6		5.4	
5.5	f	3.6		5.4	
5.5		3.7		5.5	
5.5	A	3.7		5.6	
5.5	h	3.7	C	5.6	
5.6		3.7		5.6	
5.6		3.7		5.6	
5.6		3.8		5.7	
5.6		3.8	c	5.7	
5.6	C	3.8		5.7	
5.6	B	3.9		5.7	
5.6		3.9		5.7	
5.6		3.9		5.7	A
5.8	D	3.9	D	5.7	
5.8		3.9		5.8	

while the picture of RSS in the other two scenarios is more homogeneous. In other words, we have more information to exploit in C4WIT than in the other scenarios, and this is reflected in a higher accuracy for C4WIT.

Another interesting observation is that the accuracy performance we observe is not so far from the state-of-the-art in Wi-Fi indoor localisation. While

Table 3.8: Median errors for the 4 ensembles in the 3 scenarios

	Scenario CNR	Scenario C4WIT	Scenario C4WUS
Ensemble CNR	4.3	3.7	5.6
Ensemble C4WIT	5.3	2.9	7.2
Ensemble C4WUS	5.6	3.9	4.2
Ensemble Intersect	**5.5**	**3.7**	**4.7**

Table 3.9: Legend for the Id letters used in Table 3.7

	Id	Interpolator	Distance	k	Grid width
Ensemble CNR					
	a	invdist	cosine	2	2 m
	b	strongest		1	1 m
	c	linear	pnorm,1	1	2 m
	d	invdist	freeloc,8	1	2 m
Ensemble C4WIT					
	e	invdist	cosine	3	2 m
	a	invdist	cosine	2	2 m
	f	invdist	cosine	2	3 m
	g	invdist	cosine	1	2 m
Ensemble C4WUS					
	C	linear	cosine	3	2 m
	h	linear	cosine	2	2 m
	B	linear	freeloc,5	1	2 m
	i	linear	cosine	2	3 m
Ensemble Intersect					
	A	linear	cosine	1	2 m
	B	linear	cosine	2	2 m
	C	linear	cosine	3	2 m
	D	linear	pnorm,2	3	2 m

a direct comparison is not possible, because we work with the data provided by devices occasionally sending probes in small environments with a low number of FogSenses, it is interesting to note that during the EvAAL-ETRI compe-

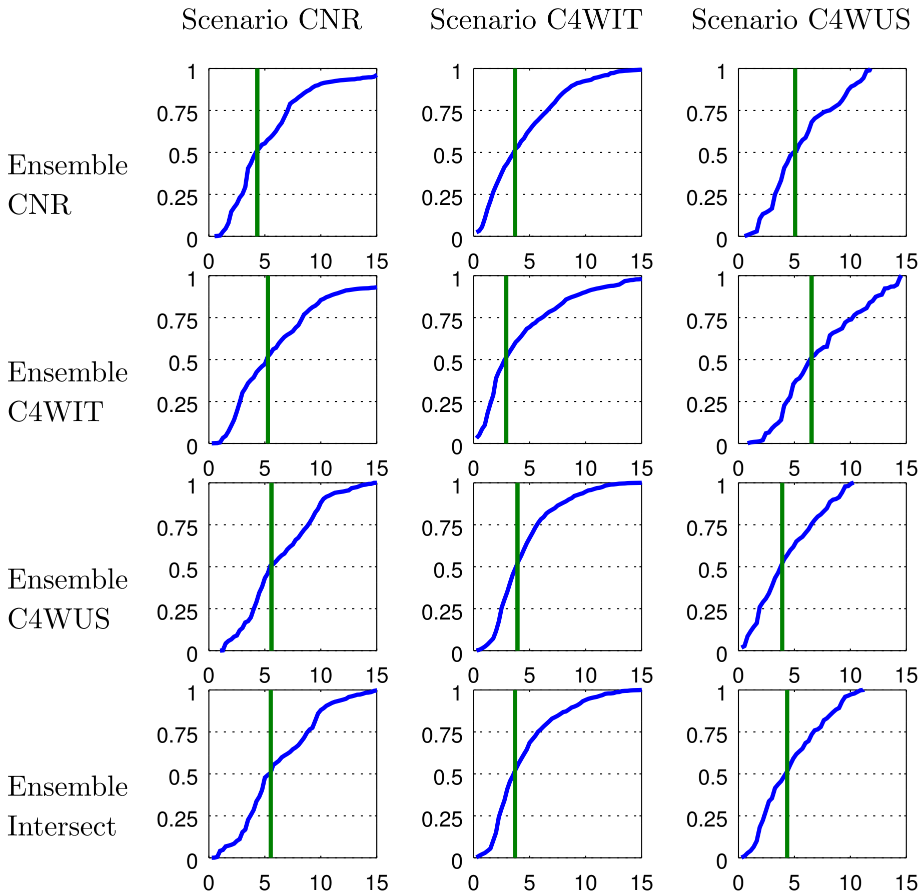


Figure 3.32: Cumulative density distribution of errors for the four ensembles and the three scenarios.

tition at IPIN 2015 [155], one of the tracks was dedicated to off-line indoor localisation done exclusively with Wi-Fi information. The results obtained by competitors vary from a median of 4.6 m (the winner) to a median of 7 m.

We derive some key takeaways as well as some considerations from this experimental campaign. First, the architecture we proposed is dynamic, in the sense that in case the already-deployed APs are not enough to get satisfying positioning accuracy, it is possible to deploy additional sniffers, without any system reconfiguration. Second, our approach is unsupervised, since it does not require the usual configuration work needed for Wi-Fi indoor localisation systems, that is to survey the environment, to select the points where to gather the RSS values and finally to collect data with one or more sensing devices. We avoid all these steps by exploiting the probes sent by the APs and the possible additional sniffers themselves. Finally, the results obtained with the described ensemble estimator are, in our opinion, remarkable. In fact, the median errors of the intersection ensemble are directly comparable with the results of some of the best localisation algorithms based on Wi-Fi fingerprint, such as those that were presented and, most importantly, independently tested, during the EvAAL-ETRI 2015 competition

We take this as a hint that the methods proposed in this contribution are indeed promising, since the figures measured during the IPIN competitions are taken in controlled and scientifically accurate conditions, rather than by the system authors themselves in their own laboratories. We claim that exploiting Wi-Fi probes promises to be a viable and cheap strategy for indoor localisation of devices. The method we describe can be the main building block of systems that sample the presence of people in a given area, a task that we call crowd localisation.

Chapter 4

An unobstrusive system for night-time monitoring

As described in Section 2.2, long term sleep quality assessment is essential to diagnose sleep disorders and to continuously monitor the health status. However, traditional polysomnography techniques are not suitable for long–term monitoring, whereas, methods able to continuously observe the sleep pattern in an unobtrusive way are needed.

In this chapter, following the recommendations offered by the analysis of the state-of-the-art provided in Chapter 2, it is presented a general purpose sleep monitoring system that can be used for to monitor bed exits, to observe the influence of medication on the sleep behaviour, and for the pressure ulcer risk assessment (bedsores). This condition, namely bedsores [131], may be early identified and addressed from nursing care and caregivers through an efficient and continuous monitoring, preventing worsening of these symptoms. Benefits of a correct posture detection method is two-fold. On one hand, self–movements can be inferred and consequently prognostications can be made. On the other hand, caregivers can adopt right care programs designed to meet accurately elderly needs and avoiding bedsores.

Moreover, we compare several supervised learning algorithms in order to determine the most suitable in this context. Experimental results obtained by comparing the selected algorithms show that we can accurately infer sleep duration, sleep positions, and routines with a completely unobtrusive approach.

4.1 The proposed Sleep Monitoring System

In this section, we describe the developed platform in terms of necessary hardware and software tools. The proposed system has been designed in order to provide an effective solution both from a cost and deployment point of view. It allows to unobtrusively provide data to an application layer and to be easily integrated in different pervasive computing scenarios, exploiting the presence of an open source middleware infrastructure.

4.1.1 Hardware components

The proposed hardware system is based on the widespread Raspberry Pi (Figure 4.1.a) single–board computer, equipped with a 700 Mhz ARMv6 processor, 512MB of RAM and several I/O peripherals. The board is running Raspbian OS, a platform–optimized Linux distribution. On the top of the board, additional shields can be mounted through the 26–pin expansion header. The sensors used to collect the bed pressure distribution are called Force Sensing Resistors (FSRs) and consist of a conductive polymer which changes its resistance proportionally with the force applied on the sensor surface. These sensors have a very low profile (less than 0.5mm), low cost and a good shock resistance. In order to acquire and manipulate the weight pressure values, it is necessary to convert the analog resistance, seen as a voltage drop between the pressure sensor and a partition resistor, to a digital format. For this reason, we used several ADC shields (Figure 4.1.b), mounted on the top of the Raspberry Pi, to convert the raw voltage value coming from the sensors. Each of the ADC shield mounts a pair of Microchip MCP3424 Analog–to–Digital converters. The MCP3424 device features 18–bit, four channels delta–sigma ADC with differential inputs, self calibration of the internal offset and gain on each conversion. It also mounts an on–board programmable gain amplifier (1x, 2x, 4x and 8x), to amplify the signal before its conversion. Each shield is therefore able to sample 8 channels (sensors). The I2C bus is used to communicate with the ADCs and their address is set by placing proper jumpers on the shields. A maximum of 4 shields can be stacked on the same Raspberry Pi board, limiting to 32 the maximum number of deployable pressure sensors.

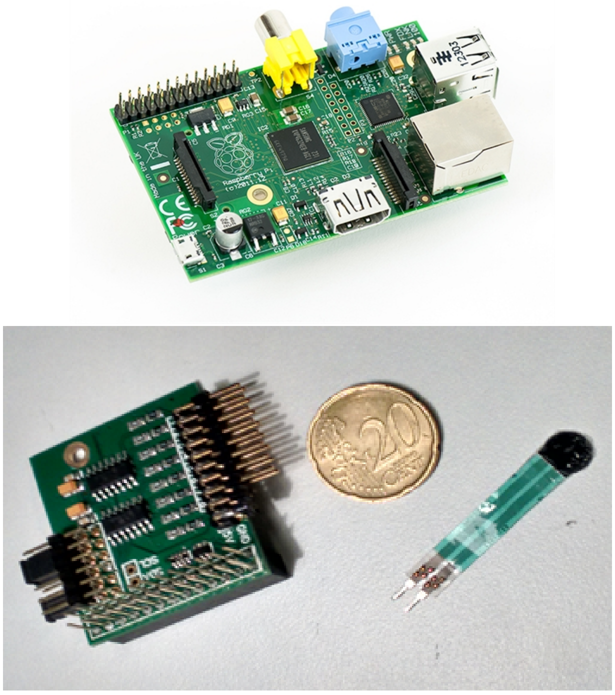


Figure 4.1: The Raspberry Pi board (a) and the used ADC shield with a Force Sensing Resistor (b).

4.1.2 Software architecture

The proposed hardware and software architecture, composing the data sensing and processing system, aims at providing high flexibility and scalability. From the software point of view, a middleware layer able to dispatch data among generic entities, called services, has been used. This interoperability layer allows the components, which are realized either as hardware devices and software modules, to interoperate seamlessly with each other by using a shared representation and communication model [163].

The concrete middleware architecture (Figure 4.2) consists of two layers: a core middleware API layer and a communication layer, that includes a publish/subscribe connector. A generic service built upon the middleware can discover both the sensors present in the environment and the other services,

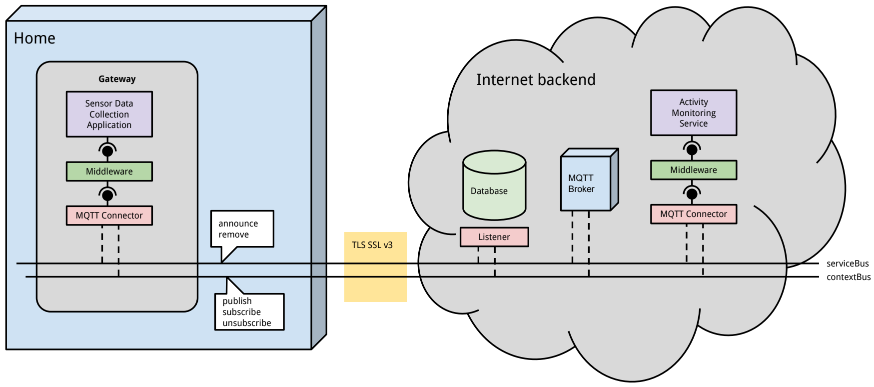


Figure 4.2: The middleware architecture.

together with their functionalities, using methods from the middleware API layer. The underlying layer fulfils these requests exploiting the available connectors. In the communication layer, an MQTT connector is present. By means of these connectors, the middleware realizes, transparently to the services, a publish/subscribe pattern and a method description and invocation mechanism. Two buses form the heart of the proposed middleware: a context bus and a service bus. All communications between applications can happen in a round–about way via one of them, even if physically the applications are located on the same hardware node. Each of the buses handles a specific type of message/request and is realized by different kinds of topics. The aim of the middleware is to provide a publish/subscribe mechanism for accessing the context information about the physical environment. This information will be exposed as different topics: topics for device discovery and description and services that form the service bus; topics for publishing and retrieving data from devices and services that form the context bus. The middleware is in charge of presenting the available sensors and services in the system, implementing the announce mechanism on the service bus.

4.2 The Proposed Algorithms

The goal of this work is to provide a sleep monitoring system able to recognize the sleeping stages and to infer the patient's position in the bed. The proposed

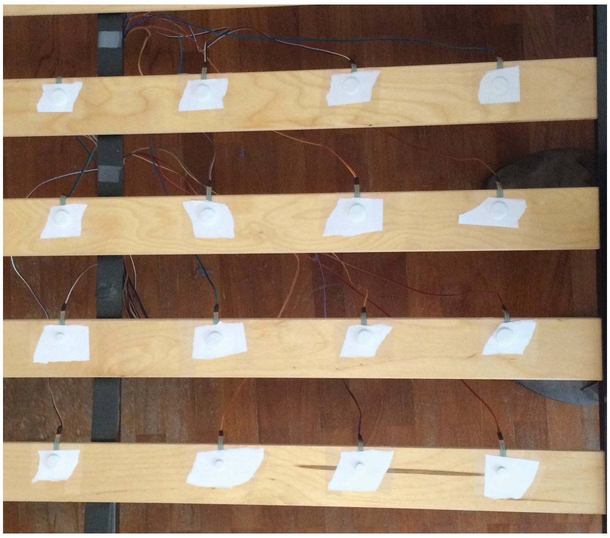


Figure 4.3: Experimental setup: A grid of Force Sensing Resistor (FSR) sensor nodes placed on the slats.

solution is based on an unobtrusive system, completely transparent to the user. Indeed, we suppose that the patient does not wear any wireless device able to monitor and to communicate data with a medical server.

From a technological point of view, the proposed system is composed by a grid of forty–eight Force Sensing Resistor (FSR) sensor nodes placed on the slats of the bed as shown in Figure 4.3. This virtual grid does not cover the entire area of the bed but, instead, it is placed at the level of the patient's chest, back, and knees.

From an algorithmic point of view, the proposed solution is based on the observation that, when a movement occurs, the pressure values change in amplitude, whereas, when the patient maintains the same position, the values of the FSRs are almost constant. The algorithm consists in two different tasks: first, the different sleep stages (begin, end, movement, limited muscle activity) are detected; then, the sleep position (supine, prone, right lateral, left lateral), corresponding to each stage, is recognized.

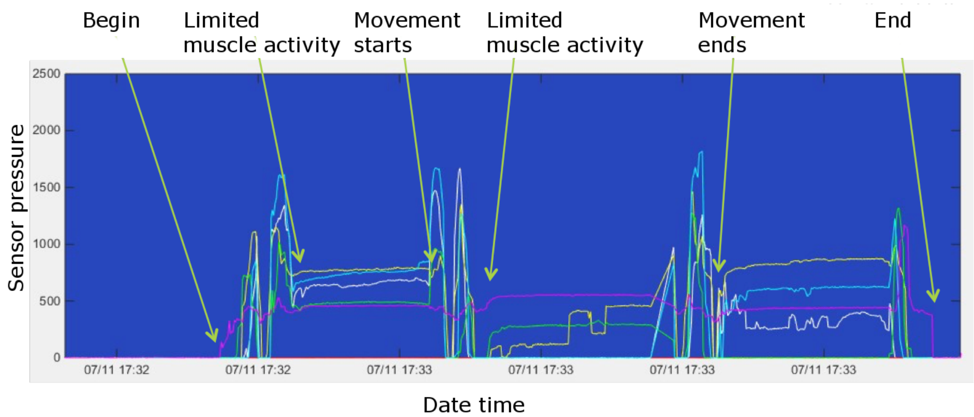


Figure 4.4: An example of six FSR time series.

4.2.1 Sleep stage detection

In order to better explain how we defined the stage detection algorithm, Figure 4.4 shows a typical behaviour of six different FSR time series, together with the ground–truth of the sleep stages, that have been collected by a video camera inside the room. When the user get in the bed, the status of the pressed sensors drastically changes and it stabilizes at a new high pressure value, whereas, when the user changes his/her position in the bed, after a period of time, the pressure value stabilize at the original value. Summing all the pressure values, of every FSR sensor, can lead to false positives and false negatives, as shown in Figure 4.5.

In order to overcome this issue, a stage detection algorithm must take into account only the variation of the most stressed FSR sensors. Based on Figure 4.5, only if the red zone changes, the algorithm must detect a movement. Moreover, the algorithm can consider as movements also external events (for example someone who makes the bed), therefore the presence of a detection filter is needed to avoid possible misclassifications.

Relying on these considerations we propose the stage detection algorithm described in the following:

1. For each FSR pressure value p_j, where $j \in N$ (being N the set of the installed FSRs), if $\sum_{j=1}^{N} p_j > \gamma$, where γ is the average pressure, the

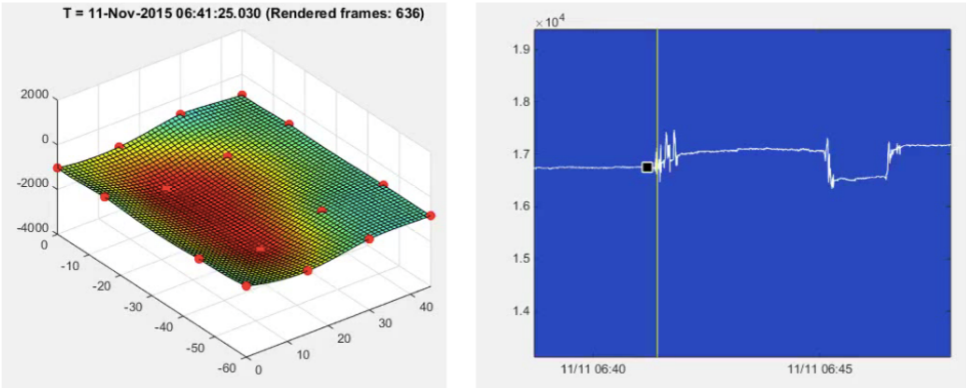


Figure 4.5: An example of a false positive considering a subset of sixteen FSRs.

presence of the patient is ascertained.

2. Only when the patient is detected, for each FSR sensor j, the mean over a W window $P_j^W = \frac{1}{W}\sum_{w=1}^{W} p_j$ is evaluated.

3. The difference between two consecutive pressure values $V_j = abs(P_j^W - P_j^{W-1})$ is calculated to find significant variations.

4. The variation values are sorted and filtered with a linear weighted filter. The obtained output is a set of sorted and weighted values V_j of significant variations in terms of pressure amplitude.

5. If $\sum_{j=1}^{N} V_j \leq \alpha$ (where α is defined as the minimum value for which the pressure variation can be considered as a real movement), the patient is not moving. The α parameter could be defined by leveraging the pressure trace of the day before or by an ad–hoc calibration procedure during the installation of the proposed system.

6. When $\sum_{j=1}^{N} V_j > \alpha$, the movement is detected and the algorithm goes back to step 2.

In particular, γ has been chosen as twice the pressure value of the empty bed, while α was fixed to the 30% of $\sum_{j=1}^{N} V_j$ (i.e. a significant variation).

4.2.2 Sleep position detection

A classification task consists in assigning a class (within a set) to a given object. In the general case, an object is defined by many characteristics (features), providing information about the object class. The information associated to a single characteristic is usually not sufficient to solve the classification problem, so that the correct class can be only inferred by combining all the features. In our case, the objects to be classified are the patient positions, the feature are the FSR signals, and four classes are considered, namely, supine, prone, right lateral, and left lateral.

Machine learning provides several techniques to solve complex classification problems [164]. In this case, a classifier model is trained on a set of examples, called the training set. After training, the classifier is able to combine the characteristics and to generalize the learned behaviour, by correctly assigning a class to unseen objects. The performance of the classifier can be evaluated by applying the trained model on a test set.

In this paper, in order to validate our system, seven different machine learning models have been applied and compared on the task of classifying FSR signals. The goal is to verify that an automatic classification of the patient bed positions is possible and to carry out a preliminary study in order to chose the best algorithm.

The considered models include statistical learning systems (Naive Bayes, Logistic Regression, IbK), ensemble methods (Bagging, HyperPipes) and rule–based learning systems (Decision trees, Decision tables). Table 4.1 shows the algorithms used in this work, along with a raw and short summary of their strengths and weaknesses. Some basic characteristics are investigated for each method: problem type — the method is able to face classification and/or regression tasks — training speed, prediction speed, automatically feature learning property, and if the classifier is parametric or not.

The automatic feature learning property is based on the assumption that not all the features are equal. Some features can be irrelevant and, for example, lead the algorithm to misclassification. On the other hand, some features should be much important than others. A learner can be able to perform automatically the feature selection task, using a scoring method to rank and select the features and, also, to find correlations between them.

Considering parametric models, we can identify a finite number of parameters. For example, linear models such as linear regressors have a finite number of weight coefficients. Vice versa, in non–parametric models, the complexity of the model grows with the number of training data, because the model has not a fixed structure.

In the following, the used classification algorithms are shortly introduced. In our experiments, machine learning methods used are obtained from the WEKA [165] package.

Table 4.1: Comparison between the used classification methods.

Algorithm	Problem Type	Training speed	Prediction speed	Auto feature learning	Parametric
Decision Table	Classification	Slow	Fast	No	No
G. Naive Bayes	Classification	Fast	Fast	No	Yes
Simple Logistic	Classification	Fast	Fast	No	Yes
IBk Lazy	Class. and Regr.	Fast	Depends on n	No	No
Hyper Pipes	Classification	Slow	Fast	No	No
Bagging	Class. and Regr.	Slow	Fast	Yes	No
Random Forest	Class. and Regr.	Slow	Moderate	Yes	No

Decision tables

Decision tables are one of the simplest machine learning techniques [166]. Basically, a decision table consists of a hierarchical table in which each entry in the higher level table gets broken down by the values of a pair of additional features to form another table. Creating a decision table might involve selecting some of the features. The problem is, of course, to decide which features to leave out without affecting the final decision. In our case, we have no a priori information about which FSR must be considered or not. In fact, each sensor, and consequently each feature, can be useful in order to identify a particular user position. Thus, a Decision table approach uses the simplest method of attribute selection: Best First. It searches the space of attributes by greedy hillclimbing, augmented with a backtracking facility.

Naive Bayes

Naive Bayes classifiers are a family of simple probabilistic tools based on applying the Bayes' theorem. Naive Bayes classifiers employ the class posterior probabilities given a feature vector [167] as the discriminant function. Therefore, approximations are commonly used, such as using the simplifying assumption that features are independent given the class. This assumption of independence is certainly simplistic. However, it is largely adopted in real scenarios and it works very well in many cases, particularly when datasets are filtered with an a priori data selection, in order to avoid redundant records. The Naive Bayes method might not be the best for our scenario because it does not work when an attribute may not occur in the training set in conjunction with every class value.

Logistic regression

Logistic regression is a well–known technique based on linear regression. The idea of logistic regression is to make linear regression produce probabilities [168]. When using linear regression for binary classification, we calculate a linear function employing regression and then we apply a threshold to decide whether it is a 0 or a 1 response. Similarly, if we want to generalize to more than two classes, we can use a separate regression for each class. We set the output to 1 for the instances that belong to that class, and 0 for the instances belonging to all the others, thus obtaining a different regression line for each class. Given an unknown test example, the class with the largest output must be chosen. That would give us n regressions for a problem where there are n different classes.

Coming back to the binary classification case, it is absolutely tempting to imagine that we can interpret the values produced by the linear regressor as probabilities, but this is actually incorrect. Such values are not probabilities, since the values are sometimes negative or greater than one. In order to get better probability estimates, a slightly more sophisticated technique is used. In linear regression, a linear sum is calculated. Instead, in logistic regression, we have the same linear sum, but we embed it in an exponential formula:

$$Pr[1|a_1, a_2, \ldots, a_k] = 1/(1 + exp(-w_0 - w_1a_1 - \ldots - w_ka_k)),$$

where $a_1, \ldots, a_k$ are real input features, and $w_0, \ldots, w_k$ are the model parameters. This is called a "logit" transform. Considering the one–dimensional problem, $Pr[1|a]$ is an S–shaped curve with respect to a, that applies a softer function, i.e. a soft version of a step function that never gets below 0, never gets above 1, and has a smooth transition in between. The parameters $w_0, \ldots, w_k$ are defined by minimizing an ad–hoc error function on the training set. Working with a logit transform, instead of minimizing the squared error, it is better to choose weights to maximize a probabilistic function, called the *log–likelihood function*:

$$\mathcal{L} = \sum_{i=1}^{n} (1 - x^{(i)}) \log(1 - Pr[1|a_1^{(i)}, a_2^{(i)}, \ldots, a_k^{(i)}]) + x^{(i)} \log(Pr[1|a_1^{(i)}, a_2^{(i)}, \ldots, a_k^{(i)}]) ,$$

where $x^{(i)}$ and $a_1^{(i)}, \ldots, a_k^{(i)}$ are the actual class and the features of the i–th pattern of the training set, respectively. We can extend this idea also to multiple classes, but in this case, a multi–response regression does not work well, because we need the probabilities to sum to 1 over the various different classes. Such a constraint introduces more computational complexity and needs to be tackled as a joint optimization problem. The result is logistic regression [169], a popular and powerful machine learning method that uses the logit transform to directly predict probabilities.

Lazy learners

Exploring different supervised approaches, it is enticing to apply a completely different point of view, using Lazy learners, also known as prototype methods. The peculiarity of this class of methods is that they are memory–based and no model is required to be fit [170]. Specifically, we consider the k–nearest neighbours (k–NN) algorithm, a classical non–parametric approach where the function is only locally approximated, whereas all the computations are deferred until classification. The principle behind k–NN is to discover the k (we consider $k = 1$) closest training examples in the feature space with respect to the new sample. The training phase of the k–NN algorithm consists in storing the features and the class label of the training objects. In the classification phase, an unlabelled object is classified by assigning the most frequent label among those of the k training samples nearest to it. During test, new objects are classified based on a voting criteria: the k nearest objects from the training set are considered, and the new object is assigned to the class most common amongst its k nearest neighbours. Variants of this method can be obtained by the choice of the distance function, used to identify the nearest neighbours. Various distance metrics can be used, the Euclidean distance being the most common. In this work, considering that data were uniformly gathered, we used the most basic settings for the algorithm: Euclidean distance and k set to 1. This means that the class label chosen was the same as the one of the closest training object.

Using k–NN, the target function is approximated locally for each query to the system. These learning systems can simultaneously solve multiple problems, which constitutes, at the same time, their strength and weakness since, for a large input space, they are computationally expensive. These methods usually allow good results when there is not a regular separation of the decision boundaries. Our case seems to fit perfectly with this definition.

HyperPipe

A HyperPipe is a fast classifier that is based on simple counts. During the training phase, an n–dimensional (parallel–)pipe is constructed for each class [171]. The pipe will contain all the feature values associated with its class. Test instances are classified according to the category that "most contains the instance". In this way, for each class, a pipe works as a boundary hyper–solid for each numeric feature. At prediction time, the predicted class is the one for which the greatest number of attribute values of the test instance fall within the corresponding bounds.

Bagging

Bagging is a meta–algorithm, that allows to combine and improve the results obtained by other methods. Actually, having a dataset composed by few classes and many samples for each class, classification algorithms may be affected by classical over–fitting problems. The bagging method is known for its capability of avoiding this problem [172]. Basically, the idea is that of creating a set of different training sets, by sampling them from the whole dataset, and combining the different outputs by averaging them or, in our case, voting. As a meta–algorithm, the Bagging method is based on a classification model for the classification phase. In our case, we chose a fast decision tree learner, namely REPTree. This base learner builds a decision and/ or a regression tree using information gain or variance and prunes it using reduced–error pruning (with backfitting).

Considering our data, even taking into account a high number of decision trees, this approach can lead us to a bad overall accuracy. This is due to an intrinsic property of the algorithm that choose, in order to make decision trees, which variable to split in order to minimize the error. In this way, decision trees have a high correlation and a low bias in their own predictions.

Random forest

A natural step over the bagging approach is represented by the random forest (RF) algorithm. It is also based on decision trees and it is considered as an improvement of the bagging model. Moreover, it allows a decorrelation between trees and, consequently, between their predictions [173]. The idea behind the decision tree methods is quite simple: to make a tree in which each internal node is labelled with an input feature. The arcs from a node representing a particular feature are labelled with each of the possible values of that feature. Each leaf of the tree is labelled with a class or a probability distribution over the classes.

In practice, random forest seems to fit well in our case. In fact, the random forest model is a non–parametric model and, consequently, it does not need any a priori assumption; it is able to face complex input–output relations; it is robust to errors in labels and outliers. This last property is very useful in our case since data are labelled even considering some transition phases from a position to another, in order to make a realistic training set, in comparison with a data acquisition campaign performed throughout the whole night.

4.3 Results

In order to evaluate the performance of the proposed unobtrusive sleep monitoring system, two preliminary experiments have been carried out. The former aims at validating the stage detection method, whereas the latter is designed to asses the sleep position classification algorithm.

Figure 4.6: The ground–truth: video recorder with a night vision synchronized with the proposed system.

4.3.1 Experimental Setup

For the experiments on stage detection, we collected data by the proposed system using a single bed and a 1.80 m height and 70 kg weight male. In order to have a ground–truth, we installed a video recorder with a night vision in the bedroom (Figure 4.6) and we synchronized it with the system. We monitored the user for three nights.

The sampling frequency has to be set considering the computing constraints and the networking overhead, which are both directly responsible for power consumption within the sensors. In this work, we have chosen a sampling rate of 10 Hz.

For the experiments on sleep position classification, a larger benchmark dataset has been constructed. A small dataset may lead to an ill posed–problem to be approached with machine learning techniques. For this reason, we prepared an ad hoc test site located in our office, with a single bed.

In particular, we carried out two hours of sleep simulation for three different users, with three different mattress thickness, in six different days. Every two days, we changed the mattress and we repeated the experiment. It is worth mentioning that the test users, inside a five minute window, permuted their postures in order to retrieve, for each class, data with small differences. More precisely, the experiment consisted in the repetition of five minute simulated sleeping, for each different class (supine, prone, left, right).

At the end of the data collection campaign, the dataset was composed by 72000 pressure samples for each user, each one labelled with the corresponding sleep position class. This approach allowed us to obtain a well–balanced benchmark. Furthermore, the three users, different by weight and height, allowed us to gather heterogeneous data in order to test the system adaptability to different users in terms of vital and physiological parameters.

4.3.2 Experimental Results

Figure 4.7 shows the stage detection algorithm output during an entire night. The presence of the above–described mattress filter is particularly useful to prevent a movement detection when the user was not laid down on the mattress. The figure shows that the movements are correctly detected: the pink square dots represent the time instances when the time series (sum of FSR pressures gathered) is strongly variable. Figure 4.7 further illustrates the mattress filter relevance. In fact, the proposed algorithm detects, approximately between 8:00 AM and 8:30 AM, that the user got out of the bed, coming back after few minutes. Moreover, at the beginning of the experiment, the user was asked to put under stress the algorithm, with frequent getting in and out of the bed. Nevertheless, all the movements were correctly detected, assessing the strong robustness of the algorithm over the three different test nights.

In order to support bedsore risk assessment, the false positive analysis is essential. In fact, if the system recognizes the immobility of the user while the user has moved, the number of the needed caregiver interventions will be overestimated. On the contrary, if the system recognizes a motion of the patient while he/she was motionless, the number of the caregiver interventions will be underestimated. The proposed algorithm shows no false positives, which is a useful result for a successive real deployment.

The performance of the sleep position classification algorithms are assessed by the correctly classified instances using confusion matrices. A confusion matrix is a compact representation describing the results of a classifier: each row of the matrix corresponds to a class and counts the patterns assigned to

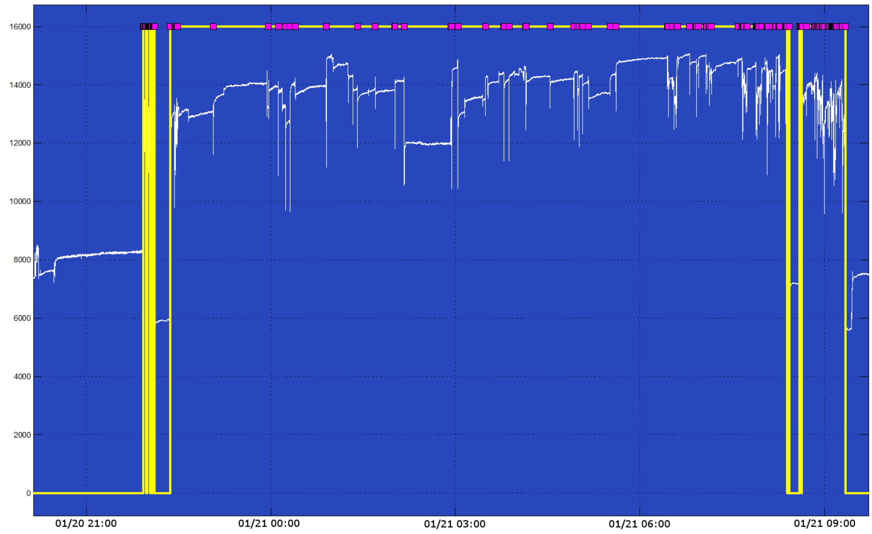


Figure 4.7: The stage detection algorithm output during an entire night. No movements are detected when the bold yellow line, which represents the presence of a person on the bed, is zero. Otherwise, movements are precisely detected (represented with pink square dots).

such class by the classifier (predicted class), while each column represents the number of pattern actually belonging to the corresponding class. A perfect classification method correctly classifies all the patterns, so that in the confusion matrix only the diagonal elements are not null. In general, the larger the diagonal elements, the better the classifier. The experimentation has also been designed to asses whether the classifier can be constructed offline, without adapting its parameters to the user under test.

In order to guarantee an unbiased estimate, the training and the test set should ideally be kept separated during the model construction procedure. Successively, the test set can be used to evaluate the obtained model. In our case, the whole dataset was split into three sub–datasets, each of which is related to a single user acquisition for two hours. Then, two experiments were carried out: in the former experiment, a single user dataset is exploited for training and another single user dataset for testing; in the latter, a single user dataset is adopted for training and the other two (merged together) for the test phase.

Table 4.2: Performance evaluation of Decision Table method.

	User1 – User2					User1 – User3					User1 – User2–3				
	Position predicted				Acc. %	Position predicted				Acc. %	Position predicted				Acc. %
GT position	S	P	R	L		S	P	R	L		S	P	R	L	
supine	3172	371	6	0		12100	0	1	0		15272	371	7	0	
prone	2635	858	0	0	44.3	7430	354	2826	219	41.6	10065	1212	2826	219	42.2
right	1599	0	1955	0		5738	348	5631	0		7337	348	7586	0	
left	1759	726	785	281		9189	942	470	1265		10948	1668	1255	1546	

Table 4.3: Performance evaluation of Naive Bayes method.

	User1 – User2					User1 – User3					User1 – User2–3				
	Position predicted				Acc. %	Position predicted				Acc. %	Position predicted				Acc. %
GT position	S	P	R	L		S	P	R	L		S	P	R	L	
supine	2964	0	2	583		12070	0	18	13		15034	0	20	596	
prone	0	2945	540	8	92.0	0	6867	1127	2835	82.2	0	9812	1667	2843	84.5
right	0	0	3554	0		6	1834	9285	592		6	1834	12839	592	
left	0	0	0	3551		0	1203	630	10033		0	1203	630	13584	

Tables 4.2,4.3,4.4,4.5,4.6,4.7,and 4.8 show the overall average percentage score for each algorithm, considering the two above mentioned configurations during both training and test.

As expected, different methods led us to different performances in terms of global accuracy. All the three statistical learning (SL) methods perform well on the tree different scenarios. Tables 4.3,4.4, and 4.5 show the performance obtained by the algorithms in the SL group with accuracies between 82.2% (worst case) and 95.9% (best case),a nd with classes, in some cases, which are perfectly predicted. The results are promising and suggest that such methods are able to correctly classify the user's postures.

Slightly worse results are obtained when considering methods of the ensemble group. In fact, as shown in Tables 4.6 and 4.7, accuracies are between 68.4% and 83.7%. The worst performance was achieved using the Decision Table method, whose accuracy ranges between 41.6 and 44.3 (see Table 4.2).

Table 4.4: Performance evaluation of Logistic Regression method.

	User1 – User2					User1 – User3					User1 – User2–3				
	Position predicted				Acc. %	Position predicted				Acc. %	Position predicted				Acc. %
GT position	S	P	R	L		S	P	R	L		S	P	R	L	
supine	2955	277	317	0		10889	0	1212	0		13844	277	1529	0	
prone	0	3493	0	0	95.8	1719	9110	0	0	88.4	1719	12603	0	0	90.2
right	0	0	3554	0		4	8	11113	592		4	8	14667	592	
left	0	0	0	3551		592	602	644	10028		592	602	644	13579	

Table 4.5: Performance evaluation of IbK method.

	User1 – User2					User1 – User3					User1 – User2–3				
	Position predicted				Acc. %	Position predicted				Acc. %	Position predicted				Acc. %
GT position	S	P	R	L		S	P	R	L		S	P	R	L	
supine	2966	396	0	187	95.9	12101	0	0	0	93.3	15067	396	0	187	93.4
prone	0	3493	0	0		1109	9624	3	93		1109	13117	3	93	
right	0	0	3554	0		2	654	10469	592		2	650	14027	592	
left	0	0	1	3550		8	0	634	11224		8	0	635	14774	

Table 4.6: Performance evaluation of HyperPipes method.

	User1 – User2					User1 – User3					User1 – User2–3				
	Position predicted				Acc. %	Position predicted				Acc. %	Position predicted				Acc. %
GT position	S	P	R	L		S	P	R	L		S	P	R	L	
supine	2487	1062	0	0	83.7	10187	481	1433	0	77.3	12674	1543	1433	0	78.8
prone	0	3493	0	0		1	6755	4060	13		1	10248	4060	13	
right	4	0	3550	0		0	4	11120	593		4	4	14670	593	
left	642	265	330	2314		2849	0	1102	7915		3491	265	1432	10229	

Actually, such a result is expected, since the main advantage of approaches based on decision tables lies in their simplicity and low computational cost, whereas the classification performance is usually lower with respect to other machine learning methods.

The Random Forest (RF) method, instead, can be considered the best method in our application as shown in Table 4.8. In terms of global performance, it shows an accuracy between 89.6% and 95.7%.

In order to justify such a result, we need to recall some notions about random forests. The Random forest approach belongs to the class of ensemble methods, based on a combination of tree predictors. Each tree is composed using a sub–sampling of the training set. Combining outputs from each tree, the algorithm is able to improve the generalization performance and avoid the over–fitting problem. Eventually, when the number of trees goes to infinity, the Strong Law of Large Numbers always guarantees that the RF accuracy

Table 4.7: Performance evaluation of Bagging method.

	User1 – User2					User1 – User3					User1 – User2–3				
	Position predicted				Acc. %	Position predicted				Acc. %	Position predicted				Acc. %
GT position	S	P	R	L		S	P	R	L		S	P	R	L	
supine	2604	571	71	303	72.5	10691	783	18	609	68.4	13295	1354	89	912	69.3
prone	0	3493	0	0		3	7616	666	2544		3	11109	666	2544	
right	604	1186	1764	0		5	1919	9201	592		609	3105	10965	592	
left	369	792	0	2390		5619	1329	620	4298		5988	2121	620	6688	

Table 4.8: Performance evaluation of RF method using 100 trees and no–replacement.

	User1 – User2					User1 – User3					User1 – User2–3				
	Position predicted				Acc. %	Position predicted				Acc. %	Position predicted				Acc. %
GT position	S	P	R	L		S	P	R	L		S	P	R	L	
supine	2963	579	0	0	95.7	11960	0	141	0	89.6	14924	579	147	0	91.0
prone	0	3493	0	0		610	10218	1	0		610	13711	1	0	
right	0	0	3554	0		2	8	11115	592		2	8	14669	592	
left	0	0	23	3528		2844	9	635	8378		2844	9	658	11906	

Table 4.9: Performance evaluation of Random Forest according to different number of trees.

	User1 – User2–3 – 200 Trees					User1 – User2–3 – 500 Trees					User1 – User2–3 800 Trees				
	Position predicted				Acc.	Position predicted				Acc.	Position predicted				Acc.
GT position	S	P	R	L		S	P	R	L		S	P	R	L	
supine	14696	583	371	0	95.4	14875	583	192	0	95.7	14742	583	325	0	95.4
prone	0	14322	0	0		0	14322	0	0		0	14322	0	0	
right	0	11	14668	592		0	11	14668	592		0	11	14668	592	
left	0	14	1222	14181		0	1	1226	14190		39	0	1230	14148	

converge to that of the optimal predictor.

Table 4.9 shows the global accuracy values, obtained by Random Forest, running the algorithm with different number of trees, and seeds fixed to 1.

Table 4.10: Classification performance of Random Forest with 500 trees, after downsampling with no–replacement.

Sample Size %	User1–User2	User1–User3	User1–User2–3
20%	95.8	94.9	95.1%
10%	95.8	91.2	92.3%
5%	91.9	89.5	90.1%

The Random Forest algorithm reaches an accuracy of 95.4% for User1–User2–User3 case, better than all the other methods previously shown. Table 4.10 shows how a different percentage of the original dataset, with no–replacement and fixed number of trees equal to 500, impacts in terms of accuracies. Random Forest, considering the number of features involved in our scenario, needs approximately 100 seconds for the learning phase. Instead, a real–time prediction can be performed. A downsampling strategy can be useful in the case in which the model construction is performed on–board at the microcontroller–level or on some other resource–constrained device. Indeed, the overall complexity of RF, in terms of computational speed, depends on several factors, such as the number of trees, features, and instances. RF, trying to find an optimal predictor scanning several levels of possibilities, can require a good deal of computing power and memory available.

Chapter 5

Conclusions

The development of services and applications enabling the paradigm of Ambient Assisted Living is expected to increase in the next years. Although huge steps have been made in providing reliable solutions able to address very specific needs in AAL, the complexity of monitoring human indoor activities requires more effort to efficiently enable the AAL paradigm.

In fact, in this scenario, these issues are mainly related to the pillar of context-aware applications in daytime settings (i.e., indoor localisation), and to the need of overcoming state-of-the-art systems for night-time monitoring, in order to offer reliable solutions for elderly people in their own house. The main goal of this thesis was to deal with the monitoring of indoor human activities, considering both daytime and night-time settings.

This thesis addressed these challenges by proposing: a suite of advancements for the indoor localisation issue, and an unobstrusive system able to perform night-time sleep monitoring. The achieved results provide improvements to support people in their own indoor scenarios, especially fragile people who live alone.

Daytime monitoring

This thesis focused on the activity recognition problem for AAL environments in terms of providing reliable and efficient IPS solutions. To this purpose, supported by the background EvAAL competition scenario, we presented four different contributions.

In Section 3.1, we introduced and discussed the EvAAL benchmarking framework, with a focus on real-time smartphone-based systems. This provided a solution to the research community, by overcoming the problem of comparing different IPSs in an efficient, shared and reliable way. This question was, in fact, answered by the EvAAL framework, which we claim has the potential to become a standard way to compare systems in different application areas and different use cases: person vs. robot, smartphone vs. custom hardware, single vs. multi-storey building, single vs. multi-building environments, on-line vs. off-line processing. We think that our proposal makes it possible to directly compare the performance of heterogeneous systems in a more reliable way with respect to any other existing method.

Through the experience as software and online smartphone-based track chair of the 2016 and 2017 EvAAL competition, in Section 3.2, three different smartphone-based indoor localisation solutions are shown. In particular, we overcame the lack of a common and public dataset for testing different IPSs by presenting a multisource and multivariate dataset. These features can be easily exploited by ILSs, by combining different data. Furthermore, we introduced a novel smartphone-based approach, based on deep convolutional neural networks. This proposal allows improvements for one of the main sensors used in this field, the pedometer, using a deep learning based algorithm. Finally, we presented a flexible, extensible and modular indoor localisation suite for Android that is accessible to researchers, thanks to the free software license used for its distribution. We believe that such a modular architecture will allow the extension of its functionalities to other services, including both daytime and night-time monitoring services in an all-in-one application.

In Section 3.3, we extended the indoor positioning concept of a single-device localisation to many devices, using cheap and reliable solutions based on well-known Wi-Fi probes. We presented a dynamic architecture designed to collect the Wi-Fi probes periodically emitted by Wi-Fi-enabled devices (e.g., embedded devices, smartphones). Our approach is unsupervised, a particularly useful feature in an AAL scenario. The results obtained with the described ensemble estimator are, in our opinion, remarkable. Therefore, we claim that exploiting Wi-Fi probes promises to be a viable and cheap strategy for indoor localisation of devices.

Night-time monitoring

While working on this thesis project, we had the research opportunity of investigating and developing innovative and personalised systems to support healthy ageing.

In particular, in Chapter 4, we proposed an unobtrusive monitoring system able to infer sleep stages, sleep patterns and to detect postures in bed. It has the ambitious purpose to infer more human sleep parameters and, subsequently, to overcome traditional invasive methods and/ or self-report diaries. Instead, our work is based on a cheap technology and does not require active interactions between the users and the system.

Regarding the aim of our contributions, that is the sleep monitoring at night-time, our proposal is suitable for long term monitoring and exploits a sensing technique based on pressure sensors. The high versatility of the proposed system allows its use in several application scenarios, such as assessing the risk of pressure ulcer, monitoring bed exits or observing the influence of medication on the sleep behaviour. To sum up, this system is particularly useful in AAL due to its unobstrusive characteristics and to the fact that a user-machine interaction is not necessary.

5.1 Future works

Based on the results provided by this Ph.D. thesis, some future research is proposed in what follows.

In our daytime monitoring context, the use of deep convolutional neural networks for smartphone-based solutions requires additional investigation to different evaluation paths involving different users. Furthermore, future work on the crowd localisation method based on Wi-Fi probes will be carried out by experimenting such systems in real-life environments. Finally, front-end and back-end developments are required in order to consolidate the proof-of-concept smartphone-based framework for AAL. We think that the modular architecture of the proposed middleware is the key feature for addressing this challenge, but several efforts have to be made in order to integrate different services and to assure the user acceptance.

In our night-time monitoring context, we plan to perform an experimental campaign in real-life environments. More specifically, future work will focus on the consolidation process of the system. In this regard, real-world testbeds will be provided by the ongoing EU H2020 NESTORE project[1]. This will allow not only to maintain the already available solution, but also to implement new features arising from the new requirements of the particular use cases related to the project. It is worth noticing that our results do not completely address the problem concerning the lack of a standard definition of the sleep quality. However, our contribution proposes an innovative method for monitoring sleep activities which will lead to precisely measure important parameters of the sleep quality in AAL scenarios.

[1] `http://cordis.europa.eu/project/rcn/211703_en.html`

Bibliography

[1] M. Weiser, "The computer for the 21st century," *Scientific american*, vol. 265, no. 3, pp. 94–104, 1991.

[2] J. E. Morley, B. Vellas, G. A. Van Kan, S. D. Anker, J. M. Bauer, R. Bernabei, M. Cesari, W. Chumlea, W. Doehner, J. Evans *et al.*, "Frailty consensus: a call to action," *Journal of the American Medical Directors Association*, vol. 14, no. 6, pp. 392–397, 2013.

[3] H. Schuurmans, "Promoting well-being in frail elderly people," *Theory and intervention [dissertation]. University of Groningen*, 2004.

[4] M. A. O'Brien, *Understanding human-technology interactions: The role of prior experience and age.* Georgia Institute of Technology, 2010.

[5] A. Bandura, "Self-efficacy in health functioning," *Cambridge handbook of psychology, health & medicine*, vol. 2, pp. 289–315, 2007.

[6] F. Potortì and F. Palumbo, "Ceo: A context event only indoor localization technique for aal," *Journal of Ambient Intelligence and Smart Environments*, vol. 7, no. 6, pp. 745–760, 2015.

[7] P. Barsocchi, M. G. Cimino, E. Ferro, A. Lazzeri, F. Palumbo, and G. Vaglini, "Monitoring elderly behavior via indoor position-based stigmergy," *Pervasive and Mobile Computing*, vol. 23, pp. 26–42, 2015.

[8] F. Palumbo, P. Barsocchi, S. Chessa, and J. C. Augusto, "A stigmergic approach to indoor localization using bluetooth low energy beacons," in *Advanced Video and Signal Based Surveillance (AVSS), 2015 12th IEEE International Conference on.* IEEE, 2015, pp. 1–6.

[9] L. Wiggs, P. Montgomery, and G. Stores, "Actigraphic and parent reports of sleep patterns and sleep disorders in children with subtypes of attention-deficit hyperactivity disorder," *Sleep - New York then Westchester*, vol. 28, no. 11, p. 1437, 2005.

[10] M. Iwasaki, S. Iwata, A. Iemura, N. Yamashita, Y. Tomino, T. Anme, Z. Yamagata, O. Iwata, and T. Matsuishi, "Utility of subjective sleep assessment tools for healthy preschool children: A comparative study between sleep logs, questionnaires, and actigraphy," *Journal of epidemiology*, vol. 20, no. 2, pp. 143–149, 2010.

[11] A. Seelye, N. Mattek, D. Howieson, T. Riley, K. Wild, and J. Kaye, "The impact of sleep on neuropsychological performance in cognitively intact older adults using a novel in-home sensor-based sleep assessment approach," *The Clinical neuropsychologist*, vol. 29, no. 1, pp. 53–66, 2015.

[12] P. Baranyi and A. Csapo, "Definition and synergies of cognitive infocommunications," *Acta Polytechnica Hungarica*, vol. 9, no. 1, pp. 67–83, 2012.

[13] P. Baranyi, A. Csapo, and G. Sallai, *Cognitive Infocommunications (CogInfoCom)*. Springer, 2015.

[14] F. Potortì, S. Park, A. R. Jiménez Ruiz, P. Barsocchi, M. Girolami, A. Crivello, S. Y. Lee, J. H. Lim, J. Torres-Sospedra, F. Seco, R. Montoliu, G. M. Mendoza-Silva, M. D. C. Pérez Rubio, C. Losada-Gutiérrez, F. Espinosa, and J. Macias-Guarasa, "Comparing the performance of indoor localization systems through the evaal framework," vol. 17, no. 10. MDPI, Oct. 2017.

[15] P. Barsocchi, A. Crivello, D. La Rosa, and F. Palumbo, "A multisource and multivariate dataset for indoor localization methods based on wlan and geomagnetic field fingerprinting," in *Indoor Positioning and Indoor Navigation (IPIN), 2016 International Conference on*. IEEE, 2016, pp. 1–8.

[16] F. Z. C. W. A. C. M. Z. T. W. Shao, H. Luo, "Depedo: Anti periodic negative-step movement pedometer with deep convolutional neural networks," in *IEEE International Conference on Communications*, Accepted for publication.

[17] F. P. F. P. A. Crivello, M. Agostini, "An open-source framework for smartphone-based indoor localization," in *3rd Italian Workshop on Artificial Intelligence for Ambient Assisted Living*, Accepted for publication.

[18] F. Potortì, A. Crivello, M. Girolami, P. Barsocchi, and E. Traficante, "Localising crowds through wi-fi probes," *Ad-Hoc Networks*, Under Revision.

[19] P. Barsocchi, M. Bianchini, A. Crivello, D. L. Rosa, F. Palumbo, and F. Scarselli, "An unobtrusive sleep monitoring system for the human sleep behaviour understanding," in *2016 7th IEEE International Conference on Cognitive Infocommunications (CogInfoCom)*, Oct 2016, pp. 000 091–000 096.

[20] A. Crivello, F. Palumbo, P. Barsocchi, D. L. Rosa, F. Scarselli, and M. Bianchini, *Understanding human sleep behaviour by machine learning.* Springer, Accepted for publication.

[21] A. C. F. D. F. D. M. E. D. C. D. D. L. R. M. M. U. Barcaro, P. Barsocchi and F. Palumbo, "Intesa: An integrated ict solution for promoting wellbeing in older people," in *3rd Italian Workshop on Artificial Intelligence for Ambient Assisted Living*, Accepted for publication.

[22] A. Crivello, F. Palumbo, and F. Potortì, *The EvAAL evaluation framework and the IPIN competitions.* Elsevier, Accepted for publication.

[23] F. Potortì, A. Crivello, M. Girolami, E. Traficante, and P. Barsocchi, "Wi-Fi probes as digital crumbs for crowd localisation," in *2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Oct 2016, pp. 1–8.

[24] S. Chernbumroong, S. Cang, A. Atkins, and H. Yu, "Elderly activities recognition and classification for applications in assisted living," *Expert Systems with Applications*, vol. 40, no. 5, pp. 1662–1674, 2013.

[25] J. A. Botia, A. Villa, and J. Palma, "Ambient assisted living system for in-home monitoring of healthy independent elders," *Expert Systems with Applications*, vol. 39, no. 9, pp. 8136–8148, 2012.

[26] L. Chen and I. Khalil, "Activity recognition: Approaches, practices and trends," *Activity Recognition in Pervasive Intelligent Environments*, pp. 1–31, 2011.

[27] L. Chen and C. Nugent, "Ontology-based activity recognition in intelligent pervasive environments," *International Journal of Web Information Systems*, vol. 5, no. 4, pp. 410–430, 2009.

[28] D. J. Cook, J. C. Augusto, and V. R. Jakkula, "Ambient intelligence: Technologies, applications, and opportunities," *Pervasive and Mobile Computing*, vol. 5, no. 4, pp. 277–298, 2009.

[29] P. Rashidi and A. Mihailidis, "A survey on ambient-assisted living tools for older adults," *IEEE journal of biomedical and health informatics*, vol. 17, no. 3, pp. 579–590, 2013.

[30] L. Atallah and G.-Z. Yang, "The use of pervasive sensing for behaviour profiling—a survey," *Pervasive and Mobile Computing*, vol. 5, no. 5, pp. 447–464, 2009.

[31] N. D. Rodríguez, M. P. Cuéllar, J. Lilius, and M. D. Calvo-Flores, "A survey on ontologies for human behavior recognition," *ACM Computing Surveys (CSUR)*, vol. 46, no. 4, p. 43, 2014.

[32] J. Ye, S. Dobson, and S. McKeever, "Situation identification techniques in pervasive computing: A review," *Pervasive and mobile computing*, vol. 8, no. 1, pp. 36–66, 2012.

[33] E. M. Tapia, S. S. Intille, and K. Larson, "Activity recognition in the home using simple and ubiquitous sensors," in *Pervasive*, vol. 4. Springer, 2004, pp. 158–175.

[34] D. J. Patterson, L. Liao, D. Fox, and H. Kautz, "Inferring high-level behavior from low-level sensors," in *UbiComp*. Springer, 2003, pp. 73–89.

[35] R. Hamid, S. Maddi, A. Johnson, A. Bobick, I. Essa, and C. Isbell, "A novel sequence representation for unsupervised analysis of human activities," *Artificial Intelligence*, vol. 173, no. 14, pp. 1221–1244, 2009.

[36] O. Brdiczka, J. L. Crowley, and P. Reignier, "Learning situation models in a smart home," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 39, no. 1, pp. 56–63, 2009.

[37] U. Maurer, A. Smailagic, D. P. Siewiorek, and M. Deisher, "Activity recognition and monitoring using multiple sensors on different body positions," in *Wearable and Implantable Body Sensor Networks, 2006. BSN 2006. International Workshop on.* IEEE, 2006, pp. 4–pp.

[38] M. Delgado, M. Ros, and M. A. Vila, "Correct behavior identification system in a tagged world," *Expert systems with applications*, vol. 36, no. 6, pp. 9899–9906, 2009.

[39] A. Yamaguchi, M. Ogawa, T. Tamura, and T. Togawa, "Monitoring behavior in the home using positioning sensors," in *Engineering in Medicine and Biology Society, 1998. Proceedings of the 20th Annual International Conference of the IEEE*, vol. 4. IEEE, 1998, pp. 1977–1979.

[40] N. Noury, T. Hervé, V. Rialle, G. Virone, E. Mercier, G. Morey, A. Moro, and T. Porcheron, "Monitoring behavior in home using a smart fall sensor and position sensors," in *Microtechnologies in Medicine and Biology, 1st Annual International, Conference On. 2000.* IEEE, 2000, pp. 607–610.

[41] G. P. Joshi, S. Acharya, C.-S. Kim, B.-S. Kim, and S. W. Kim, "Smart solutions in elderly care facilities with rfid system and its integration with wireless sensor networks," *International Journal of Distributed Sensor Networks*, vol. 10, no. 8, p. 713946, 2014.

[42] J. Kropf, L. Roedl, and A. Hochgatterer, "A modular and flexible system for activity recognition and smart home control based on nonobtrusive sensors," in *Pervasive Computing Technologies for Healthcare (PervasiveHealth), 2012 6th International Conference on.* IEEE, 2012, pp. 245–251.

[43] G. D. Abowd, C. G. Atkeson, J. Hong, S. Long, R. Kooper, and M. Pinkerton, "Cyberguide: A mobile context-aware tour guide," *Wireless networks*, vol. 3, no. 5, pp. 421–433, 1997.

[44] K. Cheverst, N. Davies, K. Mitchell, A. Friday, and C. Efstratiou, "Developing a context-aware electronic tourist guide: some issues and experiences," in *Proceedings of the SIGCHI conference on Human Factors in Computing Systems.* ACM, 2000, pp. 17–24.

[45] L. Liao, D. Fox, and H. Kautz, "Location-based activity recognition," in *Advances in Neural Information Processing Systems*, 2006, pp. 787–794.

[46] P. L. Mazzeo, P. Spagnolo, and T. D'Orazio, "Object tracking by non-overlapping distributed camera network." in *ACIVS.* Springer, 2009, pp. 516–527.

[47] A. Correa, M. Barcelo, A. Morell, and J. L. Vicario, "A review of pedestrian indoor positioning systems for mass market applications," *Sensors*, vol. 17, no. 8, p. 1927, 2017.

[48] Y. Gu, A. Lo, and I. Niemegeers, "A survey of indoor positioning systems for wireless personal networks," *IEEE Communications Surveys Tutorials*, vol. 11, no. 1, pp. 13–32, First 2009.

[49] V. Bahl and V. Padmanabhan, "RADAR: An In-Building RF-based User Location and Tracking System." Institute of Electrical and Electronics Engineers, Inc., March 2000. [Online]. Available: https://www.microsoft.com/en-us/research/publication/radar-an-in-building-rf-based-user-location-and-tracking-system/

[50] M. Youssef and A. K. Agrawala, "The horus WLAN location determination system," in *Proceedings of the 3rd International Conference on Mobile Systems, Applications, and Services, MobiSys 2005, Seattle, Washington, USA, June 6-8, 2005*, K. G. Shin, D. Kotz, and B. D. Noble, Eds. ACM, 2005, pp. 205–218. [Online]. Available: http://doi.acm.org/10.1145/1067170.1067193

[51] M. Youssef and A. K. Agrawala, "On the Optimally of WLAN Location Determination Systems," University of Maryland, College Park, Tech. Rep. UMIACS-TR 2003-29 and UMIACS-TR 4459, 2003.

[52] M. Youssef and A. K. Agrawala, "Handling samples correlation in the horus system," in *Proceedings IEEE INFOCOM 2004, The 23rd Annual Joint Conference of the IEEE Computer and Communications Societies, Hong Kong, China, March 7-11, 2004*. IEEE, 2004. [Online]. Available: http://www.ieee-infocom.org/2004/Papers/21_3.PDF

[53] W. Li, D. Wei, H. Yuan, and G. Ouyang, "A novel method of wifi fingerprint positioning using spatial multi-points matching," in *2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Oct 2016, pp. 1–8.

[54] A. Mathisen, S. K. Sørensen, A. Stisen, H. Blunck, and K. Grønbæk, "A comparative analysis of indoor wifi positioning at a large building complex," in *2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Oct 2016, pp. 1–8.

[55] M. Mizmizi and L. Reggiani, "Design of rssi based fingerprinting with reduced quantization measures," in *2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Oct 2016, pp. 1–6.

[56] P. Barsocchi, S. Chessa, F. Furfari, and F. Potortì, "Evaluating AAL solutions through competitive benchmarking: the localization competition," *IEEE Pervasive Computing Magazine*, vol. 12, no. 4, pp. 72–79, Oct.–Dec. 2013.

[57] R. Ram, F. Furfari, M. Girolami, G. Ibañez-Sánchez, J.-P. Lázaro-Ramos, C. Mayer, B. Prazak-Aram, and T. Zentek, "Universaal: provisioning platform for aal services," in *Ambient Intelligence-Software and Applications*. Springer, 2013, pp. 105–112.

[58] P. Barsocchi, S. Chessa, F. Furfari, and F. Potortì, "Evaluating AAL solutions through competitive benchmarking: the localization competition," *IEEE Pervasive Computing Magazine*, vol. 12, no. 4, pp. 72–79, Oct.–Dec. 2013.

[59] D. Lymberopoulos, J. Liu, X. Yang, R. R. Choudhury, S. Sen, and V. Handziski, "Microsoft indoor localization competition: Experiences and lessons learned," *GetMobile: Mobile Computing and Communications*, vol. 18, no. 4, pp. 24–31, 2015.

[60] B. Li, T. Gallagher, A. G. Dempster, and C. Rizos, "How feasible is the use of magnetic field alone for indoor positioning?" in *Indoor Positioning and Indoor Navigation (IPIN), 2012 International Conference on*. IEEE, 2012, pp. 1–9.

[61] J. Song, H. Jeong, S. Hur, and Y. Park, "Improved indoor position estimation algorithm based on geo-magnetism intensity," in *Indoor Positioning and Indoor*

Navigation (IPIN), 2014 International Conference on. IEEE, 2014, pp. 741–744.

[62] J. Torres-Sospedra, D. Rambla, R. Montoliu, O. Belmonte, and J. Huerta, "Ujiindoorloc-mag: A new database for magnetic field-based localization problems," in *Indoor Positioning and Indoor Navigation (IPIN), 2015 International Conference on.* IEEE, 2015, pp. 1–10.

[63] K. Chintalapudi, A. Padmanabha Iyer, and V. N. Padmanabhan, "Indoor localization without the pain," in *Proceedings of the sixteenth annual international conference on Mobile computing and networking.* ACM, 2010, pp. 173–184.

[64] J. Machaj, P. Brida, and R. Piché, "Rank based fingerprinting algorithm for indoor positioning," in *2011 International Conference on Indoor Positioning and Indoor Navigation IPIN, 21-23 September 2011, Guimarães, Portugal;*, 2011.

[65] N. Marques, F. Meneses, and A. Moreira, "Combining similarity functions and majority rules for multi-building, multi-floor, wifi positioning," in *Indoor Positioning and Indoor Navigation (IPIN), 2012 International Conference on.* IEEE, 2012, pp. 1–9.

[66] F. Lemic, A. Behboodi, V. Handziski, and A. Wolisz, "Experimental decomposition of the performance of fingerprinting-based localization algorithms," in *Indoor Positioning and Indoor Navigation (IPIN), 2014 International Conference on.* IEEE, 2014, pp. 355–364.

[67] D. Vandermeulen, C. Vercauteren, and M. Weyn, "Indoor localization using a magnetic flux density map of a building," in *The Third International Conference on Ambient Computing, Applications, Services and Technologies. Porto: IARIA*, 2013, pp. 42–49.

[68] B. Li, T. Gallagher, C. Rizos, and A. G. Dempster, "Using geomagnetic field for indoor positioning," *Journal of Applied Geodesy*, vol. 7, no. 4, pp. 299–308, 2013.

[69] J. Chung, M. Donahoe, C. Schmandt, I.-J. Kim, P. Razavai, and M. Wiseman, "Indoor location sensing using geo-magnetism," in *Proceedings of the 9th international conference on Mobile systems, applications, and services.* ACM, 2011, pp. 141–154.

[70] J. Torres-Sospedra, R. Montoliu, A. Martinez-Uso, J. P. Avariento, T. J. Arnau, M. Benedito-Bordonau, and J. Huerta, "Ujiindoorloc: A new multi-building

and multi-floor database for wlan fingerprint-based indoor localization problems," in *Indoor Positioning and Indoor Navigation (IPIN), 2014 International Conference on.* IEEE, 2014, pp. 261–270.

[71] Z. Guoping and S. Rao, "Position localization with impulse ultra wide band," in *Wireless Communications and Applied Computational Electromagnetics, 2005. IEEE/ACES International Conference on.* IEEE, 2005, pp. 17–22.

[72] Y. Guo, L. Yang, B. Li, T. Liu, and Y. Liu, "Rollcaller: User-friendly indoor navigation system using human-item spatial relation," in *INFOCOM, 2014 Proceedings IEEE.* IEEE, 2014, pp. 2840–2848.

[73] K. Liu, X. Liu, L. Xie, and X. Li, "Towards accurate acoustic localization on a smartphone," in *INFOCOM, 2013 Proceedings IEEE.* IEEE, 2013, pp. 495–499.

[74] K. Wu, J. Xiao, Y. Yi, M. Gao, and L. M. Ni, "Fila: Fine-grained indoor localization," in *INFOCOM, 2012 Proceedings IEEE.* IEEE, 2012, pp. 2210–2218.

[75] N. Hernández, M. Ocaña, J. M. Alonso, and E. Kim, "Continuous space estimation: Increasing wifi-based indoor localization resolution without increasing the site-survey effort," *Sensors*, vol. 17, no. 1, p. 147, 2017.

[76] K. P. Subbu, B. Gozick, and R. Dantu, "Locateme: Magnetic-fields-based indoor localization using smartphones," *ACM Transactions on Intelligent Systems and Technology (TIST)*, vol. 4, no. 4, p. 73, 2013.

[77] Y. Shu, C. Bo, G. Shen, C. Zhao, L. Li, and F. Zhao, "Magicol: Indoor localization using pervasive magnetic field and opportunistic wifi sensing," *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 7, pp. 1443–1457, 2015.

[78] X. Wang, X. Wang, and S. Mao, "Cifi: Deep convolutional neural networks for indoor localization with 5 ghz wi-fi," in *Communications (ICC), 2017 IEEE International Conference on.* IEEE, 2017, pp. 1–6.

[79] I. Skog, P. Handel, J.-O. Nilsson, and J. Rantakokko, "Zero-velocity detection—an algorithm evaluation," *IEEE Transactions on Biomedical Engineering*, vol. 57, no. 11, pp. 2657–2666, 2010.

[80] F. Li, C. Zhao, G. Ding, J. Gong, C. Liu, and F. Zhao, "A reliable and accurate indoor localization method using phone inertial sensors," in *Proceedings of the 2012 ACM Conference on Ubiquitous Computing.* ACM, 2012, pp. 421–430.

[81] P. H. Veltink, H. J. Bussmann, W. De Vries, W. J. Martens, and R. C. Van Lummel, "Detection of static and dynamic activities using uniaxial accelerometers," *IEEE Transactions on Rehabilitation Engineering*, vol. 4, no. 4, pp. 375–385, 1996.

[82] M. Susi, V. Renaudin, and G. Lachapelle, "Motion mode recognition and step detection algorithms for mobile phone users," *Sensors*, vol. 13, no. 2, pp. 1539–1562, 2013.

[83] H. Xie, T. Gu, X. Tao, H. Ye, and J. Lu, "A reliability-augmented particle filter for magnetic fingerprinting based indoor localization on smartphone," *IEEE Transactions on Mobile Computing*, vol. 15, no. 8, pp. 1877–1892, 2016.

[84] K. P. Murphy, *Machine learning: a probabilistic perspective*, Cambridge, MA, 2012.

[85] J. Freudiger, "How talkative is your mobile device?: An experimental study of Wi-Fi probe requests," in *Proceedings of the 8th ACM Conference on Security & Privacy in Wireless and Mobile Networks*, ser. WiSec '15. New York, NY, USA: ACM, 2015, pp. 8:1–8:6. [Online]. Available: http://doi.acm.org/10.1145/2766498.2766517

[86] A. B. M. Musa and J. Eriksson, "Tracking unmodified smartphones using Wi-Fi monitors," in *Proceedings of the 10th ACM Conference on Embedded Network Sensor Systems*, ser. SenSys '12. New York, NY, USA: ACM, 2012, pp. 281–294. [Online]. Available: http://doi.acm.org/10.1145/2426656.2426685

[87] Z. Xu, K. Sandrasegaran, X. Kong, X. Zhu, B. Hu, J. Zhao, and C. Lin, "Pedestrain monitoring system using Wi-Fi technology and RSSI based localization," *International Journal of Wireless and Mobile Networks*, vol. 5, no. 4, pp. 17–34, January 2013.

[88] K. Göktaş and İ. Özkan, "Depression in elderly," *Psychiatry in Turkey*, vol. 8, pp. 30–37, 2006.

[89] J. Zeitlhofer, A. Schmeiser-Rieder, G. Tribl, A. Rosenberger, J. Bolitschek, G. Kapfhammer, B. Saletu, H. Katschnig, B. Holzinger, R. Popovic *et al.*, "Sleep and quality of life in the austrian population," *Acta Neurologica Scandinavica*, vol. 102, no. 4, pp. 249–257, 2000.

[90] D. Foley, S. Ancoli-Israel, P. Britz, and J. Walsh, "Sleep disturbances and chronic disease in older adults: results of the 2003 national sleep foundation sleep in america survey," *Journal of psychosomatic research*, vol. 56, no. 5, pp. 497–502, 2004.

[91] H. Urponen, I. Vuori, J. Hasan, and M. Partinen, "Self-evaluations of factors promoting and disturbing sleep: an epidemiological survey in finland," *Social Science & Medicine*, vol. 26, no. 4, pp. 443–450, 1988.

[92] A. S. Lim, M. Kowgier, L. Yu, A. S. Buchman, and D. A. Bennett, "Sleep fragmentation and the risk of incident alzheimer's disease and cognitive decline in older persons," *Sleep*, vol. 36, no. 7, pp. 1027–1032, 2013.

[93] G. J. Landry and T. Liu-Ambrose, "Buying time: a rationale for examining the use of circadian rhythm and sleep interventions to delay progression of mild cognitive impairment to alzheimer's disease," *Frontiers in aging neuroscience*, vol. 6, 2014.

[94] G. J. Landry, J. R. Best, and T. Liu-Ambrose, "Measuring sleep quality in older adults: a comparison using subjective and objective methods," *Frontiers in aging neuroscience*, vol. 7, 2015.

[95] A. D. Krystal and J. D. Edinger, "Measuring sleep quality," *Sleep medicine*, vol. 9, pp. S10–S17, 2008.

[96] A. Rechtschaffen and A. Kales, "A manual of standardized terminology, techniques, and scoring systems for sleep stages of human subjects," 1968.

[97] M. A. Carskadon, W. C. Dement, M. Mitler, C. Guilleminault, V. P. Zarcone, and R. Spiegel, "Self-reports versus sleep laboratory findings in 122 drug-free subjects with complaints of chronic insomnia," *Am J Psychiatry*, vol. 133, no. 12, pp. 1382–1388, 1976.

[98] R. M. Coleman, H. P. Roffwarg, S. J. Kennedy, C. Guilleminault, J. Cinque, M. A. Cohn, I. Karacan, D. J. Kupfer, H. Lemmi, L. E. Miles *et al.*, "Sleep-wake disorders based on a polysomnographic diagnosis: a national cooperative study," *Jama*, vol. 247, no. 7, pp. 997–1003, 1982.

[99] A. D. Krystal, J. D. Edinger, W. K. Wohlgemuth, and G. R. Marsh, "Nrem sleep eeg frequency spectral correlates of sleep complaints in primary insomnia subtypes," *Sleep*, vol. 25, no. 6, pp. 626–636, 2002.

[100] E. A. Nofzinger, J. C. Price, C. C. Meltzer, D. J. Buysse, V. L. Villemagne, J. M. Miewald, R. C. Sembrat, D. A. Steppe, and D. J. Kupfer, "Towards a neurobiology of dysfunctional arousal in depression: the relationship between beta eeg power and regional cerebral glucose metabolism during nrem sleep," *Psychiatry Research: Neuroimaging*, vol. 98, no. 2, pp. 71–91, 2000.

[101] M. L. Perlis, M. T. Smith, P. J. Andrews, H. Orff, and D. E. Giles, "Beta/gamma eeg activity in patients with primary and secondary insomnia and good sleeper controls," *Sleep*, vol. 24, no. 1, pp. 110–117, 2001.

[102] M. Terzano, D. Mancia, M. Salati, G. Costani, A. Decembrino, and L. Parrino, "The cyclic alternating pattern as a physiologic component of normal nrem sleep," *Sleep*, vol. 8, no. 2, pp. 137–145, 1985.

[103] M. G. Terzano, L. Parrino, G. Fioriti, B. Orofiamma, and H. Depoortere, "Modifications of sleep structure induced by increasing levels of acoustic perturbation in normal subjects," *Electroencephalography and clinical neurophysiology*, vol. 76, no. 1, pp. 29–38, 1990.

[104] M. G. Terzano, L. Parrino, M. C. Spaggiari, V. Palomba, M. Rossi, and A. Smerieri, "Cap variables and arousals as sleep electroencephalogram markers for primary insomnia," *Clinical Neurophysiology*, vol. 114, no. 9, pp. 1715–1723, 2003.

[105] D. J. Buysse, S. Ancoli-Israel, J. D. Edinger, K. L. Lichstein, and C. M. Morin, "Recommendations for a standard research assessment of insomnia," *Sleep*, vol. 29, no. 9, pp. 1155–1173, 2006.

[106] D. J. Buysse, C. F. Reynolds, T. H. Monk, S. R. Berman, and D. J. Kupfer, "The pittsburgh sleep quality index: a new instrument for psychiatric practice and research," *Psychiatry research*, vol. 28, no. 2, pp. 193–213, 1989.

[107] M. Littner, C. A. Kushida, W. M. Anderson, D. Bailey, R. B. Berry, D. G. Davila, M. Hirshkowitz, S. Kapen, M. Kramer, D. Loube *et al.*, "Practice parameters for the role of actigraphy in the study of sleep and circadian rhythms: an update for 2002," *Sleep*, vol. 26, no. 3, pp. 337–341, 2003.

[108] D. L. Schacter and D. R. Addis, "The cognitive neuroscience of constructive memory: remembering the past and imagining the future," *Philosophical Transactions of the Royal Society B: Biological Sciences*, vol. 362, no. 1481, pp. 773–786, 2007.

[109] C. E. Carney, D. J. Buysse, S. Ancoli-Israel, J. D. Edinger, A. D. Krystal, K. L. Lichstein, and C. M. Morin, "The consensus sleep diary: standardizing prospective sleep self-monitoring," *Sleep*, vol. 35, no. 2, pp. 287–302, 2012.

[110] E. J. Pedhazur and L. P. Schmelkin, *Measurement, design, and analysis: An integrated approach.* Psychology Press, 2013.

[111] J. Backhaus, K. Junghanns, A. Broocks, D. Riemann, and F. Hohagen, "Test–retest reliability and validity of the pittsburgh sleep quality index in primary insomnia," *Journal of psychosomatic research*, vol. 53, no. 3, pp. 737–740, 2002.

[112] A. Shahid, K. Wilkinson, S. Marcu, and C. M. Shapiro, *Richards–Campbell Sleep Questionnaire (RCSQ).* New York, NY: Springer New York, 2012, pp. 299–302. [Online]. Available: https://doi.org/10.1007/978-1-4419-9893-4_73

[113] K. C. Richards, P. S. O'sullivan, and R. L. Phillips, "Measurement of sleep in critically ill patients," *Journal of nursing measurement*, vol. 8, no. 2, pp. 131–144, 2000.

[114] R. S. Bourne, C. Minelli, G. H. Mills, and R. Kandler, "Clinical review: sleep measurement in critical care patients: research and clinical implications," *Critical Care*, vol. 11, no. 4, p. 226, 2007.

[115] T. Åkerstedt, K. Hume, D. Minors, and J. Waterhouse, "The subjective meaning of good sleep, an intraindividual approach using the karolinska sleep diary," *Perceptual and motor skills*, vol. 79, no. 1, pp. 287–296, 1994.

[116] D. Minors and J. Waterhouse, "The role of naps in alleviating sleepiness during an irregular sleep-wake schedule," *Ergonomics*, vol. 30, no. 9, pp. 1261–1273, 1987.

[117] A. Westerlund, Y. T. Lagerros, G. Kecklund, J. Axelsson, and T. Åkerstedt, "Relationships between questionnaire ratings of sleep quality and polysomnography in healthy adults," *Behavioral sleep medicine*, vol. 14, no. 2, pp. 185–199, 2016.

[118] G. Keklund and T. ÅKerstedt, "Objective components of individual differences in subjective sleep quality," *Journal of sleep research*, vol. 6, no. 4, pp. 217–220, 1997.

[119] K. Aili, S. Åström-Paulsson, U. Stoetzer, M. Svartengren, and L. Hillert, "Reliability of actigraphy and subjective sleep measurements in adults: The design of sleep assessments." *Journal of clinical sleep medicine: JCSM: official publication of the American Academy of Sleep Medicine*, vol. 13, no. 1, pp. 39–47, 2017.

[120] A. Sadeh, P. J. Hauri, D. F. Kripke, and P. Lavie, "The role of actigraphy in the evaluation of sleep disorders," *Sleep*, vol. 18, no. 4, pp. 288–302, 1995.

[121] American Sleep Disorders Association *et al.*, "Practice parameters for the use of actigraphy in the clinical assessment of sleep disorders," *Sleep*, vol. 18, no. 4, pp. 285–287, 1995.

[122] D. Waltisberg, B. Arnrich, and G. Tröster, "Sleep quality monitoring with the smart bed," in *Pervasive Health.* Springer, 2014, pp. 211–227.

[123] C. A. Kushida, A. Chang, C. Gadkary, C. Guilleminault, O. Carrillo, and W. C. Dement, "Comparison of actigraphic, polysomnographic, and subjective assessment of sleep parameters in sleep-disordered patients," *Sleep medicine*, vol. 2, no. 5, pp. 389–396, 2001.

[124] P. L. Marino, *Marino's the ICU Book*. Lippincott Williams & Wilkins, 2013.

[125] S. Ancoli-Israel, R. Cole, C. Alessi, M. Chambers, W. Moorcroft, and C. P. Pollak, "The role of actigraphy in the study of sleep and circadian rhythms," *Sleep*, vol. 26, no. 3, pp. 342–392, 2003.

[126] M. A. Grandner, D. F. Kripke, I.-Y. YOON, and S. D. Youngstedt, "Criterion validity of the pittsburgh sleep quality index: Investigation in a non-clinical sample," *Sleep and biological rhythms*, vol. 4, no. 2, pp. 129–136, 2006.

[127] E. J. Van Someren, "Improving actigraphic sleep estimates in insomnia and dementia: how many nights?" *Journal of sleep research*, vol. 16, no. 3, pp. 269–275, 2007.

[128] M. J. Chambers, "Actigraphy and insomnia: A closer look part 1," *Sleep*, vol. 17, no. 5, pp. 405–408, 1994.

[129] P. J. Hauri and J. Wisbey, "Wrist actigraphy in insomnia," *Sleep*, vol. 15, no. 4, pp. 293–301, 1992.

[130] C. Acebo, A. Sadeh, R. Seifer, O. Tzischinsky, A. Wolfson, A. Hafer, and M. Carskadon, "Estimating sleep patterns with activity monitoring in children and adolescents: how many nights are necessary for reliable measures?" *Sleep*, vol. 22, no. 1, pp. 95–103, 1999.

[131] P. Barsocchi, "Position recognition to support bedsores prevention," *IEEE Journal of Biomedical and Health Informatics*, vol. 17, no. 1, pp. 53–59, 2013.

[132] F. Palumbo, P. Barsocchi, F. Furfari, and E. Ferro, "AAL middleware infrastructure for green bed activity monitoring," *Journal of Sensors*, 2013.

[133] D. I. Townsend, M. Holtzman, R. Goubran, M. Frize, and F. Knoefel, "Measurement of torso movement with delay mapping using an unobtrusive pressure-sensor array," *IEEE Transactions on Instrumentation and Measurement*, vol. 60, no. 5, pp. 1751–1760, 2011.

[134] S. Rus, T. Grosse-Puppendahl, and A. Kuijper, "Recognition of bed postures using mutual capacitance sensing," in *European Conference on Ambient Intelligence*. Springer, 2014, pp. 51–66.

[135] R. S. Campos, L. Lovisolo, and M. L. R. de Campos, "Wi-Fi multi-floor indoor positioning considering architectural aspects and controlled computational complexity," *Expert Systems with Applications*, vol. 41, no. 14, pp. 6211 – 6223, 2014. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0957417414002073

[136] L. Schauer, P. Marcus, and C. Linnhoff-Popien, "Towards feasible wi-fi based indoor tracking systems using probabilistic methods," in *2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Oct 2016, pp. 1–8.

[137] A. Mathisen, S. K. Sørensen, A. Stisen, H. Blunck, and K. Grønbæk, "A comparative analysis of indoor wifi positioning at a large building complex," in *2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Oct 2016, pp. 1–8.

[138] P. Barsocchi, M. Girolami, and F. Potortì, "Track 1: Smartphone Based (on-site)," http://www3.uah.es/ipin2016/docs/Track1_IPIN2016Competition.pdf [Last accessed June 2017], september 2016.

[139] S. Lee and J. Lim, "Track 2: Pedestrian Dead Reckoning Positioning (on-site)," http://www3.uah.es/ipin2016/docs/Track2_IPIN2016Competition.pdf [Last accessed June 2017], september 2016.

[140] T. Fetzer, F. Ebner, F. Deinzer, and M. Grzegorzek, "Multi Sensor Indoor Localisation (only abstract)," in *USB Proceedings of the 2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN 2016)*, Alcala de Henares, Madrid, Spain, oct 2016.

[141] Y. B. Bai, T. Gu, and A. Hu, "Integrating wi-fi and magnetic field for fingerprinting based indoor positioning system," in *2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Oct 2016, pp. 1–6.

[142] J. C. A. Herrera and A. Ramos, "Navix: Smartphone Based Hybrid Indoor Positioning (only abstract)," in *USB Proceedings of the 2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN 2016)*, Alcala de Henares, Madrid, Spain, oct 2016.

[143] X. Guo, W. Shao, F. Zhao, Q. Wang, D. Li, and H. Luo, "Wimag: Multimode fusion localization system based on magnetic/wifi/pdr," in *2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Oct 2016, pp. 1–8.

[144] J. L. Carrera, Z. Zhao, T. Braun, and Z. Li, "A real-time indoor tracking system by fusing inertial sensor, radio signal and floor plan," in *2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Oct 2016, pp. 1–8.

[145] L. Zheng, Y. Wang, A. Peng, Z. Wu, S. Wen, H. Lu, H. Shi, and H. Zheng, "A Hand-held Indoor Positioning System Based On Smartphone (only abstract),"

in *USB Proceedings of the 2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN 2016)*, Alcala de Henares, Madrid, Spain, oct 2016.

[146] F. Palumbo, D. La Rosa, and S. Chessa, "Gp-m: Mobile middleware infrastructure for ambient assisted living," in *Computers and Communication (ISCC), 2014 IEEE Symposium on.* IEEE, 2014, pp. 1–6.

[147] P. Kemppi, T. Rautiainen, V. Ranki, F. Belloni, and J. Pajunen, "Hybrid positioning system combining angle-based localization, pedestrian dead reckoning and map filtering," in *Indoor Positioning and Indoor Navigation (IPIN), 2010 International Conference on.* IEEE, 2010, pp. 1–7.

[148] P. Mirowski, T. K. Ho, S. Yi, and M. MacDonald, "Signalslam: Simultaneous localization and mapping with mixed wifi, bluetooth, lte and magnetic signals," in *Indoor Positioning and Indoor Navigation (IPIN), 2013 International Conference on.* IEEE, 2013, pp. 1–10.

[149] Z. Chen, H. Zou, H. Jiang, Q. Zhu, Y. C. Soh, and L. Xie, "Fusion of wifi, smartphone sensors and landmarks using the kalman filter for indoor localization," *Sensors*, vol. 15, no. 1, pp. 715–732, 2015.

[150] E. Le Grand and S. Thrun, "3-axis magnetic field mapping and fusion for indoor localization," in *Multisensor Fusion and Integration for Intelligent Systems (MFI), 2012 IEEE Conference on.* IEEE, 2012, pp. 358–364.

[151] P. Barsocchi, A. Crivello, D. L. Rosa, and F. Palumbo, "A multisource and multivariate dataset for indoor localization methods based on wlan and geomagnetic field fingerprinting," in *2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Oct 2016, pp. 1–8.

[152] J. R. Quinlan, "Learning logical definitions from relations," *Machine learning*, vol. 5, no. 3, pp. 239–266, 1990.

[153] P. Bahl and V. N. Padmanabhan, "RADAR: an in-building RF-based user location and tracking system," in *IEEE Conference on Computer Communications (INFOCOM)*, vol. 2, Mar. 2000, pp. 775–784.

[154] Y. Wen, X. Tian, X. Wang, and S. Lu, "Fundamental limits of RSS fingerprinting based indoor localization," in *IEEE Conference on Computer Communications (INFOCOM)*, Apr. 2015, pp. 2479–2487.

[155] F. Potortì, P. Barsocchi, M. Girolami, J. Torres-Sospedra, and R. Montoliu, "Evaluating indoor localization solutions in large environments through competitive benchmarking: The EvAAL-ETRI competition," in *Indoor Positioning*

and Indoor Navigation (IPIN), 2015 International Conference on. IEEE, 2015, pp. 1–10.

[156] B. Li, Y. Wang, H. K. Lee, A. Dempster, and C. Rizos, "Method for yielding a database of location fingerprints in WLAN," *IEE Proceedings - Communications*, vol. 152, no. 5, pp. 580–586, Oct 2005.

[157] S.-S. Jan, S.-J. Yeh, and Y.-W. Liu, "Received signal strength database interpolation by Kriging for a Wi-Fi indoor positioning system," *Sensors*, vol. 15, no. 9, p. 21377, 2015. [Online]. Available: http://www.mdpi.com/1424-8220/15/9/21377

[158] G. Bebis, T. Deaconu, and M. Georgiopoulos, "Fingerprint identification using delaunay triangulation," in *Information Intelligence and Systems, 1999. Proceedings. 1999 International Conference on.* IEEE, 1999, pp. 452–459.

[159] M. J. De Smith, M. F. Goodchild, and P. Longley, *Geospatial analysis: a comprehensive guide to principles, techniques and software tools.* Troubador Publishing Ltd, 2007.

[160] P. E. L. de Teruel, O. Canovas, and F. J. Garcia, "Visualization of clusters for indoor positioning based on t-SNE," in *Indoor Positioning and Indoor Navigation (IPIN), 2016 International Conference on*, 2016.

[161] J. Torres-Sospedra, G. M. Mendoza-Silva, R. Montoliu, O. Belmonte, F. Benitez, and J. Huerta, "Ensembles of indoor positioning systems based on fingerprinting: Simplifying parameter selection and obtaining robust systems," in *2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Oct 2016, pp. 1–8.

[162] T. Hayashi, D. Taniuchi, J. Korpela, and T. Maekawa, "Spatio-temporal adaptive indoor positioning using an ensemble approach," *Pervasive and Mobile Computing*, pp. –, 2016. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1574119216304102

[163] G. Barbon, M. Margolis, F. Palumbo, F. Raimondi, and N. Weldin, "Taking Arduino to the Internet of Things: the ASIP programming model," *Computer Communications*, 2016.

[164] C. M. Bishop, "Pattern recognition," *Machine Learning*, vol. 128, pp. 1–58, 2006.

[165] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten, "The weka data mining software: an update," *SIGKDD Explor. Newsl.*, vol. 11, no. 1, pp. 10–18, 2009. [Online]. Available: http://dx.doi.org/10.1145/1656274.1656278

[166] R. Kohavi, "The power of decision tables," in *Proceedings of the European Conference on Machine Learning*. Springer Verlag, 1995, pp. 174–189.

[167] G. H. John and P. Langley, "Estimating continuous distributions in bayesian classifiers," in *Proceedings of the Eleventh conference on Uncertainty in artificial intelligence*. Morgan Kaufmann Publishers Inc., 1995, pp. 338–345.

[168] J. Friedman, T. Hastie, R. Tibshirani *et al.*, "Additive logistic regression: a statistical view of boosting (with discussion and a rejoinder by the authors)," *The annals of statistics*, vol. 28, no. 2, pp. 337–407, 2000.

[169] J. F. Hair, Jr., R. E. Anderson, R. L. Tatham, and W. C. Black, *Multivariate Data Analysis (4th Ed.): With Readings*. Upper Saddle River, NJ, USA: Prentice-Hall, Inc., 1995.

[170] D. W. Aha, D. Kibler, and M. K. Albert, "Instance-based learning algorithms," *Machine learning*, vol. 6, no. 1, pp. 37–66, 1991.

[171] I. H. Witten, E. Frank, M. A. Hall, and C. J. Pal, *Data Mining: Practical machine learning tools and techniques*. Morgan Kaufmann, 2016.

[172] L. Breiman, "Bagging predictors," *Machine learning*, vol. 24, no. 2, pp. 123–140, 1996.

[173] L. Breiman, "Random forests," *Machine learning*, vol. 45, no. 1, pp. 5–32, 2001.