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An IoT based Virtual Coaching System (VSC) for Assisting Activities of Daily Life

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Abstract

Nowadays aging of the population is becoming one of the main concerns of the world. It is estimated that the number of people aged over 65 will increase from 461 million to 2 billion in 2050. This substantial increment in the elderly population will have significant consequences in the social and health care system. Therefore, in the context of Ambient Intelligence (AmI), the Ambient Assisted Living (AAL) has been emerging as a new research area to address problems related to the aging of the population. AAL technologies based on embedded devices have demonstrated to be effective in alleviating the social- and health-care issues related to the continuous growing of the average age of the population. Many smart applications, devices and systems have been developed to monitor the health status of elderly, substitute them in the accomplishment of activities of the daily life (especially in presence of some impairment or disability), alert their caregivers in case of necessity and help them in recognizing risky situations. Such assistive technologies basically rely on the communication and interaction between body sensors, smart environments and smart devices. However, in such context less effort has been spent in designing smart solutions for empowering and supporting the self-efficacy of people with neurodegenerative diseases and elderly in general. This thesis fills in the gap by presenting a low-cost, non intrusive, and ubiquitous Virtual Coaching System (VCS) to support people in the acquisition of new behaviors (e.g., taking pills, drinking water, finding the right key, avoiding motor blocks) necessary to cope with needs derived from a change in their health status and a degradation of their cognitive capabilities as they age. VCS is based on the concept of extended mind introduced by Clark and Chalmers in 1998. They proposed the idea that objects within the environment function as a part of the mind. In my revisiting of the concept of extended mind, the VCS is composed of a set of smart objects that exploit the Internet of Things (IoT) technology and machine learning-based algorithms, in order to identify the needs of the users and react accordingly. In particular, the system exploits smart tags to transform objects commonly used by people (e.g., pillbox, bottle of water, keys) into smart objects, it monitors their usage according to their needs, and it incrementally guides them in the acquisition of new behaviors related to their needs. To implement VCS, this thesis explores different research directions and challenges. First of all, it addresses the definition of a ubiquitous, non-invasive and low-cost indoor monitoring architecture by exploiting the IoT paradigm. Secondly, it deals with the necessity of developing solutions for implementing coaching actions and consequently monitoring human activities by analyzing the interaction between people and smart objects. Finally, it focuses on

the design of low-cost localization systems for indoor environment, since knowing the position of a person provides VCS with essential information to acquire information on performed activities and to prevent risky situations. In the end, the outcomes of these research directions have been integrated into a healthcare application scenario to implement a wearable system that prevents freezing of gait in people affected by Parkinson's Disease.

Abstract (Italian)

Al giorno d'oggi, l'invecchiamento della popolazione sta diventando una delle principali preoccupazioni del mondo. Si stima che il numero di persone di età superiore ai 65 anni aumenterà da 461 milioni a 2 miliardi nel 2050. Questo sostanziale aumento nella popolazione anziana avrà conseguenze significative nel sistema sociale e sanitario. Pertanto, nel contesto di Ambient Intelligence (AmI), Ambient Assisted Living (AAL) sta emergendo come una nuova area di ricerca per affrontare i problemi legati all'invecchiamento della popolazione. Le tecnologie AAL basate su dispositivi integrati hanno dimostrato di essere efficaci nell'alleviare i problemi sociali e sanitari legati alla crescita continua dell'età media della popolazione. Molte applicazioni, dispositivi e sistemi intelligenti sono stati sviluppati per monitorare lo stato di salute degli anziani, sostituirli nello svolgimento delle attività della vita quotidiana (soprattutto in presenza di impedimenti o disabilità), avvisare i loro caregiver in caso di necessità e aiutarli nel riconoscere situazioni rischiose. Tali tecnologie AAL si basano sostanzialmente sulla comunicazione e l'interazione tra sensori corporei, ambienti intelligenti e dispositivi intelligenti. Tuttavia, in tale contesto, é stato dato meno importanza alla progettazione di soluzioni intelligenti per potenziare e supportare l'autoefficacia degli anziani. Questa tesi colma il vuoto presentando un Virtual Coaching System (VCS) a basso costo, non invadente e onnipresente per supportare gli anziani nell'acquisizione di nuovi comportamenti (ad es. assumere pillole, bere acqua, trovare la chiave giusta) necessari per far fronte ai bisogni derivanti da un cambiamento nel loro stato di salute e da un degrado delle loro capacità cognitive durante la fase di invecchiano. Il VCS si basa sul concetto di mente estesa introdotto da Clark e Chalmers nel 1998. Loro hanno proposto l'idea che gli oggetti all'interno dell'ambiente funzionino come parte della mente. Nella mia rivisitazione del concetto di mente estesa, il VCS è composto da un insieme di oggetti intelligenti che sfruttano concetti e idee di Internet of Things (IoT) e algoritmi basati sull'apprendimento automatico, al fine di identificare le esigenze degli utenti e reagire di conseguenza. In paticolare, il sistema sfrutta gli smart tag Bluetooth Low Energy (BLE) per trasformare gli oggetti di uso comune (Objects of Daily life (ODLs)) utilizzati dagli anziani (ad es., portapillole, bottiglia d'acqua, chiavi) in oggetti intelligenti, monitora il loro utilizzo in base alle esigenze degli anziani e li guida progressivamente nell'acquisizione di nuovi comportamenti legati all'uso di tali oggetti. Al fine di implementare il sistema VCS, questa tesi esplora molte sfide diverse. Prima di tutto, la definizione di un'architettura onnipresente, non invasiva ed a basso costo basata sull'idea di IoT. In secondo luogo, si occupa della necessità di sviluppare soluzioni per

attuare azioni di coaching e, di conseguenza, monitorare le attività umane analizzando l'interazione tra persone e oggetti intelligenti. Infine, se si concentra sulla progettazione di sistemi di localizzazione a basso costo per l'ambiente interno, poiché conoscere la posizione di una persona fornisce a VCS le informazioni essenziali per acquisire informazioni sulle attività svolte e prevenire situazioni rischiose. Alla fine, i risultati di queste direzioni di ricerca sono stati integrati in uno scenario di applicativo implementando un sistema indossabile che impedisce il congelamento dell'andatura nelle persone colpite dalla malattia di Parkinson.

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1

Introduction

According to the 2019 World Population Prospectus [1], in 2018, for the first time in human history, persons aged 65+ years outnumbered children under 5 years. In addition, they expect that in 2050 people aged 65+ years (1.5 billion) will outnumber adolescents and youth aged 15 to 24 years (1.3 billion). This substantial increase in the elderly population has profound implications for the planning and delivery of health and social care. In fact, despite an increase in life expectancy, several people show a loss of self-efficacy as they age, and a consequent reduction of the quality of their life. This is particularly true for elderly affected by neurodegenerative diseases (e.g., dementia, Alzheimer and Parkinson), where progresses in medicine greatly contribute to prolong their lives, but are less effective in preserving their autonomy and independence. These people experience a low perception of self-efficacy, which consequently compromises their self-confidence and proportionally deteriorate their clinical picture [2, 3]. More and more elderly progressively loose the capability of living independently and need constant caregiving for the rest of their life. Unfortunately, this decreasing in autonomy comes contextually to elderly's necessity of changing some habits and of acquiring new behaviors (e.g., taking medicine at periodic intervals, doing physical activities or exercises, drinking water even if they do not feel thirsty) with respect to activities of the daily file (ADLs).

In this scenario, industrialized governments are meeting important challenges concerning the quality and cost of healthcare and wellbeing services. These challenges will intensify even more due to the population aging, which increases the probability of a multitude of persistent illnesses implying a substantial need for healthcare services. As a consequence, the cost of the healthcare sector will not be sustainable for everyone. Therefore, industrialized countries need to find and plan policies and strategies to use the limited economic resources more efficiently and effectively [4, 5]. In addition, concerning the social system, the aging of the population will have a significant impact on the quality of life not only of elderly but also on family members who perform a caregiving activity [6]. The growing demand for healthcare services implies a range of challenges in medicine and technology, which, if resolved, could benefit our global society and economy. The usage of Information and Communication Technology (ICT) for achieving self-sufficient and proactive healthcare services will be very beneficial. Nowadays, patient-driven healthcare, in combination with web-based platforms and electronic health records, has already led to an improvement in the healthcare system. In recent years, many smartphone apps, which are becoming available for physiological status monitoring, have become very popular [7–9]. With modern improvements in sensor networks research, we are on the path of revolutionary low-cost healthcare monitoring systems embedded within the home and daily life environment [10, 11].

In particular, Ambient Intelligence (AmI) and Ambient Assisted Living (AAL) technologies have the potential to improve the healthcare area dramatically. For example, such systems can be used as basic monitoring tools regarding the health in older adults or people with persistent diseases by providing assistive solutions also integrated with daily living environment and daily life objects. The aforementioned solutions can be used for the basics for the creation of persuasive services to coach people to lead a better lifestyle by making them learn new and healthier behaviors and help them to avoid more harmful ones. They also can be used in rehabilitation settings or, in general, in enhancing the well-being of individuals. Ultimately, they can support healthcare experts by providing innovative communication and monitoring tools. These systems will implement health monitoring transparently and unobtrusively [12]. Nevertheless, despite being an essential step toward personalized medicine, these ICT solutions often suffer from interoperability, scalability, security, and privacy issues. Furthermore, such solutions are generally intended for remote monitoring the health status and alerting family members or social/medical staff in case of necessity, while only few of them focus on providing a support to elderly to improve his/her capability of living independently. As stated in [13], approximately 60 to 70% of the elderly and cognitively/physically impaired people prefers to have an independent lifestyle and perform Activities of Daily Living (ADL) without a caregiver [14]. The majority of them thinks that formal care is an expensive service and also would maintain their privacy in everyday living [15]. However, this people living independently present a higher possibility of having physical and mental issues. It is, therefore, of utmost importance to develop AAL solutions that promote autonomy and independence in daily life activities of elderly and, in general, of people with neurodegenerative diseases.

To achieve this goal, AAL solutions must implement a coaching approach for "enabling the person to do something" to empower his/her feeling of being self-effective. Coaching has been defined by John Withmore as "unlocking a person's potential to maximize his/her own performance; it is helping them to learn rather than teaching them" [16], or similarly by Myles Downey as "the art of facilitating the performance, learning and development of another" [17]. Coaching is different from assistance, which might be described as "doing something on behalf of the person" and therefore potentially incapacitates the assisted person. A fundamental aspect of coaching is to positively impact the preservation of the physical, cognitive, mental and social well-being of a person. The effectiveness of the coaching process traditionally relies on a relationship between the coach and the coachee. However, this is not enough to ensure the effectiveness of coaching, when the coachee is a person, with a well consolidated set of behaviours, and possibly also with a decrease in his/her cognitive capabilities. In this situation, a coaching approach, to be effective, requires a continuous and ubiquitous action that cannot be guarantee only with periodic meetings between the coach and the coachee.

The goal of this thesis is then to investigate, develop and evaluate the feasibility of a virtual coaching system (VCS) to improve independence and autonomy, maintain functional capacity and health status, and physical, cognitive, mental and social well-being in elderly and people with neurodegenerative diseases. In particular, Virtual Coaching System (VCS) is intended as a an intelligent support system to allow people learning new behaviors in ADLs and the remote monitoring by their caregivers. Therefore, this thesis aims to integrate the coaching concept with AAL-based solutions to revise, through the implementation of an ICT system, the concept of Extended Mind defined by Clarke and Chalmers in 1998 [18]. In such a concept the environment is part and takes an active role of cognitive processes; the human organism is linked with an external entity in a two-way interaction, creating a coupled system that can be seen as a cognitive system in its own right. All the components in the system play an active causal role, and they jointly govern behavior in the same sort of way that cognition usually does. If the external component is removed the system's behavioral competence will drop, just as it would if we removed part of its brain. To mimic the idea of extened mind and perform the coaching actions, VCS implements intelligent algorithms, executed on mobile devices like smartphones and smartwatches, which exploit data gathered by wearable and environmental sensors.

In the definition and implementation of VCS, I mainly focus on four research directions. The first direction regards the creation of a low cost and easily configurable smart home architecture to collect environmental data and allow the communication between smart objects and VCS. The second direction regards the creation of a localization system in order to identify the position of the elder with respect to smart objects and indoor areas, as the baseline to develop related coaching actions. The third direction regards the creation of the coaching architecture and the recognition of human activities through the interaction between wearable devices and smart objects . Finally, the fourth direction regards the application of the VCS to the specific case of preventing the freezing of gait in people with Parkinson's Disease, as a relevant scenario in the context of supporting people with neurogenerative problems.

To develop the previous research directions were solved several scientific and technological challenges related to different computer engineering fields, like programming of wearable devices, design of body area networks, use and configuration of radio-based communication protocols, and application of machine learning algorithms.

1.1 Thesis Organization

The thesis chapters are organized as follows. The current Chapter motivated the work and introduces the concept of Virtual Coaching System (VCS). Chapter 2 discusses the state of the art and the necessary theoretical background for a better understanding of the rest of the thesis. First, the concept of Active Externalism and Extended Mind are introduced, consequently a general overview of the role of technology in everyday life and on the devices that have nowadays invaded the electronics market entering by right to the Internet of Things (IoT) context.

Furthermore, this chapter will introduce basics concepts of Assisting Technology, Ambient Intelligence and Human Activity Recognition. Chapter 3 defines the goal of this thesis and the related challenges. The following chapters present the working principle of the proposed virtual coaching system. In detail, Chapter 4 introduces the smart-home architecture for the gathering of environmental data and the assessment of the interaction between smart objects and users. Chapter 5 presents the Assisting Daily life Activities (ADA) VCS coaching architecture. Chapter 6 describes an indoor localization system. Chapter 7 characterize VCS in the context of preventing the Freezing of Gait (FoG) in people with Parkinson's disease. Finally, Chapter 8 reports the conclusion and draft recommendations for future work.

1.2 Thesis related publications

Part of this thesis is based on the following publications:

- Demrozi, F., Costa, K., Tramarin, F., & Pravadelli, G. (2018, October). *A graph-based approach for mobile localization exploiting real and virtual landmarks*.
  In 2018 IFIP/IEEE International Conference on Very Large Scale Integration (VLSI-SoC) (pp. 249-254). IEEE.
- Demrozi, F., Bragoi, V., Tramarin, F., & Pravadelli, G. (2019, March). *An indoor localization system to detect areas causing the freezing of gait in Parkinsonians*.
  In 2019 Design, Automation & Test in Europe Conference & Exhibition (DATE) (pp. 952-955). IEEE.
- Demrozi, F., Serlonghi, N., Di Marco, F., & Pravadelli, G. (2020, March). *A virtual coaching system exploiting BLE smart tags for supporting elderly in the acquisition of new behaviours*. Submitted at IEEE Transactions on Emerging Topics in Computing (TETC).
- Demrozi, F., Bacchin, R., Tamburin, S., Cristani, M., & Pravadelli, G. *Towards a wearable system for predicting freezing of gait in people affected by Parkinson's disease*.
  IEEE Journal of Biomedical and Health Informatics, 2019,

2

State Of The Art

This chapter will introduce the main concepts and research areas from whom the proposed Virtual Coaching System (VCS) takes inspiration. Section 2.1 introduces the definition of Active Externalism and Extended Mind. Section 2.2 and Section 2.3 are devoted to an overview, respectively, on the importance of technology in our daily life and on the Internet of Things (IoT) research area. Sections 2.4, 2.5, 2.6 respectively introduce the concepts of assisting technologies, Ambient Intelligence (AmI), and Human Activity Recognition (HAR), spending particular effort on the importance of such research areas in the definition and implementation of the VCS. Finally, Section 2.7 will introduce a brief overview on the state-of-the-art of indoor localization systems.

2.1 Active Externalism and Extended Mind

In 1998 Clark and Chalmers made a short question regarding the mind borders: *Where does the mind stop and the rest of the world begin? [18]*. The basic answers are; skin, skull, and "just ain't in the head"; however, Clark and Chalmers answer to such question was presented through the idea of *active externalism*. In such new concept the environment is part and takes an active role of cognitive processes, the human organism is linked with an external entity in a two-way interaction, creating a coupled system that can be seen as a cognitive system in its own right. All the components in the system play an active causal role, and they jointly govern behaviour in the same sort of way that cognition usually does. If we remove the external component the system's behavioural competence will drop, just as it would if we removed part of its brain [18]. To better understand the *active externalism* concept, Clark and Chalmers created the characters of Otto and Inga. Otto and Inga want to visit a museum. Otto is affected by the Alzheimer's disease, and has written all of his directions on his notebook to serve the function of his memory. Inga is not affected by any disease and bases her decisions on her memory. In a traditional sense, Inga can be thought to have had a belief as to the location of the museum before consulting her memory. In the same manner, Otto can be said to have held a belief of the location of the museum before consulting his notebook. The only difference between them is that Inga's memory is being internally processed by the brain, while Otto's memory is being **stimulated** by the notebook. In other words, Otto's mind has been **extended** to include the notebook as the source of his memory. The notebook qualifies as such because it is constantly and immediately accessible to Otto, and it is automatically endorsed by him.

So, as demonstrated by Clark and Chalmers, Otto's mind was extended to his notebook and stimulated by it in order to achieve it's objective and visit the museum. Based on such idea of **Extended Mind** this thesis proposes the Virtual Coaching System (VCS) concept, that basically will implement the concept of Otto's notebook on nowadays technological devices as smartphones, smartwatches, sensors, Single Board Computer (SBC) and more complex compounded architectures.

2.2 Technology In Our Daily Life

Over the last decade, technology advancements have revolutionized people life. Technology has created amazing tools and resources, putting useful information at our fingertips. Modern technology has made it possible for the discovery of many multi-functional devices like the smartwatch and the smartphone. According to the International Data Corporation (IDC) Worldwide

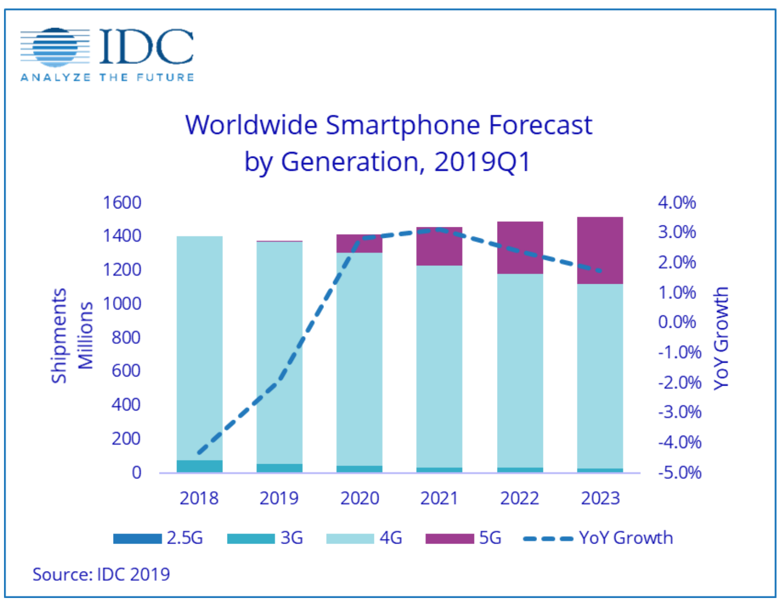


Fig. 2.1: Worldwide Smartphone Market Will Face Another Challenging Year in 2019 with a Return to Growth on the Horizon [19].

Quarterly Mobile Phone Tracker [19], Figure 2.1, global smartphone shipments face another challenging year in 2019 with volumes forecast to decline 1.9% from 2018. This will mark the third consecutive year of market contraction driven by highly saturated markets in developed countries and slower churn in some developing economies. IDC expects shipments in the first half of 2019 (1H19) will be down 5.5% compared to 1H18, but the second half of the year should see shipment growth of 1.4% driven by 5G acceleration, a growing selection of lowerpriced premium handsets, and on-going uplift from markets like India.

Meanwhile, as shown in Figure 2.2, shipments of wrist-worn wearables, inclusive of smartwatches, basic watches, and wrist bands, reached 34.2 million units, up 28.8% year over year during the second quarter of 2019 (2Q19), according to new data from the International Data Corporation (IDC) Worldwide Quarterly Wearable Device Tracker. The top 5 companies - Xiaomi, Apple, Huawei, Fitbit, and Samsung - continued to push forward with new products and promotional campaigns during the quarter, collectively capturing 65.7% of the market, an almost 12-point gain from last year [20]. As clearly visible the quantity of smartwatches have

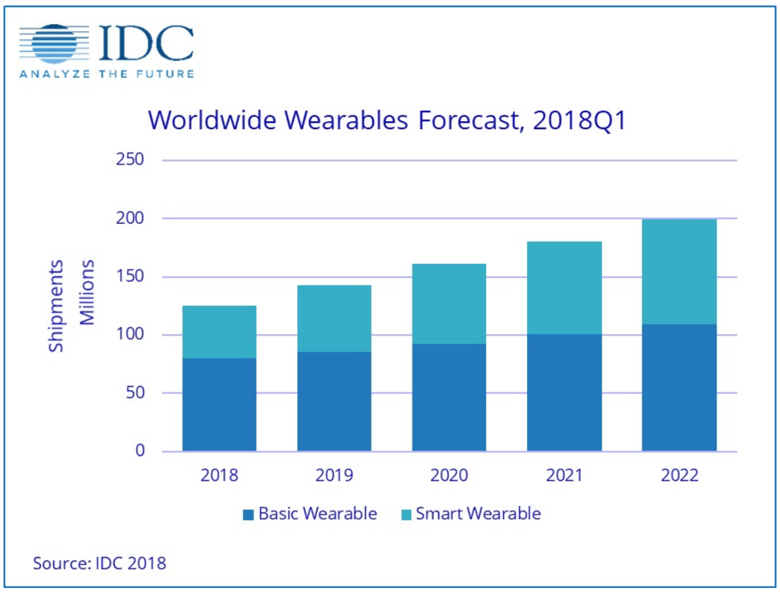


Fig. 2.2: New Wearables Forecast from IDC Shows Smartwatches Continuing Their Ascendance While Wristbands Face Flat Growth [20].

been growing very fast and nowadays such smart devices are very popular among the worldwide population. With all of these revolutions, technology provides to the scientific community new means for making peoples life easier, secure, faster, better. In general, such devices include many more sensing and actuation modules enabling complex and interesting applications. For example, when acceleration and inertial sensors are available, Human Activity Recognition (HAR) algorithms can be implemented. Furthermore, by including additional electronic modules, such as Bluetooth Low Energy (BLE) and Wireless Local Area Network (WLAN) antennas or a Global Positioning System (GPS), real-time alerting and positioning can be obtained from the wearable device in case of an risky situations and activity identification. However, in addition to smartphones and smartwatches during daily life we are encountering other types of data collection and sensing systems provided with communication capabilities, entering by right into the big Internet of Things (IoT) paradigm.

2.3 Internet of Things (IoT)

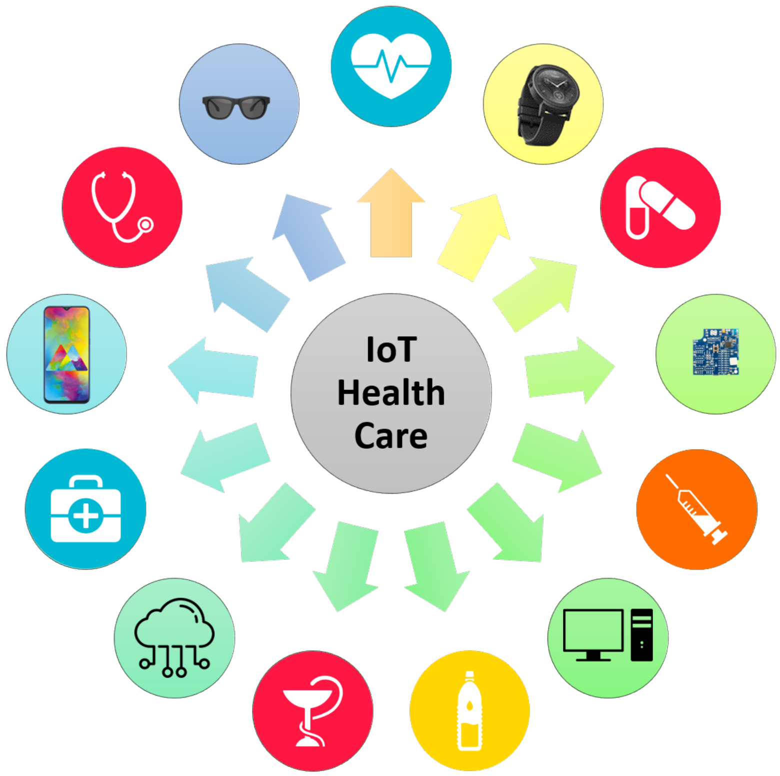


Fig. 2.3: IoT in Healthcare.

Now, Internet of Things (IoT) is becoming a powerful communication paradigms of our century, all objects in our daily life will be part of the internet due to their communication and computing capabilities (including micro controllers, transceivers for digital communication). IoT is elevating the Internet concept to a pervasive and ubiquitous mean. In the IoT concept different types of devices acquire the ability to communicate and interact among each-other (e.g. medical sensor, monitoring cameras, home appliances and so on) [21, 22]. Duo to such characteristics, IoT has become very important in areas as healthcare and as shown in Figure 2.3, IoT in Healthcare involves many kinds of cheap sensors (wearable, implanted, and environment) enabling elderly to accept this modern medical healthcare services anywhere, any time. Besides, it also greatly improves aged peoples quality of life. The Body Sensor Network (BSN) technology [23] are becoming the central technology used in IoT-based modern healthcare system. It is composed by integration of low-power and lightweight wireless sensor nodes used to monitor the human body activity and daily life environment. BSN nodes collect critical data operating in hostile environments, however, they necessitate strict security mechanisms to prevent malicious interaction with network [24].

As stated in [25], with the commercialization of wearable sensors, low-power Integrated Circuit (IC) and wireless communication technologies, Wireless Body Area Network (WBAN) are being widely used in multiple research field [26]. WBAN, also known as Wireless BSN, is a wireless network to enable the health monitoring anywhere anytime around the human body [27, 28]. WBAN are used for e-health applications, such as the assisted rehabilitation, early detection of medical issues and emergency notification [29]. With this big diffusion in the market of portable devices, especially smartphones and smartwatches have become very important for people's daily life. Therefore, they function as a bridge between the WBAN and the IoT cloud [30–32]. Instead, wearable sensors composing the WBAN are key components as they collect the physiological and physical data of the human body for further usage. In [33], was proposed a wearable photoplethysmography (PPG) sensor for the heartbeat measurement at the earlobe. Another heartbeat sensor is presented in [34], which is designed with the polymer-based flexible strain-gauge sensor. In [35] the authors proposed a sensor prototype able on measuring heart rate, blood oxygen saturation, temperature and humidity during a Magnetic Resonance Imaging (MRI). In [36] was proposed a middleware solution for the wearable sensor system of WBAN, based on a smartphone applications. However, the development of WBAN presents challenges regarding the power consumption in the long-term use of wearable devices. Energy harvesting, especially wearable energy harvesting technology, is a promising solution to enable the longterm operation of WBAN [37]. The authors of [38] proposed an energy harvesting system for ultra-low power wearable devices. It also studies the performance of a flexible solar panel under different irradiance levels. In [39] was proposed a novel wearable energy harvesting system that combines piezoelectric and electromagnetic energy sources from low frequency vibrations like human motion. The methodology proposed in [40], presents a wearable bracelet powered by hybrid solar cells and Thermoelectric Generators (TEGs), and its self-sustainability is confirmed by simulations based on experimental measurements. In [41], was proposed an autonomous wearable system manufactured and tested for vital signs measurement and equipped with energy harvesting module. The wearable system powered by a flexible solar panel can be attached to a T-shirt. In [42] the authors proposed an energy harvester device based on a flexible photovoltaic module and a Maximum Power Point Tracking (MPPT) technique based on fuzzy logic. It is used to power a sensor node with BLE module, which can measure heartbeat and blood pressure of the subject and send them to a smartphone.

In conclusion, IoT is defined as the network of devices such as vehicles, and home appliances that contain electronics, software, actuators, and connectivity which allows these things to connect, interact and exchange data [43]. Such new paradigm led to massive usage of Wireless and Bluetooth sensors and actuators, which require low computation devices and battery saving communication protocols. To handle such requirements researchers had developed many dedicated communication protocols. Among all such protocols, some of the most famous ones are LoRa [44], ZigBee [45] and BLE [46].

In particular, of relevant importance, the Bluetooth Low Energy (BLE) beacon devices broadcast their identifier to the nearby electronic devices. This technology enables smartphones, tablets, and other devices to perform actions when in close proximity to them. After their introduction in 2011 with iBeacon many other beacon protocols have been proposed, for example, Eddystone protocol by Google. Moreover, these low energy consumption protocols founded the basis for the implementation of other protocols as for example those of Estimote, Gimbal, and Aruba[1] beacons. These protocols in addition to the advertising utilization are extended in order to transmit the data collected by other built-in sensors, as for example temperature, pressure, acceleration, and brightness. As shown in Table 2.1, they allow the unique identification

iBeacon Data 31 Bytes				
Prefix 10 Bytes	UUID 16 Bytes	Major 2 Bytes	Minor 2 Bytes	TX Power 1 Bytes

Eddystone Data 31 Bytes			
Prefix 11 Bytes	Frame Data 20 Bytes		
	UUID 16 Bytes	Namespace 10 Bytes	Instance 6 Bytes

Table 2.1: iBeacon and Eddystone Payload Format.

of such devices thanks to the possibility of setting each payload field except the prefix frame. For example, on the iBeacon protocol, the Major frame can be used to identify different floors of a building and the Minor frame to identify rooms in such building, as done in [47]. The size of such devices on average varies from 10 cm to 2.5 cm (size of a 2 euro coin), as shown in Table 2.2.

Moreover, besides the advertising process and the build in sensors collected data, the aforementioned beacons can also be used regarding distance estimation or localization, basically through the use of the Received Signal Strength Indicator (RSSI) measurement. RSSI is a measurement, used often in Radio Frequency (RF)–based communication systems, related to the power perceived by a receiver. In particular, it provides an indication of the power level at which the data frame is received. The rationale is that the higher the RSSI value is and the stronger the signal is [48]. In addition the RSSI measurement can be very useful concerning environment context detection and human-objects interaction [49]. In conclusion, in a context in which all these devices possess the ability to communicate, technologies offer the possibility of using these features to increase the quality of people's lives.

2.4 The Rise of Assisting technologies

As already mentioned above in the last few decades, the world population has witnessed a steady increase in life expectancy in many parts of the world, leading to a rise in the number of elderly people. [24]. As reported by the United Nations [50] there will be 2 billion (22% of the world population) older people by 2050. In addition, research indicates that about 89% of the aged people are likely to live independently and from some existing medical research surveys estimate that 80% of older then 65 people suffers from at least one chronic disease [51]

[1] https://estimote.com/ https://gimbal.com/ https://www.arubanetworks.com/

Name	Dimension (mm)	Protocol	Price ($)	Weight (g)	Image
Gimbal	40L 28W 5.5H	iBeacon	5	6.52	
Kontakt.io	56L 56W 15H	iBbeacon Eddystone Kontakt.io	26	35	
Estimote	25L 25W 3H	iBeacon Eddystone Estimote	9-11	8-12	
RadBeacon	66L 35W 10H	iBeacon AltBeacon Eddystone	14	20-27	
GPShopper	43L 72W 16H	GPS RFID	20	25-30	
Aruba	47L 47W 16H	iBeacon	190	36	

Radio Frequency IDentification (RFID)

Table 2.2: Example of commercial beacons.

causing them difficulty in taking care of themselves. Providing a sufficient quality of life for this category of people is becoming an important challenge for the social system. On the other side, the advancing of new Information and Communication Technology (ICT) solutions is giving us the possibility to design innovative healthcare solutions and tools in order to manage those challenges [24]. The need for autonomy, independence and well being motivated the European Union and other governments to promote research in such direction. The objective was to design dedicated systems based on sensors, wearables and other technologies able to assist peoples in their daily life activities in their daily environments. Such new technologies, along with concepts, products and services aimed at serving elder and disabled persons at home are known as Ambient Assisted Living (AAL) systems.

The AAL is a sub-area of the Ambient Intelligence, that as introduced is an emerging multi-disciplinary field aiming at providing an ecosystem of different types of sensors, computers, mobile devices, wireless networks and software applications for personal healthcare monitoring and telehealth systems. AAL systems and continuous medical telemonitoring using body-worn sensors present the potential to reduce medical costs and daily life quality. As already introduced, the growing of the world population and of the estimated increase of the average age will have a great influence on the health system of the various states and also on the social system, given the need to increasingly assist a very large number of elderly people. AAL technologies use different solutions for the telemonitoring, such as wearable sensors, smart-home architectures, machine learning and deep learning algorithms [52]. The usage of smart-home architectures distributed in daily life environments produces significant amount of date that can be used to recognize coachees activities. Such activities can be appropriate or not appropriate, and in such context the coachee necessitates the supervision of a coaching system.

On this basis, the European Union (EU) has supported the research and development of AAL systems in recent years. Through its AAL Joint Programme [53], the European innovation partnership on active and healthy aging of the European Union has funded several projects for active and assisted living. Some examples include:

- project CapMouse [54], a hands-free technology that allows the elderly disabled to use computers via lip movements;
- project Rehabilitation Gaming Systems (RGS) [55], a virtual reality environment for the treatment of patients after stroke;
- project Access [56], platform that automatically integrates care plans and data surrounding the patient to be shared amongst all those involved;
- project AmCo [57], for the development of a new, innovative and integrated standard AAL-platform;
- project EMOTION-AAL [58], for the development of an integrated health care-concept for seniors in rural areas;
- project MOBECS [59], for the development of small, non-stigmatizing and scalable stand-alone wearable emergency call and service systems.

AAL tools aim to provide security, safety, autonomy and improve physical status and health conditions in eldelry, allowing them to live independently, as well as relieving the performed work for caregivers and healthcare institutions. In AAL tools the use of different types of sensors to monitor the daily life activities of elderly is of fundamental importance [60]. The sensors surrounding us in daily life environment are categorized into two groups:

- static sensors at fixed locations, e.g., PIR sensors, vibration sensors, pressure sensors, cameras, and microphones,
- mobile and wearable sensors, e.g., accelerometers, magnetometer, gyroscope, thermal sensors,, heart rate, and pulse oximeters.

Many other AAL solutions have been proposed such as fall detection [61–63], emergency response [64], video surveillance [65], automation [66], daily life activities [67], and respiratory [68] monitoring system. Since falls are a very common risky situation in the elderly and a major concern for medical professionals and their families. They are considered to be among the first ten most risky situations/disease leading to death in the US since fall injuries can imply serious complications [69, 70]. Fall detection tools for AAL reduces the severity of falls alerting the caregiver in order to help and reduce the amount of time that elderly remains on the floor. These tools increase safety and independence of the elderly, and to truly assist elderly people, an AAL system should satisfy some basic requirements [60, 71]:

- Low-cost: approximately 90% of the elderly prefer to stay in their own homes. Implying that the AAL has to be low-cost for the mean user;

- Accuracy: AAL tools has to present with very good activity recognition capabilities;
- Acceptance: AAL tools should be non invasive, pervasive and ubiquitous. Such tools should be compatible with the elderly daily life activities;
- Privacy: AAL tools should share minimal private data regarding the elderly daily life activities.

Finally, since the AAL became a hot topic due to it's importance many surveys have been published to clearly understand the stat-of-the-art in such research direction [72–74]. In [60] the authors provide an overview of trends in the AAL field by focusing on a variety of sensors as; PIR, vibration, accelerometers, cameras, depth sensors, and microphones and the related signal processing methods. Environmental sensors are used in home safety [75–77], home automation [66,78–81], activity monitoring [71,82–85], fall detection [86–91], localization/tracking [92–94], and monitoring the health status indicators of elderly and chronically diseased people outside hospitals [95–101].

Definitely, AAL tools will provide security, safety and independence for elderly people while allowing them to live independently as well as relieve the workload of caregivers and health providers [60].

2.5 Ambient Intelligence

Ambient Intelligence (AmI) regards all those environments able to respond to the actions of persons and objects and cater to their needs. Ambient Intelligence has been characterized by researchers based on features as: sensitive, responsive, adaptive, transparent, ubiquitous, and intelligent. The fact that AmI systems must be sensitive, responsive, and adaptive highlights the dependence that AmI research has on context-aware computing. Ambient Assisted Living (AAL), already introduced in the previous paragraph, concentrates on assisting persons with special needs, is viewed as one of the most promising areas of AmI this due to the challenges that the world is going to face due to the population aging. AAL attempts to address the requirements of this aging population by overcoming innovation limits to lower social costs in the future. An additional focus is on the fields of rehabilitation and preventative care to decrease the duration of disease. In an AmI and AAL context, multiple devices embedded in the environment collect and use the distributed information and the intelligence inherent in this interconnected network. The information will be recorded by distributed devices in the environment and will range from brightness, temperature, position, to physiological parameters as heart rate or blood pressure. The interaction between the user of the environment and the sensor interfaces covers all of the person's surroundings, resulting in an environment that behaves intelligently; the term Ambient Intelligence has been coined to describe it. The environment presents the ability to identify the users, their needs, and their behavior, and to act/react correctly and accordingly [102]. Such ability leads towards the direction of the so-called Context awareness [103], defined as the capacity of a system and its component to collect information about the environment at any given time and adapt behaviors accordingly [103].

In order to obtain such capacity the following components has to be designed:

- Sensing capacity for environment state monitoring;
- Context detection models;
- Interpretation;
- Action and Reaction.

Sensing Capacity

The capacity of sensing (perceiving) is based on the creation of a sensing network composed by different sensors which collect the state of the environment, objects and people composing it (e.g., temperature, brightness, acceleration, magnetic field, heart-rate, skin conductance, environment pressure, blood pressure). In general, the sensing capacity is provided by a Smart Home Architectures [104–107], regarding the environment and Body Area Network (BAN)/WBAN regarding users state [26–28].

Context Detection Model

This step regards the processing of the data perceived by the first component to recognize/detect essential patterns of information which identify the context that such data represents. A further step is provided by composing the data among all/some of the sensors and generating new data streams that possess the capability to represents particular patterns that the context detection models were not able to detect from the original data. This step is usually performed automatically by data fusion algorithms as Kalman Filter [108], Bayesian networks [109], and Particle Filtering [110]. However, the computation is not always performed over the data generated after the step of data fusion. Regarding minor tasks, it can be performed directly on the sensor (e.g., night/day detection, open/closed, rumor/not-rumor, and any threshold-based computation). Instead, when the context is detected based on the fusion of many different sensors, but not only in such cases, and the pattern is difficult to identify, the computation will require many high-performance computational devices/nodes to perform the detection task.

Interpretation

This step provides a real-world interpretation of the data, based on some additional information given by the designer. Its aim is that of describing the information in a human-readable way (e.g., what a specific person habitually does within a particular place at a specific time and what is he doing).

Action and Reaction

This final step is essential since it will be able, based on the interpretation step result, to react accordingly to the detected context. For example, in the AAL research area, older adults face many risky situations during their daily life activities as falls or also taking the wrong medication, forget the open door, or leave the house without keys. In such cases, the "aware" environment will intervene, alerting the caregiver, or the elderly person himself, showing the situation or the behavior to follow. Furthermore, a fundamental component in the context-aware environments are the Localization systems. Such systems make use of the environment sensors to identify the location of users and objects inside it. The position is then provided to the system to interpret the context and act accordingly. Such systems are already available regarding the outdoor environments thanks to satellite-based systems as GPS [111] and Global Navigation Satellite System (GNSS). and massively used in vehicle transportation, human interaction and massively used in the crowdsourcing research areas [112]. However, the localization accuracy in indoor environments is facing many issues since the GPS based-systems do not return appreciable accuracy. Therefore, context-aware environments can use the sensors in order to improve the accuracy of the location and to obtain further information to interpret human behavior within it [113]. Nowadays, beacon devices are becoming very useful in the localization and navigation process, since they give the possibility to create very accurate and low-cost positioning systems as shown in [47] and [114]. The idea of having an accurate localization system is based on the need that the reaction time of the system has to be lower and lower to act in the fastest, most precise, and correct position by reducing the intervention time towards the user.

2.6 Human Activity Recognition

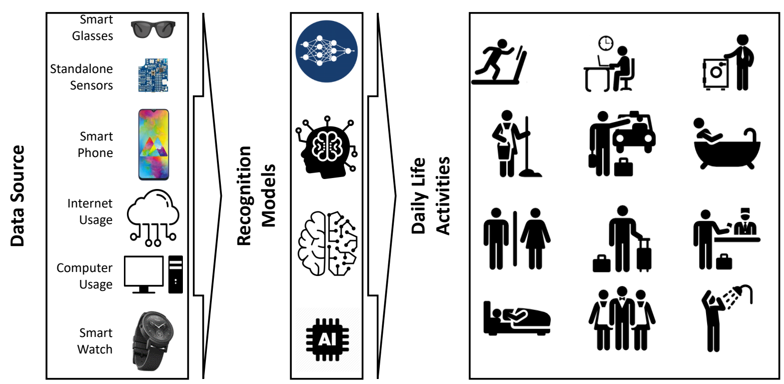


Fig. 2.4: Human Activity Recognition (HAR) Work Flow.

As mentioned, context-aware environment's are equipped with pervasive, implantable, and wearable sensors [115]. Such sensors allow continuous monitoring of health and wellbeing in Activities of Daily Living (ADL) [116]. Possible application scenarios range from food intake to medication intake to improve personal wellbeing and independence. Regarding elderly patients presenting a persistent condition, wearable and environmental sensors are used to promote the quality of care by empowering their independence in their daily life environment. Furthermore, wearable devices can be used in rehabilitation sessions of patients with physical impairments to preserve and improve their physical conditions. Concerning subjects in severe conditions, constant monitoring of vital signs is essential to enhancing therapy results by analyzing the subject's status.

A central component in such a process is performed by the Human Activity Recognition (HAR) algorithms [117]. Activity recognition presents the potentiality to generate significant social benefits, especially in human-centric applications, such as eldercare and healthcare [118]. In such direction have been done significant steps forward, regarding the recognition of basic human activities. However, recognizing complex activities still presents many challenges [118] as:

- Recognizing concurrent activities: in their daily life, people can perform more activities at the same moment (e.g., observing a video while reading a book). Such activities have to be recognized separately in order to recognize the composed activity correctly;
- Recognizing interleaved activities: other daily life activities can be performed simultaneously or during a complex activity;
- Uncertainty of interpretation: Daily life activities presenting similar patterns can be interpreted differently (e.g., open fridge door can be identified as a sub-activity of drinking or cleaning or cooking or eating);
- Multiple occupants: a daily life environment can be populated by several persons simultaneously. An activity recognition model has to recognize the activities that each person performs in parallel, even when a group performs them.

Consetuqntly, HAR provides two types of recognition allgorithms: a) activity recognition and b) pattern discovery. Activity recognition regards the precise identification of human activities based on defined activity models. Besides, in activity recognition, the first phase regards the definition of a high-level conceptual model and in the second phase, implements the model by building a pervasive system. Figure 2.4 shows an abstract view of the HAR workflow, starting from the raw data collected by the field sensors, e.g., smart-glasses, standalone sensors, smartphone, net information's, computer usage and/or smartwatches, to the used recognition model, finally to the recognized activity. On the other hand, pattern discovery regards the identification of unknown patterns directly from the sensors raw data without any initial model or assumptions. In conclusion, a HAR researcher designs a pervasive system in the first phase and then analyzes the raw sensor data to identify activity patterns. Although the two techniques are different, both aim to improve human activity technology. Besides, these two phases are complementary to each other, the discovered activity pattern can help define activities that can be later recognized and tracked.

More in detail, Human Activity Recognition (HAR) has been a hot topic in the last decade due to its importance in many aspects of human life, from health care to interactive gaming, sports, and monitoring systems for general purposes [119]. Based on the data source type, researchers have approached the activity recognition mainly in two ways: using externals sensing devices and using wearable devices. In the first case, such devices can be environmental sensors or video cameras positioned in specific points of the environment. Instead, in the second case, the sensors are attached to the human body integrated into daily life objects like smartphones and smartwatches [120–126] or integrated into clothes or specific medical devices [127–132]. Nowadays, cameras have been massively used in the HAR context, however, video data present

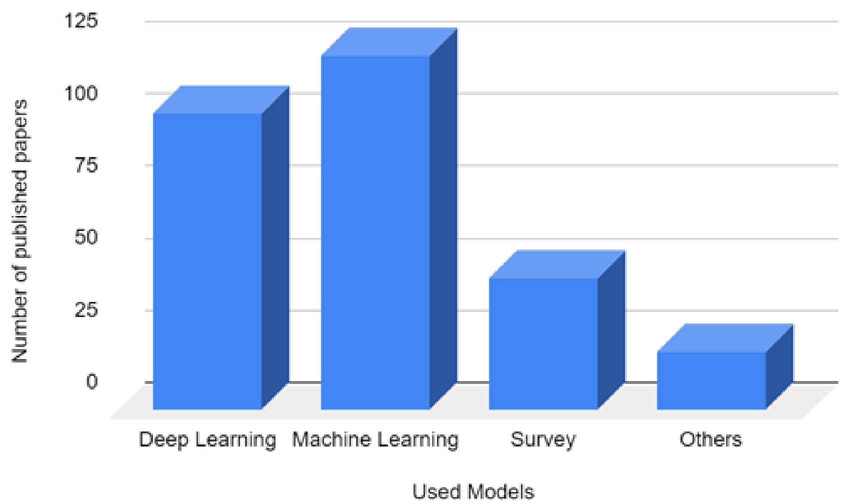


Fig. 2.5: Distribution of published papers in Human Activity Recognition research area categorize by the used pattern recognition model and/or aim. Such statistics are obtained from Google Scholar.

many concerns regarding privacy and computational requirements. Even if the use of video cameras produces excellent results in terms of recognition, these limitations have led many researchers to work increasingly with external and wearable sensors. Moreover, research in this direction has been further interested by the explosion of the Deep Learning, branch of Machine Learning, resulting in an increment of the quality of activity recognition results. However, the Deep Learning models are very complex models, and in many cases, their usage is not necessary due to the size of the problem, the dimension of the input data, and the knowledge of the used model [133]. Also confirmed by the number of works published in the last six years, from 2015 to 2020, on such topics. As shown in Figure 2.5, among a total of 293 published papers on HAR, 103 were based on deep learning models, 123 were based on basic machine learning models, 46 where surveys and 20 articles were based on other statistical models different from the ones mentioned above (e.g., threshold models).

Instead, Figure 2.6 shows how the number of HAR deep and machine learning methodologies have been increasing linearly except for the 2017. Such an increment of interest in HAR can be associated basically to the increment of the sensors and wearable devices in our daily life and mainly to the new possible application in the health care system. Besides, Figure 2.6 emphasizes how the advent of deep learning is competing with the machine learning in such research topic. This indirectly certifies the better capabilities that machine learning and deep learning models possess, also, shows that the suitable and old machine learning is still the preferred technique in the HAR context duo to its capability, compared to deep learning, to work with a small amount of training data and computing over resource-constrained devices [118]. Among those published articles, for the propose of this thesis, we were more interested in not-Video data sources because we are interested in wearable sensor-based HAR methodologies. Figure 2.7 shows the distribution of data sources type among the 103 deep learning and 123

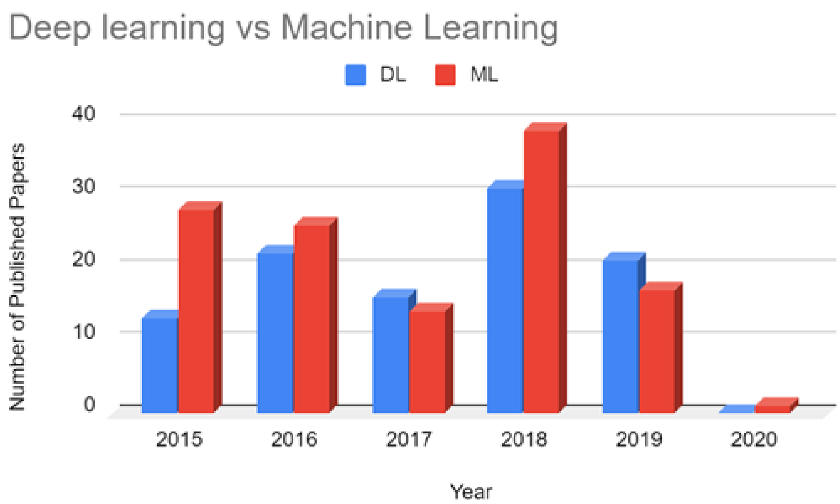


Fig. 2.6: Distribution of published papers per year in Human Activity Recognition research based on Machine Learning and Deep Learning.

machine learning published papers presented in Figure 2.5. As clearly visible over 193 articles, the authors were using the accelerometer sensor as a data source, the second most used sensor was the gyroscope (used in 107 articles), and the third most used is the magnetometer (used in 35 articles). The remaining 102 articles are based on sensors like barometer, stretch, Heart Rate (HR), Electromyography (EMG), Electrocardiography (ECG), Electroencephalography (EEG), GPS. Note that the proposed HAR methodologies, in many cases, are based on more than one sensor type. In particular, the accelerometer sensor have shown excellent results in the HAR field [116, 134–148] and that in conjunction with other sensors, such results have been raising particularly fast. The diffusion of the accelerometer sensor is strictly related to its ability to measure the movement of the human body directly. Besides, it is very low cost, and nowadays, it is integrated into almost all wearable electronic objects in our possession.

Figure 2.8 presents the default workflow in designing HAR based methodologies. Normally, starting from the *Human Activity* that we need to recognize, the first phase regards the identification of the most appropriate *data source devices*. The second step regards the *data collection*; such phase is significant and presents sub-phases/phases as the pre-processing of data and the labeling of data. The third phase regards the identification of the most appropriate *pattern recognition model* based on the given data. However, as shown (red arrow), the selected model can also influence the pre-processing data phase. Finally, in the last phase the model will be evaluated in terms of *accuracy measurements*.

2.6.1 Human activity

Human activity is defined in many ways and identifies many different contests of the ADL. ADL's can be defined as "*things we normally do... such as feeding ourselves, bathing, dressing, work, homemaking, and leisure*" and all those activities which require physical movement.

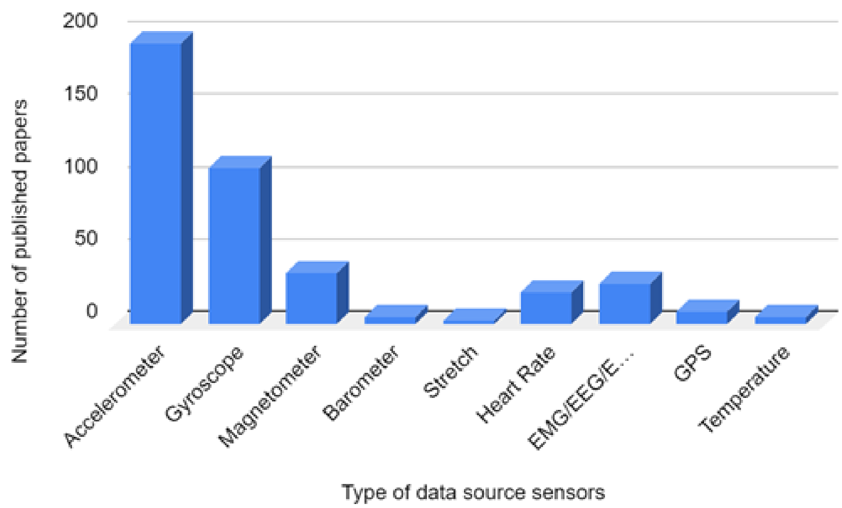


Fig. 2.7: Distribution of published papers in Human Activity Recognition research area categorized by the sensor data source.

Fig. 2.8: Default workflow in designing HAR based methodologies.

Among all ADL's the most popular activities studied in HAR regard normal activities as walking, running, standing, sitting, stairs up and stairs down. However, other type of activities have been explored in the last years by extending the recognition capabilities from normal activities to complex activities, as for example the capability to recognize complex activities as the different phases of cooking activity [149], cleaning the house [150], driving/biking [134], smoking [151], swimming [152], or going on horse [153]. In addition, the recognition of an activity regards also the identification of activities related with some specific type of location, as for example: sitting on the ground, lying on bad, driving, walking/standing in the elevator, walking/running on a treadmill, walking in a parking lot, exercising on a stepper, exercising on cross trainer. Moreover, other detailed movement recognition regards the recognition of specific movements of the arms, as reaching an object, or frontal elevation, carrying an object or releasing it and many other kinds of activities that can be performed by users in relation to other objects. To further emphasize the importance of HAR, nowadays, activity tracking devices are becoming very popular for monitoring ADL's. The scope of using such devices varies from personal, medical to fitness scope. Those devices are able to measure with a very good approximation physiological and physical parameters like heart rate, blood pressure, step counter, level changes, and consumed calories. Besides of these, the most advanced models are able to recognize the sleeping context and they are able to detect the neurological phases of sleep [154]. All the information collected by such type of devices provide the data to HAR algorithms.

2.6.2 Device Identification

This section emphasizes the diversity of data sources used nowadays in the HAR context. Figure 2.7 and Figure 2.9 respectively introduced the distribution of the most used electronic sensors and electronic devices in the last six years. Such devices, according to [155] and [119] can be categorized basically in four categories:

- body-worn sensors;
- object sensors;
- ambient sensors;
- hybrid sensors.

However, such categories are based almost on the utilization of the same sensors types, differentiating only on how the sensor is related to the human activity and physical body. Small, low-cost, and non-invasive sensors as accelerometers, gyroscopes, and magnetometer, as shown in Figure 2.7, are the most used sensors in the HAR context, respectively 193, 107, and 35 papers using at least one of such sensors or combinations of sensors. Besides to the aforementioned data collection devices, HAR algorithms do make use also of other types of sensors as for example: environmental sensors (temperature, humidity, light, presence sensors or WiFi), medical equipment as ECG, EMG or other type of build in sensors (GPS, Compass, Heart Rate, Barometer, Stretch Sensors or Audio). Moreover, Figure 2.9 shows the importance that smartphones and smartwatches are obtaining in HAR, mainly due to their explosion in the daily consumer market. Such devices can collect almost all the data mentioned above from a single device and directly transmit it to server instances for collection and processing or directly process data on the device itself.

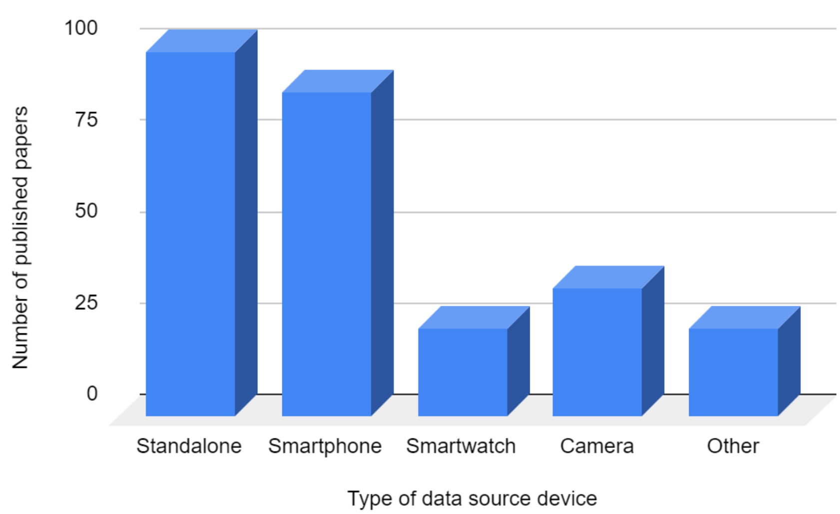


Fig. 2.9: Distribution of published papers in Human Activity Recognition research area categorized by the device data source.

2.6.3 Data in Human Activity Recognition

The third step in the HAR workflow, presented in Figure 2.8, regards the data collection and (pre)-processing. This section will briefly introduce a categorization of the sensors based on the deployment environment and measured data unit: Basically, in the human activity recognition context, sensors can collect data related to the following classes:

- Environmental data (ambient sensors);
- Physical Data (inertial sensors);
- Physiological data (physiological sensors).

Environmental data (ambient sensors)

The environmental data regards all the collection of data that represents the state of the environment. Data generally used to represent the environment state are temperature, humidity, pressure, and brightness. However, the status of the environment is not only related to the mentioned data. Besides, it is also related to the people present in the environment and objects inside it. For example, knowing the number of persons inside the environment and their position or knowing the position and the actions performed over a specific object inside the environment would be very useful in many application scenarios related to eldercare, healthcare, and service delivery.

Physical Data (inertial sensors)

In general, the physical data defines the data characterizing the physical capabilities and behaviors of any physical entity, whether it is an inanimate object, an animal, or a human being. This type of data is generally obtained through the use of inertial sensors such as accelerometers, gyroscopes, compass, gravity sensor etc. Acceleration and angular velocity are the most common data used to characterizing human activity.

Physiological data (physiological sensors)

Instead, differently by the physical data, physiological data are mainly related to human entities and represent human's physiological state. The most critical physiological data are brain electrical activity, heartbeat electrical activity, muscles electrical activity, heart rate, blood pressure, and skin conductance, respectively acquired by the following external data acquisition system: EEG, ECG and EMG. However, as previously introduced, nowadays the biggest amount of data is perceived by daily life electronic devices as: smartphones, smartwatches, activity trackers, smart thermostats, video cameras and many other types of devices. As shown in Figure 2.9, the number of smart devices like smartphone and smartwatches are outnumbering the usage of standalone devices, for the sake of completeness lets clarify that the standalone bar identifies all those devices different from smartphones and smartwatches as Actigraph, Bioharness3, or iPod.

2.6.4 Classification Model Selection and Evaluation

The identification of the classification model is a very important step of the HAR workflow, as shown in Figure 2.5 and Figure 2.6 in the last six years the most used classification models were part of the Deep Learning and of the Classical Machine Learning [2] class of pattern recognition algorithms. However, during HAR data collection process, the subject's activity is generally performed by following specific guidelines since the human movement patterns are very hard to recognize due to the significant diversity of human movements among subjects and inter-subjects. Besides, a subject can show different movement patterns in different moments of its life, this duo to personal and external factors. Consequently, the definition of a HAR model that can generalize and recognize movement patterns among all human users is still an unsolved problem. For the same reason also, the evaluation of the model is performed over data that possibly was collected following the same guidelines.

2.7 Localization System

In AAL the position of users inside the environment is very important since it provides to the system a further knowledge, increasing the quality of the provided service and the accuracy in recognition of the activity performed by users. As mentioned above, nowadays, the increasing number of sensors and smart devices provides the possibility to use the perceived and generated data for the development of different types of localization systems. A localization system is a technique for estimating the position of people and objects within a specific environment without any knowledge of previous locations. They can be roughly categorized either in radio–based (i.e. exploiting RF [156], RFID [157], ZigBee or WLAN [158]) or non radio–based (i.e. based on light impulse [159], sound [160], vibration [161], or magnetic field [114, 162] techniques). In last decades, they gained increased popularity in several areas, exploiting different technologies on both hardware and software sides, to support applications such as navigation, localization and monitoring, in the fields of security, management, health–care, etc. Even more, in the IoT context, localization systems constitute one of the fundamental components [163]. Despite this, it is worth highlighting that existing solutions are often subjected to several design and implementation issues [164, 165], mainly due to environmental constraints, involved devices and radio signal features. In outdoor environment, where a common choice is to use GPS or other satellite–based systems, the presence of obstacles and buildings may hinder received signals, and in addition such techniques require specific, complex and quite expensive components. Analogously, in the case of indoor radio–based localization, we have to consider that signal propagation depends on walls thickness, obstacles, number of people, etc., which may cause issues like shadow fading and multipath propagation [111]. On the other hand, localization in indoor environment (where GPS system lacks accuracy or may even become unavailable) is still a relevant open point and there is not a general consensus on the solutions to be deployed in this scenario. Indeed, many indoor positioning systems have been proposed during

[2] excluding the Deep learning models

time, which differentiate on the basis of the employed technologies. A typical result is that, to obtain a reasonable accuracy, localization is performed exploiting quite complex architectures, which in turn impair either on the cost and availability of the technological infrastructure for the target environment, and/or on the time, power and computational resources necessary to run (and in some case, to train) the localization algorithm. A significant example comes from the fingerprinting technique, which is becoming a very popular positioning method for indoor localization where it may achieve, under well specific circumstances, an accuracy in the order of decimeters [114, 165]. Figure 2.10 presents an overview of the existing state of the art localization techniques where fingerprinting is becoming a central figure in such systems category.

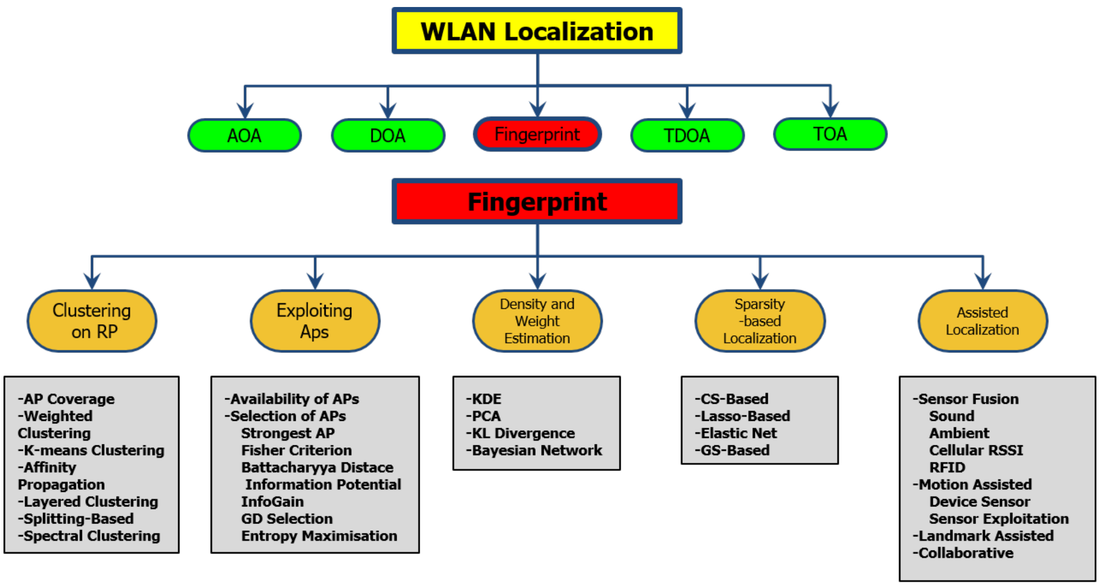


Fig. 2.10: Overwiew of the State of the Art Wireless Local Area Network (WLAN) Positioninig System [164]. Angle of Arrival (AOA), Direction of Arrival (DOA), Time difference of Arrival (TDOA), Time of Arrival (TOA), Reference Point (RP), Access Point (AP)

In fingerprinting, the environment is subdivided in sub–areas, and the user is able to univocally identify the sub–area to which she/he belongs exploiting specific algorithms based on different metrics (RSSI from WiFi and Bluetooth sources, Magnetic Field value, etc.). Nevertheless, despite the potential of fingerprinting techniques (for instance IndoorAtlas [114]) we should also take into account some relevant issues in terms of human intervention due to the initial *learning* phase, computational effort required by the algorithm for the *localization* phase, and unavoidable impairments affecting the input metrics, given the dependence of radio signals on external factors. The drawbacks highlighted above make several existing solutions unattractive for low-cost and resource-bounded application scenarios [165].

It has to be considered that the most accurate indoor localization systems typically require auxiliary or modified HW devices [156, 158–160, 166–168], hence limiting their applicability and cost effectiveness. For this reason, research efforts have focused on the definition of alternative low–cost localization techniques, where data coming from widespread available sensors and devices (such as Bluetooth or Wi-Fi) are exploited to infer the position of a user or an object as the fingerprinting. Fingerprinting requires a complete mapping of the environment, obtained during an initial learning phase. Clearly, incorrect mappings of users mobility represent potential sources of inaccuracy for these systems, and many challenges still need to be managed, as: (i) a time-consuming learning phase, from hours to days, (ii) the non-Gaussian distribution of RF signals, and (iii) the computational complexity of the proposed approaches. One of the first fingerprinting systems has been introduced in [156] for tracking users inside a building, based on triangulation on WiFi signal strength and propagation model, with an accuracy of roughly 2÷3 meters. Many other solutions based on combining sensor fusion with fingerprinting (with WiFi/Bluetooth signals) have been proposed, as in [114, 158, 162], that however still require significant computational power and present problems related to the signal nature and the movement pattern. For instance [168], that defines a system which derives the distance between client and the AP based on the signal propagation delay, and dead-reckoning [169] technique, obtaining estimation accuracy in term of decimeters. Accuracy in the order of decimeters have been obtained in [165, 168]. However, the most accurate systems present a very high computational burden, often preventing them to be implemented on mobile devices. Another well-known fingerprinting localization technology, which is designed to work on mobile devices, is represented by InDoorAtlas [114]. This technique exploits RSSI measurement from WiFi and Bluetooth radio signal emitters, which are then combined with data coming from magnetometer, accelerometer and gyroscope sensors. Furthermore, during the learning phase, it makes also use of the GPS. InDoorAtlas is released as a free project, which can be easily tested on both Android and iOS platforms. In a recent work [170] the authors proposed Locating in Fingerprint Space (LiFS), a WiFi localization approach which exploits motion sensors from the smartphone, whose principal gain is that it removes the survey process of the traditional fingerprinting learning phase.

In the AAL research area, localization systems have long been used mainly for monitoring purposes, also for the case of Parkinson's Disease (PD) patients assistance. These approaches are not appropriate for people affected by diseases that cause a deterioration of psychomotor capacity since their movements have a different frequency from that of a healthy person, as in the case of PD [171]. In [172], authors proposed a fingerprinting approach based on the comparison of the probability distribution of the signals sensed on a particular RP during the online and offline phase, achieving a median error of 2,4 meters, however, still suffers due to the signal distribution nature. In [159] authors proposed an approach based on particular LED luminaries able to transmit identification data, to the smartphone, through light pulse imperceptible by the human optical system. The limits of such approach, as for many others, are hardware extensions, e.g. this approach needs special LED lights and particular camera. Different, Fingerprint techniques have been defined, not based only on RSSI radio signal measurement, but also on other types of data, e.g. Magnetic Field. In [162], authors proposed an indoor localization fingerprint technique based mainly on Magnetic Field data and motion sensor helped by an augmented particle filter for error minimization, achieving an average accuracy from 1 meter to 2,8 meters.

As state [164], as is well known, to localize in a 2-D dimension a simple triangulation system needs at least three AP, but as we known, in an indoor environment as houses, normally, there is not more than one AP. To overcome such problem many works have proposed, as we have also done, the enrichment of the environment with low cost beacon devices in substitution of expensive AP. As in [173], were authors proposed a methodology for indoor localization based on Beacon devises, modelling the localization problem as a maximum-resolution sub-hypergraph problem. But, this approach results in very error-prone, due to the variability of RF signals[3].

[3] imagine a person that stands in front of the beacon device attenuating the signal generated by the beacon. The user behind such person will not sense the signal of that beacon, so the predicted location will not be the correct one

3

Objective

To guarantee continuity and ubiquity in coaching approaches, virtual coaching systems, mostly related to physical activity, healthy lifestyle and self-management of chronic diseases, have started to be proposed by exploiting mobile applications and wearable devices. Current Virtual Coaching System (VCS) are generally composed of mainly three components: a coaching engine, a graphical user interface, and optionally a set of embedded or wireless-connected sensors (e.g., accelerometer, gyroscope, heart rate sensor) that monitor human activity and vital parameters. Most of these solutions provides statistical information, treatment plans, reminders and recommendations, and propose training exercises [174]. A few solutions exploit also virtual/augmented reality [175] or involve serious gaming modules [176]. The main drawback of these solutions is that all rely on self-reporting [177], which works well for very motivated people, like athletes, but not for elderly or cognitively/ physically impaired people. In addition, the coaching action they provide is not contextual to the needs of the person, i.e., they do not help him to accomplish Activities of Daily Living (ADL) exactly when necessary, because their main goal is "training for the future" and "monitoring what you did", rather than "empowering right now" the self-efficacy of the person. From a different but complementary prospective with respect to virtual coaching applications based on mobile and wearable devices, Ambient Assisted Living (AAL) [178] has been emerging as a new research area, defined as the set of technological solutions designed to create and make the surrounding physical ambient active, intelligent and cooperative, able to sustain people independence, capable of providing more security, simplicity, well-being and satisfaction in carrying out ADLs. In particular, based on what introduced, managing health care at home is a challenge confronted by many people, including older persons, children, and younger adults with disabilities, who are especially vulnerable to their environments. These challenges are also actual for people with low incomes, multiple chronic illnesses, limited social supports, and health disparities, as well as those who live in unsafe neighborhoods or poor-quality housing [179]. Many assisting platforms exploiting sensor-based activity recognition systems have been proposed [104–106, 179, 180], as well as monitoring systems [181], and solutions dedicated to specific disease [182]. In [183] the importance of such systems have been widely investigated, and at the same time, tools, technologies and algorithms were identified together with their design issues, of which the most relevant are intrusiveness, safety, technology, and human impact. While these platforms are relevant to help caregiver and professionals in monitoring activities of elderly, identify risky situations and alerting, they do not implement any coaching action.

In this scenario, our work aims to integrate the coaching concept with AAL-based solutions to create a low-cost, non intrusive, and ubiquitous virtual coaching system that supports elderly in the accomplishment of ADLs. The proposed concept of VCS makes possible the interaction between Objects of Daily life (ODLs), wearables, and the surrounding environment as shown in Figure 3.1.

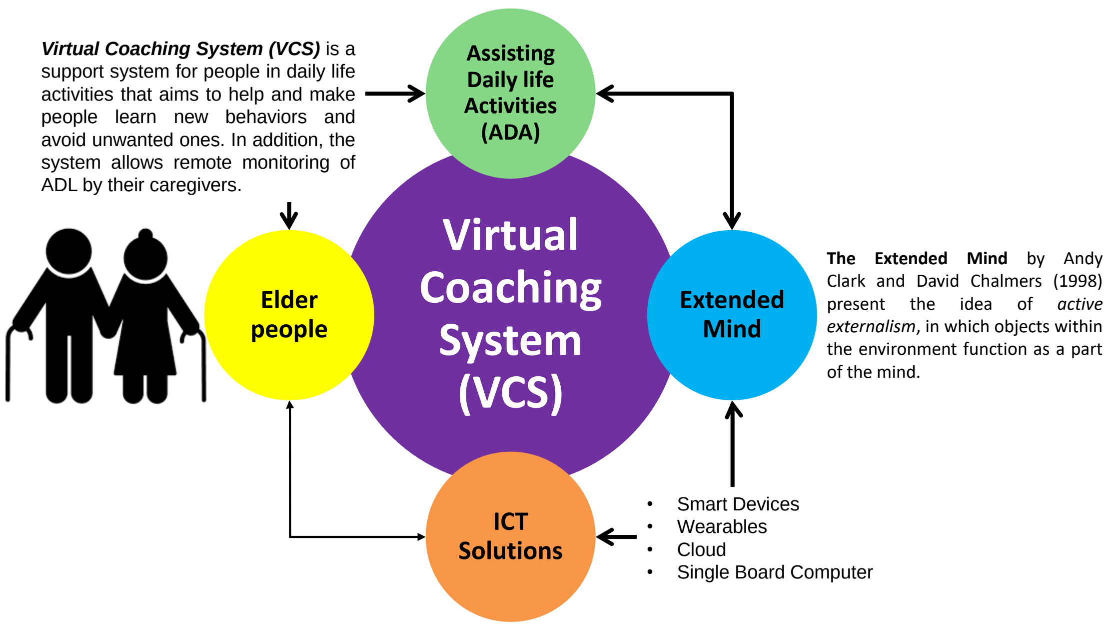


Fig. 3.1: Virtual Coaching System (VCS)

In order to define and implement VCS, whose architecture is shown in Figure 3.2, my thesis work concentrates on the following four main goals:

- Definition and implementation of a low cost and easily configurable Smart Home Platform for Intelligent Assistance (SHPIA) to collect environmental data and allow the communication between smart objects and VCS. It provides the basic architecture on which the implementation of the various components of the coaching system is built. It is based on a smartphone application that provides the user with the capability of associating and configuring smart objects to ADLs;
- Definition and implementation of a localization system in order to identify the position of the person with respect to smart objects and indoor areas, as the baseline to develop related coaching actions. The localization system is mainly intended to provide VCS with the capability of understanding if the user approaches areas relevant for his/her health status or associated to any risk;

- Definition and implementation of an effective Assisting Daily life Activities (ADA) coaching architecture. By exploiting the interaction between wearable devices and smart objects, ADA implements the idea of extended mind to help the user in the acquisition of new behaviors related to his/her needs. It allows caregivers defining ADLs to be carried out by the user, recognizes accomplished actions and implements incremental altering when these are not performed;
- Application of the VCS to the specific case of preventing the freezing of gait in people with Parkinson's Disease, to demonstrate the application and integration of SHPIA, ADA and the localization system to a relevant healthcare scenario.

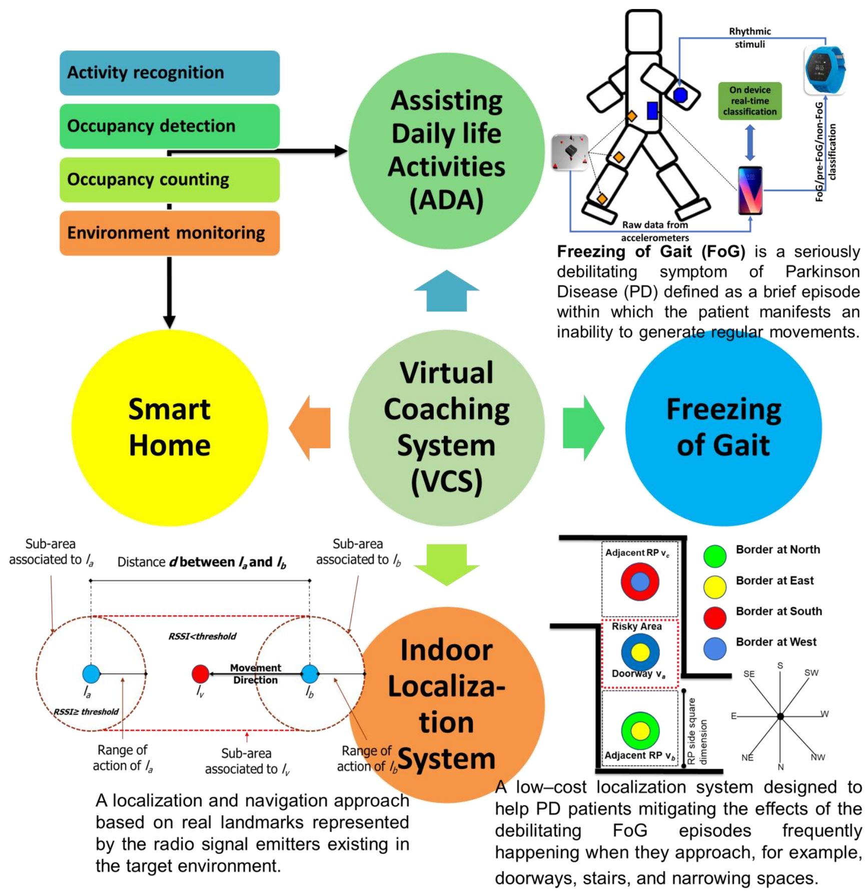


Fig. 3.2: Objectives of this thesis work

4

Smart Home Platform for Intelligent Assistance (SHPIA)

This chapter is devoted to the definition of the Smart Home Platform for Intelligent Assistance (SHPIA) architecture. SHPIA provides the base infrastructure for the development of the Virtual Coaching System (VCS) concept. Nowadays, smart systems have invaded the market and our daily life with devices like smartwatches, smartphones, beacons, Passive InfraRed (PIR) Sensors, Radio Frequency IDentification (RFID) and many other types of sensors. All these devices can communicate with each other, even if the communication takes place through different means and technologies, introducing to the concept of Internet of Things (IoT). Given this trend, the number of such devices will grow up to 24 billion devices by 2020 [43] and the opportunities provided are varied, starting from simple monitoring to activity recognition, occupancy detection and counting etc [184–186]. In the state of the art, the capabilities of this trend have been widely discussed and in many cases implemented, concerning healthcare [12], the assistance of the elderly [183], activities recognition [187], Heating, Ventilating, and Air-Conditioning (HVAC) [188] and the recognition of environmental context [189].

Furthermore, this wave has introduced the concept of smart home, whose purpose is to create environments that behave intelligently based on the perception of their state. [104]. Many works have proposed new architectures for the implementation of smart homes, in [180], was proposed a smart home architecture based on door sensors, infrared motion/light, temperature and ZigBee sensors, for a total cost of 2,765$. Such platform was able to recognize more than ten Activities of Daily Living (ADL)'s with a mean accuracy approximately of 60%. In [107], the authors proposed an activity recognition platform based on data streams of motion, door, temperature, light, water and bummer sensors able to classify more than ten ADL's. Again, this platform achieved an accuracy of approximately 55%. However, as stated in [190], all the existing approaches of ADL recognition present the limitations related to a) activity recognition models, b) time-consuming data labeling process, and c) economic cost. Besides, the need for such architectures is indispensable mainly in the healthcare system applications [12], as introduced in Chapter 1. All these applications and systems are not accessible to everyone and are usually designed for laboratory practices, such as activity recognition or monitoring system. Also, these systems are mainly constructed for individual utilization [187] and based on specific types of sensors, or they require cost-effective devices such as video cameras.

Based on what introduced, this chapter presents Smart Home Platform for Intelligent Assistance (SHPIA), an *easily accessible monitoring and data collection platform*. The main features of the SHPIA architecture are:

- Ubiquitous and not Invasive;
- Transforms an Object of Daily Life (ODL) in smart ODL;
- Smartphone based Setting and Configuration process;
- Low Cost;
- Easily integrated into other application scenarios..

In the following will be introduces the core of the proposed system shown in Figure 4.1, principal agents, the environment definition passing from the used technological instruments and finally the environmental configuration phase. From this point and forward will refer to the proposed system interchangeably as architecture, smart environment, and smart home architecture.

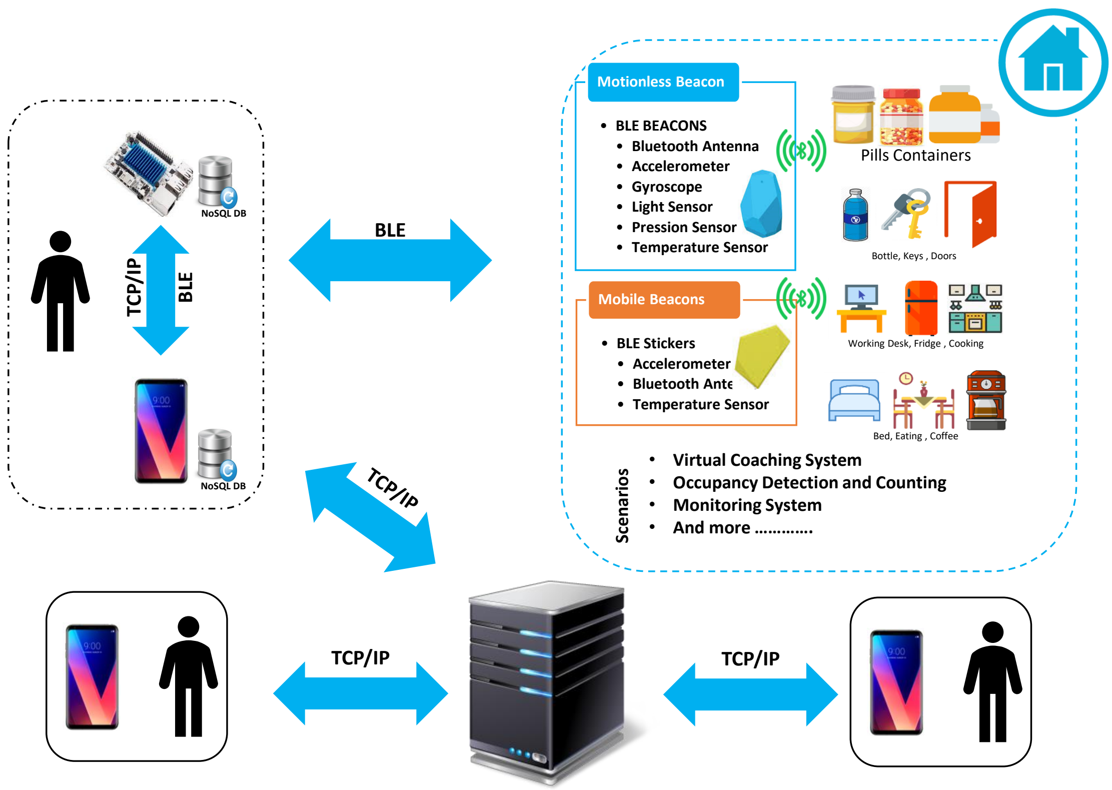


Fig. 4.1: SHPIA

4.1 SHPIA Involved Agents

As stated in the definition of the Extended Mind concept [18], our daily life environment and Objects of Daily life (ODLs) are essential concerning the tasks that we have to perform during

ADL. In particular, for people, objects play a significant role in the Extended Mind since an object can be seen as a virtual container of memories. Concerning to the SHPIA architecture, ODLs are identified as agents and/or entities involved in the creation/communication of this architecture. Accordingly, from an abstract point of view the principal agents of SHPIA are:

- environment;
  - objects of the environment;
  - environmental condition.
- people;
  - presence;
  - movements;
  - quantity;
  - actions.

Instead, from a detailed point of view the involved agents can be recognized in the electronic objects of daily life:

- Smartphone;
- Computers;
- SmartWatches;
- Standalone sensors;
- Beacons;
- Access Point (AP);
- Activity Trackers;
- Gaming Consoles;
- and others.

Based on the aforementioned categories the environment can be rigorously defined as a set composed by the home area itself, by the people inside such area and by all ODLs. On the other hand, with regard to the daily life environment, ODLs, based on their mobility property, are divided into two main categories: a) mobile objects and b) motionless objects. The mobile objects category contains all ODLs that are used in our daily life activity without being related to a specific position inside the environment, as for example:

- Bottles;
- Pills Container;
- Keys;
- and others.

Instead, the second category includes all ODLs that are motionless, are part of the daily life activity and present an immutable position inside the environment, as for example:

- Doors;
- Working/Eating Desk;
- Coffee machine;
- Bed;
- Bedroom;
- Bathroom;
- Kitchen;
- and others.

Therefore, given an environment (E) composed of mobile (M) and motionless (Mo) ODLs, the environment is formally defined as:

$$E = \{\{M \cup Mo\}, fs, fl, Bs, Bl\}$$
$$fs : M \longrightarrow Bs$$
$$fl : Mo \longrightarrow Bl$$

Where, (fs) defines the function that associates to each mobile ODL (M) a BLE Estimote Sticker (Bs) equipped with BLE antenna and motion sensor. Moreover, (fl) defines the function that associates to each motionless ODL (Mo) a BLE Estimote Beacon (Bl) equipped with BLE antenna, motion, light, pressure and temperature sensor. Such devices communicate through the following three different BlueTooth protocols:

1. Eddystone;
2. iBeacon;
3. Estimote.

Eddystone and iBeacon are used for advertising purposes. However, in SHPIA, they are used for what concerns the implementation of particular scenarios, for example, the indoor localization system, detection, and counting of people inside the environments. Instead, the Estimote protocol is used for what concerns the monitoring system, the mining of relations between the environmental conditions and/or relation between such conditions with peoples actions.

4.2 Communication Data Flow

As shown in Figure 4.1 the proposed architecture collects data perceived from the ODLs and through Bluetooth Low Energy (BLE) communication protocol are transmitted to the data collector. The idea on the basis of SHPIA is that of capturing the ODL status by associating to it a Beacon BLE sticker. Such devices, born in 2011 with the introduction of the iBeacon protocol by Apple, are Bluetooth Low Energy (BLE) devices that broadcast their identifier to nearby portable electronic devices. This technology enables smartphones, tablets, and other devices to perform actions when in close proximity to a Beacon. These devices in addition to the advertising utilization can transmit other data collected by other built-in sensors, as temperature, pressure, acceleration, and brightness. After associating the sticker to the ODL, SHPIA provides the ability to collect and recognize the status of the observed ODL. Moreover, SHPIA provides two

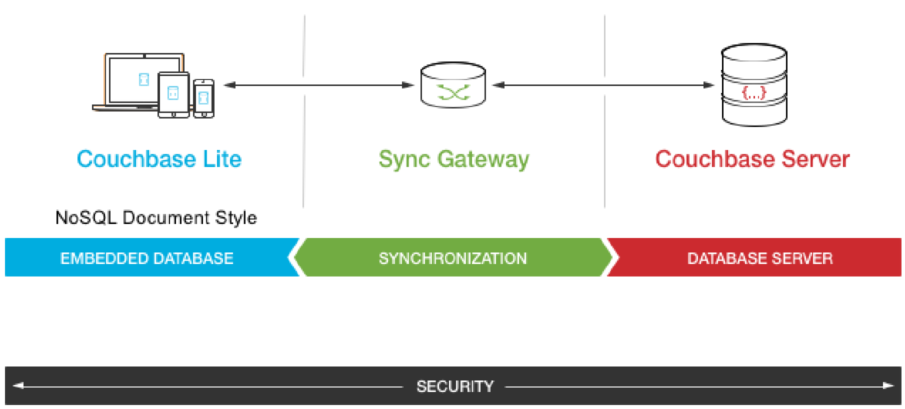


Fig. 4.2: Couchbase Lite and Couchbase Server communication thought SyncGateway

possible data collection means, a) users mobile phone and b) Single Board Computer (SBC).

An SBC is a complete computer built on a single circuit board, with microprocessor(s), memory, input/output (I/O) and other features required of a functional computer. The data collector works as a bridge between the ODLs and the server database. As shown in Figure 4.1, the data is saved remotely over a NoSQL database. From such database, data is accessible from other users whom have access to the environment. All the data is stored on an open source document-oriented NoSQL database called Apache CouchDB Server database. Such database is implemented in Erlang and uses JSON format to store data. CouchDB provides Sync Gateway tool regarding the synchronization of data between Couchbase Server (instantiated on Cloud server or PC) and Couchbase Lite (instantiated on Smartphone, Smartwatch or PC). The CoachDB architecture is shown in Figure 4.2

Instead, Figures 4.3 and 4.4 show respectively the JavaScript Object Notation (JSON) data format defined for Motionless and Mobile ODLs. In particular, for each collected data sample the proposed architecture collects, regarding the motionless ODL, information related to its ID, timestamp, ODL description, temperature, light level, pressure, acceleration and Received Signal Strength Indicator (RSSI). *RSSI* is an indication of the power level being received after antenna and cable loss. This value is often reported as an integer within a predefined range (typically an 8-bit field), where typically higher values of RSSI correspond to stronger received signal [164]. In SHPIA, the RSSI measurement associated to each recieved packet is used to estimate the distance between the smartphone (receiver) and beacon (emitter), or it can be used to estimate the distance between the SBC (receiver) and beacon (emitter).

```
{
    "beaconID": "MAC_ADDRESS",
    "timestamp":"dd/mm/yyyy hh-mm-ss:mmmm",
    "ODL":       "Description",
    "temp":      23.8,
    "light":     43,
    "pressure": 101.325,
    "accel": [{
            "X": 0.0226898,
            "Y": -0.382233,
            "Z": 9.54773,
        }],
     "rssi":     -56
}
```

Fig. 4.3: JSON data format Motionless Beacon

Instead, regarding the mobile ODLs, for each data sample, SHPIA saves the beacon ID, sample timestamp, ODLs description, acceleration and RSSI measurement as shown in Figure 4.4.

```
{
    "beaconID": "MAC_ADDRESS",
    "timestamp":"dd/mm/yyyy hh-mm-ss:mmmm",
    "ODL":      "Description",
    "accel": [{
            "X": 0.0226898,
            "Y": -0.382233,
            "Z": 9.54773,
        }],
     "rssi": -56,
}
```

Fig. 4.4: JSON data format Mobile Beacon

4.2.1 Communication protocol

As mentioned, the beacon devices perceive the environments conditions/state and broadcast them to the data collector device with a defined time interval that generally varies from 100 ms to 10000 ms. Instead, the communication between smart-devices and cloud server is performed over TCP/IP protocol, automatically managed by the NoSQL database synchronization mechanism. The transmitted data are parsed as JSON documents and transmitted over the network.

4.3 Smart Environment Configuration

One of the biggest limitations of the existing smart-home environment architectures regards the configuration of the architecture. Such phase is time consuming and generally requires specialized personnel. To overcome this limitation, SHPIA presents a user-friendly mobile application used to perform the configuration phase. Figure 4.5 explains the necessary steps required to configure the architecture.

User Account Creation

In this first step, the designed mobile application allows, if not exists, to create a user account in order to associate the data that will be collected from the architecture to such user.

Create Environment

Once registered or authenticated, the user can create one or more environments by defining its name and geographical address. Alternatively, if the environment already exists, the user can search between all the existing environments and send an association request for it.Once that the environment is created the user have complete access to it and is able to modify it's configuration and observe it's status. Figure 4.6 shows the environment instance created and associated to the user/owner in this first step.

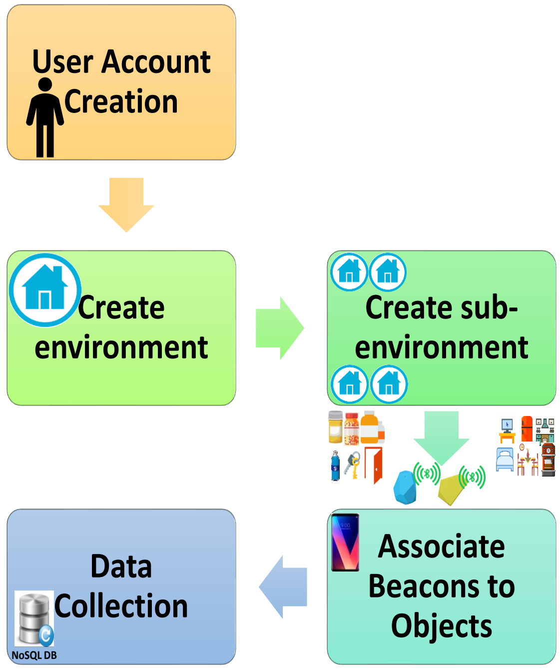


Fig. 4.5: SHPIA configuration work-flow.

```
{
    "env-name": "Apt. 4E",
    "env-location": "217 E Broadway, New York, NY, 10002"
    "env-uuid": "env-ce2fcbbd-9124-45d4-9882-66e34415d62e",
    "type": "apartment",
    "owner": "Elliot Alderson"
}
```

Fig. 4.6: Environment JSON example

Create sub-environment

Generally, each environment is typically composed of other sub-environments; in this step, the user can create as many sub-environments as needed. For each sub-environment, the system saves its description(e.g., an apartment consists of lounge, kitchen, two bedrooms, and two bathrooms).The creation of sub-environments will become useful in future data collection optimizations, which aim, for example, will be that of reducing the possibility of generating redundant data. Figure 4.7 shows an example of sub-environment JSON instance associated to the created environment in the firs step.

Associate Beacons to Objects

In this final step, after that the user has identified the ODLs of interest, to each ODL physically associates a BLE sticker. The user approaches the smartphone, closer than 10 cm to the ODL

```
{
    "sub-env-name": "Sleeping room",
    "sub-env-uuid": "env-ce2fcbbd-9124-45d4-9882-66e55555e55e",
    "env-uuid": "env-ce2fcbbd-9124-45d4-9882-66e34415d62e",
    "type": "room",
}
```

Fig. 4.7: Sub-Environment JSON example

and automatically associates it to the created sub-environment. Figure 4.8 shows the Beacon JSON instance associated to the created sub-environment.

```
{
    "beacon-MAC": "D5:7A:8E:51:AF:F8",
    "beacon-description": "water bottle",
    "env-uuid": "env-ce2fcbbd-9124-45d4-9882-66e34415d62e",
    "type": "mobile beacon"
}
```

Fig. 4.8: Beacon JSON example

Data Collection

As a result of a correct association procedure, SHPIA immediately starts the data collection process from the associated ODL. SHPIA will collect all the data percieved by the associated ODLs within a range that varies from 3 meters to 70 meters based on the defined transmission power of the beacons. The data are saved locally over the smartphone/SBC, and as soon as a connection is available, the data is synchronized on the cloud server and eliminated from the local memory.

Summing up, in the data collection phase, from each associated ODLs SHPIA collects at different frequency the following data, as shown in Figure 4.3 and Figure 4.4:

- temperature;
- brightness;
- pressure;
- acceleration of ODL;
- RSSI measurement for each received data packet.

4.4 SHPIA application scenarios

This section will illustrate some possible application scenarios in order to verify the capabilities of the proposed system. The first possible use of the SHPIA is that of collecting environmental and human activity data. On such aim, we used SHPIA regarding environmental data collection inside a working office shared by ten persons. Figure 4.9 shows the beacons deployment inside Office 1.71. Data collection is performed based on the utilization of 5 motionless BLE Estimote Beacons (red cubes in figure 4.9) and eight mobile BLE Estimote Stickers (green cubes in figure 4.9). The motionless beacons were positioned as follows: one at the office door, two

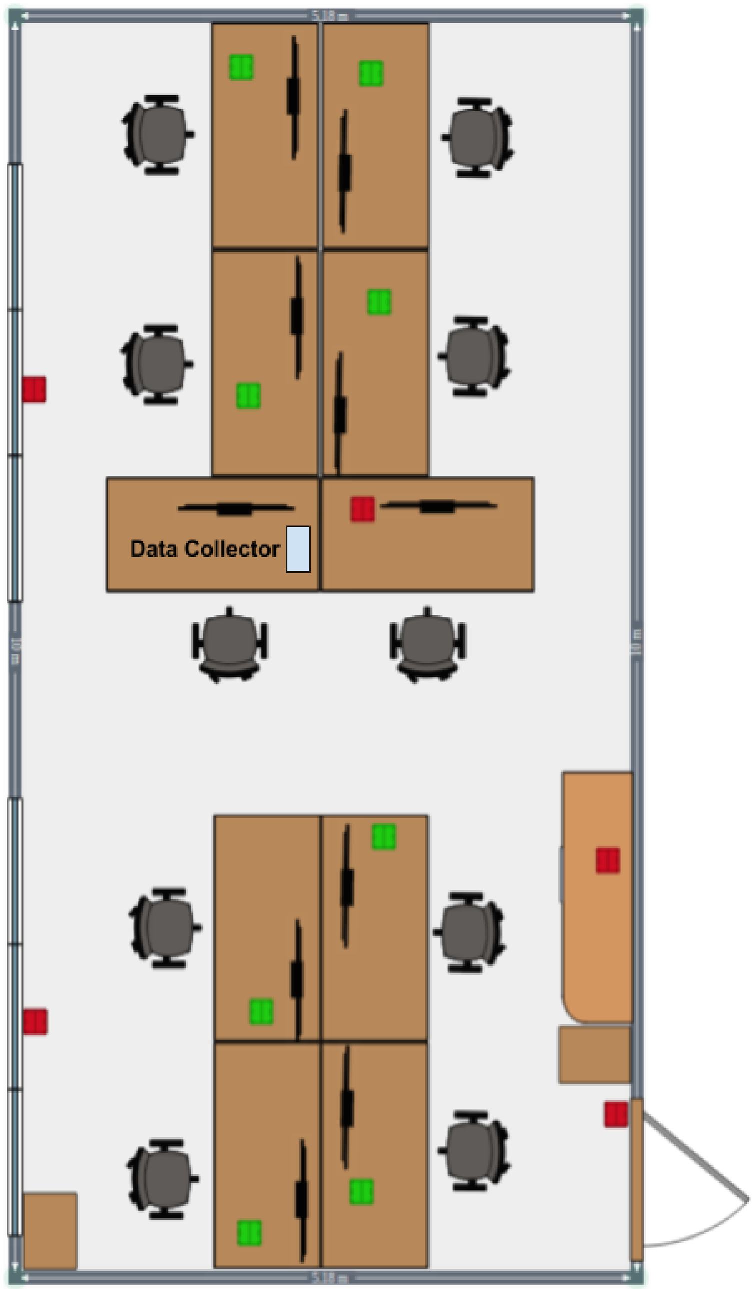


Fig. 4.9: Office 1.71. Motionless (red), mobile (green) beacons and grey) data collector

on the windows (left side), one on the desk at the office center, and one inside the locker. Instead, the mobile stickers were used to monitor the drinking activity of our office colleagues. Finally, the **Data Collector** device receives all the data sensed by the deployed beacons. The

Table 4.1: Results of Data Collection.

Source	Frequency (Hz)	Unit	# of samples	# of sensors	Dimension
Temperature	0.33	Celsius	1008000	5	≈ 15 Mb
Pressure	0.33	Bar	1008000	5	≈ 15 Mb
Brightnes	0.33	Lux	1008000	5	≈ 15 Mb
Acceleration	10	m/s^2	78624000	13	≈ 599 Mb
RSSI	10	dBm	78624000	13	≈ 599 Mb

data collection process took place for one week, and the results of such a process are shown in Table 4.1. Column one introduces the used sensors, second and third columns show the sensor sampling frequency, and the unit of measure of such sensed data. Column four shows the number of samples collected by the system during a base test of 7 days (604800 seconds). Column five identifies the number of data sources (sensors). Finally, the last column shows the memory space required to store data sensed by each sensor.

Besides, Table 4.2 shows some statistics regarding the data collector devices related to average memory, RAM, and battery consumption during the seven days of tests. As clearly visible, SHPIA mobile application presents an average memory, RAM, and battery consumption that does not affect the mobile device more than other mobile applications [191]. In addition to this, we want to emphasize that these results where obtained over a not optimized application. A possible optimization could regard the representation of data with a lower number of bits since the measured data values are within a small range.

Memory	RAM	Battery
3.2 Mb/h	18 Mb/h	56 mAh

Table 4.2: Average consume of Internal Storage Memory, RAM Memory, and Battery consumption of the designed mobile application during the seven days of test

4.5 Discussion

SHPIA, at the current development stage, presents only the sensing features, it does not implement any actuation capability. However, the main idea is that of monitoring the environment and ODLs, and finally developing our Virtual Coaching Systems over such architecture. Furthermore, SHPIA can easily integrate/upgrade additional applications scenarios as Indoor Positioning systems, Occupancy Counting, and Occupancy Detection. This section will introduce some preliminary knowledge regarding the occupancy detection and counting in shared environments and also regarding Human Activity Recognition (HAR) research area by proposing a system that can reduce the time and resources required for the labeling process.

4.5.1 Occupancy Detection

As stated in [192], Occupancy Detection/Occupancy-Related Information represents a fundamental feature for energy management, security, and safety. Occupancy Detection systems identify those systems able to recognize the presence of human activity inside the observed environment. Instead, with Occupancy Counting systems are identified these systems able to recognize the presence of human activity and return an approximated count of the number of humans inside an environment.

Usually, occupancy detection systems are categorized as follows:

- not device free users: the user has to carry a device that receives or transmits some sort of uniquely identifiable information [184];
- device free users: the user is device free, the methods are based on smart metric measurements (e.g., radio signal fluctuations, CO_2 level in the air etc) [186].

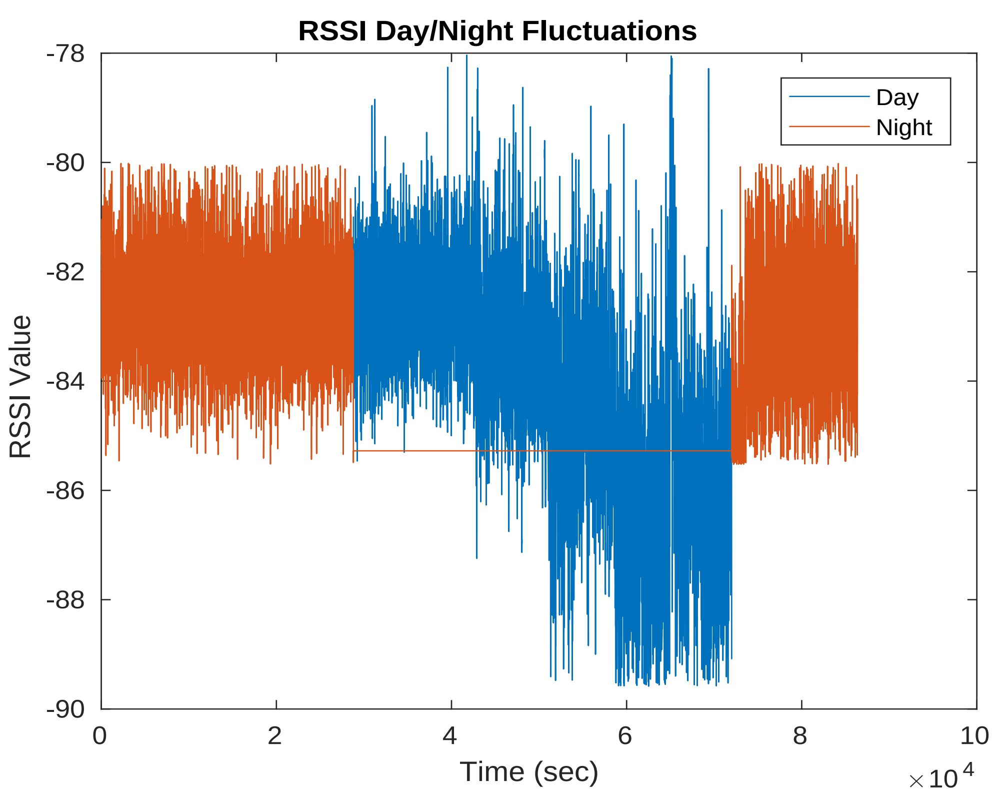


Fig. 4.10: Office 1.71. RSSI fluctuation between night and day

SHPIA architecture is adequate for both the before-mentioned occupancy detection systems. In the first category, SHPIA[1] can detect the user's position inside an environment by receiving the payload of the beacons, emitted by beacon devices deployed on such environment. Concerning to the second category, SHPIA behaves more intelligently since that users doesn't need to carry a smart device.The idea is that the data collector analyzes the RSSI measurement fluctuation to understand when users inside the monitored environment generate such fluctuations. A possible application scenario is, for example, the detection of intruders using the RSSI such fluctuations.

Starting from the data collected in the application scenario introduced in Section 4.4 Figure 4.9, and analyzing the RSSI measurments emitted by motionless beacons we designed an occupancy detection pattern recognition model which achieved an accuracy of $\approx$ 95%, precision of $\approx$ 98% and recall of $\approx$ 92% in recognizing the presence of persons inside the office. Figure 4.10 shows very clearly the difference between nocturnal (red plot [08:00 PM-08:00 AM]) and diurnal (blue plot [08:00 AM-08:00 PM]) RSSI observations at the office. The reported results were obtained by using only one of the signal emitters shown in Figure 4.9, in conclusion, SHPIA implemented an user device free Occupancy Detection system by using only a smartphone (data collector) and one beacon.

4.5.2 Occupancy Counting

Instead, Occupancy Counting extends the concept of Occupancy Detection in order to create a system that can precisely define the number of persons within an environment. Moreover, in state of the art have been proposed techniques concerning the occupancy counting context. Most of them claim that the achieved results approximate very well the real number of people inside the environment. As shown in [192], these techniques are based on different means, starting from video cameras to PIR sensors, Pressure Mats, CO_2 sensors, RFID, and Lighting Sensors. Furthermore, smart metrics as radio signal fluctuations have been studied in many proposals [186, 193]. However, the economic cost of such systems is quite high, compared to the cost of SHPIA architecture, mainly due to the use of particular emitters and signal receivers.

Based on the RSSI fluctuation in the application scenario introduced in Section 4.4 Figure 4.9, we defined a basic regression model able to identify the number of people within the environment with a not very high Root Mean Square Error (RMSA). However, it can be further improved thanks to the extension of the learning database and model optimizations. To remember that this is only another possible application scenario of SHPIA architecture and that, therefore, the result should not be compared with other existing works. In the future SHPIA will be used to model and will intgrate an optimal Occupancy Counting system.

4.5.3 Automatic Labeling of Human Activity Dataset

As known, one of the most significant limitations in Human Activity Recognition (HAR) and machine learning concerns the creation of the learning dataset through a labeling process of the collected data. This process usually requires manual effort during which a person assigns to

[1] installed on the user's smartwatch or smartphone

specific activities, recorded on video, a label that identifies the activity [72]. However, based on SHPIA, many of these activities can be automatically labeled. As shown in Figure 4.11 there are

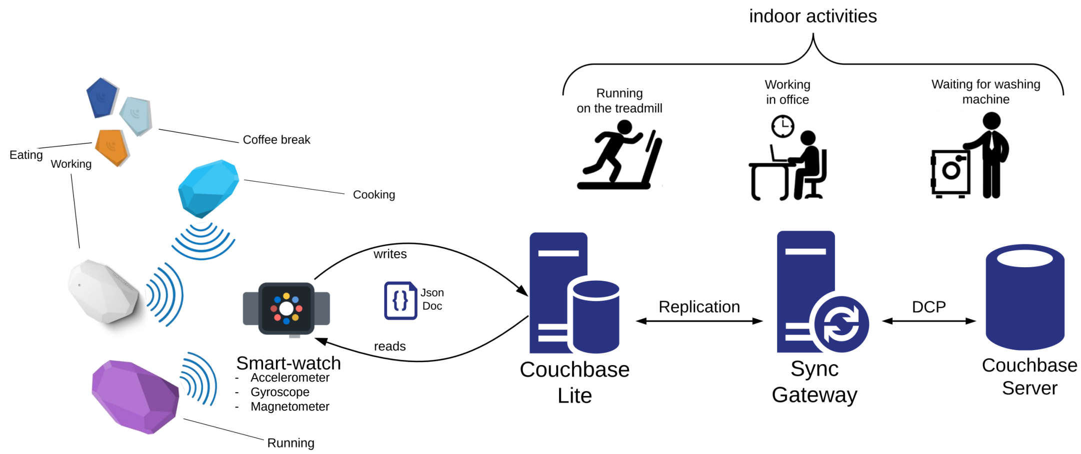


Fig. 4.11: Eliminating the labeling process in HAR

many activities that people perform inside their home, as for example, sleeping, eating, drinking, cooking, watching TV, leaving home, entering home and many others. Assume to assign to specific objects or locations of the user's daily environment one of the beacons mentioned above, e.g., assign a beacon to the eating desk, to the working desk, to the home door, to the bed and so on. The user wears a smartwatch which can detect the emitted BLE packets and estimates the distance between the smartwatch and the signal emitter thanks to the RSSI measurements. When the user is performing the eating activity, SHPIA assigns to the collected data from the wearable devices the label "eating", otherwise if the user is cooking or working the system assigns to the collected data from the wearable device the labels "cooking" or "working". All the data is automatically replicated inside a Coac hBase Server for further usage in HAR context. Figure 4.12 shows an example of the data collected by the proposed scenario of Figure 4.11. As mentioned above, the user's smartwatch will collect at each timestamp the values of accelerometer, magnetometer, and gyroscope sensors and to the collected data will be associated the beacon with the higher RSSI value, that as introduced to each beacon corresponds a specific ADL. Besides, in order to extend the system to all people and obtain a reasonable amount of data, SHPIA provides the possibility of using two different smartwatches (one per hand) in order to study in detail the activities carried out by the user. In order to verify the quality of the automatic labeling process, we can make use of video cameras and the information provided by the user. A further method that allows us to certify this labeling process involves instructing the user to carry out the activities of interest only in certain time windows.

```
{
    "timestamp":"dd/mm/yyyy hh-mm-ss:mmmm" : {
        "accelerometer": {
            "xAxis": 0.0629921259842519,
            "yAxis": -0.015748031496062,
            "zAxis": 1.007874015748031
            },
        "gyroscope": {
            "xAxis": 0.0629921259842519,
            "yAxis": -0.015748031496062,
            "zAxis": 1.007874015748031
            },
        "magnetometer": {
            "xAxis": 0.0629921259842519,
            "yAxis": -0.015748031496062,
            "zAxis": 1.007874015748031
            },
        "beacon_1": {
            "MAC": A3:17:B1:9E:FB:4C
            "rssi": -75
            },
        "beacon_2": {
            "MAC": C3:17:E1:9F:DB:2D
            "rssi": -35
            },
        "beacon_3": {
            "MAC": D3:17:D1:9D:D4:1C
            "rssi": -45
            },
            ..
            ..
        "beacon_n": {
            "MAC": C3:17:E1:9E:FB:4C
            "rssi": -45
            }
        }
}
```

Fig. 4.12: Data collection example

5

A virtual coaching system exploiting BLE smart tags for supporting elderly in the acquisition of new behaviours

This chapter introduces the first example of Virtual Coaching System (VCS) based on Object of Daily Life (ODL) and Smart Home Platform for Intelligent Assistance (SHPIA) architecture. In particular, this system, named Assisting Daily life Activities (ADA) is intended to support an elder person or people with cognitive impairments in progressively acquiring new behaviours (e.g., taking pills, drinking water, finding the right key), which is necessary to cope with needs derived from a change in his/her health status and a degradation of his/her cognitive capabilities as he/she ages. Besides, ADA enables remote monitoring of ADLs by caregivers and related alerting.

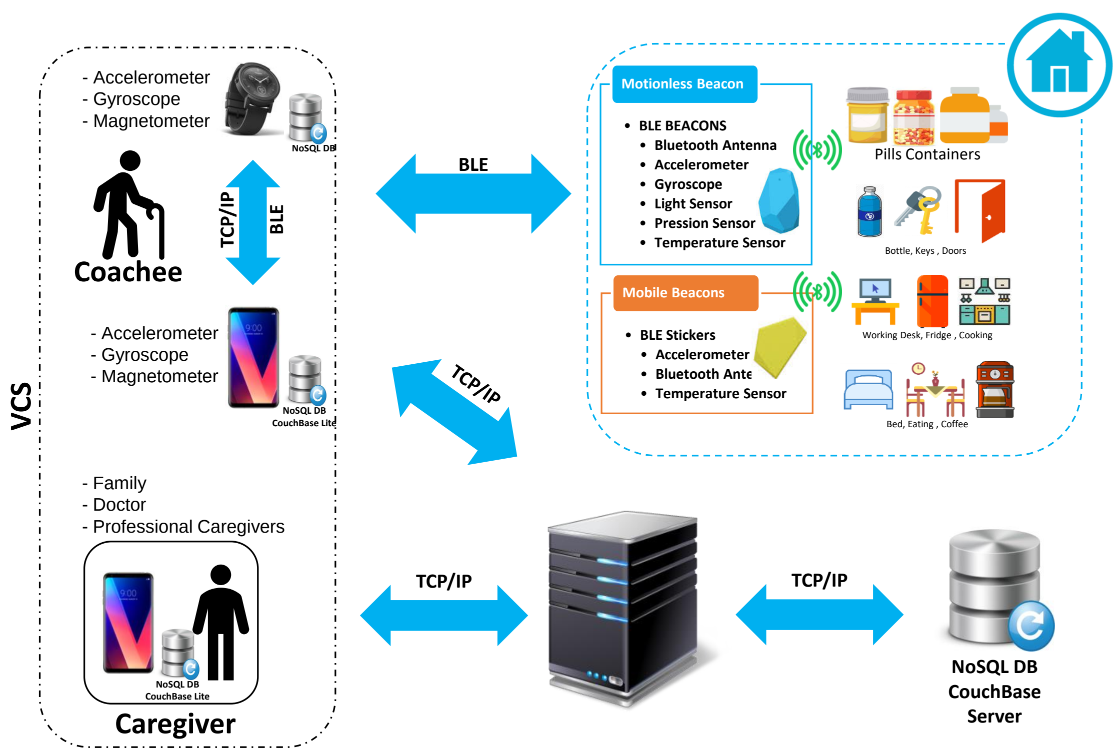


Fig. 5.1: Assisting Daily life Activities (ADA) Overview

ADA is based on the concept of *extended mind*, early mentioned, introduced by Clark and Chalmers in 1998 [18], which proposes the idea that objects within the environment operate as a part of the mind. In our revisiting of the concept of extended mind, ADA (Figure 5.1) is composed of:

- BLE smart tags used to transform common objects of the daily life (e.g., pill box, bottle of water, keys) into smart objects. Tags embed beacon devices and emit ambient radio signal;
- a coaching application running on a smartwatch. It implements the coaching plan by interacting with the smart tags and elaborating the gathered data to monitor the usage of the corresponding objects by the elderly, identify their needs and incrementally guide them in the acquisition of the new behaviour, when necessary.
- a caregiver application that allows family members and professionals of the health-/social-care system to define the coaching plan and monitor the behaviours of the elderly;
- a cloud-based architecture that allows storage of data and interaction among ADA components.

Figure 5.1 introduces an overview of the proposed assisting architecture and the involved agents. In such architecture, the VCS defines an ubiquitous 'entity' present within daily life objects and devices. It involves people with special needs, the environment, objects into such environment, and people who care for the former ones, besides, there is also the communication part and the mobile and/or cloud data storage.

5.1 Bluetooth Low Energy smart tags

ADA relies on the use of low-cost beacons embedded into small stickers, whose size is lower than a coin. Beacons are BLE devices that broadcast via radio signals their identifier to the nearby electronic devices, e.g., smartphones, tablets and IoT objects in general. In addition, BLE devices can transmit the data collected by other built-in sensors as, for example, information about temperature, pressure, acceleration, and light. Upon the reception of the BLE signal, a nearby device can then react to perform some pre-defined actions. The BLE communication protocols allow unique identification of objects/rooms associated to the emitting devices. For example, with the iBeacon protocol, the major frame can be used to identify different floors of a building, while the minor frame to identify rooms inside, as done in [47]. Finally, beacons can also be used for distance estimation and localization, basically through the use of the Received Signal Strength Indicator (RSSI) measurement. RSSI is a particular measurement, used often in modern Radio Frequency (RF)–based communication systems, to provide an indication of the power level at which the data frame is received. While these power levels are generally negative (for instance, -100 dBm are considered very low values resembling noise), the RSSI is often provided as an integer within a predefined scale (e.g. 0-255). The rationale is that the higher the RSSI value is and the stronger the signal is [48].

5.2 The Assisting Daily life Activities (ADA) Virtual Coaching System

The ADA virtual coaching system is intended to support an elder person or people with cognitive impairments in the accomplishment of ADLs that require to introduce a change in his/her lifestyle, i.e. when a new behavior must be acquired. Through ADA, the caregiver can define coaching actions for the elder and monitor his/her behaviours w.r.t. the corresponding ADLs through a smartphone application. The elder wears a smartwatch where another application monitors his/her behaviour and implements the coaching actions by alerting him/her, when necessary, through tactile, auditory and visual stimuli. Several types of behaviors related to ADLs (e.g., taking pills, dressing adequately w.r.t. the season, using the right key to open doors, doing gym) can be associated to ADA as reported hereafter. The only condition is that per each target behavior we need to develop an algorithm that automatically recognizes when the corresponding ADL is accomplished. Such a human-activity recognition (HAR) algorithm must rely on signals emitted by the BLE smart stickers associated to the objects used to accomplish the activity. Example of such algorithms are reported later in Section 5.2.5.

For sake of simplicity and to exemplify how ADA works, in the rest of this section, we consider drinking water and medication assumption as the target behavior to be acquired. Drinking water is, indeed, a very relevant scenario for elderly, since people as they age do not feel thirsty anymore. This leads many elderly towards dehydration with dramatic consequences for their health condition. To avoid this, a new behavior must be introduced in their lifestyle, i.e., the elder needs to learn that he/she must drink periodically, even if he/she is not thirsty. ADA can then be used to teach this new behaviour. In doing this, ADA acts neither just as an alerting system, which would be invasive, as it rings even if the elder has already drunk by him/her self, nor as an automatic intravenous feeding system, which would substitute the person in doing the action, thus reducing his/her self-efficacy. ADA, instead, is a virtual coach that ubiquitously monitors elder behaviour w.r.t. drinking water and acts only when necessary (i.e., if the elder does not drink for a while).

5.2.1 ADA set up

The set up of ADA requires the following steps:

1. identification of the new behaviour to be acquired and the related ADL, e.g., drinking water;
2. association of a coaching action to the target behaviour, e.g., remember that water must be drunk at least eights time per day, if the person drinks periodically enough by him/her self remains silent, otherwise alert him/her incrementally, if the person ignores alerts notify the caregiver;
3. gluing BLE tags to the objects necessary to accomplish the ADL, e.g., one tag glued on the top and one on the bottom of the bottle of water;

4. association between the tag and the corresponding coaching action; i.e., installation in the smartwatch of an application associated to tags that implements the coaching action and recognizes when water is poured[1].

According to the concept of extended mind, daily life objects are part of humans mind and can help them to understand, remember, and learn new behaviors. Consequently, the association of the BLE tags to objects allows the interaction between ADA and the surrounding environment to determine proximity of the elder w.r.t objects, through the analysis of the corresponding RSSI, and their usage, through human-recognition activity algorithms that elaborate data gathered from the tags. In the rest, we will call object of daily life (ODL) an object associated to a BLE tag.

5.2.2 ADA Involved Agents

As mentioned, in the "extended mind" concept [18], *all the daily life objects are "part" of humans mind and can help them to understand, remember and learn new behaviors*. According to such concepts, the VCS is not a single component or entity. It regards all the Objects of Daily life (ODLs) surrounding us, capable of reacting to iteration with them, returning the *Coachee* the related *Coaching Actions* in order to help them learn new behaviors. On this purpose, our coaching system defines the figures of Coachee, Caregiver, Coaching Action, and Coaching Alerts, which together compose the VCS.

Coachee

In the proposed approach, the figure of the coachee identifies elders or people with cognitive or physical impairments, which, however, are collaborative in carrying out activities suggested by specialized medical personnel. For example, think about performing a medical treatment based on assuming a specific medication. However, the patient does not always remembers to take the pills, so he needs a system that reminds him to do that, *if and only if this action does not take place*. Otherwise, the system doesn't activate. In the following, we use interchangeably the words patient, elderly, person with special needs to identify the coachee.

Caregiver

Identifies people who are in charge of helping the coachee in daily life activities. Nowadays, this figure usually corresponds to a family member of the coachee, but in some cases, it regards specialized personnel who care for them (e.g., nurses, doctors, carers, etc.).

[1] Please, note that checking if the person throws water in the sink instead of drinking is out of the scope of our system. ADA is intended for cooperative elderly that want to acquire new behaviors, but they cannot get them alone, mainly because they forget what they have to do, or they make confusion.

Virtual Coaching System

The Virtual Coaching System (VCS) is implemented into the Coachee smartwatch. Once that the caregiver defines the coaching action, such action is immediately deployed into the smartwatch, and starting from such time-instant, the coaching system will remain awake to perceive possible interaction with ODL's.

Coach Actions

Identifies the activities of daily life that the coachee usually performs or must learn to perform. Such actions can, for example, regard therapies prescribed by the doctors. On the basis of the association between ADLs and BLE tags, ADA implements three main categories of coaching actions:

1. **Precise action**: it must be done at a specific time during the day (e.g., take pills every day at 1pm $\pm$ n minutes).
2. **Periodic action**: it must be done periodically during the day (e.g., drink one glass of water every two hours $\pm$ n minutes from 8am to 10pm).
3. **Event-based action**: it must be done on the occurrence of an event (e.g., use the yellow key when you approach the main door).

Coaching Alert

Identifies the VCS interface to the coachee, in particular in such approach we introduced an Incremental Coaching System. Incremental Coaching is a type of coaching that is distinguished by how the patient is stimulated to perform the defined Coaching Action. In detail, it is based on four levels of alert, which are activated in succession if and only if the coachee does not perform the defined action. ADA implements an incremental coaching system to promote the acquisition of the new behavior. Each coaching action is then associated to an interval $I = t \pm n$, where t is the expected time for the accomplishment of the target activity and $\pm n$ represents the tolerance window; both t and n are configured by the caregiver per each coaching action. ADA remains silent when the elder respects the interval I, to foster autonomy and feeling of self-efficacy and to avoid annoying and useless alerts. Otherwise, ADA starts different levels of stimuli to guide the elder in doing the action. These stimuli are activated in a cascade fashion:

- **Level 1**: a tactile stimulus is provided by the smartwatch at time $t + n + l_1$ if the control application interacting with smart tags does not recognize the accomplishment of the expected actions in the time interval I;
- **Level 2**: if level 1 fails, at time $t+n+l_1+l_2$ both tactile and visual stimuli are provided (e.g., showing on the smartwatch a meaningful image remembering the purpose of the action, like a bottle, during vibration);
- **Level 3**: if level 2 also fails, at time $t + n + l_1 + l_2 + l_3$ a sentence will be pronounced by the smartwatch[2] in addition to the tactile and visual stimuli;

[2] Or by an associated smartphone if the smartwatch does not have speakers.

- **Level 4**: finally, a notification to the application running on the smartphone of the caregiver is sent in case all previous alerting levels have failed. The time of this notification can be at time $t + n + l_1 + l_2 + l_3 + l_4$ or just once per day.

5.2.3 ADA applications and communication workflow

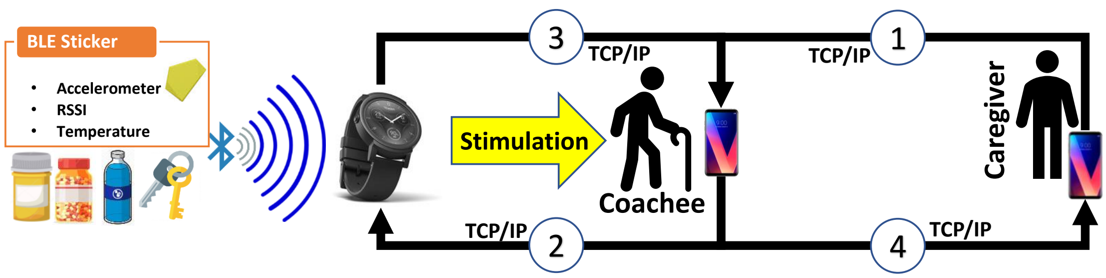


Fig. 5.2: ADA communication workflow, from Caregiver to smart-tags and vice-versa

ADA proposes a mobile applications with the possibility of running in two different modes:

1. caregiver mode;
2. coachee mode;

Concerning the coachee mode, in addition to the smartphone application, we also developed a smartwatch application. This application implements the part of the VCS dedicated to the recognition of actions performed by the coachee on ODLs, Figure 5.2 shows the interaction between the mentioned applications. The caregiver application, shown in Figure 5.3, allows registering the caregiver's personal information (Figure 5.3 (a)) according to the JSON format shown in Figure 5.4. Subsequently, the caregiver creates the coachee profile (Figure 5.3 (b)) and defines the corresponding coaching actions (Figure 5.3 (c)-(d)) according to the JSON format shown in Figure 5.5.

Once that the caregiver performs the above steps, the next step regards the association of the coaching action to the corresponding tag. This association is done by approaching the smartphone to the smart ODL created by SHPIA. Since that the ODL emits a periodic BLE package containing a unique identifier and status information's, ADA makes use of such information's in order to clearly identify the ODL. Finally, the coaching action is communicated to the smartwatch application of the coachee, where the corresponding HAR algorithm is also uploaded. At this point ADA is set up; when the elder approaches an ODL equipped with a tag, the corresponding HAR algorithm is invoked to recognize if the target action has been accomplished. Concurrently, coaching actions act as reported in the previous paragraph. Since the coaching actions are uploaded into the elder's smartwatch, there is no need of Internet connection, except during the initial configuration. Gathered data are stored locally into the smartwatch memory and transferred to the cloud as soon as the internet connection is available.

More in detail, Figure 5.2 presents the standard workflow of the ADA architectures:

- the caregiver creates its personal account using the mobile app Figure 5.3 (a); A JSON document representing the caregiver is shown in Figure 5.4;
- the caregiver creates the coachee account or if the coachee instance already exists it makes an association request to the coachee instance creator (Figure 5.3 (b)). A JSON document representing the coachee is shown in Figure 5.5;
- the caregiver creates a new ADL (Figure 5.3 (c)) and associates to such ADL a new Coaching Action (Figure 5.3 (d)) (e.g., periodic coach action drink water every two hours from 8am to 10pm). The Coaching action will be simultaneously (arrows ① and ②) transmitted to the Coachee's smartphone and smartwatch where the Virtual Coach is implemented. Once that the coach action have been defined the coachee's JSON document, Figure 5.5, is updated;
- ODLs continuously broadcast BLE data packets containing information's about their state;
- possible scenarios:
  - if the smartwatch (coaching system) perceives the BLE packet transmitted by the ODL and at the current time instants is scheduled a coaching action and the VCS recognizes a correct interaction then the VCS remains silent;
  - if the smartwatch (coaching system) perceives the BLE packet transmitted by the ODL and at the current time instants there is no scheduled coaching action and the VCS recognizes a correct interaction then the VCS alerts the coachee to not perform[3] such action;
  - if the smartwatch (coaching system) is not perceiving the packet transmitted by the ODL and at the current time instants is scheduled a coaching action the VCS emits the coaching alerts as introduced above (if and only if the coachee has not performed the coaching action).

All the changes/updates on the Cargiver, Coachee or Coach Action state immediately generates an update, respectively, of the JSON document of the Caregiver (Figure 5.4), Coachee (Figure 5.5) and Coachee Coach action (Figure 5.5).

5.2.4 Interaction with BLE tags

Beacon devices exploit different BLE protocols. ADA is compliant with BLE tags that emit signals according to Apple iBeacon, Google Eddystone and Estimote Telemetry protocols, with a transmission frequency that is generally between 1Hz and 10Hz. ADA is based on the analysis of the interaction between the elder's smartwatch and BLE tags to

(i) estimate distance from ODLs,
(ii) recognize interaction activities between smartwatch and ODLs.

The first task is based on the usage of the RSSI measurement, which allows to estimate the distance between the emitter (tag/ODL) and the receiver (smartwatch) by quantifying the strength of the signal. While the precision achieved by using RSSI for estimating distances

[3] only when the coaching action cannot be performed outside the defined time schedule

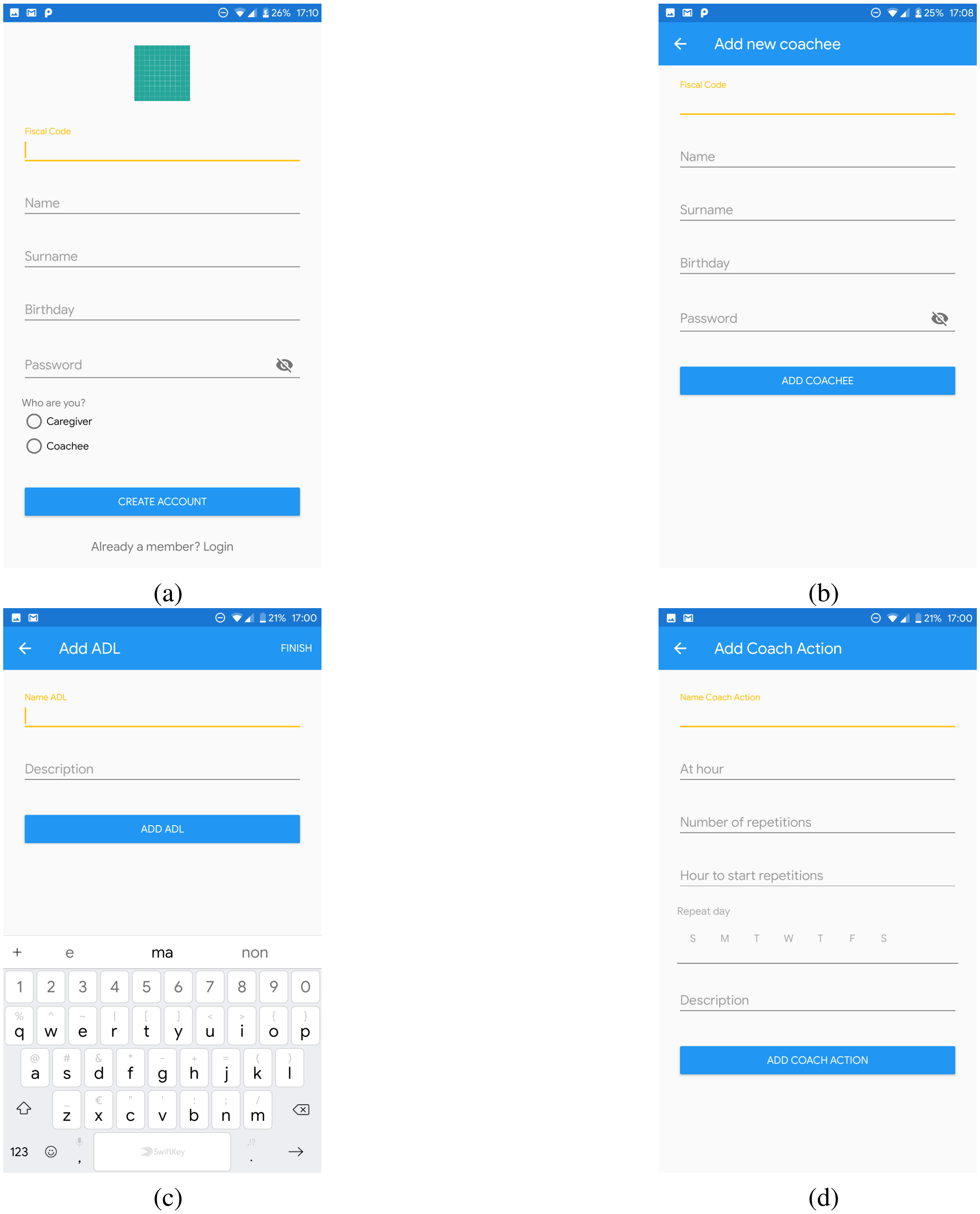


Fig. 5.3: ADA Mobile Application

in the order of meters and more is generally quite low due to well known signal propagation issues [194], we have experienced that for distances lower than one meter the accuracy is good enough for the purposed of the ADA system. In particular, ADA implements a RSSI threshold based algorithm able to accurately distinguishes when the coachee's smartwatch is at 0cm, 10cm, 20cm, 40cm, 50cm and more than 1m from the ODL. For such a short-range scenario,

```
{
    "birthday": "17/09/1986",
    "fiscal_code_fc": "ELLALD",
    "coachees_fc": [#from_zero_to_M:coachees
      "EDWALD"
    ],
    "coachees_id": [
       "0034f130-ea3a-43f0-bf7f"
    ],
    "name": "Elliot",
    "surname": "Alderson",
    "type": "caregiver"
}
```

Fig. 5.4: Caregivers JSON data format.

the relation between distance and RSSI values is quite linear, as shown in Figure 5.6, which reports tests performed with ADA.

Furthermore, by exploiting RSSI, ADA recognizes also the position of the smartwatch w.r.t. to the ODL, which is necessary to distinguish the case in which the elder holds the ODL (i.e., he/she is using it) or his/her hand is only adjacent to it. Figure 5.8 shows tests we did by putting the arm wearing the smartwatch in different positions w.r.t the ODL at 0cm distance. In particular, the difference between “over” and “direct” consists in the fact that in the first case the ODL is in contact with the smartwatch strap, while in the second the arm is turned such that the smartwatch is in direct contact with the ODL. As visible in Figure 5.8 right (Figure 5.7 (b)), left (Figure 5.7 (c)), and direct (Figure 5.7 (d)) positions are easily distinguishable among them, while only over (Figure 5.7 (a)) and holding (Figure 5.7 (e)) positions have a small overlapping in RSSI values, anyway they are still quite different. Both, Figure 5.6 and Figure 5.8 refer to RSSI samples at 5Hz frequency. The recognition of activities is instead obtained by HAR algorithms that rely on data gathered by the sensors embedded into the smart stickers. In particular, ADA exploits information provided by a 3-axial accelerometer, which allows us recognizing, for example, when the ODL is touched, moved or turned.

5.2.5 Human-activity recognition algorithms

Currently, in ADA, with the purpose of testing the overall feasibility of the system, we implemented a threshold-based algorithms to recognize two activities: drinking water and taking pills. Other HAR algorithms can be easily added by following a similar approach. Algorithm 1 shows, in particular, the pseudo-code for recognizing the drinking water activity. This requires to stick two tags, one on the cap of the bottle and one on the bottom, to recognize the following sequence of actions: the bottle is picked up, the cap is unscrewed, and the water is finally poured. The algorithm starts by searching for nearby BLE beacons (line 1). If beacons associated to the ADL are recognized, RSSI values are gathered (lines 2-3). When

```
{
     "adls": [#from_zero_to_N_coachee_actions
     {
      "coach_action": [
      {
       "chronology_coach_action": [],
       "week_day_select": [
           false,
           true,
           true,
           true,
           true,
           true,
           true
           ],
       "description": "'possible description'",
       "event": "", "from_hour": "",
       "name": "Drink Water",
       "number_repetitions": "8",
       "repeat_every": "2",
       "time_start_repeats": "7:30",
       "time_to_take": "", "to_hour": "",
       "status": "done",
       "caregivers_id": "58ee2632-adf9-49b0-",
       }],
      }],
     "caregiver_id": [ #from_zero_to_C_caregivers
       "58ee2632-adf9-49b0-83d0"
     ],
     "birthday": "09/05/1949",
     "cf": "EDWALD",
     "name": "Edward",
     "surname": "Alderson",
     "type": "coachee"
}
```

Fig. 5.5: Coachee JSON data format.

the estimated distance is lower than 10cm, then accelerometer data are continuously gathered to detect the sequence of actions (lines 4-8). Finally, if flags *move*, *unscrew*, and *pour* become true in one of the accepted orders[4], then the target ADL is recognized (line 9). It should be noted that functions *on_move*(Acc_x, Acc_y, Acc_z, I), *on_unscrew*(Acc_x, Acc_y, Acc_z, I),

[4] {move, unscrew, pour} or {move*, unscrew, move*, pour} or {pour*, move*, unscrew, move*, pour}, where * means the action is repeated more than once.

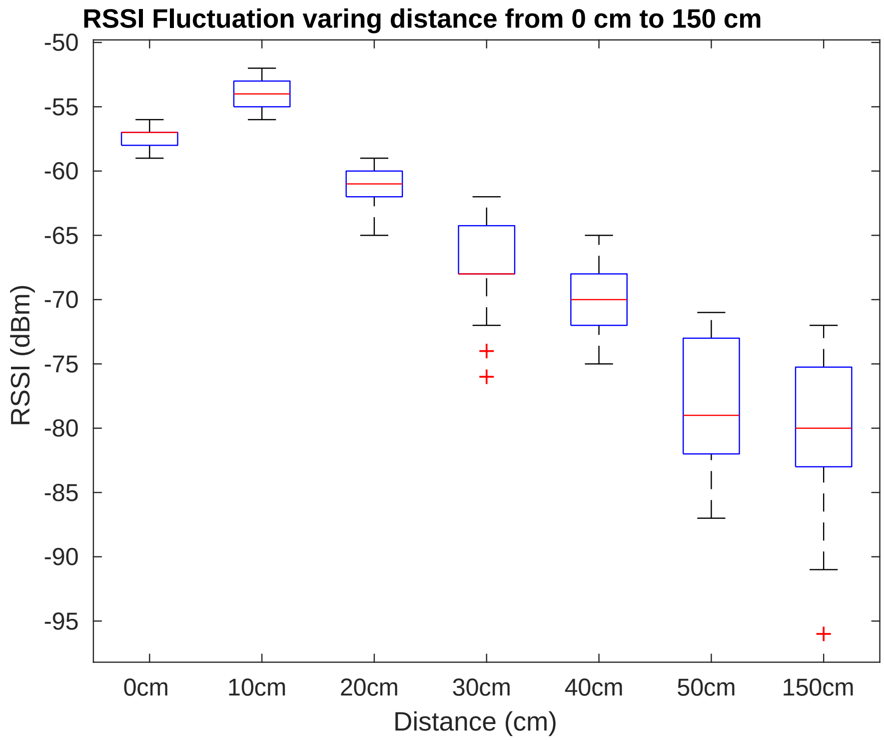


Fig. 5.6: Relation between RSSI measurements and distance of the object (emitter) from the smartwatch (receiver).

Algorithm 1: HAR algorithm for drinking water

```
while true do
    beacons = start_beacons_scan();
    if beacons matches drinking water then
        RSSI = get_RSSI(beacons);
        if check_distance(RSSI) < 10cm then
            move = on_move(Acc_x, Acc_y, Acc_z, I);
            unscrew = on_unscrew(Acc_x, Acc_y, Acc_z, I);
            pour = on_pour(acc_x, acc_y, acc_z, I);
            return(check_seq(move, unscrew, pour));
```

(a) over (b) right (c) left (d) direct (e) hold

Fig. 5.7: Hand Positions in relation with the BLE emitter

and $on\_pour(acc_x, acc_y, acc_z, I)$ are not machine learning functions but are threshold models that recognize a succession of acceleration values beyond such defined thresholds.

5.3 Experimental results

The experimental results have been performed by exploiting Estimote BLE beacons and two different smartwatches: Hexiwear[5] (approx. 60 Euros) and Ticwatch S[6](approx. 150 Euros).

The system has been evaluated by three different persons w.r.t. drinking water and taking pills, Table 5.1. The first was set up as a periodic coaching action to be performed at least 3 times per day, the second as a precise coaching action to be done at 4 different times during each day. The tester persons used ADA for two weeks. They knew what ADA does from the functional point of view, but they had no knowledge on how it works. They were asked to intentionally forget accomplishing the actions some times every day, and also using the ODLs without wearing the smartwatch, with the purpose of testing the accuracy.

At the end of the experimental campaign, we observed the achieved accuracy w.r.t. the recognition of the target ADLs and the activation of the incremental coaching, when necessary, was 100%, with neither false positives nor false negatives. More in detail we observed that:

[5] https://www.hexiwear.com
[6] https://www.mobvoi.com/us/products/ticwatch-s

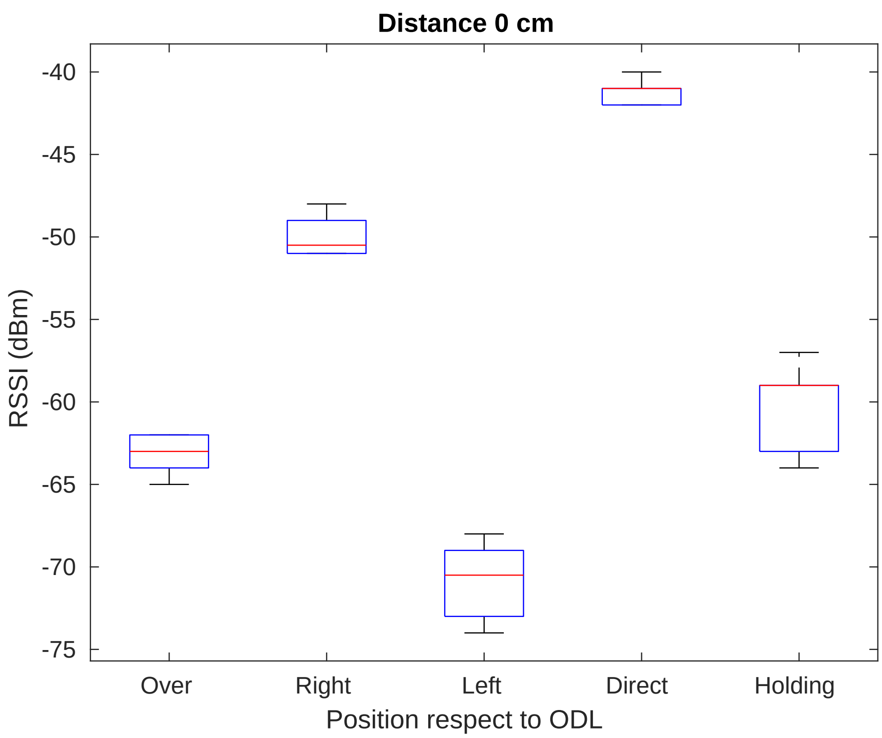


Fig. 5.8: Receiver position w.r.t. emitter position at approximately 0cm.

Coach Action	Action Type	Daily Repetitions	*AnP*	Performed ADLs	Forgotten ADLs	False Positives	True Positives	False Negatives	True Negatives	Accuracy
Drink Water	periodic	3	1	36	18	0	36	0	18	100%
Take Medicine	precise	4	1	54	18	0	54	0	18	100%

AnP → Action not performed on purpose

Table 5.1: Validation tests and Results

- when ODLs were used without wearing the smartwatch, the activity was not recognized as done; for example, ADA realized the water was poured but not by the right person, due to lack of proximity to the bottle;
- RSSI alone works well for detecting proximity to ODLs and also their movement, but estimation of more precise information on pouring and unscrewing requires the use of the 3-axis accelerometer;
- we failed in confusing ADA by acting on the target ODLs differently from how the coaching action expects. For example, Table 5.2 shows actions we performed trying to confound the system w.r.t. drinking water. In particular, columns of Table 5.2 show, respectively, first a brief description of the activity, then if only moving, or moving followed by unscrewing, or moving followed by unscrewing and then pouring was recognized (results for the cheaper smartwatch on the left, for the more expensive on the right of each column), and finally if drinking water was definitely detected as done. As shown, only "shaking the bottle insistently for more than 10 seconds" tricked ADA leading it to erroneously recognize drinking water.

Finally, we evaluated ADA from the point of view of battery consumption. BLE tag's battery lasted for at list one year (time required to define and develop the overall ADA system, during which the tags were always switched on). The most energivorous part of ADA is the coaching application running on the smartwatch, since it must remains always active to continuously scan for BLE signals. Running the application on the cheaper smartwatch consumes the battery in approximately two hours, while the same application in the more expensive one guarantees the battery lasts for one day, which reasonably fits the purpose of ADA. Battery consumption for the caregiver application is negligible.

5.4 Summary

In conclusion, in this chapter, we presented ADA, a virtual coaching system for supporting elderly in the acquisition of new behaviors to accomplish necessary ADLs. ADA is based on the idea of making everyday objects intelligent by gluing to them BLE smart stickers that emit uniquely recognizable radio signals through which proximity motion and other environmental parameters can be estimated to monitor user activities. A couple of mobile applications, interacting with BLE tags, provides a ubiquitous, non-invasive, incremental coaching process for elderly and continuous monitoring for caregivers. In the experiments, we proved that RSSI analysis in a short-range scenario (< 1 meter) is accurate enough to recognize the position of

Activity	Move		Unscrew Move		Pour Unscrew Move		Drinking water recognized	
Bottle falls on the table	✓	✓	✗	✗	✗	✗	✗	✗
Briskly moving the bottle (>5s)	✓	✓	✗	✗	✗	✗	✗	✗
Slowly moving the bottle (>5s)	✓	✓	✗	✗	✗	✗	✗	✗
Walking with the bottle	✓	✓	✗	✓	✗	✗	✗	✗
Moving without unscrew	✓	✓	✗	✗	✗	✗	✗	✗
Pouring without unscrewing	✓	✓	✗	✗	✗	✗	✗	✗
Unscrewing without pouring	✓	✓	✓	✓	✗	✗	✗	✗
Quickly moving the bottle (3-5s)	✓	✓	✗	✓	✗	✗	✗	✗
Insistently shaking the bottle (>10s)	✓	✓	✓	✓	✓	✓	✓	✓
Bottle falls to the floor	✓	✓	✗	✗	✗	✗	✗	✗

Table 5.2: Actions tested to confound ADA w.r.t. drinking water.

the tags w.r.t. the user. This allows ADA, including also the elaboration of accelerometer data, recognizing complex activities, like drinking water and taking pills, with 100% accuracy. Concerning energy consumption, we experienced that the battery of the elder's smartwatch lasts for at least one day, which fits the coaching purpose of ADA. Future work will be devoted to develop and integrate into ADA further HAR algorithms to support a more significant number of ADLs.

6

A graph-based approach for mobile localization exploiting real and virtual landmarks

As already presented in Chapter 3, since that Smart Home Platform for Intelligent Assistance (SHPIA) architecture transmits data over radio signal frequencies (WiFi/BLE) it provides the possibility to use such signals regarding the implementation of an indoor localization systems. A localization system is a technique for estimating the position of people and objects within a specific environment without any knowledge of previous locations. They can be roughly categorized either in radio–based (i.e. exploiting Radio Frequency (RF) [156], Radio Frequency IDentification (RFID) [157], ZigBee or Wireless Local Area Network (WLAN) [158]) or non radio–based (i.e. based on light impulse [159], sound [160], vibration [161], or magnetic field [114, 162] techniques). In general, localization systems exploit the knowledge of several sensor measurements, for instance the Received Signal Strength Indicator (RSSI) relevant to beacons sent by Wi-Fi Access Point (AP) to estimate the distance from known anchor points [195]. In last decades, they gained increased popularity in several areas, exploiting different technologies on both hardware and software sides, to support applications such as navigation, localization and monitoring, in the fields of security, management, health–care, etc. Even more, in the Internet of Things (IoT) context, localization systems constitute one of the fundamental components [163]. Despite this, it is worth highlighting that existing solutions are often subjected to several design and implementation issues [164, 165], mainly due to environmental constraints, involved devices and signal features.

On the one hand, in outdoor environment, where a common choice is to use Global Positioning System (GPS) or other satellite–based systems, the presence of obstacles and buildings may hinder received signals, and in addition such techniques require specific, complex and quite expensive components. Analogously, in the case of indoor radio–based localization, we have to consider that signal propagation depends on walls thickness, obstacles, number of people, etc., which may cause issues like shadow fading and multipath propagation [111]. Furthermore, localization in indoor environment (where GPS system lacks accuracy or may even become unavailable) is still a relevant open point and there is not a general consensus on the solutions to be deployed in this scenario. Indeed, many indoor positioning systems have been proposed during time, which differentiate on the basis of the employed technologies. A typical result is that, to obtain a reasonable accuracy, localization is performed exploiting quite complex architectures, which in turn impair either on the cost and availability of the technological infrastructure for the target environment, and/or on the time, power and computational resources necessary to run (and in some case, to train) the localization algorithm.

A significant example comes from the fingerprinting technique, which is becoming a very popular positioning method for indoor localization where it may achieve, under well specific circumstances, an accuracy in the order of decimeters [114, 165]. In fingerprinting, the environment is subdivided in sub–areas, and the user is able to univocally identify the sub–area to which she/he belongs exploiting specific algorithms based on different metrics (RSSI from WiFi and Bluetooth sources, Magnetic Field value, etc.). Nevertheless, despite the potential of fingerprinting techniques (for instance IndoorAtlas [114]) we should also take into account some relevant issues in terms of human intervention due to the initial *learning* phase, computational effort required by the algorithm for the *localization* phase, and unavoidable impairments affecting the input metrics, given the dependence of radio signals on external factors. The drawbacks highlighted above make several existing solutions unattractive for low-cost and resource-bounded application scenarios [165]. The goal of this work is hence to overcome some of the aforementioned limitations, in particular avoiding the initial learning phase, typical of fingerprinting, and introducing a computational efficient algorithm.

To this aim, the thesis work presents a radio-based positioning algorithm that localizes the user by exploiting a graph-based representation of the environment with respect to a set of real and virtual radio signal emitters (*landmarks*). The most significant characteristics of the proposed approach are:

- reuse of existing infrastructures (for instance, the AP of an existing WLAN installation and BLE tags of the SHPIA architecture);
- lightweight computation on mobile devices;
- introduction of the *virtual landmark concept;*
- ease of extension to other protocols (e.g. AltBeacon).

6.1 Preliminaries

This section briefly introduces some preliminary definitions required for the description of the proposed approach.

6.1.1 Technologies and Devices

Wireless communication technologies are highly pervasive and surround us in everyday life, the most widespread being WiFi and Bluetooth systems based on the IEEE 802.11 and IEEE 802.15.1 communication standards, respectively. The System on a Chip (SoC) of common mobile devices nowadays always include both technologies, making them highly available even in low–cost and resource–bounded scenarios. Although these technologies lead to very different communication systems, both can be effectively exploited for indoor localization purposes. Indeed, IEEE 802.11 infrastructure networks (the most widespread ones) are managed by an AP, a specific network device that periodically transmit *beacon* frames to signal the presence of the AP itself, and that contain information about the network. Analogously, in Personal Area Networks (PAN) based on Bluetooth, it is possible to introduce devices called Beacon, that are special hardware components periodically broadcasting a Bluetooth frame in a well–defined format (for instance iBeacon, EddyStone or AltBeacon). Independently of the adopted communication standard, these data frames allow a receiver to univocally recognize the sender, whose position is fixed and known *a priori*, and also to obtain a rough estimation of the distance between them, based on the knowledge of the received power of each data frame (e.g. RSSI).

6.1.2 Fingerprinting

In the considered communication standards, and in many others as well, devices are required to provide a mean to express the perceived power relevant to a received data frame. A widespread metrics is provided by the *Received Signal Strength Indicator (RSSI)*, which in particular is an indication of the power level being received after antenna and cable loss. This value is often reported as an integer within a predefined range (typically an 8-bit field), where typically higher values of RSSI correspond to stronger received signal [164]. In different localization techniques, fingerprinting being one of the prominent examples, such measurement is largely exploited [165]. Nonetheless, we should also recall that RSSI presents some important issues, for instance due to inaccurate RSSI readings obtained by different transceivers [196], or to impairment of the radio signal [111], which has a high sensitivity to environmental phenomena, causing considerable signal variation hence impairing on the localization accuracy. Within this approach, the available area is divided in Reference Point (RP). The distance between any two RPs can be maintained either equal or not (i.e. RPs are not equally spaced). Each RP_k is identified by a couple, (x_k, y_k) of Cartesian coordinates and a matrix r_k of RSSI values recorded from the center of the RP:

$$r_k = \begin{bmatrix} rssi_0^0 & rssi_0^1 & \dots & rssi_0^n \\ rssi_1^0 & rssi_1^1 & \dots & rssi_1^n \\ rssi_2^0 & rssi_2^1 & \dots & rssi_2^n \\ \vdots & \vdots & \ddots & \vdots \\ rssi_m^0 & rssi_m^1 & \dots & rssi_m^n \end{bmatrix}$$

where, for a generic $rssi_i^j$ element, j represents the RSSI source index (for example, an AP), and i represents the recording timestamp. For the sake of completeness, the fingerprinting technique is not constrained only to use RSSI values, since other types of data, e.g., magnetic vector, can be associated to each RP, provided they allow to uniquely identify the RP [162].

6.2 Methodology

With reference to Figure 6.1, the proposed approach is composed of two phases:

i) *Off-line graph construction*: a graph model of the environment is constructed starting from the knowledge about the location of a set of landmarks;

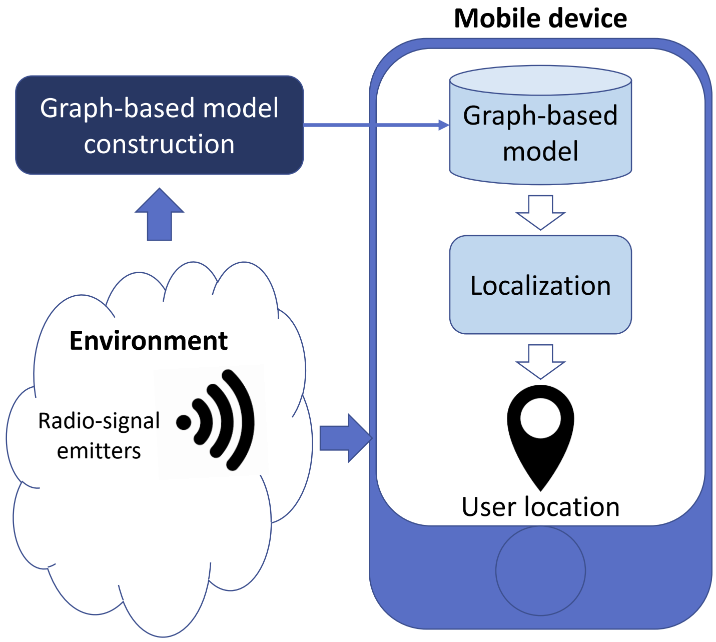


Fig. 6.1: Overview of the proposed approach.

ii) *On-line localization*: an application, running on the user's mobile device, loads and exploits the previously created graph model to compute the most probable location of the user within the environment, driving its decision through landmarks emitted signals and the user's direction.

6.2.1 Landmarks

In our approach, two kind of landmarks are considered: real landmarks and virtual landmarks. A **real landmark** is defined as a uniquely identifiable radio signal emitter (e.g., AP or Bluetooth Low Energy (BLE) Beacon) that is located in a known and fixed position. It identifies a *sub–area* of the environment where the RSSI values measured by a receiver are greater than a fixed threshold. Such a sub-area represents the **range of action** of the landmark. The **threshold** is set as:

$$T_{RSSI} = -(10 * n) * log(r) + TxPower \qquad [\text{dBm}] \tag{6.1}$$

where r is the desired range of action for the landmark in meters, n is the path loss index (normally $n = 2$) and *TxPower* refers to the landmark transmission power, expressed in dBm [164]. When the RSSI values received by the user are above the threshold, we localize the user in the range of action associated to the corresponding landmark. Smaller are the ranges of action, more accurate is the localization of the user. However, the range of action of each real landmark cannot be arbitrarily reduced, as we need to avoid having uncovered sub-areas where the user cannot be localized. Each threshold is then set according to the number of real landmarks and their distribution in the environment to reduce the risk of black holes, where the user cannot be

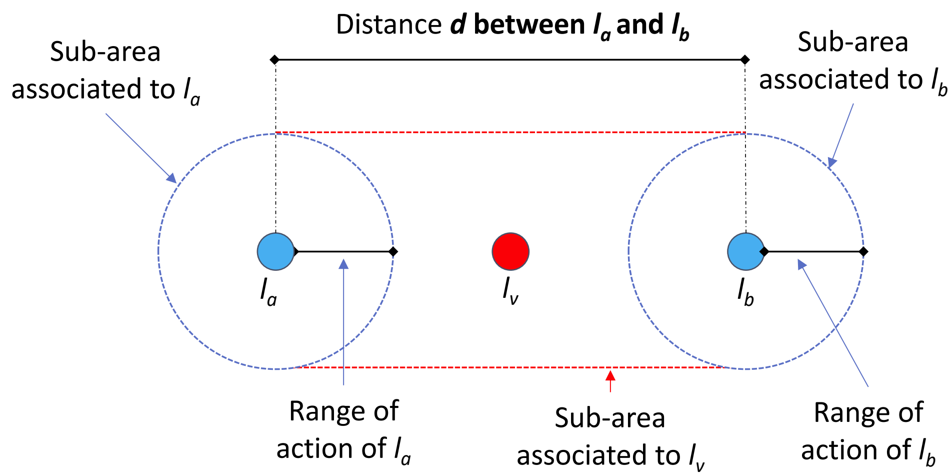


Fig. 6.2: Real and virtual landmarks.

localized.

In order to further increase the accuracy of the localization approach was introduce the concept of **virtual landmark**. Since it does not physically exist, it does not emit any signal. Anyway it is associated to a specific sub–area between two real landmarks. In particular, we virtualize the presence of one virtual landmark l_v between every couple of real landmarks (l_a, l_b), as shown in Figure 6.2. The thresholds of l_a and l_b are set such that their ranges of action are 1/4 of the physical distance d between l_a and l_b, i.e., $range(l_a) = range(l_b) = d/4$. When the signal received by the user in a given position is lower than the thresholds of the nearest real landmarks, we localize the user in the range of action of the nearest virtual landmark, according to his/her previous position with respect to the last visited real landmark, and his/her movement direction. For example, consider Figure 6.2. If, at time t, the user is located in the sub-area of l_a, and it is moving towards east (according to the information gathered by the sensors on the mobile device), as soon as the RSSI received by the device is lower than the threshold of l_a, our approach locates the user in the sub–area represented by l_v. The introduction of virtual landmarks and the sensing of the user's movement direction allow us increasing the number of *sub-areas* in the environment, thus improving the accuracy of the proposed localization approach without increasing the number of real landmarks.

6.2.2 Graph construction

Given the concept of real and virtual landmarks, the first phase of the localization approach creates a graph-based model of the environment according to the following definition.

A graph-based model is a tuple $G = (L, E, O, D, R, T)$ where:

- L=$\{\{L_r\} \cup \{L_v\}\}$ is the set of real and virtual landmarks;
- $E = \{(l_i, l_j) | l_i \in L_r \text{ and } l_j \in L_V\}$ is the set of edges between landmarks;

- $O : E \rightarrow C$ is an labeling function that assigns to each edge $e = (l_i, l_j) \in E$ a cardinal direction $c \in C = \{N, NE, E, SE, S, SE, W, NW\}$ representing that a user can reach l_j from l_i moving towards the direction c;
- $D : E \rightarrow \mathbb{R}$ is a labeling function that assigns to each edge $e \in E$ a length $d \in \mathbb{R}$ representing the distance between the landmarks connected by e;
- $R : L \rightarrow \mathbb{R}$ is a labelling function that assigns to each landmark $l \in L$ its range of action $r \in \mathbb{R}$;
- $T : L_r \rightarrow \mathbb{R}$ is a labelling function that assigns to each real landmark $l_r \in L_r$ its threshold $th \in \mathbb{R}$.

An example of a graph-based model is shown in Figure 6.3. Note that two neighbour landmarks are always connected by two edges, with opposite cardinal directions to represent that a user can move from one landmark to the other and vice versa.

Algorithm 2: Graph-based model generation

Input: *Real landmark positions (pos_L), and wall/obstacle positions (pos_W)*
Result: *Graph-based model of the environment (G)*

$G \leftarrow create\_graph(pos_L, pos_W)$;
$G.L_v \leftarrow \emptyset$ //set of virtual landmarks;
for $l_i \in G.L_r$ **do**
    $r_i \leftarrow set\_range(l_i, neighbors(l_i))$;
    $th_i \leftarrow set\_threshold(l_i, r_i)$;
end
for $e_1, e_2 \in G.E$ *//connecting two real landmarks* **do**
    $G.L_v \leftarrow G.L_v \cup add\_v\_landmark(e_1, e_2)$;
    $G.E \leftarrow update(G.L_v)$;
end
return G

Algorithm 2 explains the graph construction procedure. It takes in input the positions within the environment of real landmarks and walls/obstacles, and it returns the graph-based model according to the previous definition.

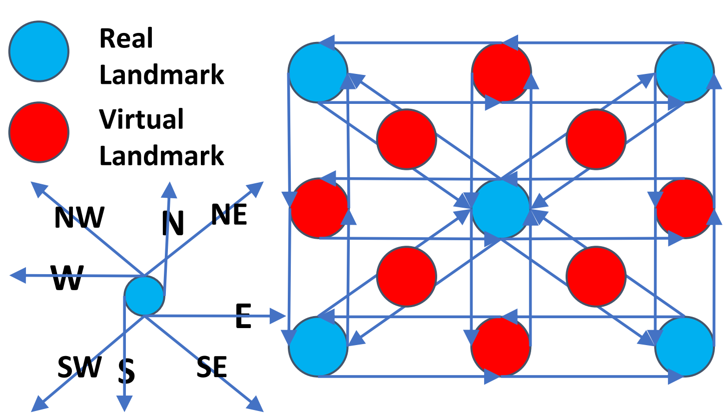


Fig. 6.3: Example of a graph model of the environment.

The procedure creates a graph composed of only real landmarks, according to their positions in the environment and taking care of constraints due to walls and obstacles (line 1). At this time, thresholds and ranges of action of real landmarks are not yet defined and the set of virtual landmarks is empty (line 2). Therefore, for each real landmark l_i, it sets its range of action and its threshold according to the distance between l_i and its neighbors (lines 3-5). In particular, the function *set_range* and *set_threshold* set the range of action and the threshold for l_i as follows:

1. select the nearest neighbour l_j of l_i according to the graph G;
2. set the range of action of l_i as $r = d/4$, where d is the distance between l_i and l_j;
3. given the range r set the threshold of l_i according to the equation 6.1 reported in Section 6.2.

Then, for each couple of edges e_1, e_2 connecting two real landmarks l_i and l_j, respectively with cardinal direction from l_i to l_j and vice-versa, the graph is updated as follows to insert virtual landmarks:

1. add a virtual landmark l_v with range of action $r_v = (d - r_i - r_j)/2$, where d is the distance between l_i and l_j, and r_i, r_j represent the ranges of action, respectively, of l_i and l_j;
2. remove e_1 and add two new edges connecting l_v with l_i and l_j whose lengths are, respectively, $r_i + r_v$ and $r_j + r_v$.
3. set the cardinal direction of the two new edges equal to the cardinal direction of e_1.
4. repeat actions 2 and 3 for e_2.

6.2.3 Localization

According to the graph-based model created by Algorithm 2, our system univocally localizes the user inside the sub-area corresponding to the range of action of the nearest landmark with respect to his/her actual position in the environment. The sub-area, returned by the localization algorithm refers to the area identified by the real or virtual landmark. Therefore, the returned position is not in terms of absolute position (pos_x, pos_y) but identifies a surface within which the measured RSSI, of the signal emitted by the real landmark, is higher or smaller than the threshold. Consequently, there is an error directly proportional to the size of the location identified by the landmark. Furthermore, the proposed approach implements a navigation mode for indoor environment.

The localization works as shown in Algorithm 3. The background process *wait_event*() (line 1) activates whenever one of the following event happens:

- *Event 1:* the transceiver of the mobile device perceives a radio signal emitted by a real landmark l_r and the measured RSSI value is higher than the threshold defined for such a landmark; this means that the user is located in the range of action of a real landmark;
- *Event 2:* the transceiver of the mobile device stops perceiving a radio signal emitted by a landmark or the measured RSSI value becomes smaller than the threshold defined for such a landmark. This means the user entered in the range of action of a virtual landmark l_v.

When Event 1 happens, the real landmark l_r associated to the perceived signal is identified and stored into a list of visited landmarks (lines 3-4). Then, it is returned as the current location

Algorithm 3: Localization

```
  Input: Graph-based model of the environment (G)
  Result: Location of the user (location)
1 event ← wait_event();
2 if event == Event 1 then
3     l_r ← get_real_landmark();
4     visited_landmarks.push(l_r);
5     location ← l_r;
6 else if event == Event 2 then
7     last_l_r ← visited_landmarks.pop();
8     c ← sense_movement_direction();
9     location ← get_virtual_landmark(G, last_l_r, c) ;
```

of the user (line 5). When Event 2 happens the algorithm extracts from the list the last real landmark l_r visited by the user (line 7) and it senses the movement cardinal direction c of the mobile device (line 8). Then, it makes a query to the graph model to retrieve the virtual landmark l_v adjacent to l_r such that l_v and l_r are connected by an edge whose cardinal direction is c (line 9). Such a virtual landmark is finally returned as current location of the user.

On the basis of the localization mechanism a shortest-path Dijkstra-based algorithm has been also implemented to provide a navigation system that guides the user between two arbitrary landmarks belonging to the same graph.

6.2.4 Navigation

Besides, this approach also includes a navigation mode based on the proposed graph model. The navigation mode, Algorithm 4, takes in input a target location (l_t) and returns the shortest *path*, form current location (l_c) to target location (l_t). The *shortest path* P, is defined as: $P = \{l_c, l_{c+1}, \ldots l_t \; | l_c, l_{c+1}, \ldots l_t \in V\}$. Furthermore, the application returns to the user the correct

Algorithm 4: Navigation

```
Input: Target Location (l_t)
Result: Path to target Location (path)
l_c = Localization();
path = Dijkstra(l_c, l_t);
while l_c ≠ l_t ∧ on_change() do
    l_c = Localization();
    path = Dijkstra(l_c, l_t);
    if on_direction_change() then
        update_indications();
    if wrong_direction(path, direction) then
        Alert();
return path
```

direction to the target position, updating the indication each time that the user direction changes,

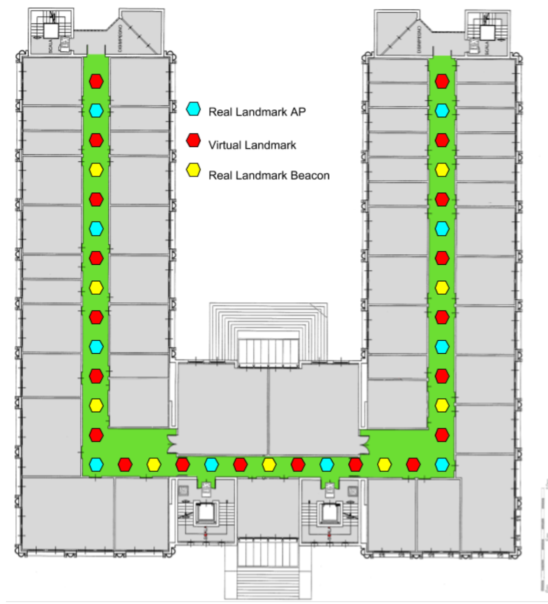


Fig. 6.4: Map of the *indoor* environment — $Id = 3$

based on compass Android API call (*on_change*()), regardless of the position in which the user is holding the phone.

6.3 Experimental Campaign

In this section the outcomes of a thorough and extensive experimental campaign are presented, based on the application of the proposed localization method. The experiments have been carried out both in indoor and outdoor environments. Furthermore, exploiting the same setups, we also performed a performance comparison between the outcomes obtained from our proposal and those obtained through the adoption of another popular localization platform, namely InDoorAtlas [114], as better detailed in the following.

6.3.1 Environment and devices characteristics

We performed our tests in two different environments, one for assessing indoor localization performance and another for assessing outdoor ones. The former indoor environment is located at the second floor of the Department of Computer Science building at the University of Verona, with a total area of $256\,m^2$. Figure 6.4 provides the actual map of this indoor environment, where we had permission to perform experiment only in the corridors represented by the green area, for security and privacy concerns.

The outdoor experiments were performed in the parking pertaining to the same Department, whose map is reported in Figure 6.5 and which is extended over an area of $3000\,m^2$. In this scenario, movements within the area were allowed to occur only in walkable roads.

To provide a thorough assessment, six different experiments have been carried out: four within the indoor environment (identified with *Id*=1..4) and two in the outdoor environment (*Id*=5..6).

To implement the real landmarks in the experimental campaign, we exploited both BLE beacon devices and IEEE 802.11 AP. For the sake of comprehensiveness, in each experiment the proposed localization technique has been tested with different sets (and combination) of real landmarks on the basis of the peculiarities of the environment where each test has been carried out. Table 6.1 presents the characteristics of the devices adopted to implement real landmarks.

In particular, tests in the indoor environment exploited any of the four possible combinations of BLE beacon devices and IEEE 802.11 beacon frames from APs of the existing WiFi network infrastructure. Conversely, in the outdoor area the application was tested at first using only BLE beacons devices, then adding a further set of simulated beacons obtained through a specific and purposely-developed mobile application (third row in Table 6.1). Finally, for the sake of completeness, we have reported in Table 6.2 data relevant to the users (ID and Height) and mobile devices characteristics (Smartphone model and operating system).

Table 6.1: Real landmark characteristics

Type	Name	Producer	Tx Power	Protocol
BLE Beacon	Location Beacons	Estimote, Inc	-16 dBm	iBeacon/EddyStone
AP	Aironet 2602i	Cisco	-17 dBm	IEEE 802.11 beacons
Beacon Simulator	Android App	Android App	-16 dBm	iBeacon/EddyStone

In this experimental campaign we evaluated the performance of the proposed localization method on the basis of two metrics:

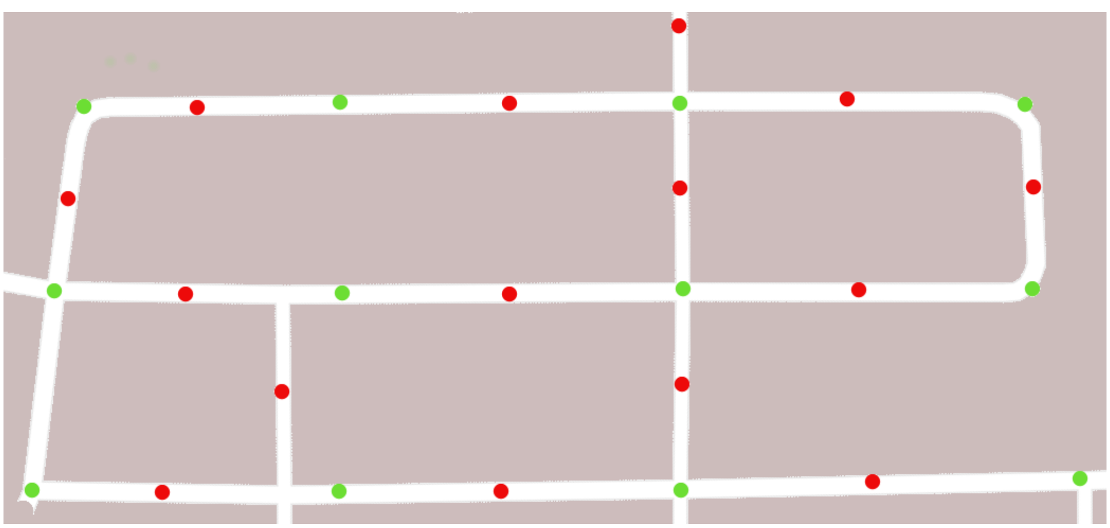


Fig. 6.5: Map of the *outdoor* environment — *Id* = 5

- *sub-area error*: this occurs when the localization algorithm fails to match the correct sub-area (i.e., landmark) with the real user location.
- *absolute accuracy*: distance in meters between the real and the estimated position.

Table 6.2: Users characteristics

User ID	Height	SmartPhone	Operating System
1	1.70 m	Nexus 5	Android 6.0.1
2	1.75 m	Huawei P9 lite	Android 6.0.1
3	1.95 m	Samsung Galaxy S7 Edge	Android 7.0.1

6.3.2 Experimental Results

A resume of the obtained outcomes is reported in Table 6.3, where we show experimental results, for both the indoor and the outdoor scenarios (Column 2), at varying the type of real landmarks (Column 4), their number (Column 5), the number of virtual landmarks (Column 6), and the range of action of the real landmark associated to the smallest sub–area (Column 7). For example, the row with $Id = 3$ represents the situation depicted in Figure 6.4, where the indoor area was divided into 39 sub–areas: 19 of them were associated to real landmarks (in Figure 6.4 APs and BLE Beacons are depicted in blue and yellow, respectively), while 20 sub–areas were associated to virtual landmarks (depicted in red). Conversely, the row with $Id = 5$ refers to the outdoor configuration reported in Figure 6.5, with 12 real landmarks (green nodes in the figure), and 15 virtual landmarks (red nodes). As it can be observed looking at Column 8, our approach resulted in a zero error rate in terms of sub-area localization, i.e. the user was always located in the correct sub–area. Moreover, even if the user enters one of the offices (grey sub–areas in Figure 6.4) the localization pointer remained correctly in the nearest sub-area.

In Column 9 the localization accuracy is reported, which is related to the range of action r of the adopted landmarks (in meters) and hence for each experiment varies between the range of the smallest and the largest sub–areas where the user was localized, and clearly improves with the increase of the number of real landmarks.

Columns 12 and 13 show instead, respectively, localization error and the absolute accuracy when the localization algorithm of Section 6.2.3.C was used by considering only real landmarks. In this configuration, we observed several localization errors, primarily due to the user entering sub-areas where no known signal (or $signal \leq threshold$) was perceived. In this case we have no meaningful information about user location and hence in the worst case, the error may tend to the number of sub-areas n_{sa} (column 12). Looking at the accuracy, in the best case it still depends on the range of action of the landmarks (r) and having maintained the same thresholds throughout the same experiment Id, the values are the same as in Column 7. In the worst case, instead, the accuracy deteriorates to $n_{sa} \times r$ meters (column 13).

This experiment hence definitely proves the benefits derived from the introduction of the virtual landmarks.

Table 6.3: Experimental Results

Experiment setup							Our approach		InDoorAtlas [114]		Without virtual landmarks	
Id	Environment	Area dimension m^2	Landmarks type	Number of real landmarks	Number of virtual landmarks	Minimum action range (m)	Error (sub-areas)	Accuracy (m) (min, max)	Error (sub-areas)	Accuracy (m) (min, max)	Error (sub-areas)	Accuracy(m) (min, max)
1	InDoor	256	Beacons	10	11	4	0	4,6	4	1,≥8	n_{sa}	4,($n_{sa} \times r$)
2	InDoor	256	AP	10	11	4	0	4,6	4	1,≥8	n_{sa}	4,($n_{sa} \times r$)
3	InDoor	256	Beacons+AP	19	20	4	0	4,6	4	1,≥8	n_{sa}	4,($n_{sa} \times r$)
4	InDoor	256	Beacons	30	32	2	0	2,5	8	1,≥8	n_{sa}	2,($n_{sa} \times r$)
5	OutDoor	3000	Beacons	12	15	10	0	10,50	3	1,≥8	n_{sa}	10,($n_{sa} \times r$)
6	OutDoor	3000	Beacons	24	24	5	0	5,20	~	~	n_{sa}	5,($n_{sa} \times r$)

~ = not performed for lack of beacon devices n_{sa} = defines the number of *sub-areas*

As a final note, during all the experiments the users followed different paths, performing changes of direction, accelerations and decelerations of the movements. Our system was able to localize the users correctly independently of the followed path, without variations in the sub-area errors and absolute accuracy. This proves that the proposed approach is not error-prone with respect to issues like the variation of the RSSI values and irregularities in the movement, which indeed may negatively affect solutions based on fingerprinting and sensor fusion.

6.3.3 Comparison with InDoorAtlas

We also carried out a comparison with InDoorAtlas [114]. This is a fingerprinting localization platform that is based on a preliminary learning phase of the environment. This phase consists on the collection of data (learning dataset) by different sources, such as magnetic field and RSSI levels, coming from selected positions called RP. At runtime, during the *online* phase, the localization algorithm continuously monitors the same types of sources, and returns the current location based on an estimation carried out by exploiting the learning dataset. Looking at Table 6.3, Columns 10 and 11 report the localization error and the absolute accuracy for the InDoorAtlas solution. For a fair comparison, the number of fingerprints was set equal to the number of landmarks. Exploiting InDoorAtlas in the indoor environment, in the same conditions, we obtained up to 8 ($Id = 4$) sub-area localization errors, since this platform keeps evolving its estimation based on the direction and the acceleration of the user at the last predicted location. Comparing the localization absolute accuracy, it is worth observing that our approach shows the best accuracy in correspondence of the smallest landmark range, but the accuracy worsen when large virtual landmark range are employed. Conversely, InDoorAtlas in the best case resulted to be more accurate than our approach, while in the worst case it provides a lower accuracy, stemming from the limitations stated above.

We also performed a test with InDoorAtlas in the outdoor scenario, although we are aware of the fact that this platform was designed for indoor localization. Nonetheless, in the outdoor environment, it showed a localization error in 3 cases, compared with no error found with our method. The localization accuracy is instead in the range of one meter when the user is very close to the RPs, becoming greater than 8 meters in the other points.

It is worth highlighting that more data are collected during the learning phase of InDoorAtlas, more accurate the localization in the online phase is. However, it should also taken into account that this learning phase is particularly time-consuming and it drastically increases with the area dimension. Indeed, as a figure of merit, to perform the learning phase in experiment with Id=3 (with 39 landmarks) we spent 25 minutes, which became 40 minutes in the case of experiment *Id*=5 (with 27 landmarks) due to the larger area dimension and distance between landmarks. In addition, this platform bases the learning phase also on data collected from the accelerometer and gyroscope sensors of the mobile device, which are then used to calculate distances among different RPs and direction from one RP to another. This hence imposes an increased attention and caution during the learning phase.

6.3.4 Battery consumption

The final figure of merit we aim to provide is relevant to a qualitative estimation of the battery consumption. Our approach provided slightly better performance with respect to InDooAtlas in this regards. Indeed, using the proposed approach on the three devices reported in Table 6.2, we found that the mean battery consumption, due to the designed application, was about 11% of the total consumption per hour. Conversely, using InDoorAtlas during the same tests, we found a mean consumption of about 13% of the total consumption per hour.

6.4 Limitations and Future Works

The proposed localization method is based on perceived RSSI values to identify real landmarks, and on the last perceived real landmark and user direction to identify virtual landmarks. Some limitations exist with our current approach. At first, it is theoretically possible to receive two different beacons whose RSSI level is above the threshold. However, since the threshold is set considering the distance between two real landmarks according to Eq. 6.1 and Algorithm 2, this should happen with a quite low probability. We are refining the proposed algorithm in order to recognize and solve such situations. Secondly, we actually do not consider the movement of the users, and this in some cases can be a limitation of the approach. Furthermore, taking as example Figure 6.3, if the user is located in the virtual landmark at the top of the graph model and moves directly to another virtual landmark, then our proposal may return a wrong location. This may be avoided, for example, exploiting the mobile device accelerometer by implementing a step counter. This further development of the application introduces a higher number of virtual landmarks, hence increasing the accuracy of the system.

In conclusion, this Chapter proposed a localization and navigation approach based on real landmarks represented by the radio-signal emitters existing in the target environment. A graph-based model of such an environment is automatically created, and virtual landmarks are added to increase the accuracy of the localization without requiring the introduction of further radio-signal emitters.

The presence of virtual landmarks allowed to reduce the range of actions of real landmarks (and then their thresholds) making this approach less susceptible to errors due to outliers signal values, users body, or obstacles, unlike existing techniques base on signal analysis. A comparison was made between the proposed approach and a commercial localization platform. The results demonstrated that our approach provides advantages in both the accuracy in identifying the user location and the battery consumption of the mobile device used for the localization application.

7

Virtual Coaching System in Parkinson's disease

Freezing of Gait (FoG) is a seriously debilitating symptom of Parkinson's disease and is defined as a brief episode within which the patient manifests an inability to continue or start normal walking. FoG causes gait to halt and may culminate with a fall and consequent physical and psychological damages [197]. As reported in [198], out of a total of 6620 patients, almost half of them claim to occasionally present FoG events, while 28% of them experience FoG episodes daily. Current symptomatic medical treatments ameliorate Parkinson's Disease (PD) motor symptoms, but they often do not address FoG [199]. In addition, evaluating FoG is an arduous task because this event depends on both environmental and psychological factors. For example, when a PD patient walks in a door, the probability of FoG increases; on the contrary, when the patient is in presence of the medical staff, FoG probability decreases [200].

This chapter will introduce a real application scenario of the proposed idea of Virtual Coaching System. In particular, in Section 7.1, we will present a prediction algorithm for the detection of FoG in people affected by Parkinson's disease. The idea of such work is based on the capability of the pattern recognition model to recognize the pre-FoG context. Furthermore, Section 7.2 introduces an indoor localization system that recognizes risky areas in indoor environments, which lead the Parkinson's patient to FoG context.

7.1 Towards a wearable system for predicting Freezing of Gait in people affected by Parkinson's disease

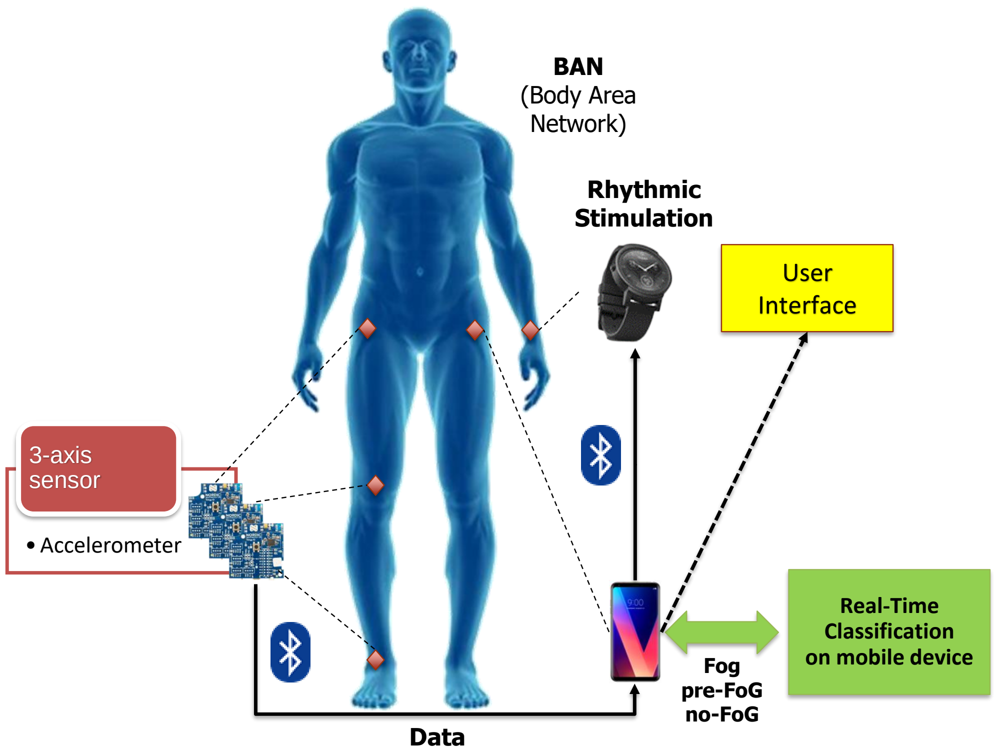


Fig. 7.1: Application scenario

The high incidence of the FoG and its difficulty of treatment and assessment by applying standard clinical methods have induced many researchers to investigate solutions based on the use of technological devices. In particular, several techniques and approaches based on wearable devices and machine learning algorithms have been proposed in the recent years [201]. Most of them essentially deal with recognizing FoG events by building on top of offline datasets gathered from the patients through wearable devices equipped with different sensors, like, for example, accelerometers [202, 203], gyroscopes [204], EEG sensors [205, 206], EMG [206, 207], and force and bending sensors [208]. These solutions are primarily devoted to help neurologists studying the nature of the FoG. In some cases, existing devices provide patients with rhythmic stimuli, once the FoG has been detected [201, 202] in order to reduce the duration of FoG episodes. This builds on the practical evidence from physioteraphy sessions that PD patiens more easily exit FoG events when they are externally stimulated with a Rhythmic Auditory Stimulation (RAS) (e.g., simulating a military march), since this focuses the attention during the movement [209]. However, only few techniques have been proposed for *predicting* the FoG (i.e., before it takes place) through the identification of pre-FoG patterns in the gathered data. Unfortunately, the results so far achieved in this direction are quite unsatisfactory [203, 205, 210].

In this context, this work addresses the application scenario reported in Figure 7.1. We propose a mobile classification approach to predict FoG based on k-nearest neighbour algorithm (k-NN) [211] with on a brand-new labeled dataset. Specifically, the labeled data is obtained by extracting features from the raw input collected from three tri-axial accelerometer sensors worn by the patient on his/her back, hip and ankle. Features are obtained by a proper data windowing, followed by non linear dimensionality reduction. Depending on the kNN classification result, a rhythmic stimuli is generated by a wearable device to help the patient to overcome the FoG.

In our experimental analysis, the approach has been proved to be effective in recognizing FoG events and pre-FoG events too. In particular, experimental results shown that we define new state-of-the-art performances overcoming the approaches of [200, 202, 212] in relation with FoG detection, and that we are capable for the very first time in the literature to individuate FoG by capturing a pre-FoG with an average sensitivity and specificity of, respectively, 94.1% and 97.1%. It is worth noting that our approach is fully explainable, without relying on deep learning architectures which may lack in interpretability in a scenario where the latter is of primary importance, and where we are capable of reaching excellent performance anyway.

Finally, we show that our approach can be implemented on a mobile/wearable solution that may provide the patient with rhythmic stimuli before the FoG episodes, to reduce their occurrence. More in the detail, our approach can be run on a standalone mobile/wearable device (e.g., a smartphone or a smartwatch) without the need of offloading the computation towards an external server. This has two main advantages: independence on an Internet connection, and consequent higher usability.

7.1.1 Preliminaries

This section reports a brief background on the machine learning algorithms that have been used in the proposed approach.

Feature extraction

In most classification pipelines, raw data are typically pre-processed to project them into different feature spaces where classification is made easier (typically, linear). This pre-processing stage is known as feature extraction [211]. The most known and used algorithms for feature extraction are summarised in the next paragraphs.

Principal Component Analysis (PCA)

It is the most common technique for reducing the dimensionality of a large set of possibly correlated input features [211]. It consists of a roto-translation of the original vectorial feature space, obtaining a new set of bases which are aligned with the most data variation. The reduction consists in projecting the data on a subset of these bases, retaining less features than the original ones.

kernel PCA (kPCA)

Kernel PCA uses the theory of the positive definite kernel and reproducing kernel Hilbert space [211] for doing (implicitly) PCA on data projected in an infinite-dimensional space. The result in the original feature space is a non linear projection, way more effective that the original PCA, with the additional cost of choosing a proper kernel.

Linear Discriminant Analysis (LDA)

It is a generalization of the Fisher's linear discriminant, a method to find a linear combination of features that separates samples of different classes. It is more effective than PCA when it comes to multi-class problem, but requires to know in advance the label of each training data [213].

kernel LDA (kLDA)

It is a kernel-based version of LDA. Using the kernel substitution, LDA is performed in a new feature space, which allows non-linear mappings to be learned [214].

Classification

Standard classification amounts to decide which class among a pool of classes does explain a new observation the best. It is the most common operation in machine learning, and depends strongly on the feature extraction step. It is usually based on a training phase, where a classification algorithm builds a classifier by analyzing a set of D-dimensional data, known as training set. In *supervised* classification, each training sample is equipped with a class-label attribute, stating which class it belongs to. The trained classifier is then used to predict the class label of an unseen *test* D-dimensional input sample. Notably, some classifiers do not require an explicit training step: for example k-NN simply uses the training data as exemplars to match the test observations [211].

The most common classification metrics are the following [215]:

$$sensitivity(recall) = \frac{\sum true\ positive}{\sum true\ positive + \sum false\ negative}; \tag{7.1}$$

$$specificity = \frac{\sum true\ negative}{\sum false\ positive + \sum true\ negative}; \tag{7.2}$$

$$precision = \frac{\sum true\ positive}{\sum true\ positive + \sum false\ positive}; \tag{7.3}$$

$$\text{F1–Score} = 2 \times \frac{precision \times recall}{precision + recall}; \tag{7.4}$$

where precision and recall (also known as sensitivity) measure how much the classifier is capable of avoiding false positives, and is capable to correctly classify all of the samples of a class, respectively. Instead, specificity and F1-Score, respectively, the classifier ability to correctly classify true negatives and the harmonic average of precision and recall.

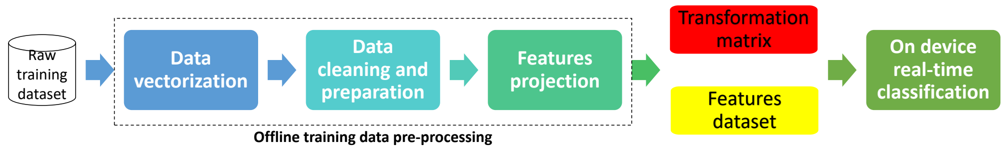


Fig. 7.2: Overview of the proposed approach.

7.1.2 Proposed Approach

This section explains the workflow of the proposed approach as reported in Figure 7.2. It is composed of two main phases:

1. *offline training data preprocessing*;
2. *on device real-time classification*.

The final goal is to set up a classification method exploiting the k-NN algorithm on time windows, capable of forecasting when a FoG event is going to happen, i.e., detecting what we dub a pre-FoG event. According to clinical studies, a 2-second window is enough to activate a RAS for finally preventing the FoG [216].
The input data is constituted by raw values gathered during patient's movement from three tri-axial accelerometers worn on the back, the hip and the ankle, respectively.

In the detail, the atomic entity of the input is the record, that is, a vector composed of 9 elements (3 per each accelerometer) measuring the acceleration of the patient in a specific instant with respect to the three axis of an Euclidean space. The number n of records in a given interval depends on the accelerometer sampling rate, so we can conclude that the input data is a matrix M with n 9-dimensional rows (the records), with n augmenting with the time passing. In conclusion, the input dataset is as a matrix M with n rows and 9 columns as reported on the top of Figure 7.4. The input data can be distinguished into training data and testing data. The training data is used to populate the vector space where k-NN should work (this corresponding to the offline training data preprocessing step), while the testing data is classified by the k-NN classifier (the on device real-time classification step)

Offline training data preprocessing

This section presents the steps performed in order to preprocess the raw data included in a *training* matrix M, generating two alternative datasets: a windowed dataset W, and a statistical feature dataset S. The preprocessing phase works as follows. Initially, it performs a data vectorization step, followed by data cleaning and preparation, and finalized by a feature projection procedure. The detailed work flow of this phase is shown in Figure 7.3.

Data Vectorization

In such a step, a low-pass filter is firstly applied to the elements of M to obtain a new matrix M', where the sensor noise is reduced. Then, two alternative steps are performed starting from M': data windowing and extraction of statistical features.

In **data windowing**, the rows of M' are grouped according to time windows of size w seconds with an overlap of t seconds. For example, in case the sampling frequency is 1Hz[1] with $w = 3$ and $t = 1$, the data included in rows from 1 to 3 of M' are associated to the first time window and they become, preserving their order, the elements of the first row of matrix W. Then, the data included in rows from $w - t = 2$ to $w - t + w = 5$ of M' become the elements of the second row of W, and so on, as shown in the middle of Figure 7.4. The size of W is then $m \times 9 * w$, where m is the total number of time windows.
During the **extraction of statistical features**, a new matrix S is generated from W by extracting 129 statistical features per each row of W. Thus the size of S is $m \times 129$ as shown at the bottom of Figure 7.4. The extracted features are similar to those used also in [210], e.g., variance, mode, standard deviation, maximum and minimum values of row data.

Data Cleaning and Preparation

Subsequently, the **normalization** of the values in W and S takes place. A unity-based normalization [217] is carried out over the elements of both W and S. The goal is to re-scale the values of W and M into the range $[0, 1]$ by using equation 7.5, where X is a generic element of the matrix, while X_{min} and X_{max} are the minimum and the maximum value in the matrix:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{7.5}$$

At this time, the next transformation step for both matrices is the **outlier substitution**. An outlier is a value that is more than 3 median absolute deviation away from the median [218]. Each outlier in W and S is substituted with the corresponding nearest not-outlier value.

At the final step of the preprocessing phase, each row of both matrices W and S is associated to a **class label** that represents the movement pattern observed on the patient during the corresponding time window. Such labels can be *no-FoG*, *FoG* and *pre-FoG*. Consistently with the existing literature [203, 205, 210], we assume the gait performance of PD patients deteriorates in the phase immediately preceding a FoG event. The association is assigned such that *FoG* is used when the time window includes at least one sample where the patient actually experienced a FoG episode; *pre-FoG* is assigned to the time windows of type *no-FoG* immediately preceding a *FoG* time window by at maximum s seconds, where reasonable values for s are between 2 and 4 seconds; finally, *no-FOG* is used for all the remaining time windows.

Feature Projection

In the final step of the preprocessing phase we use four different feature projection algorithms in order to observe which of them performs better in our scenario. The experimental analysis are performed in four different ways according to the applied training features and the number of target classes considered for the classification. The four alternatives are:

1. training features extracted from W, and 2 classes (FoG, no-FoG);

[1] 1Hz is a too low frequency for predicting FoG. It has been assumed in Fig. 7.4 for simplifying the exemplification. The dataset used in our experiments has been created at 65Hz.

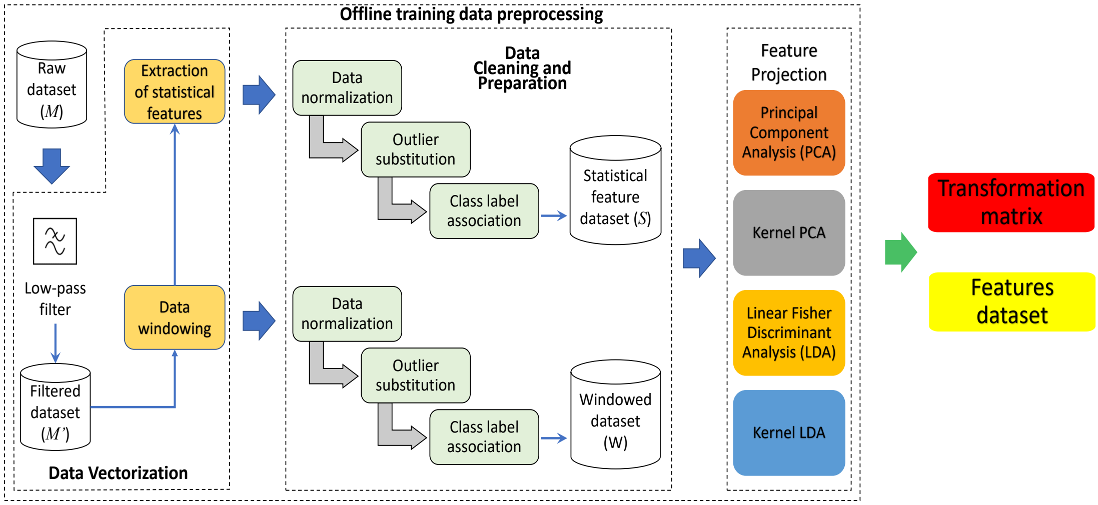


Fig. 7.3: Detailed Work Flow of the Offline data preprocessing phase.

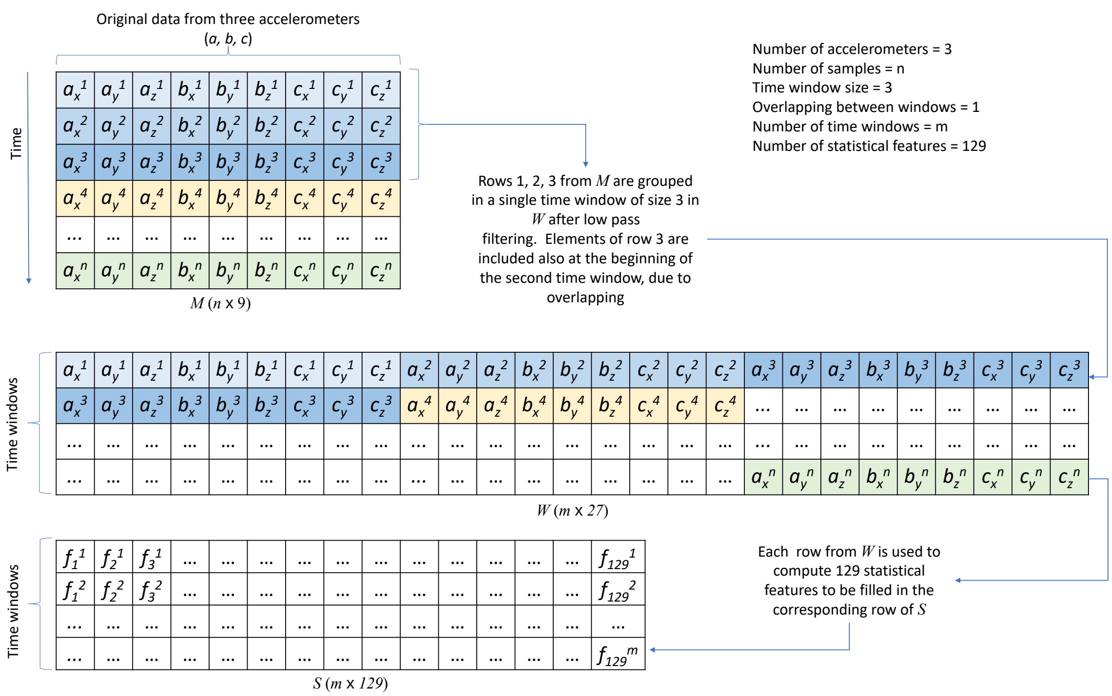


Fig. 7.4: From raw data to the training sets.

2. training features extracted from W, and 3 classes (FoG, no-FoG, pre-FoG);
3. training features extracted from S, and 2 classes (FoG, no-FoG);
4. training features extracted from S, and 3 classes (FoG, no-FoG, pre-FoG).

For each of the previous alternatives, the four algorithms cited in Section 7.1.1, i.e., PCA, kPCA, LDA, kLDA, are applied for extracting the final projected features to be provided to the k-NN classifier. In practice, the projection takes place through a matrix multiplication of the input data by a *transformation matrix* coming from each of the above quoted feature extraction approaches. Thus, we conduct a total number of 16 experimental campaigns by combining all the different possibilities. In Section 7.1.3, we show that alternatives 1 and 2 associated with the kLDA algorithm provide the better results.

Finally, as shown in Figures 7.2 and 7.3, the training data preprocessing phase returns the new training features dataset and the transformation matrix that are the input for the *on device real-time classification* phase.

On device real-time classification

Our system is intended to be used for real-time classification of FoG, no-FoG and pre-FoG directly on the patient. Thus, after the off-line training data preprocessing, the workflow (Figure 7.5) proceeds as follows. The data gathered by the accelerometers on the patient body are transmitted to the mobile phone through the Bluetooth Low Energy (BLE) protocol. Once the data are received, they are elaborated through the same data vectorization process presented in Section 7.1.2. After vectorization, the data are multiplied with the transformation matrix obtained by the offline data preprocessing phase, projecting into a reduced features space $(p_1, \ldots, p_f)$, where, f (≥ 1), defines the number of features generated after the projection. In the case of the LDA and kLDA algorithms f will be equal to the number of treated classes (no-FoG, FoG, and pre-FoG) minus one. Finally, such new features are passed to the k-NN classifier that, based on the *features dataset* recognizes the movement context as FoG, no-FoG or pre-FoG. The value of k is found after a cross-validation step.

In conclusion, during the classification phase, the initial data are transformed from a matrix $(m \times 3n)$, where m is the number of samples and n is the number of accelerometers for a defined time window, to a vector $(1 \times (m3n))$ after the data vectorization step. Such a vector, multiplied with the transformation matrix produces a reduced vector $(1 \times k)$, with $k << (m3n)$.
In addition, since we use a k-NN classification model, the proposed methodology does not present a training phase, which implies a reduction in the necessary time-computation to perform the steps from the raw data to the classification phase. It is worth noting that the use of the k-NN ensures fast performances and no need of an explicit training procedure (in fact, we have solely training features that are used as comparison w.r.t. the testing data). Additionally, by looking at the training features, one can individuate topological properties (features overlapped) which are indicating an easy or hard classification scenario. [219]

7.1.3 Experimental Results

This section presents the experimental results performed in order to prove the effectiveness of the FoG prediction and the possibility of implementing the proposed solution on mobile and wearable devices.

Dataset Characteristics

To obtain expressive yet comparable results w.r.t. the related literature, we focus on the DAPHNET benchmark [202]. This dataset was created by the joint work of a interdisciplinary in-

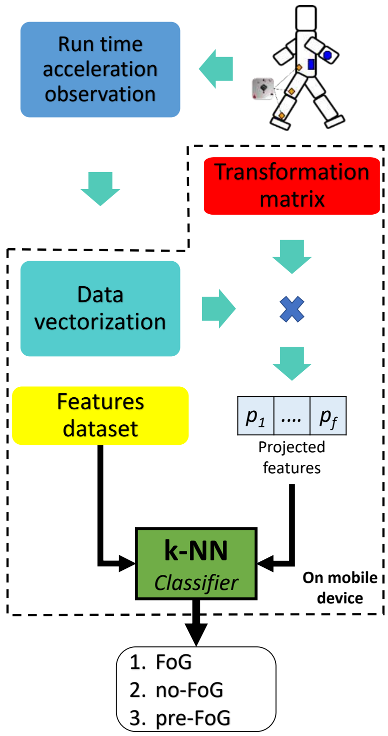


Fig. 7.5: On device real-time classification

Table 7.1: Average F1-Score, at varying of w and t, respectively, in $[1,6]$ with step 1 and $[0,w/2]$ with step 0.5.

Patient ID	#no-FoG	#FoG	PCA	kPCA	LDA	kLDA	#no-FoG	#pre-FoG	#FoG	PCA	kPCA	LDA	kLDA
P_01	465	18	0.72	0.70	0.64	0.99	460	*5*	18	0.44	0.43	0.42	0.86
P_02	124	9	0.64	0.63	0.61	0.99	120	*4*	9	0.31	0.32	0.31	0.96
P_03	405	68	0.75	0.73	0.73	0.99	357	*48*	68	0.39	0.42	0.40	0.84
P_05	263	120	0.72	0.70	0.70	0.99	243	*20*	120	0.17	0.18	0.18	0.96
P_06	526	33	0.68	0.66	0.65	0.98	514	*12*	33	0.44	0.44	0.46	0.98
P_07	362	12	0.57	0.56	0.55	0.99	356	*6*	24	0.38	0.36	0.39	0.99
P_08	203	53	0.78	0.77	0.73	0.99	194	*9*	53	0.48	0.41	0.42	0.94
P_09	471	128	0.85	0.84	0.82	0.99	463	*8*	128	0.58	0.61	0.60	0.98
	2-Class						3-Class						

ternational team composed of the Laboratory for Gait and Neurodynamics, Tel Aviv Sourasky Medical Center and the Wearable Computing Laboratory, ETH Zurich. DAPHNET is composed of data recorded over 10 patients ($P_1,\dots,P_{10}$); among them, 8 exhibited several FoG events, while 2 (P_4 and P_{10}) did not exhibit any FoG. Each patient wore three accelerometer sensors, respectively, on the back, the hip and the ankle. Each sensor collected acceleration over three axes x,y,z. The recordings were performed in a laboratory environment on three kinds of tasks: walking with curve trajectories, walking over a rect line, and performing other activities as, for example, entering different rooms and opening doors, with the aim of triggering the greatest number of FoG events. Data were recorded with a sampling frequency of 65Hz. Therefore, each sample is composed of the time instant of acquisition, 9 accelerometer values (3 accelerometers $\times$ 3 axes), and a binary class label (e.g., no-FoG, FoG) corresponding to the observed event. The DAPHNET dataset contains a total of 8h 20m of video recordings, where 237 FoG occurrences were identified, with an average of 23.7 FoG occurrences per patient, minimum 0 (for patients P_4 and P_{10}) and maximum 66 (for patient P_5), and standard deviation 20.7. The duration of each FoG occurrence varied between 0.5 seconds and 40.5 seconds with an average duration of 7.3 seconds and standard deviation of 6.7 seconds.

Dataset preprocessing

Following the procedure described in Section 7.1.2, starting from the raw DAPHNET data we generated two different datasets, the *windowed dataset* W and the *statistical feature dataset* S. Both W and S depend on the time window size w and the overlapping parameter t to collect short overlapping sequences of acceleration values. Thus, we performed grid search on w and t; specifically, we varied w in the range $[1 : 6]$ with step 1, and for each t, t assumed values in the range $[0 : w/2]$ with step 0.5, ending up with 27 (w, t) combinations. For every combination (w_i, t_i), $1 \leq i \leq 27$, a couple (W_i, S_i) of different datasets was created. Then, we performed the feature-wise data normalization and the outlier removal. Finally, for each (W_i, S_i), we re-label as pre-FoG all windows immediately preceding a FoG window, obtaining a novel class, namely the pre-FoG. The introduction of pre-FoG windows shrank the distribution of no-FoG windows, on average, of a factor 1/8.

Results for the windowed dataset

The classification of our approach has been cross-validated by extracting from DAPHNE training and testing partitions using k-fold (k=3, 5) and Leave-One-Out (LOO) schemes on individual patient and also cross-patient. It is worth noting that training and testing partitions were curated so that no partial overlap between windows was present. No significative difference was observed among the results achieved with these cross-validation schemes. Thus, for lack of space, in the following, we report and comment only the results achieved by using k-fold with $k = 3$.

Experimental results are reported in Table 7.1, Table 7.2 and Table 7.3. These tables refer only to the experiments conducted by using the windowed dataset W, because, as shown later in Section 7.1.3, this configuration guarantees the best performances with respect to using the statistical feature dataset S. The tables report the average results obtained by varying w and t, respectively, in the ranges $[1, 6]$ with step 1 and $[0, w/2]$ with step 0.5. Concerning the feature extraction algorithms, for kPCA and kLDA we tested the Gaussian, the polynomial and the linear kernel. The best result was obtained with the Gaussian kernel to whom the results in Tables 7.1, 7.2, 7.3 refer.

Specifically, for each patient that exhibited FoG episodes, Table 7.1 shows the average F1-Score, for both 2-Class (no-FoG, FoG) and 3-Class (no-FoG, FoG, pre-FoG) cases, achieved by applying different strategies for feature projection (i.e., PCA, kPCA, LDA, kLDA). Columns

Table 7.2: Average Sensitivity, Specificity and F1-Score, at varying of w and t, respectively, in $[1, 6]$ with step 1 and $[0, w/2]$ with step 0.5.

	2-Class			3-Class		
Name	Sensitivity	Specificity	F1	Sensitivity	Specificity	F1
PCA	0.72	0.71	0.71	0.40	0.49	0.44
kPCA	0.71	0.69	0.70	0.40	0.48	0.44
LDA	0.68	0.67	0.68	0.40	0.48	0.44
kLDA	0.99	0.99	0.99	0.94	0.97	0.94

#no-FoG and #FoG indicate the number of windows that have been labelled as normal and freeze of gait, respectively. Column #pre-FoG instead refers to the number of windows preceding those labelled with freeze of gait. It turns out that, by construction, the #pre-FoG value indicates how many episodes of freeze of gait are in the data of each patient.

Table 7.2 shows instead the average Sensitivity, Specificity and F1-Score among all the 8 patients of Table 7.1. As visible, the worst case is given by the PCA, while the best results were achieved with kLDA. This clearly implies that the classes cannot be linearly separated, highlighting the considered problem is challenging. Supervised feature extraction approaches (LDA, kLDA) work better than the unsupervised counterparts (PCA, kPCA) especially in the 3-Class case. In the 2-Class case LDA is almost equivalent to PCA probably due to the low dimensionality of the former (= 1).

Table 7.1 reports average values at varying the parameters w and t, thus hiding information related to the result achieved by each configuration of t and w. In addition, it does not show the distribution of the correct classifications and errors among the different classes. Therefore, to analyze more in detail the achieved results, Figure 7.6 reports two confusion matrices related to patient 3, which, according to Table 7.1, exhibits the lowest average F1-Score (84% with kLDA). By analyzing the results achieved for each configurations of parameters w and t, we discovered that the configuration ($w = 4$, $t = 0.5$) provides the worst results, as the classifiers erroneously recognizes the instances of FoG and pre-FoG as no-FoG (Figure7.6(a)). On the contrary, the best results are achieved by using the configuration $w = 2$, $t = 1$, for which the matrix has almost a perfect diagonal structure, thus showing that the classifier has almost always recognized the correct class. Similar considerations apply for the other patients. Selecting the correct (w, t) configuration is then fundamental for an effective classification. In almost all cases, the configuration $w = 2$ and $t = 1$ guarantees the best sensitivity and specificity.

Table 7.3 compares our approach, on the DAPHNET dataset, with three state-of-the-art techniques [200, 202, 212]. Only a comparison with the 2-Class problem was possible, as the considered works do not use the pre-FoG label. Additionally, the related literature report specificity instead of precision, so that we adopt this protocol for the sake of comparison. As visible, our solution with kLDA achieves the best results. In addition, it is worth noting that the approaches in [200, 202, 212] make use of more complex classification algorithms than the k-NN used in our solution. In [212] the authors used AdaBoost, in [200] Support Vector Machine (SVM), and finally, in [202] the classification process exploits a set of features based on the frequency do-

Patient 3 w=4,t=0.5	*Ground truth*			
Predicted	*Classes*	no-FoG	FoG	pre-FoG
	no-FoG	**305**	0	0
	FoG	**73**	0	0
	pre-FoG	**27**	0	0

(a)

Patient 3 w=2,t=1	*Ground truth*			
Predicted	*Classes*	no-FoG	FoG	pre-FoG
	no-FoG	**1084**	0	0
	FoG	**1**	**250**	0
	pre-FoG	**1**	0	**83**

(b)

Fig. 7.6: Worst case (a) and best case (b) confusion matrices of Patient 3 on two different (w,t) configurations.

Table 7.3: Comparative Sensitivity, Specificity and F1-Score of the proposed approach with respect to state-of-the-art approaches on 2-Class classification.

	Existing Approaches on 2-Class classification			Our Approach
	[202]	[212]	[200]	kLDA
Sensitivity	0.92	0.98	0.87	0.99
Specificity	0.89	0.99	0.92	0.99
F1-Score	0.90	0.98	0.90	0.99
Method	Freez Threshold	AdaBoost	SVM	kNN

main of the movements, which among others also requires the fast Fourier transformation. This makes our approach more suited to be used for a real-time classification on a mobile/wearable device, with limited computing and memory resources, than the state-of-the-art approaches.

Finally, Table 7.4 reports some statistics over the obtained results. The first column reports the name of the feature extraction algorithm, while columns from the second to the fourth are referred to min, max and standard deviation in term of Sensitivity, Specificity and F1-Score.

Results for the statistical feature dataset

Results showed in the previous tables are obtained by setting up the classifiers with the windowed dataset W, as the statistical feature dataset S gave worse performance. In order to better

Table 7.4: Min, max, and standard deviation of the achieved results in 2-Class classification.

Name	Sensitivity min,max,std	Specificity min,max,std	F1 min,max,std
PCA	0.41, 0.90, 0.09	0.46, 0.92, 0.10	0.45, 0.90, 0.93
kPCA	0.41, 0.90, 0.09	0.41, 0.91, 0.20	0.44, 0.88, 0.90
LDA	0.41, 0.88, 0.09	0.47, 0.90, 0.10	0.44, 0.87, 0.93
kLDA	0.70, 1.00, 0.08	0.66, 1.00, 0.94	0.68, 1.00, 0.86

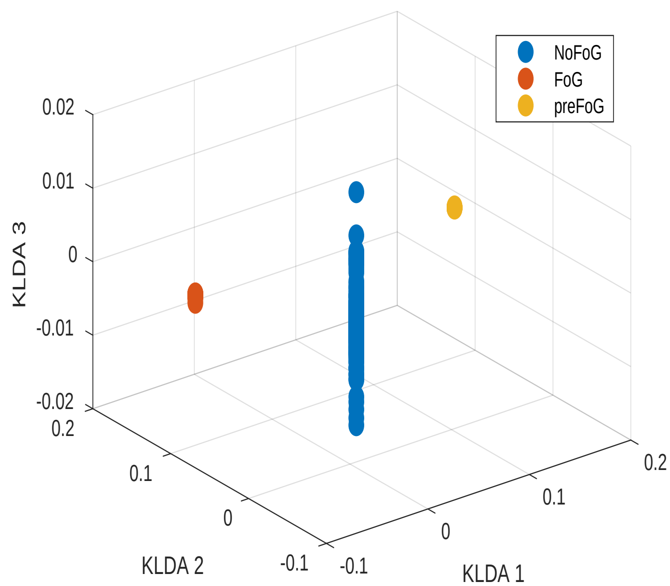


Fig. 7.7: Kernel linear discriminant analysis on Patient P_1 with $w = 4$ and $t = 1$ using the windowed dataset.

emphasize and clarify the different results obtained by using W and S, Figure 7.7 and Figure 7.8 present the mapping after applying Gaussian kLDA on, respectively, W and S, for patient P_1 with $w = 4$ and $t = 1$, for the 3-Class problem. It appears that the data are more clearly separated in Figure 7.7 than Figure 7.8. Similar results, omitted for lack of space are obtained for the other patients. Figure 7.9 further highlights the differences between using W and S for the 3-Class problem: (a) and (c) show the average sensitivity, respectively, on W and S, for all the possible configurations of (w, t) and for all patients $(P_1, ..., P_{10})$; (b) and (d), instead, compare the average specificity. As visible, in (a) and (b) the sensitivity and specificity values achieve approximately 98%, while in (c) and (d) they stop approximately at 94% and 70%, respectively.

Analysis of individual accelerometers

In order to study in depth the behavior of the proposed approach, and to reduce the number of accelerometers to be used, we have studied how the proposed approach works by using only one accelerometer at time. As introduced in Section 7.1.3, the DAPHNET dataset contains data gathered by three accelerometers on the ankle, hip and back. As a result of our analysis we

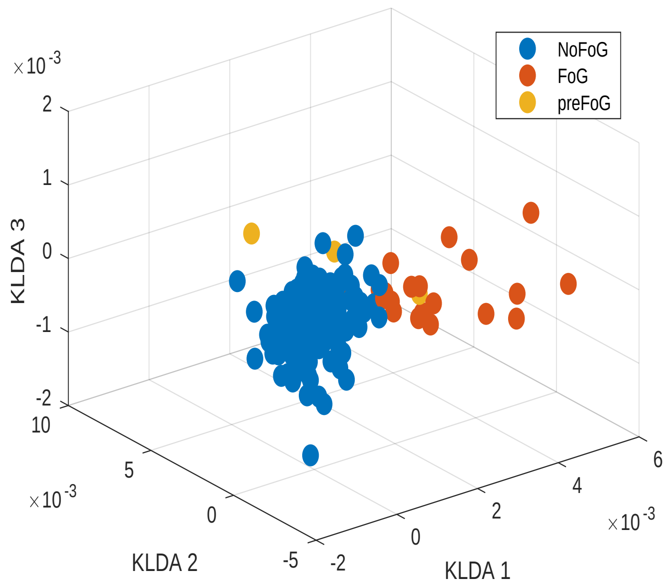


Fig. 7.8: Kernel linear discriminant analysis on Patient P_1 with $w = 4$ and $t = 1$ using the statistical feature dataset.

identified the best position for using just one accelerometer. Figure 7.10 emphasizes the results obtained on individual devices in terms of F1-Score varying the window and overlap size for each single accelerometer (a) Ankle (b) Hip and (c) Back. The best results are obtained based on the accelerometer on the back. As shown, this accelerometer achieves very good results regardless of the value of window size and overlap interval. Table 7.5 shows the average results in terms of Sensitivity, Specificity, and F1-Score by comparing the values achieved by using all the accelerometers and the values achieved by using only one of them at the time. Among the four configurations, the best result is achieved by the contemporary usage of all the accelerometers. However, when only one accelerometer is used, the best results are achieved by positioning it on the back, when, in the best configuration of the window (2 seconds) and overlap (1 second) size, the values of sensitivity, specificity and F1-Score are respectively of 97.2%, 97.7%, and 97.7% as visible in Figure 7.10. The high accuracy in classifying the FoG, pre-FoG and no-FoG

Accelerometer	Sensitivity	Specificity	F1-Score
All	0.94	0.97	0.93
Ankle	0.88	0.82	0.87
Hip	0.87	0.76	0.86
Back	0.91	0.82	0.90

Table 7.5: Comparing accelerometer results

contexts achieved by the accelerometer positioned on the back, allows, therefore, to reduce the number of accelerometers from three to one. Thus, the number of calculations to be performed is also reduced due to the reduced number of inputs, allowing to implement the classification

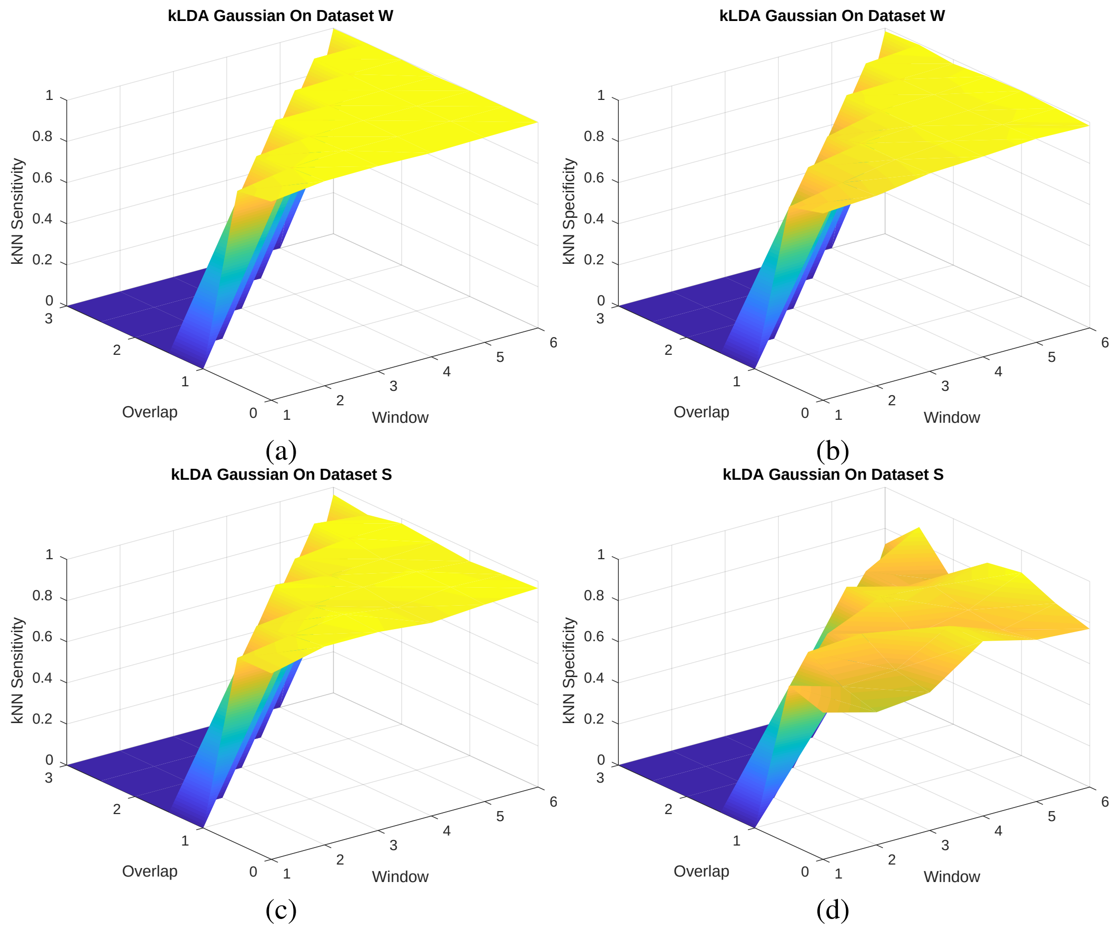


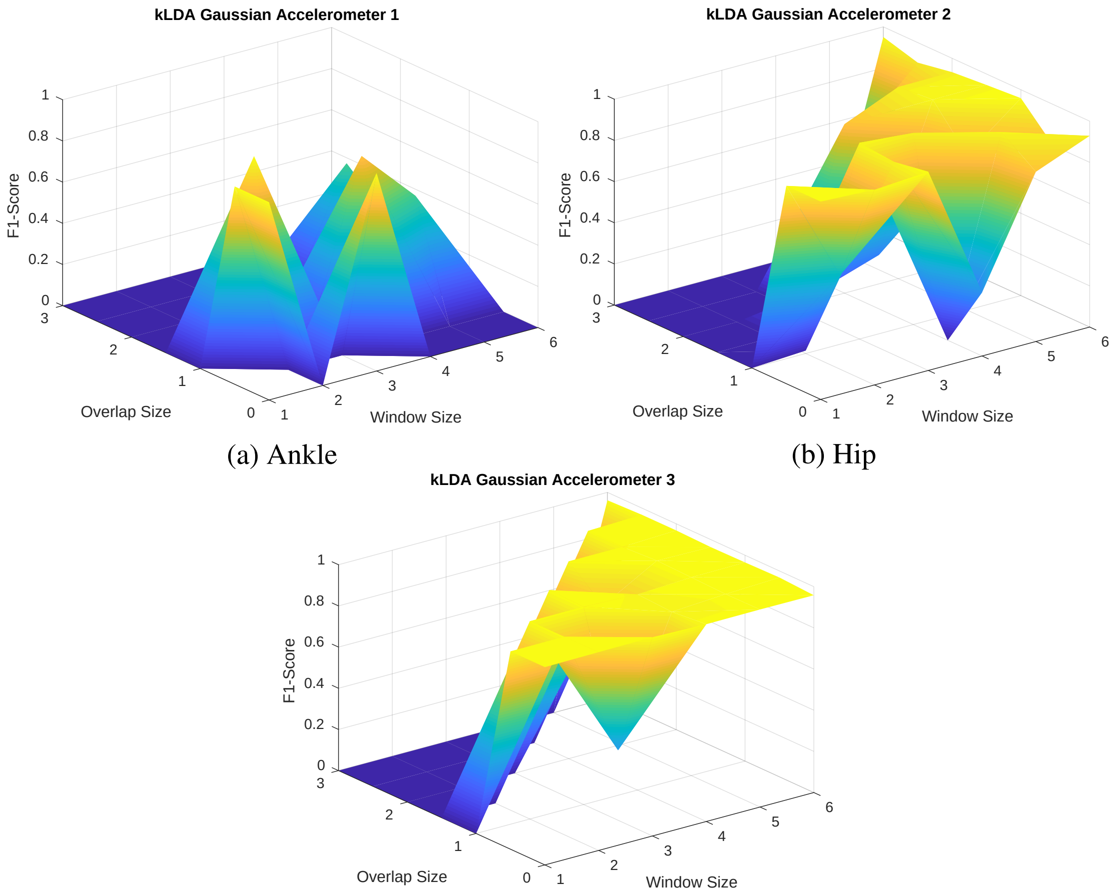
Fig. 7.9: Average sensitivity (a) and specificity (b) using W, and average sensitivity (c) and specificity (d) using S, obtained with kLDA at varying of the window size w and the overlap interval t.

phase of the proposed approach in resource constrained wearable devices.

Performance on Mobile Device

One of the main limitations of the existing approaches for FoG detection regards the computation of the classification phase (Figure 7.5) over a resource constrained wearable device, as smartphones and smartwatches. However, the proposed approach, thanks to the "lightness" of the used classifier and the reduction in the number of features, avoids such limitations, anyway preserving the quality of the classification.
To verify the above observation, we evaluated the classification performance on three different smartphone devices and evaluated the results in terms of response latency, RAM and ROM memory consumption and finally, battery consumption.

The upmost part of Table 7.6 shows the characteristics of the used smartphones. Columns two, three and four show the device models, instead, the rows from two to six show respec-



(a) Ankle (b) Hip

(c) Back

Fig. 7.10: Average F1-Score using W, obtained with kLDA Gaussian at varying of the window size w and the overlap interval t, on (a) Ankle (b) Hip and (c) Back accelerometer.

tively: CPU frequency, Number of cores, RAM size, ROM size, and Battery Capacity. All the smartphones run Android O.S.

Table 7.6: Devices Performances metrics

Metrics	Nexus5	S7 Edge	6T
CPU (GHz)	2.3	2.3	2.8
Core	Quad	Octa	Octa
RAM (GB)	2	4	6
ROM (GB)	16	64	128
Battery Capacity (mAh)	2300	3600	3700
Latency (ms)	$\approx$ 120	$\approx$ 100	$\approx$ 105
Used ROM (Mb)	$\approx$2	$\approx$2	$\approx$ 2
Used RAM (Mb/h)	113	114	120
Battery Consumption (mAh)	78	76	80

The bottom part of Table 7.6 shows the achieved results. *Latency*, shows the time spent for the computation of the workflow presented in Figure 7.5, i.e., the time elapsed from the reception of the input data gathered from the accelerometers till the classification of patient's gait. The time taken to transmit data from the accelerometers to the smartphone and the stimulus command from the smartphone to the smartwatch is negligible. Rows seven and eight, show the size of the ROM and RAM used memory, mainly to save the transformation matrix and the features dataset obtained after the offline training data preprocessing phase, (Figure 7.3). Finally, *Battery Consumption*, shows the average consumed battery for an hour in terms of mAh, for a total of 10 hours. Regarding the quality of classification, the results are equal to those obtained in computation on an external machine as shown in Tables 7.1, 7.2 and 7.3. In conclusion, the performed test show that the computation over resource constrained devices presented outstanding results in terms of accuracy in the pre-FoG, FoG and no-FoG recognition and device memory and battery consumption. Moreover, although we have not been working yet on the optimization of the proposed system, we can affirm that our prediction algorithm can execute without interruption for more than 15 hours.[2]

7.1.4 FoG dedicated Body Area Network and future steps

In this work we presented a methodology based on machine-learning algorithms to classify the movement of PD persons with respect to pre-Freezing of Gait (FoG), FoG and no-FoG patterns. The contributions of the work was mainly focused on two aspects: (i) the definition of a work flow to generate effective datasets for the k-NN classifier starting from raw data gathered from accelerometer sensors, and (ii) a thorough experimental analysis where we compared different feature projection algorithms from the point of view of the achieved Sensitivity, Specificity and F1-Score with three state-of-the-art approaches. Overall, the tests preformed on the DAPHNET dataset have led to the following conclusions:

- the windowed dataset W performs better than the statistical feature dataset S;
- the application of k-NN after kLDA achieves very high average Sensitivity, Specificity and F1-Score in both 2-Class problem ($\approx$ 99%) and 3-Class problem (>= 93.9%). In particular, for 3-Class, this proves we are able to recognize the pre-FoG episodes, and then we can predict the FoG w seconds in advance. As shown in Fig.7.9 the best results are achieved with the configuration $w = 2$, $t = 1$.;
- in comparison with state-of-the-art approaches for the 2-Class problem our work flow achieved more accurate results;
- tests over smartphones showed that the proposed FoG prediction algorithm can be efficiently executed on mobile devices.

As already presented in Figure 7.1, the proposed prediction algorithm is based on a Body Area Network (BAN) where acceleration data are gathered from three different sensors and transmitted to a data collector device (smartphone). However, the used sensors also collect, not used additional data, as the magnetic field and angular velocity. In future works we will verify

[2] taking into account only the execution our application together with operating system processes.

the prediction algorithm accuracy also adding the data mentioned above. Furthermore, in order

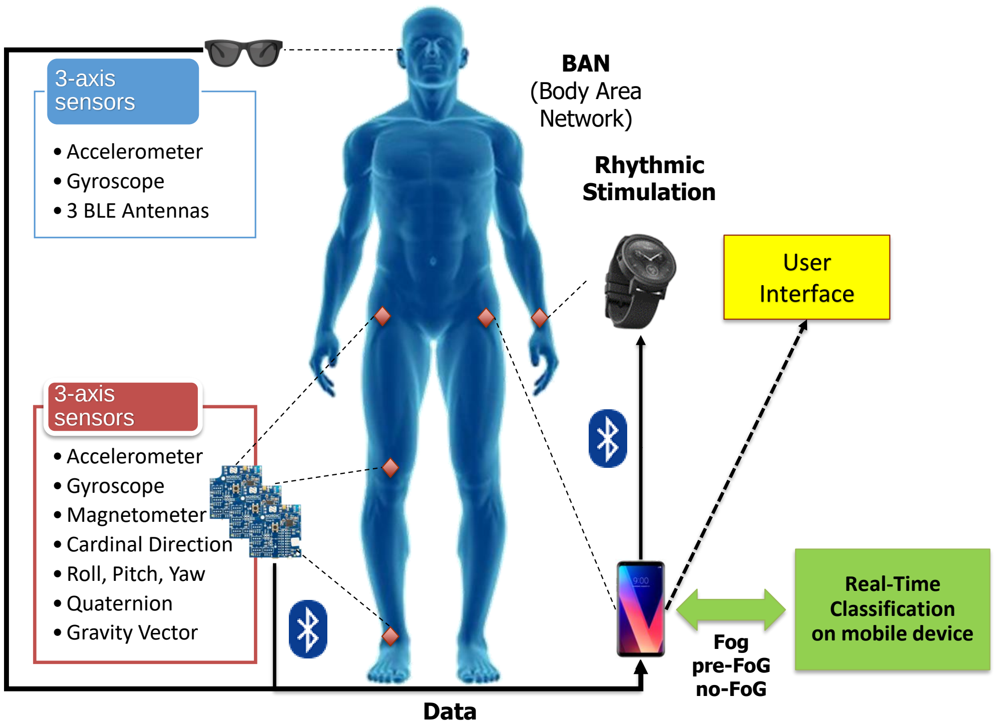


Fig. 7.11: Next Application scenario

to extend the capabilities of the prediction algorithm, we extended the designed BAN through the usage of smart glasses [220]. Such smart glasses gather data related to acceleration and angular velocity; in addition, the smart glasses provide the possibility to stimulate the patient through rhythmic visual and audio stimulation.

Moreover, since the proposed methodology is a supervised machine learning algorithm, it requires for each sample of learning data a class label. As well known, the labeling process is a time-consuming phase of the supervised machine learning process since it requires a manual effort from a human expert regarding the activity that we aim to recognize. Normally, such a process is performed offline by an expert through the usage of video-recorded data. A possible solution to the labeling process for the FoG scenario is shown in Figure 7.12. Figure 7.12 presents a mobile application that allows to the Parkinson's expert, who observes the patient wearing the BAN, to label the activity that the patient is performing in real-time. The label inserted by the expert is associated to the data samples, presenting the same timestamp, collected by the BAN. In detail, such application provides the capability to the medical expert to set:

- Figure 7.12 a) personal information of the patient;
- Figure 7.12 b) stimulation setting:
  - stimulation type:

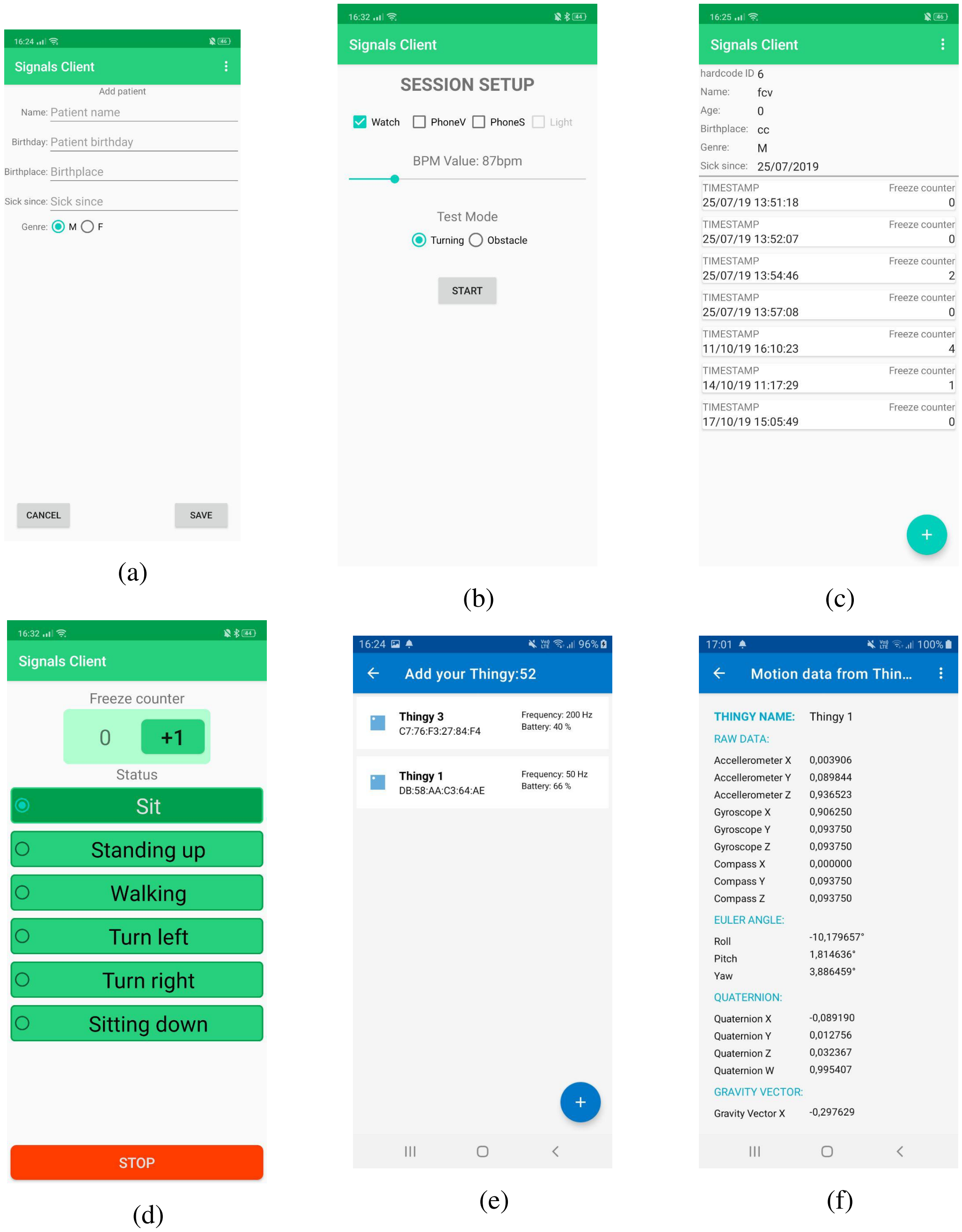


Fig. 7.12: Smart Labeling Mobile Application.

- vibration on smartphone;
- vibration on smartwatch;
- audio on smartphone;
- audio on smartwatch;
- audio on smart glasses;
- light on smart glasses;

  - stimulation frequency;
  - stimulation duration;
- Figure 7.12 c) for each patient the system can create different trials and for each trial the system will save the information as in the following;
- Figure 7.12 d) once that the activity trial starts the activity expert has the possibility to set real-time the activity that the patient is performing, as sitting, standing up, walking, turn left , turn right, and sitting down;

Related to the patient body area network, once that the patients have worn the BAN and installed the developed mobile application into the smartphone, on such mobile application can be performed the following operations:

- Figure 7.12 e) associates the sensors to the BAN[3]
- Figure 7.12 f) for each sensor the system acquires and saves on an external database the following data:
  - Nordic Thingy 52 sensors:
    · Acceleration x, y, z;
    · Angular Velocity x, y, z;
    · Cardinal directions x, y, z;
    · Roll, Pitch, Yaw;
    · Quaternion x, y, z, w
    · Gravity vector x, y, z
  - Smart Glasses:
    · Acceleration x, y, z;
    · Angular Velocity x, y, z;

In addition to each received BLE packet that the data collector receives we associate also the RSSI measurement of the received radio signal. Such value will give us the possibility to estimate the distance between the signal emitters and the data collector.

Finally, a further future objective, given the good results obtained with the not supervised feature extraction methods kPCA, would be to define a methodology that does not require the intervention of medical personnel for the creation of the learning dataset.

[3] the proposed BAN can be associated, using the basic mode, in parallel with at most seven sensors

7.2 An indoor localization system to detect areas causing the freezing of gait in Parkinsonians

As already introduced, people affected by the Parkinson's disease are often subject to episodes of Freezing of Gait (FoG) near specific areas within their environment. In order to prevent such episodes, this thesis presents a low–cost indoor localization system specifically designed to identify these critical areas. FoG episodes frequently happen when the person either encounters a visible obstacle in his/her path, or approaches an area with a different design pattern on the floor, or is traversing a narrow space, which will be referred generically as risky areas in the following [221]. The final aim is to exploit the output of this system within a wearable device, to generate a rhythmic stimuli able to prevent the FoG when the person enters a risky area. Such localization system is fully compatible with the proposed Smart Home Platform for Intelligent Assistance (SHPIA) architecture already introduced in Chapter 4. Rhythmic stimulation by an accompanying person proved to be effective in solving the FoG, allowing the patient to restart the movement [171]. In this context, the design of wearable devices able to automatically recognize the FoG and provide such a stimulation is a hot research topic. In some implementations, these devices try to detect FoG episodes by analyzing data gathered from on-body sensing devices, like, for example accelerometers or ECGs [201, 222]. These solutions are quite effective in detecting the FoG after it happens, thus allowing the patient exiting from the block. On the contrary, applications able to prevent FoG episodes are still at an earlier stage, and the results are unsatisfactory [203].

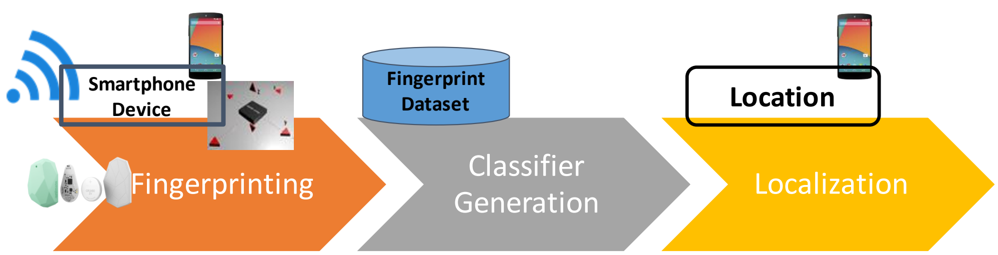


Fig. 7.13: Overview of the proposed approach.

This thesis hence focuses on the problem of FoG prevention. To this aim, an effective and low–cost localization system is defined, which triggers the generation of the aforementioned rhythmic stimuli, through a wearable device, when it recognizes that the patient is approaching a risky area, thus anticipating the FoG episode. The proposed approach is intended to be used indoor, such as in the house of the patient, or in his/her working environment. It also requires that the patient wears a device able to provide such stimuli (e.g, a smart watch or a smart bracelet), and that the environment is equipped with one or more radio–signal emitters, such as Wireless Local Area Network (WLAN) Access Point (AP) or Bluetooth Low Energy (BLE) beacons.

In the following, the description of the proposed system focuses on the localization approach. A schematic representation of the proposal is reported in Figure 7.13. A fingerprinting technique is used to map the risky areas within the environment and to train the localization system. The adopted data sources are Magnetic Field Vector (MV) values and Received Signal Strength Indicator (RSSI) values. For the sake of the present work, these data are gathered by a common smartphone, exploiting its internal compass and Wi–Fi/Bluetooth receiver, respectively. On the basis of this learning phase, a localization engine is created, which exploits a set of classifiers and a probabilistic graph model of the environment. Its role, once deployed in the wearable device, is to detect when the person enters a risky area such that a rhythmic stimuli can be generated.

7.2.1 Methodology

From a practical point of view, the proposed approach is based on two main types of devices. On the one hand, smartphones are exploited to carry out RSSI and MV measurements, as well as to execute computations. On the other hand, this proposal needs the availability of several emitters of meaningful radio signals, which in turn have to be manageable by the employed smartphone to extract the RSSI readings. In this work, we hence consider both Wi-Fi AP and BLE beacons. A detailed view of the proposed method is provided in Fig. 7.14 and described hereafter.

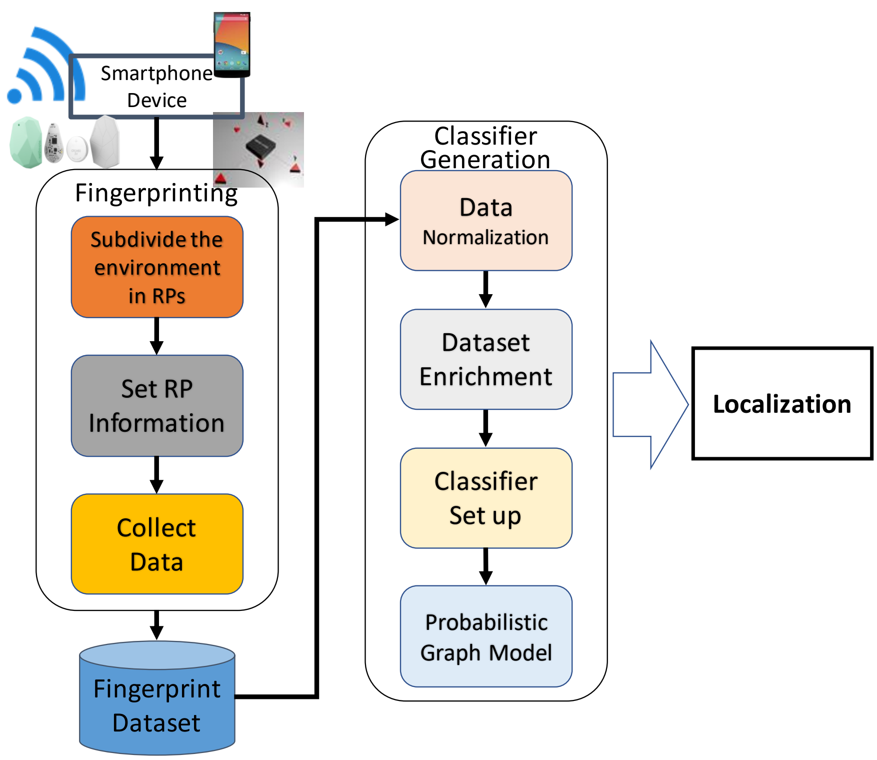


Fig. 7.14: Detailed view of the proposed methodology.

Table 7.7: Training data for the proposed classifiers.

RP ID	Pos. X	Pos. Y	Borders	Description	Timestamp	Direction	$RSSI_{[1...n]}$	$MV_{[x\ y\ z]}$	$CRSSI_{[1...n]}$	$CMV_{[x\ y\ z]}$	Group
1	1	1	North	doorway	t_1	North	[-72 -93 -44 … -56]	[13 9 8]	[3 2 3 … 3]	[2 3 1]	l_1
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
i	7	4	East	pattern	t_j	East	[-75 -88 -47 … -59]	[13 8 7]	[3 2 3 … 2]	[2 3 2]	l_2
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
m	23	15	West	narrowing	t_h	West	[-45 -58 -60 … -76]	[5 42 28]	[1 3 3 … 2]	[1 3 2]	l_k

Fingerprinting

According to Section 6.1.2, the first goal is to create a dataset of RSSI measurements and MV values, based on the following three steps.

1. *Subdivide the environment in Reference Point (RP)*
   a) map all risky areas into a set of RP, not necessarily contiguous;
2. *Set RP information*
   a) its x, y position;
   b) existence of borders in any cardinal direction (e.g., wall on North);
   c) environmental description (e.g., doorway or floor pattern changes);
3. *Collect data*
   a) capture RSSI and MV data for each RP.

Algorithm 5: Data collection and fingerprinting dataset creation

Result: fingerprinting dataset f
$f \leftarrow \emptyset$;
for *RP center* c_{xy} **do**
  for *direction* $d \in \{N, S, E, W\}$ **do**
    for *timestamp* $t \in [1 \dots 30]$ *seconds* **do**
      $rssi$ = collect_RSSI_Measurement(c_{xy}, d, t);
      mv = collect_MV_Values(c_{xy}, d, t);
      $f = f \cup$ add($c_{xy}, d, t, rssi, mv$);
    end
  end
end

Data collection is carried out by following Algorithm 5. The final outcome is the *fingerprinting dataset*, which contains all RSSI measurements and MV values.

Columns 1-9 in Table 7.7 show how the training set appears after the execution of the aforementioned procedure. Column 1 represents the RP identifier, Columns 2 and 3 are referred to the coordinates of its center c_{xy}, Column 4 reports information about the presence of borders, Column 5 associates the risky area the RP belongs to, Column 6 is the timestamp, Column 7 records the movement direction of the person, finally, Column 8 and Column 9 report the RSSI and MV measurements. Timestamps are in the form *dd:mm:yy:hh:min:sec:ms*. RSSI values are vectors of length n, where n is the number of radio signal emitters placed within the environment.

Classifier generation

The classifier generation is characterized by a sequence of operations detailed below.

Data normalization

Both the RSSI and the MV datasets have been normalized through a classical min-max feature scaling technique, as shown in Eq. (7.6).

$$x' = \frac{x - min(x)}{max(x) - min(x)} \tag{7.6}$$

where x is the original value and x' is the normalized value. Such a technique normalizes data within a fixed range, while preserving their mutual relationships. This makes the training less sensitive to the scale of features [217].

Dataset enrichment

The original fingerprinting dataset is further enriched by associating to each record (i.e., each RP) the result of two elaborations on RSSI and MV measurements (Columns 10 and 11 in Table 7.7), and a grouping label (Column 12 in Table 7.7).

Column 10 categorizes each single RSSI value of Column 8 in classes, according to the following procedure:

a. We apply the k-Means clustering algorithm to the original RSSI data of Column 8, by considering each single $RSSI_i$ measurement, per each timestamp t, uncorrelated with respect to all the others. In practice, we forget that the set of values $RSSI_{[1...n]}$ corresponding to timestamp t, were measured all together when the smartphone was in the same (x, y) position at time t. Given the whole set of RSSI values, k-Means groups them in k clusters, where k is automatically selected to maximize the similarity among the elements belonging to the same cluster.
b. We extract the minimum and maximum RSSI values, min_p and max_p, for each cluster p.
c. We associate each value $RSSI_i$, with $i \in [1 \dots n]$, per each timestamp t, to one of the k clusters according to the following rule: if $min_p \leq RSSI_i \leq max_p$, then $RSSI_i$ is associated to cluster p.

The aforementioned procedure associates a specific cluster to each RSSI values measured with respect to a specific radio–signal emitter in a given instant providing the new categorized RSSI vectors (CRSSI). This maps each RSSI measurement into a set of virtual spatial-temporal locations, not necessarily adjacent neither in space nor in time, that anyway show similar characteristics. An analogous procedure is applied to MV values in Column 9 to obtain the categorized MV classes of Column 11 (CMV).

Finally, the grouping labels in Column 12 are also obtained by using the k-Means clustering algorithm. Nevertless, k-Means is now applied by adopting, as training set, records composed of both RSSI and MV vectors. In addition, differently from the above procedure, in the training set we preserve the correlation among measurements related to the same position at the same time stamp, i.e. we provide k-Means with RPs instead of single RSSI and MV values. Hence, in this case, the goals is to group RPs into a set of clusters on the basis of the similarity of their respective RSSI and MV measurements.

Classifier set up

The proposed localization systems is composed on five classifiers, all of them based on the k-NN [211] machine learning algorithm. They are set up by exploiting in different ways and instants the information reported in Table 7.7, which are extracted according to the procedure described in the previous sections.

The first classifier, **C1**, is set up by using the data of Columns 8 and 9 as input and the labels in Column 12 as target classes. Its role is filtering the RPs. Given the RSSI and MV values measured by the smartphone of the person to be localized, C1 associate theses values with one specific target class. Thus, C1 filters the known RPs by restricting the possible location of the person among the RPs belonging to the recognized class.

After **C1** is applied, four different classifiers, **C2**, **C3**, **C4** and **C5** are each one used to select the most representative RP, among the set of RPs returned by **C1**, providing with a narrower set of at most 4 RPs. The datasets for these classifiers are Column 8 for **C2**, Column 10 for **C3**, Column 9 for **C4** and Column 11 for **C5**. For all of them the target classes are represented by RPs returned by C1. Therefore, their choice is based on different aspects that may characterize the actual position of the person.

The four RPs so far returned are used in conjunction with a **probabilistic graph model** of the environment, that is generated as reported in the following section.

Probabilistic graph model

To increase the localization accuracy and to preserve the environment knowledge this thesis work proposes, as seen in Table 7.7, to record for each RP, possible borders (e.g., walls and furniture) and environment characteristics (e.g., doorway, stairs, floor pattern changes and narrowing of the environment) in one (or more) cardinal directions. Each RP can be seen as a square of side m meters.

Thus, at least one RP is associated to each risky area in the environment, m meters away from it, per each possible direction. The value of the parameter m can be fixed according to the medical experience. In general, a rhythmic stimuli for preventing a FoG episode, while approaching a risky area, should be generated 1.5-2 meters far from it, as the gait speed and the stride length in PD patients is on average, respectively, 1m/s and 1.06m [223]. Different values for m risk to uselessly disturb the patient, if the stimuli is generated too in advance, or being ineffective, if the stimuli is delayed. Figure 7.15 shows an example of three RPs, where the doorway v_a identifies a risky RP, while v_b and v_c identify adjacent RPs to such a risky RP. Furthermore, colors identify the presence of borders in at least one direction per each RP.

Hence, we map the characteristics of the environment as a graph model $M = (V, E, P, B, T)$ where:

- $V \in \{V_r \cup V_{ar}\}$ is the set of RPs composed of:

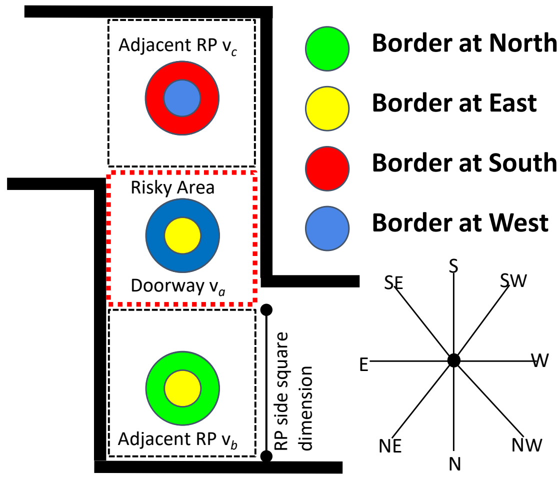


Fig. 7.15: Abstract view of RPs in proximity of a risky area (doorway).

  - V_r: RPs identifying risky areas as for example doorways;
  - V_{ar}: identifying RPs adjacent to risky areas;
- $E = \{(v_i, v_j) | v_i, v_j \in V \wedge v_i, v_j \ are \ neighbors\}$ is the set of edges between RPs;
- $P : E \rightarrow [0, 1]$ defines, for each edge $e \in E$, the probability of crossing e;
- $B : V \rightarrow \mathcal{P}(\{N, S, W, E\})$ associates each RP to its set of adjacent borders (e.g., walls) represented as cardinal points.
- $T : V \rightarrow D$, where D ={pattern change, stairs, doorway, ...}, defines per each RP the characteristic of the environment where the RP is located.

The probability of the edges is first statically computed and then dynamically adjusted during actual localization. Per each edge $e = (v_i, v_j)$, the static value is defined as $1/n$, where n is the number of outgoing edges from v_i, including e, i.e. n counts the possible directions that a person can take starting from v_i, considering that he/she cannot cross obstacles. The maximum number of outgoing edges from v_i is 8 (corresponding to the 8 cardinal points N,NE,E,SE,S,SW,W,NW). During the actual localization, the probability of an edge e is then adjusted by considering the arrival direction of the person, according to the fact that going straightforward for a while is more likely than continuing turning. In practice, if the person reached v_i from South, the probability of edges outgoing from v_i towards RPs located at North, North-Est and North-West with respect to v_i are increased of a quantity $d > 0$. In our experiments we empirically fixed d at $1/3$.

Localization

At run-time, the localization phase performs as follows. Let us assume, at time t, the person is located at RP v_i. During walking, the mobile phone perceives radio signals, computes magnetic field vectors and gets movement directions that are periodically provided to the localization system described in the previous section. At time $t+1$, the perceived RSSI and MV values, after being normalized, are provided to the **C1** classifier. **C1** filters the RPs in the graph model of the environment as reported at the beginning of Section 10. Survived RPs are then concurrently

Table 7.8: Smartphone and user characteristics

Name	Operating System	User height (ID)	AP_RSSI_{freq}
Samsung S7 Edge	Android 7.1.1	1.95 m (1)	$\approx 1Hz$
Nexus 5	Android 5.0.1	1.95 m (1)	$\approx 3Hz$
Huawei P10 Lite	Android 7.1.1	1.75 m (2)	$\approx 1Hz$
One Plus Three	Android 7.1.1	1.70 m (3)	$\approx 1Hz$
Huawei P8 Lite	Android 5.0.1	1.75 m (2)	$\approx 3Hz$

considered by classifiers **C2**, **C3**, **C4** and **C5**, which finally return at maximum 4 different candidates, one for each classifier, to predict the new position of the person. At this point, we have two possibilities:

1. At least three classifiers among **C2**, **C3**, **C4** and **C5** agree on the same RP v_j. In this case, the person is located at v_j. Then, the probabilistic graph model is used only to decide if generating the rhythmic stimuli or not. The rhythmic stimuli is provided only in two cases: when $v_j \in V_r$, and when $v_j \in V_{ar}$ but the movement direction perceived by the smartphone goes towards an RP adjacent to v_j belonging to the risky set V_r.
2. When there is no agreement among the classifiers, given that the person was located in v_i at time t, the probability of the edges outgoing from v_i are temporarily updated according to the movement direction perceived by the smartphone, as reported in Section 10. Then, the system computes the shortest paths from v_i to each of the RP returned by classifiers **C2**, **C3**, **C4** and **C5**. The RP belonging to the highest probability path is finally selected as new location of the person. In case there is still a tie, the system locates the person at the nearest RP toward the movement direction perceived by the smartphone.

7.2.2 Experimental Campaign

This section presents the outcomes of an experimental campaign aimed at assessing the performance of the proposed approach. As a first observation, tests were performed with different types of smartphones and different users, as it is reported in Table 7.8. In the first two columns, the device models along with their operating system versions are indicated. The third column shows the user height and his/her ID). Finally, the table reports the sampling frequency of RSSI measurements emitted by the AP. The sampling frequencies relevant to the magnetic field and to RSSI measurements from BLE beacon devices are not shown in the table, as they are the same for all the devices. Specifically, the magnetic vector sampling frequency is ≥ 30 Hz, while the RSSI measurement frequency from BLE devices is ≈ 10 Hz.

The proposed system has been tested in three private indoor home environment, where, generally, a PD patient spends most of his/her time. The initial fingerprinting phase for these three environments, focused on the identification of the risky areas. In particular, we associated an RP (graph model vertex) to each risky position, such as doorway, stairs, floor pattern changes, etc. In each environment, we exploited the same number of signal emitters, namely 10, of which five APs and five BLE beacon devices. In our implementation, each RP is represented by a square whose side length is 1.5 meters (area is 2.25 m2). This hence produced a different number of RPs for each environment.

Accuracy of the localization

In this experimental campaign we mainly evaluated the performance of the proposed localization method in terms of *absolute accuracy*, defined as the distance in meters between the real and the estimated position. The outcomes of our experiments are reported in Table 7.9. In particular, per each environment, we may observe the number of its RPs, and, in the third column, the accuracy achieved by the proposed localization approach. In all the tests carried out, our localization system has been able to correctly recognize the risky RPs, with an absolute accuracy of 1.5m. As a further note, through the use of the probabilistic graph model the system computes also the likelihood of the user continuing to move in the direction of the risky area or turning towards a non-risky area, based on the movement direction. This allows reducing the number of unneeded stimuli when the user moves to the opposite direction with respect to (or tangent to) the risky area.

Table 7.9: Accuracy of the proposed localization approach.

Environment	Number RPs	Our Approach (min,max)	InDoorAtlas (min,max)
Indoor (H_1)	14	$1.5m, 1.5m$	$1m, 8m$
Indoor (H_2)	12	$1.5m, 1.5m$	$1m, 8m$
Indoor (H_3)	17	$1.5m, 1.5m$	$1m, 8m$

To further validate the proposed approach, the last column of Table 7.9 compares its results with the results achieved by using the InDoorAtlas platform [114]. This platform exploits RSSI measurement from WiFi and Bluetooth radio signal emitters, which are then combined with data coming from magnetometer, accelerometer and gyroscope sensors. Furthermore, during the learning phase, it makes also use of the GPS. InDoorAtlas is released as a free project, which can be easily tested on both Android and iOS platforms. During all the tests we have carried out, we have observed that InDoorAtlas tends to provide a better accuracy than our approach in terms of minimum absolute accuracy (1 meter vs. 1.5 meters), as can be observed in Table 7.9. However, the comparison with the maximum absolute accuracy (8 meters vs. 1.5 meters) revealed that InDoorAtlas is actually unsuitable for the target problem of generating rhythmic stimuli for PD patients when they approach a risky area.

Furthermore, we also observed that InDoorAtlas is very sensitive to particular movements, especially in areas hardly recognizable or not previously mapped by an RP. Particularly, in a the context of a person affected by the Parkinson's disease, where the type of movements (short step distance and high frequency movement) are different from those of a healthy person (greater step distance and lower frequency movement), dependence on acceleration measures may become a significant source of error.

As a concluding remark, in all the considered environments, InDoorAtlas performed very well in terms of best absolute accuracy (1 meter), but suffered a higher number of positioning errors than the proposed approach when it located the person more than 2.5 meters from the actual location. This resulted in a higher number of false positives, which in a context of patient stimulation might become very disturbing.

Energy consumption and on-device computation

The comparison between our system and InDoorAtlas let us draw some considerations about energy consumption. Indeed, we noticed that the battery consumption on the used smartphones for one hour of usage with the proposed localization system has been on average 12% of total battery charge (≈3500 joule). Conversely, with InDoorAtlas the average battery consumption for one hour of tests was 15% (≈4400 joule). Such a difference can be attributed mainly to the higher utilization of internal sensors (accelerometer, magnetometer, gyroscope and GPS sensors) needed by InDoorAtlas with respect to our approach. Furthermore, we would like to emphasize that in our approach, the localization is executed directly on the smartphone without the risk of running out of memory. This is because, due to the small number of RPs necessary to detect a risky area, the memory occupancy for k-NN classifiers is limited. The possibility of running the localization algorithm directly on the smartphone, instead of offloading it towards a cloud server, eliminates the need of an Internet connection and thus of any communication latency. This might also reveal valuable in contexts with low internet connection coverage, as for example rural areas. In this way, the patient's stimulus, when generated, is not delayed, thus minimizing the risk a patient enters a FoG context.

8

Conclusion and suggestions for future research

This thesis presented the concept and implementation of the **Virtual Coaching System (VCS) for Assisting Activities of Daily Life** based on the idea of *active externalism* proposed by Clark and Chalmers in 1998 and the Internet of Things (IoT) concept discussed as early as 1982.

8.1 Thesis Summary

In the context of Ambient Assisted Living (AAL) and assisting technologies, this thesis explored many different research directions and relative challenges in order to implement and test the first examples of VCS. Starting from the design and implementation of a smart home architecture to the design and implementation of activity recognition algorithms for daily life activities. Regarding the smart home architecture, this thesis presented Smart Home Platform for Intelligent Assistance (SHPIA), a ubiquitous, non-invasive, and low-cost smart-home architecture based on the IoT concept and daily life smart objects. Such architecture was extended to integrate additional Human Activity Recognition (HAR) algorithms on different complexity levels, from simple threshold-based HAR algorithms to machine learning-based HAR algorithms, achieving excellent accuracy in detection and recognition of the activities performed by users and its interaction with objects of daily life. Additionally, since one of the most crucial knowledge about daily life environment regards the position of users and objects, this thesis presented two different mobile phone-based positioning systems, implemented starting from SHPIA smart-home architecture. Moreover, in some particular pathology as Parkinson's disease, the location is related to a precise symptom, and the knowledge given by the localization system is fundamental in case of necessity. Furthermore, regarding the activity recognition, this thesis presented two different techniques related to the activity recognition of people in daily life. Starting from SHPIA, we presented the ADA (Assisting Daily life Activities) architecture. Assisting Daily life Activities (ADA) aims to recognize daily life activities such as medication intake, water assumptions, and other types of activities based on the interaction between users and Objects of Daily life (ODLs). ADA provides to a caregiver an instrument to help and monitor if the coachee (elder, a person with cognitive impairments, a person with a neurodegenerative disease) is following the assigned therapy or is performing harmful behavior for his health. The ADA activity recognition logic computes over the smartwatch by stimulating the coachee if and only if he/she is not performing the assigned therapy or is performing a harmful behavior, otherwise ADA remains silent. In addition, the economic cost of ADA from the HW point of view is meager since it needs only a smartwatch and some BLE stickers and does not need a constant internet connection. Besides ADA, this thesis presented a HAR algorithm able to predict the Freezing of Gait (FoG) occurrences in Parkinson's disease. Starting from data gathered by three different accelerometer sensors, the FoG prediction algorithm was able to recognize the pre-FoG context and stimulate the patient through a rhythmic audio/tactile stimulation. Our study showed that: (i) we achieved higher performances with respect to the state-of-the-art approaches in terms of FoG detection, (ii) we were able, for the very first time in the literature, to predict FoG by identifying the pre-FoG events with an average sensitivity and specificity of, respectively, 94.1% and 97.1%. Furthermore, the performed tests showed that the proposed FoG prediction algorithm could efficiently execute on resource-constrained devices like smartphone and smartwatch. Based on such results, we developed a dedicated Body Area Network (BAN) composed by a) three 3-axial accelerometer sensors, b) smart-glasses, c) smartphone, and d) smartwatch. The smartphone collects all the data generated by the sensors, smart glasses, and smartwatch and implements the FoG prediction algorithm. The smartwatch takes care of stimulating the patient when the FoG or pre-FoG context is recognized by emitting a rhythmic vibration at the same frequency as that of the patient walking pattern. Smart-glasses will be used instead of the smartwatch to stimulate through visual and audio stimulation. In addition, the BAN also provides the possibility to collect other types of data as angular velocity and magnetic field from all the components of the BAN. Experimental results confirmed that both ADA and the FoG prediction algorithm achieved excellent results in terms of specificity, sensitivity, precision, and accuracy, also in comparison with the state-of-the-art approaches. Besides, it shows that our classification algorithm does not require high computation and memory resources, are explainable and can be run on mobile and wearable devices.

8.2 Directions for future research

Although the feasibility and other essential implementation aspects of the proposed VCS concept have been verified in this thesis, some exciting aspects still need to be explored in future. Since the presented work regards experimental results related to not optimized architectures and algorithms, the first step to perform will be the optimization of the current state of SHPIA and ADA. The aim will be to improve specific features as execution time, response speed, battery consumption, and memory consumption. Second, the VCS concept has to be evaluated over a more significant number of users in real daily life environments in order to further enhance the generalization capabilities of the platform. The acceptability and usefulness of the VCS systems are of principal importance for us, and this requires a further miniaturization of the used devices. Third, extension of the VCS concept to new pathology's, symptoms, and activities of daily life by also extending the VCS architecture, integrating new medical and non-medical devices with regard to the user's health context. Regarding ADA, in addition to the optimization process already in act, we are working in order to extend the activity recognition models to a full set of daily life activities, as activities related to the indoor environments as cooking, eating, staying, watching TV, sleeping, bath activities, drinking, getting outside the house with or without the keys, wearing your clothes in the correct order etc. To facilitate this extension of the recognized activities, we are already using SHPIA architecture in order to create the training dataset for the activities mentioned above, as introduced in Chapter 4, Section 4.5.3. Furthermore, SHPIA will integrate the application scenarios proposed in Chapter 4, Section 4.4. Finally, regarding Parkinson's disease, the next step is towards the integration of our BAN within an object of daily use of the patient (e.g., socks). The aim is to reduce the usability barrier of the system and extend the VCS to the problem of hypertension in such patients.

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List of Acronyms

AAL	Ambient Assisted Living
AD	Alzheimer's disease
ADA	Assisting Daily life Activities
ADL	Activities of Daily Living
AmI	Ambient Intelligence
AOA	Angle of Arrival
AP	Access Point
AR	Activity Recognition
BAN	Body Area Network
BAS	Body Area Sensors
BLE	Bluetooth Low Energy
BSN	Body Sensor Network
CNN	Convolutional Neural Networks
DOA	Direction of Arrival
ECG	Electrocardiography
EEG	Electroencephalography
EMG	Electromyography
EU	European Union
FFT	Fast Fourier Transformation
FI	Freezing Index
FoG	Freezing of Gait
FPGA	Field-Programmable Gate Array
GDP	Gross Domestic Product
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
HAR	Human Activity Recognition
HR	Heart Rate
HVAC	Heating, Ventilating, and Air-Conditioning
HVAC	Heating, Ventilating, and Air-Conditioning

ICT Information and Communication Technology
IMU Inertial Measurement Unit
IoT Internet of Things
JSON JavaScript Object Notation
k-NN k-Nearest Neighbour
kLDA kernel LDA
kNN k-Nearest Neighbor
kPCA kernel PCA
LDA Linear Discriminant Analysis
LFDA Linear Fisher Discriminant Analysis
MAD Median Absolute Deviations
ML Machine Learning
MPPT Maximum Power Point Tracking
MRI Magnetic Resonance Imaging
MV Magnetic Field Vector
ODL Object of Daily Life
ODLs Objects of Daily life
OECD Organisation for Economic Cooperation and Development
PAN Personal Area Networks
PCA Principal Component Analysis
PD Parkinson's Disease
PIR Passive InfraRed
PPG photoplethysmography
PS Positioning System
RAS Rhythmic Auditory Stimulation
RF Radio Frequency
RFID Radio Frequency IDentification
RGS Rehabilitation Gaming Systems
RMSA Root Mean Square Error
RP Reference Point
RSSI Received Signal Strength Indicator
SBC Single Board Computer
SC Skin-Conductance
SHPIA Smart Home Platform for Intelligent Assistance
SoC System on a Chip
SVM Support Vector Machine
TDOA Time difference of Arrival
TEGs Thermoelectric Generators
TOA Time of Arrival
UWB Ultra Wide Band
VCS Virtual Coaching System

VS	Voting System
WBAN	Wireless Body Area Network
WLAN	Wireless Local Area Network