# *Human-smart rollator interaction for gait analysis and fall prevention using learning methods and the i-Walker*

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# Human - Smart Rollator Interaction for Gait Analysis and Fall Prevention Using Learning Methods and the *i*-Walker

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## Abstract

The ability to walk is typically related to several bio-mechanical components that are involved in the gait cycle (or stride), including free mobility of joints, particularly in the legs; coordination of muscle activity in terms of timing and intensity; and normal sensory input, such as vision and vestibular system. A walk is composed of the stance and swing phases. The faster we walk, the shorter the stance phase will be. Thus, gait requires input from the brain, spinal cord, peripheral nerves, muscular power and joint and cardiovascular health. Because all of these systems are required to coordinate gait, gait speed is an indicator of the health of many physiological systems. At the same time, a relation between gait and cognition has been widely analysed from the medical point of view, and we can find several reviews in the literature. As people age, they tend to slow their gait speed, and their balance is also affected. Also, the retirement from the working life and the consequent reduction of physical and social activity contribute to the increased incidence of falls in older adults. Moreover, older adults suffer different kinds of cognitive decline, such as dementia or attention problems, which also accentuate gait disorders and its consequences.

Assistive technologies (AT) play a key role in today's' society, especially when it comes to the older adults. ATs have enabled improvements in their Quality of Life, extending their autonomy and community living. This is important, as they can stay active safely and independently. During the last decade, research has focused on developing ATs with a sensor system integrated with the device or located in the human body. Efforts are focused especially on mobility assistance for different targets of people (visual impairment, frailty, chronic diseases or rehabilitation) and activity recognition, which could be used, for instance, to monitor elderly population living in autonomy and community-dwelling.

This thesis proposes a methodology to analyse how do older adults at high risk of falling interact with a smart rollator, the *i*-Walker, to navigate in indoor, flat environments. The *i*-Walker is equipped with a set of sensors and actuators and can collect data for long periods of time (several hours). It has already been tested in post-stroke rehabilitation and fall prevention clinical trials with successful results. In this work, we present results on our approach from a narrative perspective. Results are promising since we can relate the data obtained from human-rollator interaction to clinical parameters. The machine learning approach uses the data obtained with the force sensors of the *i*-Walker based on the interaction of individuals of different ages and health conditions. The analysis complements our extracted gait parameters with biological and clinical data to learn new characteristics of human gait at a stride-to-stride level.

We believe that users, caregivers and clinicians would benefit from the new knowledge that the *i*-Walker can generate from this work.

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# Chapter 1

# Motivation

Demographic ageing proceeds apace in all world regions, more rapidly than first anticipated in Nations (2003). The proportion of older people fastly increases as mortality falls and life expectancy increases. Population growth slows as fertility declines to replacement levels. Latin America, China and India are experiencing unprecedentedly rapid demographic ageing. The proportion of the population aged 65 and over is expected to triple in less developed countries over the next 40 years, rising from 5.8 to 15% of the total population, while in the more developed countries this figure is expected to grow from 16 to 26% (an increase of more than 60%), the ISSA report says (Scardino (2009)).

In nowadays ageing society, many people require appropriated and personalised assistance and new technologies to offer them an extraordinary opportunity to perform their activities of daily living (ADL) and improve their autonomy. A demographic study conducted by Brault (2010) showed that 56.7M people from the US (18.7% of the population) had some level of disability and 38.3 million (12.6%) had a severe impairment. Older studies by Brault (2005) and Brault (2000) show that these numbers are steadily increasing year after year, but also that the majority of this population is concentrated on more older adults. Of people aged 15 and older, 30.6 Million (12.6%) had difficulty with ambulatory activities of the lower body and 15.2M people (6.3%) had trouble with cognitive, mental or emotional functioning.

In the case of the EU25, in 2011 there were more than 80 million people with a disability in the population age group of 16-54 years, and it is estimated that this number increases up to 84 to 107 million people in the European Union (de Pejil et al. (2011)). Of all world regions, Europe has the highest proportion of the population aged 65 or over, a statistic that becomes more pessimistic according to the baseline projection of Eurostat, which shows that this percentage will almost double to more than 25% in the year 2050 (WHO (2012). Besides, life expectancy has continued to rise systematically in all of the EU Member States in recent decades (Kotzeva (2015)).

Besides, in this population sector, the frequency of falls increases with age and frailty level and are the leading cause of unintentional injury (WHO (2007)). A combination of biological factors and disease-related conditions are the primary cause of most falls among seniors. This combination has several implications for the Quality of Life (QoL) of the elderly population: as they reduce their activity, they increase their frailty and fear of falling while losing their residual skills. This will represent a challenge for the public health systems that will have to face a substantial socio-economic impact to deal with this demographic situation. This is already not sustainable in some countries and will be a worldwide issue shortly. One of the primary objectives of the H2020 program is to focus on the analysis of the causes and consequences of pathologies to find patterns that will support early detection of a disease or associated risks. Consequently, the care community could take decisions on intervention and educational information to delay the physical or cognitive decline of the elderly and try to keep them independent as long as possible living in the community.

The evolution of ICT tools (regarding cost, size or availability) in collaboration with medical knowledge has empowered the design and development of innovative solutions to provide tailored, remote and preventive care of people with special needs. In particular, there is an increasing interest in ambient assisted living technology, where individuals (in this case, elderly non-autonomous persons) and their environment are equipped with a system of sensors (from localization to bio-metric, among others) that will collect different types of measures allowing experts to monitor their activities in real-time, or by reports generated by the system. Ambient assisted living environments are expected to gain particular relevance with the incoming Internet of Things paradigm as a tailored, cost-effective solution to improve health systems (Vermesan and Friess (2013)).

Assistive technologies (AT) play a crucial role in the care of challenged individuals, such as older adults or people with physical and/or cognitive dysfunction. Their primary purpose is to maintain or improve individual's functioning and independence in order to facilitate participation in the society and to enhance overall well-being (WHO (2014)). ATs aim to provide assistance to different sorts of target publics, including low vision devices, hearing aids, augmentative and alternative communication, and especially technologies involving the use of mobile platforms, such as canes, scooters, wheelchairs and rollators or prostheses, such as artificial legs. Cane use has been prevalent among the elderly for years, followed by walkers (Brault (2000)). Lately, research has focused on the robotisation of these devices to assist persons with physical and/or cognitive disabilities in their activities of daily living (ADLs).

Independent mobility is one of the most critical factors in maintaining the quality of life for elders, and other clinical populations who need assistive devices, by delaying their institutionalisation. Mobility is crucial for performing ADLs, as well as for maintaining fitness and vitality (Alwan et al. (2007)). While robotised wheelchairs have been mainly studied to assist in the mobility and autonomy of the user (see §3.1), smart walkers can go a step further according to Martins et al. (2012): they are useful to a broader range of users and help in the recovery of ambulatory skills. Recent studies on real individuals have tested the potential of robotised rollators in the rehabilitation process of people hospitalised due to some type of impairment, like a stroke recovery or a car accident (Giuliani et al. (2012) and Morone et al. (2016)). Thus smart walkers not only promote mobility and navigation assistance but also can provide gait monitoring and partial body weight. New trends in research and future model business solutions will combine ATs with different embedded or on-body (wearable) sensors that will provide benefits to different groups of interest: assistance to the end-user, monitoring to relatives or caregivers, activity or clinical reports to specialists.

## 1.1 Scope of the thesis

This thesis work presents a new methodology for analysing the results of the interaction between a smart rollator equipped with different sensors, the *i*-Walker, and a group of older adults with physical dysfuntions due to the natural ageing progress or due to a recent fall. The *i*-Walker (see §4) is used to collect data during the execution of different walking tests and exercises performed by a group of volunteer participants from various centres and nationalities. Datasets will be completed with biological information from each individual, such as age, gender, the number of falls during the last year, as well as some cognitive and physical assessment measures. The *i*-Walker will be tested with two groups: a baseline of elder users performing a short walking test (10 Meter Walk Test) and a group of people from a wider age range performing a longer walking test (3 minutes Walk Test).

It is difficult to establish a boundary that defines whether an elder is healthy or not but, since we work with in-patients from hospitals and residences, we must discriminate the target population with whom we want to work. As the test involves walking for several minutes, we seek for elders with ambulatory capabilities and good cognitive status, so they can understand and perform the exercises. Following the clinical advice of doctors and physiotherapists from the Fondazione Santa Lucia (FSL), we have defined a protocol with the inclusion and exclusion criteria along with a description of the test and expected outcomes. In §5 we provide a detailed justification of the protocol that can also be consulted in Appendix §A for the complete version.

It is well-known that the *walking ability* of an individual can be affected by its cognitive and/or physical condition (Jahn et al. (2010)). One of the primary manifestations of *gait disturbance* in old age is the slow gait pace in comparison with the normal age-related slowing. Qualitative abnormalities of locomotion, such as disturbances in the initiation of locomotion or balance while walking are also indications for qualitative impairment of walking. Therefore, we need to identify which will be the most relevant variables from the human-robot interaction able to determine gait disturbance in a group of elderly individuals so that we can define a set of user profiles. We expect this information to be useful in two-folds: on the one hand, we aim to assess the quality of the information obtained from this human-robot interaction; on the other hand, we assume that this data will be useful to find some patterns on walking habits according to these user profiles. On future works, and with more tests, new control strategies could be developed to tailor the amount of help a user profile will need and improve the communication between the two parties. If we can find some patterns linking walking and medical parameters, the *i*-Walker could be used as an assistive device that is not only able to assist in elders mobility but is also able to diagnose a possible health decline by monitoring an individual's activity, or at least to contribute as a decision support system to the clinician.

In a first phase, we will use the *i*-Walker with elder individuals presenting different physical and cognitive conditions, separating initially between fallers and non-fallers (*i.e.* people that have fallen at least once during the last year). We have also collected other personal characteristics such as the presence of neurodegenerative diseases or prosthesis situated in legs and whether the person is using a traditional assistive walking device. Once the analysis is done, we will test the *i*-Walker again with a new set of users and check if it is possible to correctly classify the income of new data and give the appropriate assistance. We expect the results of this analysis could help clinicians in the diagnosis of cognitive decline and personalise the aid that the *i*-Walker could offer to the end-user.

As we will see later, along with the text, the research on smart walkers during the last years has been mainly focused on studying the mobility of healthy young people (or challenged healthy individuals) and, in a lower proportion, elderly or blind individuals. Little work has been done in the area of people with physical and/or cognitive disabilities, that may include the old. Moreover, in general, the works presented are performed with a short number of participants, probably due to the difficulties found when asking for a protocol approval in hospitals and care centres.

When we think about the opportunities that Assistive Technologies can provide to older adults, several questions or issues are raised regarding navigation support, human-robot interaction and user's satisfactibility with the whole system. Taking into consideration the components and characteristics of the *i*-Walker (see §4), there were a set of problems that I considered important to take into account for the future design of an intelligent support system for the *i*-Walker:

- *Where are we? Where are we going? : Interpretation of user's intentions*
  The *i*-Walker is equipped with a set of onboard sensors (forces, odometry and laser readings) that could be used to study *how* does each person face different navigation scenarios and define user profiles according to their driving skills. This kind of solutions usually includes a known indoor environment and the agenda of activities of the user (Cortés et al. (2010)).

- *Are you in trouble? : Prediction of user's intentions*
  Depending on the navigation situation, a person *may* require an extra amount of help (*e.g.* when there are many obstacles around his/her path). However, it is important to assist the users *only* when necessary and with the *appropriate* amount, otherwise the user gets used to make a minimal effort, and s/he may eventually end up losing residual skills.

- *Was I helpful? : Getting user's feedback*
  Studies have shown that if a person does not feel attracted to the assistive device, they tend to stop using it (Martins et al. (2012)). Thus, if users are not satisfied with the assistance, provided by the device, they will tend to refuse it. If the *i*-Walker can interpret the user's driving intentions, it could provide some guiding assistance by correcting directionality. In Urdiales (2012), a method for evaluating user's disagreement is proposed to implement a collaborative control between the individual and the robot (see §3.2.1).

- *Do you understand me? : Human-Machine Interaction*
  The sensors onboard could also be used to enhance the right interaction between the user and the *i*-Walker. State-of-the-art of the kind of alarm signs that have been used for blind

people or post-stroke recoveries has to be done. When dealing with people with cognitive disabilities, we can not abuse the use of alarms because they might not be understood or remembered. Also, the interaction should be smooth by making these alarms discrete enough to avoid stressing the user.

As a result, the *i*-Walker would be an assistive device providing physical and cognitive support to impaired and/or older adults. Safety and monitoring are included in the solution, making the *i*-Walker a potential aid that would allow a semi-autonomous life to persons with some disability, allowing them to live longer, with an acceptable QoL, in the community.

However, this is the first time that the outcomes of the *i*-Walker are analysed and assessed from a technical point of view. Until now, the *i*-Walker has been only used as a mobility or rehabilitation aid used to be compared with traditional assistive devices, and the assessment was done regarding clinical scales regarding the user (see §4.3.1). Therefore, the primary objective of this PhD thesis has become to process the dataset obtained from sensor measurements to provide a methodology for data cleaning and preparation. Since the data has been collected in different sites, there is a need for unification and normalisation methods as a primary step. The second objective is to analyse the data to provide a service that can classify a user according to walking and medical parameters and assist him/her in safe navigation. **We hypothesise that a fusion of sensors' data with biological data will allow identifying characteristics of walking behaviour for different groups of individuals**, in this case, elderly people with high risk of falling. We will base our analysis on the evaluation metrics that are traditionally used from a clinical, descriptive gait analysis. Taking leverage of the onboard sensors, we believe we will be able to provide information of the human-robot interaction at step or meter detail, instead of obtaining global metrics. Although other studies have analysed gait characteristics, few are the works found on studying walking behaviour when using a rollator. We expect to define different user profiles according to their driving and walking skills using the *i*-Walker but also related to their clinical condition. The *i*-Walker could be then used as a support tool for clinicians when making a diagnose of a new user.

## 1.2 Plan of the Work

The organisation of this PhD Thesis is as follows. In §3 a review on assistive devices, and more specifically smart walkers, is given. §2 contains a review of gait analysis from a clinical perspective, from observation to the involvement of different sensors that will complete the medical assessment. We then provide a technical description of the *i*-Walker in §4, the smart walker that is used to perform tests with real users in this thesis, as well as the previous projects in which it has been involved. A full description of the clinical trials involved in this work is given in §5. The methodology used in this PhD proposal is described in §6 and §7 show the results obtained at the moment. Conclusions and Future work are presented in §8. A detailed version of the pilots' protocol is given in Appendix §A. The Appendix §C contains the list of papers published so far, as well as the different conferences where I have assisted. Finally, Appendix §B contains an example of a social network managed by a multi-agent system where the *i*-Walker provides intelligent services to the user, relatives and doctors.

Results on this PhD could bring a new level of information that could be used in mHealth solutions like the one proposed, generating activity reports, acting in dangerous situations and serve as a patient remote monitoring tool. For this PhD work, I have studied the gait characteristics that are identified in the clinical literature and the analysis performed by several Authors. I have proposed a methodology using AI-based techniques to translate these clinical concepts into the domain of the *i*-Walker, to learn how to characterise an individual's walking behaviour while using a robotised assistive device. This perspective is complemented with a machine learning analysis that provides further knowledge on human motion body and how to categorise it.

# Chapter 2

# A review of Gait, Cognition and Falls

The ability to walk normally is related to several bio-mechanical components involved in the gait cycle (also known as *stride*), including *(i)* free mobility of joints, particularly in the legs; *(ii)* coordination of muscle action in terms of timing and intensity; *(iii)* normal sensory input, such as vision and vestibular system (see Rubenstein (2006)). Thus, gait requires input from the brain, spinal cord, peripheral nerves, muscular power and joint and cardiovascular health. Because all of these systems are needed to coordinate gait, the individual's walking speed is an indicator of the health of many physiological systems (see Fritz and Lusardi (2009) and Pahor (2006)).

The relation between gait and cognition has been widely analysed from the medical point of view, and we can find several reviews in the literature (see Haggard et al. (2000), Montero-Odasso et al. (2012) and Rosso (2013)). As people age, they tend to slow their gait speed, and their balance is also affected. Also, the retirement from the working life and the consequent reduction of physical and social activity contribute to the increased incidence of falls in older adults. Moreover, older adults suffer different kinds of cognitive decline, such as dementia or attention problems, which also accentuate gait disorders and its consequences (Scherder et al. (2007), Yogev-Seligmann et al. (2007) and Plummer-D'Amato et al. (2012)). Also, current concepts in disablement emphasise the importance of identifying mobility impairments in ageing humans to enable timely intervention and, ultimately, prevent disability as stated by McGibbon et al. (2001).

It is estimated that after age 70, 35% of the population present gait disorders due to different reasons related to cognitive and/or physical decline. Most of them associated with the ageing process, but other factors, such as education and lifestyle, are also influential (see

Yogev-Seligmann et al. (2007)). One of the most common and dramatic consequences of gait disorders is falling. Over a third of the population, aged 65+ years fall every year (50% for adults aged 80+ years). As a consequence, 4-15% of falls cause significant injuries, while 23-40% of injury-related deaths in older adults are due to a fall Organization (2015)).

## 2.1 Gait characteristics in elderly population

The capability to get from one place to another and successfully reach the desired destination is essential to every animal and therefore for humans[1]. Walking is a fundamental part of everyday life and depends on balance, joint motion, endurance, and muscle strength (Graham et al. (2008)). Human locomotion has been studied for decades, although the perspective, as well as the tools used for measurement, have evolved to these days. This field of research includes all ages of the human being, but also to the animal domain. This chapter focuses on gait analysis as the study of the human walking, which analyses the body mechanics and the activity of the muscles involved in the walking process (Whittle (2007)). Data used in this field can both come from clinical assessments (physical or cognitive) and different sorts of measurement tools that will collect some gait characteristics.

Gait analysis is a systematic technique for recognising negative deviations in the gait pattern and determining their reason and effects (Prakash et al. (2016)). As mentioned before, several conditions might affect the ability to walk, and it affects mainly to people when ageing. For these reasons, it is essential that clinicians regularly assess their gait to diagnose and plan optimal treatments for each situation. Although it is not possible to provide a general description of *gait* without including all the singularities given in each pathology, it is well accepted that a *normal gait* involves the locomotive action of the two legs, alternately to provide both support and propulsion, having always at least one foot in contact with the ground Whittle (2007). The walking activity is composed of the stance and swing phases. The faster we walk, the shorter the stance phase will be. A *gait cycle* is thus defined as the time interval between two successive occurrences of a repetitive event (*e.g.*, the right leg initial contact with the ground). Figure 2.1 shows the different phases included in a gait cycle starting with the right leg (in grey colour), taken from Whittle (2007). Body equilibrium is a key factor to correctly alternate leg displacements and sustains the body weight.

[1]For the elderly, walking, standing up from a chair, turning, and leaning are necessary for independent mobility. Gait speed, chair rise time, and the ability to do tandem stance (standing with one foot in front of the other, which

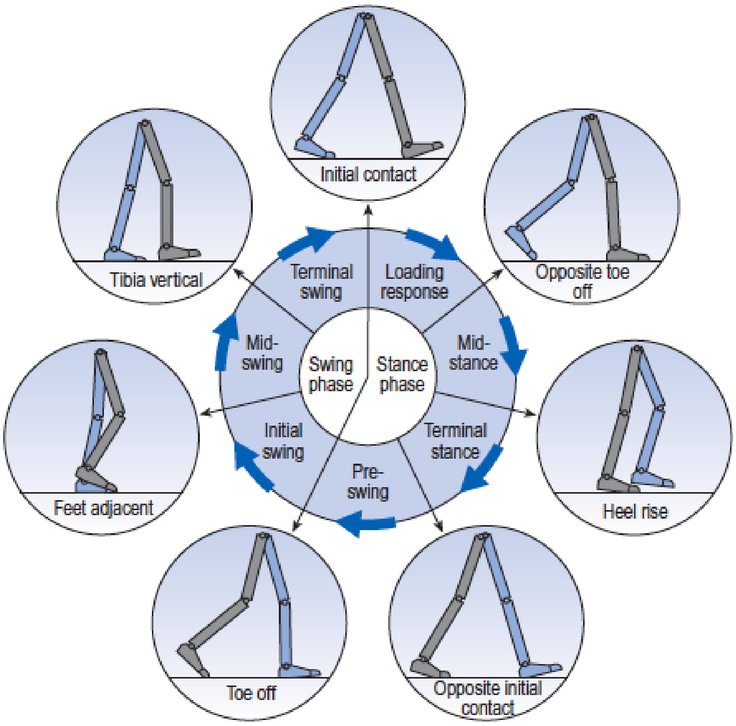


Figure 2.1: Different positions of the legs during a gait cycle.

Jahn et al. (2010) provides a detailed clinical classification of gait disturbances, where different types of gaits are defined and related to various aspects of the clinical history of patients. In Snijders et al. (2007), authors also propose a clinical approach to classify geriatric gait disorders based on three levels of categorisation. This classification has been used and adapted in different works (see Jahn et al. (2010)). Previous to this approach, another proposed by Nutt et al. (1993) was more commonly accepted, where gait disturbances were classified into *higher, intermediate and lower-level disturbances*. While the latter approach focuses purely on the outcomes of an individual's physical condition, the former also includes clinical diagnoses and a post-mortem examination. Additionally, it has been suggested that older people presenting gait disturbances have a higher risk of falling than healthy ones (Hausdorff (2005a)).

Scherder et al. (2007) present a review of the close relationship between gait and cognition in ageing and associated dementias. A common conclusion in the works they mention is that gait, and gait-related motor disturbances are present in all subtypes of dementia. Even though there are more studies with healthy older individuals (mainly because it is easier to pilot),

is a measure of balance) are independent predictors of the ability to perform instrumental ADLs.

results show in general a positive correlation between intense physical activity and cognitive functioning, for both men and women. Thus, we can consider that maintaining an active life will delay the cognitive decline, but there is not enough available information in the literature to confirm this. Moreover, patients with gait disturbances may not be able to increase their level of physical activity sufficiently to improve cognition. In general, authors agree on the effects of ageing in gait regarding gait speed and step length, which tend both to decrease.

With the aim to find causes and consequences of gait disturbances, dual-task tests have become more popular in recent years (Johansson et al. (2016)). These tests combine the walking task with executive function exercises to assess both physical and cognitive conditions of individuals, especially on older adults. Several authors have studied the assessment of gait in ageing people, such as gait variability in time (see Hausdorff (2005a); Jahn et al. (2010)), and especially its relationship with cognition and gait (Haggard et al. (2000); Montero-Odasso et al. (2012); Parihar et al. (2013); Scherder et al. (2007)). The research done embraces different kinds of dementia (*e.g.*, Parkinson or Alzheimer Diseases) and physical diseases (*e.g.*, Chronic Obtrusive Pulmonary Disease (COPD)), but also includes studies with healthy older adults, as single target group or as a baseline for comparing with a given illness.

Initially, human motion and physical condition were measured by observation and with simple tools, such as chronometers or video sequences and outcomes were usually related to the walking speed or body posture. Walking platforms have also been used in many studies, offering new insight on feet posture and force exerted to the ground, but also to spatiotemporal characteristics such as step length. One of the most popular platforms in the GAITRite, which has been used in many studies related to functional walking (see, for instance, Bilney et al. (2003); Rampp et al. (2015); Schülein et al. (2017)). Thus, the interest on gait recognition and further analysis has grown in the last decade, looking for patterns that would identify or help to categorise different types of pathologies.

With the introduction of wearables and smartphones, it is nowadays easier to collect continuous and ubiquitous health data, in addition to lifestyle routines. Smartphones already provide personal health information, such as the number of steps or kilometres walked during the day. This measurement is done with inertial sensors (*i.e.*, accelerometers, gyroscopes), which are nowadays found behind many commercial solutions of human motion tracking but have also become very popular in the research field of gait analysis due to their reduced price and size. This last characteristic also allows different localisation possibilities in the human body (*e.g.*, wrist, waist, ankle, foot insoles). Accelerometers have been widely used to develop new quantitative approaches that provide empirical, objective results. The main differences between all the studies found in literature about sensor-based gait analysis are:

- Components of the study: age population, number of participants, the test performed
- Measurement tool: type of sensor(s) or data collected, sample time
- Gait recognition algorithm: how the data is processed to proceed with the objective of the analysis

The most critical step in gait identification is the segmentation of the raw data provided by the sensors into steps or strides that will be then analysed. Gait detection can be obtained with different techniques, such as frequency-based algorithms, gait cycle identification, local maxima among others. Research on gait analysis has lately been focused on pattern recognition and classification using different machine learning techniques. Sprager and Juric (2015) provide a complete review of the various approaches found in the literature for sensor-based gait detection and identification.

## 2.2 Ageing and Falls

The ageing process affects older adults and their relatives. As they reduce their mobility, they become more dependent in their Activities of Daily Living (ADL), and eventually, their Quality of Life (QoL) declines. Nowadays in the US, 80% of the elderly population suffers a chronic disease (*e.g.*, Parkinson, Alzheimer or diabetes), and 50% of them have at least two. One of the common medical problems in the elderly is the appearance of gait disturbances and loss of balance (see Jahn et al. (2010)). Thus, the probability of falling increases when growing older and it is one of the main causes of unintentional injury. In this population sector, the frequency of falls increases with age and frailty level. Up to a 35% of people aged over 65 years fall each year, and this number goes up to 50% for people aged over 80 years old (see figure 2.2). Falls are associated with various risk factors that are categorised as follows:

- **Biological factors:** Embrace characteristics of individuals such as age, gender or race. It is also associated with characteristics of ageing such as a decline of cognitive, physical or affective capacities (including visual and hearing impairment, blood pressure, dizziness or arthritis, among others), or chronic illness.

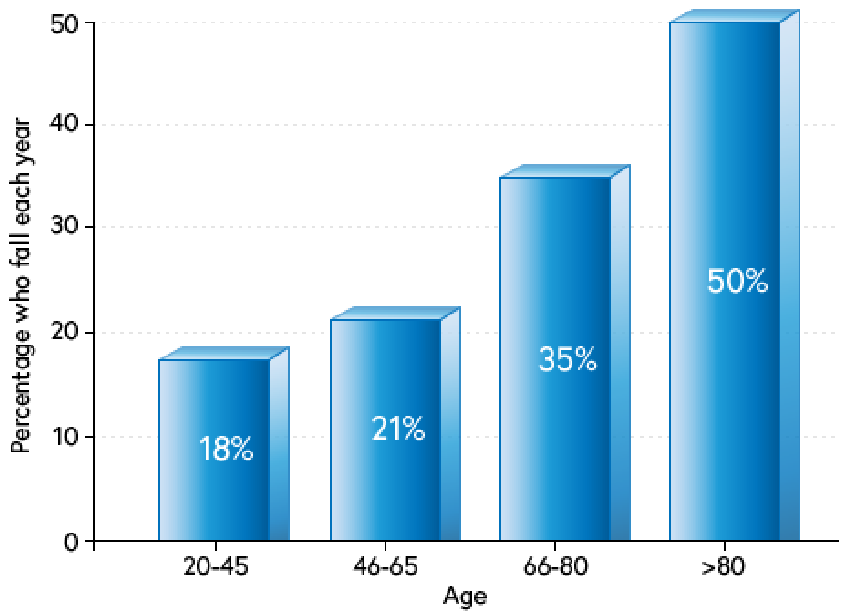


Figure 2.2: Falls prevalence. Source: Ageing Well, Newcastle University (2014).

- **Behavioral factors:** Risky behaviours include the intake of multiple medications, alcohol, smoke abuse or carrying a sedentary lifestyle. They are potentially modifiable over time as they directly depend on each individual choices and lifestyle.

- **Environmental factors:** Includes home hazards or hazardous features in public environment such as slippery surfaces, looser rugs or insufficient lightening. They are not a cause of fall by themselves, but they may interact with other factors to enhance an individual's risk of fall.

- **Socio-economic factors:** The socio-economic status of individuals may influence in their interaction with society. People with low income or education, limited access to health and social care or inadequate housing are potentially vulnerable regarding falling.

Usually falls involve a combination of risk factors, since the impact of suffering from one of them may impact in the lifestyle of the individual and make him/her more vulnerable to other risk factors. For example, people affected by their socio-economic status may not be aware of other risk factors due to a lack of information and access to medical services. Moreover, people having mild to moderate cognitive problems may suffer up to twice more falls than other adults cognitively intact (see Montero-Odasso et al. (2012)).

At the same time, people who fall increase their fear of falling and reduce their ambulatory routines. Consequently, this tends to cause a decline in their residual skills and enhances their dependence in performing their ADLs.

Falls are expected to represent a substantial world-wide socio-economical impact. Usually falls come with a period of rehabilitation which may also include institutionalisation in hospitals or residential care centres. It is expected to represent a significant part of public health system's budget. This situation will not be sustainable in a few years since it is already affecting some countries and will be soon a world-wide problem. Governments and organisations are giving awareness on the importance of promoting active, healthy living among the elderly population. One of the primary objectives is to reduce the risk of falling and its consequent fear of falling to avoid an increasing number of falls. Most of the research works mentioned above propose different physical and/or cognitive training that aims to contribute to this question.

Trends in medical and engineering research have focused in the recent years in combining resources to empower mHealth solutions and reduce costs to the traditional medical services. In the field of ageing and fall recovery, efforts are centred on gait analysis, early detection of walking behaviours and pathologies, cost-effective rehabilitation or improving autonomous navigation systems to support mobility aids. Assistive devices like canes or walkers not only provide support to the mobility of older adults but also help to prevent falls (see Chapter §3).

# Chapter 3

# A Review on Assistive Technologies

Older adults usually suffer from at least one health condition, from visual or auditive impairment, muscular weakness, to neuro-degenerative disease and others. Most of these situations lead to a decline in the locomotive functions, which is manifested as the difficulty to solve complex ambulatory situations (*e.g.*, avoid obstacles or turns to left or right), or gait disorders (*e.g.*, decreasing gait speed, unsteady gait). The combination of the mentioned factors increases the risk of falling in this population. Assistive Technologies are essential for the recovery or replacement of the mobility functions at all ages and enhance the autonomy and quality of life of patients and relatives.

Through this section, I will briefly introduce some research works in the field of assistive technologies designed for the mobility recovery (*e.g.*, exo-skeletons) and assistance (*e.g.*, Autonomous Robotic Wheelchairs or canes). However, rollators and more specifically smart walkers are a potential tool to study, since it can be involved in solutions for both problems, reaching a higher number of possible end-users. This review is needed to understand and synthesise the background of this thesis. It also introduces the work performed within two EU funded projects: *(i)* SHARE-*it*, where different assistive technology was developed to enhance autonomy and quality of life of elderly people [1]; and *(ii) I-DONT-FALL*, where the *i*-Walker is used as a rehabilitation tool for fall prevention.

[1]The KEMLG group coordinated the project at UPC.

## 3.1 Assistive Devices

It is interesting to observe the fast evolution of assistive mobility devices over the last two decades. Although we are used to seeing people around us using traditional assistive devices (and, more recently powered wheelchairs or scooters), solutions involving robotic technology and Artificial Intelligence are still under research development. However, the evolution of new technologies (*e.g.*, diminishing in size and cost while growing potential) are helping to create many different solutions that will someday improve our way of living. Different robotised versions of each traditional device have been recently proposed, aiming to help in either diagnosis, mobility or rehabilitation.

Assistive devices can be classified into two categories depending on the person's level of mobility: *alternative* for people with the total or temporal incapacity of mobility and *augmentative* for people with remaining mobility capacities. In Martins et al. (2012), authors represent this classification as shown in Figure 3.1.

In the field of alternative assistive devices, different models of Autonomous Robotic Wheelchairs (ARW) are proposed in the literature (Weston (Hillman et al. (2002)), Wheelesley (Yanco (1998))), *CARMEN* (Urdiales et al. (2011)). ARWs provide solutions for autonomous and assistive navigation, but those are normally restricted to people with the total incapacity of mobility. It is recommended that people with residual mobility skills avoid the use of wheelchairs during long periods of time, as it may lead to a loss of capabilities ( see Martins et al. (2012)).

During the last decade research has focused on the development of robotized augmentative devices, such as rehabilitation tools for ambulatory-training for people suffering from musculoskeletal or neurological disorders like strokes or spinal injury (HapticWalker, (Schmidt et al. (2007)), KineAssist, (Patton et al. (2008)), LokoHelp, (Swinnen et al. (2010))). The disadvantage for this kind of devices is that they are used in-hospital and require the expertise of a clinician or physiotherapist that ensures that the tools are being correctly applied.

One of the most important augmentative devices is the smart walker (see §4) because of its potential, not only in mobility but also in rehabilitation. It is well accepted that smart walkers offer enough weight balance, and thus help to raise self-confidence and autonomy to patients with locomotion problems. During the last decade, many solutions have been proposed, being equipped with different kinds of sensors to provide not only mobility but monitoring as well. Solutions also vary in the number of wheels, going from the two-wheeled models to rollator

| Mobility Assistive Devices | | Examples | Purpose | Degree of incapacity |
|---|---|---|---|---|
| Alternative | Wheelchairs | • Manual<br>• Autonomous with assistive navigation and/or bipedestation | Transportation | Total incapacity of mobility |
| | Autonomous especial vehicles | • Autonomous vehicles to improve cognitive capacities;<br>• Bipedestation | Transportation. Improvement of cognitive capabilities. | |
| Augmentative | Mobility-training devices | • Parallel Bars<br>• Treadmill-training devices<br>• Ambulatory-training devices<br>• Feet-manipulator training device | Mobility Rehabilitation Training | Residual mobility capacities |
| | Self-ported devices | • Orthoses | Functional Compensation (Supplement the function of the limbs) | |
| | External devices | • Canes<br>• Crutches<br>• Walkers | Functional compensation (support during walking, to increase gait stability, and balance) and rehabilitation training. | |

Figure 3.1: Categories of Assistive Devices (Martins et al. (2012))

walkers, with four wheels. Smart walkers are expected to present the following functionalities (Frizera-Neto et al. (2011)):

- *Physical support:* smart rollators should provide better gait stability.
- *Sensorial assistance:* smart rollators should also collect and process data from different onboard sensors to assist in navigation and increase security to the final user (useful for obstacle avoidance or fall prevention)
- *Cognitive assistance:* users having problems related to memory or orientation may need some guidance and localisation system
- *Health monitoring:* used to keep the medical history of the user

- *Human-machine interface (HMI):* directly or indirectly, HMIs are used to communicate with the user through a system of alerts, alarms and commands.

Rollators allow the performance of a natural gait pattern during locomotion. However, they are also considered the most unstable version and the risk of falling while using it increases in the situations that require the full-body weight support of the user (Neto et al. (2015)).

Regarding the physical aspect, most of the smart rollators found in the literature are not based on a traditional rollator, so there is a vast variation regarding physical designs. For instance, the number of wheels and handlers varies among the proposed solutions, but also the degree of assistance that each of them offer.

There are also different applications of these smart walkers regarding sensorial assistance: each solution is equipped with different sets of sensors, usually focused on object detection or user localisation. Some of these solutions are designed to assist blind people in navigation (Yu et al. (2003b)). In Glover et al. (2004) a walker is provided with navigation guidance for older adults who are cognitive or mentally frail by learning people's motion behaviours and providing directions through a touch-based interface. Smart walkers empower the mobility of the user, providing support while walking and increasing the confidence and safety perception during ambulation.

Regarding driving assistance, there are three strategies of human-robot interaction that are usually found in the literature, depending on which one has a higher decision control. These strategies are more commonly developed for ARW systems since a disagreement in the driving decision shall not have major physical consequences for the end-user. However, in the case of smart walkers, a strong disagreement could lead the user to lose balance, provoking some injury or even a fall. Driving control strategies are described below:

- *Human full-control:* The user takes control of the assistive device to move towards a given goal. This solution is not suitable for people presenting cognitive disabilities, as security issues can be monitored but the robot cannot take any decision.

- *Robot full-control:* The robot is aware of the ADLs and the environment of the user, and takes all decisions but, as stated before, this may lead to a serious loss of users capabilities and frustration.

- *Shared (or collaborative) control:* A combination of the previous strategies in which the robot will provide an amount of assistance according to user's skills. The idea is to help only when necessary, so the user does not get used to the robot doing all the job.

This last strategy is the most commonly used in the last decades Cowan et al. (2012) in the field of ARWs (see *CARMEN* Urdiales et al. (2011), Boy et al. (2002) and Carlson and Demiris (2010)). Research on smart walkers has been more focused on navigation assistance as a guide but not as a way of control. For instance, the EU FP7 funded project DALi developed a portable motion planning using a standard rollator equipped with a Kinect and a tablet to guide the user in crowded environments. The aim is to relieve the stress suffered by people with reduced cognitive or physical ability, especially older adults. The system does not actively assist on the navigation, but it provides a brake control when it detects that the user has deviated significantly from the objective.

Some examples that have been developed in the last decade are:

- PAMM (Spenko et al. (2006); Yu et al. (2003a)) is a smart robotic walker, designed at the Massachusetts Institute of Technology. It aims to provide support, guidance, and health monitoring to elderly users in order to delay to transition to nursing homes. The latest version of PAMM was based on a four-wheeled structure with two handler (a smart cane version with two wheels and one handler is has also been developed). It also contains a camera for localisation and obstacle avoidance.

- COOL Aide, (Wasson et al. (2008)), built on a standard three-wheeled rollator. Force and moment sensors have been added to the handlers, as well as encoders in the wheels to obtain the position, velocity and heading. It also contains a Hokuyo laser to assist the user avoiding obstacles. In Huang et al. (2005), authors propose a shared control strategy to help users dealing with possible collisions and reaching short-term goals in predefined paths.

- iWalker (Kulyukin et al. (2008)), developed collaboratively by the Carnegie Mellon University and the University of Pittsburg. It is based on a standard four-wheeled rollator equipped with encoders, RFID sensors and a laser to provide autonomous navigation and self-parking option.

- Smart Walker (Wada et al. (2016)) have built a sitting-type walker, which is a solution half-way between the wheelchair, where people will not require any motion force to move, and the rollator, which some challenged adults will not be able to use due to the lack of support force in arms or legs. The Smart Walker is equipped with an active-caster driving system which will help the user moving is given situations.

- UFES (Neto et al. (2015)) was developed under a research project between the University of Espirito Santo (Brazil) and the Univerisity of San Juan (Argentina). It presents a stricture of 3 wheels with encoders and motors, inertial movement sensors and 3D force sensors placed on top of two forearm support platforms. UFES provides a control architecture which enables an emergency braking in unsafe situations. It also collects gait parameters with additional IMU sensors placed on the user's body. The force sensors detect the guidance intentions

- ASBgo++ (Alves et al. (2017)) is a four-wheeled motorized rollator with forearm support platforms, built at the Minho University (Portugal). It provides safety navigation control and information about the user gait pattern. It contains a joystick which captures users movement intentions (Martins et al. (2014)).

- Cheng and Wu (2017) have developed a smart rollator with pressure sensors added to the handlers to capture user's driving intention using a support vector machine and AdaBoost classifier to identify the movement vectors.

**One of the objectives of SHARE-*it* and also of *I-DONT-FALL* and *FATE*, the EU projects in which the *i*-Walker has been involved in, was to ensure that the assistive device was user friendly**, *i.e.* a device the user is familiar with, so s/he will be more comfortable using it. The cost of production is also reduced as well, as we started from a standard frame with electrical components embedded instead of building the robot from scratch. A full description of the *i*-Walker is provided in Chapter §4.

## 3.2 SHARE-*it*

Within the frame of SHARE-*it* EU, funded project FP6-045088[1], at the Universitat Politècnica de Catalunya, two PhD thesis have been defended by Cristian Barrué and Cristina Urdiales (see Barrué (2012) and Urdiales (2012) respectively) at the UPC Artificial Intelligence PhD programme. These theses introduced different solutions developing and applying a research

[1] SHARE-*it* was a three years project funded by the European Commission whose primary objective was to develop AT which enable older adults to live independently and with the high quality of life as long as possible. The aim was to create scalable, adaptive systems of add-ons to the sensor and AT, mainly focused on supporting autonomous mobility, so that they can be modularly integrated into an intelligent home environment to enhance the individual's autonomy.

approach to improve the quality of life among individuals suffering some disabilities. That technology was further applied in other two EU funded projects *I-DONT-FALL* and *FATE*.

The primary goal of the SHARE-*it* project (Cortés et al. (2010)) was to contribute to the development of the next generation of intelligent and semi-autonomous assistive devices for older persons and people with disabilities (both cognitive and motor). When it comes to ageing, usually diseases do not come alone. When losing mobility, people's ability to be self-dependent in performing their ADLs decreases and they end up hospitalised or in a day-care institution, losing their social environment. If the person also has some cognitive disability, the possibilities of having an autonomous life go reduced. The objective of SHARE-*it* was to develop a scalable, adaptive system of components (*i.e.* sensors and ATs) integrated into an intelligent home to enhance individual's autonomy and thus, its Quality of Life.

Regarding the mobility aspect, four different assistive devices were developed and deployed in real environments and with real users, three ARWs (*CARMEN* (Urdiales et al. (2011)), Spherik (Martínez et al. (2005))and Rolland (Christian et al. (2008)) and a former version of the *i*-Walker (Annicchiarico et al. (2008)). The main purpose was to provide mobility assistance for a wide range of users with different capabilities and needs.

We tested the mobile platforms in an Ambient Intelligence environment, a house equipped with a set of domotic capabilities and sensors. A multi-agent system controlled all the data collected and managed the interaction between the assistive devices and the intelligent house through a set of cognitive services.

In 2009, I developed my Bachelor's project (PFC) at the Fondazione Santa Lucia (FSL) within the SHARE-*it* project. The objective was to design and perform a benchmark with real in-patients to test the interaction between *CARMEN* and the intelligent home through a multi-agent system. The agent controlling the wheelchair was responsible for deciding the amount of help that every user needed at any given time. A localisation system allowed the intelligent house to monitor the user's movements; when the user was driving in a narrow space (like a corridor) or crossing a door. The two agents interacted to increase the amount of help, if required, and decrease the security distance between the wheelchair and walls to facilitate the manoeuvrability. We proved that the users were able to end up their tasks easier and their navigation was smoother thanks to the multi-agent system.

Other agents should have been involved in the benchmark, but due to external delays, it was not possible to test it during my stay at FSL. However, they were included in the final tests of the SHARE-*it* project and results were very promising as well. Users passed a usability and disagreement tests, and the feedback was also very positive.

The successful results of this project led to the further development of the *i*-Walker, both regarding design (*e.g.*, reduction on electric components, European homologation as the medical device) and services for mobility assistance and recovery. It has since then been involved in three EU funded projects (I-DONT-FALL, FATE and ASSAM) and two Spanish national projects (*SiRC* and RehAdapta) all of them related with the development of Assistive Technologies. Chapter §4 contains a complete description of the *i*-Walker used in this thesis, along with the main contributions in research developed during the last years.

### 3.2.1 CARMEN: an ARW with collaborative control

Within the SHARE-*it* project, Urdiales (2012) designed and built a robotised wheelchair, *CARMEN*, with a collaborative control that aimed to assist a person's mobility. *CARMEN* can detect how much help a given user needs depending on his/her abilities and current condition and to provide the required help: *not more, not less*. The concept behind this approach is to avoid loss of residual skills due to excessive help but to provide, nevertheless, the required assistance to achieve mobility in everyday environments with a powered wheelchair. Following the medical team advice, as a security measure, the wheelchair could not be driven backwards.

The wheelchair is only driven by a joystick which translates user's commands into directionality and provides a navigation aid by adapting to the amount of help required by each user, according to their level of disability. A therapist previously determines the amount of assistance of every user.

*CARMEN* was built to be driven in an intelligent, adapted home following an agenda of ADLs defined by a medical team. It was first tested with a set of in-patients of the FSL using a purely reactive control for benchmarking, which mainly avoids obstacles thanks to the information transmitted by a frontal Hokuyo laser. Users had to test *CARMEN* in different defined paths (always including a door or corridor crossing), first without any aid (as a conventional powered wheelchair) and then with the reactive control.

The system gathered data about the user's commands, its relative position in the environment and the objects (or potential obstacles) surrounding the wheelchair along with other variables, like the time required by each user to complete the path. This information was used to measure *how well* did the user perform a given task. Urdiales finally formalised the information into different task metrics, although the most relevant for the rest of this work where:

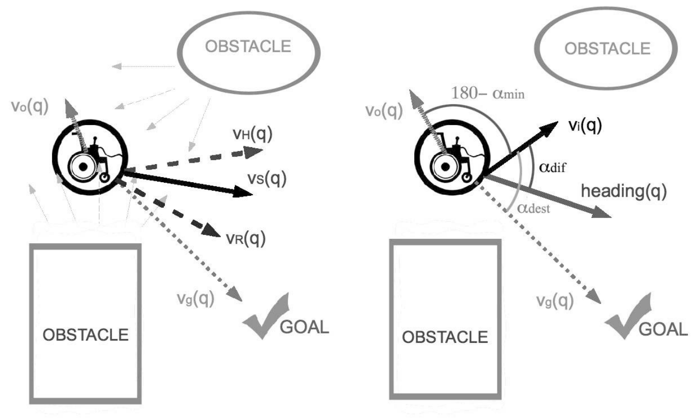


Figure 3.2: Vectors involved in motion command calculation.

- *directness:* the user drives keeping the goal ahead
- *smoothness:* the user's navigation (interpreted through the joystick movements) presents sharp direction changes
- *safety:* the user drives with a safe distance to obstacles

A person's *efficiency* performing a given task according to these metrics is then calculated. Figure 3.2).a depicts vectors involved in collaborative control (VR, VH and VC for robot, human and collaborative); Figure 3.2).b shows the angles involved in estimating smoothness (R), safety (G) and directness (B): local efficiency at a given location can be visually evaluated from its RGB colour. In addition to these metrics, users had to complete different tests regarding medical scales that measure cognitive and physical disabilities, or usability and disagreement questionnaires. Urdiales finally tested it with a collaborative control that gives driving control to the wheelchair when the user does not reach a minimum threshold of success in achieving the goal or avoiding an obstacle. Results were promising, as they showed that users were able to perform better their tasks (without the navigation aid, they were often unable even to accomplish them).

The second phase of her work consisted of creating skill-based wheelchair navigation profiles. The objective of using all the data gathered from previous tests is to separate users in profiles according to their navigation performance and the medical scales to predict the amount of help required at every moment instead of fixing it in advance. Urdiales used navigational information from both healthy people and persons with different kinds of disabilities. According to Minguez et al. (2004), in robot navigation, we can deal with six different situations to achieve collision avoidance in troublesome scenarios, depending on the level of safety of the robot within the environment (*security zone*), and the reachability of the goal (*free walking area*). Figure 3.3[1]:

- *Safety criterion:* High Safety (**HS**) or Low Safety (**LS**) represents the absence and presence of obstacles respectively.

The first criterion is applicable to every situation. The following criteria correspond to HS situations.

- *Goal within the free walking area criterion:* Corresponds to the High Safety Goal in Region (**HSGR**), which means that we are in HS and the goal location is within the free walking area

- *Free walking area width criterion:* When the goal is not in the free walking area, two new situations are defined depending on whether the area is wide or narrow: High Safety Wide Region (**HSWR**) and High Safety Narrow Region (**HSNR**)

Finally, they obtain three new situations in LS.

- *Goal within the free walking area criterion:* This criterion is similar to the second one, but this time the free walking area presents some obstacles. The resulting situation is Low Safety Goal in Region (**LSGR**).

- *Dangerous obstacle criterion:* Two possible situations may occur applying this criterion. The first one, Low Safety 1 Side (**LS1**), is given when there are obstacles within the security zone, but only on one side of the discontinuity (closest to the goal) of the free walking area. The latter one, Low Safety 2 Sides (**LS2**) means there are obstacles within the security zone on the two sides of the discontinuity

In Urdiales et al. (2013) authors used all the information gathered during the tests described above, adding the data of healthy people that performed the same tasks, to obtain a sample of 100 people. Their baseline user profile is built in a three-step clustering process.

[1]This figure is extracted from Minguez et al. (2004) shows these six possible situations which are defined according to the following criteria

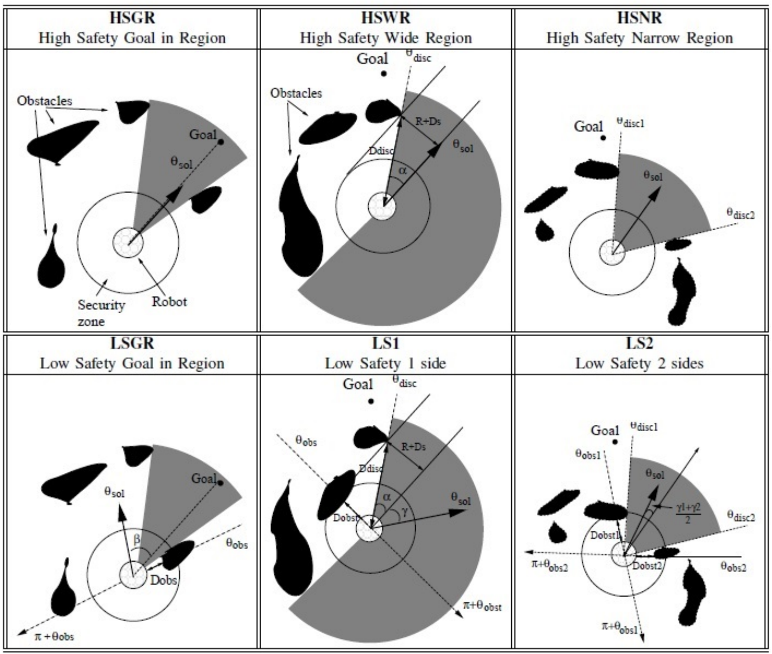


Figure 3.3: Examples of robot navigation situations

1. *Indoor Navigation Classification:* They first use a binary decision tree to classify all the situations that the users faced during the tests into six bins corresponding to the six possible configurations mentioned before.

2. *Headed-Based Clustering:* Second, they split each bin into classes depending on the wheelchair heading concerning the goal and the surrounding obstacles. For each of the original six general configurations, we will have now different specific situations.

3. *Solution-Based Clustering:* Finally, the resulting classes are classified into subclasses depending on the solution proposed by users when dealing with each navigation situation. They limit all possible commands to six possibilities: extreme-left, left, left-centre, right-centre, right, extreme right. They obtain a cluster prototype for each subclass as a result of the average of these commands weighted by their respective efficiency. Figure 3.4 shows all the resulting situations of navigation the user may face.

The objective is not to have the *best result* for each situation, as perfect solutions do not exist, but to obtain the commands more frequently used with the better efficiency. Now a user can drive the wheelchair with the collaborative control for a few times and the system classifies

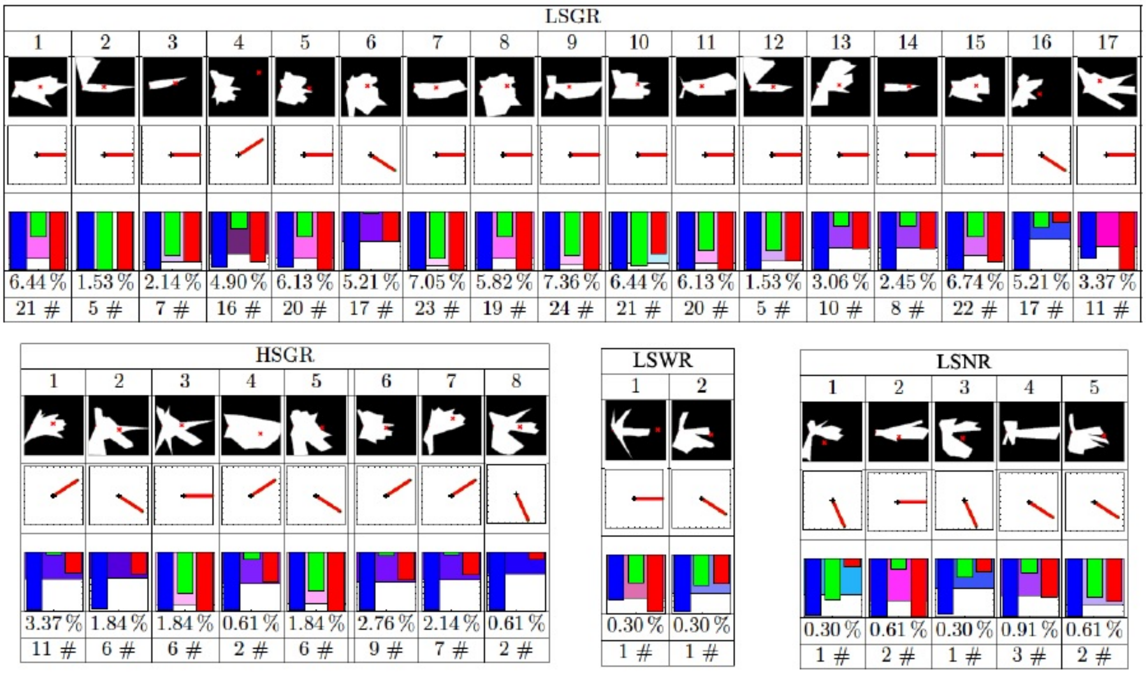


Figure 3.4: Resulting classes for each of the 4 non-empty bins

him/her into one of the navigation profiles to provide a more specialised aid. The data collected during my Bachelor PFC was used in this work.

## 3.3 *I-DONT-FALL*

The *I-DONT-FALL* project (*IDF* from now on) assembly and pilot integrated ICT services to detect and prevent falls able to adapt to different configurations and target groups. The project focuses on people aged 65 years and over that are susceptible to suffer a fall due to different risk factors. As said before in §2, we can categorise risk factors although usually, an individual falls as the consequence of a combination of different factors. The *IDF* project works with four different categories where to classify target users:

- Individuals that are likely to fall as a result of biological factors. *IDF* includes differentiation between the various biological and disease-related health factors, through considering fallers associated with balance and gait problems, cardiovascular diseases, vision problems, depression sufferers and more (Moyer (2012)).

- Individuals associated with behavioural factors that can lead to falls, including the intake of multiple medications and the excessive use of alcohol.

- Individuals associated with socio-economic factors that make them vulnerable regarding falling.

- Secondary fallers, *i.e.* individuals that have already fallen once and therefore represent high-risk groups. It is possible to classify secondary fallers in more than one of the above groups.

The above user groups are in need of solutions that could minimise the risk of falling (prevention), while at the same time supporting them efficiently in case of falls (detection). To reduce economic and personal costs by attending these target users and allowing them to live longer in community ICT-based services may guarantee a safe and effective solution that provides direct assistance to users. In particular, the solution must ensure *(i)* easy, and direct access to health and social care systems in case of falls and *(ii)* an undertake in-home physical and mental training which could help users reduce fall incidents. However, not all target users have the same needs or require the same training. These are the reasons why the *I-DONT-FALL* project deploys a personalised fall management services to seniors with high fall risk, covering both fall prevention and fall detection phases.

### 3.3.1 Fall Management Service

The *IDF* services were deployed for *(i)* elderly people living at home or *(ii)* elders residing in nurse/care centres. The offered services are mainly operated in *(i)* indoor controlled environments and *(ii)* in supervised outdoor environments, like the care centres gardens. The IDF project offered an integrated fall management solution, which deploys two primary services. Both of them have been tested within different pilots that took place in 7 care centres associated with the IDF project and involved 500 users. The results from this clinical trial are summarised in §4.3.2.

#### Fall Prevention Management Services

The Fall Prevention platform provides two different services. On the one hand, it offers real-time support to the elderly while and when they are falling. On the other hand, it offers offline prevention of falls, along with ICT-based cognitive training games and physical training. With these services, it is aimed to reduce or minimise the risk of falling of individuals with mild dementia. More specifically, the fall prevention management includes these services:

- *Balance Training: IDF* platform provides a set of balance training applications that are used as preventive measures against fall incidents. The medical team according to the target fallers profile configures these applications. The exercises will be performed through the integration of the *IDF* technological platform and the *i*-Walker.

- *Cognitive Training:* potential fallers undertake mental training as a fall prevention measure (tailored to some causes such as demented patients).

- *Pervasive Fall Prevention: IDF* integrates services that monitor an individuals ADLs by using wearable sensors and associated processing algorithms to prevent fall behaviours. A home management platform is deployed to inform about the activity and navigation of a user.

**Fall Detection Management Services**

The Fall Detection services are based on a wearable fall detection sensor (WIMU, see 2.2.2) that is integrated again to both the *i*-Walker and the *IDF* platform. This wearable device can generate signals or information about the activities of the user. More specifically the Fall Detection Service includes the following atomic services:

- *Fall Detection Alarm:* the wearable devices such as wrists or bell devices trigger alarms and accordingly instigate processes for handling the incident (*e.g.* send notifications to medical team or family).

- *Call/Contact Centre Integration for Tele-care / Tele-assistance services:* once a fall incident is detected, the service provides a connection with a call centre, so a two-way interaction is established to select the best possible alternative to deal with the incident.

The Fall Detection service aims to verify the system's ability to function appropriately (*i.e.*, it can detect false positives and negatives, diagnostic specificity and diagnostic sensitivity). The evaluation of this service is made through a validation study, not a clinical trial. The study has been carried out on a total of 22 elderly volunteers living at home in Rome (FSL).

### 3.3.2 IDF components

The *IDF* project integrated different innovative devices to work together to both assist users mobility and inform family and medical teams about their activities. Three main services compose the *IDF* project: the *i*-Walker (see Section §4), the WIMU and the SOCIABLE platform.

The WIMU (Wearable Inertial Measurement Unit) is composed of a tri-axial sensor: accelerometer, gyroscope and a magnetic sensor. The WIMU offers information about an individual's movements, and so is used to boost fall detection and prevention. When an incident occurs, the WIMU detects it, and within the integration of other services, it will trigger an alarm to the health care centre or family to take the best possible solution.

For the cognitive training, the *IDF* project engaged older adults and potential fallers to perform a set of cognitive exercises to improve their balance. The project leveraged readily available activities (and related gaming applications) that have been tested, validated and piloted based on surface computers under the SOCIABLE project. The target cognitive skills embrace memory, attention, orientation, executive functions, abstract reasoning and constructional praxis. The effectiveness of the *IDF* SOCIABLE cognitive training system will be primarily determined by the efficacy of cognitive training to reduce the risk of fall. From the technical point of view, the project aims to test and ensure the successful integration of the cognitive training service into the platform, *i.e.*, ability of the cognitive training service to exchange information with the *IDF* platform and provisioning of full-service functionality.

### 3.3.3 The *IDF* protocol

The *IDF* service was tested within a multi-centre and multinational clinical trial conducted on 500 elderly volunteers living at home or in residential care centres during nine months. The centres involved in this clinical trial are associated to the *IDF* project: Fondazione Santa Lucia (FSL) (Rome, Italy), Fondazione Salvatore Maugeri (Pavia, Italy), Servicio Madrileño de Salud (SERMAS) (Madrid, Spain), Hospital General de Granollers (HGG) (Granollers, Spain), Social Policy Center of Kifissia (Athens, Greece), Frontida Zois (Patras, Greece), and Municipality of Stari Grad (Belgrade, Serbia). The principal outcome is to reduce the number of falls, the risk of falling and the fear of falling between experimental and control groups, together with the evaluation of usability of the system and user satisfaction concerning the applied training program. As a matter of example, consider a typical application of the *IDF* platform for potential fallers. First, the medical expert will check the health record of the patient and be informed about the health status of the potential faller. According to the medical protocol, the medical expert will assign rehabilitation IDF program to the potential faller based on the randomisation process. After the definition of the *IDF* rehabilitation program, the end user will start regular *IDF* sessions as specified in the medical protocol. In particular, the end user will visit the pilot site and perform his/her *IDF* training sessions (two sessions of 1 hour per week for 12 weeks). During the sessions, the end user will perform his/her exercises according to the *IDF* rehabilitation program. After each training session, the personal health record is updated with the new data generated, allowing the medical expert to assess the end user's evolution. The following pilot protocols describe how the fall prevention and detection services come to be used together during this process:

- *Fall Detection:* Provides support to the end user in case of fall. On the base of the data monitored by the WIMU/*i*-Walker, the system identifies a possible fall of the user, and it produces an alarm event.
- *Call centre family notification:* depending on the kind of alarm generated the call centre will notify a person from the user's list of contact.
- *Provisioning of cognitive training:* Medical experts will include cognitive training sessions in patient's *IDF* training platform to improve his/her cognitive skills to reduce the risk of falls.
- *Provisioning of walking training:* same with physical training using the *i*-Walker to assist users during exercises.
- *Patient assessment and feedback:* Users will regularly answer a set of questions that will be stored for future consultation.
- *ADL monitoring:* data collected by WIMU/*i*-Walker about the level of activity during daily life is monitored for the prevention and study of falls.

For this PhD work, we will focus on the pilot protocol provisioning of walking training by integrating the *i*-Walker into the *IDF* platform as an assistive platform to support the physical exercises.

All participants are aged 65+ years, they already had previous falls and/or present a very high risk for falling measured by the Tinetti Test (score $\leq 20$), and they meet the minimum cognitive level needed to be able to co-operate in this part of the study (MMSE $\leq 20$). Volunteers need to be stable patients, with at least one month from last acute event. The presence of a caregiver during the sessions is mandatory. On the other hand, persons presenting aphasia and/or neglect or major behavioural disturbances were excluded from the study. Also, people involved in rehabilitative training cannot participate in the pilot due to safety reasons. Participants who satisfied inclusion criteria were assigned randomly to one of these four groups:

- MOTOR: 125 participants in walking training that perform a set of exercises with a physiotherapist using the *i*-Walker.
- COGNITIVE: 125 participants in cognitive training that perform a set of exercises using the SOCIABLE platform.
- MIXED: 125 participants in the combined training (motor + cognitive training).
- PLACEBO: 125 participants as a control group (placebo activity to control the subject-expectancy effect).

The walking training process is executed in 2 sessions per week for 12 weeks (24 sessions). Each training session takes 1h of duration. Volunteers are free to drop out of the study if the subject fails to participate in the training for more than two consecutive weeks (4 sessions), then s/he is considered as a dropout. Each training session is dedicated for 1/2 to balance and 1/2 to gait exercises after a brief session on warm-up exercises.

- Walking training session of 30 minutes:
  - 3 of warm-up exercises (exercises selected from warm-up pool)
  - 15 of balance (exercises selected from balance pool)
  - 15 of gait (exercises selected from gait pool)
- Walking training session of 60 minutes:
  - 3 of warm-up exercises (exercises selected from warm-up pool)
  - 15 of balance (exercises selected from balance pool)
  - 15 of gait (exercises selected from gait pool)
  - 5 pause
  - 15 of balance (exercises selected from balance pool)

- 15 of gait (exercises selected from gait pool)

The central objective of this study is to reduce the number of falls in the experimental group respect to the control group. As a consequence, it is also expected to minimise the risk of falling (measured by the Tinetti test) and the fear of falling (measured by the Fall Efficacy Scale FES test). We also aim to evaluate the usability of the system and user satisfaction concerning the applied training program (*i.e.*, if they have performed walking and cognitive training or just one of the two). The secondary outcomes of this study are the improvement of mobility using users balance and gait (measured by Tinetti test, 6 minutes Walking Test and 10 meters Walking Test) (see Tinetti et al. (1986)), as well as the improvement of the QoL and the functional and cognitive abilities. We will also analyse the dynamic relationship between pushing forces and walking dynamics, crossed with the user medical profiles. Outcomes will be evaluated through a multidimensional assessment that will be administered two times: before the training period starts (T0) and after the training period ends (T1).

# Chapter 4

# The *i*-Walker

The assistive device presented in here is based on the prototype developed on EU funded project SHARE-*it* (see SHAREit and Cortés et al. (2010)) at the Universitat Politècnica de Catalunya (UPC). The consolidated version, the one used for this work, is based on a standard 4-wheeled Rollator AD-100 with a set of embedded sensors and actuators, aiming to assist to the mobility and the rehabilitation of persons with physical and/or cognitive disabilities and monitoring their activities (see Annicchiarico et al. (2008)). In the end, the *i*-Walker looks *like* a traditional rollator. It is designed to provide potential users with sufficient ambulatory capability in an efficient, cost-effective way. It follows the ISO requirements for walking aids manipulated by both arms (see ISO) and has obtained the EU approval as a medical device for clinical research. The actual version of *i*-Walker has been used in the *I-DONT-FALL* , *FATE* and ASSAM EU projects funded by the Competitiveness and Innovation Framework Programme (CIP) of the European Union (see I-DONT-FALL, FATE and ASSAM respectively). For this PhD, part of the data generated by the *i*-Walker in the *I-DONT-FALL* project has been used, which has been described in §3.3.

In this chapter, a full description of the smart walker (the *i*-Walker, see Figure 4.1) used in this PhD is given, including an introduction to its main components and the role they play in the system; the reactive control that has been developed to provide compensation and safety in the ambulatory activities in indoor and outdoor environments; a possible approach to shared control navigation. This chapter contains also an overview to the *i*-Walker's assistive environment, describing its role in different research projects: three master thesis developed at UPC, where data collected from the *i*-Walker in different scenarios was analysed with different perspectives and aims. This section also provides a summary of the *I-DONT-FALL* project results from a clinical point of view.

In Appendix §B introduces the results of integrating the *i*-Walker as an intelligent service within a Social Network (Barrué et al. (2015)). This work was a part of a preliminary study to assess the plausibility of learning from the interaction of several *i*-Walkers and their respective users and caregivers. In that work, the *i*-Walker interacted in the Social Network as one more agent in a Multi-Agent system.

## 4.1 Main components

The *i*-Walker is a distributed micro-controller architecture which drives the system and records and provides structured information to therapists. All the electronics are embedded inside the handlers (1) and rear wheels (9) of the *i*-Walker. A box (3) under the seat (2) contains the computing power onboard (a Raspberry Pi) and a set of sensors that will provide information about movement and tilt. For this work, we have also added a frontal Hokuyo laser to detect obstacles and avoid possible collisions. Table 4.1 summarises all the different variables captured and gave a brief description of each one. The names appearing in parenthesis will be the ones used along the rest of this document.

| **Variable** | **Description** |
|---|---|
| **Left Hand Force X** (lhfx) | Longitudinal (Forward-Backward) pushing force exerted by the user on the left handlebar |
| **Left Hand Force Y** (lhfy) | Transversal (Left-Right) pushing force exerted by the user on the left handlebar |
| **Left Hand Force Z** (lhfz) | Vertical (Up-Down) pushing force exerted by the user on the left handlebar |
| **Right Hand Force X** (rhfx) | Longitudinal (Forward-Backward) pushing force exerted by the user on the right handlebar |
| **Right Hand Force Y** (rhfy) | Transversal (Left-Right) pushing force exerted by the user on the right handlebar |
| **Right Hand Force Z** (rhfz) | Vertical (Up-Down) pushing force exerted by the user on the right handlebar |

| | |
|---|---|
| **Left Normal Force** (lnf) | Left Rear Wheel Normal Force. This is the force that the floor exerts on the wheel. When the value is below a given positive threshold, it means that the *i*-Walker is losing its contact with the floor |
| **Right Normal Force** (rnf) | Right Rear Wheel Normal Force. This is the force that the floor exerts on the wheel. When the value is below a given positive threshold, it means that the *i*-Walker is losing its contact with the floor |
| **Tilt** (tilt) | Angle over the lateral axis of the *i*-Walker |
| **Roll** (roll) | Angle over the longitudinal axis of the *i*-Walker |
| **Hand Brake Left** (hbl) | State of the break: 1 if blocked, 2 if manually activated |
| **Hand Brake Right** (hbr) | State of the break: 1 if blocked, 2 if manually activated |
| **Estimated Pose X** (epx) | Pose estimated from the beginning of the exercise in Y axis (starting from point [0,0] in a Euclidean space) |
| **Estimated Pose Y** (epy) | Pose estimated from the beginning of the exercise in Y axis (starting from point [0,0] in a Euclidean space) |
| **Estimated Pose Orientation** (psi) | Estimated orientation of the *i*-Walker regarding the initial orientation (the orientation that the *i*-Walker had when the exercise has started) |
| **Left Wheel Speed** (ls) | Left wheel speed |
| **Right Wheel Speed** (rs) | Right wheel speed |

Table 4.1: *i*-Walker variables and definitions.

### Handlebars

The original handlebars have been replaced by another model also used in standard rollators. These new handlebars (1) measure the user's force exerted along the longitudinal, lateral and vertical directions (*X*, *Y* and *Z* respectively) through embedded force sensors. Height graduation is maintained in this new design (8)[1]. By adding these force sensors in the grips of the handlebars, we can register at any time the force exerted by the user. The handlebars can also monitor the states of the brake levers, having a manual brake (7) with two different states:

[1]This is useful in post-stroke patients, as they may need different height graduation on each hand

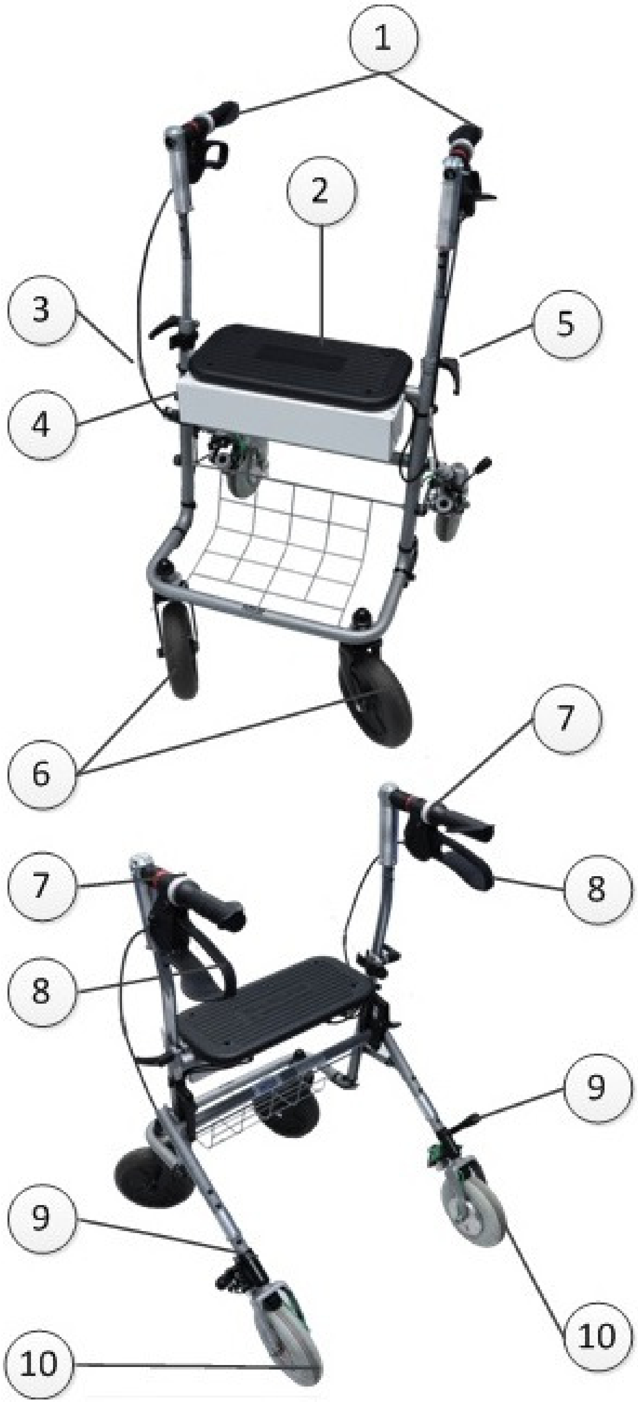


Figure 4.1: The *I-DONT-FALL* version of the *i*-Walker.

- *Parking brake:* a mechanical brake can be operated by pushing down the brake lever (*braked* state). This action is recommended when the user wants to stop in the middle of a slope or wants to rest in the seat.

- *Dynamic brake:* the brake lever can be pulled up to slow down the speed of the walker. This will increase the pushing forces exerted by the user, giving him/her a higher sense of security. This functionality is useful in downhill, as the user does not have to be pulling the *i*-Walker and, thus, avoiding this one to go away too fast (a more detailed description is given in §4.2).

All the information provided by the handlebars is collected and stored so the medical staff can control if the user is doing a good use of the device.

The new handlebars include some features that aim to improve the interaction between the *i*-Walker and the person using it. On the one hand, a bright multicoloured lighting ring is used to indicate the different states of the *i*-Walker: calibration status and battery levels. Handlebars also embody a vibrator that can be used as a haptic device to enhance the interaction between the user and the *i*-Walker, *e.g.* when the user is getting too close to a wall or an obstacle. This lighting ring can be handy for users with visual or cognitive impairments. In both cases, the intensity and duration of the flashes of lightning/vibrations can be defined for every type of signal.

#### Rear wheels

The rear wheels (10) have been modified by adding a motor and electronics in each one. The external structure of the wheel is maintained, but the internal part is redesigned, changing the axis of rotation to couple with the motor. The rear wheels collect odometric information from three Hall-effect sensors integrated inside each engine. The gathered data is useful to calculate the $(X,Y)$ user's position, as well as the longitudinal and rotational speeds. In the end, these motors work by helping the user to move around safely, especially in up and down slopes.

The motors can work in four different operating modes described in Table 4.2. The reactive control (see §4.2) uses these different modes depending on the amount of pushing/pulling help it is required in every moment.

#### Central box

The central box contains a Raspberry Pi, the battery and three new sensors that have been added to have a complete Inertial Measurement Unit (IMU):

| Operating Mode | Description |
|---|---|
| **FREE** | No action applied on motor. The wheel turns freely, like a conventional wheel. It is useful when we want the wheel to turn freely, but it also maintains access to information about kinematics, temperature, *etc* |
| **AS** (Active Speed control) | The motor is driven by a set point of angular speed. Useful when any user is not using the *i*-Walker but we want it to behave like an autonomous vehicle. |
| **AC** (Active Current control) | The motor is driven with an actual set point proportional to a torque set point. Useful to compensate the forces required from the user. |
| **AB** (Active Braking control) | The wheel is braked by setting a current set point that opposes to the movement. |

Table 4.2: *i*-Walker Motor operating modes.

- *Gyroscope:* detects the three angular speeds of rotation. This information strengthens the data gathered from odometry, having more precise monitoring of the user's movements.
- *Accelerometer:* detects if the user is walking on a slope and/or the *i*-Walker is being accelerated.
- *Magnetometer:* detects the projection of the magnetic earth filed on the integrated circuit.

## 4.2 Reactive control

The most innovative feature of the *i*-Walker is the design of a reactive control, developed at the Automatic Control Department (ESAII-UPC), which provides mobility aid to the user. The amount of helping force and braking force in each hand ought both to be determined previously by a clinician.

The *i*-Walker platform provides four primary services. Three are related to elder/impaired assistance; we use the fourth for data logging. A physiotherapist should plan all the support given to a user. Services provided at this moment are:

- Active motor assistance to compensate lack of muscle force on climbs.
- Active brake assistance to compensate lack muscle force on descents.

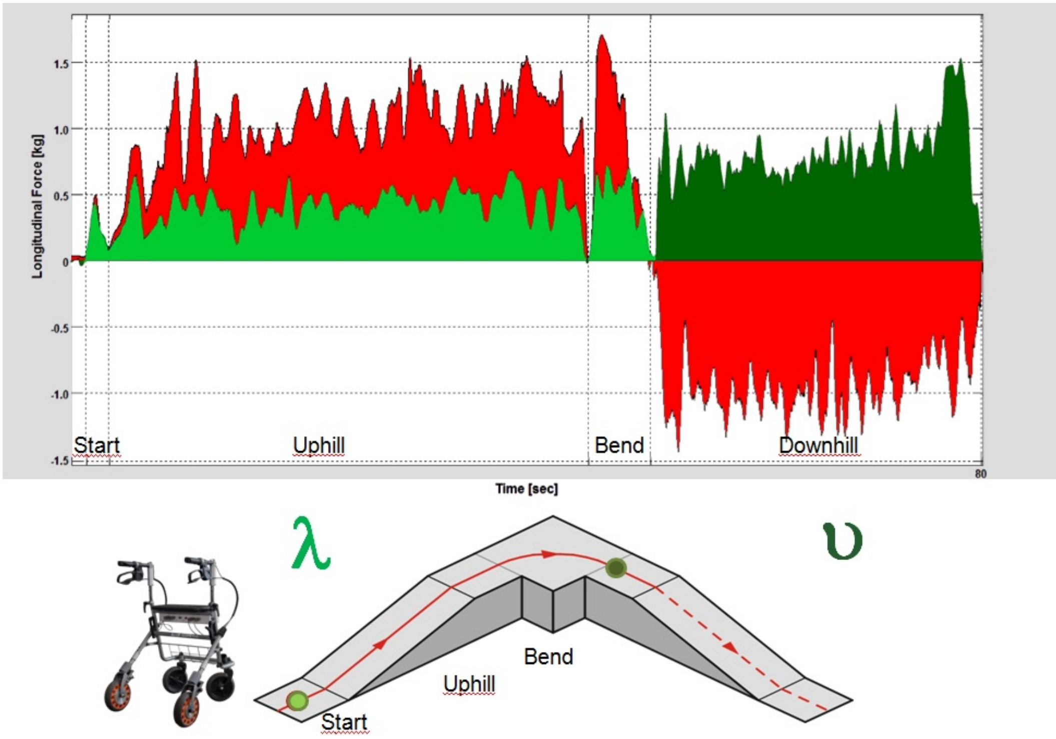


Figure 4.2: Example of left-hand force compensation.

- Active differential assistance to compensate unbalanced muscle force.

- Recording of sensor measurements and actuators activities for later evaluation (left and right-hand forces, normal forces, tilt and odometry)

Described strategies are not exclusive: we can have the user pushing the *i*-Walker going downhill and at the same time the *i*-Walker relieving him from part of the necessary pulling/pushing force to move around. For safety reasons the *i*-Walker automatically stops when the user releases the handlers, that is when no forces are detected on them.

#### Hand force compensation

The reactive control works with two primary variables: $\lambda$ and $\nu$. The former represents the amount of helping force that the user receives, while the latter one is a helping brake force. The combination of both parameters allows the therapists to create a patient's tailored configuration. These parameters are set during the initial setup of the *i*-Walker by a physiotherapist.

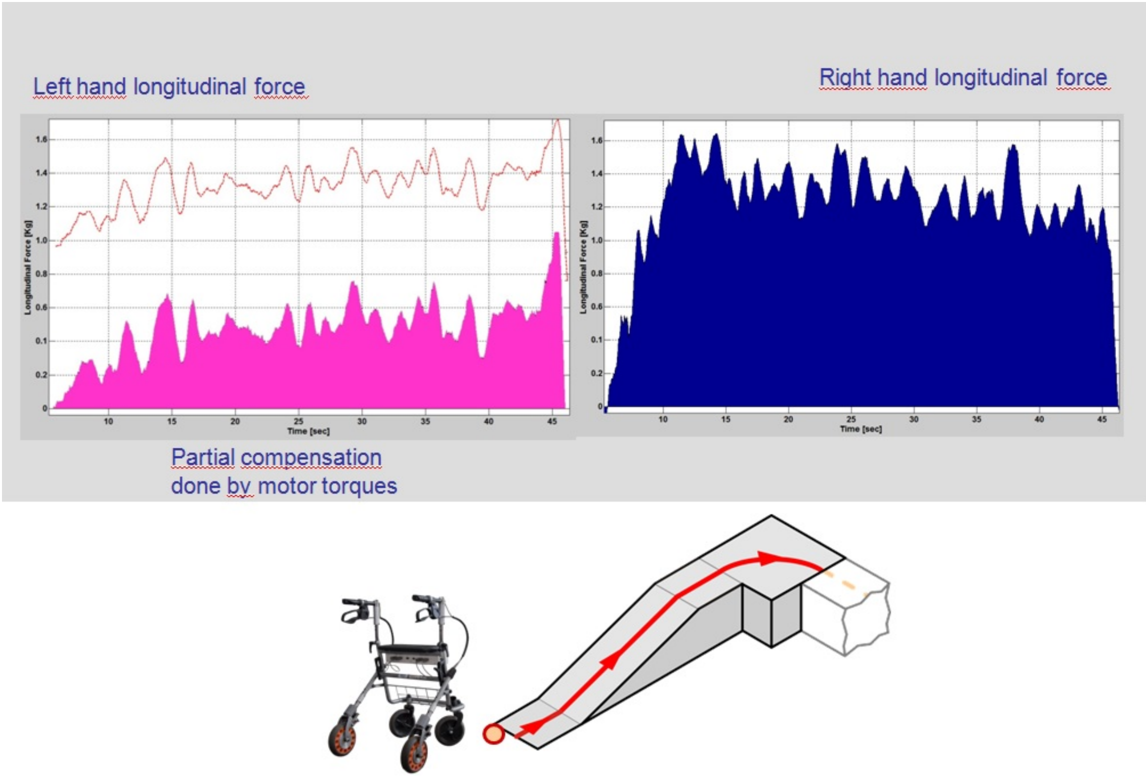


Figure 4.3: Hand force compensation strategies in an uphill scenario.

When a user is going uphill with the *i*-Walker, the $\lambda$ parameter will release the user from part of the pushing force s/he has to do. In Figure 4.2, red areas represent the longitudinal force that the user should be exerting in the given scenario. The green areas correspond to the force compensation provided by the *i*-Walker. During the uphill, the rollator will compensate the lack of pushing force; when going downhill, it will assist the user by sending active break signals to the rear wheels. This compensation will avoid excessive retaining force (*i.e.*, negative longitudinal force), and thus a possible fall. The aid provided in downhill is independent of the value of $\lambda$, as it is a safety mechanism that aims to prevent falls.

The *i*-Walker allows to determine different amounts of compensation strategies in each side of the body according to the user's dysfuncions. Figure 4.3 shows that the configuration of $\lambda$ and $\nu$ parameters is independent on each handlebar (*e.g.*, an individual with hemiparesis needs different help on each hand). In this case, the user received helping force on the left hand (the difference between the pink area and the dotted line is the contribution of the *i*-Walker's compensation), where the dotted line represents the real force required and the pink area is the force finally exerted by the user. The right hand did not require any help, so $\lambda$ is set to 0, and the user has to apply all the force by himself (blue area). As we can see, even though the user has applied less force on the left hand than on the right one, s/he succeeded in following the path.

### 4.2.1 Applying the collaborative control philosophy to the *i*-Walker

One of the possible applications to the mobility assistance with a smart rollator is to design a collaborative control similar to the one presented in Section §3.2.1. As mentioned before, the main difference between *CARMEN* and the *i*-Walker is the driving control. The wheelchair is considered an active assistive device, where the user only gives a directionality through the joystick (which does not even have to be the right direction to the goal) and the wheelchair will move him/her until the final goal. The *i*-Walker pretends to be a passive assistive device. In this case, the user's intended directionality should be interpreted by using the three resulting vectors extracted from the force sensors, but the user's motion is also necessary: *it is the user that has to move by him/herself*. The philosophy behind the *i*-Walker is that it will never push an individual towards a direction, as this could lead to sharp changes of directionality, ending in a possible fall of the user. The *i*-Walker could instead offer a counterforce in the rear wheels by changing the value of $\nu$ that would guide the user in the right direction. A study on human-machine interaction state-of-the-art shall be done to determine different types of alarms, *e.g.* when the walker is too close to an obstacle or when the control is actuating on the walker against users directionality. The *i*-Walker should also be able to move around a known indoor environment, learn the user's agenda to match it with its directionality to interpret the intention according to the activity s/he is supposed to be taken next.

## 4.3 The *i*-Walker's Assistive Environment

During the last decade, different services or tests have been performed with the *i*-Walker within various European and Spanish national funded projects. The shared goal has been the aim to contribute to the quality of life of older adults, but also to the design of intelligent, tailored and valuable services for experts, patients and caregivers. Data used in these projects have been analysed from a clinical perspective, where clinical assessments measured the expected outcomes. Additionally, sensor-based analysis has also been carried on to discover new knowledge about the walking behaviours of the participants. Also, Annex §B provides a preliminary proposal for an assistive social network supported by a multi-agent system. This proof of concept shows one of the main opportunities of moving towards a digital health environment, where health data can be shared among entities or persons of interest, smart or seniorized devices like the *i*-Walker could provide ubiquitous data and generate reports or alerts when necessary.

### 4.3.1 The role of the *i*-Walker in post-stroke rehabilitation

Stroke is known to be the leading cause of disability in the elderly, with a significant impact on individual, family and community health. 35% of stroke patients, as a group, have severe residual disability and marked limitation in their activities of daily living. The health expenditure for stroke accounts for 2% -4% of the total in developed countries and the acute phase of stroke accounts for 25% -45% of all spending in the first year after the event. Considering the *lifetime cost*, for example, all costs that the patient meets after the event, it was shown that these costs would be reduced by 10% if there was less than 1% mortality while acting on disability reduction would be 25%. One of the main consequences that affect stroke survivors is hemiparesis, which causes weakness or inability on one side of the body. It affects the hands, arms, legs and facial muscles of the person, which may lead to:

- Loss of balance
- Difficulty in walking
- Impaired ability to grasp objects
- Decrease in movement precision
- Muscle fatigue
- Lack of coordination

These impairments naturally generate a difficulty in performing some ADLs, like eating, getting dressed or going to the toilet; it also limits individual's mobility. Rehabilitation treatments and assistive devices play a vital role in the recovery of a post-stroke patient. In common practice, people with hemiparesis do not use a standard walker during rehabilitation. In the traditional version of rehabilitation, this aid is difficult to manage by patients who cannot exercise the same control on both sides of the upper and lower limbs, both regarding recruitment of muscle tone. The traditional treatment consists of two treatments with a training diary for ambulation done through the use of parallel bars.

A first attempt to use *i*-Walker in the field of rehabilitation was conducted by Dr R. Annicchiarico M.D. and physiotherapist B. Giuliani, in the period between July and November 2011. This pilot study with 20 in-hospital patients with an outcome of a stroke took place at the facilities of the Fondazione Santa Lucia (FSL), in Rome Giuliani et al. (2012). The study aims to combine both the traditional treatment and an experimental one using the *i*-Walker, which offers the lack of stability described above.

**Inclusion criteria** for patients within the trial were as follows:

- Diagnosis of stroke-hemiparesis (acute event arose from no more than a year)
- Age 18+
- Minimental state examination (MMSE) 20+
- Canadian Neurological Scale-upper limb and lower limb $> 0$

**Exclusion criteria** for this study were:

- Hemiplegia
- Severe cognitive impairment entities
- Global aphasia
- Severe neglect

The pilot study considered 20 subjects, nine men (45%) and 11 women (55%), born between 1927 and 1984, with a mean age of 59.9 years. About the diagnosis of the hemiparesis: 5 subjects were suffering from left hemiparesis and 15 from right hemiparesis. The subjects were divided into two groups: one would follow the traditional therapy and the other performed the experimental treatment by combining the parallel bars and the *i*-Walker. Each subject group underwent the following assessments and related scales:

- Assessment of the gait: Tinetti Scale, Six Minute Walk Test (6MWT), Ten Minute Walk Test (10MWT).
- Assessment of the balance: Tinetti Scale.
- Assessment of the tone in the various districts of the upper limb (shoulder, elbow and wrist) and lower limb (hip, knee and foot): modified Ashworth scale.
- Assessment of the state of consciousness, orientation, language, motor function, and facial deficits: Canadian Neurological Scale.

- Assessment of autonomy in AVQ: Barthel Index.

Additionally to the sensors mentioned in §4, a strap with sensors was placed on the patients' shoes to measure the speed, length and symmetry of the pitch. This strap was later substituted by a Kinect device, as it is less expensive and user-invasive.

The results showed how the use of the *i*-Walker allows improving the gait and in general the user's motor performance. From this, it follows that the *i*-Walker can be a valuable aid in gait training for hemiparetic patients, resulting in a tool that they can efficiently complement traditional therapy. Moreover, this aid, having regard to its structural characteristics, is presented as a device able to increase the intensity and duration of rehabilitative treatment even in complete autonomy and safety of the patients. For further detail on the medical results of this pilot study, see Giuliani et al. (2012).

The role of the *i*-Walker in rehabilitation has also been investigated in the EU funded project *I-DONT-FALL* [1], focusing on elderly people with high risk of falling. Results from this project have been published in Cortés et al. (2012) and Giuliani et al. (2012); a further analysis on post-stroke rehabilitation with the *i*-Walker was published by Morone et al. (2016), focusing on gait stability assessment.

### 4.3.2 *I-DONT-FALL Results*

A preliminary analysis of the *I-DONT-FALL* data was presented in Cortés et al. (2015). In this paper, authors used a subset of 77 patients from 3 different pilots (FSL, HGG and SERMAS) and presented results from a clinical point of view, observing the evolution of the results in a set of medical assessments. This analysis is complemented with information extracted from the *i*-Walker on average linear speed performance. A graphical representation of Average Linear Speed[2] measured during 10MWT at T0 and T1 evaluation is represented in Figure 4.4. Results show an improvement for the users in Motor and Mixed group before and after treatment. However, users show a different trend in the Cognitive group; in fact, one of these remains stable, and the other demonstrates an improvement. Finally, the users in Placebo group show no effect. These and other pre/post treatment assessments are found in Barban et al. (2017); Cortés et al. (2015).

[1] http://www.idontfall.eu/

[2] Average linear speed during the time that the patient is moving.

The preliminary analysis supports the hypothesis of *IDF* study that a period of distributed treatment of three months contribute to reducing the fear of falling and risk of falling that represent the primary outcomes of the project (see Morone et al. (2016)). Moreover, the *i*-Walker in the context of *IDF* contributes to improving motor and cognitive abilities that represent secondary outcomes of the study. However, no further effects on functional abilities were appreciated at the moment of the publication, probably due to the size of the sample.

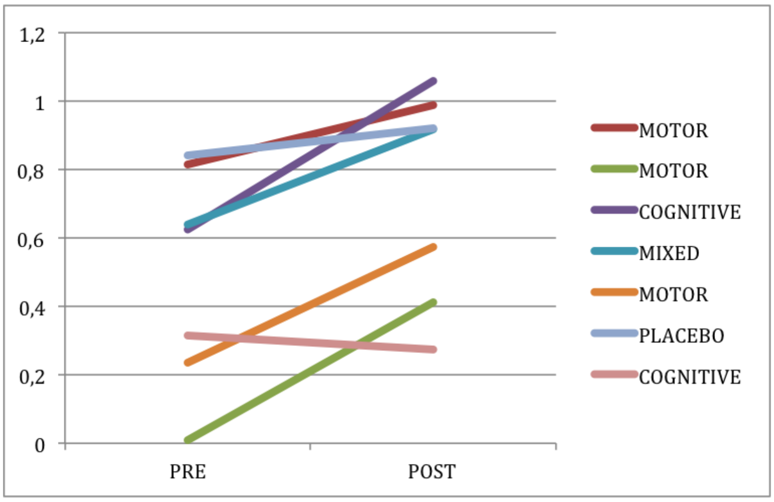


Figure 4.4: Average Linear Speed during 10 meter walking test before and after treatment

One of the datasets selected for this works is composed by 88 participants of three of the *IDF* pilots: *SERMAS*, *HGG* and *FSL*. Results on gait velocity from the *i*-Walker sensor data are shown in §7, as well as a prediction model of the risk of falling taking the pre and post-treatment data. The rest of this thesis presents a new methodology applied to the *IDF* dataset for the 10 Meter Walking Test that has later on been applied to other datasets collected during this thesis with the aim to find.

### 4.3.3 Detecting Walking Behaviour Patterns

This section introduces two master thesis works developed with the aim to propose different approaches to categorise groups of individuals by their walking behaviour using unsupervised learning techniques.

The first work was developed by Moreno (2015). The main objective was to use the *i*-Walker as a sensory platform that assists in elderly mobility that also can extract relevant information from the interaction that could be used as early detection of symptoms related to ageing or some pathology. A methodology to analyse the data measurements taken by the *i*-Walker is used to find patterns in gait behaviour with two different groups of people: healthy elderly individuals (not suffering from any disease or fall injury) and non-healthy elderly people. The second group were part of the pilot of the EU funded project *I-DONT-FALL*. The protocols followed to collect both datasets are described in Appendix §A and I-DONT-FALL (2013) respectively.

For each exercise, the *i*-Walker produces a dataset that is composed of several Time Series ($TS$), representing each one specific sensor data (see Table 4.1). A $TS$ is a sequence of real values, in this case representing a sensor reading during the exercise. It could be defined as T = ($t_1$, $t_2$, ..., $t_n$). Therefore, the $TS$ that represents the sensor data recorded in several exercise sessions were analysed by finding relevant patterns that could be determinant to differentiate between various target populations using the gait behaviour that they present. The methodology presented here targets to cluster the exercises into different groups regarding the patterns that they present. For each $TS$ belonging to an exercise, patterns are extracted, and a vectorised format that preserves the relevance of patterns is reached. By comparing all the resulting vectors, a cluster relying on the relevant patterns is obtained.

To extract the patterns given a TS, a Symbolic Aggregate Approximation (SAX) is applied, which is a technique widely used in the $TS$ analysis domain. It allows dimensionality reduction and indexing with a lower-bounding distance measure. By applying SAX, it is possible to transform the given $TS$ into a list of patterns. The relevance of the patterns is computed after they are extracted. Two factors influence the relevance: number of occurrences and resolution. To perform the clustering, a condensed distance matrix is calculated. To fill the distance matrix the distance between the vectors that we want to analyse is computed. Afterwards, an Agglomerative Hierarchical Clustering (AHC) is executed to obtain the different clusters.

This methodology was applied in two use cases, where the first tried to classify the type of exercise performed while the second aimed to identify healthy older adults from non-healthy (*i.e.*, fallers). Results were presented in Moreno et al. (2015), offering promising observations on the correct classification of users into one the two mentioned categories. Figure 4.5 shows the hierarchical clustering representation for the right longitudinal force ($rhfx$). As it can be observed, most of the participants were successfully classified into their corresponding category.

In this work, clustering was applied to whole exercises but with single parameter configuration. Since a combination of joint segments defines motion, it would be interesting to use a

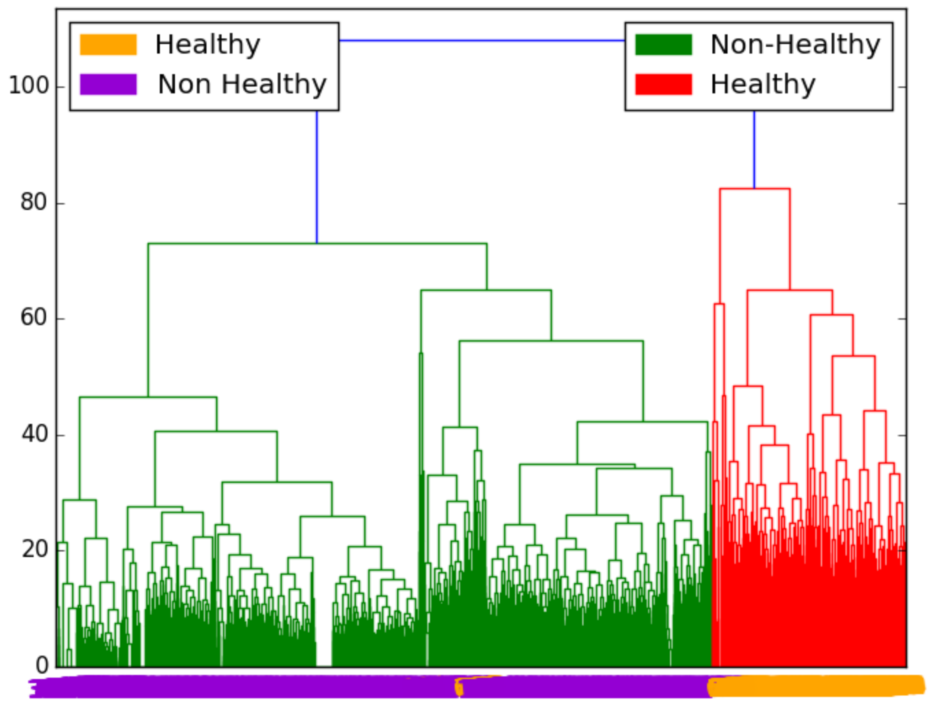


Figure 4.5: Dendrogram representing the clustering applied to Right Hand Force X (longitudinal force $rhfx$).

similar methodology with a multi-variable approach to identify significant data fusion useful to learn new concepts on an individual's walking behaviour. Moreover, it would be of particular interest to identify variables that together can define different gait disturbances and associate them with the pathologies affecting elderly people.

A similar a methodology was used to classify users into two groups of age. This time, the selection for the study included 42 individuals of ages between 22 and 94, which consisted in performing a 3-minute walking test in an indoor corridor of 40 metres. The work has been developed by Ojeda (2018) as her Master thesis, which I have co-directed, and results will be presented in Ojeda et al. (2018).

The methodology uses the Bag-of-SFA-Symbols (BOSS) model for the representation and

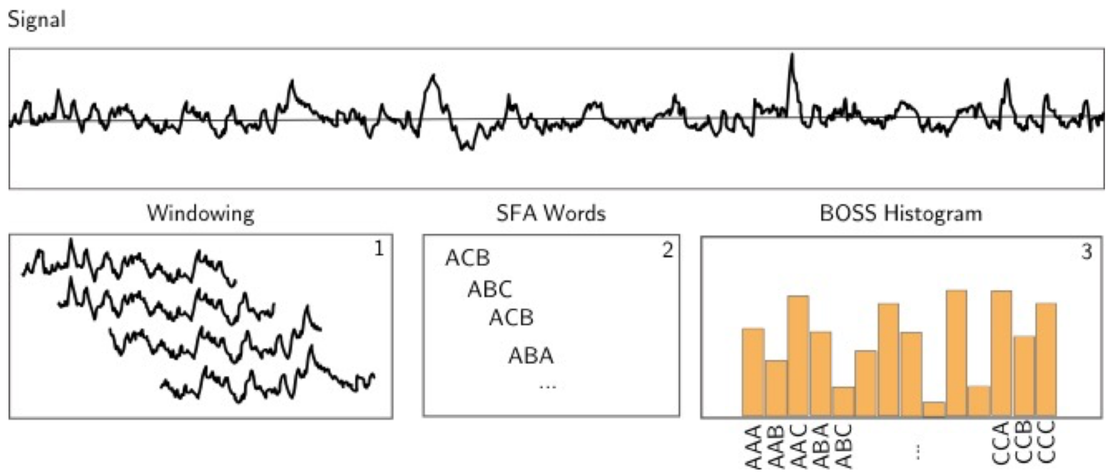


Figure 4.6: BOSS Model is used for indexing and representation and transforms the time series into BOSS histograms

indexing. This method transforms the numeric time-series into a bag of words representation to later create a $k$-dimensional matrix. The BOSS model describes time series as an unordered set of substructures using Symbolic Fourier Approximation (SFA) words. The BOSS flow model is represented as follows (see Figure 4.6): parameters definition, windowing, SFA and histograms aggregation and reduction (Schäfer (2015)).

**Representation and indexing**

The goal of this step is to transform each time series to a new representation based on a vocabulary extracted from the behaviour of the data in the frequency domain.

This transformation has a set of parameters that need to be tuned in order to find the optimal configuration: length of the windows, the number of Fourier coefficients for a window and the number of letters for the word representation.

For each time series, a set of fixed-size windows are generated using a sliding window of length $w$. The first window begins at 0 and ends in the position $w$, the second one will offset one position ending at position $w+1$ and so on until the end of the series is reached. The result will be transformed into a vocabulary where each window represents a *word*. The length of the words are defined by the quantization of the Fourier coefficients of the window as explained in the following paragraphs.

The transformation of the windows into a vocabulary uses the SFA method, which aims to simplify information by removing the unnecessary data and keeping only the most representative characteristics. The SFA performs three steps to achieve its goal: approximation, quantization and words computation.

The SFA uses a discretization method based on the Momentary Fourier Transform (MFT), for the approximation process. The MFT targets to keep the critical data extracting the Fourier coefficients of the signal (Albrecht et al. (1997)). This method allows to incrementally compute the first $f$ Fourier coefficients of a sliding window in a series in efficient manner.

The idea behind this discretization is to decompose the time series into two basic type of functions (Schäfer and Högqvist (2012)). The former consists in identifying *slow* changes in the data, while the latter identifies *rapid* changes. For the approximation, those with slow changes are enough for a fair description of the signal. These types of functions also provide a smoother signal with low pass filtering.

The decomposition represents a time series by its Fourier coefficient. The magnitude of the coefficient represents the amplitude of the signal. The proposed approximation uses only the first $f$ coefficients. The first Fourier coefficient can be optionally discarded because it stands for the mean value of the signal, obtaining this way offset invariance.

The quantization step reduces the granularity of the data by dividing the values of the Fourier coefficients into a histogram of equal frequency bins (Gurajada and Srivastava (1991)) and mapping each coefficient to its range. To define these histograms, a number of bins is defined as a parameter, representing the letters of the discretization alphabet that will be used for computing the words representing the windows extracted from the time series. Each position of the Fourier coefficients is discretized separately. This is done by computing Multiple Coefficient Binning (MCB), and it aims to minimize the lost information when performing the discretization process.

The discretization works as a map that contains intervals of numeric values per each coefficient. The outcome of the SFA is a word of $f$ letters per window and a set of words per time series. In order to avoid a bias due to large periods of stable signal, the BOSS model reduces the length of the vocabulary by numerosity reduction, removing identical consecutive words.

The final stage of the BOSS model is to transform the vocabulary for a time series into a histogram of relative frequencies of words. This transforms the series into a vector, so we can compare different series using different similarity measures. The main advantage of this final transformation is to allow the comparison of time series of different lengths.

**Similarity Measure and Space Embedding**

The next step is to evaluate *how* similar are the sets of time series. From the possible similarity functions that can be defined, the one that better fits the model is the cosine similarity measure because this metric considers only the orientation of a vector and not the magnitude (Steinbach et al. (2000)); this characteristic is useful when working with symbols instead of numbers. The output of this process is an affinity matrix that will be further transformed before clustering the data.

For this model, a Spectral Embedding (Strange and Zwiggelaar (2014)) is applied to the affinity matrix to embed the data in a metric space and to enhance the relevant characteristics by using a non linear transformation. This embedding transforms the affinity matrix into a $k$-dimensional matrix. The number of dimensions $k$ is part of the configuration parameters. For this paper, the transformation was limited at most to three dimensions.

**Clustering**

A Bayesian Gaussian Mixture Model (BGMM) with Dirichlet priors (Li and Mihaylova (2017); Sanjay-Gopal and Hebert (1998)) is used for partitioning the data represented by the $k$-dimensional data matrix. A Gaussian mixture model is a probabilistic model that assumes all the data points are generated from a mixture of a finite number of Gaussian distributions with unknown parameters. Each cluster is formed with a set of points that shape a Gaussian distribution using a Expectation Maximization (EM) algorithm. The use of a Dirichlet prior includes the determination of the number of clusters in the optimization process.

The EM for mixture models consists of two steps. The first step calculates the expectation of the component for each data point given by the model parameters. The second phase maximizes the expectations calculated in the previous step concerning the model parameters. Then these two steps are repeated until the result converges.

**Evaluation**

To assess the quality of the clustering, it is necessary to apply some evaluation techniques. This approach considers two techniques: *(i)* the adjusted rand index (ARI, de Vargas and Bedrega (2013)) to measure the stability of the clustering to random initialization and *(ii)* the Silhouette index (SI, Verma et al. (2015)).

**Scenarios**

The work is based on the recognition of the patterns of the forces applied by the users to the $i$-Walker while walking. From the forces recorded by the $i$-Walker, the vertical ones seem to be the most related to the individuals′ compensation strategies. Therefore, this study examines two scenarios. The first model is provided with all the forces to find if the transversal and longitudinal forces add relevant information. The second one considers only the vertical forces to study whether the transversal and longitudinal forces add noise instead of contributing to the results.

**Results**

This methodology has been tested with different initial setting parameters to create the vocabulary. After finding the suitable combination of parameters, the clustering was applied to the two above-mentioned scenarios. Results show that the proposed approach is able to divide participants by age using the applied forces to the *i*-Walker. Moreover, it can be observed how the standard deviation of the leaning forces increases with age, which might be an indicator of the loss of balance that people presents as they age. Figure 4.7) shows that the variability is directly related with the magnitude of the vertical force. The results obtained are coherent with the literature: *(i)* gait velocity is reduced with ageing, implying a higher risk of falling; *(ii)* older adults with different sorts of pathologies present an abnormal gait that is identified in a particular cluster and, moreover, is related to unbalanced use of forces, which might lead to disfunctional gait. In addition, clustering results were more accurate when combining the the three resulting forces from the handler sensors than using the vertical force as single-variate clustering.

## 4.4 Summary

Research prototypes, like the *i*-Walker, are beginning to achieve the performance needed to make a difference in the daily life of the elderly society. By the moment, the market still offers only limited solutions to substantially prolonging the time that older adults can live independently at home, but these should be supported with relevant health and social care services in an integrated manner (see Barrué (2012), Wasson et al. (2008)). Older adults are becoming a predominant aspect of our societies and are expected to substantially affect the economy at world-wide level, changing the paradigm of public health systems ir order to maintain them as sustainable as possible. As such, solutions both efficacious and cost-effective need to be sought (Sun et al. (2014)). In particular, there is a need to improve more the cost-to-benefit ratio of robot-assisted therapy strategies and their effectiveness for rehabilitation therapy.

It is clear that the *i*-Walker is an assistive device that offers many possibilities to clinicians, patients and relatives, and it could become a powerful tool for the design of the incoming digital health solutions. It has been designed to collect data for long-term periods, which could be useful in solutions involving the remote monitoring of elder people performing their ADLs.

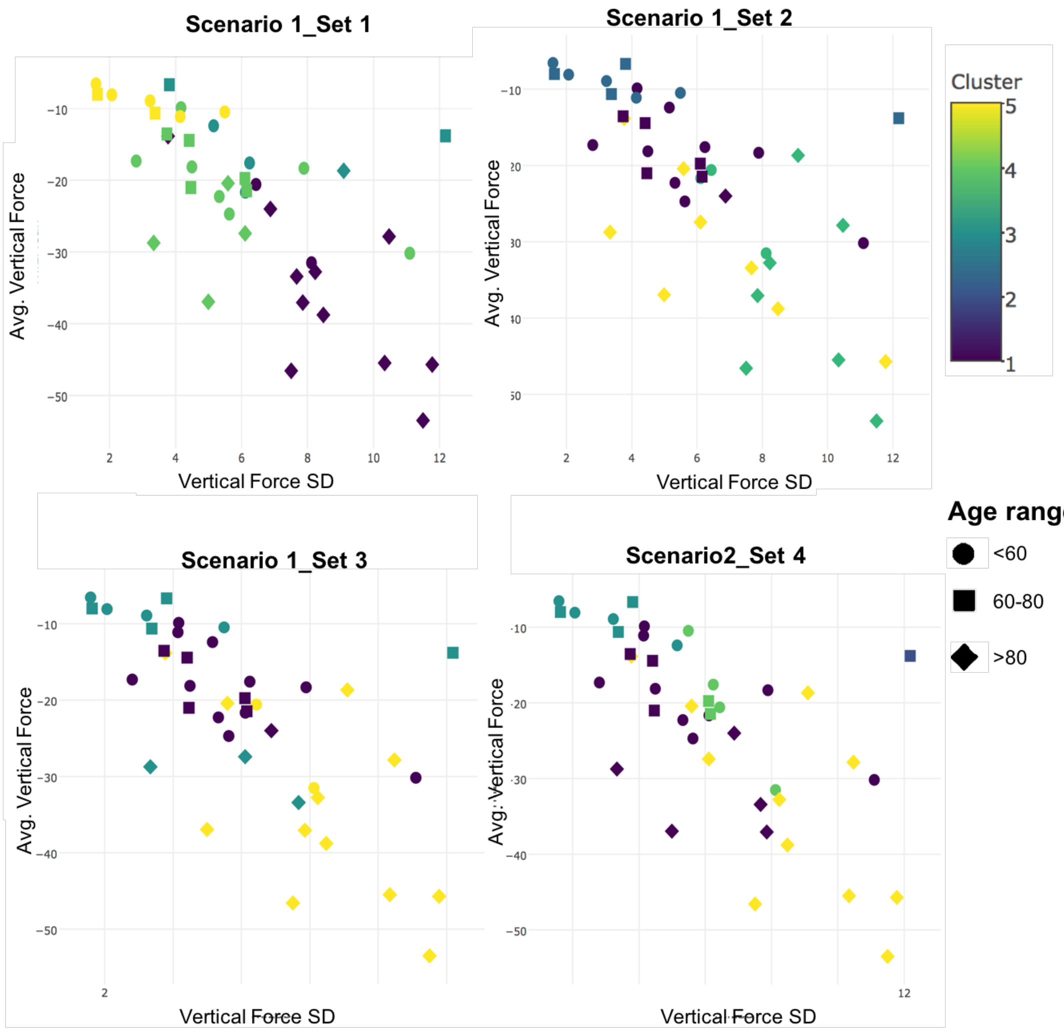


Figure 4.7: Comparison of the vertical force and its variability per cluster and age.

Authors in Barrué et al. (2015) have already shown the value of elders' activity recognition and monitoring since it might be an early symptom of some decline that must be prevented as soon as possible.

The *i*-Walker can be easily integrated with other stakeholders or assistive devices to share information, generate reports or alerts and process specific data (see Appendix §B). It has also been designed to offer constant mobility assistance to the user, providing safety and ensuring compensation on the upper limbs forces.

The objective of this PhD is to combine different outputs of the *i*-Walker's sensors and biological data obtained by clinicians through cognitive and physical assessments to extract some characteristics of their gait and try to identify different users profiles. This analysis will identify the strides performed by individuals while walking and try to find groups of people who walk similarly. The existence of those profiles could allow the *i*-Walker to provide tailored assistance while it learns new features of the patient. The main difference with the research presented in this chapter is that instead of analysing exercises as a whole, it will use the force used at each stride performed during an exercise to learn how do people walk and use the *i*-Walker. In §6 we first describe the methodology used in this PhD proposal to study the walking behaviour resulting from the interaction between the user and the *i*-Walker. Then a model of fall risk prediction is presented and tested with a group of participants of the *I-DONT-FALL* project (see §5.3.1).

# Chapter 5

# Clinical Tests: design and implementation of a pilot protocol

Health research has become an essential mainstay for to improve the actual state of the art in its different fields, such as epidemiology, biomedicine, health services, personalised medicine as well as its socio-economic impact on society. One of the most common forms of health research is the clinical trial, where volunteer individuals participate in studies to assess a new medical product, device or treatment. Most of this research is done through collecting different types of personal data, from biological characteristics to physical and/or cognitive assessments among others. During the last years, it has also included new data coming from sensors that will interact directly with the individual (*e.g.*, through bio-metric or wearable sensors) or environmental sensors. Although health research aims to promote individuals' health and well being, as well as to improve care and social services, its management might also represent a risk to the society due to the type of data that is stored and processed.

Ethics is an essential dimension of human philosophical research, considered both as discipline and practice. Philosophers today usually divide ethical theories into three general subject areas: metaethics, normative ethics, and applied ethics. For clinical research, ethically justified criteria for the design, conduct, and review of clinical investigation can be identified by obligations to both the researcher and human subject (see Aita and Richer (2005); Guraya et al. (2014); World Medical Association (2001)). Informed consent[1], confidentiality, privacy, privi-

[1]Informed consent refers to an ethical and legal doctrine based on the understanding that all interventions (diagnostic, therapeutic, preventive, or related to scientific studies) in the medical field should only be performed after a participant has been informed about the purpose, nature, consequences, and risks of the intervention and has freely consented to it, see Glickman et al. (2009).

leged communication, and respect and responsibility are critical elements of ethics in research. The European Commission has published several documents that describe, from an ethical and regulatory point of view, the different aspects that should be respected when working in a clinical trial with human subjects (see CAREGIVERSPRO-MMD (2016)).

The data collected and analysed during this PhD work comes from different hospitals and care centres distributed in Spain and Italy. As a result, we built four datasets, although we excluded the first one from the analysis. The respective Ethical Committee approved each pilot test following the Clinical Trial Directive 2001/20/EC (see Council of European Union (2001)), and was supported by clinicians in the participants' selection and recruitment and the execution of physical and cognitive assessments specified in each protocol.

## 5.1 Definition of a protocol

According to the International Conference on Harmonization (see ICH (1996)) a *protocol* is a document that describes the objective(s), design, methodology, statistical considerations, and organisation of a trial. A clinical trial protocol should include:

- *General Information* about investigators and sponsors (*i.e.*, names and contacts).
- *Background Information* of the tested product (*i.e.*, its potential risks and benefits, the description of the target population or references to the literature that are relevant to the trial).
- *Trial Objectives and Purpose*.
- *Trial Design* should include: *(i)* primary endpoints and the secondary endpoints, if any, to be measured during the trial; *(ii)* a description of the type of trial (*e.g.*, double-blind, placebo-controlled or parallel design); *(iii)* a description of the measures taken to minimize/avoid bias (*e.g.*, randomization or blinding); *(iv)* a description of the trial treatment; *(v)* the expected length of the subject's participation and a description of the duration of all trial periods and follow-up.
- *Selection and Withdrawal of Subjects* defines the subject inclusion and exclusion criteria, as well as the withdrawal criteria and procedure.
- *Assessment of the product* includes methods, timing and scales for assessing, recording and analysing the efficacy and satisfaction parameters.

## 5.2 Protocol design

The protocols presented include a brief description of the project involved and the tools that will be used during the test (in this case, the *i*-Walker). In that document, we report the sort of trial and the generated outcomes generated. Finally, a list of inclusion/exclusion criteria such as age, or thresholds in motor and/or cognitive assessments were also included. We needed to adapt these lists to each centre according to the population present in each centre (see Appendix §A for a complete version of each protocol).

The first protocol was presented to the Ethical Committee of the Fondazione Santa Lucia (FSL). It was designed in collaboration with a clinical team of the centre to define the criteria for a baseline dataset that could be used to compare users interaction with the *i*-Walker and their performance while walking in an indoor environment (see §A.1). Although this dataset was not included in the analysis presented in this PhD, it was useful to improve the pilot protocol applied in the rest of tests.

The second dataset presented here is part of the EU funded project *I-DONT-FALL* (see §3.3), and the description of the protocol can be found in I-DONT-FALL (2013). As mentioned before, participants from *I-DONT-FALL* are seniors that have fallen at least once in the last year. This protocol has been adapted and presented in two care centres in Madrid and Barcelona (see §A.2) to increase the dataset of this study. Differences among the different pilots are presented in the following sections in addition to the physical and cognitive assessments performed by the pilots. Participants from the IDF and Madrid pilots where used for a baseline study, the pilot in Barcelona was designed for validation.

### 5.2.1 Baseline Pilot

Usually, in research, and especially in medical research with human subjects, perform a set of assessment tests before randomisation and entry to a clinical trial. The data obtained is called *baseline data* and is used to compare the evolution of the subject after the treatment involved in the trial. In medical research, baselines are essential to determine the effectiveness of a treatment and observe possible secondary outcomes. It is important to determine the variable that has to be assessed and what sort of comparison will be made. For instance, in *I-DONT-FALL* participants where physically and cognitively evaluated to identify those at high risk of falling, but also to determine their level of autonomy. In this case, the pre-treatment data obtained through assessments is considered the *I-DONT-FALL* baseline.

The first baseline pilot was designed with the aim of adapting the control strategies of the *i*-Walker to provide balance to people with ambulatory problems based on the work introduced in §3.2.1. For this, a first dataset was collected during three months at the Fondazione Santa Lucia (Rome, Italy) but it was finally not to included in the analysis presented in this thesis. The protocol of exercises is different than the rest, especially regarding the duration of the walking test and the objective of the study. However, living the whole process from writing the first protocol proposal to be presented to the Ethical Committee to being in charge of the execution of the pilot and data collection was very enriching for the rest of the experimental work performed during this thesis. A full version of the protocol presented at the FSL Ethical Committee is available in Appendix §A.

As a consequence of this, the baseline used for this analysis is the data obtained from the *IDF* subset and the care centre in Madrid (MAD), where participants performed the 10 Meter Walk Test as physical exercise. The baseline was used to develop the methodology presented in this work and described in §6. Additionally, we have collected data from another care centre in Barcelona (CVI), where another group of volunteers performed a more prolonged exercise, the 3 Minutes Walk Test (which is an adaptation of the 6 Minutes Walk Test). This last dataset will be used to validate the methodology.

The following sections present the target population, the clinical scales and the test exercises performed at each pilot.

### 5.2.2 Target Population

The methodology presented in this thesis is mainly focused on people with ambulatory problems. However, and with the purpose to determine differences in walking behaviours among different ages, the target population of each pilot has varied. For the baseline, only people aged over 65 years old where included, with special interest to people having suffered a fall. In the last pilot young and middle-aged individuals were also included in the dataset.

As above mentioned, lifespan is steadily and globally increasing. Even if the social group of older adults starts at 65 years old, our baseline includes volunteers aged up to 98 years old, so we are dealing with a target population within a variation of over 30 years of age. This variation represents a huge difference, especially taking into account the physical and cognitive deterioration related to ageing. It is possible to find an individual aged 85-90 years old who has never fallen and, according to some assessments, is still considered *healthy*. However, it is hard to include this kind of persons in the same group as an individual aged 65 years, who has just retired from professional life and keeps a physical and mental active living. Moreover, in the last dataset, young adults were included in the protocol. Thus, the age range gets extended. From now on, three age ranges will be used to divide our study population:

- $Y$: people aged under 65 years old
- $M$: people aged between 65 and 80 years old
- $O$: people aged over 80 years old

The age categorisation divided first the baseline into three groups (65-75 years old, 75-85 and 85+), at this point, no significant differences were found between the two first groups. However, it had more sense to separate between people under and over 80 years old. The $Y$ category was added for the $CVI$ dataset. Table 5.1 summarizes the age and gender distribution for each pilot. The $CVI$ population presents the most heterogeneous distributions as a new age range was incorporated. In general, all pilots are unbalanced in gender. A combination of *could explain this (i)* women have a larger life span; *(ii)* women have been in general more willingly to volunteer.

We expect to find significant indicators while processing the data obtained from the pilots that will allow identifying clusters of the population according to their health status and their age.

To build the baseline, I have collected in 2015 data from 60 subjects from the residential care centre Los Nogales, in Madrid, Spain (MAD)[1]. A total of 87 participants of the *IDF* project complete the baseline.

The validation pilot was executed at the Centre de Vida Independent (CVI) a care centre in Barcelona. In this pilot, the age range was increased to obtain data from young and middle-aged healthy people and older adults with cardiologic problems. Data were collected from 42 volunteers, being residents of the centre, relatives and employees from CVI. In this case, only residents were cognitively and physically assessed since it was assumed that younger adults as healthy people with no risk of falling nor falls in the last year.

### 5.2.3 Clinical Scales

As subjects' complementary information, doctors involved in the trials collected biological data (*e.g.*, age and gender), and clinical data (*e.g.*, chronic illness, falls or the use of a cane

[1] Los Nogales collaborated with the SERMAS pilot of the *I-DONT-FALL* project.

| Pilot | **IDF** ($N$ = 85) | **MAD** ($N$ = 58) | **CVI** ($N$ = 42) |
|---|---|---|---|
| **Age Range** | | | |
| *Y* | 0 (0%) | 0 (0%) | 17 (41%) |
| *M* | 35 (41%) | 7 (12%) | 9 (21%) |
| *O* | 50 (59%) | 51 (88%) | 16 (38%) |
| **Age** | | | |
| Mean (± SD) | 82,7 (± 8,3) | 87,6 (± 5,8) | 64,1 (± 23,1) |
| Min | 65 | 70 | 22 |
| Max | 97 | 96 | 94 |
| **Gender** | | | |
| Female | 58 (68%) | 37 (64%) | 34 (81%) |
| Male | 27 (32%) | 21 (36%) | 8 (19%) |

Table 5.1: Participants' age and gender distribution for each pilot. Each column represents a pilot.

or rollator), level of education and level of autonomy. They performed the following cognitive and physical assessments, which can be used as indicators of risk of falling:

- **Mini-Mental State Examination (MMSE)[1]:** 30-point questionnaire measuring cognitive deterioration, like memory or mental abilities. *I-DONT-FALL* used it as a part of the assessment for dementia.
- **Tinetti Scale:** test for assessing a person's static and dynamic balance abilities.
- **Geriatric Depression Scale (GDS):** self-report assessment to identify depressive disorders in elderly.
- **Barthel Index:** measures the performance of Activities of Daily Living.
- **10 Meter Walk Test:** measures gait speed in a 10 meters straight line.
- **6 minute Walk Test:** measures travelled distance during 6 minutes; gait speed can then be inferred as well (only in *I-DONT-FALL*).

Subjects participating in the pilots had an excellent MMSE, higher than 24, but are more variable regarding autonomy or depression (see Table 5.2). Once we have an analysis of the sensor readings, it will be interesting to complete the results with this biological and clinical data, as more accurate patterns may arise.

### 5.2.4 Ambulatory Exercises

When designing the pilot exercises, it was aimed to define a simple test that would not take much time to volunteers (*i.e.* around 15 minutes), but that would be able to embrace different complex navigation situations like door crossing or turning to left/right. The *i*-Walker is used as a measuring tool: for each one of the exercises, a log file is generated and stored containing all the data collected by the onboard sensors every 100 ms. We consider each exercise as a collection of time series, one for each sensor, that, once processed and/or combined, brings new knowledge about the characteristics of the exercises.

For the first data collection at FSL, four paths were defined, considered as complex guiding tasks. All the exercises were executed four times with different $\lambda$ values (0, 25, 50, 80). The protocol defined for the FSL mainly differs from the rest of protocols on the type and duration

[1] http://www.alzheimers.org.uk/

of ambulatory exercises performed (see §A). The paths on the second version of the protocol are as follows:

- Roundtrip (counted as two exercises) in a corridor performing the 10 Meters Walk Test (10MWT).
- 10MWT in corridor + turn to the right to enter a room.
- Get out from a room, turn into left and 10MWT in the corridor (see Figure 5.3).

Although it was aimed to define a general protocol, independent from the environment, it was rapidly realised that this would not be feasible. Medical centres have a huge traffic of people. Thus, the space for testing was usually previously bounded, and we needed to adapt to it. It is hard to stop this traffic of people passing through the corridor, so in some cases, volunteers had to alter their path to avoid them. These conditions also affect the results in the laser data, as it may detect the false presence of obstacles. We, furthermore, had to deal with the distribution of the space: before getting to the centres we expected to perform a symmetric test regarding the 10MWT and turn to left or right, but this was not possible. For this reason, we modified the original protocol presented at FSL the frontal laser was excluded from the onboard sensors, and some paths were simplified to obtain a better dataset.

As mentioned before, the protocol presented at the FSL was different from the others. In this case, the scenario was suitable for an almost symmetric test, so the tests performed started with a 6MWT and then turn left or right to enter into a room (see Figure 5.1). First, the user begins the exercise at the right side of the corridor, walks straight and turns to the left to get into a room. Then the participant repeats the same exercise on the opposite side of the hallway. The environment in Los Nogales was similar, but with a long corridor (more than 10 meters) and a room entrance on the left. However, instead of the 10MWT round trip, we proposed a different exercise: an obstacle was situated in the middle of a room and users had to round it and then return to the origin point (see Figure 5.2). The user should follow a circular path around an obstacle and return to the origin point but with no guideline.

This exercise was performed twice (one rounding the obstacle to the right and the other to the left). Results were highly variable and difficult to compare due to the central problem: the exercise was not well understood. It was hard to make them start and finish at the same point since sometimes they kept turning around the obstacle or stopped before reaching the goal. In other occasions, the barrier was not visible enough, and thus it was repeatedly hit. Moreover, it

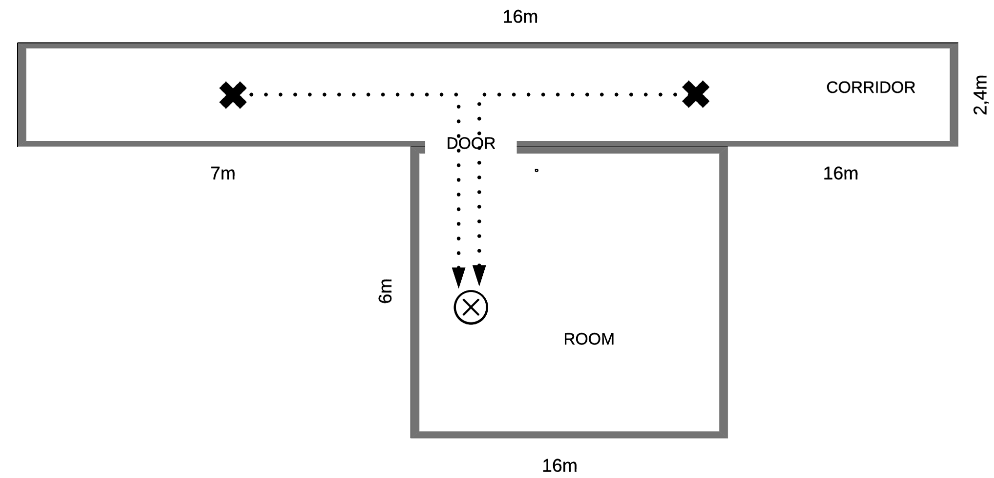


Figure 5.1: Map of the Fondazione Santa Lucia environment and the two first driving tests.

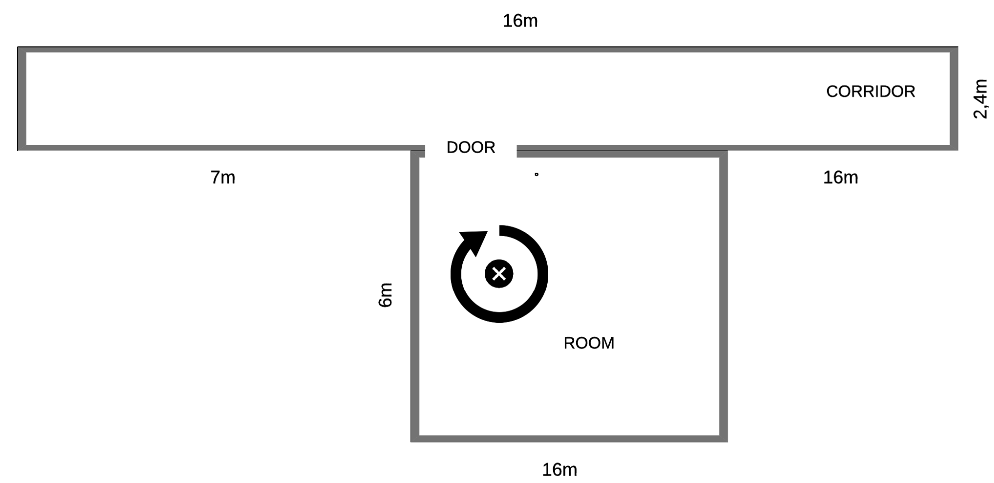


Figure 5.2: Map of the Fondazione Santa Lucia environment and the two last driving tests.

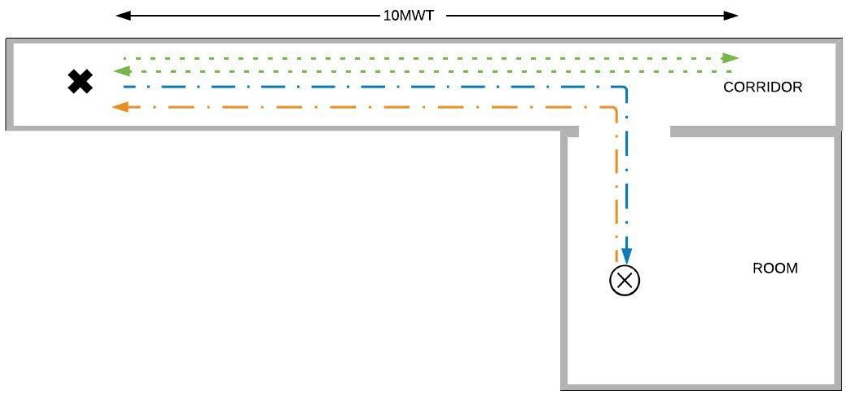


Figure 5.3: Map with the three scenarios of MAD pilot.

created confusion among some participants. On the other hand, the straight lines were too short to extract any significant gait feature. For this reason, it was decided to improve the ambulatory exercises thanks to the experience obtained during the FSL pilot.

This is why we decided to substitute this test with the 10MWT, which is a well-accepted performance measure used to assess walking speed in meters per second (m/s) over a short distance. 10MWT can also be employed to determine functional mobility, gait and vestibular function. As it is a widely used measure, it is easy to find information about gait speed according to different profiles (*i.e.*, healthy adults, hip fracture, stroke, *etc.*) [1]. Figure 5.3 shows the updated paths that will be used in future pilots.

#### 5.2.4.1 Ten Meter Walking Test

The traditional 10 Meter Walk Test (10MWT) is a performance measure used to assess walking speed in meters per second over a short distance. It can be employed to determine functional mobility, gait and vestibular function (see Adell et al. (2013)). Conclusions are made from an expert's observation.

The intended population is ranged as: preschool children (2-5 years), children (6-12 years), adolescents (13-17 years), adults (18-64 years), elderly adults (65+) with a range of diagnoses including, among others:

[1] http://www.rehabmeasures.org/

- Acquired Brain Injury
- Geriatrics
- Hip Fracture
- Lower Limb Amputation
- Movement Disorders
- Multiple Sclerosis
- Parkinson's Disease
- Spinal Cord Injury
- Stroke
- Traumatic Brain Injury

The 10MWT is performed by an individual who is instructed to walk without assistance in a distinct pathway where a straight line of 10 meters is marked off. Additional milestones were placed at meters 2 and 8. The clinician indicates to the user when s/he can start walking and will measure the time used to complete the distance. Usually, the clinician will only take into account the time spent during the intermediate marked 6 meters to allow some space for acceleration and deceleration (see Figure 5.4). The Start and Finish points are indicated to the user before the test execution, but no lines are marked on the floor as a guide. The timed zone corresponds to the six central meters of the exercise. The use of assistive devices is permitted but must be kept consistent and documented for each test. The 10MWT only assesses walking speed and does not consider the amount of physical assistance required devices or endurance. The 10MWT is not appropriate if the individual needs physical assistance to ambulate.


Figure 5.4: The 10 Meter Walk Test measurement

In the 10MWT the subject has to walk 10 meters in a maximal straightway, as above said the only measurement tool is a stopwatch (see Ali and Raad). In addition to this, the *i*-Walker can measure the travelled distance, the duration time, the maximal speed, the maximum of the lateral deviation and the pressure on the handlers. From the additional post-processing, it is possible to extract new indicators.

Other researchers have been using robotic rollators (see for example Wang et al. (2014) and Ballesteros et al. (2015)) and/or other automatic means to measure users' performance in the

10MWT (see Yorozu et al. (2015)). In other cases, kinematic data from infra-red cameras are recorded to study the walking behaviour of individuals (see Nooijen et al. (2009)).

The traditional 10MWT is measured by the time duration of the performance and the resulting average speed of the participant. It is considered that gait speed can be used as a useful outcome to assess the physical condition of older adults as well as to predict the risk of falling, other health deterioration or even survival (see Studenski et al. (2011)). There is a general belief that gait speed is related with ageing process (such as muscle weakness or balance loss), although results are uncertain on this theory due to biological and behavioural differences among the population (see Shimada et al. (2010)).

#### 5.2.4.2 Timed Walking Tests

Timed walking tests measure the distance an individual can walk during a given time (usually 6 minutes, named 6mWT) on a flat surface at self-paced. The 6mWTfirst applied in frail elderly patients 60-90 years of age referred to a geriatric hospital, and it targets community-dwelling frail elders. However, the test has been used in the study of a variety of chronic disease adults (Annegarn et al. (2012)) or healthy adults (Harada et al. (1999)). In this last case, authors show that active older users obtained better performances of 6mWT than non-active healthy users. Moreover, it could be used to predict morbidity and mortality.

The 6mWT was used in the *I-DONT-FALL* project as an assessment along with other metrics to measure participants risk of falling at pre and post-treatment. The objective of this test was to evaluate the effectiveness of the different treatments (motor, cognitive, mixed, placebo) to decrease the number of falls, risk of falling and fear of falling.

For the last phase of data collection, a new group of adults performed a reduced version of the 6mWT, the 3mWT. This exercise was performed in an indoor corridor or 40 meters length as depicted in Figure 5.5. The main instructions given to the participants to perform the test were:

- Walk for three minutes along the corridor.
- Do not drop the handlers while performing the exercise.
- Turn when reaching the end of the hallway to continue with the walking trajectory.
- If the time finishes and the person is in the middle of the corridor keep walking until returning to the starting point.

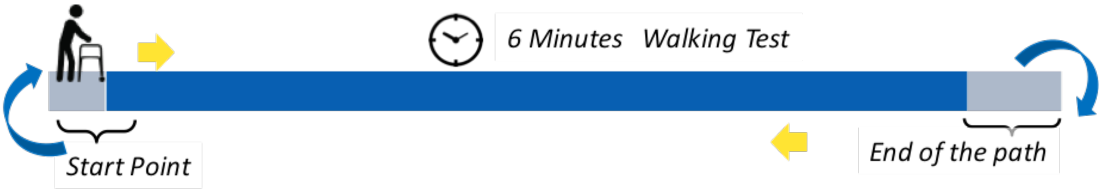


Figure 5.5: The 6 minutes Walk Test measurement.

The Start and Finish points are indicated to the user before the execution of the test, but no lines are marked on the floor as a guide. The timed zone corresponds to the six central meters of the exercise. This test is expected to provide further knowledge on gait variability and walking patterns due to its higher time and effort consumption in comparison with the 10MWT (Hausdorff (2005b)).

## 5.3 Pilots

In this section, we provide some highlight of each pilot site. The anthropometric characteristics of all the participants involved in this study are depicted in Table 5.2. Since we were collecting data from hospitals and care centres, it was hard to find a balance in age, being most of the participants from the baseline aged over 80 years. Besides women were, in general, more willing to participate. Hence their representation is higher. At the time of designing the protocol, we aimed to collect balanced handedness data, although this was almost impossible. It was quickly remarked that at the beginning of the last century, schools tend to correct left-handed children, thus nowadays most of the old age people are right-handed.

### 5.3.1 *IDF* Pilot

The *I-DONT-FALL* dataset is composed of three of the pilots involved in the project: FSL, HGG and SERMAS from Italy and Spain. As mentioned before, participants in these pilots share the characteristic of having suffered at least one fall during the year previous to the experimental phase. Participants of the *I-DONT-FALL* project where assessed physically and cognitively before the beginning of the three-months training (motor, cognitive, mixed or placebo) and at the end of this period (see §3.3.3). The generated dataset includes biological and clinical

| Characteristics | **IDF**<br>($N$ = 85)<br>N(%) or<br>Mean ± $SD$ | **Baseline (MAD)**<br>($N$ = 60)<br>N(%) or<br>Mean ± $SD$ | **Baseline (FSL)**<br>($N$ = 30)<br>N(%) or<br>Mean ± $SD$ |
|---|---|---|---|
| **Age** | | | |
| <80 years | 32 (37.64%) | 8 (13.33%) | 29 (96.67%) |
| ≥ 80 years | 53 (62.36%) | 52 (86.67%) | 1 (3.33%) |
| Total | 82.53(± 8.47) | 87.58(± 5.79) | 70.97(± 5.53) |
| **Gender** | | | |
| Male | 26 (30.58%) | 21 (35%) | 13 (43.33%) |
| Female | 59 (69.41%) | 39 (65%) | 17 (56.67%) |
| **MMSE** | 25 (± 3) | 25.79 (± 2.97) | 28.5 (± 1.59) |
| **Tinetti** | 17 (± 4) | 16.56 (± 3.90) | 24.47 (± 3.77) |
| **Barthel** | 79 (± 19) | 81.95 (± 14.77) | 96.33 (± 6.15) |

Table 5.2: Anthropometric Characteristics of the Study Participants.

| Criteria | Variable | Mean | Std Dev |
|---|---|---|---|
| Elderly | Age | 74.7 | 7.9 |
| Formal Education | Years | 9.9 | 4.2 |
| High Risk of Fall | POMA total | 19.8 | 5.5 |
| High Risk of Fall | Previous Falls | 1.33 | 1.16 |
| Non-demented | MMSE | 25.8 | 4.6 |

Table 5.3: Inclusion Criteria for the *I-DONT-FALL* final dataset. Results under 21 for the POMA analysis along with more that one fall in the recent year are criteria used to determine high risk of falling.

data along with the *i*-Walker measurements of the 10MWT exercises performed at pre and post-treatment phases.

During the cleaning process, we had to exclude several participants who passed the inclusion criteria but had inaccurate sensor readings (probably due to a bad calibration at the beginning of the exercise, a wrong exercise tagging or a failure in the communication system of the *i*-Walker), remaining only 87 in total from the three pilots. Table 5.3 shows the inclusion criteria parameters of the *I-DONT-FALL* protocol and the mean and standard values of the studied population.

### 5.3.2 *MAD* Pilot

This pilot took place in March 2015 during two weeks at Los Nogales (MAD) centre, in Madrid. People participating in this pilot were older adults living in a residential care centre, with reduced mobility but good cognitive conditions, or relatives. A total of sixty individuals participated in the study, with only one drop-out. Although the objective was to collect data only from healthy older adults with no falls, finally 15 of them presented a fall during that year (see Figure 5.6 for an overview representation of *MAD* population). The exercises included in the final study were the 10MWT performed with no helping parameters ($\lambda = 0$). The clinical team at Los Nogales provided the same assessment results to complete the *i*-Walker data.

As it can be readily observed in Table 5.2, participants from the *MAD* pilot are apparently in a better cognitive condition and present higher scores in independent living despite being older than the *IDF* population. Moreover, although most of the *MAD* participants did not suffer any fall, they present a higher risk of falling in the Tinetti Scale than individuals from *IDF*. In the case of FSL. Although half of the population had a previous fall, results from physical and

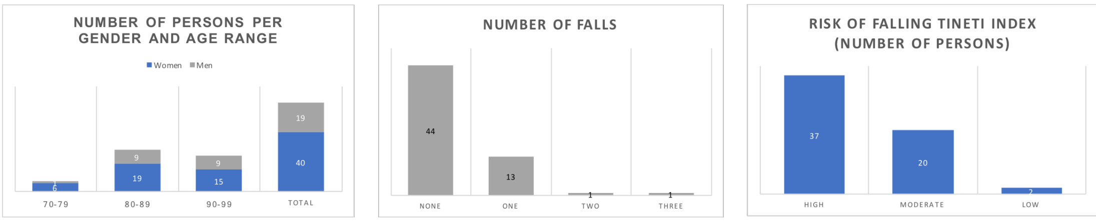


Figure 5.6: Distribution of *MAD* participants represented demographically by age and gender, but also clinically by number of falls and risk of falling

cognitive scales are much better than the other groups. This is probably related to age factor since only one participant from FSL was older than 80 years old. The reduction of autonomy and mobility that older adults usually face in residential centres could explain this distribution.

### 5.3.3 *CVI* Pilot

This last pilot was collected in July 2017 during two weeks at the Centre de Vida Independent (CVI) in Barcelona. People in this pilot are quite heterogeneous regarding age, which goes from 22 up to 94 years old. This dataset is composed of 42 participants, 18 of them presenting cardiac problems or injuries caused by a fall. The clinical team that supported us assessed this group both physically and cognitively, but the rest of the volunteers were considered as healthy individuals with no risk of falling (all of them were autonomous non-retired adults, with no previous falls or neurological nor physical issues).

This time, the exercise performed in this study was a short version of the 6mWT. The duration of the exercise reduced by recommendation of the clinical team at CVI to three minutes (3mWT). The objective was to collect more extended bags of strides of each participant since the 10MWT exercises where too short to obtain a good profile of each person. We executed the pilot in a long indoor corridor of more than 40 metres; once participants reached the end of the hallway, they were indicated to turn around and keep walking to the starting point until the time ends. The corridor had an area wide enough to allow round turns with a rollator.

## 5.4 Summary

In this section, we have described the anthropometric characteristics of the participants in the different clinical trials. We aimed to create a baseline with similar criteria than in *I-DONT-FALL* since it is essential to isolate anthropometric effects on gait analysis (Prakash et al. (2015)). In our case, the only differentiation among trials is the number of falls. Participants in both clinical tests used an *i*-Walker with the vertical position of handlers adapted to their height. A brief description of the pilot (start and end point, number of repetitions and led lights function) was given before the volunteers signed the protocol agreement.

During the tests, we tried to let them navigate as independent as possible, although some individuals presenting visual impairments received some indications when turning and getting into a room. We also had some issues with individuals presenting hearing impairments, especially when we needed them to stop walking. In some occasions, these exercises where repeated. In the case of people stopping later than required, data was conserved but then processed to exclude unnecessary information (see §6).

Although I already had participated in other clinical trials before this work, being involved at all stages, from the design of the protocol to the test execution and later processing has been challenging but has also provided me new expertise in the design and management of this kind of experimental research field. With every clinical test, new lessons were learnt from previous mistakes, which helped to tune the protocol. Also, when dealing with a robotic device, particular attention must be given to the precision of the execution of the exercises or the calibration of the sensor system. Many internal or external factors might affect the proper collection of data and further results and analysis.

A total of 632 individuals have used the *i*-Walker, although only 168 of them will be included in the analysis proposed in this thesis. The size of the dataset is considerably good to validate the methodology presented here, but it would be suitable to increase it in the future, especially if the objective is to characterise gait patterns by pathologies. In that case, the protocol presented should be applied to specific groups of population, *e.g.*, people diagnosed with Alzheimer Disease, Parkinson, post-stroke, *etc*.

# Chapter 6

# Methodology

Throughout this document, we have highlighted the relationship between human motion and cognition and risk of falling, describing different approaches developed by several authors in the last decades to analyse gait characteristics. We aim to provide a new approach to the definition of gait characteristics of older adults using rollators, introducing the data obtained by the *i*-Walker sensors. The challenge of this thesis is, thus, to infer these gait characteristics from the interaction between the user and the assistive device and extract new information on how older adults walk, whether are there differences in walking behaviours among different groups of adults, from healthy to challenged.

In Prakash et al. (2016), authors propose a classification of gait parameters in five categories, each one defined by the type of input information taken into account in the study. However, authors recommend combining parameters for better visualisation and analysis.

1. *Anthropometric parameters:* biological data such as age, gender, height or Body Mass Index. The study presented in this thesis has also included other parameters obtained from clinical assessments that were performed by a group of clinicians in each pilot centre. We describe the anthropometric data in Table 5.2.

2. *Spatio-temporal parameters:* assessment of general human gait parameters, such as step/stride length and time, cadence or number of steps.

3. *Kinematic parameters:* measures the movements or geometric description of the motion of body segments, which include the foot, shank (leg), thigh, pelvis, thorax, hand, forearm, upper-arm and head.

4. *Kinetic parameters:* analysis of the force involved in producing ground reaction forces, torque, pressure patterns and joint forces. These studies are generally performed with force plates.

5. *EMG parameters:* studies the muscular activity during walking.

This PhD work aims to translate some of these different categories regarding the data obtained from the *i*-Walker along with the biological data provided by clinicians. The methodology will be first applied to the 10MWT exercise (see §5.2.4.1) with the baseline group since it is a well-known study with several examples of application in the literature. Thanks to the simplicity of the exercise, it is possible to extract the different characteristics mentioned in the previous list. However, due to the small sample size (in general, a 10MWT contains no more than 20 gait cycles per exercise), it is hard to provide empirical conclusions on the performance result. For this reason, it was decided to validate results with another exercise, the 3 Minute Walk Test (3mWT) which is expected to provide further information on the user walking trends.

The following sections will describe five different studies performed with the *i*-Walker data. The former involves a method that has been developed to extract steps from a straight line exercise performed with the *i*-Walker using the pushing forces exerted by the user while walking. To reproduce the technique applied to measure the 10MWT the acceleration and deceleration periods are discarded to clean the data. This technique takes each stride detected as a single time series and involves a clustering analysis aiming to identify characteristics in strides and exercises based only on the interaction between the individual and the *i*-Walker through its force sensors. This analysis will also be used to extract spatiotemporal data of each stride and exercise. The second approach uses these calculated metrics to study how is the population in the different pilots distributed in terms of gait quality. The third study extracts driving skills regarding directivity and laterality. This kinematic information can be useful to complete the analysis of walking patterns from the clustering analysis. Then, a study using supervised machine learning techniques, and that was part of the final results of the *I-DONT-FALL* project, is described. Taking only into account the 10MWT from the IDF dataset, a prediction model for risk of falling was developed using the pre-treatment data as training and the post-treatment data as a test. Finally, we introduce the methodology to model groups of individuals from their spatiotemporal gait characteristics along with their force interaction with the *i*-Walker using also supervised learning methods. The objective is to classify new exercises based on the mentioned variables and compare it to the clustering results.

## 6.1 Gait Analysis based on Human-Rollator Interaction

Especially when ageing, people suffer from gait disorders that can be both associated with physical and/or cognitive decline (Snijders et al. (2007)). For example, a high number of stops and short steps is related to a cautious gait developed with ageing and fear of falling. Maki (1997) observed that gait speed along with other gait parameters was associated with the fear of falling, however, it is the study of stride-to-stride variability that apparently provides better predictions of future falls and risk of falling among older adults. This hypothesis has also been tested in Hausdorff et al. (2001). Their methodology assesses first different physical and cognitive scales separately and then seeks for correlations among them to determine which are the parameters that define the risk of falling.

Different techniques have been used to analyse human gait behaviour, which has already been described in Chapter §2. As a general trend, gait analysis studies use wearable sensors located at joint angles (*e.g.*, knee) to track human motion or walking platforms to detect the contact with the feet. Others use visual equipment to monitoring the exercise performed. In this work, gait parameters will be extracted from the interaction between the user and the *i*-Walker, in particular, the data obtained from the force sensors located in the handlers of the rollator. In this case, step and stride duration are measured in relation to the amount of longitudinal hand force ($lhfx$ and $rhfx$) exerted at each moment to the *i*-Walker. Data will be first cleaned to discard acceleration and deceleration phases. Then, strides will be identified by using a local maxima approach. Each stride will be then stored as an independent time series, where each instance represents the longitudinal force applied at that moment of the stride (every 100ms). Additional spatiotemporal information will also be generated and stored at each stride, along with the already provided anthropometric data (a first version of this approach was presented in Cortés et al. (2016)). A first clustering using $K$-medoids and the Dynamic Time Warping as distance measure will be applied to this set of time series. A vocabulary of strides is generated, containing different descriptive characteristics of the stride that will be useful to the gait analysis. The distribution of strides among clusters for each user and exercise will be used to represent different sorts of exercises as *bag-of-strides*, that is the proportion of each type of stride within an exercise. Additionally, a second clustering will be applied to this bag-of-strides using $k$-medoids and KL Divergence as a distance measure to compare the distribution of the first clustering in each exercise.

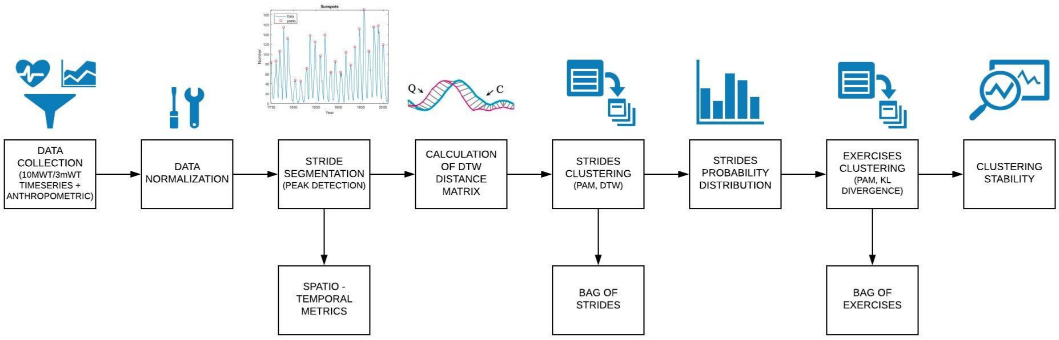


Figure 6.1: Illustration of the signal processing workflow for the gait analysis based on the forces applied by an individual on the *i*-Walker.

Figure 6.1 shows the processing workflow of the presented methodology. The following sections provide a more detailed description of each step of this approach.

### 6.1.1 Data preparation

As explained before, the traditional 10MWT does not take into account the first and last 2 metres of the exercise to discard the acceleration and deceleration phases. Hence, it only measures the average walking speed during the central phase of the exercise (see §5.4). For this study, the distance of an exercise can be extracted from the estimated position provided by the *i*-Walker at each sample time (*epx* and *epy* respectively). The *i*-Walker takes the origin and orientation positions when it is turned on and calibrated. Using the `trotz` library of MATLAB and the first orientation value, it is possible to translate and rotate each exercise to make them all start at (0,0) position, adapting the *epx* and *epy* values in their time series. This action is necessary for visualisation and further processing of the data. At this point, several exercises where discarded from the datasets, especially in the *IDF* pilot, due to the erroneous recording of the sensors or wrong categorisation of exercises (the obtained trajectory drawn with the estimated position was enough to identify exercises different from the 10MWT).

When analysing the data obtained in *IDF*, it was observed that most of the 10MWT exercises were not exactly 10 metres long: some exercises were a bit longer, which is not an issue, but others did not reach the required distance. To harmonise the length of the initial and final phase, we normalised the data as follows:

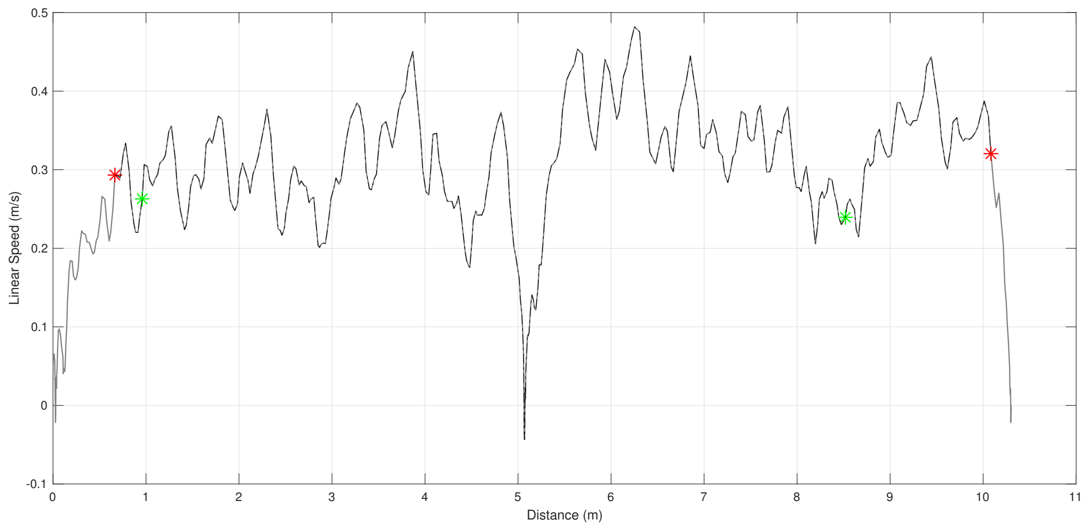


Figure 6.2: Linear walking speed of an individual performing 10MWT.

1. Instead of discarding two metres at the beginning and at the end of the exercise, extract the 20% of the total distance on each side
2. Calculate the average walking speed resulting from the central phase.
3. Retrieve the original exercise and look for the first and last moment at the average walking speed
4. Generate final working space within the resulting distance

Figure 6.2 depicts this process. The original dataset is represented in grey. Green marks point to the initial and final 20% of the exercise that should be discarded. Red marks indicate the beginning and end of the average walking speed moment, which will be the final dataset considered for the analysis (black).

The data reduction is applied to all the time series generated by the *i*-Walker within the exercise (*i.e.*, to the data collected by each sensor onboard). At this stage, new data has been generated and stored: duration of the part of the exercise considered to the study walked distance and average speed. With this data it is possible to compare results from the literature (*e.g.*, Montero-Odasso et al. (2012)) and observe how is the studied population distributed in these terms (see Tables 7.2, 7.3,7.4 and 7.5 presented in §7).

### 6.1.2 Vocabulary of strides

It has been observed that people, and especially women, present a hip sway during the swing phase to balance the weight. When using a rollator, this swaying is accompanied by a pushing force coming from the arm that will allow to move it from one point to another. Figure 6.3.a represents the longitudinal hand force on each handlebar: $lhfx$ is on the left side of the plot represented by black line and $rhfx$ is on the right side represented by a grey line. We can observe that the left and right-hand pushing forces are opposed, *i.e.*, when one signal increases, generally the second decreases. Hence, we can extract the movements of the *i*-Walker by using its force sensors and, moreover, we might be able to interpret the number of steps performed during an exercise by using the following formula:

$$F_x diff = rhfx - lhfx;$$

where $rhfx$ corresponds to the right hand pushing force and $lhfx$ is the left hand is pushing force. Hence, we will interpret that positive values on the resulting signal $F_x diff$ are those where the individual was pushing stronger with the right hand than with the left one. Figure 6.3.b shows the result of combining left and right-hand pushing forces. Thus the final signal we will work with. This approach has been developed in MATLAB, using the predefined function:

$$[pks, locs, w, p] = findpeaks(data, [x, FS], [< Name, Value > options]);$$

where:

- $data$ correspond to the input signal to study, in this case, we will use the longitudinal hand forces and the resulting vector of combining both force hands.
- $pks$ is a vector with the local maxima (or peaks) of the input signal vector $data$. A local peak is a data sample that is either larger than its two neighbouring samples or is equal to the signal endpoints. If a peak is flat, the function returns only the point with the lowest index.
- $locs$ is a vector with the indices at which the peaks occur.

- $w$ and $p$ correspond to the width and prominences of the peaks and are returned as vectors as well. The prominence of a peak is the minimum vertical distance that the signal must descend on either side of the peak before either climbing back to a level higher than the peak or reaching an endpoint. On the other hand, the width of each peak is computed as the distance between the points to the left and right of the peak where the signal intercepts a reference line.

- $< Name, Value > options$ specify optional comma-separated pairs of *Name*, value arguments that will help adapting the local maxima identification with filtering options. Name is the argument name, *i.e.*, the filter applied to the signal, and *Value* is the corresponding value for this filter. We will use these options to define peak filtering, which can be done by minimum prominence height or width and minimum peak distance. Other options include filtering by a threshold, by the maximum number of peaks or by peak sorting.

- $x$ and $Fs$ are optional parameters that specify a location vector $x$ or a sample rate $Fs$ of the data. When using this argument, $w$ and $locs$ are given in terms of $x$ or converted to time units for the second case.

Another approach to gait detection is to use distance as a reference instead of time and force prominence. In this case, the $x$ optional argument is used, which will be a vector containing the incremental position of the *i*-Walker during the exercise. Figure 6.4 show a $F_x diff$ signal filtered by minimum peak distance.

Working with raw data implies that the signal is not smooth and thus, the search for local maxima peaks needs to be filtered to avoid false positives. In this case, we use the distance as reference or the `findpeaks` function. Depending on the physical condition or height of the person using the *i*-Walker, the distance between steps (and thus, the number of steps) varies significantly, needing several steps of filtering to include all types of behaviours in the model. After trying different approaches, the variable that best filtered the steps positions was the average speed, and the total walked distance to infer an estimated length of the step. As before mentioned, the detected peaks are steps performed with the right foot; between two peaks of right steps, there is always a negative peak, which indicates when the left foot step has taken place. Therefore, we can consider that the action between two detected positive peaks is a stride that begins with the right leg (a right stride from now on).

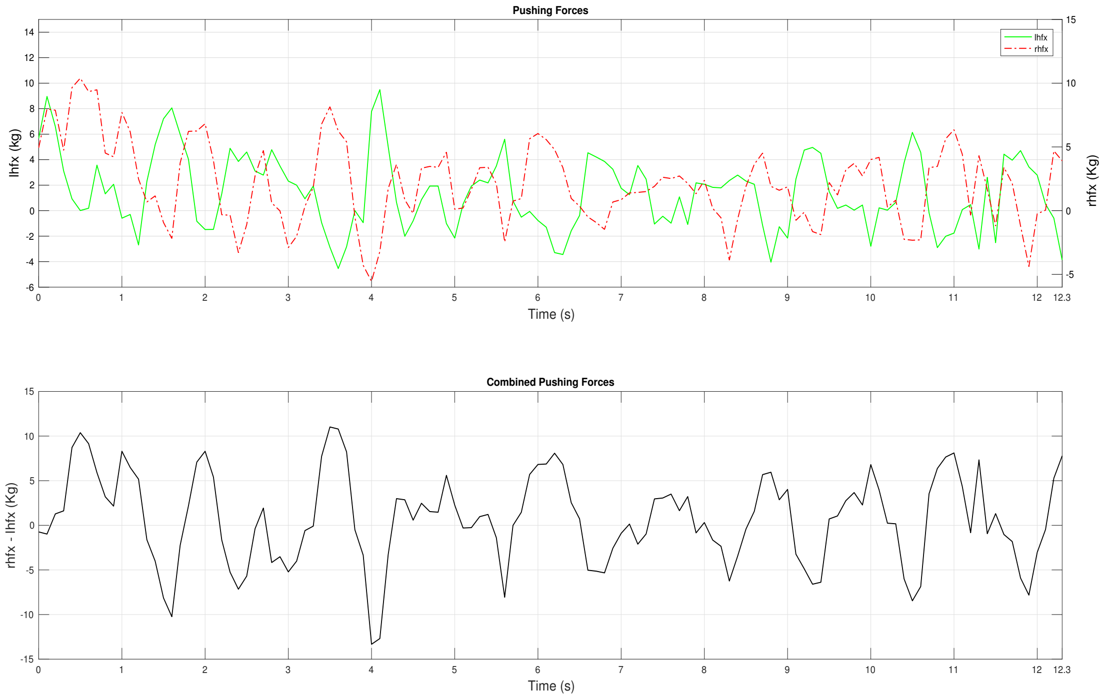


Figure 6.3: Identification of steps in a 10 Meter Walk Test exercise. a) Individual longitudinal hand forces; b) Resulting pushing vector $F_x diff$.

At this stage, a vocabulary of strides has been generated, where each instance is a time series containing the force applied at each sample time along the stride (*i.e.*, every 100ms). Also, the spatiotemporal information of each right stride is also completed with identifiers for the user, exercise and step number within the exercise, the overall stride length and time, and the average pushing force exerted during the stride. This set of characteristics allows forming a dictionary (or vocabulary) of strides, aiming to emulate the dictionary of words used in the bag-of-words methodology. This technique is well-known in text and document classification, where the frequency of each word is used as a classifier feature. The bag-of-words has also been used in computer vision applied to image classification, where image features are treated as words. This approach is also known as bag-of-X due to its adaptability to other fields. In general, this technique relies on identifying relevant key-words and analysing their frequency of appearance. In this thesis, the stride vocabulary will be used to characterise types of exercises

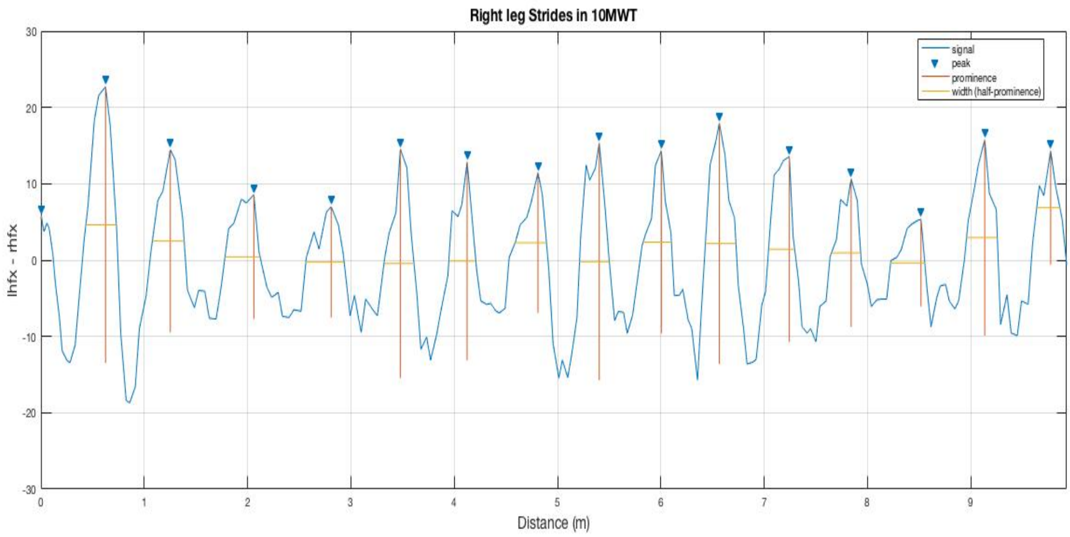


Figure 6.4: $F_x diff$ signal filtered by minimum peak distance. The incremental position vector has been used as location reference of the peaks.

according to the occurrences of each type of stride. In this case, a bag-of-strides will be used to study the results of the clustering process. The concept of *bag-of-steps* was introduced in Pla et al. (2017), where authors used it to predict the rehabilitation length and discharge date of a patient using insole force sensors. Other than the final application, these two methodologies differ on the vocabulary generated (strides *vs* steps) and the tools used to collect them.

The rest of the approach presented is developed with the aim to determine whether these bags-of-strides contain information that allows emerging new knowledge on walking patterns on strides or groups of individuals with similar walking patterns.

### 6.1.3 Clustering Time Series

A time series is a sequence of observations collected at a given period in chronological order. A time series dataset $D$ is thus a collection of time series $TS$ with the same time base, although, the number of observations can vary among the instances of the dataset and is represented as $D = \{TS_1, TS_2, ..., TS_n\}$. Traditional time series analysis focus on smoothing, decomposition and forecasting, but they are later used also to solve clustering and classification problems. Time series clustering is becoming popular in recent studies since it allows exploring large amounts of data in more complex data mining algorithms such as rule discovery, indexing, classification and anomaly detection. Time series clustering has been applied to different fields, such as finances or medical research (the most commonly used example would be in ECG analysis). The increasing use of sensors in many sorts of studies has also enhanced the interest in temporal analysis. Time series can be analysed on frequency or time base, depending on the expected outcomes and the type of analysis applied.

Usually, time series clustering has two steps: the first step consists of working out an appropriate distance/similarity measure and then, at the second step, to apply an existing unsupervised partitioning technique, such as $k$-means, hierarchical clustering, density-based clustering or subspace clustering. As a result, the time series dataset $D$ will be divided into $C = \{C_1, C_2, ..., C_k\}$ clusters, in such a way that homogeneous time series are grouped together based on a specific similarity measure (Aghabozorgi et al. (2015)). The primary challenge on time series clustering relies on the high dimensionality of datasets and the selection of the similarity measure. Also, time series are naturally noisy and might contain outliers, hence it is required to apply some signal filtering to obtain a useful similarity matrix.

Time series clustering can be applied *(i)* as a whole, where all the individual time series are clustered concerning their similarity; *(ii)* as a subsequence of time series obtained with a sliding window; (iii) as a time point clustering, where time series are segmented. In the case of the study presented here, a time series clustering is applied to both baseline and validation datasets. The size is not excessively large due to the short time of exercise, but the $i$-Walker can work for several hours and generate large amounts of data. Moreover, since data is broken into strides, each instance of the dataset will be presumably short and of different size. This might present a computational challenge when comparing the similarity among them, but solutions can be found in the literature to tackle this. In traditional clustering, the distance between objects of a dataset is calculated based on exact match, but this is not possible in time series clustering due to the nature of time series objects, where sample intervals and lengths can be irregular.

As mentioned, there are different distance measures applied to time series, such as Hausdorff distance, Dynamic Time Warping, Euclidean distance or Longest Common Sub-Sequence among others. The decision on which one is more appropriate relies on the clustering objectives, *i.e.*, the type of similarity among objects that is being studied. Three primary goals have been identified: similarity in time, in shape or change. Finding similarities in time means to look for the similarity at each step time and is usually based on Euclidean distances. However, due to the dimensionality of time series datasets, it is recommended to apply first a transformation to reduce the computational cost. Similarities in change look for similar structural differences between time series, *i.e.*, time series with identical correlation structures. This approach is not recommended for short time series like the ones used in this thesis.

In the case of this thesis, it aims to find similar strides by the shape of the pushing forces along the stride. A popular method to compare and identify patterns of time series is the Dynamic Time Warping (DTW from now on, Deza and Deza (2013)). DTW finds optimal alignment between two-time series, regardless of the time points that each one contains. In fact, DTW has already been used in the context of gait analysis. For example, in Barth et al. (2015) authors propose a methodology for automatic single stride segmentation from walking exercises. Sequences were extracted from inertial movement sensors located at the participants' footwear. In Boulgouris et al. (2004) authors use video sequences for gait recognition and use DTW to compare test and reference gait cycles. Derawi et al. (2010) presents another methodology using video sequences and wearable sensors to recognise gait cycles and DTW is again the similarity measure to compare them.

In this thesis, a DTW distance is calculated for each pair of strides from the previously generated vocabulary of strides, generating a $M \times M$ distance matrix, where $M$ is the number of objects in the time series dataset. This was performed in RStudio using the `dtw` and `dist` libraries; each DTW distance matrix took several hours to be generated. The resulting distance matrix is then used as input of the clustering, instead of the original time series, which will save a massive amount of time when computing the time series clustering analysis. Since the learning algorithm used is unsupervised, the clustering process will require several repetitions until finding the right partition; once the distance matrix is generated, the computational time of trying different values of $k$ (partitions) is reduced to few seconds. In this case, the partition around medoids algorithm (Kaufman and Rousseeuw (1990)), also known as $k$-medoids, was applied in Rstudio using `cluster` and `proxy` libraries. The term *medoid* refers to an observation within a cluster for which the sum of the distances between it and all the other members of the cluster is a minimum.

The main challenge of working with an unsupervised learning technique is to determine the number of clusters ($k$) that better represents the analysed data. Unfortunately, there are no definitive criteria to determine that value, but it is somewhat subjective and depends on the method used for measuring similarities and the parameters applied to the clustering algorithm. The partition around medoids algorithm can be evaluated with some well-known techniques such as the within-cluster sums of squares or the average Silhouette among others (Arbelaitz et al. (2013)). The latter is an output of the `pam` algorithm available in RStudio when performing $k$-medoids. It returns an average value for each object of the dataset, representing how well does it lay within its cluster. Values can be either negative or positive, but the higher the values are, the better is for the clustering quality. Thus, the optimal number of clusters $k$ is the one that maximises the average silhouette over a range of possible values for $k$.

However, in this case, the Silhouette method might not be entirely suitable for evaluating DTW distances since it is based on Euclidean similarity. Therefore, clustering will be executed with different values of $k$ and assessed in the second part of the gait analysis.

At this stage, the time series clustering returns a clustering vector that assigns each stride of the time series dataset to a group of strides, regardless of the user, they belong to. This approach applies to any exercise performed with the $i$-Walker within a straight line and will be applied to both the 10MWT exercises from *IDF* and *MAD* pilots and to the straight lines extracted from the 3mWT collected at the *CVI* pilot.

### 6.1.4 Exercises as bags-of-strides

Once the optimal $k$ (types of strides) is defined, the outputs of the partitioning can be grouped by clusters to study the distribution of strides from the same exercise in the different obtained $k$ groups. As a result, a new dataset is created, with as many objects as exercises had the original datasets (IDFMAD and CVI), where each object represents a pair {user, exercise} and the representation of the strides extracted from that exercise in terms of clusters *i.e.*, the proportion of strides of an exercise that fall in each strides cluster. In other terms, we obtain a histogram for each pair {user, exercise} representing the frequency of appearance of each stride cluster by exercise. A set of histograms $H = \{h_1, h_2, ..., h_n\}$ is generated, where each $h_k$ is composed by a number of bins which sum up to one. Clustering histograms have become popular thanks to the bag-of-words categorisation method (Nielsen et al. (2014)). This provides a first visual overview of the distribution of each exercise, but there are still too many objects to analyse. Therefore, a second $k$-medoids partitioning is applied to this new dataset, using two different similarity metrics (Deza and Deza (2013)):

- Euclidean distance is the similarity measure used by default in partitional clusterings.
- Kullback-Leibler (KL) Divergence: also called relative entropy, measures how one probability distribution diverges from a second expected probability distribution.

The symmetrised KL Divergence is used to obtain a distance matrix of the dataset. Previous research has shown that it has better performance than the Euclidean distance. This second partition will be executed with both distances, although only KL Divergence will be considered for the final analysis. Again this clustering process will be performed with different values of $k$ to determine the most suitable partition. The result of this clustering will be a set of bag-of-strides that represent exercises characterised by a given vocabulary of strides. In Chapter §7.2 a graphical representation of these bag-of-strides is given as well as the analysis of the content of the clustering result.

### 6.1.5 Cluster stability

In this second clustering, it was noticed that each execution of the `pam` algorithm returned a different clustering vector. Therefore, each $< pam, k' >$, where $k'$={2,3,4,5,6}, was executed 20 times in order to determine the optimal partitions. Then the normalised mutual information (NMI, Wagner and Wagner (2007)) index was applied to measure the mutual dependence between each pair of clustering vectors obtained. As a result, for each $< pam, k' >$, a $20 \times 20$ matrix was generated with the NMI results. The partition is considered stable when all the results from the $20 \times 20$ NMI matrix returned 1 (*i.e.* all the clustering vectors are equal). In case any combination returns 1 for all the repetitions, then the most stable should be chosen, considering the number of 1 appearing in the $20 \times 20$ matrix and the value of the other cases (the higher, the better).

This process was applied using both the Euclidean and the KL divergence as a distance measure for the $k$-medoids. The pairs $< pam, k' >$ where NMI was equal to 1 were the partitions selected for the final analysis. Table 6.1 shows the combinations that will be obtained and presented in Chapter §7. This table only includes the clusters of exercises with the KL divergence, as it is more used in the literature when clustering histograms. In addition, the combinations obtained with the Euclidean distance were part of the KL results as well.

## 6.2 Spatio-temporal Analysis

In this section, we will describe in detail the different parameters that were proposed in Prakash et al. (2015) and relate it to the corresponding *i*-Walker outcomes. Although parameters are here presented separately, we will later combine them to obtain a better understanding of our studied population and the differences they present in relation to the *i*-Walker data.

| **Pilot** | **Stride Clustering** | **Exercise Clustering** | **Name** |
|---|---|---|---|
| *IDFMAD* | k = 4 | k’ = 5 | idfmad4k5k’ |
| *CVI* | k = 3 | k’ = 3 | cvi3k3k’ |
| | k = 5 | k’ = {3,5} | cvi5k3k’<br>cvi5k5k’ |
| | k = 6 | k’ = {3,4} | cvi6k3k’<br>cvi6k4k’ |

Table 6.1: Resulting combinations of strides per exercises to be analysed in different scenarios

Spatio-temporal parameters provide the simplest form of objective gait evaluation in terms of time and distance. This section describes the metrics that are commonly used in the literature to assess individuals’ walking performances. Relation of these metrics to the extracted variables from the *i*-Walker raw data is also provided, although the previous section already showed how these were obtained. To review the definitions of step, stride and gait cycle, see Chapter §2.

### 6.2.1 Descriptive Gait Parameters

Most of the human gait research focus on the same set of metrics to assess the gait quality of the user. In normal walking patterns, a gait cycle is the continuous repetition of strides or, as defined in Pappas et al. (2001), a succession of 4 phases for a given foot: stance, heel-off, swing and heel-strike. Considering a step as the movement of one foot in front of the other, and a stride (or gait cycle) as a step from one foot followed by a step from the other foot, we can define the following quantitative metrics:

- *Step length:* distance (in meters or centimetres) between the heel-off and heel-strike of one foot.
- *Step time:* duration (in seconds) between the heel-off and heel-strike of one foot.
- *Number of steps:* total number of steps during an exercise.
- *Number of stops:* total number of stops during an exercise
- *Stride length:* distance (in meters or centimetres) of a gait cycle.

- *Stride time:* duration (in seconds) of a gait cycle (or the time between steps of the same foot)
- *Cadence:* Number of steps per minute

The metrics included in this thesis are the stride length and time, the number of steps and cadence. In this work, the number of strides was collected instead, and the rhythm was modified to represent the number of strides per minute. Although the presented methodology allows also extracting the information at step level, these were not considered in the analysis. Stride-to-stride fluctuations have been traditionally used in literature to study gait variability, which is a complementary way to evaluate human locomotion and its change with age or disease. It has also been closely related to gait disorders, leading the results to categorise individuals participating in these studies in terms of frailty or risk of falling (Hausdorff (2005a)).

As mentioned before, steps (and thus, strides) are obtained by local maxima of the $F_x diff$ pushing force. We use the walking distance as the reference. Therefore, it is easy to extract the distance between peaks of local maxima. In addition, we know that data is collected at a periodical and chronological time, so the time between peaks can be obtained by counting the number of observations and converting it to seconds. We provide the number of strides at the end of the dictionary of strides generation, and the cadence is a simple conversion from the number of strides along the exercise (usually few seconds) to minutes.

### 6.2.2 Gait Velocity

There are several approaches that use gait velocity (*e.g.*, Montero-Odasso et al. (2012)) as an assessment metric for cognitive decline and risk of falling, although one of the most commonly used is the 10 Meter Walking Test. Traditionally, this test is measured by direct observation of the performance and a simple time measurement through a chronometer. More recent studies include the use of wearable sensors (usually accelerometers placed at wrist or ankles) or walking platforms for foot tracking (see §2). Less frequent are the studies where assistive devices are involved. However, authors like Wang et al. (2014) and Ballesteros et al. (2015) have proposed different methodologies using different versions of robotised rollators. This sort of studies ought to be very careful with the target population selected since the rollator is not adequate to specific pathologies, *e.g.*, people with hemiparesis who have no lateral balance generally due to the consequences of a stroke. As mentioned in Chapter §4.3.1, the *i*-Walker can provide a helping force that would give the required balance to walk safely. However, this was not considered in this thesis due to the difficulty to pass the protocol in each pilot and to get access to people with this pathology.

According to Montero-Odasso et al. (2005), older adults can be divided in three groups based on gait velocity (GV): high GV ($>$ 1 m/s), medium GV (0.7-1 m/s) and low GV ($<$ 0.7 m/s). It is considered that people not belonging to the high GV group, and especially those belonging to the low GV group, have more probabilities to suffer from adverse events due to physical or cognitive decline. We divided participants according to this methodology, and it will be used to observe the trends in different periods of time for the *I-DONT-FALL* population.

We will perform an analysis on Gait Velocity for both the *IDF* as an independent dataset, the baseline datasets ($IDFMAD$) and the validation dataset ($CVI$) to study the distribution of our population. Participants will be classified according to the approach proposed by Montero-Odasso et al. (2005), and we will determine whether our population follows the clinical hypothesis mentioned during this work: (i) poor performances of gait velocity are related to age, and cognitive status; (ii) physical and/or cognitive training helps to improve gait velocity and, thus, reducing gait variability; (iii) training will also help to reduce the risk of falling and fear of falling. For the *IDF* data, we will compare the performance before and after the three-months training (T0 and T1 respectively), and we will study the evolution for each of the training groups (motor, cognitive, mixed and placebo).

## 6.3 User Driving Skills

There are several methods of evaluating the human-robot interaction while driving. Urdiales (2012) provides methods to *(i)* analyse user driving skills and obtain user profiles according to their performance, and *(ii)* interpret user disagreement in a collaborative control driving strategy. In our case the *i*-Walker works with a purely reactive control for now, as no control strategies have been added to assist in the effectiveness of the driving skills of the user. Hence, it will act as a sensing platform that collects data from different sensors during the exercise at a rate of 10Hz.

In this thesis, we will follow the same philosophy than in Urdiales (2012) to assess human driving skills, which has been fully described in §3.2.1, but adapting it to the characteristics of the *i*-Walker architecture. The main difference is that the *i*-Walker requires human body motion to move, *i.e.*, users must use angle joints such as legs to create motion and arms to exert a force on the handlers of the rollator. By analysing how does an elder person use the

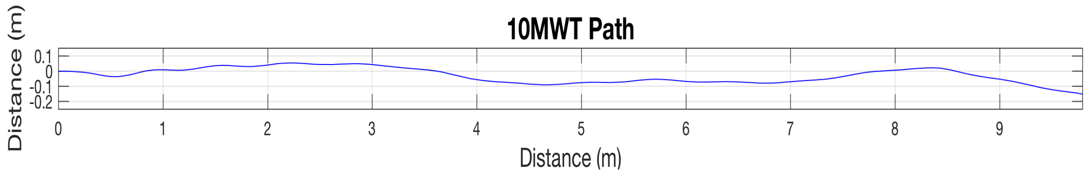


Figure 6.5: 10MWT, first case: the user follows a straight line to the target. In this case, deviations are under 10 centimetres from the origin of the $Y$-axis

*i*-Walker to move in terms of driving skills, we can infer information on bad postural behaviour or gait disturbance that cause unbalanced, and thus unsafe, movement.

Hence, we have defined two evaluation metrics that can provide further information on the walking patterns of individuals performing a timed walking test in straight lines. Since the objective is to follow as possible a straight line, we will determine how successful was the user in performing this task. By observation of the estimated poses and incremental travelled distance, we have identified three different types of trajectories performed by users in the *IDF* dataset:

1. the user follows an almost perfectly straight line (see Figure 6.5).

2. the user follows a straight line but with a deviation angle (see Figure 6.6).

3. the user drives towards a given direction and changes orientation at some given point (see Figure 6.7).

For this, we have defined two different evaluation metrics, *laterality* and *directivity*, which measure the ability to walk directly to an objective and with small oscillations in a straight line. It will also provide information on how balanced are user's movements and force load to the *i*-Walker in relation to the deviation angle.

These deviations are being considered as lateral errors and occur when the user is not driving on the desired path. These lateral errors are calculated in terms of areas (square meters). The smaller the area is, the better the driving ability. However, in a controlled exercise like the 10MWT (which is usually performed in a corridor), deviations are expected to be relatively small (less than 50 centimetres).

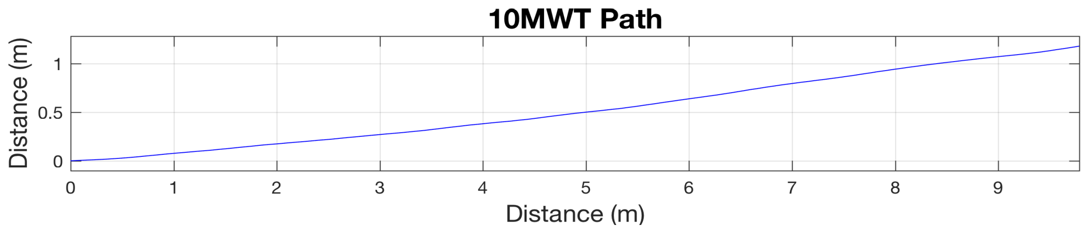


Figure 6.6: 10MWT, second case: the user follows a straight line but with an initial deviation angle

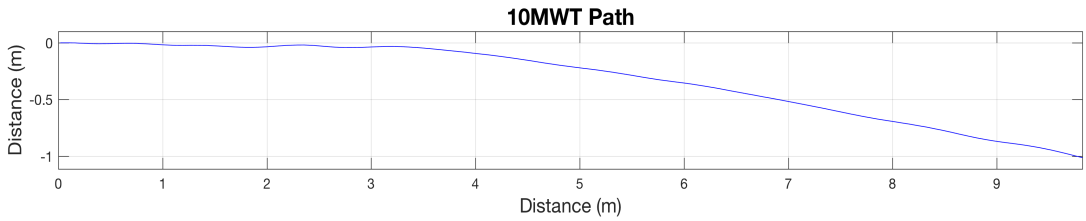


Figure 6.7: 10MWT, third case: the user follows a straight line during the first meters of the exercise, but changes directionality and continues with another straight line

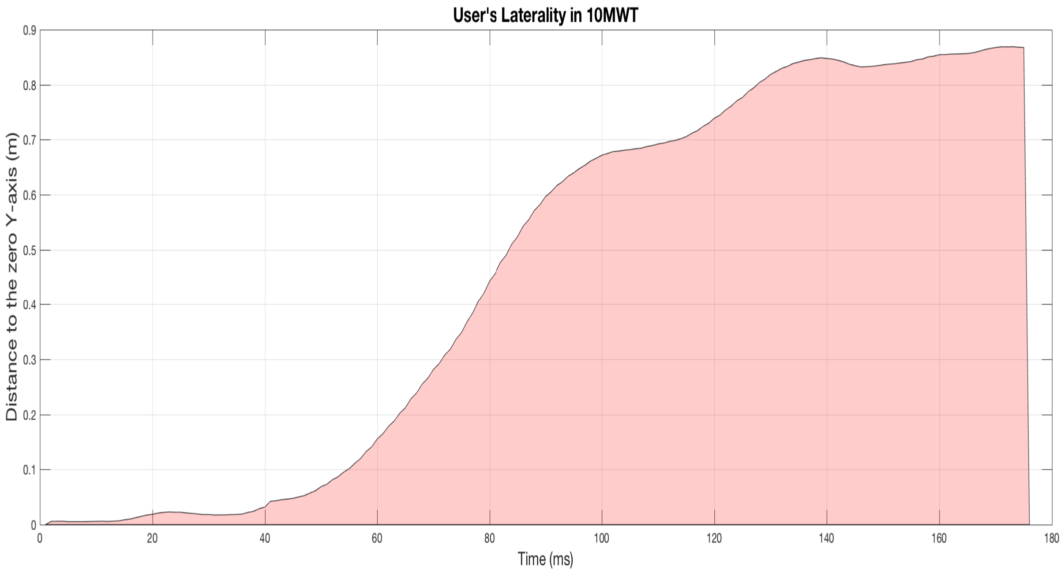


Figure 6.8: Area of lateral deviation while performing a straight line exercise.

### 6.3.1 Laterality

The first term that we have defined is the *Laterality* of the trajectory. Based on the 10MWT, where the user is supposed to follow a straight line but only having the starting and ending point markers as path indicators, the *Laterality* measures the area between the starting point and user's ending point in relation to the predetermined ending point (the final goal). An ideal straight line would always have zero values in the $Y$-axis, while the $X$-axis would increment with the travelled distance. Figure 6.8 shows the laterality area of a user that would suit into the third case of trajectory patterns described above, see Figure 6.7. As it can be observed, the user begins the exercise with a good orientation to the final point. Then it starts deviating to the left after 4 seconds walking. The deviation is continuous up to almost one metre. This user then modifies its path leaning to the left at a given point and maintains the new direction to the end. Although the user maintains its new direction, the motion presents an oscillation while walking. Further analysis will determine if this patterns respond to gait distrubances and, in the end, higher risk of faling.

### 6.3.2 Directivity

The second term defined is the *Directivity* of the user. Given the user's trajectory and his/her ending point (not the original goal, but the new one determined by the orientation of his/her path), we calculate how straight did he/she go to that final destination (see Figure 6.9). The estimated straight line that the user is following according to his original deviation is calculated using a least squares linear regression.

Not only are we representing *how* straight did the user go to the predetermined destination point, but also how balanced was the user's navigation, *i.e.*, did the user drive on the left or right side of a straight (imaginary) line. As it can be observed in Figure 6.10, the estimated line has been rotated to be zero-values $Y$-axis. Therefore, dimensions of the areas are proportional to this projection of the linear regression. Even though there are other possibilities to measure this metric, this rotation was made to simplify the visualisation of the areas of deviation in terms of a straight line (*i.e.*, to simulate the ideal case where the user would follow a perfectly straight line).

## 6.4 Modelling Exercises by Spatio-Temporal Gait Characteristics

In this chapter, we have proposed a methodology to identify strides from the walking exercises performed by three groups of individuals with differents ages and characteristics. On the one hand, we have applied unsupervised learning methods to define different sorts of strides based on the stride shapes obtained through the hand forces applied to the *i*-Walker, and to the bags-of-strides generated at each exercise. On the other hand, this approach offers means to extract some of the main spatio-temporal gait characteristics used in the literature of gait analysis. In this section, we use the $CVI$ pilot dataset and applied two supervised learning method, Random Forest and Support Vector Machine. The objective is to obtain a model of classification of exercises based on the spatio-temporal gait characteristics of the individuals performing them.

The dataset is composed of 13 variables:

- cadence: strides/min
- walking speed during the exercise (m/s)
- stride length (m) and its coefficient of variance during the exercise.
- stride time and its coefficient of variance during the exercise (s).


Figure 6.9: Estimated straight line (in red) calculated from user's directivity

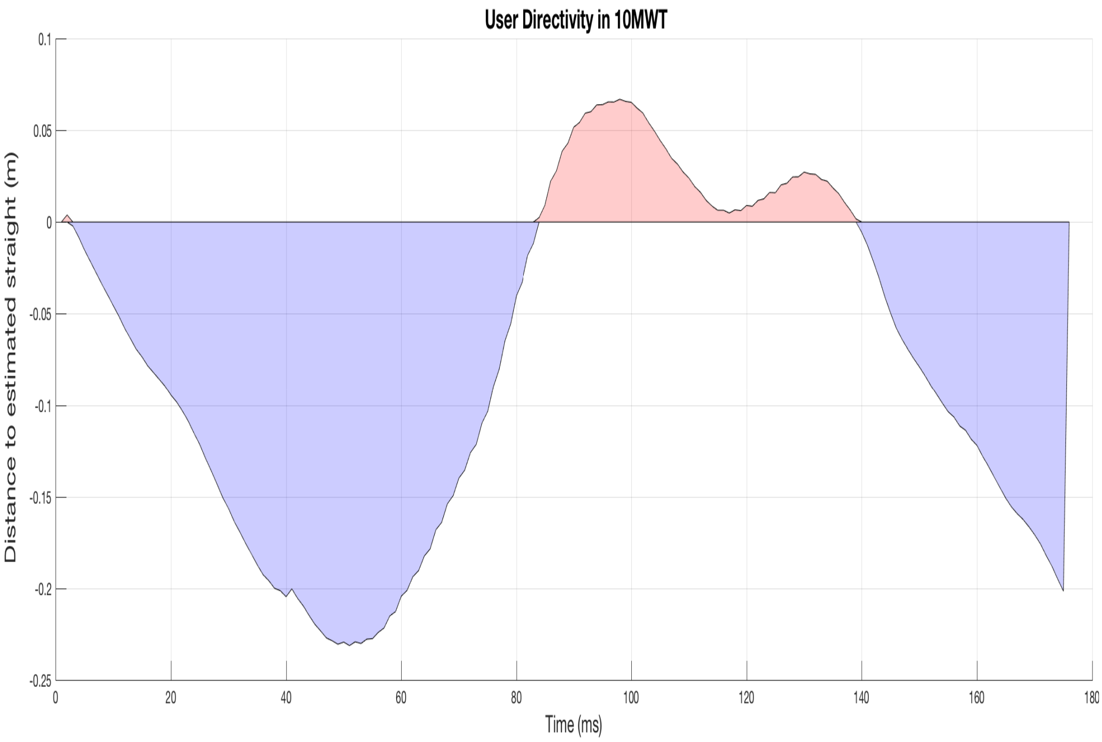


Figure 6.10: Representation of the directivity with positive and negative areas around the straight line. Positive areas are considered those falling to the left of the estimated straight line (in red), while negative areas are those falling to the right (in blue)

- round: exercise identifier for each participant (the 3mWT was divided in straight lines, excluding the curve areas; each straight line was stored as a single exercise).
- average hand forces of both body sides during the exercise: pushing, lateral and leaning forces (N).

The coefficients of variance of the stride time and length were calculated as we considered they might be useful to characterise the exercises performed by the older adults. Gait variability has been widely studied as is strongly correlated to the risk of fall (Hausdorff (2005a); Hausdorff et al. (2001); Matsuda et al. (2015)).

The common spatio-temporal features of each stride were computed. The raw data from the sensors was filtered and averaged too for all the exercises. The final dataset also excluded the acceleration and deceleration phases as explained in §6.1.1. The exercises were divided in two datasets: training and test. A 10-fold Cross Validation was applied to each of the supervised learning methods in order to obtain an average accuracy of each scenario. The training test is used to get a classification of individuals based on their spatio-temporal characteristics. The objective is to compare the coherence of the clustering methodology presented in §6.1.

To obtain the moded, we applied first a Random Forest with all the described variables. A Random decision forest (Breiman (2001)) is an ensemble learning method used for classification and regression, using a collection of decision trees to train the model and provides the classification and its accuracy as ouput. The Random Forest also return a ranked list of the essential features, where all values are numbers between 0 and 1, and all values sum up to one.

The Support Vector Machine was also computed as a linear model for classification. It represents the observations of the dataset as points in space, mapped so that the method finds linear hyperplane that separate the data into categories (Steinwart and Christmann (2008)). The training data is used to generate this map of instances that will be divided into as many dimensions as classes cointained in the original dataset. The test set contains new inputs to be assigned to the already defined categories. As a result, variables are sorted by largest coefficients. Values represent weights of importance of each feature and can be both positive or negative, but we will work with their absolute values.

For each scenario, we will compare the most relevant features of each model, and we will analyse the relation with the results obtained from the unsupervised learning method of strides and exercises clusterings.

## 6.5 Modelling Fall Risk Assessment

One of the objectives of the *I-DONT-FALL* project was to reduce the risk of falling in elderly population through different types of training. As mentioned before, data obtained from clinical scales at baseline was compared to the post-training results to evaluate the effectiveness of the system.

We used the *i*-Walker data generated during the 10MWT exercises before and after the training and applied a machine learning technique to the prediction of the risk of falling for an individual. We selected several variables for the 10MWT exercises from the study sample using the *i*-Walker. These variables combined raw data with other calculated variables. They correspond to the average values from the force sensors ($X$, $Y$ and $Z$ directions) of both hands and the average speed. The dataset has a total of 20 variables. The average was computed for all the 10 meters of the exercise and also for the values discarding the first and last two meters (the central part of the exercise). The reason for dropping values from the beginning and the end of the exercises was to reduce noise from acceleration and deceleration phases and focusing on the stable regime of the exercise.

The exercises were divided into two datasets. The first corresponds to the exercises performed before treatment (T0) and the second to the exercises performed after treatment (T1). The data before treatment was used as a training set to obtain a predictive model for the risk of falling. The second dataset is used as test to detect if the population has changed their status as an effect of the treatment.

To obtain the model for fall risk, a logistic regression was performed using $L_1$ regularisation, first with all the variables, and then selecting only the relevant ones, by discarding all variables that were assigned zero weight by the regularised logistic regression. From all the variables only 10 were used by the model that included variables for all the exercise (average speed, mean force on the $X$ direction, right hand force on the $X$ direction and left hand forces on the three directions) and only for the central part (left hand forces on the $X$ and $Z$ directions and right hand forces on the $Y$ and $Z$ directions). A Support Vector Machine (SVM) model with linear kernel was also computed, obtaining identical results. It is clear that the information collected from the force exerted by the user to the *i*-Walker is essential to characterise its walking behaviour.

This model was not applied to the rest of datasets since they did not follow the same protocol. The rest of pilots executed the test in one day, and hence no temporal comparison of their evolution is possible.

## 6.6 Summary

The *i*-Walker offers several sources of information that can be related to the human walking behaviour. The main idea is to translate data sensor readings into readable and understandable reports, aiming to complement the observations of clinicians while the user is performing an exercise. Fusing the expert knowledge on human body motion with the data obtained from older adults using *i*-Walker would allow the design of messages to alert or inform the user about a situation (see a first approach to the implementation of this service in Appendix B). Moreover, the *i*-Walker would be able to take decisions in dangerous situations and assist the user in his/her mobility.

One of this PhD work aims is to find those known gait parameters represented in data obtained from the *i*-Walker for the selected target population. For this, we have first focused on a descriptive analysis of the studied parameters. We have also proposed a model to predict the risk of falling for the *I-DONT-FALL* population. Finally, previous results on applying clustering techniques to identify individuals with falls are promising (see Chapter §4.3.3), although they consider exercises as a whole. Thus, it cannot process information on user's interaction at each moment. We expect that by clustering users' strides, we will be able to identify gait disturbances associated with non-healthy older adults.

As a result of the methodology presented here, a bag-of-strides and a bag-of-exercises are created for each dataset ($IDFMAD$ and $CVI$), containing the spatiotemporal metrics above-mentioned and the exerted forces by the human to the *i*-Walker at stride level while performing the exercise. We are confident as we have robust sets of data coming from *I-DONT-FALL* and other campaigns.

# Chapter 7

# Results

In this chapter, we present the results obtained from the proposed methodology and the already introduced datasets. To describe these results we will discuss the relevance of each of the gait characteristics extracted from the interaction between the participants and the *i*-Walker.

For this analysis, we have selected some evaluation metrics that can be found in the literature of human gait research (see Chapter §6) that will be evaluated by means of the data obtained from the *i*-Walker sensors. First, the methodology will be applied to the baseline population (both fallers and healthy older adults) regarding gait velocity while performing the 10 Meter Walk Test. The relevance of this measure in the early detection of the decline in older adults has already been explained in this document. The objective is to observe how are the participants distributed regarding gait velocity and whether significant differences are observable between groups. Second, the results of the spatiotemporal analysis are shown, focusing on the characteristics of an elder individual's gait (length, time, velocity). Following, a study users' driving skills concerning directionality and laterality is given. Then, the results from the clustering approach to gait analysis are presented for both the baseline and validation datasets (*i.e.*, observations for 10MWT and 3mWT). Finally, the results of a regression model of fall risk prediction applied to the *IDF* dataset are introduced in this chapter.

## 7.1 SpatioTemporal Analysis

In this section, we will show preliminary results on the time and distance parameters of human gait through its interaction with the *i*-Walker.

### 7.1.1 Descriptive Gait Parameters

We have seen that steps can be represented by frequency or by distance, but both require the use of filters to discard noise from human oscillations. Once steps are detected and located in the data signal, it is possible to represent it in different understandable ways as shown in Figure 7.1. Here the signal has been filtered by distance, *i.e.*, by a minimum of walked distance between strides based on the average walking speed. According to our interpretation, exercises start when the first right stride is detected. With a similar process, we can extract the strides performed with the left leg. Furthermore, this figure adds a new layer of information, introducing the concepts of prominence and width defined in §6.1.2. In this case, the width represents the time in seconds between peaks, *i.e.*, the average time the user has spent pushing between steps. This concept can also be interpreted in terms of distance travelled between peaks. However, for the rest of the analysis, the width was represented in terms of distance, as already explained in §6.1.

As above said, the positive parts of the signal corresponding to those moments where the user was exerting more force with its right hand. It is expected that in an exercise like the 10MWT, where the trajectory is assumed to be a straight line, the signal will be balanced. A person drifting to one side while driving will present less zero-time moments since the increase in the opposite side will not be high enough to compensate the movement. The comparison of the force prominence for both arms aims to illustrate how does the individual interact with the *i*-Walker and associate it with its physical or cognitive dysfunction.

Figure 7.2 represents the evolution of the step length for each foot while performing the 10MWT. Usually, 10MWT assessments disregard the beginning and the end of the exercise (2 meters on each side) since they correspond to the acceleration and deceleration phases and the gait pace is not regular. In Figure 7.2.a, we can observe this behaviour for both feet. Moreover, it strengthens the hypothesis that the individual has started the exercise with the right foot and finishes it with the left one. Figure 7.2.b represents the increments of each foot's strides in terms of distance (meters). As we observe, in this case, the individual does bigger strides with the right foot. The same analysis and representation can be given in terms of stride time.

After applying the bag-of-strides approach described in the methodology, a database is generated where, for each stride, the following information is being stored:

- user ID, gender, age range, fall risk (Tinetti), faller (yes/no)

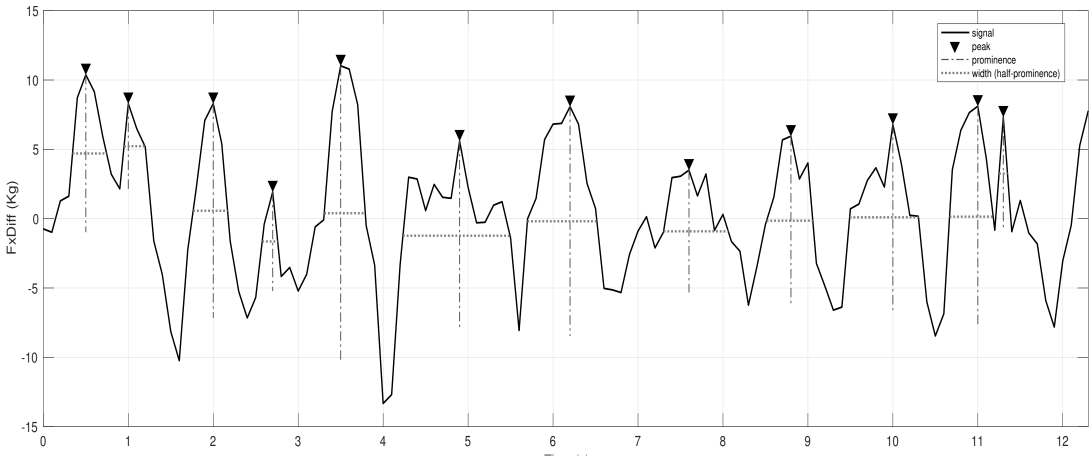


Figure 7.1: Right leg strides, pushing force increments and average pushing time within peaks

- timestamp and number of exercise (being T0-T1 for the *IDF* dataset, or round number in the case of *MAD* and *CVI*)
- stride ID (incremental within the same exercise)
- total number of strides in exercise
- distance travelled, duration of the exercise, average speed and cadence (in metres, seconds, metres/seconds and strides/minute respectively)
- stride length and time (in metres and seconds respectively)
- average stride length and time in exercise(in metres and seconds respectively)
- average pushing force along the stride in terms of $F_x diff$

This will allow depicting the distribution of our studied population from different perspectives that will be presented in the following sections. Table 7.1 shows the main spatio temporal characteristics for the *IDFMAD* pilot population.

### 7.1.2 Gait Velocity

The Gait Velocity has been calculated for both the *IDF* and *MAD* pilots for the 10 Meter Walk Test. It was also applied to the *CVI* pilot, where each straight line was considered as an

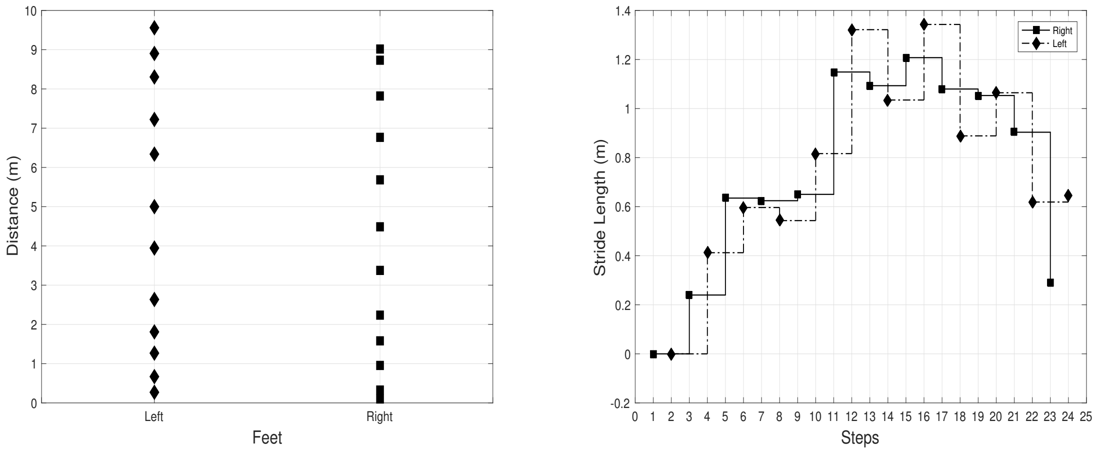


Figure 7.2: Evolution of an individual's stride length during the 10MWT: (a) Estimated feet position; (b) Stride length for each foot.

independent exercise. In the case of *MAD* and *CVI*, gait velocity was obtained by calculating the average walking distance and walking time of all the exercise performed by the same participant; this technique is known in the literature as the test-retest. For the final analysis, some participants were excluded due to sensor failure or drop-out. At a first stage, participants from *MAD* with falls were excluded, but we finally decided to treat *IDF* and *MAD* as a single baseline dataset.

The distribution of each pilot is depicted in separated tables and commented below. The

| | Spatio Temporal Characteristics | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Biological Characteristics** | **N** | **Cadence** | **Speed** | **sLength** | **sLength CV** | **sTime** | **sTime CV** | **FxDiff** |
| *Age M* | *85* | *49,88* | *0,80* | *0,93* | *42,45* | *1,04* | *54,31* | *1,72* |
| Gender F | 49 | 49,14 | 0,80 | 0,94 | 42,63 | 1,05 | 55,37 | 1,36 |
| Gender M | 36 | 50,89 | 0,79 | 0,91 | 42,21 | 1,02 | 52,87 | 2,19 |
| *Age O* | *200* | *45,83* | *0,61* | *0,76* | *42,06* | *1,28* | *55,98* | *1,66* |
| Gender F | 140 | 45,56 | 0,57 | 0,71 | 42,12 | 1,35 | 55,91 | 1,60 |
| Gender M | 60 | 46,48 | 0,71 | 0,87 | 41,91 | 1,12 | 56,16 | 1,81 |
| **Total general** | **285** | **47,04** | **0,67** | **0,81** | **42,18** | **1,21** | **55,49** | **1,68** |

Table 7.1: Spatio-temporal characteristics of the *IDFMAD* population.

| **Characteristics** | | **Low GV** ($N$ = 52) N(%) or Mean ± *SD* | **Median GV** ($N$ = 27) N(%) or Mean ± *SD* | **High GV** ($N$ = 6) N(%) or Mean ± *SD* |
|---|---|---|---|---|
| **Age** | $<80$ | 14 (26.9%) | 15 (55.5%) | 6 (100%) |
| | $\geq 80$ | 38 (73.1%) | 12 (44.5%) | 0 (0%) |
| | Total | 85.3 (± 6.8) | 79.2 (±9.4) | 75.3 (± 5.2) |
| **Gender** | Female | 36 (69.2%) | 18 (66.7%) | 4 (66.7%) |
| | Male | 16 | 9 | 2 |
| **Treatment** | Mix | 15 | 4 | 4 |
| | Motor | 8 | 6 | 1 |
| | Cognitive | 12 | 7 | 1 |
| | Placebo | 17 | 10 | 0 |
| **Risk** | Low | 1 | 3 | 4 |
| | Medium | 11 | 17 | 2 |
| | High | 40 | 7 | 0 |

Table 7.2: Distribution of the *IDF* participants before 3-months training (IDF-T0) performing the 10MWT. Data is represented by Gait Velocity groups. These results are used to evaluate the effectiveness of the *IDF* solution after the training phase.

distribution has been observed in terms of age, gender, treatment and original risk of falling. Table 7.2 and Table 7.3 provide the same structure for the *IDF* population. Tables 7.4 and Table 7.5 show the same information for the *MAD* and *CVI* pilots respectively, except for the treatment information which only regards the *IDF* protocol. In these two latter pilots, participants repeated several times the same exercise. Thus the walking speed has been obtained from the average walking speed of each exercise performed by the same user, as before-mentioned.

Even though the *MAD* population is supposed to be healthier than the one from *IDF*, they are also older (the proportion of people aged 80+ is significantly higher than in the *IDF* pilot, which corresponds to the typical age of people living in care centres). Hence, only three individuals (5%) reached the High GV group and, surprisingly, they present a medium or high risk of falling. Unfortunately, the Low risk of falling is poorly represented, and thus no definite conclusions can be extracted from this result. The rest of groups are coherent with the litera-

| **Characteris-tics** | | **Low GV** (*N* = 50) N(%) or Mean ± *SD* | **Median GV** (*N* = 22) N(%) or Mean ± *SD* | **High GV** (*N* =12) N(%) or Mean ± *SD* |
|---|---|---|---|---|
| **Age** | <80 | 15 (30%) | 10 (45.5%) | 11 (91.7%) |
| | ≥ 80 | 35 (70%) | 12 (55.5%) | 1 (8.3%) |
| | Total | 84.8 (± 6.6) | 82.7 (±9.3) | 73.3 (± 6.9) |
| **Gender** | Female | 37 (74%) | 13 (59.1%) | 7 (58.3%) |
| | Male | 13 | 9 | 5 |
| **Treatment** | Mix | 13 | 4 | 6 |
| | Motor | 11 | 3 | 1 |
| | Cognitive | 10 | 8 | 2 |
| | Placebo | 16 | 7 | 3 |
| **Risk** | Low | 0 | 4 | 7 |
| | Medium | 24 | 17 | 4 |
| | High | 26 | 1 | 1 |

Table 7.3: Distribution of the *IDF* participants after 3-months training (IDF-T1) performing the 10MWT. Data is represented by Gait Velocity groups and is used to assess the usability of the fall risk prevention system.

ture: most of the people with higher risk of falling are classified in the low GV group. After contacting Los Nogales clinical team, it was possible to retrieve updated assessments one year after the pilot took place of those participants that were still living in the care centre. It was observed a general improvement in terms of Tinetti scale results, especially for those having a better cognitive status (measured with the MMSE scale). Thus, it is presumed that people with a particular cognitive condition and ability (or willingness) to keep an active living were able to improve their mobility and thus reduce their risk and/or fear of falling. This data will not be shared for ethical issues, as it was not included in the consented inform signed by the participants at the time of the pilot testing.

In the case of the *CVI* pilot, the age range is expanded, including now the Young category (≤ 65 years old). In this test, 13 participants had some cardiac pathology or physical injuries resulting from a fall and were living in the care centre. The rest of people are healthy people, most of them are still employed or retired in the last year, and were living independently. The distribution of the GV groups by age follows the same trend than in the rest of pilots. It also

| **Characteristics** | | **Low GV** ($N$ = 34) N(%) or Mean $\pm$ *SD* | **Median GV** ($N$ = 21) N(%) or Mean $\pm$ *SD* | **High GV** ($N$ = 3) N(%) or Mean $\pm$ *SD* |
|---|---|---|---|---|
| **Age** | <80 | 3 (8.8%) | 4 (19%) | 0 (0%) |
| | $\geq$ 80 | 31 (91.2%) | 17 (77.78%) | 3 (100%) |
| | Mean | 88.3 ($\pm$5.8) | 86.9 ($\pm$6.2) | 87.6 ($\pm$5.8) |
| **Gender** | Female | 27 (79.4%) | 9 (42.8%) | 1 (33.3%) |
| | Male | 7 | 12 | 2 |
| **Risk** | Low | 1 | 1 | 0 |
| | Medium | 8 | 10 | 2 |
| | High | 21 | 10 | 1 |

Table 7.4: Distribution of the *MAD* participants after a 10MWT test-retest represented by Gait Velocity groups.

shows that 8 of the 13 challenged participants fall in the Low GV group; these people where even the eldest from this challenged group, which was the expected. The other five users are classified in the Median GV group correspond to middle-aged people with premature cardiac pathologies. It has also been noticed that young participants change their walking behaviour when using an assistive device, reducing their walking speed, which might affect the results of the clustering presented in §7.2. It was also expected that participants (especially challenged or elder) would show some trend in the walking speed among rounds (*i.e.*, elder people performing each straight line slower than the previous one), but this is merely observable. People tend to walk at a similar speed between each round, especially the youngest and eldest participants; people in middle age are the ones that show more variations, but never more than 0.2 m/s, and usually always within the same GV class.

Results on Table 7.2 and Table 7.3 show that the group of participants are distributed as expected in terms of age and gait velocity: the younger they are, the faster they walk. Moreover, people under 80 years old tend to improve their performance in terms of velocity after the 3-months training. On the other hand, men walk faster than women on average, taking into account the proportion of gender representation, although this could easily be related to

| Characteristics | | **Low GV** ($N$ = 8) N(%) or Mean ± *SD* | **Median GV** ($N$ = 18) N(%) or Mean ± *SD* | **High GV** ($N$ = 16) N(%) or Mean ± *SD* |
|---|---|---|---|---|
| **Age** | <65 | 0 (0%) | 8 (44.4%) | 9 (56.3) |
| | 65-80 | 0 (0%) | 3 (16.7%) | 1 (6.2) |
| | ≥ 80 | 8 (100%) | 7 (38.9%) | 6 (37.5%) |
| | Mean | 87 (±4.2) | 63.2 (±24.4) | 52.5 (± 19.1) |
| **Gender** | Female | 7 (87.5%) | 14 (77.8%) | 13 (81.2%) |
| | Male | 1 | 4 | 3 |
| **Risk** | Low | 0 | 11 | 14 |
| | Medium | 1 | 6 | 2 |
| | High | 7 | 1 | 0 |

Table 7.5: Distribution of the *CVI* participants performing the 3mWT. Data is obtained by extracting the straight lines of the exercise, which go from 25 to 35 metres long, and applying the test-retest method to obtain the average speed. Data is represented by Gait Velocity (GV) groups.

anthropometric parameters, such as height. Finally, as it was expected in the outcomes of the *I-DONT-FALL* project (see I-DONT-FALL), people having been assigned to the Mixed Training group have obtained better performances than the rest of the groups. However, the Motor Training group did not present the expected improvements in terms of velocity, although the sample is small to extract a reliable conclusion with this single metric. In general terms, results are coherent with those existing in the reviewed literature: *(i)* gait velocity is related to some biological characteristics of the individual; *(ii)* it is essential to promote active, healthy ageing both in physical and cognitive tasks; *(iii)* gait velocity can be used as an early indicator of decline in older adults.

Results were also represented graphically to observe the distribution among the different pilots. Figure 7.3 shows the difference in gait velocity between T0 and T1. The red area represents the *MAD* pilot, which is concentrated around the zero value (*i.e.*, no differences between T0 and T1). The three studied pilots from *IDF* (HGG in green, FSL in blue and SERMAS in yellow) show different distributions in gait velocity. Areas on the right side of the

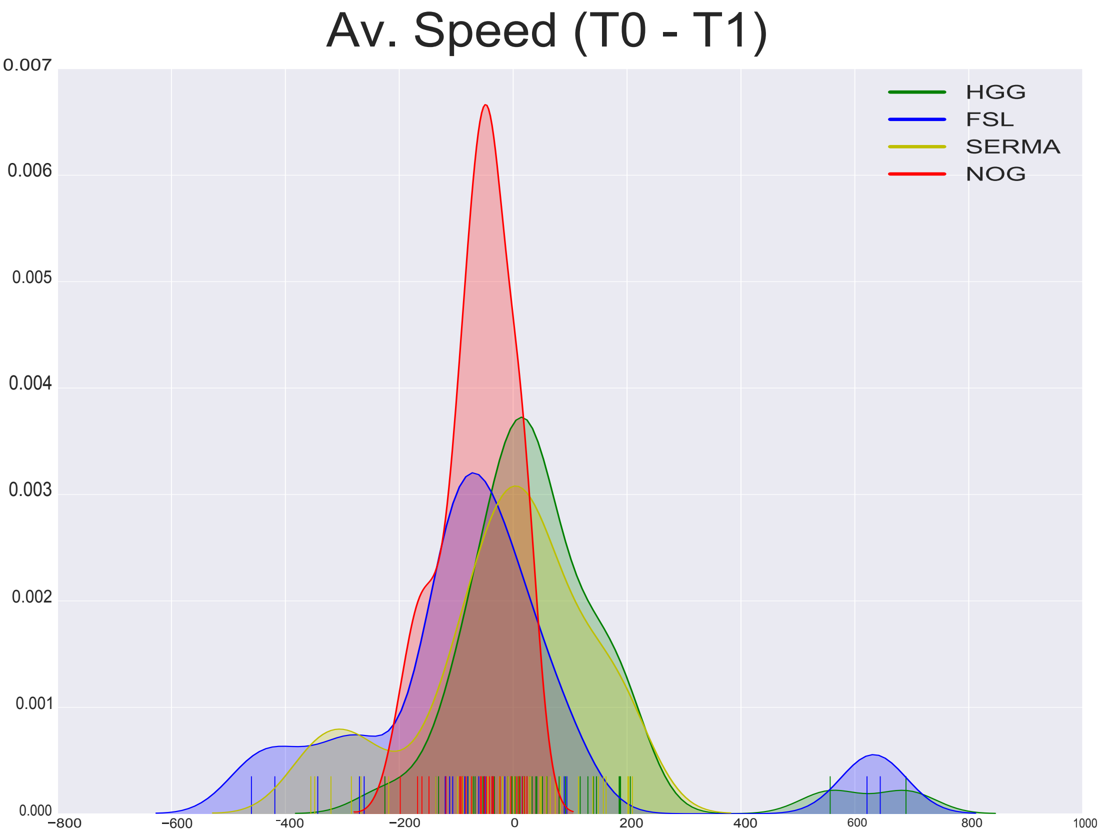


Figure 7.3: Gait Velocity differences between pre and post treatment

zero point represent higher speeds in T0 and thus, a decline in user performance. On the other side of the zero value are situated those users that have improved their gait velocity. Since 10MWT was performed twice in the baseline pilot, the first time is considered T0 and the repetition in T1. As expected, *MAD* participants present little variations in gait velocity since the exercises were performed consecutively. However, the distribution of *IDF* participants varies among pilots. These representations were designed as a supporting material for the clinical assessment of the *I-DONT-FALL* system in terms of effectiveness of the treatment.

## 7.2 Clustering Results of the Gait Analysis

One of the initial hypothesis of this work was that the *i*-Walker could be able to contribute to clinicians thanks to the interaction with its user. Moreover, it would provide significant information to contribute in some way to health reports by detecting certain patterns in groups of people while walking. The results presented until now are based on referred literature and corroborate those results. Even though the device to measure such outcomes and the approach to obtain them is different to the own nature of the *i*-Walker, this information could be achieved by other means.

In Chapter §6.1, a methodology has been proposed with the aim to find some characteristic on the walking behaviour of a group of individuals of different ages and physical conditions based on the force sensors embedded in the *i*-Walker's handlers. For this, a bag-of-strides is used to study the pushing forces characteristics of different groups of individuals, with different physical and/or cognitive conditions and ages. Also, exercises have been defined as bag-of-strides, representing the distribution of strides within an exercise. This has been created to find common patterns among individuals when walking in a straight line with the *i*-Walker, independently of the straight length. Results will be commented first for the baseline dataset, where participants performed the 10MWT, and then for the $CVI$ dataset and the straight lines obtained from the 3mWT.

### 7.2.1 $IDF + MAD$ pilots

As shown in Table 6.1, a scenario with four types of strides and three sorts of exercises is going to be analysed for the $IDFMAD$ dataset, represented in Figure 7.4. Each subplot of this figure (and those found in the following section) represent one of the stride clusters, ordered from top to bottom. The red line depicts the medoid of the cluster, and the grey ones are its ten closest neighbours (*i.e.*, the most representative strides of the cluster). In case the stride clustering has two parts, the first one will contain the first clusters in numerical order, and each following part continues with the ascending cluster id. Strides are represented in terms of stride time, although the $X$-axis is represented by the number of instances that take each stride (time in seconds is obtained by dividing the number of instances by 10). At first sight, it can be observed that the DTW clustering grouped strides by stride time and forces applied. Also, a table containing some of the anthropometric data of the participants and spatiotemporal gait characteristics extracted from their performances are given in Table 7.6. For each exercise cluster obtained, the spatiotemporal data is explained by a more general categorization: *(i)* fall risk that is defined as High, Low or Medium), and *(ii)* age group (being Middle or Old age) and (iii) the gender (Female or Male).

Once the strides are identified and treated as single time series for the DTW clustering, we obtain four types of strides in the first scenario (see Figure 7.4), which are then grouped in five sorts of exercises as depicted in 7.5. The first group of strides are the longest ones in terms of stride time, but we can see that some strides are shorter. The gait shape reveals many oscillations in the body compensation while walking, with a trend to push stronger with the right hand. The second and third stride types are similar in length, although they differ in the amount of required pushing force, being the latter the cluster with fewer force variations along the stride (*i.e.*, people performing these strides use a similar amount of force from the two parts of the body). Strides from the second cluster present a significant oscillation to the left part of the body when switching the footstep, and then compensate with a substantial amount of force from the right side when the gait cycle comes to an end. The fourth group contains the shortest strides in length. Regarding forces, the fourth stride type stands out as the one with the lowest values in the resulting pushing force $F_x diff$, being most of the time under zero values. This means that the proportion of force exerted in the left hand is higher than the right one at all times until the end of the gait cycle, where the right forces are superior. This stride is prevalent in the first Exercise cluster (see Figure 7.5), but it is also the cluster with fewer observations.

If we observe at the distribution of the cluster in Table 7.6, the stride length is similar in all the groups of exercises (77 cm in average for women, 88 cm for men), but cluster one contains the exercises with higher stride lengths for men. As a result, the cadence obtained in these exercises is also the highest from all the clusters obtained in all GV categories. On the other hand, if we analyse the performance in directionality and laterality of these people, we can observe a tendency to drive to the right, *i.e.*, people push stronger with the left hand, making them turn their directionality on the other way. Figure 7.6 depicts this situation. In this 10MWT, it is clear that the user oscillates the directionality while walking. Although the exercise begins with a first step (probably right step), once the first stride is completed, the left part of the body will always push the user to the other side. The blue area reveals that the user tries to compensate his directionality, and thus his body force towards the *i*-Walker and even corrects the trajectory at a given point. The maximal deviation is given at the end of the exercise. Thus it tends to increase, although it is a deviation of 35 cm.

Exercise Clusters 4 and 5 present each one also a prevalent stride type (in Figure 7.4, strides 1 and 3 respectively). These two gait shapes correspond to those strides with a similar left and right pushing force. The main difference between these two types of strides lies in the force variation along the gait cycle and its length. Table 7.6 shows that people in the fourth cluster did better performances in terms of spatiotemporal gait characteristics since they present higher cadence and gait velocity with similar values of stride length. The third Exercise cluster also has a significant representation of the stride type 1 along with the second type as well. This cluster has the bigger proportion of older adults and especially older adults at high risk of falling (in fact this group has clustered the biggest amount of exercises performed by the more elderly population). It is presumable that people performing the exercises found in this third cluster are those presenting a higher gait dysfunction or body force compensation. They also those who present a higher interaction with the *i*-Walker while completing the gait cycle, *i.e.*, their body force moves to the side where the step is taking place. It would be interesting to do further analysis with more people with this stride pattern to learn how could the *i*-Walker assist them with some strategies of control that would help them compensating the pushing forces performed while walking.

The Exercise cluster with more observations is the second one, which also presents the most heterogeneous distribution. From an anthropometric perspective, this cluster is also balanced in terms of gender or age. Exercises performed by middle-aged participants have similar outcomes in the spatiotemporal analysis, while in the older group these results present slight differences in gender, *i.e.*, women from this group perform shorter strides at a higher cadence, but still walk slower than males in this age group.

The methodology proposed can define different types of strides and, using the *bag-of-X* approach, identify sorts of exercises based on the most observed strides of each exercise. Since we use an unsupervised learning technique, the hardest part is to evaluate whether the presented partition is suitable for the given dataset. Although the algorithm can recognise dysfunctional patterns, such as a body balance decompensation, which is depicted in Figure 7.6, it is hard to find other pattern characteristics in the rest of Exercise clusters. This is probably due to either of the following reasons:

- the anthropometric characteristics of the participants are too homogeneous (older adults, generally female, with a high risk of falling due to different comorbidities but with a healthy cognitive condition),

| Cluster | 1 | | | | 2 | | | | 3 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Risk | N | Speed | Cadence | Stride Length | N | Speed | Cadence | Stride Length | N | Speed | Cadence | Stride Length |
| Risk H | 10 | 0,52 | 46,99 | 0,65 | 30 | 0,63 | 45,80 | 0,76 | 48 | 0,54 | 45,53 | 0,70 |
| Age M | 2 | 0,49 | 45,33 | 0,63 | 8 | 0,66 | 44,148286 | 0,85 | 10 | 0,53 | 46,98 | 0,68 |
| F | 2 | 0,49 | 45,33 | 0,63 | 5 | 0,64 | 39,71 | 0,85 | 5 | 0,48 | 46,83 | 0,61 |
| M | | | | | 3 | 0,70 | 51,55 | 0,86 | 5 | 0,59 | 47,14 | 0,74 |
| Age O | 8 | 0,53 | 47,40 | 0,65 | 22 | 0,62 | 46,40 | 0,73 | 38 | 0,54 | 45,15 | 0,70 |
| F | 7 | 0,56 | 49,46 | 0,65 | 11 | 0,56 | 49,14 | 0,62 | 31 | 0,51 | 44,74 | 0,67 |
| M | 1 | 0,31 | 33,01 | 0,66 | 11 | 0,67 | 43,65 | 0,83 | 7 | 0,64 | 46,92 | 0,84 |
| Risk L | 3 | 1,162 | 64,31 | 1,07 | 10 | 0,97 | 50,13 | 1,01 | 2 | 1,21 | 52,65 | 1,44 |
| Age M | 2 | 1,33 | 69,76 | 1,19 | 7 | 1,06 | 53,31 | 1,11 | 2 | 1,21 | 52,65 | 1,44 |
| F | 1 | 1,02 | 43,17 | 1,05 | 3 | 1,16 | 61,16 | 1,16 | 1 | 1,15 | 41,96 | 1,47 |
| M | 1 | 1,64 | 96,35 | 1,34 | 4 | 0,99 | 47,42 | 1,07 | 1 | 1,27 | 63,34 | 1,41 |
| Age O | 1 | 0,82 | 53,40 | 0,84 | 3 | 0,77 | 42,71 | 0,77 | | | | |
| F | 1 | 0,82 | 53,39 | 0,84 | 2 | 0,88 | 47,39 | 0,87 | | | | |
| M | | | | | 1 | 0,53 | 33,34 | 0,57 | | | | |
| Risk M | 14 | 0,76 | 53,54 | 0,88 | 34 | 0,75 | 47,80 | 0,91 | 16 | 0,72 | 47,76 | 0,89 |
| Age M | 4 | 0,96 | 52,21 | 1,066 | 11 | 0,83 | 49,96 | 1,02 | 6 | 0,73 | 46,97 | 0,87 |
| F | 3 | 0,97 | 51,97 | 1,05 | 6 | 0,81 | 49,34 | 1,02 | 2 | 0,76 | 50,53 | 0,92 |
| M | 1 | 0,93 | 52,93 | 1,09 | 5 | 0,86 | 50,72 | 1,03 | 4 | 0,72 | 45,19 | 0,84 |
| Age O | 10 | 0,68 | 54,07 | 0,80 | 23 | 0,72 | 46,76 | 0,85 | 10 | 0,72 | 48,24 | 0,90 |
| F | 7 | 0,62 | 56,27 | 0,77 | 13 | 0,66 | 47,52 | 0,77 | 8 | 0,69 | 47,16 | 0,87 |
| M | 3 | 0,81 | 48,96 | 0,88 | 10 | 0,80 | 45,77 | 0,96 | 2 | 0,81 | 52,57 | 1,01 |
| Total | 27 | 0,716433037 | 52,31 | 0,81 | 74 | 0,73 | 47,30 | 0,86 | 66 | 0,60 | 46,29 | 0,77 |

| Cluster | 4 | | | | 5 | | | |
|---|---|---|---|---|---|---|---|---|
| Risk | N | Speed | Cadence | Stride Length | N | Speed | Cadence | Stride Length |
| Risk H | 29 | 0,57 | 44,57 | 0,72 | 30 | 0,52 | 41,20 | 0,69 |
| Age M | 5 | 0,63 | 45,91 | 0,78 | 3 | 0,55 | 42,91 | 0,76 |
| F | 2 | 0,66 | 46,40 | 0,78 | 2 | 0,68 | 36,72 | 0,98 |
| M | 3 | 0,61 | 45,59 | 0,77 | 1 | 0,28 | 55,31 | 0,31 |
| Age O | 24 | 0,56 | 44,29 | 0,71 | 27 | 0,52 | 41,01 | 0,68 |
| F | 21 | 0,53 | 43,85 | 0,66 | 21 | 0,49 | 39,20 | 0,67 |
| M | 3 | 0,73 | 47,41 | 0,92 | 6 | 0,61 | 47,34 | 0,72 |
| Risk L | 4 | 0,81 | 53,86 | 0,89 | 4 | 1,38 | 63,18 | 1,33 |
| Age M | 2 | 0,93 | 53,12 | 1,01 | 4 | 1,38 | 63,18 | 1,33 |
| F | 1 | 1,10 | 57,71 | 1,16 | 3 | 1,37 | 63,43 | 1,31 |
| M | 1 | 0,77 | 48,54 | 0,86 | 1 | 1,39 | 62,42 | 1,39 |
| Age O | 2 | 0,69 | 54,59 | 0,77 | | | | |
| F | | | | | | | | |
| M | 2 | 0,69 | 54,59 | 0,77 | | | | |
| Risk M | 32 | 0,72 | 49,18 | 0,86 | 19 | 0,68 | 45,70 | 0,87 |
| Age M | 10 | 0,72 | 52,10 | 0,86 | 9 | 0,74 | 47,73 | 0,93 |
| F | 6 | 0,78934359 | 50,80 | 0,90 | 7 | 0,74 | 49,09 | 0,94 |
| M | 4 | 0,63 | 54,05 | 0,81 | 2 | 0,73 | 42,96 | 0,90 |
| Age O | 22 | 0,72 | 47,85 | 0,85 | 10 | 0,63 | 43,88 | 0,82 |
| F | 12 | 0,65 | 46,84 | 0,79 | 6 | 0,57 | 43,48 | 0,76 |
| M | 10 | 0,80 | 49,06 | 0,93 | 4 | 0,70 | 44,47 | 0,91 |
| Total | 65 | 0,66 | 47,41 | 0,80 | 53 | 0,64 | 44,47 | 0,80 |

Table 7.6: Anthropometric and spatiotemporal gait characteristics of IDFMAD

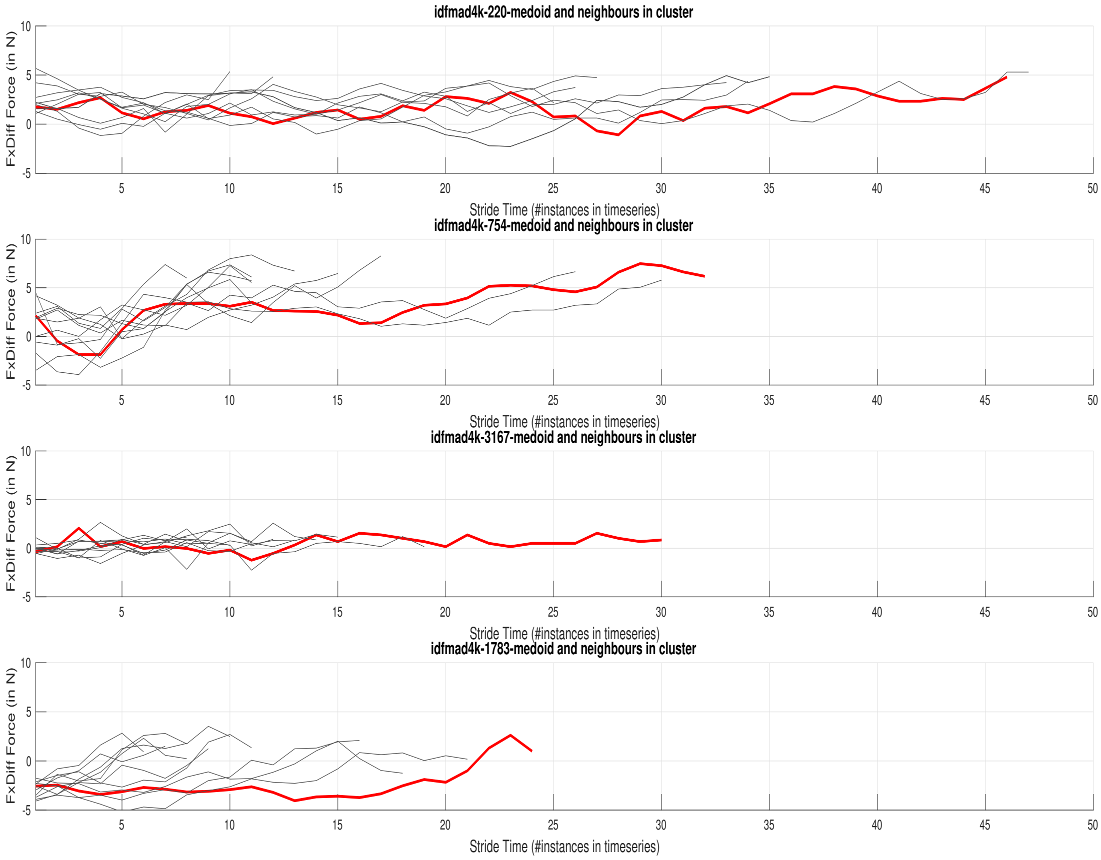


Figure 7.4: Gait shapes in IDFMAD with four types of strides

- the short duration of the exercise. With a 10MWT exercise we are obtaining few strides from each participant and, thus, it is difficult to achieve a useful categorisation of the individual's gait

With the following pilot trial, we aimed to amend these two issues. We first proposed a new test exercise, the 3 minutes Walk Test (3mWT), where participants had to walk in a 40 metres corridor for three minutes. Exercises were cut into straight lines, considering each one as an independent exercise. With this approach, we were able to collect between 80 and 200 metres of walking performance for each volunteer (the *IDFMAD* contained only 20 metres in total for each participant). It was decided to include also younger participants, to study if the proposed methodology can find differences in the interaction with the *i*-Walker among group ages. Also,

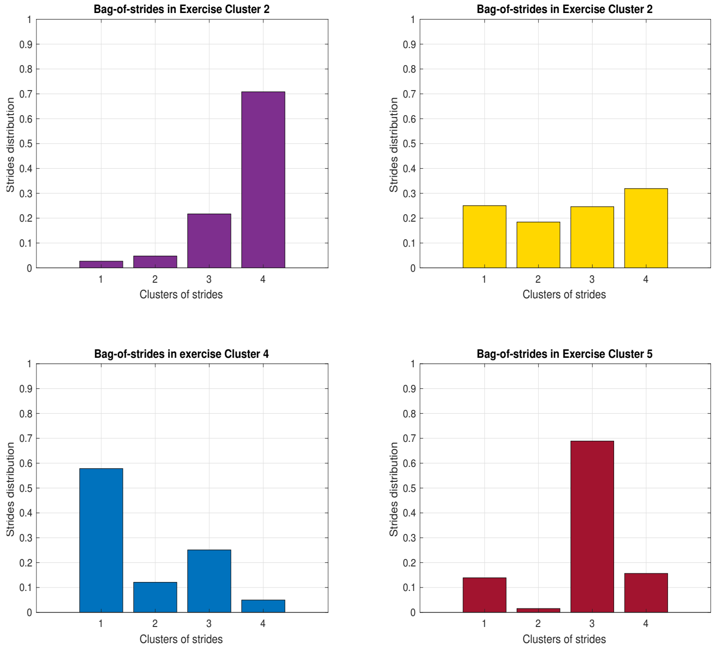


Figure 7.5: Scenario 1: *idfmad4k5k'*. Cluster representation of bags-of-strides with four types of strides, grouped in five sorts of exercises.

we aimed to focus on a common pathology (in this case, cardiologic dysfunction) for the elder group of participants. However, it was not possible to reach the minimum number of volunteers. Thus we had to increase the number of young participants, obtaining an unbalanced pilot in terms of biological data. Results are presented in the following section.

### 7.2.2 *CVI* pilot

The *CVI* dataset provided different combinations of stable clustering results, which are presented in Table 6.1. Each combination will be studied in this section and justifications of the selected option will be given at the end. In principle, the more clusters we obtain, the more accurate will their information be. However, we must observe the type of groups that have been formed in order to determine their intra similarity in terms of gait shape and anthropometric characteristics of the people belonging to a same bag-of-strides.

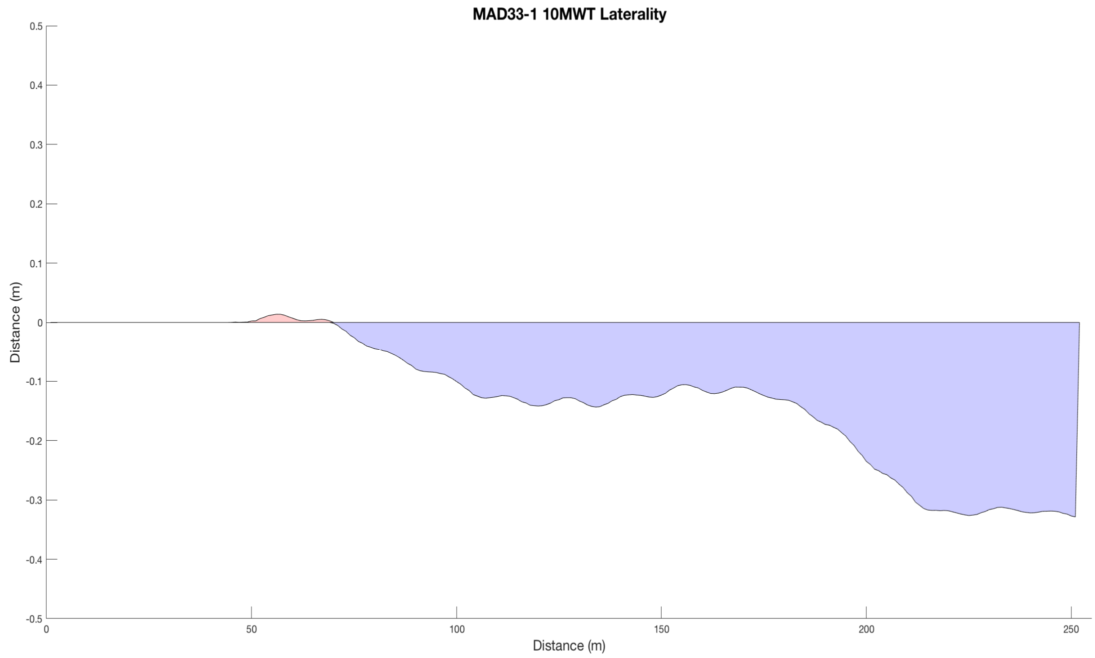


Figure 7.6: Right deviation during a 10MWT

#### 7.2.2.1 First Scenario

The first scenario studies the results of categorising strides in three clusters. The bags-of-stirdes of each exercise are then distributed three types of exercises. Figure 7.8 depicts the distribution of the bag-of-strides for each kind of exercise and Table 7.7 contains some details about the anthropometric and spatio-temporal characteristics of the participants belonging to each cluster, along with the general distribution. Users' information is classified by age range (Middle, Old, Young) and then by gender (Female, Male). The risk of falling has not been included since it is highly correlated to the age group in this dataset.

Figure 7.8 depicts that each group of exercises has a gait shape which prevails over the rest, and in each case, it is a different stride type. In the first type of exercise, users performed mainly strides of type 1, with over a 70% of representation. In the second group of exercises, again over 70% of strides belong to the second cluster of strides. Finally, more than 80% of the strides performed in the third kind of exercise belong to the third cluster of strides. As it can be observed in Figure 7.7, the shape of these strides share some common characteristics at first glance. The two first clusters have similar time length, while strides in the third group are

| *Cluster* | *1* | | | | *2* | | | | *3* | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Age** | **N** | **Speed** | **Cadence** | **Stride Length** | **N** | **Speed** | **Cadence** | **Stride Length** | **N** | **Speed** | **Cadence** | **Stride Length** |
| *Age M* | *6* | *1,17* | *61,58* | *1,18* | *6* | *1,09* | *59,81* | *1,14* | *26* | *1,05* | *55,20* | *1,18* |
| F | 6 | 1,17 | 61,58 | 1,18 | 6 | 1,09 | 59,81 | 1,14 | 16 | 0,99 | 53,24 | 1,14 |
| M | | | | | | | | | 10 | 1,14 | 58,34 | 1,25 |
| *Age O* | *7* | *0,95* | *54,16* | *1,11* | *24* | *0,75* | *53,03* | *0,82* | *16* | *0,56* | *52,82* | *0,65* |
| F | 2 | 0,70 | 56,22 | 0,77 | 19 | 0,73 | 51,12 | 0,80 | 16 | 0,56 | 52,82 | 0,65 |
| M | 5 | 1,05 | 53,33 | 1,24 | 5 | 0,86 | 60,31 | 0,86 | | | | |
| *Age Y* | *37* | *1,05* | *56,62* | *1,13* | *7* | *1,20* | *59,48* | *1,28* | *24* | *1,05* | *55,87* | *1,18* |
| F | 37 | 1,05 | 56,62 | 1,13 | 7 | 1,20 | 59,48 | 1,28 | 16 | 1,07 | 56,91 | 1,18 |
| M | | | | | | | | | 8 | 1,00 | 53,80 | 1,18 |
| **Total** | **50** | **1,05** | **56,87** | **1,14** | **37** | **0,89** | **55,35** | **0,96** | **66** | **0,93** | **54,87** | **1,05** |

Table 7.7: Anthropometric and spatiotemporal gait characteristics of Scenario 1

slightly longer. The other difference relies on the amount of pushing force applied. The second group differs from the other having the biggest difference in the resulting pushing force: users in this cluster uses a larger pushing force on the part of the body that is making the step. Most of the exercises from this cluster are performed by participants aged 85+ years old with several comorbidities; it is presumable that these individuals require more support on the *i*-Walker to perform the exercise and thus present this gait pattern that clearly shows the foot transition in the swing phase. The other two groups remain in positive values even when the left step is taking place, which means that the compensation between both sides of the body while walking is more unbalanced. This situation is more remarkable in the third cluster which is the most heterogeneous group in age and gender representation. Finally, Exercise cluster 1 has mainly classified female participants, especially young women.

#### 7.2.2.2 Second Scenario

The second scenario considers five types of strides. The correspondent bags-of-strides are then grouped in either three or five sorts of exercises, as represented in Figure 7.10 and Figure 7.11 respectively. Gait shapes of this clustering are depicted in Figure 7.9. In the first case, it can be observed that each group of exercises has one or two dominant types of strides, and in each case, these differ. In the first group, the second stride type prevails with over 65% of the strides performed in the exercises clustered in this group. This group of strides is also the one with more observations, including one-third of the total amount of them. People in this group are

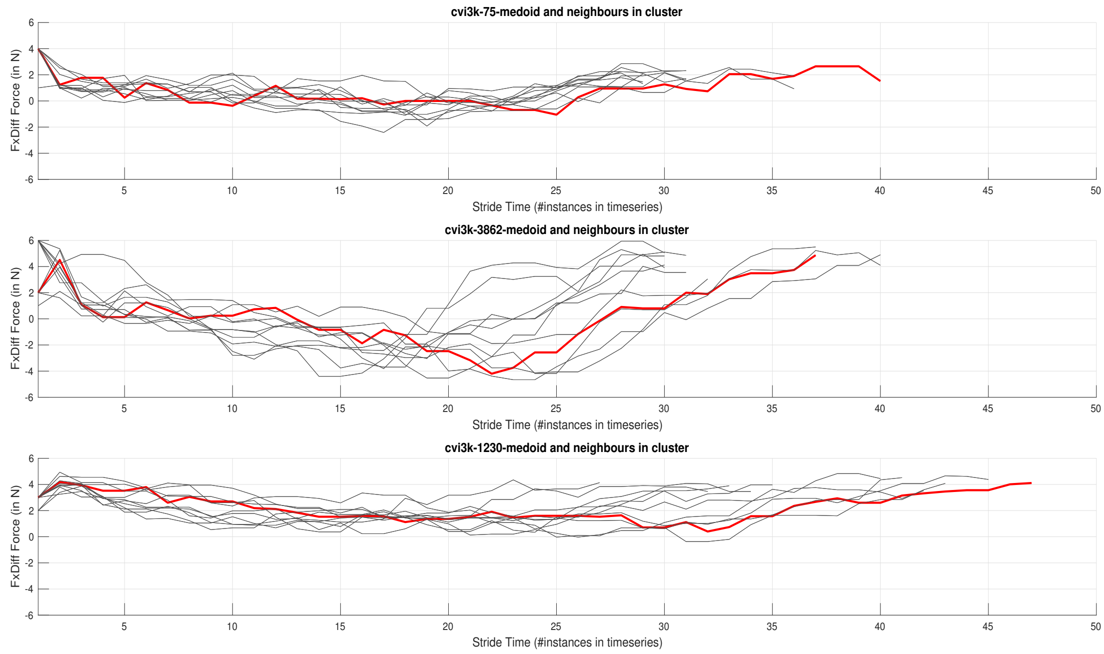


Figure 7.7: Gait shapes in CVI dataset with three clusters of strides

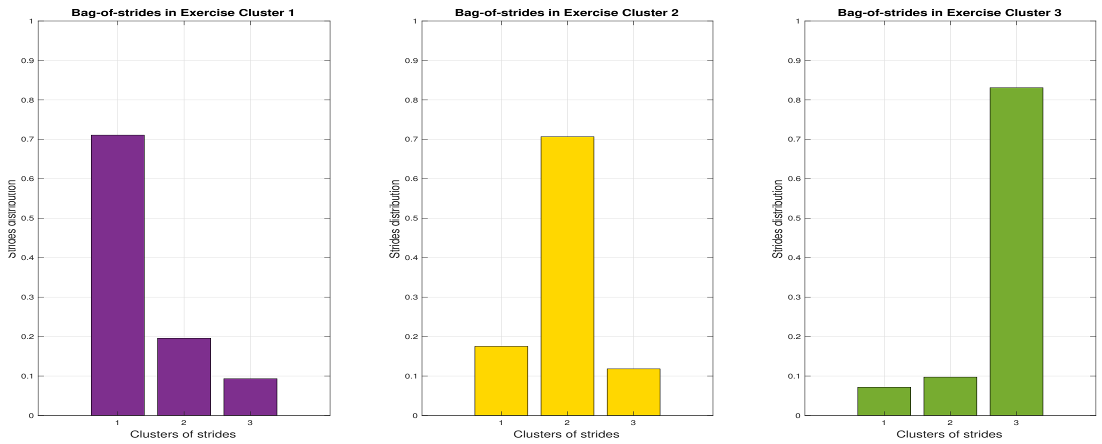


Figure 7.8: Scenario 1: *cvi3k3k'*. Cluster representation of bags-of-strides with three types of strides, grouped in three sorts of exercises.

those presenting a minimal force variation. The gait shape indicates that a significant right-hand force was exerted during the phases regarding the right step, and then the forces applied from the two parts of the body get balanced to perform the left step. This cluster is again the most heterogeneous in age and gender and coincides with the one obtained in the previous scenario.

In the second group of exercises, almost 80% of the strides are represented by two types, strides 1 and 3, which are also the shorter ones. As depicted in Table 7.8, this group is mainly formed by exercises performed by women, especially young ones, and one single man from the older age group. The stride length is strongly related to the individual's height, which is generally lower in women. In this case it appears to be the main discriminator, along with the amount of force employed, to categorise most women together. Finally, the third cluster of exercises is mostly represented by the two last types of strides from Figure 7.9. The shape of the fourth stride reveals that the force compensation between both parts of the body during the left step are more balanced, since they are close to zero. The shape of the fifth stride is the one with more variation between right and left hand force, but both start and end the gait cycle (*i.e.*, the right step phases), using a considerable amount of force with the right hand. As previously observed, this is a pattern in exercises performed by the older volunteers, which were diagnosed with several comorbidities (mostly related to cardiological problems). Most of the people executing this type of force along the gait cycle, and especially those falling in this last Exercise Cluster, are those presenting more comorbidities, and thus have presumably more disturbances while walking. Table 7.8 shows that this cluster is composed by half of the exercises performed by the older adults, but has also some representation from the young and middle-age groups. During the execution of this pilot, it was observed that some people from the control group (*i.e.*, not needing a mobility support device) modify they walk when using the *i*-Walker[1], which could explain the walking behaviour of those young people appearing in this Exercise cluster.

If we take a look at the second case of this scenario (Figure 7.11), where bags-of-strides are categorised into five sorts of exercises, it can be observed that in general, a pattern is emerging in two clusters. In this case, the first Exercise cluster corresponds to the previously explored clusters that were mainly formed by young women (in this case 28 exercises performed by

[1]This remark is given under a personal, empirical evidence. It was observed that some young and middle age participants could cause some false lead during the analysis: some changed their walking speed during the exercise, or others were very focused on the interaction they were having with the handlers.

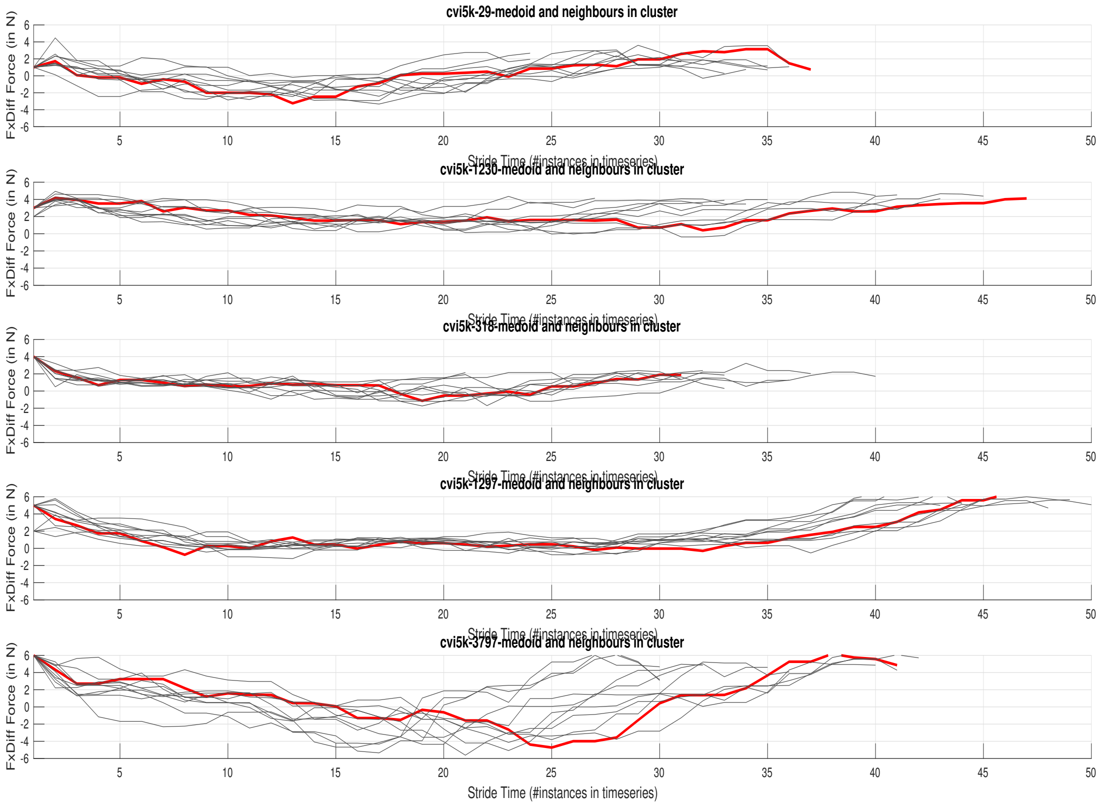


Figure 7.9: Gait shapes in CVI dataset with five clusters of strides

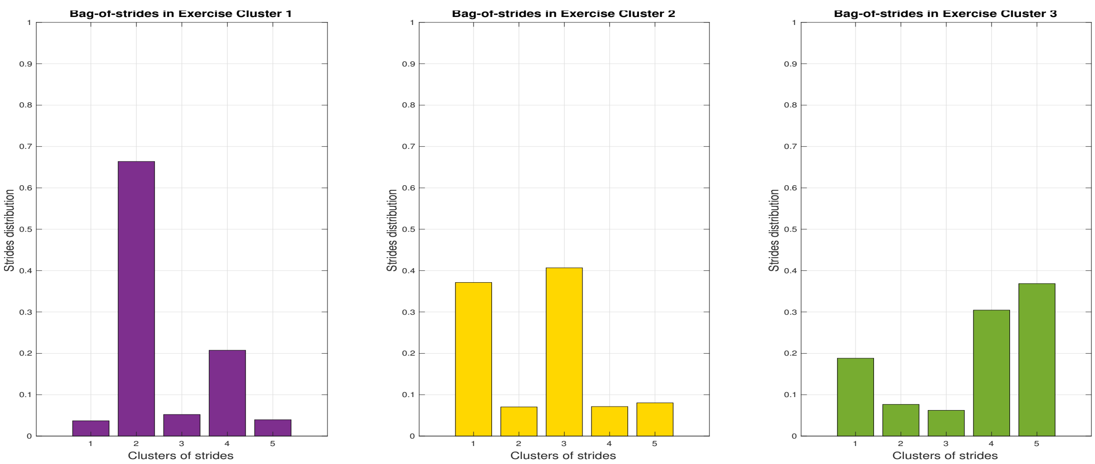


Figure 7.10: Scenario 2.1: *cvi5k3k'*. Cluster representation of bags-of-strides with five types of strides, grouped in three sorts of exercises.

| Cluster | 1 | | | | 2 | | | | 3 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Age** | **N** | **Speed** | **Cadence** | **Stride Length** | **N** | **Speed** | **Cadence** | **Stride Length** | **N** | **Speed** | **Cadence** | **Stride Length** |
| *Age M* | *26* | *1,05* | *59,52* | *1,18* | *5* | *1,18* | *67,46* | *1,18* | *7* | *1,09* | *63,84* | *1,14* |
| F | 16 | 0,99 | 57,32 | 1,14 | 5 | 1,18 | 67,46 | 1,18 | 7 | 1,09 | 63,84 | 1,14 |
| M | 10 | 1,14 | 63,04 | 1,25 | | | | | | | | |
| *Age O* | *13* | *0,50* | *54,13* | *0,58* | *11* | *0,89* | *57,80* | *1,02* | *23* | *0,76* | *55,71* | *0,82* |
| F | 13 | 0,50 | 54,13 | 0,58 | 7 | 0,74 | 58,25 | 0,80 | 17 | 0,74 | 53,15 | 0,82 |
| M | | | | | 4 | 1,17 | 57,01 | 1,41 | 6 | 0,81 | 62,96 | 0,82 |
| *Age Y* | *20* | *1,01* | *59,26* | *1,15* | *40* | *1,05* | *61,37* | *1,14* | *8* | *1,27* | *66,42* | *1,32* |
| F | 12 | 1,01 | 59,84 | 1,14 | 40 | 1,05 | 61,37 | 1,14 | 8 | 1,27 | 66,42 | 1,32 |
| M | 8 | 1,00 | 58,39 | 1,18 | | | | | | | | |
| **Total** | **59** | **0,91** | **58,25** | **1,04** | **56** | **1,03** | **61,21** | **1,12** | **38** | **0,93** | **59,46** | **0,99** |

Table 7.8: Anthropometric and spatiotemporal gait characteristics of Scenario 2.1

young female and two from a middle-age). The second Exercise cluster characterises the mixed group, where now all the exercises executed by male volunteers appear together. Surprisingly, the exercises coming from women have the worst average performances of all age groups and clusters (*i.e.*, women in this cluster performed at the lowest average gait velocity in comparison to women in same age category but different clusters). The second Exercise cluster is again the one containing more instances, being most of them of middle-aged people (26 out of 58). Since most of the strides are of type two, it is likely to say that it is the more general gait shape of all the strides collected in this dataset. This cluster of strides falls in the middle of stride length, being some of them very short (around 2.5 seconds). The force compensation in the swing phase of the gait cycle is quite balanced, with a general trend of applying more right forces, especially when reaching the end of the period.

The other three clusters could be understood as a splitting of the group formed mainly by old ladies in scenario 2.1. As it can be observed in Figure 7.11, the step type has lost relevance in the three first Exercise clusters to become more significant in the last two classes of exercises. It is especially important in the fifth Exercise cluster since people in this group combine the two steps with major force variation during the swing phase, which should be analysed by an expert eye to determine if this is a possible identifier of gait disturbance or fall risk.

#### 7.2.2.3 Third Scenario

The third scenario presented with the *CVI* dataset is the one with six types of strides. Once the bags-of-strides are generated, the clustering of the histograms returns two possible solutions

| **Cluster** | **1** | | | | **2** | | | | **3** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Age** | **N** | **Speed** | **Cadence** | **Stride Length** | **N** | **Speed** | **Cadence** | **Stride Length** | **N** | **Speed** | **Cadence** | **Stride Length** |
| *Age M* | *2* | *1,16* | *64,61* | *1,16* | *26* | *1,05* | *59,52* | *1,18* | *2* | *1,03* | *65,22* | *1,04* |
| F | 2 | 1,16 | 64,61 | 1,16 | 16 | 0,99 | 57,32 | 1,14 | 2 | 1,03 | 65,22 | 1,04 |
| M | | | | | 10 | 1,14 | 63,04 | 1,25 | | | | |
| *Age O* | | | | | *13* | *0,50* | *54,13* | *0,58* | *11* | *0,88* | *61,33* | *0,93* |
| F | | | | | 13 | 0,50 | 54,13 | 0,58 | 8 | 0,85 | 60,00 | 0,91 |
| M | | | | | | | | | 3 | 0,97 | 64,88 | 0,97 |
| *Age Y* | *28* | *1,05* | *61,38* | *1,14* | *19* | *1,02* | *59,25* | *1,17* | *5* | *1,18* | *65,22* | *1,23* |
| F | 28 | 1,05 | 61,38 | 1,14 | 11 | 1,02 | 59,87 | 1,16 | 5 | 1,18 | 65,22 | 1,23 |
| M | | | | | 8 | 1,00 | 58,39 | 1,18 | | | | |
| **Total** | **30** | **1,06** | **61,59** | **1,14** | **58** | **0,91** | **58,22** | **1,04** | **18** | **0,98** | **62,84** | **1,02** |
| **Cluster** | **4** | | | | **5** | | | | | | | |
| **Age** | **N** | **Speed** | **Cadence** | **Stride Length** | **N** | **Speed** | **Cadence** | **Stride Length** | | | | |
| *Age M* | *6* | *1,16* | *65,50* | *1,20* | *2* | *1,12* | *65,78* | *1,14* | | | | |
| F | 6 | 1,16 | 65,50 | 1,20 | 2 | 1,12 | 65,78 | 1,14 | | | | |
| M | | | | | | | | | | | | |
| *Age O* | *12* | *0,84* | *57,46* | *0,97* | *11* | *0,68* | *50,26* | *0,75* | | | | |
| F | 5 | 0,70 | 55,68 | 0,80 | 11 | 0,68 | 50,26 | 0,75 | | | | |
| M | 7 | 0,95 | 58,74 | 1,09 | | | | | | | | |
| *Age Y* | *7* | *1,23* | *64,84* | *1,31* | *9* | *1,02* | *60,80* | *1,10* | | | | |
| F | 7 | 1,23 | 64,84 | 1,31 | 9 | 1,02 | 60,80 | 1,10 | | | | |
| M | | | | | | | | | | | | |
| **Total** | **25** | **1,03** | **61,46** | **1,12** | **22** | **0,86** | **55,98** | **0,93** | | | | |

Table 7.9: Anthropometric and spatio-temporal gait characteristics of Scenario 2.2

with three and four sorts of exercises, which are represented in Figures 7.14 and 7.15 respectively. As a general observation from these two figures, and in comparison with the other two scenarios, it is clear that the more types of strides we have, the more difficult it will be to obtain a type of stride which strongly represents an Exercise cluster. In this third scenario,the more prevalent types of strides reach up to half of the strides appearing in that cluster, while in the first scenario this could go up to 80%. Also, the more types of strides we have, the harder it is to find significant differences among them. Observing Figures 7.12 and 7.13, we can see that the first strides cluster represent the shorter strides in time and cluster 5 has the longer ones; the rest of clusters have a mix of short to long strides, going from 3 to 5 seconds per stride.

In the first case (Figure 7.14), from the three Exercise clusters, only the second has a prevalent type of stride. This cluster is again mainly composed by a mix of young and middle-aged people but also has a significant representation of the more elderly population: 25% of

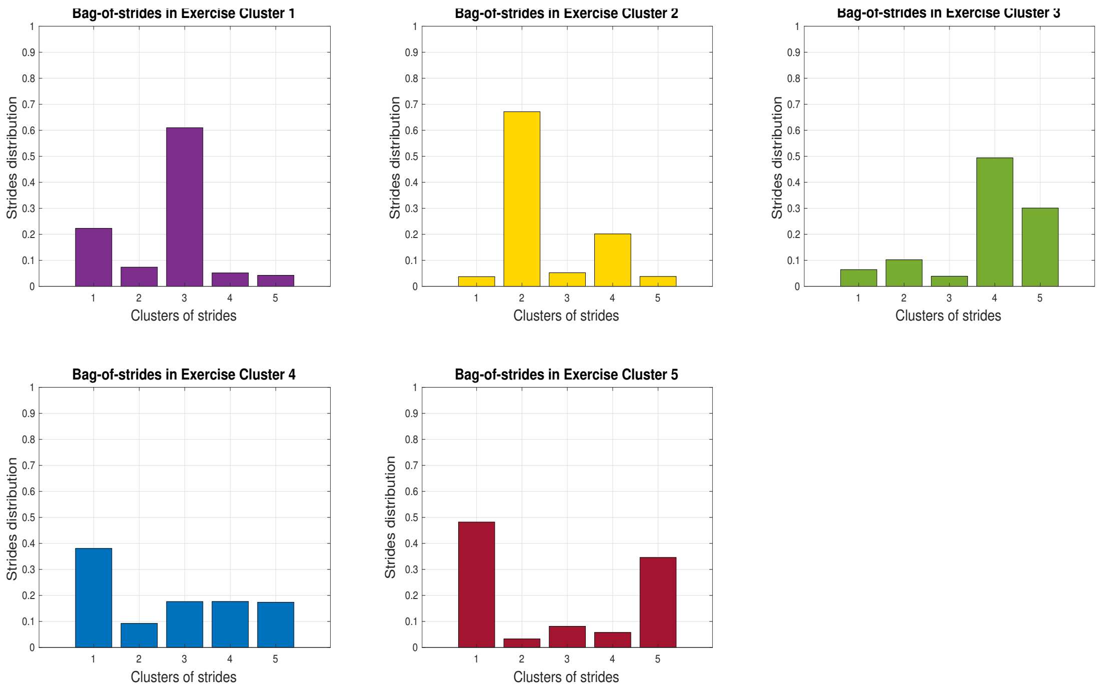


Figure 7.11: Scenario 2.2: *cvi5k5k'*. Cluster representation of bags-of-strides with five types of strides, grouped in five sorts of exercises.

the exercises performed by people aged 80+ fall in this cluster, despite being those with the lowest gait velocity (0.5 m/s) within the older people. As it can be observed, people in this group apply more right-hand force since values of $F_x diff$ are always positive, although they remain balanced during the swing phase (there are no sharp changes in the gait shape during the gait cycle). The third Exercise cluster is mainly represented by strides type 1 and 4 (which are barely present in the other two exercise clusters). These strides are the shortest in time. The stride shape also indicates that the force applied to the *i*-Walker varies at each phase of the cycle: when the right step is taking place, the pushing force is mainly given by the right force and changes to the left force at the left step. The amount of force applied in each case is quite similar; thus in that sense, they are compensated. In this case, 38 out of 46 exercises falling in this cluster were performed by young people, and in general, the gait velocity was high, even for the three exercises performed by old adults. It is coherent that strides that are short in time belong to those people who walk faster or to those with shorter legs, as stated before.

The first Exercise cluster is the most homogeneous in stride distribution, except for the

| *Cluster* | *1* | | | | *2* | | | | *3* | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Age** | **N** | **Speed** | **Cadence** | **Stride Length** | **N** | **Speed** | **Cadence** | **Stride Length** | **N** | **Speed** | **Cadence** | **Stride Length** |
| *Age M* | *7* | *1,09* | *66,04* | *1,14* | *26* | *1,05* | *61,68* | *1,18* | *5* | *1,18* | *69,97* | *1,18* |
| F | 7 | 1,09 | 66,04 | 1,14 | 16 | 0,99 | 59,36 | 1,14 | 5 | 1,18 | 69,97 | 1,18 |
| M | | | | | 10 | 1,14 | 65,39 | 1,25 | | | | |
| *Age O* | *32* | *0,78* | *57,16* | *0,87* | *12* | *0,52* | *56,50* | *0,59* | *3* | *0,82* | *58,56* | *0,96* |
| F | 23 | 0,72 | 54,71 | 0,81 | 12 | 0,52 | 56,50 | 0,59 | 2 | 0,68 | 60,92 | 0,73 |
| M | 9 | 0,94 | 63,42 | 1,01 | | | | | 1 | 1,11 | 53,83 | 1,41 |
| *Age Y* | *10* | *1,27* | *69,51* | *1,33* | *20* | *1,01* | *61,46* | *1,15* | *38* | *1,04* | *63,34* | *1,13* |
| F | 10 | 1,27 | 69,51 | 1,33 | 12 | 1,01 | 61,97 | 1,14 | 38 | 1,04 | 63,34 | 1,13 |
| M | | | | | 8 | 1,00 | 60,69 | 1,18 | | | | |
| **Total** | **49** | **0,93** | **60,95** | **1,00** | **58** | **0,92** | **60,53** | **1,05** | **46** | **1,04** | **63,75** | **1,12** |

Table 7.10: Anthropometric and spatiotemporal gait characteristics of Scenario 3.1

stride types three and four which have almost no representation: these two types are the two more relevant in the other two clusters of exercises. Strides can be grouped in two categories, according to the amount of force required during the right step phase: in the first two strides, people employ around 2N of pushing force in $F_x diff$, which is a reasonable quantity. The two last types of strides exert around 6N of force in the same phases, which means that users performing these steps rely more on the support offered by the rollator. In addition, these strides can also be differently grouped by shape: the second and fourth stride represent gait cycles where body forces were compensated during the left step part of the cycle, with an increasing amount of right force applied during the right step phases. The first and last gait shapes present a higher oscillation of forces during the swing phase, *i.e.*, participants performing these strides require higher support for both parts of the body while walking. In Table 7.10, we can see that this group is mainly composed of older adults, with some representation of the younger and middle-age groups. The strides more relevant from the k-medoids result belong to challenged older adults with vascular dementia or hypertension diagnosed, among others.

The second case, with four types of exercises, is quite similar to the previous one: clusters 1 and 4 have a prevalent stride each one, which is the same than Scenario 3.1, but also those found in the second scenario. Cluster 1 is mainly composed of the younger female participants (although ten have moved to other clusters) but still contains few exercises performed by women from different age ranges. Cluster 4 is once more the heterogeneous one, with a similar representation of all groups of ages but slightly higher in middle-age individuals. This cluster also has grouped together all the exercises performed by men aged 80- years old. As

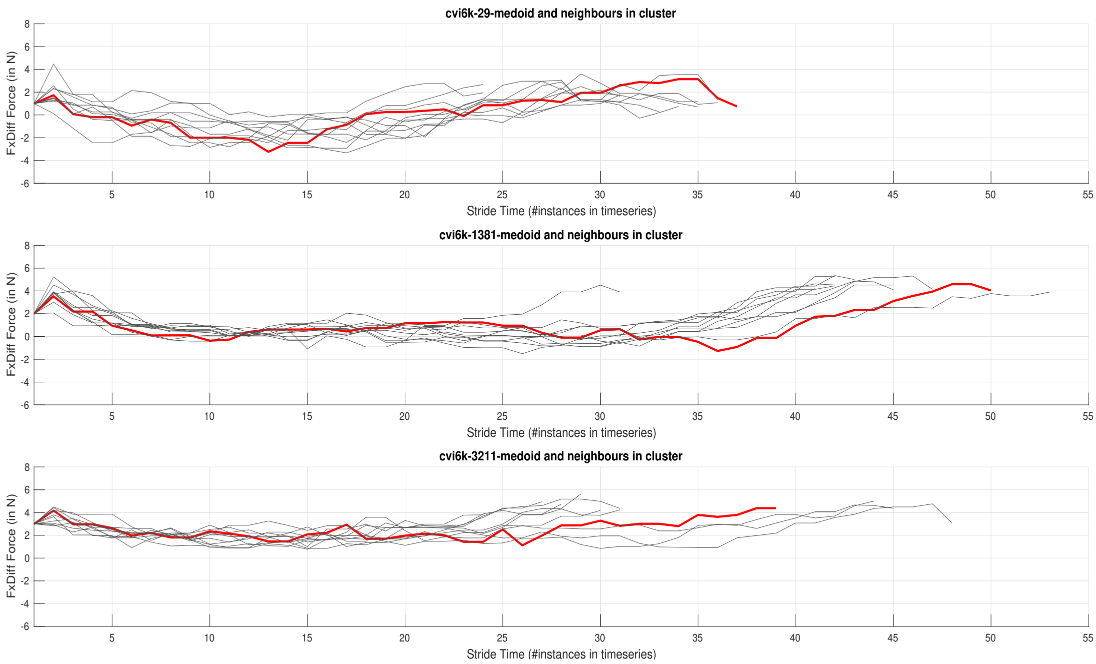


Figure 7.12: Gait shapes in CVI dataset with six clusters of strides (Part I)

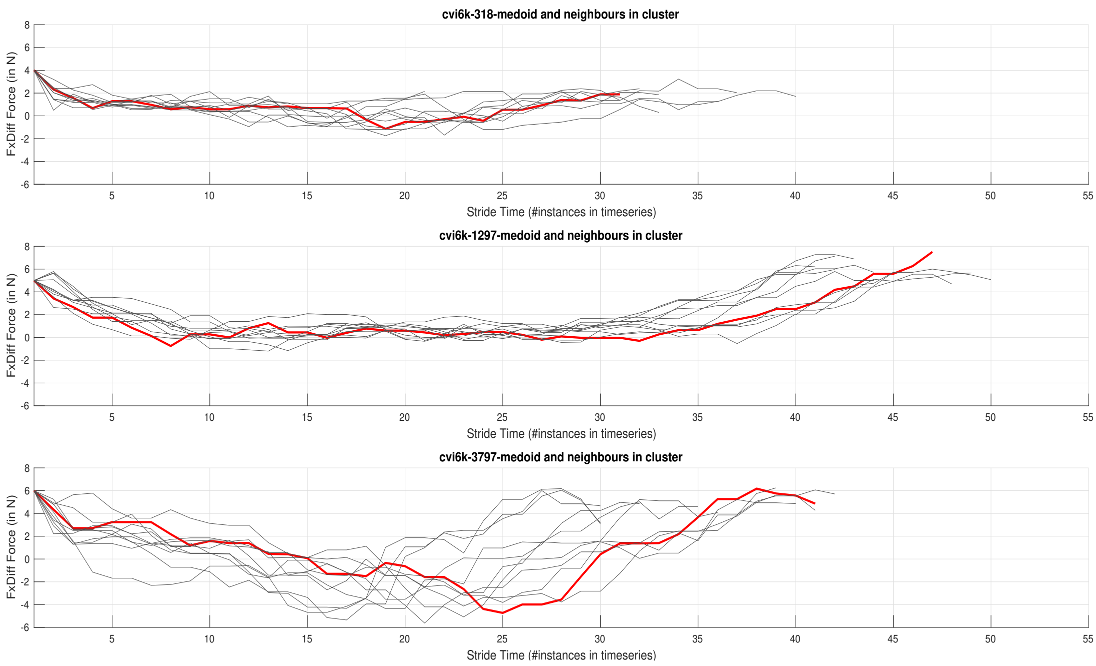


Figure 7.13: Gait shapes in CVI dataset with six clusters of strides (Part II)

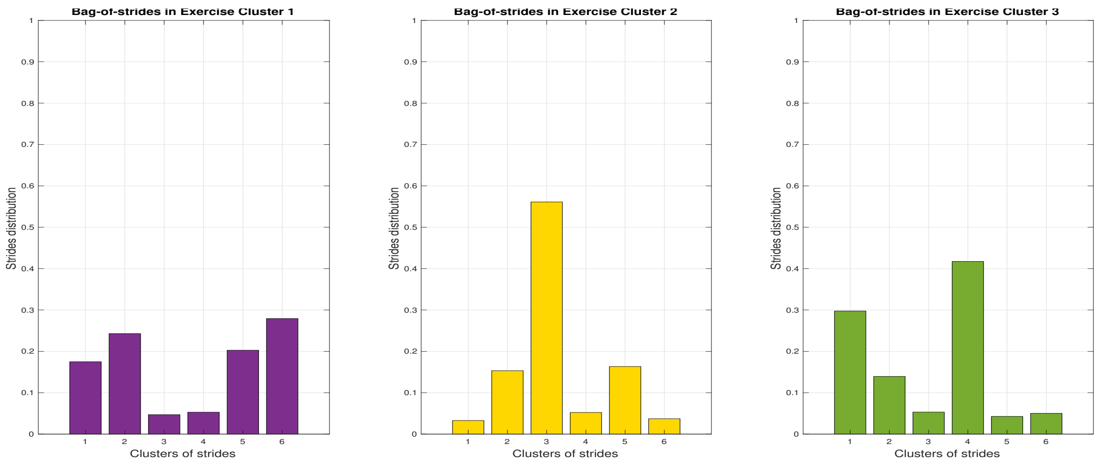


Figure 7.14: Scenario 3.1: *cvi6k3k'*. Cluster representation of bags-of-strides with six types of strides, grouped in three sorts of exercises.

before-mentioned, the gait shape in these two clusters is similar, but it differs in the resulting pushing force $F_x diff$ exerted along the stride: while both start pushing at values around 4N, the mixed grouped compensates with the left-hand force during the left step of the gait cycle, reaching zero values in this phase. However, the young female group applies less force when arriving at the end of the gait cycle, while the mixed group increases significantly the amount of force used at the end of the gait cycle: this means that people in this group exert a larger pushing force during the right step part of the gait cycle, and the user applies almost no force on the left part of the body. This might be because, the longer the stride is, the higher support is required during the phases where there is no toe or heel contact with the floor.

The other two Exercise clusters could be explained as a splitting of the first cluster in scenario 3.1. Exercise cluster 2 is mainly represented by stride types 1 and 2, whereas in Exercise cluster 3 stride types 5 and 6 prevail. Shapes have already been described in the previous scenario, where they were sharing the same Exercise cluster. If we take a look at the distribution of these clusters in Table 7.11, the second type of exercises are almost equally performed by older and younger participants. However, the third Exercise cluster is mainly composed of older adults, and in less proportion by people from other age groups. People in this cluster are those exerting the highest force variation in swing phases, which is probably characteristic of the people at highest risk of falling. The rest of the exercises in this group were performed by people who walked at high gait velocity and cadence, with stride lengths

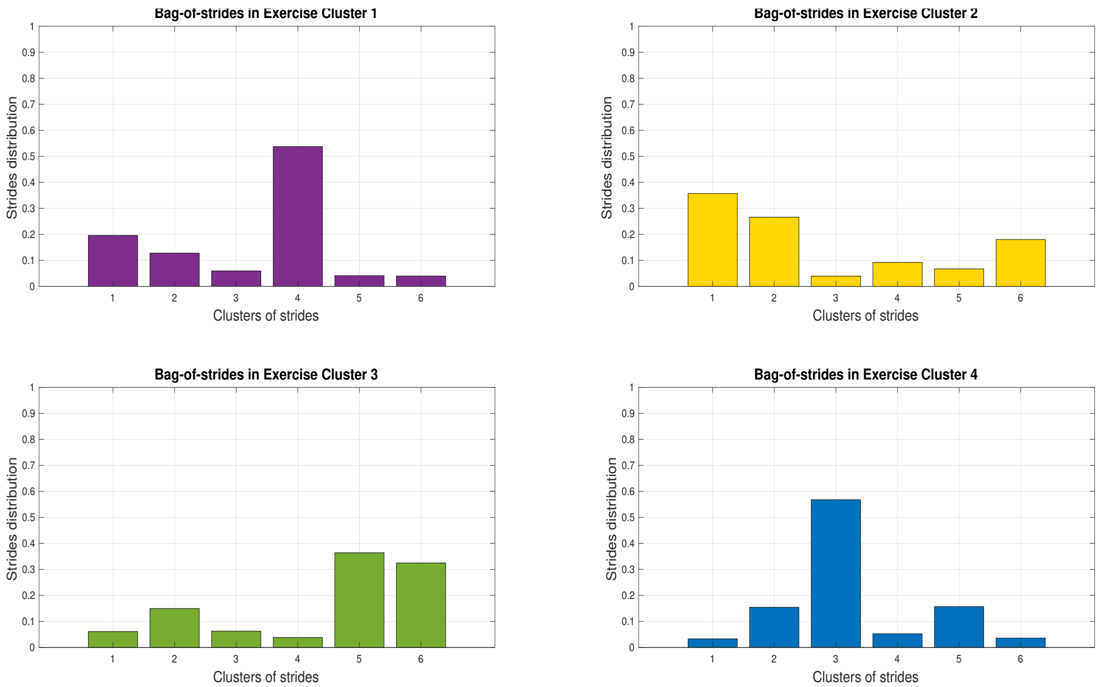


Figure 7.15: Scenario 3.2: *cvi6k4k'*. Cluster representation of bags-of-strides with six types of strides, grouped in four sorts of exercises.

greater than one metre. These two groups also contain all the exercises performed by older male participants. Other than the proportion of elder people against the rest, these two clusters are quite similar, since both contain gaits with high variation at step transition, but also have others where almost same forces were applied during the left step phase. It would be necessary a higher representation of exercises performed by senior and challenged adults to determine whether this partition provides further information than the one in scenario 3.1.

In this section, we have reviewed five different scenarios, with different size of stride and exercise types. As it has been previously observed, the more sorts of strides we include, the more distributed is the stride representation in each Exercise Cluster. However, with a larger number of strides it is also possible to obtain more detailed gait cycles than in the lower case ($k$=3). In the first *CVI* scenario, we could already observe a stride pattern indicating some gait dysfunction, based on the use of the pushing forces while walking. The other two stride shapes add few values, since they are quite similar. Moreover, it is possible to match each exercise cluster with an anthropometric characteristic (*e.g.*, prevalent age group or gender), but this

| *Cluster* | *1* | | | | *2* | | | | *3* | | | | *4* | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Age** | **N** | **Speed** | **Cadence** | **Stride Length** | **N** | **Speed** | **Cadence** | **Stride Length** | **N** | **Speed** | **Cadence** | **Stride Length** | **N** | **Speed** | **Cadence** | **Stride Length** |
| *Age M* | *3* | *1,17* | *68,80* | *1,16* | *5* | *1,14* | *67,12* | *1,21* | *4* | *1,07* | *67,53* | *1,09* | *26* | *1,05* | *61,68* | *1,18* |
| F | 3 | 1,17 | 68,80 | 1,16 | 5 | 1,14 | 67,12 | 1,21 | 4 | 1,07 | 67,53 | 1,09 | 16 | 0,99 | 59,36 | 1,14 |
| M | | | | | | | | | | | | | 10 | 1,14 | 65,39 | 1,25 |
| *Age O* | *1* | *0,59* | *62,02* | *0,65* | *20* | *0,81* | *59,00* | *0,92* | *14* | *0,76* | *54,48* | *0,83* | *12* | *0,52* | *56,50* | *0,59* |
| F | 1 | 0,59 | 62,02 | 0,65 | 13 | 0,74 | 58,11 | 0,82 | 11 | 0,70 | 51,15 | 0,79 | 12 | 0,52 | 56,50 | 0,59 |
| M | | | | | 7 | 0,95 | 60,65 | 1,09 | 3 | 0,97 | 66,68 | 0,97 | | | | |
| *Age Y* | *28* | *1,05* | *63,69* | *1,14* | *16* | *1,11* | *65,05* | *1,19* | *5* | *1,18* | *67,80* | *1,23* | *19* | *1,02* | *61,49* | *1,17* |
| F | 28 | 1,05 | 63,69 | 1,14 | 16 | 1,11 | 65,05 | 1,19 | 5 | 1,18 | 67,80 | 1,23 | 11 | 1,02 | 62,06 | 1,16 |
| M | | | | | | | | | | | | | 8 | 1,00 | 60,69 | 1,18 |
| **Total** | **32** | **1,05** | **64,11** | **1,12** | **41** | **0,97** | **62,35** | **1,06** | **23** | **0,90** | **59,65** | **0,96** | **57** | **0,93** | **60,52** | **1,05** |

Table 7.11: Anthropometric and spatiotemporal gait characteristics for Scenario 3.2

information is still quite mixed in the end. For this reason, we discard this scenario as the most suitable one to represent our pilot population in terms of walking performance.

The second scenario, with five types of strides, maintains the group of strides with the highest force variation in the swing phase (fifth stride cluster). However, two new groups (stride clusters 1 and 4) appear also presenting this force switch from body side to side passing from the right to the left step. However, the force variation ends up being balanced for most of the gait cycle, especially in stride cluster 3. The Exercise cluster which groups most of these types of gait shapes is the third one from the Scenario 2.1 (Figure 7.10), which contains mostly exercises performed by older adults with some diagnosed cardiologic pathology. However, in the Scenario 2.2, with the same number of stride types, we obtain three clusters (3, 4 and 5) which differ in strides distribution but have similar proportions of exercises performed by older adults in comparison with the rest of groups. The mentioned stride types are prevalent in general in these three clusters, but with no more clinical knowledge or data volume, it is not possible to determine if this splitting adds any value to the study. However, this scenario can categorise together almost half of the exercises performed by young women in Exercise Cluster 1, with no male representation (in Scenario 2.1, there was a mix of gender).

Finally, the third scenario considers six types of strides, where the three first gait shapes start with an increment in the right pushing force, while the other three show an initial decrease. Also, the last three stride shapes show that initially, the gait cycle begins with a higher input of pushing force. This could be associated with a higher need to use the *i*-Walker as a support device while walking. This is coherent with the obtained results obtained in scenarios 3.1 and 3.2 (in Figure 7.14 cluster 3 and Figure 7.15 cluster 3) since they contain mostly exercises performed by older adults with diagnosed pathologies. On the other hand, stride types 1 and 4 represent the shorter strides in time, which in general correspond to women, especially young women as it can be appreciated in Tables 7.10 (Exercise cluster 3) and 7.11 (Exercise cluster 1). Strides type 3 are performed by people which apply a considerable amount of pushing force, but also decompensated to the right and usually belong to exercises performed people aged 80- years, but also we find a group of elder female with the worst performances in the spatiotemporal gait characteristics (this group was also present in Scenario 2.2). However, the exercises performed by younger participants in this group present the worst results in terms of gait speed and cadence in comparison to the rest of exercises performed by these two age groups.

## 7.3 CVI Cluster Explanation from the Spatio-Temporal Gait Characteristics

The previous section shows the results of an unsupervised learning approach that categorizes exercises in clusters according to the force interaction resulting from each stride performed by the participants of this study. In this section, we present the results of training two models to classify the CVI population into the classes of exercises. We will use two supervised learning algorithms, Random Forest (RF) and Linear Support Vector Machine (SVM), with the spatio-temporal gait characteristics and the Exercise clustering obtained in each of the previously scenarios, as the answer vector. Both models were trained with each of the previously presented scenarios. The objective is to extract the most relevant features in each scenario, aiming to complete the analysis carried on along this chapter.

The variables used in the training and test sets are:

- the gait characteristics: stride cadence, walking speed, stride length and time, and their respective coefficients of variance
- the six forces applied by the participants during the exercise (longitudinal, lateral and vertical forces for right and left hands)

The accuracy obtained for each scenario and machine learning algorithm are found in Table 7.12. Values are obtained using a 10-fold cross validaton of RF and SVM respectively. In general terms, Random Forest performs better than SVM. In fact, while RF obtains better results as the number of stride types increases, while SVM is more accurate with few strides and exercise types. Each scenario will be reviewed individually as in the previous section.

| | Cross Validation Accuracy | |
|---|---|---|
| **Cluster** | **Random Forest** | **SVM** |
| *cvi3k3k* | 0.78 | 0.80 |
| *cvi5k3k* | 0.73 | 0.80 |
| *cvi5k5k* | 0.78 | 0.71 |
| *cvi6k3k* | 0.79 | 0.75 |
| *cvi6k4k* | 0.80 | 0.70 |

Table 7.12: Accuracy results of the Random Forest and Support Vector Machine for each scenario

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Exercise Clus 1 | 0.88 | 0.72 | 0.79 | 61 |
| Exercise Clus 2 | 0.43 | 0.73 | 0.54 | 22 |
| Exercise Clus 3 | 0.98 | 0.93 | 0.96 | 70 |
| avg / total | 0.86 | 0.82 | 0.83 | 153 |

Table 7.13: Accuracy results of the SVM in Scenario 1

### 7.3.1 First Scenario

The accuracy with RF obtained using the full dataset for training was 1.0, classifying correctly all the observations in the dataset, while the mean accuracy is 0.79. In the case of SVM, the best accuracy was 0.82, presenting a smaller deviation from the Cross Validation result (0.8) depicted in Table 7.12. The model failed at classifying 21 out of 37 exercises of the second cluster (see Table 7.13), which contained a significant representation of the older aged participants (see Table 7.7). Most of the misclassified instances have fallen in the first Exercise cluster, which present a similar stride shape but with a smoother use of the pushing force during the swing phase (see Figure 7.7). In general, instances that were wrongly classified to cluster 1 correspond to exercises performed by young or middle aged women. There are also some exercises of old aged women misclassified, but those fall into the third cluster.

The most relevant variable in both the RF and SVM algorithms is $rhfx$, *i.e.*, the right hand pushing force, which is the prevalent force used by individuals while walking acording to the stride shapes. In the case of the RF, this variable has an importance score of 0.45 [1]. The next important feature is the right vertical, or leaning, force ($rhfz$), with only a 0.14

[1] RF computes an importance score that sums up to 1

| y = Ec1 | | y = Ec2 | | y = Ec3 | |
|---|---|---|---|---|---|
| **Weigth** | **Feature** | **Weigth** | **Feature** | **Weigth** | **Feature** |
| 1.49 | rhfx | 0.83 | rhfx | 2.18 | rhfx |
| 0.41 | rhfz | 0.66 | rhfz | 0.51 | lhfy |
| 0.31 | sLengthCV | 0.59 | lhfy | 0.48 | lhfx |

Table 7.14: Most relevant features of SVM in Scenario 1

of representation. In the case of the SVM, Table 7.14 shows the most relevant features by Exercise cluster(which correspond to each $y$ column). The weight is an absolute value and it mainly represents the importance of a feature over the others: the larger are the weight values, the more significance has their associated variable.

In this first scenario, Exercise cluster 1 contains mainly instances of young female that, as previously described based on Table 7.7 and Figure 7.7, have the shortest stride shape in length. The pushing force applied in these exercises is quite balanced. This is coherent with the relevant features obtained in Table 7.14. Moreover, this is the only class containing a spatio-temporal gait characteristic (the coefficient of variance of the stride length) among its most relevant ones. This support the observations made in the previous section related to the common pattern of the stride shape of this group. The second Exercise cluster represents those strides with higher force variation during the gait cycle. In this case, the SVM considered almost as important the pushing and leaning forces, but it also gives relevance to the lateral force. This class contains most exercises performed by older adults with cardiologic pathologies. This again backs up the sorts of strides that represent this Exercise cluster: people requiring of walking assistance show a higher variance in the pushing force, a pattern that is probably present in the rest of applied forces. The third class considers $rhfx$ as the most relevant feature, far from the scores obtained by the rest of variables.

### 7.3.2 Second Scenario

The second scenario has five sorts of strides and presents two possible options for the number of Exercise clusters, separated in scenarios 2.1 and 2.2.

In this case, the RF obtains its worst accuracy (0.73) while SVM has its best performance (tied with the first scenario result, see Table 7.12). Comparing Tables 7.14 and 7.15, we observe that the accuracy results are quite similar. On the one hand, one of the Exercise clusters have

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Exercise Clus 1 | 0.98 | 0.87 | 0.92 | 67 |
| Exercise Clus 2 | 0.89 | 0.77 | 0.83 | 65 |
| Exercise Clus 3 | 0.37 | 0.67 | 0.47 | 21 |
| avg / total | 0.86 | 0.80 | 0.82 | 153 |

Table 7.15: Accuracy results of the SVM in Scenario 2.1

| **y = Ec1** | | **y = Ec2** | | **y = Ec3** | |
|---|---|---|---|---|---|
| **Weigth** | **Feature** | **Weigth** | **Feature** | **Weigth** | **Feature** |
| 1.85 | rhfx | 1.71 | rhfx | 0.74 | rhfz |
| 0.52 | speed | 0.36 | speed | 0.70 | lhfz |
| 0.50 | lhfx | 0.26 | rhfz | 0.55 | lhfy |

Table 7.16: Most relevant features of SVM in Scenario 2.1

very low precision scores (0.43 in the first scenario, 0.37 in this case). On the other hand, another class has obtained a 0.98 of precision in both scenarios.

The exercises falling in each case are very similar. The cluster with better performances corresponds to the previously named as the mixed group, with higher gender and age balance (it is also the cluster with more observations). On the other hand, the third cluster is mainly composed by older participants and a few young and middle-aged women. Almost half of the original exercises of this cluster are classified in the second cluster (which includes most of the exercises performed by young women). It is possible that people performing the fourth stride type depicted in Figure 7.9, which has a similar shape than the second stride type, corresponds to the younger individuals found in the third Exercise cluster.

The most relevant features for the RF are again $rhfx$, $lhfz$ and $rhfz$ with weight values of 0.38, 0.16 and 0.14 respectively. In the case of the SVM, Table 7.16 depicts how the pushing force along with the speed are equally represented in classes 1 and 2, while the third class gives more importance to the leaning forces. If we observe the fifth stride type in Figure 7.9, we can conclude that individuals in this cluster rely more on the *i*-Walker as a support device while walking. The amount of exerted pushing force can only be compensated by a significant leaning force in order to compensate the body balance during the gait cycle. Moreover, the left lateral force is also relevant in this class. It seems that the combination of the applied forces is different than in the other age ranges, which could be an indicator of a pathological gait.

Scenario 2.2, with five types of strides and of exercises, differs from the previous one in the accuracy deviation for the SVM algorithm. This case is the first time that the RF Cross Validation accuracy excels the SVM. In here, the results in accuracy are better in average compared to the previous scenarios, as depicted in Table 7.17, being the worst score 0.52 for the fourth Exercise cluster. The bags-of-strides belonging to this class are the most heterogeneouly distributed as depicted in Figure 7.11, with almost 40% of the strides belonging to the first type and the rest equally distributed (except for the second stride which has almost no relevance in this group of exercises). It is pressumable that the walking pattern of these people show characteristics of gait variability. In addition, based on the spatio-temporal data depicted in Table 7.9, people in this group have the longest stride lengths, independently of their age range.

Table 7.18 shows the three more relevant coefficients per class. In the case of the fourth cluster, previously commented, the SVM gives more relevance to spatio-temporal characteristics such as the walking speed or the stride length. The instances from this cluster that have fallen in the fifth class belong to and elder male adult with high risk of falling, with a stride length and walking speed significantly below the performances of other male adults in this class. In addition, these characteristics are more similar to those found in the fifth Exercise cluster. However, due to the lack of male representation in this dataset, we cannot be sure of the accuracy of this affirmation.

The third class, which contains exercises that have a similar age distribution and stride length mean values, also relies in spatio temporal features for the classification (walking speed and the coefficient of variance of the stride time). However, these two classes have obtained the worst precision and recall scores; they are also those paying less attention to the hand forces respect to the others. In general, we can observe that the more stride and exercise types we have, the more relevant become the spatio-temporal features, although the pushing or leaning forces are still present at each class. In fact, RF keeps considering them the most relevant features, giving 0.38 of importance to *rhfx*, 0.14 to *rhfz* and 0.11 to *lhfz*. We can say that the interaction of the human with the *i*-Walker is very important to classify correctly the exercises, although results are better when the walking speed is also considered.

### 7.3.3 Third scenario

The third scenario considers two possible numbers of exercises for bags-of-strides composed by six types of strides.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Exercise Clus 1 | 0.80 | 0.73 | 0.76 | 33 |
| Exercise Clus 2 | 0.97 | 0.92 | 0.94 | 61 |
| Exercise Clus 3 | 0.67 | 0.75 | 0.71 | 16 |
| Exercise Clus 4 | 0.52 | 0.65 | 0.58 | 20 |
| Exercise Clus 5 | 0.82 | 0.78 | 0.80 | 23 |
| avg / total | 0.82 | 0.80 | 0.81 | 153 |

Table 7.17: Accuracy results of the SVM in Scenario 2.2

| **y = Ec1** | | **y = Ec2** | | **y = Ec3** | | **y = Ec4** | | **y = Ec5** | |
|---|---|---|---|---|---|---|---|---|---|
| **Weigth** | **Feature** | **Weigth** | **Feature** | **Weigth** | **Feature** | **Weigth** | **Feature** | **Weigth** | **Feature** |
| 2.79 | rhfx | 5.53 | rhfx | 4.471 | sTimeCV | 2.21 | sLength | 6.96 | rhfx |
| 2.63 | sLengthCV | 4.41 | speed | 2.93 | speed | 1.90 | speed | 5.19 | lhfx |
| 1.58 | lhfx | 3.83 | rhfy | 2.36 | lhfz | 1.28 | rhfx | 2.98 | cadence |

Table 7.18: Most relevant features of SVM in Scenario 2.2

The first case represents three clusters of exercises. The accuracy obtained with Cross Validation is 0.79 for RF and 0.75 for SVM. The most important features in RF are again $rhfx$, $rhfz$ and $lhfz$ with 0.41, 0.19 and 0.14 of the total reprentation. In this case, the left leaning force is the one discriminating the observations of the second Exercise cluster, while $rhfz$ is more relevant for the other two clusters. If we go a step further in the decision tree, we find that the cadence and the stride time are strongly correlated to the classification of the Exercise clusters 1 and 3; more specifically, small values of these variables are distinctive of the exercises classified in cluster 3. This is coherent with the distribution of bags-of-strides in Exercise cluster one (see Figure 7.14) and with the prevalent strides of this histogram (strides 1 and 4, depicted in Figures 7.12 and 7.13 respectively). This is also represented in Table 7.20, where the stride time appears as one of the most valuable coefficients of the third class.

The first Exercise cluster has obtained the worst precision score, with more than half of the exercises distributed in the other two clusters, as shown in Table 7.19. The pattern is similar to the ones described in the previous scenarios. The most relevant variables of this cluster according to the SVM explanation in Table 7.20 are $rhfz$ and $lhfz$, which is coherent with the stride shapes represented in this Exercise cluster (see Figures 7.12 and 7.14). It is pressumable that the SVM has classified people with a more latent force interaction with the *i*-Walker together, taking the younger participants to other clusters. That means that the individuals showing this

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Exercise Clus 1 | 0.47 | 0.74 | 0.58 | 31 |
| Exercise Clus 2 | 0.98 | 0.85 | 0.91 | 67 |
| Exercise Clus 3 | 0.85 | 0.71 | 0.77 | 55 |
| avg / total | 0.83 | 0.78 | 0.79 | 153 |

Table 7.19: Accuracy results of the SVM in Scenario 3.1

| **y = Ec1** | | **y = Ec2** | | **y = Ec3** | |
|---|---|---|---|---|---|
| **Weigth** | **Feature** | **Weigth** | **Feature** | **Weigth** | **Feature** |
| 0.94 | rhfz | 1.86 | rhfx | 1.42 | rhfx |
| 0.68 | lhfz | 0.50 | lhfx | 0.55 | rhfz |
| 0.59 | lhfz | 0.48 | lhfy | 0.38 | sTime |

Table 7.20: Most relevant features of SVM in Scenario 3.1

interaction with the *i*-Walker are those with higher dependence on the supporting device and, thus, those with higher risk (or fear) of falling.

Finally, the second case of this third scenario consists of six types of strides and four clusters of exercises. The RF has a mean accuracy score of 0.8 while the SVM returns the worst mean accuracy among all (0.70). This time, the three most important features of RF are $rhfx$ (0.33), $rhfz$ (0.23) and $lhfz$ (0.09, which is closely followed by the stride time coefficient of variance), *i.e.*, almost 60% of the data can be explained with these variables. Surprinsingly, the right leaning force does not appear among the most relevant coefficients of SVM, as shown in Table 7.22. These variables are specially relevant for Exercise cluster 4, which is the one with best precision performance and is also the one with more classified objects, which corresponds to already mentioned the mixed group (see Table 7.11). According to Table 7.22, its most important variables are the walking speed, the right pushing force $rhfx$ and also the stride length. This cluster contains most of the exercises performed by male participants, which pressumably are stronger and taller than women. Thus it combines spatio-temporal characteristics with the force interaction between the individual and the *i*-Walker.

On the other hand, the first and thrid Exercise clusters are those with worst results on precision and recall, although they have significantly improved compared to the results obtained in the first case of this scenario. Its most relevant features are $rhfx$ and $lhfz$ and $rhfy$; however, it has been previously mentioned that this cluster is mainly formed by young women, which main gait characteristic is the short stride length. It is likely to think that the first case of this

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Exercise Clus 1 | 0.69 | 0.76 | 0.72 | 29 |
| Exercise Clus 2 | 0.85 | 0.74 | 0.80 | 47 |
| Exercise Clus 3 | 0.61 | 0.78 | 0.68 | 18 |
| Exercise Clus 4 | 0.95 | 0.92 | 0.93 | 59 |
| avg / total | 0.83 | 0.82 | 0.82 | 153 |

Table 7.21: Accuracy results of the SVM in Scenario 3.2

| **y = Ec1** | | **y = Ec2** | | **y = Ec3** | | **y = Ec4** | |
|---|---|---|---|---|---|---|---|
| **Weigth** | **Feature** | **Weigth** | **Feature** | **Weigth** | **Feature** | **Weigth** | **Feature** |
| 2.56 | rhfx | 6.47 | sLength | 14.75 | vel | 9.18 | vel |
| 1.94 | lhfz | 6.35 | rhfx | 12.56 | sLength | 6.11 | rhfx |
| 1.44 | rhfy | 6.17 | vel | 4.53 | sLengthCV | 5.92 | sLength |

Table 7.22: Most relevant features of SVM in Scenario 3.2

scenario is more accurate in this sense, since it also considers gait characteristics to obtain a more general description of a gait cycle.

## 7.4 Modeling Fall Risk

As already explained in Chapter §3.3, the main objective of the *I-DONT-FALL* project was to design a physical and cognitive treatment focused on older adults at high risk of falling or having suffered a fall along the last year. This treatment aimed to reduce, not only the number of falls, but also the risk and fear of falling. The *IDF* dataset used, introduced in §3.3.3 and Table 5.1, was also used to develop a model able to predict the fall risk of those individuals after the treatment period. The methodology has been introduced in Chapter §6.5 and the following results were published in Cortés et al. (2016).

The best accuracy obtained from the model measured using 10-fold cross validation was 0.88 with standard deviation 0.1. The accuracy of the model for all the data was 0.95. Table 7.23 presents the results from the model for each class.

The resulting model was applied to the T1 dataset, dividing the data between the individuals that were submitted to treatment and the individuals that performed no treatment (placebo). The goal is to test if their fall risk status had changed or not.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Low Fall Risk | 0.91 | 0.77 | 0.83 | 13 |
| High Fall Risk | 0.96 | 0.99 | 0.97 | 72 |
| avg / total | 0.95 | 0.95 | 0.95 | 85 |

Table 7.23: Accuracy results of the logistic regression model for the training set.

The placebo group is formed by 27 individuals, 24 of them had high fall risk, and 3 had low fall risk. The model obtained with the T0 data fits well to this data, predicting the correct label for all the subjects except for two high fall risk individuals that are classified as low fall risk.

The treatment group is formed by 68 individuals, 48 of them had high fall risk, and 10 had low fall risk. The model predicts the same label for 43 individuals (36 high fall risk and seven low fall risk). The remaining 20 individuals have changed their status.

This means that this part of the dataset has deviated from the initial model and the treatment has had some effect on the fall risk status of the individuals. Specifically, 12 high-risk fall individuals are now considered low risk. Still, it seems that many individuals have not had enough benefit from the treatment in terms of fall risk, and just a minority have improved their condition. Also, some individuals have worsened their status, probably because of the natural course of their medical conditions.

Most of the observations in this dataset belong to people at high risk of falling. Moreover, it is hard to observe evident improvements in people at this age, since they continue to develop comorbidities that in the end affect their locomotion and other abilities. It would be interesting to extend the dataset with a broader age range and risk fall. It could also be instrumental to enlarge the treatment period and the post-treatment evaluation to study the effects of such rehabilitation at long-term perspective. Possible future work could combine the predicted risk of falling with the categorisation of the walking performance to complement the strategies of control to provide assistive and safe navigation.

# Chapter 8

# Conclusions

Older adults are becoming the predominant demographic group in most developed societies. The process of this ageing society is already affecting, or will soon affect, both developed and developing countries. Seniors usually suffer from one or more diseases and disabilities related to age, causing a loss of residual skills and, hence, autonomy. This often poses a barrier for the elderly, limiting their access to relatives, friends and social activities, which may lead to isolation, depression and severely impacts their QoL. Ageing also challenges the ability to perform the activities of daily living, such as dressing, bathing or self-feeding, but also to the functional mobility. As such, solutions both efficacious and cost-effective need to be sought with two main objectives: *(i)* improve, or at least maintain, the QoL of seniors and their relatives, and *(ii)* rethink public health systems, taking leverage of technological solutions that allow a remote and ubiquitous health management (see §3.2, §B or Barrué et al. (2017)).

The Internet of Medical Things is a new concept emerging recently that takes into account this current situation. It aims to enable the machine to machine interaction and real-time intervention solutions to create a network of connected devices continuously collecting and/or processing data. Concepts already explained in this document, such as smart wearable or assistive devices, home-use medical devices or mobile healthcare applications, will be the principal components that will allow communicating with medical experts remotely. This system could not only be used for monitoring, but also for prevention, healthy lifestyle promotion or remote intervention in emergency situations. This is also empowered in Europe by the H2020 funding programmes, which aim to include the new generation of mHealth solutions that will help users to manage their health and communicate with related stakeholders of the care process (*e.g.*, doctors, informal caregivers, relatives, *etc.*). The *i*-Walker is a definite candidate to play a role in this health system architecture as it meets the requirements needed to contribute to its achievement.

Through this work, the strong relationship between cognition and mobility has been shown, as well as the importance of being active while ageing to maintain, not only our skills but also our autonomy in community-dwelling. In the case of mobility recovery and assistance, we have reviewed several solutions developed during the last two decades that involve different assistive technologies and sensors and interact at various levels with end-users and health professionals. Within this field, smart walkers offer an exciting opportunity to the senior population as a support tool for gait and balance. However, they also present some limitations for specific users with physical or cognitive impairments depending on the number of legs and wheels, such as post-stroke users (see §4.3.1 and Giuliani et al. (2012), Morone et al. (2016)).

The *i*-Walker has been presented in this document as a smart walker with a system of sensors and actuators that is already able to assist people in different types of environments with a reactive control, providing safety and self-confidence to the user. We have also reviewed previous research works in which the *i*-Walker has an essential role as a rehabilitation tool (Giuliani et al. (2012)) and as an intelligent service integrated into a medical social network (Barrué et al. (2015)).

One of the main challenges when working with a robotic tool with sensors is the interpretation of raw data. In the previous works developed with the *i*-Walker (see Chapter §4.3 and Annex §B). In this PhD, we have been working in turning these data to readable and understandable information for clinicians in different formats such as activity reports, graphics showing the evolution of a sensor reading through an exercise or messages via social network communication channels. The results obtained in the works as mentioned above were studied from a clinical perspective, where scales and performances are compared between periods. In §4.3.3, we have also presented two approaches for data analysis using unsupervised learning techniques to categorise exercises by type (straights, turns) or by participants' age. However, it is also interesting to analyse the human-robot interaction from a biomechanical point of view, *i.e.*, by interpreting the data extracted from the onboard sensors and relate it to the study of gait characteristics of old-age individuals with high risk of falling. The *i*-Walker offers a unique opportunity to learn the effect of forces exerted directly by a person at every moment while walking and to validate our hypothesis that with this information it is possible to determine patterns of user interaction with the *i*-Walker as well as assessing the risk of falling in a near-future. Through this document, we have mentioned different techniques of gait analysis and the measurement tools used for it, such as video cameras, walking platforms or wearable sensors. For this PhD, only the data collected by the *i*-Walker has been used. One of the objectives of the research and development of the *i*-Walker is to build a device that is able, not only to support the mobility of challenged users but also to be used as a clinical product able to offer new insights to medical experts.

Hence, we have focused on extracting different characteristics of an individual's gait using the force sensors located at the handlers of the *i*-Walker (see Figure 4.1). These data are not only fused with other sensors onboard (such as odometry, linear and angular speed, and estimated pose), but also with anthropometric data from a group of participants introduced in Section §5. We have used two well-known mobility measure, the 10 Meters Walk Test and the 3 minutes Walk Test, to assess a parameter that usually is manually studied by clinicians, which is the gait velocity. As it has been explained through this document, gait velocity is an indicator used by clinicians to assess an individual's post-rehabilitation recovery, but it can also be used as an early detector of cognitive decline or even a mortality predictor. We aimed to validate the hypothesis proposed by clinical studies with the data obtained from our participants while using the *i*-Walker (see §7).

Besides, we have identified other evaluation metrics of an individual's gait behaviour that are defined in clinical studies, named spatiotemporal gait characteristics. Thus, for each exercise performed within the different clinical tests carried on for this work, we can obtain the number of strides, duration and length. With this information, we can provide a qualitative gait analysis of an individual's performance within the 10MWT as shown in §6 and §7. The stride detection function has appropriately worked for an exercise like the 10MWT, a short and straightforward path where few angular motions are given. In fact, we can observe the expected acceleration pattern of the 10MWT, where the two first and last meters have an irregular pace due to acceleration and deceleration moments, while the central part usually goes with a regular cadence. However, due to the short duration of this walking exercise, it is difficult to characterise an individual's gait with such few observations. Thus, the same methodology was applied to the 3 minutes Walk Test with a new pilot and target people.

## 8.1 Discussion

The proposed methodology for gait analysis was applied in different datasets that have been studied separately in §7.2. This approach aims to find first some stride types performed by the participants. Then, using the bag-of-$X$ technique, we were able to define a vocabulary of strides according to their appearance in each exercise and participant. This allowed us to group these bags-of-strides into exercise clusters, which were expected to identify individuals with similar walking behaviours. Besides, a supervised learning method has been used to classify participants of the $CVI$ pilot by their spatiotemporal characteristics. The objective was to compare these results with the ones obtained with the clustering approach. Based on the obtained results explained in §7 we can conclude that:

- The DTW algorithm can find some patterns in the gait shape of the exercises and group them mainly by two characteristics: stride length and the pushing force exerted by the human

- The more stride types we consider, the more groups of strides with relevant differences will appear. However, the challenge with unsupervised learning techniques is to find the appropriate number of clusters. Based on the analysis presented, we estimate that there are five or six types of strides that provide useful information. With only three types of strides, we could be able to correlate stride shapes with age, but if we aim to learn more about different pathologies or walking patterns in the older adults, we need to include more stride clusters.

- The stride shape based on the hand pushing force interaction is relevant enough to identify groups of exercises with some common characteristic. The more usual relations found in this work were: *(i)* the amount of pushing force can determine the navigation skills of an individual, *(ii)* shorter strides usually belong to women or old men, *(iii)* male individuals aged 80- usually exert a higher amount of force, but balanced in terms of body compensation in the swing phase, *(iv)* stride shapes presenting significant force variation along the gait cycle usually belong to older adults, thus people that need the support of the rollator to feel safe while walking. However, this pattern is also given in several exercises performed by young women.

- The classification of individuals using supervised learning methods contributes to the identification of most relevant features that should be taken into account to study walking patterns. Results are quite coherent with those obtained with the clustering analysis, but it also brings new information. The hand pushing force is, in general, the most important variables in all the studied scenarios. However, we have seen that the hand leaning force also takes protagonism, especially in those clusters formed by challenged participants (older adults diagnosed with a cardiologic pathology, *i.e.*, , those requiring higher support while walking). These methods have also confirmed that the stride time and length are relevant to identify strides (or exercises) by gender: in general, the exercises performed by women are those with shorter strides, which is coherent with the anthropometric pattern. Also, the coefficients of variance of the stride length and time are present in those exercises performed by seniors, confirming the gait variability, or instability, that is expected in this type of users.

However, the methodology presented here was not able to identify in a single cluster those exercises performed only by people at high risk of falling. Ballesteros et al. (2016) showed that exercises performed by younger adults give higher errors in estimating the risk of falling. This is probably because young people are not used to interacting with a rollator and, moreover, they do not need the support while walking. During the $CVI$ trial, it was observed that younger adults tend to modify they walking behaviour when using a rollator, mainly represented by a reduced gait velocity or by a weak interaction with the handlers. The inclusion of this target group is justified to validate the methodology with different age groups regarding gait identification. However, for further analysis, it would be recommended to exclude them and focus on specific physical or cognitive pathologies affecting the senior population.

The innovation of this PhD relies on the use of the data generated from the interaction between the user and the *i*-Walker, which we have been able to interpret and translate into these well-known metrics. It also provides a detailed knowledge, meter-to-meter or second-to-second of different segment joints of the body in relation to the rollator. The stride-to-stride analysis contributes to the understanding of the results of the clustering analysis, in comparison to those presented in §4.3.3, which considered the whole exercise as an observation of the dataset. With the expertise of a medical team, we could be able to turn this information into a new support tool that would assist clinicians in a patient's diagnostic. Furthermore, in relation to the medical social network, this would also define another level of knowledge and would allow providing a more detailed system of alerts to both doctors and relatives. The services we are building on top of the *i*-Walker are meant to support various aspects: diagnostic, rehabilitation and daily living including fall prevention. Further work with more specific target groups would be necessary to determine the utility of the approach presented here as a decision support tool for clinicians and to develop tailored strategies of control to assist mobility. For this, it would be necessary to collaborate with a specialist, which could provide further insights on the obtained results and on the type of tests to be executed in future clinical trials. Recently, works that relate gait analysis with cognition use dual-task exercises that have proved to deliver significant results from a clinical perspective. We believe that the future of the research with the *i*-Walker should follow this trend. Also, it would be interesting to add new scenarios of complex navigation to work in the control strategies.

The challenge for the future is *to ensure that people everywhere can grow old with security and dignity and that they can continue to participate in social life as citizens with full rights*. At the same time, *the rights of old people should not be incompatible with those of other groups, and reciprocal intergenerational relations should be encouraged* (Nations (2001)). The *i*-Walker is expected to be a powerful tool in the future, able to extend the autonomy of older adults with reduced mobility but healthy cognitive conditions, allowing them to live in a community. The next years will be critical to design the appropriate intelligent services to improve the quality of life of seniors, but also to be used as a clinical device for rehabilitation or research. One of the main challenges will be to deal with real-time information to be fully-adapted to the Internet of Medical Things philosophy.

# Appendix A

# Pilot Protocol

This annexe contains the full version of the pilot protocols presented to the Ethical Committees at the Fondazione Santa Lucia and Residencia Los Nogales (the second one is shown in Spanish, as in the original version).

## A.1 Fondazione Santa Lucia

The test will take around 30 minutes to be performed in a single session. The test will consist of accomplishing four different routes using the *i*-Walker twice, the first time with the *i*-Walker without utilising the compensation systems (*i.e.* acting like a regular walker) and the second with the compensation systems active.

Paths within the laboratory:

1. Go through a door coming from the hallway with a turn to the left
2. Go through a door coming from the hallway with a turn to the right
3. Turn around a chair placed in the centre of the room with a turn to the right
4. Turn around a chair placed in the centre of the room with a turn to the left

The routes will be drawn and performed in a room of the laboratory of assistive technologies, namely the laboratory of clinical neurology and behavioural. During this test, the subjects will use a dedicated *i*-Walker that technically differs from that used for the previous protocol (FATE FATE) by the introduction of a laser and a system of detectors that will be able to record useful information about the trajectories performed using with the *i*-Walker.

The change in the procedures of data collection was determined to allow the objective of evaluating the effectiveness of the *i*-Walker in the performance of complex tasks such as those described in the test. The ultimate goals of the project are FATE, in addition to the detection and reduction of falls, to improve the gait and balance and functional ability. Through the study of complex trajectories, we think we can show how the system can help the patient at risk of falls in the daily management of activities per diem. Moreover, we expect to study and analyse users driving abilities in indoor environments to provide personalised assistance for each person according.

**Inclusion Criteria**

- Age greater than 64 years
- At least 2 falls in the previous six months
- Need to use a walker for the journey

**Exclusion Criteria**

- Bearer of an implantable electronic device: pacemaker, defibrillator, *etc.*
- Mental disorders such as dementia known (in rushed the clinical criteria of the DSM IV) and MMSE 24 or other neuropsychiatric disorders

**PRIMARY OUTCOME:**

- Improved users gait and balance.
- Evaluation of system usability and user satisfaction.
- Analysis of users navigation skills in indoor environments: We will calculate the users efficiency in driving towards a given goal according to three parameters, namely: directionality, safety and equilibrium. This work is based on previous experimentation performed at FSL, within the EU funded project SHARE-*it*, with the wheelchair CARMEN Urdiales et al. (2011).

**SECONDARY OUTCOME:**

- **Creation of a standard user profile:** Based on this previous work, we will define different indoor navigation situations that users may face during their trajectories. This is done by analysing the laser sensor readings. By adding the directionality captured by the sensors onboard, we obtain information about *how* every single user faced each one of these situations. We create a standard user profile which represents an average of the solutions provided by users in each situation. In the second phase of the experimentation, this standard user profile will be used as a compensation system.

- **Tailored assistance:** To design a mechanism to adapt the *i*-Walker compensation system to each user type to avoid an excess or loss of assistance.

**TOOLS AND TIMES OF ASSESSMENT**

Each variable will be measured through the use of assessment tools and indicators as described below in detail. These instruments will be administered after the test.

- *Improvement of the gait and balance:* The gait and the balancing analysis will be assessed through the administration of the Tinetti balance and gait scale, and Up and Go test performed before the test with a standard *i*-Walker and after the test with the *i*-Walker set with parameters as during the trial.

- *Usability evaluation of the system and user satisfaction:* This parameter will be assessed through the administration of the QUEST (Quebec User Evaluation of Satisfaction with Assistive Technology) and SUS (System Usability Scale)

- *Analysis of users navigation skills:* A frontal scanning laser will read the environment and build a map of the testing paths. We will also use the force sensors embedded in the handlers of the *i*-Walker and the gyroscope and accelerometer to detect the directionality of the user. We will also need a laptop on the top of the *i*-Walker seat to log all the data from the laser and the rest of sensors already integrated into the *i*-Walker. **None of the added components (see A.1 to the FATE *i*-Walker model is invasive for the final user.**

- *Analysis of users forces balance:* We will collect data from handlers sensors to compare the leaning, lateral and pushing forces with and without the compensation system (Forces $X$, $Y$, $Z$ for both handlers).

**HOKUYO LASER**

The *i*-Walker used during this experimentation phase will be the same model that is used in FATE project with a new sensor on it. The sensor is a Hokuyo URG-04LX laser2, which is a scanning laser range finder used for environment recognition. The laser will be used to build a map of the test environment[1] and track the paths performed by individuals. The laser is placed in the frontal part of the *i*-Walker, so no physical contact with the user is required.

## A.2 Residencia Los Nogales

Proponemos[2] realizar un test usando el *i*-Walker con $X$ ancianos (mitad hombres y mitad mujeres) residentes en Los Nogales. Cada test tendrá una duración aproximada de 30 minutos y se realizará en una sola sesin. El test consiste en completar 3 tipos de recorrido, primero sin ningn sistema de compensación (como un andador normal) y después con un sistema de compensación activo.

Los recorridos que se realizarán son:

- Recorrer 10 metros en línea recta en un pasillo
- Recorrer 10 metros en línea recta en un pasillo y entrar a una habitación girando a la derecha
- Recorrer 10 metros en línea recta en un pasillo y entrar/salir a una habitación girando a la izquierda

El *i*-Walker tiene un parmetro de configuracin ($\lambda$) que proporciona al usuario ayuda a la hora de ejercer fuerza en el andador. El objetivo de la campaa es el de construir un banco de datos con diferentes niveles de ayuda para poder luego extraer conclusiones sobre la efectividad del *i*-Walker en la ejecución de tareas complejas como las descritas en este test.

Cada recorrido se ejecutará cuatro veces, la primera sin ningún tipo de ayuda y el resto con diferentes niveles de ayuda que afectarán al sistema de compensación.

Durante los ejercicios, los voluntarios usarán un *i*-Walker dotado de varios sensores que recogerán datos sobre el usuario y el entorno. Ninguno de los sensores es invasivo ni requiere contacto físico con el usuario. Tampoco requiere ninguna habilidad tecnológica.

[1]A similar one was used in the experiments with CARMEN (above referred)
[2]This protocol is originally in Spanish.

El *i*-Walker está dotado de unos sensores de fuerzas, en el interior de las manetas, para medir las fuerzas de empuje, apoyo y lateral que cada mano ejerce sobre el *i*-Walker. Además se puede detectar si el usuario está frenando o no el andador. También se miden las fuerzas normales ejercidas con unos sensores situados en las patas traseras del andador.

Por otra parte, en la caja central del *i*-Walker hay un giróscopo y un acelerómetro que permiten calcular la odometría y aceleraciones del andador. Finalmente, se ha añadido un láser en la parte frontal del andador. El láser será usado como sensor de escaneo para el reconocimiento del entorno. Este sensor no es agresivo con los usuarios ni el entorno.

**Criterios de inclusión**

- Edad superior a 65 aos
- Ninguna caída en el último ao

**Criterios de exclusión**

- Portadores de un dispositivo electrónico implantable: marcapasos, desfibrilador, etc
- Trastornos mentales como demencia, MMSE $\leq 24$ u otros trastornos neuropsiquiátricos

**RESULTADOS PRIMARIOS**

- Evaluación de la usabilidad del sistema y de la satisfacción del usuario
- Análisis del paso y equilibrio del usuario
- Análisis de las fuerzas de equilibrio del usuario

**RESULTADOS SECUNDARIOS**

- Perfilado de usuarios según sus habilidades de navegación en entornos cerrados y conocidos
- Diseño de un mecanismo que adapte el sistema de compensación del *i*-Walker a cada perfil de usuario con tal de proporcionar el nivel de ayuda mínimo necesario para que su navegación sea segura

**HERRAMIENTAS DE EVALUACIÓN**

- Análisis del paso y equilibrio del usuario: los voluntarios deberán pasar los tests de Tinetti y Up and Go para obtener datos clínicos de cada uno.

- Evaluación de la usabilidad del sistema y de la satisfacción del usuario: se evaluará a través del QUEST (Quebec User Evaluation of Satisfaction with Assistive Technology) y SUS (System Usability Scale).
- Análisis de las fuerzas de equilibrio del usuario: se medirán las fuerzas de empuje, lateral y apoyo (fuerzas X, Y, Z en cada mano) con y sin el sistema de compensación. Esto nos servirá de banco de pruebas para establecer un umbral de los valores de fuerzas aplicadas por un grupo de ancianos sanos para poder comparar con futuras pruebas con ancianos con algn tipo de discapacidad física o cognitiva.
- Análisis de las habilidades de navegación del usuario: a través del láser, junto con el análisis de las fuerzas, obtendremos una evaluación de la habilidad de navegación y de la percepción de la ayuda recibida. De esta manera podremos clasificar los usuarios por perfiles según sus resultados.

# Appendix B

# Integrating the *i*-Walker as an intelligent service in a Social Network

Social support is important in daily living activities (ADLs) for the elderly living in community settings, and several studies have provided evidence of an association between social support and cognitive function. A socially engaging lifestyle is correlated with higher cognition scores in both community and nursing home settings (Christensen et al. (1996)). Because social activities provide the challenge of effective communication and participation in complex interpersonal exchanges, social support has been thought to inhibit cognitive decline in the elderly (Berkman (2000)). New research challenges endeavoured by the European Commission in the late H2020 program includes the new generation of mHealth solutions that might help users to manage their health and communicate with related stakeholders of the care process (*e.g.*, doctors, informal caregivers, relatives, *etc*). The demographic shift is also reflected on the web, especially in the case of elderly citizens who constitute one of the fastest growing demographic groups of Internet users (see Manafo and Wong (2012)). Despite their disadvantage due to inexperience and difficulty in navigation given their disabilities, these people often understand the benefits of the Internet and show themselves to be very enthusiastic in using it for all kinds of activities. Social networks and online discussion forums can be used to engage in social contact with people everywhere, regardless of their age or state of health. The opportunity to maintain social relationships is especially significant for the elderly and when done extensively is one of the key elements of ageing well. One benefit of social media for the elderly population is the possibility to keep in touch with friends and family through yet another medium, and one that is increasingly popular. It is socially relevant to give them the same technological opportunities as those given to younger people without disabilities.

Social networks and family ties are among the core institutions providing support and, opportunities for engagement to older adults around the world (Berkman (2000)). Loneliness is related to adverse physical health outcomes in older adults, including higher systolic blood pressure, elevated hormone levels, and less restorative sleep, in other words, sleep that is less effective in restoring alertness and in improving mood and performance (Hawkley and Cacioppo (2007), Fowler and Christakis (2008)).

An assistive social network empowered with a multi-agent system (MAS) has been developed by Pérez-Pasalodos (2014). The social network provides an ecosystem for integration of assistive services (or devices, *e.g.*, the *i*-Walker) to support elderly users with disabilities in their ADLs, allowing them also to stay connected and in communication with relevant stakeholders in their care environment (*e.g.*, relatives, caregivers, doctors, *etc*). The role of the MAS in the social network is to pro-actively mediate and manage the outputs of the assistive services in the system, sharing selected information and contents among the elderly user environment. Therefore, the social network will work as a conventional communication tool that will allow the older adult to stay connected with his preferred environment and at the same time, will be used by assistive services to post authorised information related with the elderly activity on behalf of the user. The assistive social network provides different ways of interaction depending on the type of user that is using it at each moment (*e.g.*, a doctor profile can prescribe assistive services). The work described below was presented in Barrué et al. (2015).

## B.1 Architecture

Social networks and MAS share to some extent both the structure and the scope; they are distributed systems where individual components are connected among them with some relationship enacting a certain role. Therefore, it is natural to think about possible synergies between both approaches (Franchi and Poggi (2011)). In the literature, MAS has been used to model complex systems, and social networks have been a good use case to simulate users' behaviour and social interactions (Epstein (2007)). Agent-based techniques also have been used to solve the *expert finding* problem, navigating an SN and searching for a determinate profile or to provide a matchmaking service finding people with common interests. Another common approach using agent-based techniques in social networks are for reputation and trust calculation (Sabater and Sierra (2002)). Moreover, MAS could implement successful means for the realisation of intelligent services for social networks, providing coordination, distribution, knowledge management and learning capabilities able to cope with complex services delegating part of the users' tasks and interactions (Franchi and Poggi (2011)). In our case, the synergy between social networks and MAS will allow us to deploy a tool that will pursue the following goals:

- Enhancing elderly population socialisation channels, allowing them to stay in touch with their relatives, friends, caregivers and medical professionals.
- Providing a framework to deploy agent-mediated assistive services to the elderly persons, empowering their autonomy and self-management of their health (*e.g.* services for promoting, maintaining and restoring health).
- Enabling a communication channel that agent-mediated assistive services can use to deploy care information on behalf of the elderly user to his selected care environment.

This will contribute to the creation of age-friendly community services and among those *e*-Health services.

## B.2 Social Network (SN)

Social networks are prevalent in our society. SN are heterogeneous and multi-relational dynamic data sets that can be represented as a graph $G = (V, E)$. The vertices ($V$) of this graph are known as *social actors* and may be connected using links ($E$) depending on the different types of relationships. Both nodes and links may have attributes (as name, weight *etc*). Objects may have class labels, and links can be directed or undirected (Boyd and Ellison (2007)). Social networks available on the Internet have enjoyed a lot of attention in the last decade, finding successful examples like Facebook, Twitter or Goggle+ with hundreds of millions of users abroad the world. In the literature we can also find thematic SN initiatives devoted to elderly population or related with specific diseases support (Cronhnology, IHadCancer), some born as research projects for ambient assisted living programs (OSTEOLINK) or initiatives from elderly associations (MyALZspot). We can also find commercial networks devoted to supporting caregivers in the care process of the elderly population with dementia (CaregiversPRO). None of these projects allows the seamless integration of assistive services that can pro-actively interact with the SN empowered by the features of intelligent agents.

In the definition of this new framework were a social network and MAS are integrated, it is necessary to define the nodes that will compose it. Most essential vertices in the graph of our social network are individuals, but may also represent other concepts, such as assistive devices, reports or messages that can be navigated depending on their connection with person nodes.

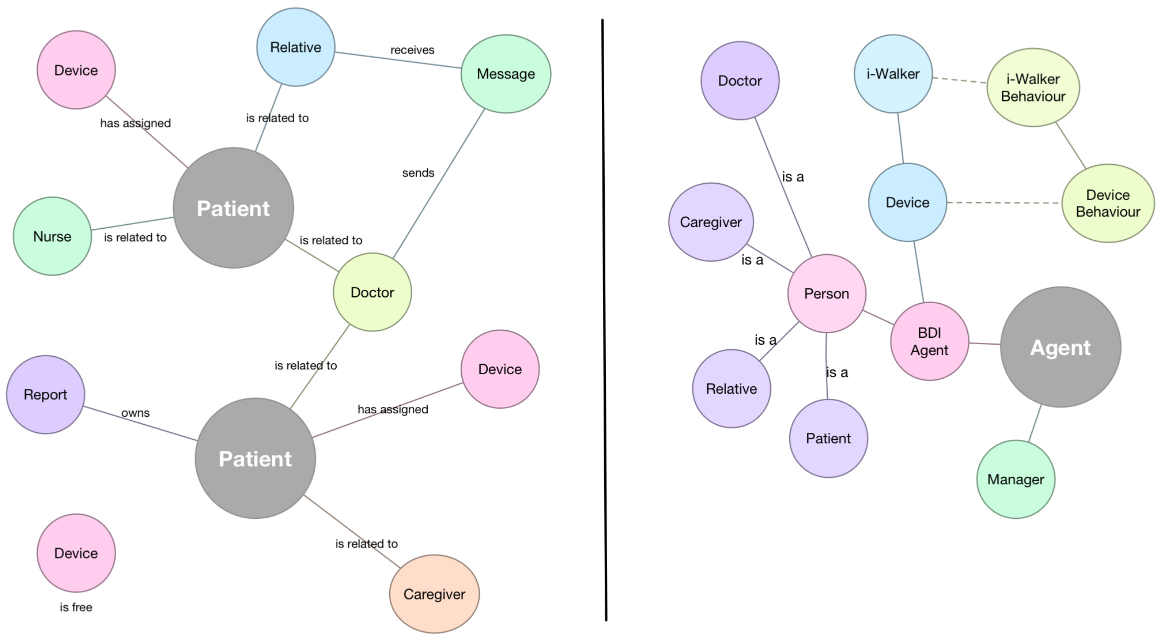


Figure B.1: The Social Network Graph (l) and the Multi-Agent System Architecture (r). In (l) all the actors of our SN and their possible connections are represented. In (r) we relate these actors with their type of agent in the MAS structure.

### B.2.1 People

Therefore, among the individual participants in the SN, we will define a set of roles. In this setting, an individual *plays* only one role at the time. Those are: a set of Patients as $[p_1 \dots p_n] \in \mathcal{P}$; the set of Doctors as $[d_1 \dots d_i] \in \mathcal{D}$, the set of Nurses as $[n_1 \dots n_z] \in \mathcal{N}$, the set of Relatives as $[f_1 \dots f_y] \in \mathcal{F}$ and, the set of Caregivers as $[c_1^{p_x} \dots c_m^{p_y}] \in \mathcal{C}$, we read this $c_j^{p_z}$ as caregiver$_j$ takes care of patient $p_z$. This list of roles can be easily expanded to include other roles. Each node stores a series of personal information related to the user (*e.g.*, name, id, email, password, *etc*). The main connections between personal roles are between patients and doctors/caregivers/relatives/nurses. As the main focus of this first prototype is providing assistive services, another kind of interesting connections as $p_i - p_j$ or $d_i - n_j$ have been postponed for future versions. It must be noted that there exist indirect links between nodes in the network, for instance between a relative and the doctor assigned to his patient relative; a relative could navigate to the patient node and from there access to his assigned doctor or caregivers. Also, the system includes a set of Agents as $[a_1 \dots a_n] \in \mathcal{A}$. Whenever an agent $a$ is assigned to a $p_h$ it denoted as $a^{p_h}$, we call this the Patient's agent. Agents can be assigned any individual according the role(s) she can play.

In Figure B.1 we can see a sample representation of the nodes and links of the network.

### B.2.2 Devices, Reports and Messages

Devices represented as $[w_1 \dots w_n] \in \mathcal{W}$ have two mutually exclusive states, depending if they are assigned to a user or not. When a device is assigned to a given patient $p_i$ it denoted as $w_j^{p_i}$. Each $p_i$ can have an indefinite number of $w_{j,\dots,m}^{p_i}$ devices assigned. Medical roles will be the responsible for assigning assistive devices to the users (*i.e.*, by prescription). Each device node stores a set of parameters like its *id*, type of device, password to access the network, a timestamp $t_i$ for each event or the data structure that it produces. The information produced by each device $w_j^{p_i}$ can only be accessed by authorized users, all related with the patient $p_i$, for instance his caregiver $c_z^{p_i}$ or and an authorized doctor $d_z$. An assistive device $w_i$ can be assigned to different patients during its use life, so it is possible that the link that connects $w_j^{p_i}$ to its patient changes becoming free or assigned to a different patient. Reports are nodes of the network $[r_1 \dots r_k] \in \mathcal{R}$ generated pro-actively by the MAS (*i.e.* when needed) or the care community. They contain information related to the user and have different categories depending if they are $activity - report$, $alert$, $appointment$, $information$, $help$, $etc$. Messages $[m_1 \dots m_n] \in \mathcal{M}$ are nodes connected to the sender and the receivers.

### B.2.3 Multi-Agent System

Multi-agent systems (MAS) support complex interactions between entities, using high-level semantic languages. Such a feature is essential in social and caregiving environments dealing with heterogeneous users (that are not necessarily technological savvy) and their preferences. One of our system goals is to investigate social connectedness using a social network supported by a MAS in the scope of Ambient Assisted Living (AAL). Appropriated, efficient and, timely communication with patients and among other agents is essential to the success of this kind of systems.

Three dimensions can be used to describe the MAS from an organisational point of view: its structure, its functionality and, its norms. In this work, we will address the structure (see Figure B.1) and functionality view, especially detailing the organisation roles, groups and role relationships. The structure of our MAS will be inherited from the SN described in §B.2. The SN can be seen as an augmented environment where individuals, assistive devices, and intelligent agents are actively communicating with each other. The agents in our MAS may enact roles of individuals or assistive devices.

Our MAS has been implemented using the agent framework *Smart Python multi-Agent Development Environment* (SPADE) (Gregori et al. (2006)). We chose this framework because it accomplishes our initial requirements (*i.e.*, FIPA compliance, many MTPs like HTTP, multi-platform) and also because it is built using Python, which is the native language used by Raspberry Pi board computer that commands the *i*-Walker (see §4). SPADE also brings integrated BDI and allows development of the agents in several programming languages, which makes it easier to integrate off-the-shelf existing services or devices to the social network-MAS just using their API. It also provides the versatile *behaviour* approach to programming the different agents' capabilities. All the agents (*e.g.* $a^{p_h}$ or $w^{p_i}_{j,\dots,m}$) related to individuals, modeled with BDI agents, have the related information of the user that they are representing and his/her/its role.

Among all the personal agents, the Patient agent is the most interesting as it includes special features to manage its assigned devices and stores their information that can be used, for instance, in the gamification scenarios where we want to encourage users to participate pro-actively. Doctors, Relatives and Nurses have each one a specific agent but share a common behaviour: wait for messages from the patient and process the information according to three factors:

- **Danger:** Patient agent sends a message to all the agents involved in informing about a dangerous situation (*e.g.* the patient does not generate any activity for a long period)
- **Alert:** Related agents will be notified when a device produces an alert (*e.g.* a fall using the *i*-Walker is detected)
- **New exercise or activity:** Patient agent will inform others when the device agent sends a report of a new exercise or session.

The Device agents, also following a BDI structure, are designed to bring specific features like *commit_data* that allows the creation of reports in the SN or send *MsgToPatient* that allows the agent to communicate through the social network with its assigned patient. The *DeviceBehaviour* allows for the programming of device/service specific features. The Manager agent is the interlocutor between the SN and the rest of agents, taking the role of the Agent Manager Specification and Directory Facilitator from FIPA standard. It takes care of creating and eliminating the agents of the platform and keeps a reference to all the individuals, devices, services and groups keeping the record of the stakeholders of the social network and their relationship.

### B.2.4 Integration

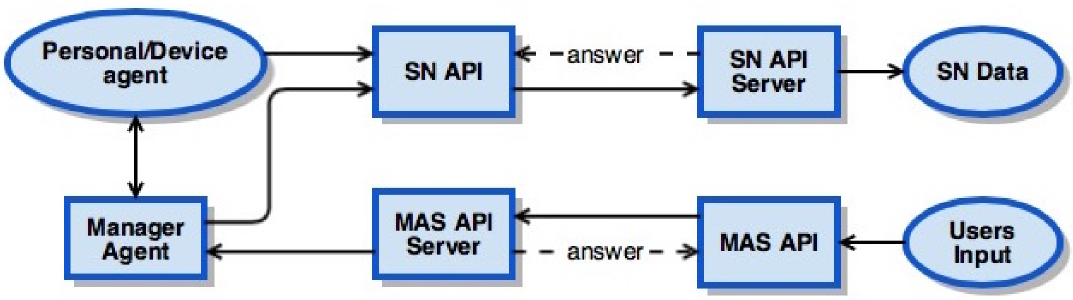


Figure B.2: Interface Scheme between MAS and SN.

Up to now, we have described the MAS that models the different agents that provide various services under the *Beliefs*, *Desires* and *Intentions* paradigm. Furthermore, we have described the SN, which is the interface where our stakeholders playing different roles can interact with the MAS' mediated services (*e.g.*, see information related to the patient, assign a device to a patient, *etc.*).

Hence, both systems need to be integrated to work appropriately since from an external point of view they constitute a unique system. To implement the integration, a middleware interface between both subsystems was designed. This interface provides all the functionalities needed to accomplish a full communication between both subsystems while being understandable to both of them. Such interface will be present partially in both subsystems in such a way that each subsystem will have a server where to receive the petitions from the other and a module to send the requests. Thus, the interface will be composed of the servers and modules present in both subsystems. As depicted in Figure B.2 we can see that both sides of the system are provided by an API to send the petitions (*e.g.*, MAS API, SN API) and a server where to receive requests from others (*e.g.*, API Server).

The servers on each side will provide a series of services to allow the communication between both subsystems in such a way that all the functionalities needed by the system are supplied. To do that we have to take into account the nature of each subsystem. On one side we have the MAS for which we use SPADE which is implemented in *Python*. On the other hand, we have the SN network implemented by extending the *Elgg* platform that works over an *Apache* server that mostly uses *PHP*. The need to choose a language understandable by both sides drove us to use the *HTTP* protocol to communicate both parts. This choice is perfect since the system is implemented on top of a network and nowadays all the languages are capable of dealing with the *HTTP* protocol. However, the shape/content of the data sent through this channel has to be understood by both parts too. To describe the contents of the communication messages, we decided to use *JSON* for the same reason as almost every programming language has libraries to process it.

To implement the servers, in the case of the SN *Elgg* already has a specific module to allow these kinds of interactions. On the MAS side, since SPADE is implemented in *Python*, it allows creating a *HTTP* server in a quite straightforward way using a *Python* module called *Bottle*.

Since the interface has to communicate the *MAS* with the *SN*, it works with the *HTTP* protocol. The requests are basically *GET* methods (to request data) and *POST* methods (to set data). To perform the communications each system knows the *URL* of the other, and for security reasons, each interaction will require a *key*, not allowing the interaction of external agents not belonging to the system. Each request has a specified format (method, arguments, *etc.*) and the response will be always a tuple with two variables: **status**, that returns *True* or *False* and **result** that contains the result itself or the error if it is the case. Both MAS and SN servers will accept different requests to promote the communication between them and allowing the different actions required by the system (*e.g.*, proactively posting a report by a device agent, sending an alarm by a device agent, assigning a device to a patient, *etc.*).

Through the use of this interface, the MAS and the SN can be viewed as a whole system where the different agents on the MAS are linked and depicted accurately in the SN.

## B.3 Service Implementation

One of the main challenges lies in the translation from the raw numerical values obtained through sensor logs to a friendly and meaningful description of the patient's performance. The MAS and SN have been developed within the specific domain of the *i*-Walker although it can be applied to other intelligent assistive devices. The agent of the *i*-Walker aims to collect all the data from the embedded sensors and send it to the Patient agent in an intelligible format. For each exercise a patient performs, the *i*-Walker generates a report containing accumulative variables extracted from the initial set-up and sensing measures: *(i)* start time and type of exercise; *(ii)* end of exercise; *(iii)* total walking distance; *(iv)* brake usage; *(v)* time spent in up or downhill; *(vi)* number of stops. The agent will pay special attention to critical events such as an excess of vertical or lateral forces, or the detection of possible falls.

The Patient Agent $a^{p_e}$ is responsible for handling the different events received, to process them and update the BDI database and generate messages to the appropriate agents in the system when necessary (see §**??**). When it detects *dangerous* events, the agent will create a warning or alert message and will contact the affected agents for each situation. It will also inform of every new exercise performed. The Patient Agent can generate three types of messages:

- **walker-new-exercise**: adds a `(B(Inform))` of a new exercise to the list of the current session;
- **walker-fall**: adds a `(B(Danger)) EventBehaviour` that defines the protocol that the affected agents must follow to handle this situation;
- **walker-vertical-force-alert** adds a `(B(Alert)) EventBehaviour` that defines the actions that might be taken in order to avoid a Danger situation (the same happens with **walker-horizontal-force-alert**, as both are indicators of a possible fall due to an excess of leaning forces) (see §)

When the system generates an alert message (`AlertVerticalForce`, `AlertHorizontal-Force`) or danger message (`AlertWalkerFall`), the $a^{p_e}$ will add a new task to be performed in the following cycles in case the situation is still not being tackled.

To reduce the processing time for each exercise, exercises will be grouped into sessions that will not last more than two hours. The agent will record some information related to the sessions performed with an *i*-Walker $w_{p_e}$, like maximum distance, walked or total distance walked, as well as a list of the last fifteen sessions. Once a session is finished, the agent generates a report that will be sent to the appropriate elements of the patient's SN. The report will contain a summary of the user's performance in terms of time, distance and amount of force used; a list of events generated during the exercise; a fictional estimation of the mood of the patient; and a trend in the patient's evolution. Also, a graphical tool is used to show the duration of each session, walking distance, initial configuration and type of exercise.

# Appendix C

# Research Activity

## C.1 European Projects

During the development of this PhD work I have been involved as a researcher in the following EU funded projects:

- ASSAM: Assistance for SAfe Mobility
  - The project aims to compensate for declining physical and cognitive capabilities of elderly persons by the user-centered development of modular navigation assistants for various mobility platforms, such as a walker, a wheelchair, and/or tricycle
  - AAL-2011-4-062
  - www.assam-project.eu
- IDONTFALL: Integrated prevention and Detection sOlutioNs Tailored to the population and Risk Factors associated with FALLs
  - Deploy, pilot and evaluate a range of innovative ICT solutions for fall detection and prevention management.
  - CIP-ICT-PSP.2011.3.1
  - http://www.idontfall.eu

From January 2016, I have been involved in the following EU funded project:

- CAREGIVERSPRO-MMD

  - Self-management interventions and mutual assistance community services, helping patients with dementia and caregivers connect with others for evaluation, support and inspiration to improve the care experience
  - GA No 690211
  - http://caregiversprommd-project.eu/

## C.2 National Projects

- Rehabilitación Personalizada y Adaptativa en Tratamientos Post-Ictus: el *i*-Walker. Funded by the national programme TIC. (TEC2011-29106-C02-02).
- Sistema Inteligente *i*-Walker: Rehabilitación Colaborativa (SiRC)". Funded by the national programme TIC. (TEC2014-56256-C2-2-P).

## C.3 Participation in research courses and/or seminaries

- SSTiC 2013. Universitat Rovira i Virgili (Tarragona), 22-26 of July 2013. This seminary offered 50 six-hours courses dealing with diverse topics in the whole spectrum of computer science. This seminar offered several scientific and technical conferences on e-Health and smart cities, and workshops to provide general training on communication skills that are needed to perform a thesis. Participation in a PhD seminar with an oral presentation and poster exposition.
- Introduction to ROS. A one-week introductory course about ROS technology and its applications in Universidad de Málaga projects. Seminar presented by Joaquín Ballesteros (Universidad de Mlaga) in November 2013.
- Impact of ageing on mental health and well-being, 29-30 of January 2014[1]. Topics discussed: factors involved in mental health and well-being in ageing population, prevention and management strategies to improve the quality of life and the economic and social burden concerning the older adults.
- The transparent brain. Universidad Internacional Menéndez Pelayo - Consorci de Barcelona (CUIMPB), 3-4 of July 2014. Topics discussed: the human connectome, recommender

[1] http://www.bdebate.org/en/forum/impact-ageing-mental-health-and-well-being

systems to predict human behaviour, personal digital assistants, human rights in the digital era.

- Ageing well: Falls. December 2014. Four weeks online course by the University of Newcastle from at FutureLearn (https://www.futurelearn.com/courses/falls). Topics discussed: Explore why people fall, discover practical methods to reduce the risk of falling and recognise when to seek expert help.

- EU Falls Festival. Stuttgart, Germany, 24-25 March 2015 (http://www.eufallsfest.eu/). Topics discussed: Technology in the prediction, detection and prevention of falls.

- Ethics of Artifical Intelligence. New York University (NYU), United States, 14-15 October 2016 (https://wp.nyu.edu/consciousness/ethics-of-artificial-intelligence/). Topics discussed: near-term and long-term future questions on artificial *vs* human moral values, personal data privacy and the development of ethical principles in specific technology fields.

## C.4 Participation in conferences

- A2HC Workshop (Agents Applied in Health Care), AAMAS 2015. International Conference on Autonomous Agents and Multi-Agent Systems. 4-8 of May 2015. Istanbul, Turkey (http://www.aamas2015.com/en/).

- TRANSED 2015. 14th International Conference on Mobility and Transport for Elderly and Disabled Persons. 28-31 July 2015. Lisbon, Portugal (http://www.transed2015.com/).

- CCIA 2015. 18é Congrés Internacional de l'Associació Catalana d'Intelligència Artificial. 21-23 October 2015. Valencia, Spain (http://www.uv.es/congressosdi/ccia2015/index.html).

- REHAB 2016. $4^{th}$ Workshop on ICTs for improving patients rehabilitation research techniques. 13-14 October 2016. Lisbon, Portugal (http://rehab-workshop.org/).

- CCIA 2016. 9é Congrés Internacional de l'Associació Catalana d'Intelligència Artificial. 9-21 October 2016. Barcelona, Spain (ccia2016.upf.edu/)

## C.5 Publications

1. *Using Multi-Agent Systems to mediate in an assistive social network for elder population.* C. Barrué, **A. Cortés**, J. Moreno, U. Cortés. A2HC Workshop, AAMAS 2015. (same paper as in 3).

2. *A fall prevention protocol using the* i-*Walker robotic rollator: the I-DONT-FALL project.* **A. Cortés**, C. Barrué, J. Moreno, F. Barban, M. Melideo, U. Cortés & R. Annicchiarico. TRANSED 2015

3. *Using Multi-Agent Systems to mediate in an assistive social network for elder population.* C. Barrué, **A. Cortés**, J. Moreno, U. Cortés. CCIA 2015.

4. *A Methodology for Pattern Detection in Walking Behaviours using the* i-*Walker.* J. Moreno, **A. Cortés**, C. Barrué, U. Cortés. CCIA 2015

5. *Using the i-Walker as a measurement tool for walking behaviour analysis.*, **A. Cortés**, A.B. Martínez-Velasco, J. Béjar. REHAB 2016.

6. *Assessing Falling Risk in Elderly with the Ten Meter Walking Test: A Machine Learning Approach.* **A. Cortés**, J. Béjar, C. Barrué, A.B. Martínez, U. Cortés. CCIA 2016.

7. *CAREGIVERSPRO-MMD: community services, helping patients with dementia and caregivers connect with others for evaluation, support and to improve the care experience.* Cristian Barrué, **Atia Cortés**, Ulises Cortés, Frédéric Tétard, Xavier Gironès. Computación y Sistemas. ISSN 1405-5546 (2017).

8. *Reducing Fall Risk with a Combined Motor and Cognitive Training in Elderly Fallers. I-DONT-FALL* Consortium. Brain Science Journal.

9. *Automatic classification of gait patterns using a smart rollator and the BOSS model* M. Ojeda, A. Cortés, J. Béjar, U. Cortés. PErvasive Technologies Related to Assistive Environments (PETRA) 2018.

### Submitted Papers

- *An Unsupervised Learning Approach for Gait Analysis using Human-Rollator interaction*, A. Cortés, M. Ojeda, J. Béjar, A.B. Martínez, U. Cortés. CCIA 2018

- *Stride-to-stride identification and analysis to characterise walking patterns in adults* A. Cortés, J. Béjar, A.B. Martínez

## C.6 Research stays and visits

- February 2013 (2 weeks). Research stay in ISIS research group at UMA, supervised by Cristina Urdiales
- May-June 2014 (4 weeks). Research stay in ISIS research group at UMA, supervised by Cristina Urdiales
- October-December 2014 (3 months). Research stay at Fondazione Santa Lucia, Rome, supervised by Dr Roberta Annicchiarico. Compulsory stay for European PhD mention.
- March 2015 (2 weeks). Visit Residencia Los Nogales, Madrid, supervised by Dr Nuria Montero

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