Smart technology for ageing in place

Machine learning for continuous sensor monitoring of the functional health of independently living older adults

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Ahmed NAIT AICHA

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Yesterday is history,
tomorrow is a mystery,
but today is a gift.
That is why it is called
the present.

MASTER OOGWAY

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1

General Introduction

1.1 Ageing world

The worldwide population over 65 years of age will more than double, from 617 million in 2015 to 1.6 billion, by 2050,[1] meaning that the proportion of older adults in the global population will shift from 8.5% to 16.7%. This shift is not equally distributed, as shown by the two maps in Figure 1.1, which demonstrate that Europe and Japan currently have the highest proportion of the $65+$ population and will retain that position by 2050. In addition, Asia and Latin America will have an accelerated increase of the $65+$ population in the upcoming decades, which will result in an enormous total number of the $65+$ population worldwide. The population in Africa, meanwhile, is at the moment young and will remain relatively young by 2050.

[1] Census report www.census.gov

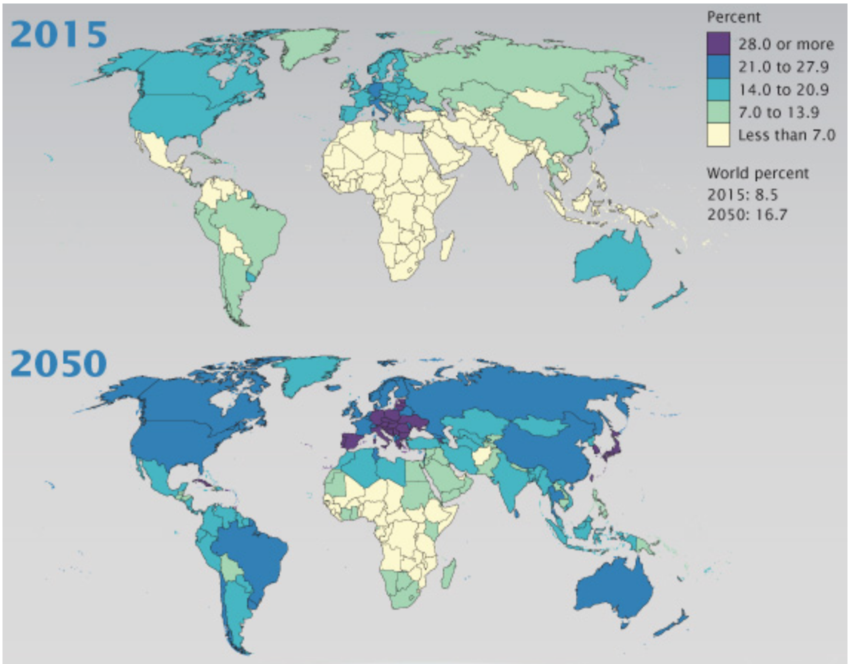

Figure 1.1: The distribution of the 65+ proportion of the population worldwide in 2015 and 2050. Figure taken from www.census.gov

There are two major reasons for the ageing worldwide population, according to the Census report. The first reason is the declining fertility rate caused by later marriage, better education about contraceptives and women choosing to pursue a career before having children. The second reason is the increasing life expectancy as a result of medical advances and lifestyle improvements. As people live longer, they pursue new activities such as a new career, an education or a neglected hobby. The functional health status of older adults is the major factor on which all these new activities depend. Functional health refers to the capability to perform activities that a person needs and wants to do, without being limited by pain or injury. Improving the functional health and independence of this part of the population is the focus of this work.

The process of ageing involves many unavoidable changes. Older adults can suffer from changes related to the decline of their cognitive and mental health, including the deterioration of memory and thinking, which may result in dementia and depression. In addition, they can suffer from changes related to their physical health, including problems of mobility (standing, walking, climbing stairs and carrying objects), agility (difficulty in bending, co-ordination and poor balance) and chronic pain (Sternberg et al., 2011). Ageing therefore has major implications for healthcare services. However, the ageing population is also an important resource in terms of human capital and therefore must be seen as an investment rather than a cost. By 2050, one in three Europeans will be over 65 years old. This ratio will have a huge impact on every market and industry, including home accommodation, transport, food, insurance, robotics and health, all of which must adapt to an ageing population as demographic change leads to new needs and to new markets for products and services (Tiago et al., 2016). All these markets will and must adapt to ageing population as demographic change leads to new needs and to new markets for products and services (Tiago et al., 2016). This Silver Economy (referring to the greying hair of the elderly) can be seen as an opportunity for economic growth as long as the older adults are healthy and able to live independently. Problems arise when these older adults suffer from mental or physical health issues resulting in the need for support in their activities of daily livings (ADLs). The support for some of these older adults can be on an incidental basis and easy to realize. For others, the support of several professional healthcare providers may be needed every day for the remainder of their expected life. The ageing of the increasing population will result in increasing demands from the healthcare system, and actions to address this pressure are therefore needed.

1.2 Addressing an ageing population

Countries have forwarded many suggestions for how to deal with the issue of an ageing population. Increasing income taxes and the retirement age are two examples of these solutions from an economic point of view, because they lead to more tax revenues, which can be partly invested in the healthcare system (Fine, 2014a,b). A disadvantage of these solutions is their unpopularity, especially among those near retirement age. Furthermore, these solutions do not solve the main problem of increasing demands placed on healthcare systems due to the worldwide increase in the ageing population. Another solution is a policy to encourage people to work in the healthcare sector in order to address the lack of caregivers. In particular, encouraging skilled immigrants to live and work in a country may solve a large part of the problem. In general, a policy that encourages an increase in the rage of immigration will result in an increase in the labour workforce of the country. This workforce will support a high proportion of the older population, because the healthcare services are organized, financed and delivered by the government in the majority of countries (McDonald, 2015, 2017). A disadvantage of this solution is that the proportion of the ageing population in the countries of origin of immigrants increases, making the problem worse in these countries. Another disadvantage of the immigration policy is that these immigrants will age and therefore contribute to the ageing population in the future. A long-term solution is to encourage child bearing in order to boost fertility rates. These children can look after their ageing parents. This solution will necessitate huge investment in the encouragement policies, such as creating a financial incentives depending on the number of children and providing cheap child care (Lutz et al., 2017). Unfortunately, this solution is difficult to effectuate, and the continued growth of the human population is untenable, given the planets finite resources. The other long-term solution is to maximize the quality of life and independence of the ageing population, so that the burden on society does not grow beyond reason.

Given the increasing older population, much discussion has surrounded who should be responsible for the elderly: the person him or herself, their family or the government? Some believe that the government should take care of older adults, as these elderly have paid their share to society through taxes. But this leaves the problem of those who have paid less taxes or were not able to pay taxes at all and whether the government should take care of them too. Others believe that children should take care of their parents as an obligation for being raised, as family is more likely to provide a more personal and comforting standard of care. But what if the families cannot provide adequate care for their elderly family members then who should take care of these older adults? Others still believe that the elderly themselves are responsible for their care, but this still leaves the question of what if the elderly cannot provide adequate care. This thesis does not aim to determine who should take care of the elderly. Ageing in place is emerging as the best solution for both the individuals, the family and the government. It is more economical and more closely aligned with the needs of the elderly population (Pereira et al., 2018; Wiles et al., 2012). Ageing in place has the benefit of allowing older adults to be supported in living independently in a familiar and safe home environment. For the family members, it offers greater ease to look after the health and well-being of the older adult. The current situation in developing countries compared to the non-developed countries is that the majority of older adults live in senior care facilities such as assisted living homes or nursing homes, for which the annual fees, usually paid by the government, are very high in comparison to aging in place.

1.3 Ageing in place

As people age, they undergo inevitable physical, mental and emotional changes. Their vision, hearing, movement and mobility may decline, and these impairments may affect, with varying severity, basic ADLs. Some older adults prefer to stay in nursing homes, where they are assisted in almost everything, in particular in healthcare. Those who choose to stay in their homes may have concerns about safety, taking care of their health and performing the ADLs. Living alone also increases the risk of social isolation and loneliness. Despite all these risks, however, the majority of older adults choose to continue to live at home rather than to be in assisted living facilities or nursing homes (N. Farber and Harrell, 2011; Steels, 2015), because ageing in place offers a strong feeling of independence and autonomy and allows individuals to maintain their social networks (Wiles et al., 2012).

Ageing in place requires modification to the home for safety and comfort. The major home modifications include making sure that there is a bedroom and bathroom on the first floor compliant with the needs of older adults (high bed and high toilet, grab bars in the bathroom). The minor home modifications include adding grab bars and a non-slip surface in the bathroom and a no-threshold entrance and improved lighting (bright and remote controlled) in the home. However, adapted housing is not sufficient. In addition, suitable healthcare is an important condition for the older adult to be able to age in place. This condition can be fulfilled using assistive technology, which is defined by the United Nations as technology adapted or specially designed to improve the functioning of people with disabilities (Rosenbaum and Stewart, 2004). Assistive technology for ageing in place refers to any piece of equipment, software or other tool used to support older adults in coping at home with little or no help from formal and informal care givers.

Examples of these assistive technology devices include fire alarms, medication devices and surveillance cameras. Assistive technology for ageing in place is expected to grow rapidly during the next few years.

1.4 Assistive technology for ageing in place

In order to age in place, older adults may require some tools and services to be able to accomplish their normal tasks and address new needs in their daily life. Examples of low-tech solutions include walkers, which can increase mobility for older adults who experience trouble walking; grab bars in the bathroom to support independently taking a shower without the fear of falling; and joining a voluntary organization for social activities to decrease the risk of social isolation and loneliness. These solutions improve peoples daily quality of life, but they do not address emergency situations, such as falls, strokes or other medical emergencies. Medium-tech solutions can provide help and peace of mind in these situations. Examples include a special button that older adults wear to call for medical assistance in case of emergency, an automated medication dispensing system to reduce the health risks associated with medication errors and a tablet designed for seniors to stay connected with distant family and friends, reducing the risk of social isolation and loneliness. Such medium-tech solutions still do not help when the person is incapacitated, however, and ideally, problems should be detected before emergencies arise. Technology solutions supporting this are referred as high-tech solutions. Research about the use of technology for ageing in place is rapidly emerging and is multi-disciplinary in nature. It has resulted in various devices used to support healthcare (Kruse et al., 2017). The authors of the survey Assistive Technology Devices and Applications for Ageing in Place provided a categorization of these devices with respect to the device types and their application (O'Brien and Ruairi, 2009). In this section, we describe the types of devices used in three emerging application areas, namely, health telecommunication, robotics for health and health monitoring devices.

The simplest form of health telecommunication or tele-health is to send text, audio or video messages for interventions using a cell phone. This form of tele-health is commonly used in lower-income nations (Durrani and Khoja, 2009) and may result in significant improvements in compliance with taking medicine, fewer missed appointments and more rapid diagnosis and treatment (Santosh Krishna and Balas, 2009). Examples of tele-health systems are the systems aimed to support older adults with medication compliance. These systems vary from standalone devices that operate independently to networked devices that are part of an advanced compliance solution that may communicate with an emergency response system. The major limitation of the tele-health tools is that their success is greatly dependent on the motivation of older adult and the support that they receive when using them (Kampmeijer et al., 2016). A recent population survey shows that a substantial proportion of the German population, mainly older adults, did not use smart phones or health apps (Ernsting C, 2017).

Another emerging assistive technology is the use of robotics for healthcare. Some robots have a primary function to support users with some disabilities in taking medications.

Other functionalities of the robots include entertainment using voice and video communication with the aim of increasing the quality of life of older adults. Deploying robots in the home environment of elderly individuals may have positive effects, reducing the utilization of primary healthcare (Orejana et al., 2015). The major disadvantage of the use of robots is that they are expensive for large-scale deployment due to the complexity of the incorporated technology, which may also introduce some technical challenges in rural settings.

Another example of assistive technology to support older adults in ageing in place while still having sufficient security standards in case of emergency is ambient technology. Ambient technology falls within the category of information technology and aims to help people in their everyday lives through a smart environment that is aware of their presence and is adaptive and responsive to their needs. To accomplish this, wireless sensor network (WSN) are used. A WSN consists of a set of autonomous nodes/devices that can communicate using a wireless protocol and are dedicated to monitoring the physical condition of an environment. The key advantages of WSN are their multi-functionality, low cost, energy-efficient sensors and ease of deployment. Some applications of WSN focus on the monitoring of ADLs with the aim of detecting odd conditions such as falling, wandering and skipping a meal. Other applications include medication intake monitoring, which aims to support older adults with medication compliance, as medication noncompliance is common in elderly people with cognitive disabilities. Ambient technology also has its limitations. The first is the wide variety of devices available. While the applications of WSN can be categorized into one or a combination of three classes environmental data collection, security monitoring and object/subject tracking the devices suitable for one application area can be widespread, which makes it difficult to choose the right device for a certain application. The second limitation is the privacy issue, as the devices are connected to the internet and the data is usually not stored in the elderly persons home, but elsewhere. While ambient sensors can provide rich, unobtrusive information that is not privacy-sensitive, a deficiency in the security and handling of the data may leave the subjects data vulnerable. Even if the collected subjects data is secure, it can be used by the device supplier for other purposes. The third limitation is the algorithms in the ambient system. The usability of ambient systems largely depends on the intelligence of the software used for decision-making. A good performance of the implemented algorithms results in a device that performs well, and vice versa. The performance of the algorithms usually depends on the quality of the collected data sets. The analysis of these data sets is, however, challenging for several reasons, including the presence of a lot of noise in the data and the lack of accurate labels. The focus of this thesis is the development and use of machine-learning algorithms for the purpose of monitoring the functional health condition of older adults, in particular detecting changes in health condition. This thesis is part of a healthcare monitoring project that aims to use pervasive technology to support older adults in independently living longer in their own homes and their familiar, safe environment.

1.5 Focus of the thesis

The purpose of this thesis is the improved monitoring of the functional health condition, and changes thereto of older adults living alone. To achieve this, this research is focused on the systems for the monitoring of the activities of older adults, such as bathing, going to the toilet and preparing meals using networks of ambient and wearable sensors. Monitoring these activities allows the detection of change in these activities and their execution. This change may be an indication of a change (usually a decline) in the functional health condition of the older adult.

Most studies on activity recognition, anomaly detection or trend detection assume that there is only a single resident in the home. The sensor data analysed for these studies consist of sensor readings collected while only the subject monitored is alone at home. In reality, the resident may receive visits from family members and care givers. The target group of this thesis are older adults living alone and willing to age in place and maintain their independence. Some of these subjects are dependent on some facilities, such as a cleaner, while others are independent of formal or informal care givers. The sensor data collected for this thesis consists of sensor readings obtained over several years of monitoring the subject. Older adults living together are not taken into account in this thesis, as they can take care of each other and can act as monitors of each other. The first part of this thesis focuses on the methods to detect visits to the older adult. Detecting and analysing visits allows for more accurate automatic activity recognition and gives insights in the social life of the resident.

Many studies on the monitoring of ADLs focus on the recognition of ADLs and therefore on the metrics for the measurement of these activities, such as number of steps per day and the duration of the sleep time. More important is the measurement of the ability of older adults executing their ADLs. In other words, it is better to focus on the quality of the ADLs of older adults over time. As we are interested in the change in the execution of ADLs, especially a decline in ability, we focussed on the factors that cause this decline in the ability to independently execute these activities. Two important factors are investigated in this thesis: decline of gait velocity and risk of falling.

Gait velocity is an important predictor of functional health that is shown to predict the risk of falling (Montero-Odasso et al., 2005; Quach et al., 2011), as well as hospitalization and survival (Studenski et al., 2011). For that reason, gait velocity is an important measure in comprehensive geriatric assessment in clinical settings. The disadvantage of the clinical assessments is that the tests are usually carried out over a short period of time in an unnatural setting using dedicated sensors. Moreover, the measurements may be subjective to the therapist and are also sensitive to the white coat effect. In this thesis we focus on the continuous measurement of gait velocity in an objective manner using data collected in a natural environment from an ambient WSNs.

Falls among older adults are one of the major functional health problems that lead to a decreased quality of life and increased morbidity and mortality. More than one-third of community-living older adults fall each year. Moreover, approximately 10% of falls result in a major injury, such as a fracture, serious soft tissue injury or traumatic brain injury (Tinetti and Kumar, 2010; Tinetti and Williams, 1997). Existing models for the assessment of fall risk of older adults use handcrafted extracted features (Rispens et al., 2015b; van Schooten et al., 2015). These features rely on the expertise and experience of the movement scientist. In this thesis, we focus on the prediction of fall risk using deep learning methods on accelerometer data acquired in the home environment. Compared to conventional models, deep learning methods have the advantage of automatically extracting the best features from the data.

1.6 Contributions

The main purpose of this thesis is to use sensor monitoring collected in a smart home using an ambient and wearable sensor networks to support a healthy and active ageing in the home environment. Based on this and on the information presented in the previous sections, the main contributions of the thesis are as follows.

Visit detection: The first contribution of this thesis pertains to the detection of visits to older adults from ambient sensor data. Such visits can be occasional or regular, and modelling this allows more accurate and more informative visit detection. We explored both supervised and unsupervised methods to detect visits to the homes of older adults. A Markov modulated multidimensional non-homogeneous Poisson process (M3P2) allows us to incorporate multiple feature streams. The nonhomogeneous property allows us to model weekly and daily cycles.

Gait velocity: The second contribution of the thesis pertains to the continuous measurement of the gait velocity (indoor walking speed) of the elderly from unconstrained sensor data. Many studies have showed that gait velocity is an important predictor of functional health. We have developed a method to collect walking trajectories and calculate their duration and length in a simultaneous manner.

Fall risk assessment: Early detection of high fall risk is an essential component of fall prevention in older adults. The third contribution of the thesis pertains to the assessment of fall risk using deep learning methods. Fall risk assessment is a process in which the probability of a future fall is estimated, usually within a time frame of six to twelve months. We showed that applying deep learning models to accelerometer data acquired in the home environment provides comparable accuracy to conventional models in the assessment of fall risk, with the advantage that these models do not rely on handcrafted extracted features.

1.7 Outline of the thesis

This section provides a brief overview over the thesis chapters.

The general introduction provides a description of the ageing population in the world, the opportunities and the issues regarding this population, different strategies for how to deal with this issue and the role of assistive technology to support ageing in place.

The background and related work chapter provides an overview of the related work, describing the role of the smart home in elderly (health) care and describing related work in the area of visit detection, measurement of walking speed and fall risk assessment.

Visit detection: Most of the research on smart homes assumes that a living space is occupied by a single person, the resident. In reality, older adults could receive guests such as care professionals and family members. This chapter provides a description of the methods used to detect regular and irregular visits of the older adult in the smart home. The chapter also provides a description of the data sets used for both visit detection and continuous measurement of gait velocity. This chapter is based on the work published in Nait Aicha et al. (2014) and Nait Aicha et al. (2013).

Continuous measurement of walking speed: Many studies have showed that gait velocity is an important predictor of functional health. This chapter describes the method for the continuous measurement of gait velocity. The chapter provides a description a description the challenges involved when dealing with collection of the walking trajectories and gives a description of different ways to (simultaneously) calculate their duration and length. This chapter is based on the work published in Nait Aicha et al. (2015).

Fall risk prediction: Early detection of high fall risk is an essential component of fall prevention in older adults. Conventional methods to assess fall risk rely on handcrafted extracted features, which is time consuming. This chapter provides a description of several deep learning methods applied to accelerometery truck data to assess fall risk. First, the data set is described. Then, a set of deep learning methods are compared to the conventional methods and to each other. This chapter is based on the work published in Nait Aicha et al. (2018).

General conclusions: This chapter summarizes the overall conclusions of the thesis, as derived from the previous chapters.

2

Background and Related Work

This thesis describes the research on systems for monitoring the daily activities of older adults using sensors installed in their homes (smart homes). In particular, the detection of changes in the execution of these activities may be an indication of a change (usually a decline) in the functional health condition of the older adult. This chapter begins with a description of smart homes, providing a definition, categories, background and an overview of how they have developed in the past two decades. The ambient sensors used in the smart home of this thesis are binary sensors and do not have the ability to distinguish the resident from visitors. This is problematic for models of resident behaviour, and in the second section, we describe work related to the problem of visit detection, its relation to the identification problem and how these problems can be solved.

Many studies have shown that gait velocity is an important predictor of the functional health of older adults. The third section describes work related to the assessment of walking speed in relation to walking ability and how to continuously measure this velocity in a smart home. The fourth section describes work on another important predictor of functional health, that is, the assessment of fall risk, presenting work on the possibilities of digital technology to support fall risk assessment. The fifth section introduces how data-driven methods can be used for the automatic analysis of sensor data and sets the stage for the algorithms proposed in this thesis. We focused on algorithms related to visit detection, continuous measurement of indoor walking speed and the assessment of fall risk in a smart home.

2.1 Smart homes

Smart homes have been researched for more than two decades. A pioneering work in this area is the Smart Rooms project of MIT, which resulted in a system that can be sued to track people in an environment and interpret their behaviour (Darrell et al., 1997; Pentland, 1996). During these two decades, many definitions were provided for a smart home, for example, by Lutolf (1992) and Allen et al. (2001). A smart home is defined as a home equipped with computing devices (such as sensors and actuators) and information technology (such as WSNs) which anticipates and responds to the needs of the resident.

An example of a simple smart home is a home in which the lights in a room automatically turn on when the resident enters the room. An infrared sensor installed in the room detects a person entering the room, and an actuator in the switch turns the lights on. For a more complex smart home, one can imagine a smart home consisting of many smart devices, each with a different purpose. For example, a smart doorbell can allow an older adult with limited mobility to see who is at the door. Using his or her smart phone connected to the smart lock, the individual can open the door for the visitors without needing to walk to the door. A smart speaker, such as Amazon Alexa or Google Assistant, allows an older adult to use his or her voice to turn lights on and off without needing to walk. Smart hallway lights with motion sensors turn on when the older adult gets up in the night to use the bathroom, which helps prevent falls. Wearable smart fall sensors automatically send an alert to relatives and to emergency assistance if the older adult does fall and cannot get back up.

During the first decade of in the emergence of smart homes, the major review papers categorized the smart homes into three categories: 1) health care smart homes, aiming to provide assistance to occupants by recognizing their actions; 2) comfort smart homes, aiming to ease the daily life of older adults by increasing their comfort; and 3) security smart homes, providing surveillance systems able to alert residents in case of security threats (Alam et al., 2012; Silva et al., 2012). Recent review papers identified more specific categories of smart homes (Kon et al., 2017; Pal et al., 2017). For example, environmental monitoring smart homes (smoke-detectors, electronic door openers) aim to satisfy the physiological needs of the elderly and provide them with a sense of safety, while social communication smart homes aim to reduce social isolation and depression by connecting older adults with family and friends and physical activity smart homes aim to stimulate older adults in maintaining an active lifestyle by providing programs ranging from exercise applications to behaviour recognition systems.

The major focus of the research on the smart home during the first decade was the recognition of activities of daily living, such as walking, sitting, bathing and cooking. The smart homes were in general labs at the university, and the students were asked to participate in the research. To recognize these activities, the participants were asked to conduct some activities in a certain order. Students and researchers were responsible for collecting and labelling the data. The machine-learning algorithms used to recognize these activities from the data usually achieved high performance because of the limited number and variety of activities, the clean data collected and the presence of accurate labels. In recent years, there has been a shift in the smart homes used from university labs to living labs. Some research on smart homes is still conducted at the university, but instead of using students as participants, older adults are asked to conduct some activities of daily living in a certain order. The reason for this shift is the large difference in the execution of activities between younger and older adults. In some studies, the older adults are asked to live in the lab for a short period of time, ranging from a day or a night to a week, depending on the aim of the research. This is done because it is easier, quicker and cheaper to transform the university lab into a living lab than to shift the equipment needed to monitor the older adults and collecting data in their home. The equipment usually consists of sensors developed at the universities and sophisticated cameras that collect the labelled data which is required to analyse behaviour. The acceptance and adoption of this technology in a home situation is usually beyond the scope of the research. The development of miniature sensors, however, especially wearable sensors, has resulted in more research in the homes of older adults (the wild). The ease of deployment and use of such miniature sensors has increased the use of these sensors by older adults in their daily routines, even while sleeping (Deen, 2015; Mendona et al., 2019). This has resulted in the emergence of technology for ageing in place. This new miniature technology used in the home environment has now given rise to new issues with respect to acceptance and adoption (Kruse et al., 2017).

The two most important factors which appear to affect the adoption of technology for ageing in place are privacy and high costs (Peek et al., 2014). With respect to the first factor, various studies have shown that older adults are willing to give up some privacy, such as sharing monitoring information with family members and health professionals, as long as using the technology is beneficial to them (Boise et al., 2013; Fischer et al., 2014). The use of cameras is considered to be the most serious privacy issue in the monitoring of older adults. With respect to the second factor, high costs can be monetary, as well as non-monetary, such as the time and effort needed for the adoption and the use of the technology.
Ambient sensors, such as motion, contact and pressure sensors, installed in the home of the older adult seem to be able to address both privacy and high cost problems. These sensors provide rich, unobtrusive and non-privacy-sensitive information. In a comprehensive review of smart homes that are related to ambient assisted living projects, the authors included different types of ambient-sensor-based monitoring technologies and concluded that ambient sensors are able to collect relevant data while preserving the privacy of the user (Uddin et al., 2018). Moreover, these sensors see high acceptance by the elderly due to their unobtrusive monitoring characteristic.

The problem that arises when using ambient sensors to monitor the elderly is the identification problem: It is difficult to identify the source of the data using these sensors, because they do not record any audio or video information. Especially, when dealing with smart homes inhabited by more than one person and possibly by pets (Benmansour et al., 2015). In this situation, known as the multi-occupancy problem, data association and interaction must be taken into account. The multi-occupancy problem is not within the scope of this thesis, because the purpose of the thesis is to predict changes (usually a decline) in the functional health condition of the *single* resident. In a smart home with multiple occupants, the residents can take care of each other and alert health professionals in case of emergency. The problem of identifying the resident from the collected data remains an issue in a single-occupant smart home, however, as the resident often receives visitors such as family members and healthcare professionals.

To summarize, while the first smart homes consisted of labs at universities simulating the living areas of older adults, recent smart homes have used the living areas of the elderly as labs (living labs). These living labs are set up in such a way that the data generated by the older adults is collected and stored without disturbing their normal day and night patterns. This setup results in the collection of rich real-life data sets, which make it possible to analyse some behaviour of the resident. The analysis of these data sets using machine-learning algorithms is, however, challenging for several reasons, including the presence of a lot of noise in the data and the lack of accurate labels. The first problem that rises when dealing with data collected in living labs is the identification of the source of the data. When researching some behaviour of an older adult who is being monitored in a living lab, it is important to know that the data analysed is generated by the older adult himself and not by visitors. The following section describes different means of solving the problem of visitors that have been proposed in the literature.

2.2 Visit Detection

This thesis describes the monitoring of the daily activities of older adults living alone in their homes for several years. As the residents may receive visits from family and caregivers, it is important to distinguish the activities of the visitors from those of the resident. There are two possibilities for dealing with the monitored activities with respect to the collection of data: a) Monitor the activities of both the resident and the visitor simultaneously or b) monitor the activities of the resident and ignore those of the visitor. The first case is known as the identification of multiple persons in a smart home (identification problem). However, the identification problem is outside the scope of this thesis, because our purpose is to detect changes in the functional health of the resident and not of the visitor. In this section, we describe the background and related work on possible ways to deal with the detection of visits in a smart home.

During the first decade of the emergence of smart homes, the majority of research was based on experiments executed in a lab at a university. The focus of this research was the recognition of predefined simple activities of an individual person. The activities were usually scripted and carried out by the researchers or students. Research experiments involving more persons aimed to recognize interrupted or interwoven activities (Crandall and Cook, 2010). Over the years, smart homes have shifted from university labs to living labs, and the duration of the monitoring periods has increased to several months or even years. The resulting increase in extraneous data from visits can be dealt with in three ways:

1. The resident or the visitor manually indicates the visits.
2. An additional device is used to detect the visits.
3. Sophisticated algorithms are used to detect visits based on existing sensor data.

The remainder of this section addresses these three methods.

Manual indication of visits:
Manual actions from the resident or visitor are usually used in case the research experiments last only a few days to a few weeks. If the resident is required to manually indicate visits to a recognition system, this results in a number of unintended consequences. First, the resident can forget to indicate a visit or the end of a visit, resulting in a corruption of the data. Even if the resident performs the indications perfectly, the mere act of indicating visits modifies the residents normal behaviour and is detrimental to activity recognition.

This latter point can be solved by asking visitors to indicate visits to the system but leads to practical problems due to visitors not being familiar with the system.

Use of additional devices:
Visual sensors are a popular type of sensor used in several research projects to solve the identification problem in general and the detection of visitors in particular(Skubic et al., 2009). Because of their ability to record and store audio and images of the resident, the processing and analysis of this type of data results in well-labelled data sets and good performance of the developed algorithms. Privacy, however, remains a major issue when using such sensors in the living labs, as these devices can record sensitive information on the resident, especially video material. To address the privacy issues, approaches such as silhouettes, depth images and low resolution images are used instead of raw video material. For example, Banerjee et al. (2012) extracted the silhouettes of the persons from the videos and used them as features to detect visits. Clustering techniques are used with the hypothesis that each residents data will cluster and the visitors will appear as outliers. In another study aiming to evaluate the socialization level of the older adult, the authors used a low-resolution visual sensor network to detect the visitors (Eldib et al., 2015). The privacy concerns are generally best addressed by executing the processing and the prediction tasks locally on the camera device. The disadvantage of this method is that the requirements of the camera devices (CPU, memory and GPU) are high, which make them expensive for deployment in living labs.
To address the privacy issue in situations in which the experiments last for a long period of time, nonvisual wearable sensors are usually used to solve the identification problem. For example, in a research project aiming to detect abnormal behaviour in older adults suffering from dementia, the authors solved the visitors problem using an radio-frequency identification (RFID) reader located next to the front-door. Visitors are asked to wear a badge containing an RFID tag during their visits and to use it to register their entrance and leaving times (Lotfi et al., 2012). In another study, Hu et al. (2017) incorporated the activity data from a Fitbit activity tracker (wearable watch) into the ambient sensor data to improve the performance of the visitor detection algorithm. Recent research showed the possibility of estimating the number of occupants in a room by using environmental sensors able to measure environmental parameters such as temperature, humidity, pressure and CO_2 concentration (Jiang et al., 2016; Wolf et al., 2019). The disadvantage of this type of CO_2 sensor is that the accuracy of the detection is small when the number of occupants is small (less than four persons), which is often the case when detecting visits in smart homes designed for the elderly.

Use of sophisticated algorithms:
A better way to detect visits is to use the same data collected for monitoring the functional health to also detect the visits. This method works well because the collection and processing of the data is reduced to one set using a single monitoring system. In addition, no need to use additional devices means no need for additional maintenance of the devices and the related software systems. However, the identification problem is very challenging because the same data set collected for the monitoring is also used for another purpose (the detection of visits). This challenge is even bigger in smart homes consisting of ambient sensors, which do not record any audio or video and only generate binary data. Singla and Cook (2009) addressed this problem and demonstrated an ability

to identify multiple individuals and their activities in a smart home using hidden Markov models (HMMs). The disadvantage in this study is that the smart home used for the experiments was very dense, consisting of more than fifty sensors, and in addition, the occupants were students. In a study aiming to automatically observe and model the daily behaviour of older adults, the authors used anomaly detection techniques as a method to detect visits (Aran et al., 2016). The disadvantage of this method is that the collected sensor data in living labs may contain many anomalies which do not correspond to visits, for example, a sensor failure or a change in the daily routine of the subject due to health problems. Another disadvantage of the proposed anomaly detection technique is that the regular visits (same time and same duration) are not seen as visits.

In this thesis, we focus on the detection of changes in the functional health of older adults living independently and alone. We therefore propose a method to detect visits to older adults when dealing with only ambient sensors. Inchapter 3, we describe this method and how we are able to detect both regular and irregular visits in an unsupervised manner.

2.3 Continuous gait velocity measurement

In the first decade in which smart homes were emerging, the walking ability of older adults was assessed in a clinical setting. Typical assessment tests include the Berg balance scale (BBS) test (Berg KO, 1989) and the timed up and go (TUG) test (Podsiadlo and Richardson, 1991). For these tests, the subject is asked to walk a distance of three to five meters, and the occupational therapist measures the walking speed using a stopwatch. The major advantage of these tests is that they are simple and have the ability to provide a global indication of the walking ability of the subject, but the tests also have many disadvantages. The accuracy of these tests may be inconsistent, as they rely on the experience level of the assessor, the mood of the subject during the test and the environment in which the tests are conducted. Furthermore, these clinic-based tests do not provide a complete picture of the true physical state of the elderly individuals, because the walkway in a clinical setting is not representative of the complex environment of a home setting. To address these problems, several sophisticated home setups have been developed in recent years. The assessments are therefore shifted from a clinical to a living environment, which supports continuous gait assessment.

In a living environment setup (smart home), two types of device are usually used: wearable devices and ambient sensors. The majority of wearable systems designed for the analysis of gait are incorporated in shoes, belts or wristbands (Bamberg et al., 2008; De Rossi et al., 2011; Xu et al., 2012). The sensors used for such systems are mainly pressure sensors and pedometers. An additional advantage of insole-based solutions is the possibility of continuously measuring the weight of a subject, especially for frail older adults (Campo et al., 2015; Charlon et al., 2018). Belt- and wristband-based solutions are suitable for long-term measurement of the physical activity, but not for measuring indoor walking speed, and pedometers significantly underestimate the gait velocity of older adults (Cyarto et al., 2004). In general, the major disadvantage of wearable devices for gait analysis is that the subject must not forget to wear the device and must recharge it regularly. The acceptance of wearable sensor applications for indoor long term monitoring is therefore low.

The majority of ambient systems can be grouped into visual and non-visual sensors. The visual sensors have been widely investigated for human activity analysis. For example, Wang et al. (2013) used a low-cost webcam-based system to extract gait parameters including walking speed, step time, and step length from silhouette images. Stone and Skubic (2011) evaluated the use of the Microsoft Kinect for passive gait assessment against an existing web-camera-based system. Among other limitations such as lighting condition and occlusion, privacy remains one of the largest concerns in the long term implementation of a visual system in real-life smart homes. The most used non-visual sensors are passive infrared sensors, contact switches and pressure mats. These devices are popular because they are simple, ambient and cheap. Furthermore, they can be deployed in smart homes without affecting the daily life routines of older adults, as they can be incorporated into furniture such as bed, couch or closet. A network of these sensors has been successfully used for = investing purposes, such as the assessment and monitoring of gait and balance parameters (Kasteren et al., 2010; Rantz et al., 2008; Skubic et al., 2009). To calculate walking speed, sophisticated systems have been developed such as smart carpet (Cantoral-Ceballos et al., 2015) and smart floor systems (Muheidat et al., 2017). An example of a system incorporated in furniture is the TUG chair, introduced by Frenken et al. (2011) and used for the automated assessment of TUG parameters. Walking speed is measured by incorporating force and laser sensors into a chair. The disadvantage of these sophisticated systems is that they are expensive for large-scale implementation.

An emerging solution for the human gait analysis is to use the Doppler radar sensor (Boroomand et al., 2018; Diraco et al., 2017; Rui, 2017), which is popular because of its multiple functionalities. The sensor can distinguish humans from pets and can detect the presence of a subject in an environment and measure their speed. fast Fourier transform (FFT) is usually used as a technique for the processing and analysis of the raw signals. Doppler radar sensors have the advantage that they are non-obtrusive and that their signals can penetrate through walls, which makes them suitable for installation in closets. However, the sensor may not have a wide viewing angle compared to a passive infrared sensor. Therefore, distributing several sensors in a smart home is necessary to cover each room. The application of multiple radar sensors in a smart home is an open research area.

In chapter 4, we propose a method for the continuous measurement of gait velocity using a network of simple ambient sensors. One of the reasons is that this kind of sensor is already installed in many smart homes for long-term purposes, such as the reduction of energy usage and lifestyle monitoring. The data collected for these purposes can also be used to calculate the walking speed of older adults.

2.4 Digital technology for fall risk assessment

About one-third of people older than 65 years and a half of those older than 85 years fall at least once a year. A significant portion of those falls leads to injury-related hospitalization. Falls among older adults are one of the major health problems that lead to a decreased quality of life and increased morbidity and mortality. In addition, falls pose a high cost to public health services (Cameron et al., 2018; Rubenstein, 2006). Most falls occur in the home or in the immediate home surroundings while older adults are undertaking their usual daily activities.

Fall risk factors are generally categorized into intrinsic and extrinsic factors. Intrinsic factors are related to the subject and include factors such as cognitive decline and muscle weakness, while extrinsic factors include the use of medication and environmental hazards. Among these risk factors, a history of falls and gait and balance disorders have been identified as strong predictors (Deandrea et al., 2010; Rispens et al., 2016; van Schooten et al., 2015). For effective fall prevention, it is important to identify those older adults with a high risk of falling and determine the appropriate interventions to reduce the risk of future falls (Ambrose et al., 2013).

Fall risk assessment is a process in which the probability of a future fall is estimated, usually within a time frame of six to twelve months. In many of the intervention programs proposed for fall prevention, fall risk assessment is performed as the initial step to identify persons at the highest risk. The assessment of fall risk is commonly conducted in a clinical setting and based on questionnaires and functional tests of mobility such as the TUG test (Podsiadlo and Richardson, 1991), the performance oriented mobility assessment (POMA) test (Tinetti, 1986) and the BBS test (Berg KO, 1989). These tests are carried out by specialists who observe the quality of a patients gait during the test. The questionnaires are also carried out and evaluated by specialists. The disadvantage of these validated clinical assessments is the subjectivity of the assessment, which may have a negative effect on the diagnosis. Retrospective studies (looking backwards and examining fall history) and prospective studies (tracking fall occurrences during the study) are other techniques to assess fall risk. Retrospective studies have the disadvantage that subjects recollection of falling may not be reliable, which affects the fall risk assessment (Cummings et al., 1988). Furthermore, a history of falling may lead to a fear of falling, which can therefore affect the gait pattern of the subject, which in turn affects the assessment of fall risk. For the assessment of future fall risk, prospective studies are more suitable compared to retrospective studies. The use of novel technology in prospective studies offers the possibility of accurately monitoring and evaluating gait characteristics, which may provide an accurate and objective fall risk assessment.

Much research has been conducted on the use of digital technology for fall risk assessment (Howcroft et al., 2013; Rispens et al., 2015b; Weiss et al., 2013). This research has resulted in a lot of technological devices supporting the detection, assessment and prevention of falls. The variety of these devices is huge and dependent on the setting in which they are used (acute hospital or at home), who is using them (non-fallers or recurrent fallers) and the objective of the use (detection or assessment). For example, an alarm button integrated in a bracelet is useful to detect falls in a home setting for recurrent fallers but is unsuitable for a person who has physical or cognitive impairments, as they may experience difficulty pushing the button or forget to wear the bracelet. Another example is the incorporation of balance training games in a fall prevention program using devices such as a Wii balance board or a Kinect. These games can be useful for non-fallers but are unsafe for recurrent fallers. The devices used for the assessment of fall risk can be categorized into non-wearable and wearable sensors.

Non-wearable sensors consist of two major categories: visual and non-visual sensors. Microsoft Kinect is the most used example of a low-cost visual sensor to assess fall risk (Ejupi et al., 2016; Stone and Skubic, 2015). The Kinect provides the possibility of tracking joints in the body without the need for markers or any calibration process, but the major disadvantage is the privacy concern. Pressure sensing systems such as the Wii board (Clark et al., 2018; Young et al., 2011) and smart floors (Daher et al., 2017; Muheidat et al., 2017) are the most used non-visual sensors for fall risk assessment. This type of sensor provides accurate information about the postural stability and gait pattern of the subject. A disadvantage of these sensors is that they are expensive to deploy in a home setting. In addition, motion ambient sensors such as radar and laser sensors are emerging due to their capacity to unobtrusively track movement.

Wearable sensors are increasingly applied for gait and balance assessment due to their low cost and light weight. In a systematic review focusing on the use of wearable sensors, Howcroft et al. (2013) concluded that inertial sensors have the potential to provide objective fall risk assessment in older adults. An additional advantage of the use of wearable compared to non-wearable sensors is that the subject is identified by the sensor that he or she is wearing. Another advantage is their portability, meaning that they can be deployed in a variety of settings, including a home. The sensors can be incorporated in clothes and shoes, which makes them feasible for the measurement of various body segments. From the measurements of a wearable sensor, several features related to the quantity of the movement of the subject, such as the duration and intensity of activities, can be extracted from the sensor data. Features related to the quality of the movement of the subject, such as gait stability, variability and smoothness can also be extracted from the sensor data collected by inertial sensors (Doi et al., 2013; Rispens et al., 2015b; van Schooten et al., 2016; Weiss et al., 2013).

Digital technology has been shown to have the potential to provide an objective, accurate and inexpensive means of assessing fall risk through the extraction of both quantitative and qualitative movement characteristics of the subject (Sun and Sosnoff, 2018; van Schooten et al., 2016; Weiss et al., 2013). The extraction of these features from sensor data is, however, preserved for professionals in the biomechanical research area. The feature extraction is time consuming, however, in case of a lack of knowledge and experience in this area. The models used for the analysis of the data by the biomechanical researchers, meanwhile, are not sophisticated. In chapter chapter 5, we explored deep learning models for the assessment of fall risk. We automatically distilled features from raw sensor data, which has the advantage that the probability of missing features is small compared to the way biomechanical features are selected. The performance of the deep learning models is compared to a base model which used biomechanical features to assess fall risk. The sensor data used was collected during a prospective study that lasted for more than one year. This data came from wearable sensors, because the monitored area is the subjects home and its surroundings.

2.5 Data Processing and Analysis

The typical architecture of a smart home system consists of at least four layers: The bottom layer consists of the hardware such as sensors and actuators. The top layer is an application layer in which different types of applications can be built, such as fall alarms or a rehabilitation feedback. These two layers are connected through a communication and an information layer. The communication layer is responsible for the transportation of the raw sensor data to the information layer, in which the data is stored, processed and transformed so that it can be analysed by the algorithms in the application layer.

The algorithms in the application layer are considered to be the main step in the data processing and analysis phase. They solve the main problem in the smart home according to manually predefined rules or by learning from data (machine learning). Compared to rule-based algorithms, machine-learning algorithms are less predictable, require less to no human intervention to update and are much easier to maintain. Especially when dealing with a system with too many rules, adding new rules without introducing contradictory rules is almost impossible. Applying rule-based systems to monitor older adults is thus not preferred, because it is too complex to capture the daily activities of the older adult in the form of rules, and even if it were possible, these activities evolve over time, and it is nearly impossible to capture these changes.
Data-using algorithms can be divided into two main categories: supervised learning and unsupervised learning algorithms. Supervised learning algorithms use labelled data from which to learn, which means that the algorithm is trained to learn some task or behaviour using labelled data, after which the trained model is applied to new, unseen data to predict the learned task/behaviour. For example, Kasteren et al. (2010) used supervised techniques to classify the activities of daily living. Labelled data is used to learn the machine the relationship between the activities and raw sensor data. Unsupervised learning algorithms learn from unlabelled data. These algorithms are able to discover new patterns from data without the use of labels. For example, Banerjee et al. (2012) used clustering techniques as an unsupervised method to detect anomalies from sensor data. The hypothesis is that the residents data (daily rhythm) is captured in clusters and that anomalies appear as outliers.

The major disadvantage of supervised learning technique compared to unsupervised technique is the labelled data-sets have to be available. Especially when dealing with data collected in the wild, it is difficult to collect labels without affecting the daily routine or privacy of the older adult. The approach we used in chapter 3 to detect the visits is fully unsupervised. The method is based on the Markov modulated Poisson process (MMPP) but is extended to allow the incorporation of multiple feature streams. Markov modulated poisson process models are composed of a stochastic process component, representing observed events over time (sensor transitions, in our case), and a latent component, which modulates the observed process (visits, in our case). For the continuous measurement of the indoor walking speed of the older adult, we also used unsupervised methods, as described in chapter 4. Indoor walking paths of the resident are collected from the data and modelled as trajectories in a graph. The length and duration of these trajectories (the sequence of sensor events) are simultaneously estimated by solving a set of equations using the least squares method. The analysis of the data showed that the majority of the walking paths of the resident are interwoven with some activity. Therefore, the estimation of the duration is done by fitting a probabilistic model, consisting of a mixture of a Poisson and a normal distribution, on the collected data.

In chapter 5, we studied the use of deep-learning neural networks by supervised learning to model fall risk on the basis of accelerometer data. The collected sensor data was subject of a study of fall risk factors and consisted of a population of 296 older adults. Fall incidences and descriptions (labels) were obtained monthly during a six-month follow-up period (Rispens et al., 2015a; van Schooten et al., 2015, 2016). Deep-learning methods can be applied as a supervised and as an unsupervised method. Because of the presence of labels, we trained three deep-learning model architectures convolutional neural networks (CNNs), long short term memory (LSTM) networks and ConvLSTM which is a combination of these two architectures to predict fall risk. The ground truth (labels) needed for the training of our models consists of the fall incidences, which were collected monthly. No further labelling of the sensor data was needed. These trained deep-learning architectures are compared to each other and to the strong baseline model, which uses biomechanical features. The advantage of deep-learning techniques is that the features are automatically distilled from raw sensor data, with the advantage that the likelihood of missing features is small compared to the way biomechanical features are selected. The performance of the three deep-learning architectures compared to the baseline model with biomechanical features showed comparable accuracy. Fine tuning the deep-learning models using multi-task learning resulted in significantly better performance. Further fine tuning by excluding the non-gait data samples resulted in even better performance.

In summary, this thesis proposes and evaluates methods to continuously monitor functional health by applying state-of-the-art machine-learning algorithms to raw sensor data collected in the wild for the purpose of detecting visits, continuously measuring walking velocity and predicting fall risk.

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3 Unsupervised Visit Detection in Smart Homes

Assistive technologies for elderly often use ambient sensor systems to infer activities of daily living (ADL). In general such systems assume that only a single person (the resident) is present in the home. However, in real world environments, it is common to have visits and it is crucial to know when the resident is alone or not. We deal with this challenge by presenting an novel method that models regular activity patterns and detects visits. Our method is based on the Markov modulated Poisson process (MMPP), but is extended to allow the incorporation of multiple feature streams. The results from the experiments on nine months of sensor data collected in two apartments show that our model significantly outperforms the standard MMPP. We validate the generalisation of the model using two new data sets collected from an other sensor network.

3.1 Introduction

Intelligent technology that supports elderly to live independently needs information about their activities. There is an increasing interest in networks of ambient sensors, such as motion detectors and door switches, for monitoring human activities (Acampora et al., 2013; Chen et al., 2012; Pol et al., 2013). Often the focus is on ADLs, such as sleeping, toileting and cooking. ADLs are considered important indicators for the functional health status of older adults (Covinsky et al., 2003).

In our group, researchers from different disciplines (information technology, machine learning and occupational therapy) work together to develop monitoring systems for older adults. The objective of the research is to use pervasive technology to support older adults to independently live longer in their own homes and their familiar and safe environment. Currently our group monitors about 20 elderly living alone using sensor networks. For a correct health assessment it is important that we are sure that the data originates from the activities of the resident only and, therefore, that we know when there are visitors. Furthermore, the type and the frequency of visits are important indicators of the social participation of elderly. One solution to identify the visitors is using RFID tags (Lotfi et al., 2012), but this method has some practical disadvantages in real life situations such as the ease of forgetting to scan a visit. It is also possible to use a video sensor to count persons (Skubic et al., 2009), but this is hard to realise in real life situations because of privacy reasons. An unobtrusive supervised method is used in (Petersen et al., 2012). A more holistic solution, multi-person activity recognition in smart homes, has been presented (Nait Aicha et al., 2013; Phua et al., 2011; Singla et al., 2010; Wang et al., 2011). Hence simple sensors, both wearable and ambient, can be used for the detection and monitoring of multiple persons in smart homes. Unfortunately, these methods rely on large supervised data sets which brings the difficulty of collecting the ground truth data.

Because the number of apartments we are monitoring is large and future projects will involve even more apartments, we cannot rely on supervised learning methods to build accurate individual models for visit detection. In this paper we present an unsupervised method for visitor detection. The method specifically looks at transitions between sensors and models the regular pattern as a normal (non visitor) pattern. An anomaly in this pattern (for example non-modeled transitions between two distant sensors) may indicate that visitors may be present. A model that has been successfully applied for the detection of anomalous events using counts as features is the Markov modulated non-homogenous Poisson process (MMPP) (Scott and Smyth, 2003), which takes into account both the periodic and non-periodic influences present in the data. This fits our situation, assuming that the resident has periodic (daily and weekly) living patterns and non-periodic patterns such as a visit on an occasional basis. However, MMPPs are univariate, and as such cannot deal with the richer, multidimensional, datasets that are common to ambient assisted living (AAL).

In Nait Aicha et al. (2014) we showed, on a single data set, that multidimensional Markov modulated non-homogenous Poisson process (M3P2) can be used for visit detection. The M3P2 model extends the MMPP by allowing the use of a multidimensional feature stream. In this paper we present a more extensive evaluation on a more elaborate data set. We studied the effect of feature selection, the assumption on periodicity of data and the generalisation to other sensor networks.

The contribution of our research is two-fold: a) we show that properly designed unsupervised methods can be used to detect visits with networks of a small amount of simple sensors and b) we show that M3P2, a novel model that deals with multiple data streams, is significantly better at this task than MMPP. Moreover, it allows us to distinguish between regular and non-regular visits automatically, and to have a model of daily and weekly cycles in the person's routine. We evaluate the performance of our model on real-life sensor data. We use two data sets, that we make public, consisting of nine months of sensor data collected in the apartment of two elderly persons. The results show that our model significantly (significance level, $p < 0.05$) outperforms the standard Markov modulated Poisson process (MMPP). Two additional data sets are used to evaluate the generalisation of the M3P2 model.

3.2 Related Work

The issue of dealing with multiple persons in a smart home is an important problem that recently became the subject of extensive study. In his survey Teixeira et al. (2010) described the ability to detect the presence, count, track and identify persons using different methods and sensor types. Binary sensors in a network are able to count and localize individuals with an accuracy that depends on the number of the nodes. Using a large number of sensors in a network, Singla et al. (2010) described a method that focuses on the recognition of ADLs in multi-user contexts. Using the same dense sensor network, Crandall et al.applied standard supervised classification techniques , such as Naive Bayes and HMM, to identify and track multiple smart home residents (Crandall and Cook, 2009, 2011, 2013). Phua et al. (2011) noted that standard supervised techniques yield high accuracies only if a) the number of simple sensors is large, b) the training data is accurately labelled and c) the activities are simple and done in habitual way. These assumptions are unrealistic in real life situations. Using a small sensor network, comparable to our situation, Petersen et al. (2012), applied Support Vector Machines to detect the presence of a visitor in a smart home during a period of 6 weeks. However, supervised techniques have the weakness that they assume that the activities do not evolve over time (Phua et al., 2011). The collection of annotated data to train supervised classifiers is difficult and involves other (invasive) sensors or a strict administration from the elderly. Unsupervised methods for the detection of abnormal behaviour in smart homes have been presented in applications like fall detection or wandering. Clustering methods such as K-means are used for the identification and prediction of abnormal behaviour of elderly dementia sufferers, but these methods are not effective in the presence of visitors or pets (Lotfi et al., 2012).

MMPPs, as unsupervised methods, are widely applied for the detection of anomalous events in various areas: to detect intrusions in a telephone network (Scott, 1999). Scott (2001) introduced the non-homogeneous MMPPs, which take into account the natural cyclic nature of the variations in telephone traffic. A similar model was used by Hutchins et al. (2007) to model the occupancy in a building and by Scott and Smyth (2003) to model web traffic data. These models are all univariate, and as such cannot deal with the richer datasets that are common to AAL. Multivariate MMPPs have been described in detail in Sumita and Masuda (1992) for the homogeneous case, but lack the capacity of non-homogeneous MMPPs to model regular variations.

3.3 Sensor Data

We have collected multiple data sets, in several ambient assisted living apartments, for a duration of up to more than a year. Different sensor networks were used to collect data as described in section 3.6. These sensor networks consist of off-the-shelf binary sensors that measure motion, pressure on the bed, toilet flush and the opening and closing of cabinets and doors. An overview of the location of the sensors in the apartment of one resident is shown in Figure 3.1. The elderly are living their routine life and are not told

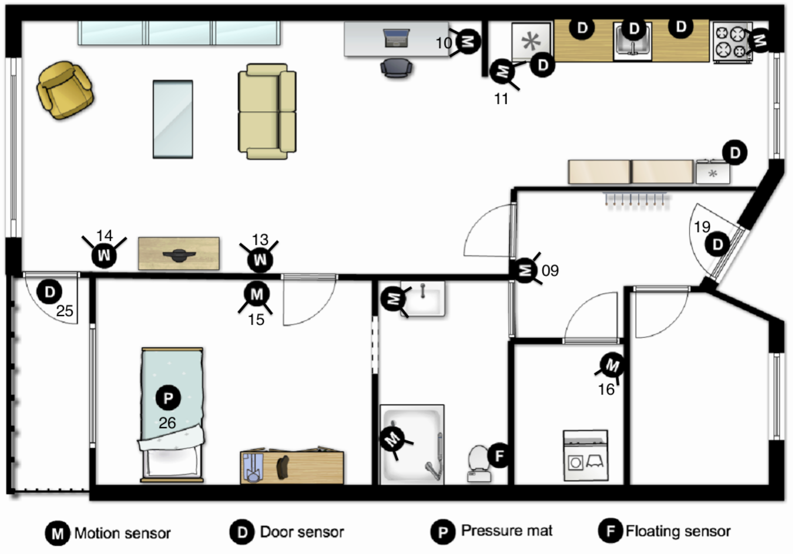


Figure 3.1: A map of the apartment of volunteer A equipped with sensors. The number of used sensors, their types and their position do not differ a lot between the different apartments.

to modify their behaviour in any way. The location of the sensors is chosen so that all the important rooms in the apartment are covered and so that the network does not affect the elderly's daily life. For instance, the pressure sensor for the bed is installed under the mattress and sensors in the kitchen are installed above the stove, under the freezer, etc. A detailed description is provided in Nait Aicha et al. (2013, 2014).

3.4 Features: description and extraction

The binary sensors generate a continuous stream of sensor-events. Our experience is that sensor-transitions are better than the number of sensor-events in the measurement of ADLs. Two consecutive sensor events are referred to as a sensor-transition. The number of these sensor-transitions during some time slice is likely to be smaller when there is only one person in the house (i.e. the resident) than when there is more than one person in the house (i.e. a visitor). Therefore, the number of all possible sensor-transitions, referred to as $N(t)$, can be considered as a feature to detect visits.

When the resident is alone at home, we can assume that $N(t)$ only consists of sensor-transitions from *topologically connected* sensors, i.e., sensors that the resident can activate in sequence without tripping a third sensor in between. A graph representing the sensors that are topologically connected in the apartment of volunteer A is given in Figure 4.2. The node identities in this figure correspond to the sensors shown in Figure 3.1.

An example of a sensor-transition of not-topologically connected sensors is the sensor-transition coming from the front-door sensor followed by the living-room sensor (edge $19 \rightarrow 13$). It is unlikely that this transition is generated by the resident alone, because he/she must go through the hall-sensor resulting in two transitions (edges $19 \rightarrow 09$ and $09 \rightarrow 13$). To detect visits, the number of sensor-transitions for which the sensors are *not* topologically connected, referred as , can also be considered as a feature. Because a visitor always enters and leaves the apartment through the front-door, a third feature $N^D(t)$ can also be considered and used with the M3P2 model described in subsection 3.5.3. $N^D(t)$ is defined as the number of sensor-transitions during time slice t, for which one of the sensor readings originates from the front-door sensor. For a formal definition of the features, we define a sensor-transition $\tau_{ij}^{(t_n)}$ between the sensors i and j starting at time stamp t_n by:

$$\tau_{ij}^{(t_n)} = \begin{cases} 1 & \text{if sensor } i \text{ fires at } t_n \text{ and sensor } j \text{ fires at } t_{n+1} \\ 0 & \text{otherwise} \end{cases} \tag{3.1}$$

The feature $N(t)$ can then be expressed as:

$$N(t) = \sum_{\substack{b(t) \leq t_n < e(t) \\ i,j \in S}} \tau_{ij}^{(t_n)} \tag{3.2}$$

where S is the set of all sensors and the function $b(t)$ (respectively $e(t)$) returns de beginning (respectively the end) of the time slice containing t_n.

Similar equations hold for and $N^D(t)$ by redefining S to be the subset of the topologically not-connected sensor tuples and the subset of the tuples where the front-door sensor is involved, respectively.

3.5 Models

3.5.1 Markov Modulated non-homogeneous Poisson Process (MMPP)

A Markov modulated Poisson process is a widely used stochastic process for modelling counts of random events that occur during a sequence of time intervals, in which different Poisson processes are switched between by an underlying Markov chain. The probability density for every Poisson process is given by a Poisson distribution:

$$\text{Pois}(N = n; \lambda) = \frac{\lambda^n}{n!} e^{-\lambda} \tag{3.3}$$

In Scott (2001), a MMPP was introduced, where the rate $\lambda(t)$ of the count data $N(t)$ varies over time. We follow Ihler et al. (2007), where both the periodic and the non-periodic influences on the count data are modelled. The periodic aspects (in this case, weekly and daily cycles) are modelled by decomposing the rate $\lambda(t)$ as follows:

$$\lambda(t) = \lambda_0 \cdot \delta_{d(t)} \cdot \eta_{d(t),h(t)} \tag{3.4}$$

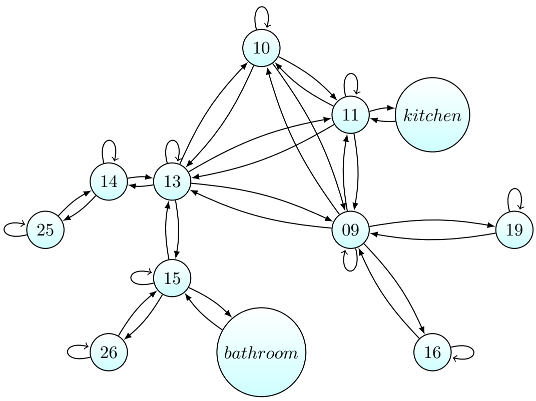
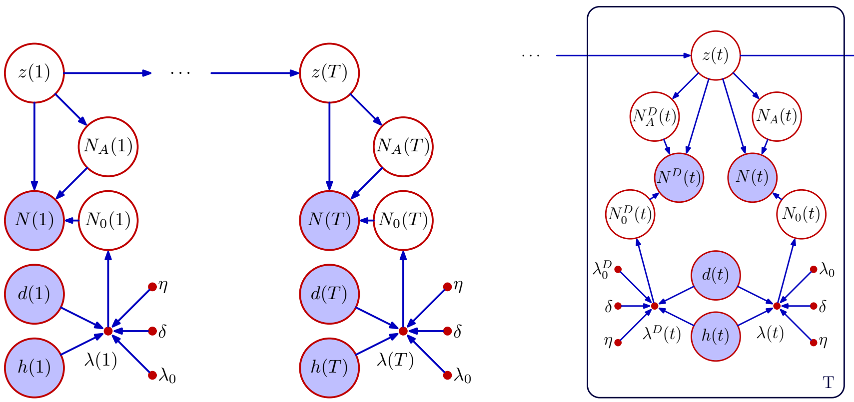


Figure 3.2: A graph indicating the sensors that are topologically connected to each other. The node id's correspond to the sensor id's depicted in Figure 3.1. The node bathroom (resp. kitchen) consists of six (resp three) sensors that are topologically connected to each other. These sensors are omitted to keep the overview of the graph clear.



(a) MMPP (b) M3P2

Figure 3.3: Graphical model for different distributions and variables defining the MMPP and the M3P2 models. The shaded nodes are observed and the small solid nodes indicate deterministic parameters. The directed edges indicate conditional dependence of the nodes. $\lambda(t)$ depends on the parameters $\lambda_0, \delta, \eta, d(t)$ and $h(t)$, while $N(t)$ depends on $N_0(t), N_A(t)$ and $z(t)$.

where $d(t) \in \{1, \ldots, 7\}$ indicates the day of week in which t falls, and $h(t) \in \{1, \ldots, K\}$ indicates the time interval of a day in which t falls. δ_j represents the effect of the day j of the week and $\eta_{j,i}$ represents the effect of the time interval i given day j of the week. These effects are normalised by requiring that $\sum_{j=1}^{7} \delta_j = 7$ and $\sum_{i=1}^{K} \eta_{j,i} = K \; \forall j$. For example, $\delta_6 = 2$ would imply that the counts on Friday are twice λ_0. Figure 3.4 illustrates the overall average λ_0, the effect of the day of week, δ_j, and the effect of the time of day, $\eta_{j,i}$.

We learn the model parameters using Maximum a Posteriori optimisation, using Gamma and Dirichlet distributions as conjugate priors for the model parameters λ_0, δ and η, following Ihler et al. (2007); Nait Aicha et al. (2013).

$$\begin{aligned} \lambda_0 &\sim \mathrm{Gamma}(a^L, b^L) \\ \frac{1}{7}[\delta_1, \cdots, \delta_7] &\sim \mathrm{Dir}(\alpha_1^d, \ldots, \alpha_7^d) \\ \frac{1}{D}[\eta_{j,1}, \cdots, \eta_{j,D}] &\sim \mathrm{Dir}(\eta_1^h, \ldots, \eta_D^h) \; \forall j \in \{1, \ldots, 7\} \end{aligned} \tag{3.5}$$

The presence of anomalies in the counts is modelled with the latent variables $z(t)$, which form a Markov chain with transition probabilities $m_{zz'}$ of the transition matrix M. Anomalies are modelled as resulting in an increase (positive anomaly) or decrease (negative anomaly) of the observed counts. The values of the hidden states $z(t)$ are as follows:

$$z(t) = \begin{cases} 0 & \text{no anomaly in time slice } t \\ 1 & \text{anomalous count increase in time slice } t \\ -1 & \text{anomalous count decrease in time slice } t \end{cases} \tag{3.6}$$

In our case, a positive anomaly corresponds to a visit, while a negative anomaly may correspond to either the absence of the resident or the absence of a regular visit. In both cases, they correspond to deviations from the regular pattern. We expand on these concepts in Section 3.5.2. We model the event counts $N(t)$ as:

$$N(t) = N_0(t) + N_A(t) \; , \tag{3.7}$$

the sum of $N_0(t)$, the number of "normal" events, and, $N_A(t)$, the anomalous counts for that time period. Both of these are Poisson-distributed, and $N_A(t)$ is conditioned on $z(t)$. We use conjugate priors for the model parameters:

$$\begin{aligned} N_0(t) &\sim \mathrm{Pois}(\lambda(t)) \\ z(t)\, N_A(t) &\sim \mathrm{Pois}\left(\lambda_A\left(z(t)\right)\right) \\ \lambda_A(z(t)) &\sim \mathrm{Gamma}(a^A, b^A) \\ (m_{s0}, m_{s1}, m_{s,-1}) &\sim \mathrm{Dir}(\alpha_{s0}, \alpha_{s1}, \alpha_{s,-1}) \; \forall s \in \{0, 1, -1\} \end{aligned}$$

Notice that in this formulation λ_A is state-specific, meaning that the expected count increase ($z(t) = 1$) does not necessarily follow the same distribution as the count decrease ($z(t) = -1$). In the experimental section, we show that this extra flexibility is important to our application.

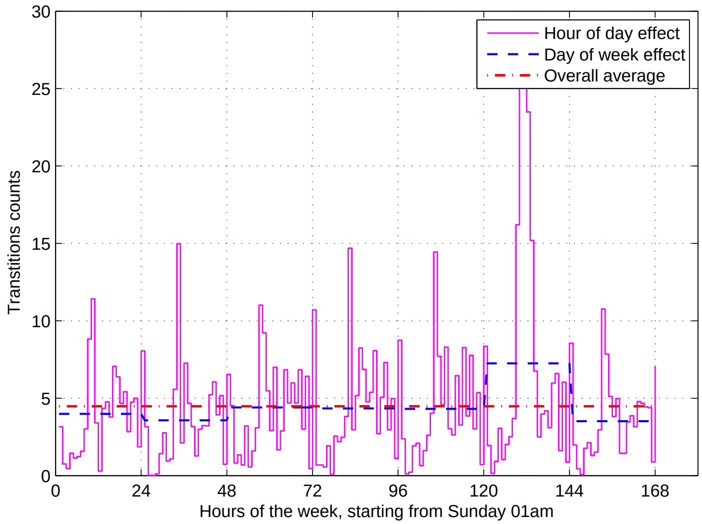


Figure 3.4: An illustration of the overall average (λ_0), the day of week effect combined with λ_0 ($\lambda_0 \delta_{d(t)}$) and the effect of the hour of the day of the week combined with λ_0 ($\lambda_0 \delta_{d(t)} \eta_{d(t),h(t)}$). The effect of $\eta_{d(t),h(t)}$ during the night is clearly lower than the day. The effect of Friday is higher than the other days. The morning rhythm is also clearly visible.

Our model is unsupervised: during training we jointly optimise the model parameters and the latent states using the EM algorithm. We use Markov chain Monte Carlo (MCMC) sampling from the posterior of the latent state to estimate the parameters of the posterior Dirichlet distributions (Ihler et al., 2007).

3.5.2 Regular visits, irregular visits and long-term temporal variations

The periodic effects in the MMPP model are governed by $\delta_{d(t)}$ and $\eta_{d(t),h(t)}$. Because of our choices for these parameters, anomalies are defined with respect to the weekly patterns. A visit that occurs at a specific time at a specific day in the week (for example the cleaner that comes on Friday) is not considered as anomaly, but is learned as a regular pattern, or *regular visit*. A visit that does not follow such a periodic behaviour is detected as *irregular visit*. If we choose another setting for these parameters we can modify the period with which we model effects. For example, if we do not learn the δ from the data but set $\delta_i = 1\ \forall i$, we assume that every day of the week follows the same pattern. In that case the cleaner that comes every week on Friday will be detected an an anomaly. We can also use prior knowledge to set some parameters, for example η can be set to model daytime or night cycles.

The MMPP learns the characteristic activity pattern and the anomalies from a data set that spans some time period W. During that time period we assume that there are no other effects than the effects captured by our model. However, long term effects, which are not modelled, may occur. In the experiment section we study how far this assumption is warranted.

3.5.3 Markov Modulated Multidimensional non-homogeneous Poisson Process (M3P2)

An important limitation the above-described MMPP is that the model is restricted to one-dimensional observations. In our application, detecting the presence of multiple persons, we are dealing with more than one feature that is informative. Although multivariate MMPP have been analysed before (Sumita and Masuda, 1992), this does not extend to non-homogeneous MMPP. We therefore extend the model to multiple simultaneous count features, resulting in the Multidimensional MMPP, abbreviated as M3P2 in the remainder of this text. A graphical representation of the M3P2 is given in Figure 3.3(b). We define the M3P2 similarly to the MMPP, where the observation streams are assumed to be independent. Let $N^i(t)$ denote the ith observation stream at time t. Similar to the MMPP, define

$$N^i(t) = N_0^i(t) + N_A^i(z(t)) \tag{3.8}$$

and $p(N^1(t), N^2(t), \dots) = \prod_i p(N^i(t))$.

As a consequence of the increased expressiveness of the M3P2, it is advantageous to increase the cardinality of the latent states $z(t)$. In particular, in our application we explicitly model the usage of the front door. Since a visitor cannot enter or leave the house without making use of the door, we introduce a new state that models the entering or leaving of the house. The states are now:

$$z(t) = \begin{cases} -1 & \text{irregular absence of a visit} \\ 0 & \text{Normal situation} \\ 1 & \text{irregular visit} \\ 2 & \text{irregular door activity} \end{cases} \tag{3.9}$$

The state $z(t) = 2$ acts as a *gating* state without which it is impossible to transition from the absence of an irregular visit to its presence, and vice-versa. We encode our knowledge that it is impossible for visitors to enter or leave without using the door in the priors, setting $\alpha_{0,1}, \alpha_{-1,1}, \alpha_{1,-1}$ and $\alpha_{1,0}$ to 0.

In case we are dealing with two data streams (e.g. $N(t)$ and $N^D(t)$), the calculation of the posterior probability $p(z(t)|N(t), N^D(t))$ is also done using the MCMC sampling method. We consider $N(t)$ and $N^D(t)$ to be independent given $z(t)$, so that $p(N(t), N^D(t)|z(t)) = p(N(t)|z(t))p(N^D(t)|z(t))$.

In the first part of each MCMC-iteration, the hidden states $z(t)$ of the Markov chain are sampled by iteratively computing the conditional distribution $p(z(t), N(1 \dots t), N^D(1 \dots t)))$

in a forward step, as follows:

$$\alpha_t(s) = p(z(t) = s, N(1 \ldots t), N^D(1 \ldots t)) = \\ p(N(t)|s)p(N^D(t)|s) \sum_r M_z(r,s)\alpha_{t-1}(r) \quad (3.10)$$

Define f_+ (respectively f_-) to be the probability of $N(t)|z(t)$ in case there is a positive (respectively a negative) anomaly, which is computed by marginalising out both the number of additional (respectively, missing) events, $N_A(t)$, and the actual parameters of the distribution for the anomaly, giving raise to:

$$f_+(t) := \sum_i \mathrm{Pois}(N(t) - i; \lambda(t))\, \mathrm{NB}(i; a^A, \frac{b^A}{1+b^A}) \quad (3.11)$$

$$f_-(t) := \sum_i \mathrm{Pois}(N(t) + i; \lambda(t))\, \mathrm{NB}(i; a^A, \frac{b^A}{1+b^A}) \quad (3.12)$$

where NB indicates the Negative Binomial distribution.

Defining f_+^D and f_-^D on the same way for the second data stream N_A^D, the likelihood functions $p(N(t), N^D(t)|z(t))$ can be expressed as given in Equation 3.13. Note that an irregular visit, $z(t) = 1$, is mainly caused by an increase of visit transition counts, while an increase of the door counts will cause an irregular visit coming in or leaving.

$$p(N(t), N^D(t)|z(t)) \\ = \begin{cases} \mathrm{Pois}(N(t); \lambda) \cdot \mathrm{Pois}(N^D(t); \lambda^D) & \text{if z(t)=0} \\ f_+(t) \cdot \mathrm{Pois}(N^D(t); \lambda^D) & \text{if z(t)=1} \\ f_-(t) \cdot f_-^D(t) & \text{if z(t)=-1} \\ \mathrm{Pois}(N(t); \lambda) \cdot f_+^D(t) & \text{if z(t)=2} \end{cases} \quad (3.13)$$

The model parameters are then updated using the samples obtained using Equation 3.10 as for a standard MMPP, following Ihler et al. (2007).

3.6 Experiments

3.6.1 Objectives

A set of six experiments is conducted to evaluate the performance of the models. In the first experiment, we studied the effect of the time discretization: the duration of the time-slice in which we count the transitions. If this is too small we may have too few counts to make a good model. If it is too large we lose resolution and will miss information as the duration of a visit may vary from few minutes to several hours. The second experiment is conducted to select the most relevant feature: are the general sensor-transitions sufficient, or are the more specific sensor-transitions (these involving the topologically not-connected sensors) more informative for the visit detection? A third experiment was

Data Set	Volunteer	Period	Experiment(s)
A	M, 84	Apr 2013 - Dec 2013	1, 2 and 3
B	F, 80	Oct 2013 - Jun 2014	4 and 5
C	M, 84	Jul 2012 - Sep 2102	6
D	F, 87	Jul 2012 - Sep 2102	6

Table 3.1: A summary of which data set is used for which experiment(s).

carried out to investigate how well the model performs in the face of slow changes in the patterns over long periods of time. For example, do we need to take any influence of meteorological seasons into account or not? In the fourth experiment, we compared our model, the M3P2, with the baseline, the standard MMPP model: does the incorporation of a second data feature stream, $N^D(t)$, result in better performance or is one feature stream, $N(t)$, sufficient. The fifth experiment is conducted to evaluate how regular and irregular visits are detected when different periodicities are considered. The last experiment is conducted to test the generalisation of our model. The M3P2 model is applied to two new data sets collected using a different sensor network.

3.6.2 Sensor data

For the first three experiments, a dataset collected during 9 months between April 2013 and December 2013 in the apartment of a volunteer A is used. This resident, a male of 84 years old, received visits from a caregiver every day around 8:30 in the morning and around 9:00 in the evening and weekly visits of a cleaner every Friday between 9 and 12 in the morning. The resident also occasionally got visits from his children. For the fourth and fifth experiments we used two datasets: a) the same dataset used for the first three experiment and b) an extra dataset collected in the apartment of a volunteer B during 9 months between October 2013 and June 2014. This resident, a female of 80 years old, rarely got visits, except a visit of the cleaner twice a month. For generalisation experiment (last experiment), we used two data sets collected using a different sensor network. This sensor network, described in van Kasteren et al. (2008), consists of simple binary sensors communicating with a receiver using RFM DM nodes. The data set C was collected between July 2012 and September 2012 in the apartment of volunteer A, while the data set D is collected in the same period in the apartment of a different volunteer: a female of 87 years old. A summary of which data sets is used for which experiment is given in Table 3.1.

3.6.3 Annotation and performance measure

To measure the performance of the model we used annotated data. The annotation of the data is done using self report and by visually inspecting the raw sensor data. The volunteers are asked to register some information about the visits they received during at least two weeks. A special form was designed to make the registration easy for them.

K	slice length (hours)	non-regular visits ($z = 1$) precision	recall	F-value
8	3	0.661	0.667	0.661
12	2	0.653	0.854	0.728
24	1	0.735	0.792	0.762
48	$^1/_2$	0.750	0.752	0.750
96	$^1/_4$	0.858	0.664	0.743

Table 3.2: Precision, recall and F-value of MMPP applied on $N(t)$ using different $K's$.

After the period of annotation, an interview with the elderly took place to clarify the annotations. The start and end time of the visits registered by the elderly seemed to be approximate times. For this reason the exact time generated by the front- and back-door sensors are used for the annotation in stead of the times filled in by the elderly.

In order to map the ground truth into discrete time slices, we decided to label all the time slices that are fully or partially covered by a non-regular visit as a positive class ($z = 1$). For example, a non-regular visit on Friday September, 13 between 18:55 and 20:04 lasted one hour and 9 minutes, but spans 3 time slices (respectively 4 time slices) in the annotation when $D = 24$ (respectively $D = 48$) is used. These 3 (respectively 4 time slices) are labelled as a positive anomaly class. The same procedure holds for the irregular absence of visit ($z = -1$). The precision, recall and the F-value are computed separately for the two states ($z = 1$ and $z = -1$). The values stated in section 3.7 are obtained by calculating the average of at least 10 experiment repetitions. A non-regular visit lasting more than one time slice is defined to be correctly detected if at least one time slice of this irregular visit is correctly detected by the classifier.

3.7 Results

3.7.1 Effect of time discretization

We varied the number of time slices in a day $K \in \{8, 12, 24, 48, 96\}$, corresponding to time slice length of $\{3, 2, 1, ^1/_2, ^1/_4\}$ hours. The reason to limit to only these values is because most non-regular visits have a duration of 3 hours or less. A 3-fold cross validation is used to determine the best model parameters (*e.g.,* λ_0 and λ_A) during the training phase. The results, listed in Table 3.2, are obtained by taking the average of 10 repetitions when MMPP is applied on $N(t)$. The results show that the highest F-value is obtained when $K = 24$. The results also show that the precision increases with K. This can be explained by the fact that increasing K, which is equivalent to decreasing the time slice length, will decrease the number of observation per time slice, which will increase the variance. As a consequence, the number of false positives will increase, which decreases the precision. The results of the irregular absence of visits ($z = -1$) are not reported because of lack of data, resulting in a very large standard deviation of the F-value. The first fold (calendar weeks 14-27) and the third fold (calendar weeks 40-53)

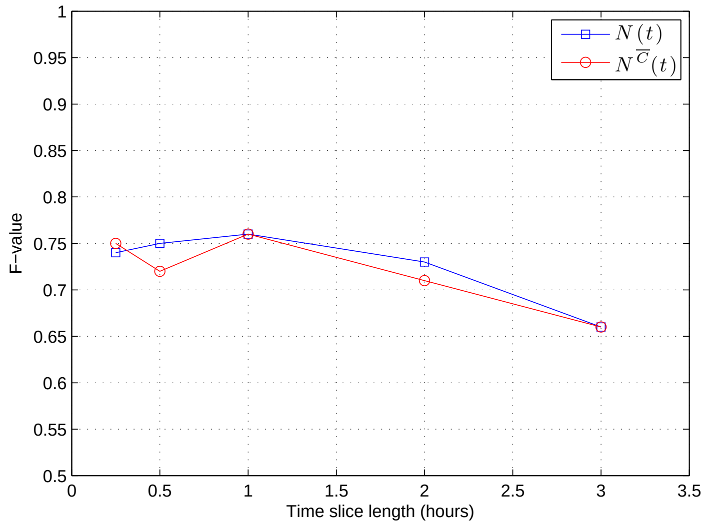


Figure 3.5: The F-value obtained when MMPP is applied on $N(t)$ and using different time slices. The standard deviation varies between 0.03 and 0.1 in all cases after 10 repetitions.

have only one or two 'irregular absences of visits', while all the other 'irregular absences' lie in the second fold. In our case, the recall was almost always equal to 1 (respectively equal to 0) when testing with the first fold (respectively the third fold). For this reason, we omit absence of visit for the rest of our experiments. Unless mentioned otherwise, we chose for $K = 24$ in the following experiments because it gives the best compromise between the performance and the practical usage.

3.7.2 Feature Selection

To investigate the value of topological connected sensors, the MMPP is applied using the features $N(t)$ and described in section 3.4. Similar to the first experiment, a 3-fold cross validation is used during the training phase. Figure 3.5 shows the F-values when MMPP is applied to these features using different time slice lengths. The results show that the F-values corresponding to the features $N(t)$ and do not differ a lot from each other and confirms that different features do not affect which time discretisation is optimal. This means that the use the general sensor-transition counts, $N(t)$, is sufficient for the detection of the visits.

3.7.3 Temporal variations

For this experiment, we varied the number of weeks, W, during which we assume that the resident's behaviour does not change. Using the feature and time slice duration

W (weeks)	non-regular visits ($z = 1$) precision	recall	F-value	std dev F-value
4	0.511	0.670	0.579	0.15
6	0.636	0.626	0.630	0.10
8	0.826	0.690	0.752	0.05
13	0.749	0.784	0.765	0.04
39	0.748	0.749	0.748	0.01

Table 3.3: Precision, recall and F-value obtained when MMPP is applied on $N(t)$ using $D = 24$ and different values for the period W.

Model (MMPP/M3P2)	data set	non-regular visits ($z = 1$) precision	recall	F-value
MMPP	A	0.749	0.784	0.765
M3P2	A	0.856	0.800	0.827
MMPP	B	0.842	0.800	0.821
M3P2	B	0.849	0.854	0.851

Table 3.4: Precision, recall and F-value obtained when MMPP (resp. M3P2) is applied on $N(t)$ (resp. $N^D(t)$) using one hour as time slice length (*i.e.,* $D = 24$) and a season as a temporal variation (*i.e.,* $W = 13$). The data set A (resp. B) corresponds to the volunteer A (resp. B).

found above, we varied W between 4 and 39 weeks. Setting $W = 4$ assumes there are 'monthly' variations in the behavior, while setting $W = 39$ assumes there were no variations for the whole duration of the data collection. The results, given in Table 3.3, are obtained by taking the average of 10 repetitions of MMPP for each value of W. The results show that the best performance is obtained when using a period of 13 weeks long. This is remarkably close to the duration of a meteorological season, and it seems very plausible that there is a seasonal effect in the data. It will be fascinating, in future work, to incorporate this in the model and evaluate it on multi-year data. Note that the computational time to build such model is less than 10 minutes.

3.7.4 Comparison between M3P2 and MMPP

In this experiment, we investigate whether the M3P2, using an additional feature stream, outperforms the MMPP. We do this by combining the $N(t)$ feature used by the MMPP with the $N^D(t)$ feature, the number of front-door transitions, and keep $K = 24$ and $W = 13$ as found above. The results of this experiment, listed in Table 3.4, show that the M3P2 results in significantly higher F-values than the MMPP. The significance is tested using the two-sample t-test using a threshold level $\alpha = 0.05$. The normality assumption is tested using the Kolmogorov-Smirnov test using the same threshold level. The better precision of M3P2 compared to MMPP reflects the lower number of false positives obtained by the M3P2. Most of the false positives are caused by slight temporal shifts of the nurse's daily visits. An earlier (respectively later) visit of the nurse results in a higher value of $N(t)$ in the preceding (respectively following) time slice than the one in which the visit normally takes place. Another reason for false positives, in both models, is the lack of an accurate annotation for such large data sets. As mentioned earlier, the annotation is based on visual inspection of the raw sensor data combined with several interviews with the residents. Time slices that are detected as visits by the model and that cannot be clarified by the resident may result in erroneous false positives. We think that these false positives correspond to unexpected visits which the resident cannot remember.

3.7.5 Periodicity

In previous experiments we have considered visits as a deviation from the normal patterns for the resident within their weekly cycle. Such anomalies depend on how the cycle is defined, however, and it is therefore useful to evaluate how visits are detected when a different periodicity is considered. In particular, we experimented with the following four periodicities:

- a periodicity 'day/night', meaning that we assume that every day has a day cycle (08:00 - 00:59) and a night cycle (01:00-07:59) and that all the days of the week are the same. All hours of the day cycle, respectively night cycle, are the same. Furthermore, all the days of the week are the same.
- A periodicity of a day, meaning that we assume that every day is the same, but the hours of the day are not. Visits that do not have a periodicity of 24 hours are detected as an anomaly.
- A periodicity 'weekday/weekend', meaning that we assume that the weekdays (Monday-Friday) are the same and that the weekends are the same. Weekly visits are considered as an anomaly and are detected.
- A periodicity of a week, meaning that we assume that only the weeks are the same. The days of the week and the hours of the day are assumed to be different. Visits that do not have a periodicity of one week are detected as an anomaly. This is our setting for the first four experiments.

The periodicity of a day, for example, is obtained by setting $\delta_j = 1\ \forall j \in \{1, \cdots, 7\}$. For this experiment, we use the optimal values of $K = 24$ and $W = 13$, as found before, and use the M3P2 model with the features $N(t)$ and $N^D(t)$ described above. The results of this experiment, listed in Figure 3.6, show that the best performance of the model M3P2 is obtained with the periodicity of a week. This is conform with our assumption that the residents have daily and weekly living patterns. The standard deviation of the F-values is large for both the two data-sets in the case of periodicity 'day/night' because the assumption that the residents have a constant behaviour throughout the day (08:00-24:00) is not warranted. The large standard deviation in case of data set B is due to a long visit period (guest) lasting more than three days between December 31 and January 3.

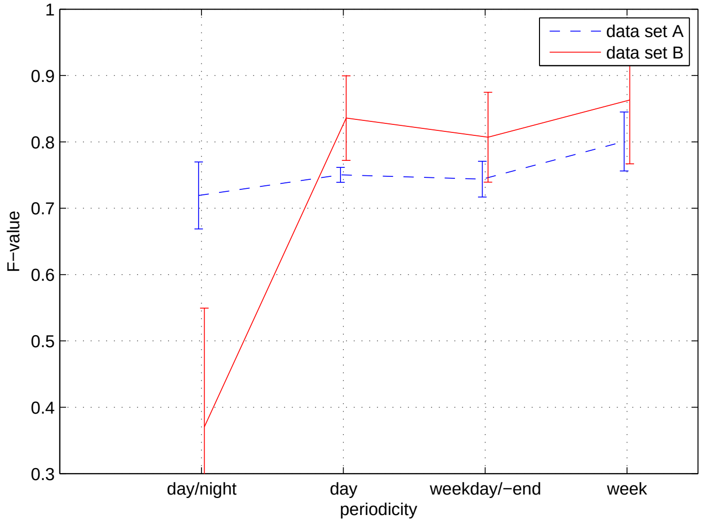


Figure 3.6: The F-value with the corresponding standard deviation, obtained when M3P2 is applied on $N(t)$ and $N^D(t)$ using different periodicities.

data set	# weeks annotated	non-regular visits $(z = 1)$ precision	recall	F-value
C	4	0.686	0.917	0.785
D	1	0.611	1.000	0.759

Table 3.5: Precision, recall and F-value obtained when M3P2 is applied on $N(t)$ and $N^D(t)$ using one hour as time slice length and a season as a temporal variation. The values are averages of 10 repetitions with a corresponding standard deviation smaller than 0.015.

3.7.6 Generalisation

With this last experiment, we confirm that our model is not specific to our particular dataset and generalises well, both to different people and to different types of sensor network. To achieve this, we use two new datasets which are different from the datasets used in the previous experiments: 1) they use fewer sensors, and of a different type, 2) the datasets were collected at different times of the year 3) the sleep time of the sensors is much smaller, resulting in numerically very different data, and 4) one of the datasets is from a new, previously unseen volunteer. The results, listed in Table 3.5 and Figure 3.7, are obtained using the optimal values of the parameters found from the previous experiments. Hence, $W = 13$, $D = 24$ and the periodicity is set to a day to capture the weekly visits. The results show that the performance of our model on the new two data sets is comparable to the performance on the data sets A and B.

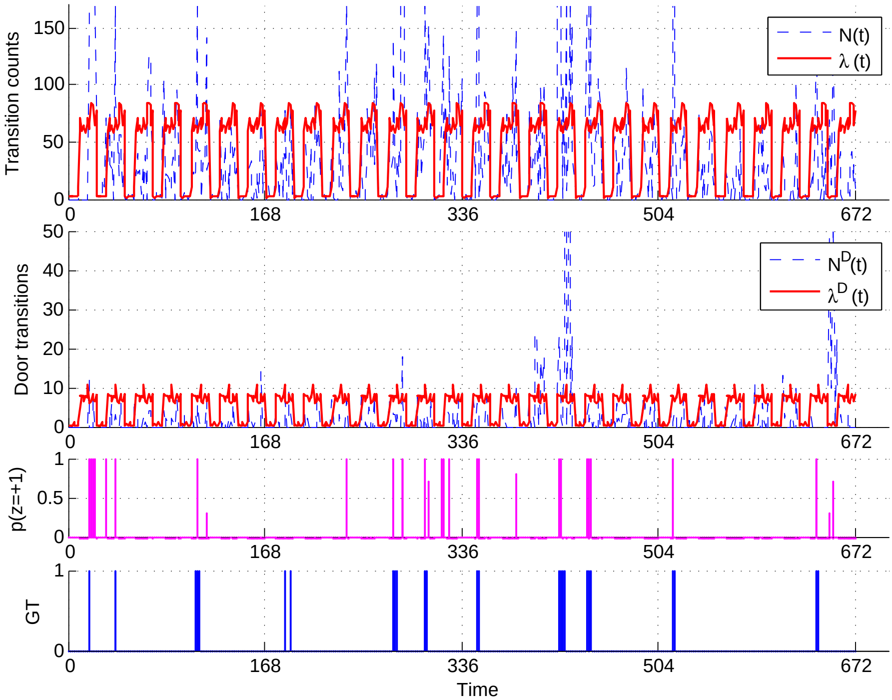


Figure 3.7: Feature data streams $N(t)$ and $N^D(t)$ along with $\lambda(t)$, the corresponding posterior probability of non-regular visits ($p(z = +1)$) and the ground truth (GT).

3.8 Conclusions

We presented an unsupervised method for the detection of visits in the home of older adults living alone. A Markov modulated multidimensional non-homogeneous Poisson process (M3P2) is described, which allows us to incorporate multiple feature streams. The non-homogeneous property allows us to model weekly and daily cycles. As features we looked at transitions between sensors, both general transitions and transitions with knowledge on the sensor placement. The M3P2 is tested on two real-life data sets collected between April 2013 and June 2014 in the apartment of two older adults living alone. The study has shown that M3P2 is able to detect visits with a significantly ($p < 0.05$) higher F-value than the traditional MMPP. In particular, the reduced number of false positives, reflected in the much higher precision, is of great practical importance in care environments. In addition, the approach is able to model daily and weekly characteristics, and can distinguish between regular and irregular visits. The conducted experiments show that the a) the simple sensor-transitions are sufficient for the detection of visits; b) the meteorological seasons and the weekly patterns are reflected in the parameters of the model and c) the proposed mode can deal with the different lifestyles of different people and different types of sensor networks.

Detecting and analysing visits gives us an insight in the social life of the resident, and allows for a more accurate automatic activity recognition in general. These can allow the elderly to live in their own home for longer, with better monitoring and improved security.

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Continuous Measuring of the Indoor Walking Speed of Older Adults Living Alone

We present a method for measuring gait velocity of older adults using data from existing ambient sensor networks. Gait velocity is an important predictor of fall risk and functional health. In contrast to other approaches that use specific sensors or sensor configurations our method imposes no constraints on the elderly. We studied different probabilistic models for the modeling of the duration and the distance of the indoor walking paths. Experiments are carried out on 27 months of data and include repeated assessments from an occupational therapist. We showed that the measured gait velocities correlate with these assessments.

4.1 Introduction

With the increasing number of older adults that live independently in their own homes, sensing systems that monitor someone's health are becoming popular. A wide range of sensor systems exists, often aimed at specific applications such as sleep monitoring or medicine intake monitoring. For more general lifestyle monitoring, ambient sensor networks consisting of motion and switch sensors mounted in the environment have been presented. In this paper, we focus on measuring gait velocity (walking speed) of elderly with such systems. Gait velocity is an important predictor of functional health; it is shown that it predicts the risk of falls (Montero-Odasso et al., 2005; Quach et al., 2011), but also of hospitalization and survival (Studenski et al., 2011). For that reason, gait velocity is an important measure in comprehensive geriatric assessment in clinical settings.

The disadvantage of the clinical assessments is that the tests are usually carried out over a short period of time in an unnatural setting. For assessments in home settings, measurements have to be carried out by a therapist in the home, which is time consuming and therefore expensive. The measurements may also be subjective to the therapist taking the tests.

Continuous domestic monitoring may provide a clearer and more objective picture of a person's mobility. Systems have been presented that suggest specific sensors in the home such as RGB-D cameras, radar sensors (Wang et al., 2013), motion sensors placed in an array (Kaye et al., 2011), or use wearable sensors such as accelerometers (Plasqui et al., 2013).

We developed a system for measuring gait velocity from an existing ambient sensor network. Because the elderly are not instructed to follow predefined paths, the variations in walking patterns will be large. The contributions of this paper are: (1) we propose a method for automatically identifying useful paths for speed estimation, (2) we show that unconstrained daily activities result in non-trivial distributions over path durations and propose a model to deal with those (3) we simultaneously estimate the duration and the distance of the collected paths. Finally, we compare the results with measurements from an occupational therapist over a period of 27 months.

4.2 Related Work

Approaches for continuous walking speed assessment for elderly use either *wearable* sensors or *ambient* sensors. A review of wearable sensors for gait analysis is given in Tao et al. (2012). Apart from velocity, other characteristics of the gait may be measured such as under-foot pressure and rotation of the foot (the GaitShoe (Bamberg et al., 2008), the Smart Insole (Xu et al., 2012) and the In-Shoe device (De Rossi et al., 2011)). These gait characteristics can be measured using gyroscopes. Pedometers are suitable for a long-term measurement of the physical activity. However, the accuracy of these pedometers is dependent of the implemented algorithm to count the steps. Furthermore, pedometers significantly underestimate the gait velocity of older adults (Cyarto et al., 2004), and a major disadvantage of using wearable sensors in general for gate analysis is that the subject must not forget to wear the device and has to recharge it regularly. The acceptance of wearable sensor applications for long term monitoring is therefore low. Ambient pressure sensors can be used to build large sensor mats for the analysis of gait. GAITRite® is a portable electronic walkway of $0.89m$ wide and between 5 and $8m$ long where pressure sensors are embedded in a grid. This system is frequently used for clinical and research purposes, but not in a home setting (Bilney et al., 2003; Van Uden and Besser, 2004). Imaging devices such as the Microsoft Kinect have been presented to evaluate the gait (Stone and Skubic, 2011; Stone et al., 2015). The advantage of using the depth RGB-D is the ability to capture different parameters of gait such as walking speed, stride time and stride length. The disadvantages are, however, privacy related although only a silhouette of the subject is captured. An unobtrusive way for the continuous measurement of gait velocity is using motion sensors. A specific lay-out of motion sensors was used in Hagler et al. (2010), who mounted four motion sensors with a restricted view to $\pm 4^{\circ}$ in a line on the ceiling of a hallway with approximately $61cm$ distance between them. The assumption of this method is that a long and narrow hallway is available to enforce the subject to walk in a line. This is not always the case in elderly apartments.

Frenken et al. (2011) introduced a fully automated approach to calculate the TUG, including the walking speed, using ambient sensors. These sensors consisting of force, light barriers and a Laser Range Scanner are incorporated in a chair to measure the walking direction and the speed. Both the GAITRite® and the TUG-chair are suitable for periodic instrumented clinical tests, but the systems are expensive for continuous gait monitoring.

4.3 Sensor Data

We have continuously collected data, in several ambient assisted living apartments, for more than a year. The sensor networks used to collect data use the Z-Wave protocol and consist of off-the-shelf binary sensors that measure motion, pressure on the bed, toilet flush and the opening and closing of cabinets and doors. An overview of the location of the sensors in the apartment of one resident is shown in Figure 4.1. The elderly are living their routine life and are not told to modify their behaviour in any way. The location of the sensors is chosen so that all the important rooms in the apartment are covered and so that the network does not affect the elderly's daily life. For instance, the pressure sensor for the bed is installed under the mattress and sensors in the kitchen are installed above the stove, under the freezer, etc. A list of the all the sensors installed in the apartment of volunteer A is shown in Table 4.1.

4.4 Approach

To calculate the gait velocity, we collect the walking paths of the residents in their home during a period of time (*e.g.,* week). We represent these walking paths by trajectories in a graph where the nodes represent sensors and the edges represent the distances between them, and calculate the corresponding durations. For each collected trajectory, the gait velocity is then equal to the length of the trajectory divided by its duration. Because of the variations in the duration we consider the duration as a stochastic variable. We fit a probabilistic model to this variable and estimate the model parameters. Before describing our approach in detail, we describe the challenges involved first.

4.4.1 Challenges

In instrumental tests, both the walking path and its duration are known. As the subject is instructed to walk without stopping, the gait velocity is therefore easy to compute. The calculation of the walking speed from ambient sensor data used for continuous monitoring is more challenging:

- The walking path is neither fixed nor precisely known, as the resident is not instructed to follow a specific walking path.

Id	Sensor name	Sensor type	Room (number)
09	Hall	Motion	Hall (3)
10	Desk	Motion	Living room (6)
11	Kitchen	Motion	Kitchen (4)
12	Kitchen hob	Motion	Kitchen (4)
13	Living front	Motion	Living room (6)
14	Living back	Motion	Living room (6)
15	Bedroom	Motion	Bedroom (2)
16	Laundry	Motion	Laundry room (5)
17	Washbasin	Motion	Bathroom (1)
18	Shower	Motion	Bathroom (1)
19	Front Door	Door	Hall (3)
20	Freezer	Door	Kitchen (4)
21	Fridge	Door	Kitchen (4)
22	Cupboard1	Door	Kitchen (4)
23	Cupboard2	Door	Kitchen (4)
24	Cupboard3	Door	Kitchen (4)
25	Balcony	Door	Living room (6)
26	Bed	Pressure	Bedroom (2)
27	Toilet	Floating	Bathroom (1)

Table 4.1: A list of the sensors (id, name, type and room) installed in the apartment of Volunteer A, as shown in Figure 4.1. Cupboard1 contains coffee/tea items, cupboard2 contains spices and cupboard3 contains dinner dishes

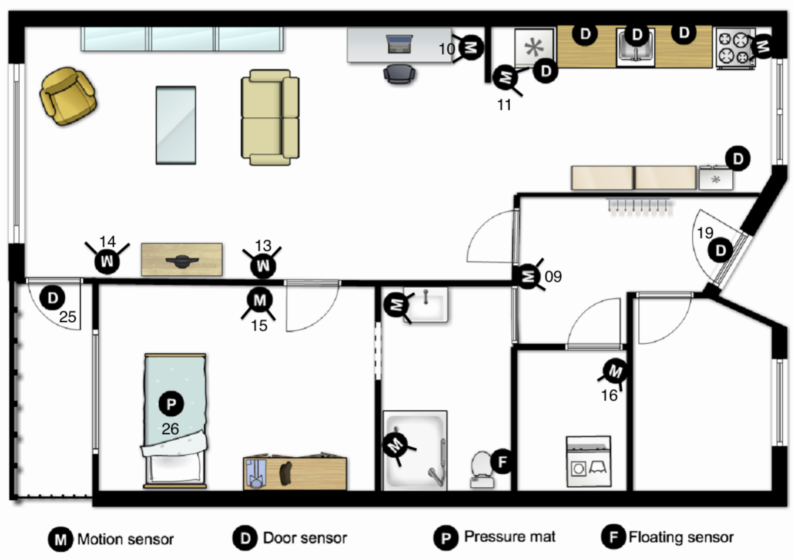


Figure 4.1: A map of the apartment of volunteer A equipped with a wireless sensor network. The three apartments have the same basic size and layout. The number of used sensors, their types and their positions were kept as similar as possible between the apartments.

- The walking paths of the resident do not necessary follow straight lines.
- It is unknown if the resident's walking paths are interwoven with some other activity or not.
- Motion sensors do not provide us with accurate locations, and to save their batteries the sensors do not transmit every detection they make. The start time and location and the end time and location of the walking path are, therefore, not known precisely due to the nature of the sensors.
- There is more variation in the walking paths and speeds in natural conditions than during a controlled test.

4.4.2 Features

When the resident performs his activities of daily living during a period of time, the binary sensors generate a continuous stream of sensor-events. A sensor event $e_n = (t_n, s_n)$ is defined as a tuple consisting of the time stamp t_n of the sensor signal (ON or OFF) and the identity of the sensor that fired that signal, $s_n \in \{s_1, s_2, \ldots, s_{|S|}\}$. [1] The sequence of N sensor-events collected during some period of time can be represented as

[1]The actual value of the event is not relevant to our purposes: we are interested in the knowledge that the resident is present at a certain location, not in their activity.

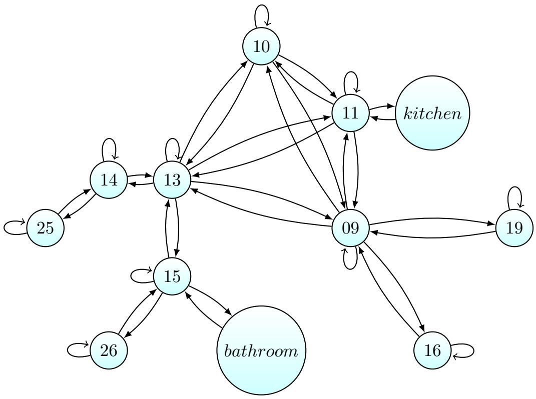


Figure 4.2: A graph indicating the sensors that are topologically connected to each other. The node ids correspond to the sensor ids depicted in Figure 4.1. The node kitchen (resp. bathroom) consists of six (resp. three) sensors that are topologically connected to each other. These sensors are omitted to keep the overview of the graph clear

$e =< e_1, e_2, \ldots, e_N >$. The OFF-signals of the motion sensor correspond to the end of the sleep-time of the sensor. These OFF-signals are ignored as they do not necessarily correspond to the end of the movement of the resident. For the same reason, the OFF-signal of the float sensor is filtered out as this signal indicates the end of filling up the toilet water tank. Furthermore, if more than two consecutive sensor events come from the same sensor, only the first and last event are taken into account. The reason is that many consecutive events of a sensor usually do not correspond to a displacement of the resident, and we cannot associate any walking distance with them. For example, consecutive events of the bed sensor mean that the resident is changing his posture. Finally, the sequence of events caused by the presence of multiple persons in the home is detected and excluded from the data under consideration using the method presented in chapter 3.5 To estimate gait velocity, we rely on durations of walking paths inside the home.

4.4.3 Model

We represent the walking paths of the resident in his home by trajectories in a graph. Figure 4.2 shows a graph of all possible walking paths of volunteer A. The node identities in this figure correspond to the sensors shown in Figure 4.1. The sensor ids, indicating the location of the resident, are used as nodes and the sensor-transitions, indicating the movement of the resident, are used as edges. As example, a trajectory corresponding to sensor sequence $< 15, 27, 17 >$ consists of three nodes and two edges. This trajectory represents the walking path 'bedroom-toilet-washbasin' resulted from a toileting activity.

The mathematical representation of the graph is $G = (V, E)$ where $V = \{s_1, s_2, \cdots, s_{|V|}\}$ and $E = \{(i, j)| \ i \text{ is topologically connected to } j\}$. To calculate the gait velocity in a period of time, we assume that the duration of natural paths in the house is representative of the person's gait velocity. For the calculation of the duration of the walking paths, we follow the approach:

1. Identify walking trajectories from sensor data and calculate the corresponding durations.
2. Model the duration of each collected trajectory.
3. Estimate the distance of each collected trajectory.
4. calculate the average gait velocity of the resident.

Identification of walking trajectories:
Given a sequence of sensor events $< e_1, e_2, \ldots, e_N >$ collected during a period of time T (*e.g.,* a week), we need to identify subsequences that correspond to actual walking. We do this by cutting this sequence at edge $(n, n+1)$ if the edge duration is larger than some threshold τ. Cutting the sequence at $(n, n+1)$ means that one walking path ends with event e_n and a new path starts with event e_{n+1}. The variable τ correspond to a 'rest moment' of the resident. This cutting action results in K sensor sequence segments. Some segments correspond to the movement of the subject in the same room and are therefore not suitable for the calculation of the gait velocity. Other segments, on the other hand, correspond to long and complex activities. These activities may contain walking paths that are suitable for the calculation of the gait velocity. Therefore, two possibilities to extract valid potential walking trajectories from theses segments have been investigated:

1. Automatically detect all trajectories that involve at least two rooms to ensure that the collected trajectories correspond to a movement of the resident and not to some activity within a room. These trajectories are referred as *auto-detected* trajectories.
2. Search within the K segments for some predefined walking trajectories. The start and end point of these trajectories are selected so that the obtained walking trajectories are as long and straight as possible. The start and end point are selected by manually inspecting the map of the apartment. These trajectories are referred as *predefined* trajectories.

For each collected (instance of a) trajectory, both auto-detected and predefined, its duration is calculated by substracting the time stamp of start point from the time stamp of the end point.

Modeling the durations of each trajectory:
The Poisson is a widely used distribution to model time durations and is the correct model to use if our collected sequences all correspond to the same physical walking path in the space. We therefore selected this distribution as a candidate model for the duration of the collected trajectories. Some trajectories may, however, sometimes be interwoven with another trajectory, in which case a mixture of Poisson distributions would be a more accurate model. Trajectories may also be interwoven with one or more activities, whose

duration is not adequately modelled by a Poisson distribution. We therefore also selected a mixture of a Poisson and a Normal distribution as a candidate model.

In our experiments we evaluated the following set of three candidate models:

1. a Poisson distribution with parameter $\Theta_1 = \lambda$,
2. a mixture of two Poisson distributions with parameters $\Theta_2 = (\pi, \lambda_1, \lambda_2)$,
3. a mixture of a Poisson and a Normal distribution $\Theta_3 = (\pi, \lambda, \mu, \sigma)$.

The probability distribution function (PDF) of a Poisson and a Normal distribution are given in Equation 4.1 and Equation 4.2. The PDF of a mixture a Poisson and a Normal distribution is given in Equation 4.3. The PDF of the mixtures of two Poisson distributions can be obtained in the same way.

$$P\left(x\right) = \frac{\lambda^x}{x!}\, e^{-\lambda} \tag{4.1}$$

$$P\left(x\right) = \tag{4.2}$$

$$P\left(x\right) = \pi \frac{\lambda^x}{x!}\, e^{-\lambda} + (1-\pi) \tag{4.3}$$

For each collected unique trajectory, the parameters π, λ, λ_1, λ_2, μ, and σ corresponding to the three candidate models are estimated by using the maximum likelihood method. To determine the model that fits the data the best, the 'goodness of fit' function of each candidate model is calculated using the Akaike information criterion (AIC) (Akaike, 1974) and the Bayesian information criterion (BIC) (Schwarz et al., 1978) metrics given by:

$$AIC = -2\log(\hat{L}) + 2\,K \tag{4.4}$$

$$BIC = -2\log(\hat{L}) + K\log(N) \tag{4.5}$$

In these equations, $\hat{L}$ represents the likelihood function of the model, K represents the number of parameters of the model and N is the number of observations. Both AIC and BIC metrics measure a penalized likelihood of the model. The penalty portion of AIC is only dependent of the number of the parameters of the model, while the penalty of the BIC is also dependent of the number of observations.

The estimate of the duration of each collected trajectory $\hat{\lambda}_i$ is then equal to the estimate of the Poisson-parameter (λ) of the model with the best (smallest AIC and BIC values) goodness of fit.

Modelling the length of each unique trajectory:
In Nait Aicha et al. (2015), we extracted the length of each unique trajectory from the map of the apartment. The disadvantage of this method is that the more complex the collected trajectory is, the least accurate estimate we get for its length. Moreover, an increase of the number of the unique collected trajectories results in a bigger error of the estimated gait velocity of the resident as we need to estimate more distances. Therefore,

we experimented with two methods where only the length of one single unique trajectory is 'manually' set (*e.g.,* extracted from the map of the apartment) and the length of the other trajectories is derived from this single length. In other words, under the assumption that the velocity is the same for each trajectory, we can do *simultaneous* relative length and velocity estimation.

Denote k to be the index of the unique trajectory for which the length l_k is manually set. The length of each other unique trajectory can be expressed by:

$$l_i = \alpha_i l_k \;\; \forall i \in \{i, 2, \ldots, k-1, k+1, \ldots, |R|\} \tag{4.6}$$

where R is the set of all collected trajectories. To calculate l_i, we explored two methods, referred to as *Simultane*$_1$ and *Simultane*$_2$, and based on the two assumptions:

1. the overall average gait velocity of the resident is constant and is the same for each unique trajectory i over the whole/complete measurement period W,
2. the average gait velocity of the resident is constant and is the same for each trajectory i during a short period of time (*e.g.,* a week).

The first assumption is formally given in Equation 4.7 and the second assumption is given in Equation 4.8,

$$\bar{v} = \frac{l_i}{\bar{\lambda_i}} \;\forall i \in R \tag{4.7}$$

$$v_i^{(w)} = \frac{l_i}{\widehat{\lambda_i}^{(w)}} \;\forall i \in R \;, \forall w \in W. \tag{4.8}$$

where $\bar{\lambda_i}$ is the average duration of trajectory i and $\widehat{\lambda_i}^{(w)}$ is the etimated duration of the trajectory i during a short time of period $w \in W$.

To calculate the lengths l_i using the first method, we combine the Equation 4.6 and Equation 4.7 to get a set of N equations with N unkown variables $\alpha_1, \alpha_2, \ldots, \alpha_{k-1}, \alpha_{k+1}, \ldots, \alpha_N$, where N is the number of the collected unique trajectories ($|R| = N$).

To calculate the lengths l_i using the second method, we combine the equations Equation 4.6 and Equation 4.8 to get a set set of $M \times (N-1)$ equations with $M+N-1$ unkown variables $v^{(1)}, v^{(2)}, \ldots, v^{(M)}, \alpha_1, \alpha_2, \ldots, \alpha_{k-1}, \alpha_{k+1}, \ldots, \alpha_N$. This set of equations is then solved using the least squares method. The resulted values for $\alpha's$ are then used to compute the distance l_i of each trajectory i using the Equation 4.6.

4.5 Experiments

4.5.1 Objectives

A set of five experiments is conducted to evaluate the approach. In the **first experiment**, we investigate the effect of varying the duration of the rest time on the collected trajectories, and find the optimal value of τ corresponding to each subject. Our hypothesis is that small values of τ will result in the collection of few useful trajectories (*i.e.,* , trajectories involving at least two rooms), while large values of τ will result in long sensor trajectories corresponding to walking paths with too many interwoven activities. We seek for a value of τ that results in sufficient useful trajectories, so that we can estimate our model parameters accurately, and that does not result in too many trajectories with interwoven activities.

In the **second experiment**, varied the length of the period in which we collected statistics on duration. On one hand, if a short period is chosen we assume that the functional health of the subject will not vary a lot, resulting in a constant gait velocity. On the other hand, the period of time must be large enough so that the number of collected trajectories during that period is sufficient to fit a probabilistic model to the corresponding durations.

In the **third experiment**, we study the effect of modeling the duration by a single distribution and by a mixture of distributions. Our hypothesis consists of two parts: on one hand, we expect the most frequently *auto-detected* trajectories to be short (between rooms) and therefore should be fitted by one probability distribution as these trajectories correspond to walking paths without interwoven activities. On the other hand, the *predefined* trajectories are long and may correspond to different walking paths or to paths interwoven with some activity and therefore need to be fitted using a mixture of probability distributions.

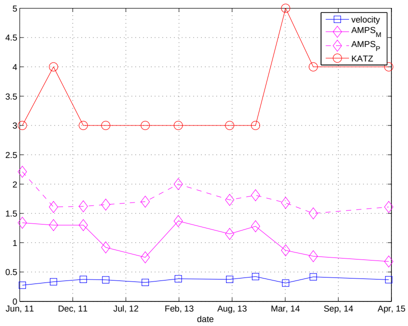
The **fourth experiment** is conducted to model the distance of the trajectories. The three methods described in section 4.4 are evaluated and compared to each other.

In the **last experiment**, we compare the walking speed measured by the occupational therapist with the gait velocity estimated from the sensor data. Our hypothesis is that the walking speed measured by the therapist is higher than the gait velocity estimated from the sensor data, because the residents tend to improve their behavior as a response of being watched. We also expect that continuous monitoring of the gait velocity results in more insights with respect of the functional health of a resident.

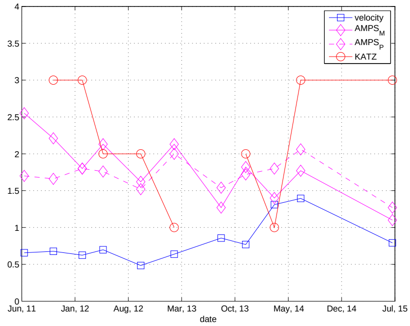
4.5.2 Sensor data and annotation

Three sensor datasets collected in our living labs are used to conduct the described experiments. The three sensor datasets are collected during 27 months between April 2013 and July 2014 in the apartment of three volunteers living alone. Volunteer A, a male of 85 years old, has difficulties with getting up from a chair and with walking. Volunteer B, a female of 80 years old, has no difficulty with walking in her home. Volunteer C, a female of 87 years old, also has no difficulty with walking, but has a diagnose of Alzheimer's dementia since April 2014. She is, therefore, at a day care for two days a week.

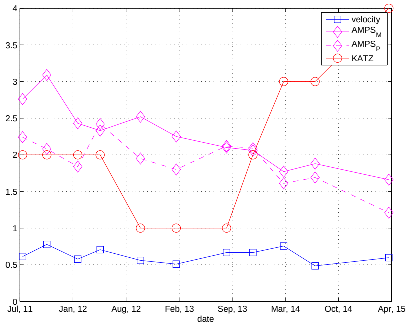
During the period of sensor data collection, the three volunteers are visited by the same occupational therapist for the KATZ (Katz et al., 1963) and assessment of motor and processing skills (AMPS) assessments (Fisher and Jones, 1999). The walking speed test taken over 3 meters is part of these assessments. The KATZ-score varies between a minimum value of 0, indicating the subject needs NO assistance, and a maximum value of



(a) Volunteer A.



(b) Volunteer B.



(c) Volunteer C.

Figure 4.3: Assessment data consisting of the AMPS, KATZ and the gait velocity test over 3 m distance. The gait velocity (m/s) is repeated twice and the mean value is notated. An increase of the KATZ score ($\{0, 1, \ldots, 6\}$) indicates more need of assistance. A decrease of the AMPS ($[-3, 4]$) indicates a decrease in the functional health.

6 indicating the subject is dependent of assistance for performing the ADLs. Two values of the AMPS, the motor part ($AMPS_M$) related to physical skills and the process part ($AMPS_P$) related to cognitive skills, are calculated from the assessment. A decrease of the AMPS indicate a decrease in the functional health of the subject.

4.6 Results

4.6.1 Occupational therapist assessments

The assessment scores, given in Figure 4.3, show an approximately stable functional health of volunteer A since January 2011. This may be concluded from the gait velocity and the AMPS scores, which show no significant increase or decrease. For volunteer B, the assessments show conflicting observations. On one hand, the AMPS show a decrease indicating the functional health of the resident is decreasing, while on the other hand the gait velocity shows an increase indicating the functional health is increasing. The decrease of the motor AMPS score of volunteer C indicates a decrease of her functional health. The speed test is however stable. Furthermore, the KATZ score of the subject indicates she needs assistance for preforming her ADLs.

4.6.2 Experiment 1: Effect of the rest time τ

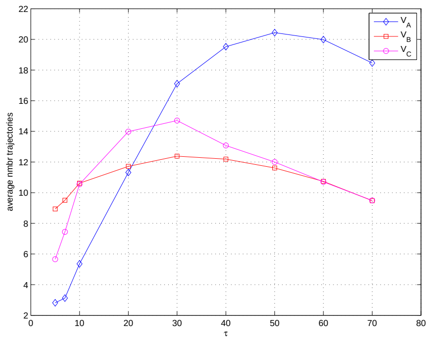
For each subject, we collected sensor data collected during 50 random weeks in the period between April 2013 and July 2015. We ensured that the selected weeks do not lack any sensor data. For each obtained sequence of sensor readings, valid trajectories are extracted using the two proposed methods, *auto-detected* and *predefined* trajectories, as described in section 4.4. The plot of the collected predefined trajectories as a function of τ, given in 4.4(a), shows that the value of $\tau = 50$ results in a maximum average number of predefined trajectories per week for volunteer A. This value of $\tau = 50$ seconds results also in sufficient average number (more than 40 per week) of collected auto-detected trajectories, as given in 4.4(b). Note that the most auto-detected trajectories have a low frequency, which means that during a week, many different trajectories are collected. For example, Figure 4.4(c) shows that for $\tau = 7$ more than 85% of the collected 8172 trajectories occurred only once. Comparable figures hold for the other values of $\tau \in \{5, 10, \ldots, 70\}$. Following the same procedure for volunteers B and C resulted in an 'optimal' value of $\tau = 30$ for collecting both auto-detected and predefined trajectories. Note that this higher values of τ for volunteer A compared to the other volunteers correlates with the measured low walking speed of volunteer A.

4.6.3 Experiment 2: Modeling the period of time the trajectories are collected

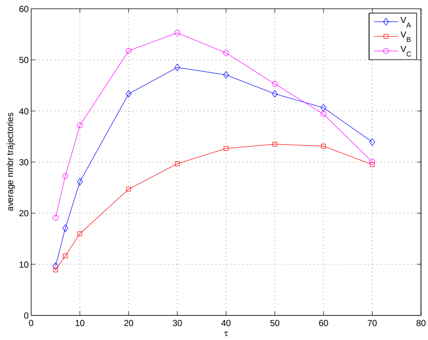
In the first experiment, we set the period of time the trajectories are collected to 1 week, because of the ease of interpretation. In this experiment, we have experimented with other values around a week as a period of time. The periods above one week are chosen to test if this results in collecting significantly larger number of trajectories. The periods less than a week are chosen to test if these values still results in a sufficient number of trajectories. For each value of period of time in $\{1, 3, 5, 7, 9, 14, 21\}$ days, a set of 50 random samples of sensor data is selected. Also, the 'optimal' value of τ obtained from the first experiment is used. The results, given in Figure 4.5, show that one week is a reasonable choice.

4.6.4 Experiment 3: Modeling the duration of a trajectory

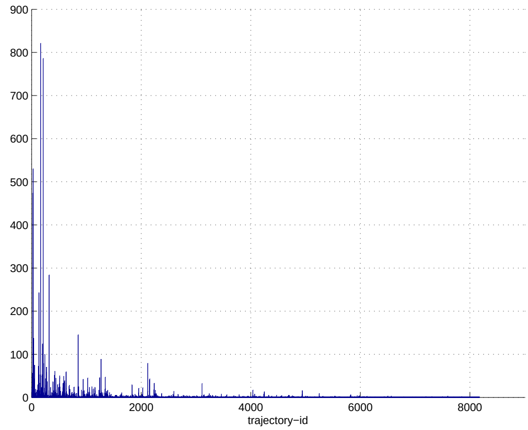
In this experiment, we have selected 50 random weeks of sensor data and we used for each subject his/her 'optimal' value of τ obtained in experiment 1. The durations of



(a) Average number of collected *predefined* trajectories versus τ (sec).

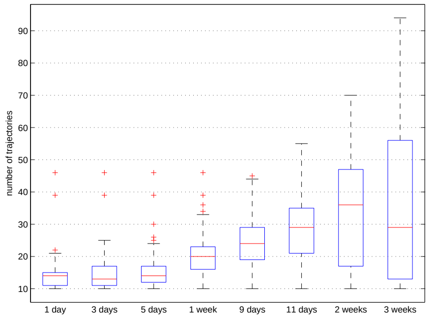


(b) Average number of collected *auto-detected* trajectories versus τ (sec).

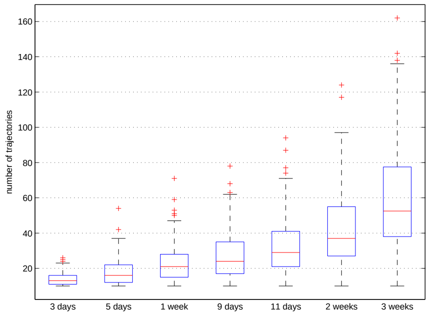


(c) Histogram of the number of auto-detected trajectories using different values of τ.

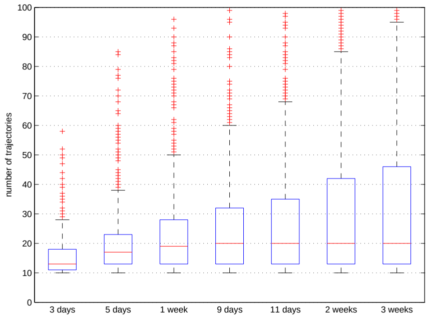
Figure 4.4: Visualisation of the collected predefined and auto-detected trajectories using different values of τ (seconds). V_i denotes volunteer i. A sample of 50 random weeks extracted from the sensor data collected between April 2013 and July 2015 is used.



(a) Volunteer A.



(b) Volunteer B.



(c) Volunteer C.

Figure 4.5: Boxplot of the number of collected trajectories per period of time ($\{1, 3, 5, 7, 9, 11, 14, 21\}$ days). The sensor data used is collected between April 2013 and July 2015.

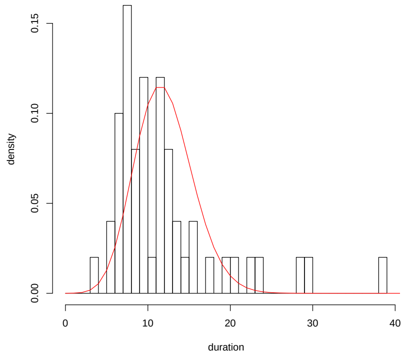
	average of standard deviations		
Method	Volunteer A	Volunteer B	Volunteer C
Map	0.336	0.317	0.491
Simultane$_1$	0.261	0.051	0.177
Simultane$_2$	0.172	0.012	0.183

Table 4.2: The average of standard deviations calculated using the three methods described in section 4.4 for modeling a trajectory length. The values are calculated using a sample of 50 random weeks extracted from the sensor data collected between April 2013 and July 2015 is used.

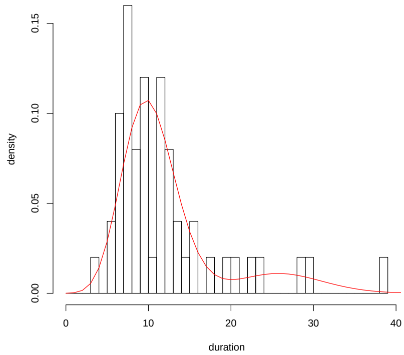
the collected trajectories are fitted to the selected three models. Figure 4.6 gives an example of the observed durations in a histogram and the fitted mixture of a Poisson and a Normal distribution. For each model and each trajectory we calculated its AIC and BIC values. Figure 4.7 shows the AIC average values for the collected auto-detected and predefined trajectories. Comparable figures hold for the BIC scores. The results show that the Poisson distribution fits the calculated duration significantly less well than the two mixtures of probabilities. We therefore reject the first part of our hypothesis that the auto-detected trajectories are best modeled using one distribution. The results also show that the mixture of two Poisson distributions gives significantly the best fit in almost all cases for each subject. Only in case of auto-detected trajectories of volunteer B, there is no significant ($p < 0.01$) difference between the calculated AIC_{PP} and AIC_{PN}. A paired t-test resulted in a p-value of 0.19. We may, therefore, conclude that any collected trajectory (both auto-detected and predefined) is occasionally interwoven with an other trajectory or some activity.

4.6.5 Experiment 4: Modeling the length of the trajectories

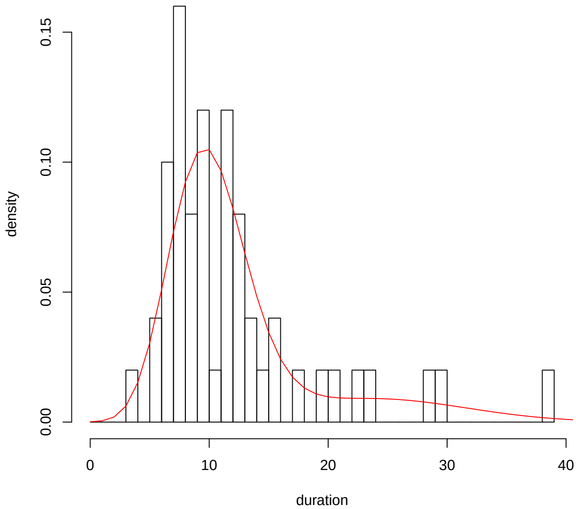
Similar to the previous experiments, we selected 50 random weeks of sensor data collected between April 2013 and July 2015. For each week, we collected walking trajectories and we estimated for each single trajectory its average duration and the corresponding standard deviation using the best fitting model. The average of these standard deviations, calculated for each subject, are given in Table 4.2. As expected, the estimation of the length of each single trajectory from the map (Map method) results in a large error in comparison with the use of a simultaneous method. The comparison of the two simultaneous method (Simultane$_1$ and Simultane$_2$) to each other using a paired t-test results in a significantly better performance of the method Simultane$_2$ over the method Simulate$_1$ for both the volunteer A and B. There is, however, no significant difference between the two methods for volunteer C (p-value = 0.383). This may indicate that Volunteer C's walking speed is particularly stable, when evaluated on all recorded motion. Further investigation with more volunteers will be needed to ascertain this.



(a) Poisson distribution.

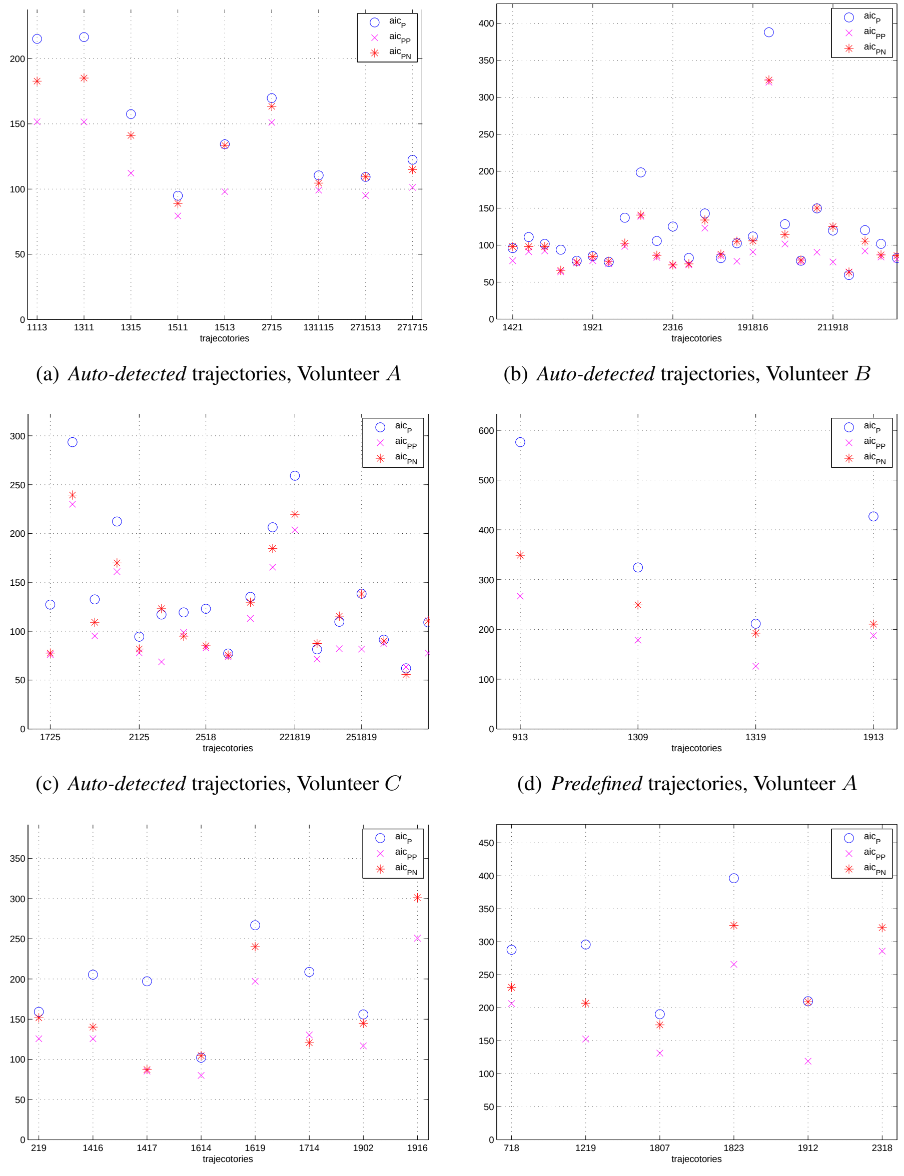


(b) Mixture of two Poisson distributions.



(c) Mixture of a Poisson and a Normal distribution

Figure 4.6: A histogram of the duration of the collected *'living room to kitchen'* trajectories in one week. The data is fitted using (a) a Poisson distribution, (b) a mixture of two Poisson distributions and (c) a mixture of a Poisson and a Normal distribution.



(a) *Auto-detected* trajectories, Volunteer A

(b) *Auto-detected* trajectories, Volunteer B

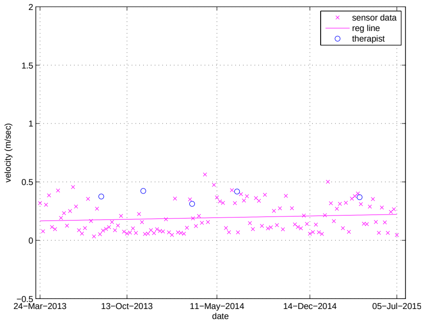
(c) *Auto-detected* trajectories, Volunteer C

(d) *Predefined* trajectories, Volunteer A

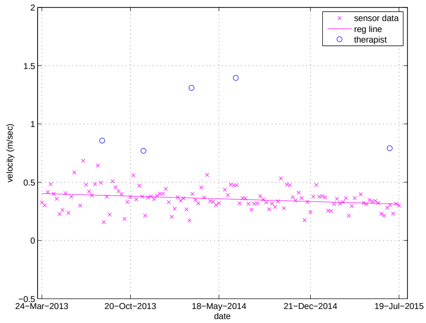
(e) *Predefined* trajectories, Volunteer B

(f) *Predefined* trajectories, Volunteer C

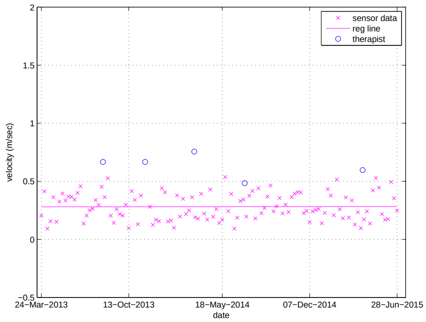
Figure 4.7: A plot of the AIC values calculated for the most occurred collected *auto-detected* and *predefined* trajectories. aic_P (resp. aic_{PP} and aic_{PN}) denotes the AIC calculated when the Poisson model (resp. a mixture of two Poisson and a mixture of a Poisson and Normal) is applied. Collected trajectories, represented by their sensor ids, are given in the x-axis. Note that these trajectories do not have any order.



(a) Volunteer A.



(b) Volunteer B.



(c) Volunteer C.

Figure 4.8: Gait velocity measured by the occupational therapist (circles) and estimated from sensor data using Simultane$_2$ method (crosses).

4.6.6 Experiment 5: continuous measurement of the gait velocity versus measurement by an occupational therapist

For this experiment, we estimated the gait velocity using the Simultane$_2$ method applied on trajectories collected each week in the period between April 2103 and July 2015. These gait velocities, referred to as sensor data velocities, are given Figure 4.8 together with the gait velocity measured occasionally by the occupational therapist. The results show that the walking speed values measured by the therapist are higher than the average gait velocity estimated from sensor data. These results are in line with our hypothesis that the subjects tend to improve their behavior as a response of being assessed. Furthermore, the results show a stable gait velocity of the subjects A and C while the gait velocity of subject B is decreasing. These trends are more clearer than the measurements performed by the occupational therapist.

4.7 Conclusion

This study shows the potential of continuously monitoring the indoor gait velocity of older adults living alone using a simple sensor network. We have shown that unconstrained behavior leads to a multimodal distribution of path durations, as walking is interwoven with other activities. We have shown that we can nevertheless extract the gait velocity from unconstrained sensor data, by fitting a mixture model to the durations. In particular, the results show that the durations of the collected trajectories can be best fitted using a mixture of a Poisson and a Normal distribution as a model. Apart from the gait velocity, the method also allows us to detect the most recurrent indoor walking trajectories.

We applied this model to three sets of sensor data collected in three different living labs in a period of 27 months. Our results showed that the estimated gait velocity is in line with the motor AMPS scores extracted from the assessments conducted by an occupational therapist. In accordance with the findings in the literature, our results also show that the walking speed measured by the therapist is significantly higher than the average gait velocity. Moreover, the few assessments of the therapist do not provide a solid ground truth about the functional health of the resident, while our method gives a clearer trends.

In a real-time situation, we could imagine a sliding window of one week needed to collect enough valid walking trajectories to be fitted by the model. Currently, our group is involved in a monitoring older adults after having a hip surgery using comparable sensor networks. This project gives an opportunity to apply our findings to a new situation where we expect the walking speed to increase in a relative short period, as the functional health of these subjects gets better during the rehabilitation. It will be fascinating to have the same pattern from the gait velocity estimated from the sensor data. An interesting future challenge is the measurement of the gait velocity in a multi-person home setting.

This chapter was previously published as:
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5 Deep Learning to Predict Falls in Older Adults Based on Daily-Life Trunk Accelerometry

Early detection of high fall risk is an essential component of fall prevention in older adults. Wearable sensors can provide valuable insight into daily-life activities; biomechanical features extracted from such inertial data have been shown to be of added value for the assessment of fall risk. Body-worn sensors such as accelerometers can provide valuable insight into fall risk. Currently, biomechanical features derived from accelerometer data are used for the assessment of fall risk. Here, we studied whether deep learning methods from machine learning are suited to automatically derive features from raw accelerometer data that assess fall risk. We used an existing dataset of 296 older adults. We compared the performance of three deep learning model architectures: CNN, LSTM and a combination of these two (ConvLSTM) to each other and to a baseline model with biomechanical features on the same dataset. The results show that the deep learning models in a single-task learning mode are strong in recognition of identity of the subject, but that these models only slightly outperform the baseline method on fall risk assessment. When using multi-task learning, with gender and age as auxiliary task, deep learning models perform better. We also found that preprocessing of the data resulted in the best performance (AUC = 0.75). We conclude that deep learning models, and in particular multi-task learning are good for assessment of fall risk on the basis of wearable sensor data.

5.1 Introduction

Falls among older adults are one of the major health problems that lead to a decreased quality of life and increased morbidity and mortality. In addition, falls pose high costs to the public health service. **Risk factors** for falls are for example weak muscles, unsteady gait, cognitive decline and psychoactive medications. Early detection and monitoring of fall risk factors can significantly reduce the risk of future falls (Ambrose et al., 2013;

Rubenstein, 2006). Among these factors, history of falls and gait and balance disorders have been identified as the strong predictors (Deandrea et al., 2010).

Fall risk assessment is a process in which the probability of a future fall is estimated, usually within a time frame of 6 to 12 months. In many intervention programs proposed for **fall prevention**, fall risk assessment is performed as the initial step to identify persons at highest risk. The assessment of fall risk is commonly conducted in a clinical setting and based on questionnaires and functional tests of mobility such as the Timed Up and Go (TUG) (Podsiadlo and Richardson, 1991), the Performance Oriented Mobility Assessment (POMA) (Tinetti, 1986) or the Berg Balance Scale test (Berg KO, 1989). Although these tests provide a good indication of one's optimal mobility and performance, their predictive ability for prospective falls is limited (e.g. Barry et al. (2014)), possibly because this optimal ability might not be representative of one's use in daily life behavior.

In previous research, we studied the use of ambient sensors for continuous monitoring of human activities in their **natural environment** (Nait Aicha et al., 2017b; Ordonez et al., 2014). In this paper, we focus on body-worn inertial sensors which are used in many research studies for ambulatory monitoring of humans in daily life providing reliable insight into an individuals daily activities and gait quality characteristics (Howcroft et al., 2013).

Much research is done in the characterization of the **quantity of the movement** of subjects, including the duration of the low, moderate and high intensity of activities, the total number of daily steps and the daily percentage of time spent in lying, sitting, standing and walking (Howcroft et al., 2013). Recent research showed the added value of the characterization of one's **quality of the movement** in the determination of fall risk in older adults (van Schooten et al., 2015). These studies revealed that biomechanical features such as gait stability, variability, and smoothness Rispens et al. (2015b); Weiss et al. (2013), but also mean turn duration Mancini et al. (2016) and number of abnormal sit-to-stand transitions Najafi et al. (2002), are associated with fall risk. However, estimation of these features often requires event detection, which deserves improvement, and may not exploit the wealth of information contained in the data. Deep learning, on the other hand, allows for data-driven generation of features and does not suffer from these shortcomings.

In machine learning, deep convolutional and LSTM recurrent neural networks have shown to be successful for recognition of activities Ordónez and Roggen (2016) and gait patterns Hu et al. (2018) from inertial sensor data. However, the assessment of fall risk with such models has not been done before. The contributions of this paper are: a) a comparison of the performance of deep learning models for the assessment of fall risk with a baseline model based on biomechanical features using a large data set of 296 subjects and b) the extension and testing of these models with multi-task learning to improve their performance.

	Male (%)	Age (Years)	Weight (Kg)	Height (Cm)
Mean	74.1	75.3	49.2	170.6
Standard deviation		6.8	13.3	8.8
25% Quantile		70.0	64.0	165.0
75% Quantile		80.0	81.8	176.0

Table 5.1: Descriptive statistics of the population.

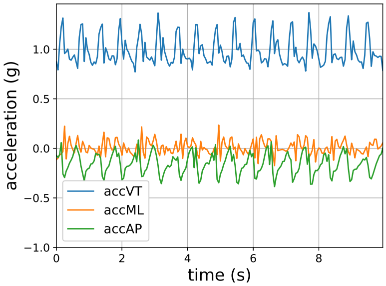
5.2 Sensor Data

The data used in this paper were collected between March 2011 and January 2014 as part of the Fall Risk Assessment in Older Adults (FARAO) cohort study performed at the Vrije Universiteit Amsterdam. The FARAO study collected data on fall risk factors in older adults with questionnaires, physical tests and wearable sensors. Participants in the cohort were between 65 and 99 years of age, had a mini mental state examination score (MMSE Folstein et al. (1975)) between 19 and 30, and were able to walk at least 20 meters with the aid of an assistive device, if needed. We re-analysed the data described in (van Schooten et al., 2016), which consisted of a population of 296 older adults. These participants wore a triaxial accelerometer (Dynaport MoveMonitor, McRoberts) on their lower back, which registered 3D trunk accelerations at 100 Hz and +/- 6 G, during 1 week of their daily life. During a 6 month follow-up period, in which fall incidences and descriptions were monthly obtained, 101 subjects (34.1%) had experienced at least one fall and were identified as fallers. Table 5.1 provides an overview of the descriptive characteristics of the population. A detailed description of the population and the methods for data collection can be found in Rispens et al. (2015a) and in van Schooten et al. (2015, 2016).

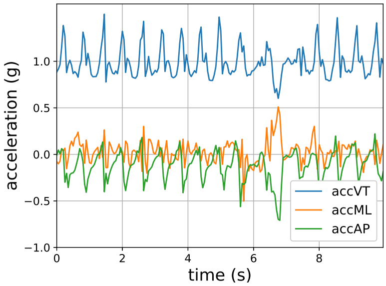
Participants were instructed to wear the accelerometer with an elastic belt around their lower back at all times, except during aquatic activities such as showering. The distribution of the total time that the sensor was worn was similar for fallers and non-fallers. Bouts of non-wearing, locomotion, sitting, lying and standing were identified using the manufacturer's activity classification algorithm (Dijkstra et al., 2010). Only the locomotion bouts were analysed in the current study. For each locomotion bout, the acceleration in three directions, i.e., anteroposterior (AP), mediolateral (ML) and vertical (VT) was recorded. Figure 5.1 shows two examples of locomotion bouts lasting 10 seconds each.

5.3 Approach

On the basis of this data set containing bouts of accelerometer data of 296 participants and the identification of the participants into fall or non-fall category, a model is made that predicts falls from accelerometer data. In van Schooten et al. (2016), a linear model was used, based on biomechanical features from the accelerometer data. In this paper we used deep neural networks. Deep learning allows creating computational models



(a)



(b)

Figure 5.1: An example of two locomotion samples. (a) a typical walking sample and (b) a walking sample interwoven with a turning activity round second 7.

that are composed of multiple processing layers and learn representations of data with multiple levels of abstraction (LeCun et al., 2015). This can result in more powerful models, because the complexity of the feature computations are dictated directly by the data and by the quality of the model predictions, rather than by preconceptions of the operator. On the other hand, no prior knowledge is leveraged in the creation of the model, and so it is useful to compare deep learning approaches to traditional machine learning methods.

We evaluated two types of deep neural networks (DNNs) for the analysis of fall risk. First, we considered the convolutional neural network (CNN), which constrains the number of parameters by sharing parameter values in different parts of the network. It has been used with great success in speech recognition (Abdel-Hamid et al., 2012) and in the detection, segmentation and recognition of objects and regions in images (Krizhevsky et al., 2012; Toshev and Szegedy, 2014). We then looked at the long short term memory (LSTM) model, a specific type of recurrent neural networks (RNNs). RNNs specifically model sequential inputs, such as speech and language (Graves, 2013; Sutskever et al., 2014). In this work, we used a model that combines convolutional and recurrent models, which we refer to as the 'ConvLSTM'.

We trained the model parameters and evaluated the resulting models by minimising the loss, a function that expresses how many prediction errors the model makes, and evaluated the models for different values of their so-called "hyper-parameters", which include the number of layers and the number of nodes in each layer, based on their the receiver operator Characteristics (ROC) curves. The models can make different types of errors, false positive and false negative predictions, and a single model can be tweaked to minimise one type of error at the expense of the other. The ROC curve shows the model's performance for multiple choices of this trade-off. The Area Under the (ROC) Curve (AUC) is a robust metric of a model's performance. The training, validation and testing of the DNN was performed on a Distributed ASCI Supercomputer 5 (DAS-5) server (Bal et al., 2016).

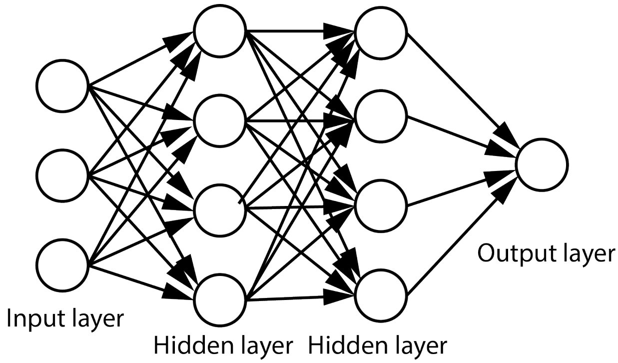


Figure 5.2: A 3-layer neural network with three input neurons, two hidden layers of 4 neurons each and one output layer.

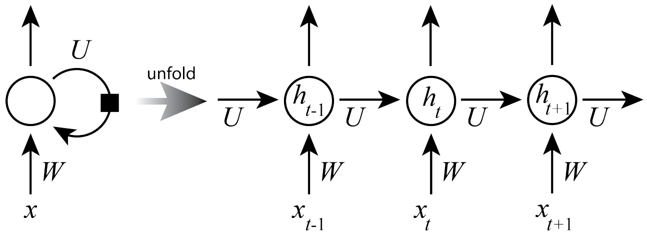
5.4 Deep Learning Neural Network Models

5.4.1 Feed-forward Neural Networks

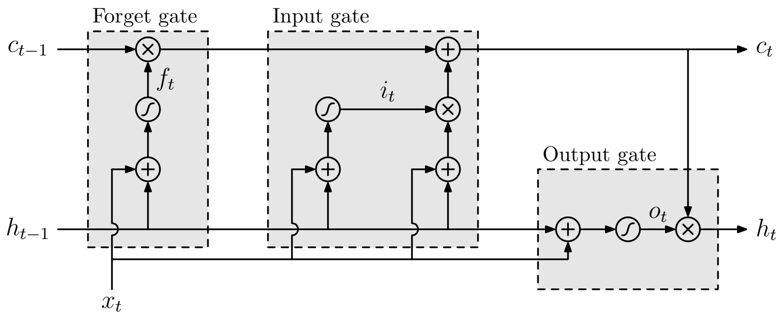
Deep neural networks consist of large numbers of simple processing modules, the ”neurons”, which compute a fixed function — the “activation function” — of the weighted sum of their inputs and are organised in separate layers. The simplicity of the neurons make training of the network possible, while the large number of nodes and their organisation in a large number of layers allows them to perform complex tasks. DNNs have the ability to learn representations of the training data and relate them to the output variable(s) that we train them to predict. An example of a DNN consisting of two hidden layers is given in Figure 5.2. The number of nodes in the input layer is determined by the dimensionality of the data, while the number of nodes in the output layer is determined by the chosen representation of the intended prediction. The structure of the network is determined by the complexity of the task being predicted. In addition to the number of nodes and layers, the connections between layers affect the complexity of the network. In a dense layer, each neuron is connected to all neurons of the previous layer and has its own set of weights. In a convolutional layer, a neuron is connected to a subset of the neurons in the previous layer, and shares its weights with the other neurons of that layer.

5.4.2 Long Short Term Memory (LSTM) network

Recurrent neural networks is a type of neural networks where inputs are organized sequentially, and the output at time t is connected to all inputs from time 0 to t (see Figure 5.3(a)). Such a network is still a feed-forward network, but the number of layers between an output and previous inputs increases as the time difference increases. In practice, the training of recurrent neural networks (RNNs) with long-term temporal de-



(a) RNN



(b) LSTM

Figure 5.3: (a) A cyclic connection of an RNN folded and unfolded. (b) An LSTM memory block consisting of one cell at time t and the three gates (i_t, o_t and f_t) which control the activation of the cell c_t and its output h_t.

pendencies can be problematic because the gradient of the loss function decays exponentially with the number of layers, and therefore with time (Bengio et al., 1994). long short term memory (LSTM) networks, introduced by Hochreiter and Schmidhuber (1997), are a type of RNN that uses special units to solve this so-called vanishing gradient problem by "gating" the propagation of information over time. They extend RNNs with memory blocks (Figure 5.3(b)) to store information, easing the learning of temporal relationships over long time periods.

5.4.3 Multi-task learning

Multi-task learning has been proposed by Caruana (1993) to learn several related tasks by a single model. Having a network learn multiple tasks increases the complexity of the function it computes but, when the tasks are related, the models can share parameters. The complexity of a network performing multiple tasks is then lower than the complexity of multiple networks learning the tasks separately. In addition, the fact that tasks essentially compete for the resources of the network tends to force the network to avoid modeling non-essential aspects of the problem, thereby also improving the performance on the individual tasks.

5.5 Experiments and Results

We conducted a set of five experiments to evaluate the presented approach. In the **first experiment**, we compared deep neural networks (DNNs) with the current state-of-the-art model, described in subsection 5.5.1 which relies on manually engineered feature extraction. In the **second experiment**, we investigated the performance of DNNs in the prediction of fall status at sample level, *i.e.*, when allowing the model to train and test on different data from the same person, and show drastically improved results. In the **third experiment**, we explored whether these improvements are due to the model learning to identify people from their gait, rather than from better modeling of fall risk. We observed that the model is capable to identify people from their gait, but that this does not by itself explain all of the performance increase. In the **fourth experiment**, we therefore explored how person-specific but not fall-related information can improve the model. We showed that multi-task learning improved fall prediction. Finally, in the **fifth experiment**, we showed how improving the focus of the model on cleaner data further improved the overall prediction performance. To train a model and calculate its performance, the complete dataset is split into a training and a validation set (90%) and a test set (10%).

5.5.1 Experiment 1:

We compared the performance of three types of DNNs using raw inputs to the performance of the state-of-the-art model. This base model has been previously described by van Schooten et al. (2016) and is based on a dataset of ten-second gait samples from which several features such as walking speed, variability, smoothness and complexity were extracted. principal components analysis (PCA) was applied to these features (as well as other parameters obtained from questionnaires and tests), keeping 18 principal components, and a multivariate model was developed to predict time to prospective falls. The median of a person's ten-second segments' predictions provided that person's risk assessment. This base model resulted in a performance of AUC=0.67 (95% confidence interval $[0.59, 0.73]$) at 6 months (van Schooten et al., 2016).

The same complete dataset was randomly split into three subsets (training, validation and testing set) at **subject level**, where all the 10-second samples of a subject A occur in a single subset. The ratio of fallers to non-fallers was approximately the same in these three sets. The DNNs were given 10-second samples x and the corresponding faller/non-faller label $y \in \{0, 1\}$ for training and testing. For each sample x the predicted value using an DNN architecture was denoted by $\hat{y}$. The median of the predicted values for all of a subject's samples was used as the predicted value for that subject. The subjects' predicted values and their actual values (label) were used to plot the ROC and to calculate the corresponding AUC. Figure 5.4 shows an illustration of predicted values ($\hat{y}$) for multiple 10-second sequences grouped by subject.

As described in section 5.3, three types of DNN architectures CNN, LSTM and ConvLSTM were applied to a small set of the data to determine the best fitting model. The mod-

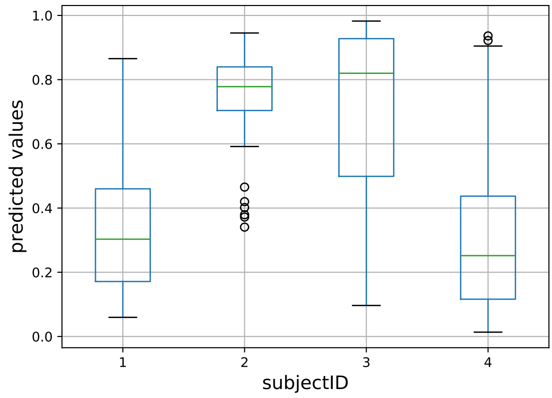
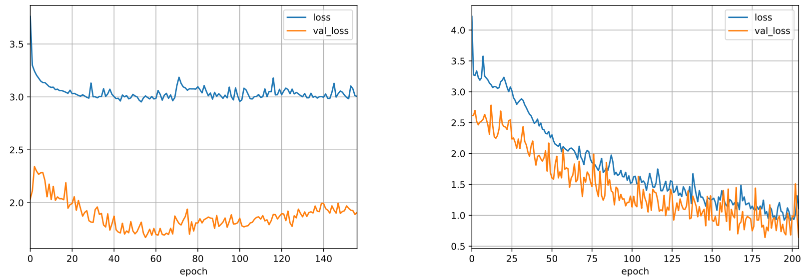


Figure 5.4: Example boxplots of the normalized predicted values ($\hat{y}$) for multiple 10-second sequences, grouped by subject. Subjects 1 and 4 were non-fallers and the other two were fallers. The final prediction per subject was given by the median of the predictions, as per van Schooten et al. (2016).

els were trained by minimizing the Binary Cross Entropy loss function (Figure 5.5(a)), and evaluated in terms of the Area under the ROC Curve for each subject (Figure 5.6(a)). The corresponding AUC was used to measure the performance of the models (Figure 5.7(a)).

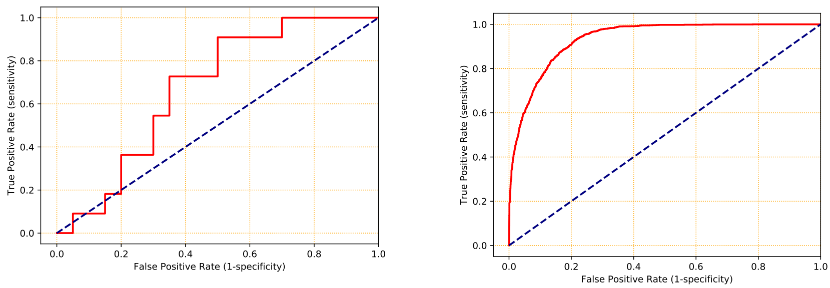
From these, we can conclude that the LSTM and ConvLSTM architectures resulted in a slightly better performance than the CNN architecture (p-values are respectively 0.056 and 0.022) and that there is no significant difference in the performance between LSTM and ConvLSTM ($p = 0.480$). The time needed for the training of the LSTMs was very long compared to the ConvLSTM architecture (Table 5.4), because two or more LSTM layers were used in the LSTM architecture while the ConvLSTM architectures was set to have exactly one LSTM layer. For this reason, we selected a ConvLSTM architecture and its corresponding hyper parameters to be trained on larger datasets. Table 5.2 illustrates the architecture of the ConvLSTM type used. The AUC and the corresponding training time of this architecture is given in Table 5.5.

We compared the performance, in terms of average AUC, of the best fitting model to the base model using a z-test and found no statistically significant difference ($p = 0.209$). In addition, the results also showed a poor generalization ability of the DNN model when trained at the subject level as indicated by the gap between the two loss functions in Figure 5.5(a). Perhaps the model learnt concepts from the training data that did not apply to the test data and therefore negatively impacted the performance of the model. For the investigation of the cause of this generalization problem, we conducted a second experiment, where we applied the same types of DNNs on different training and testing subsets.



(a) Subject level (b) Sample level

Figure 5.5: A typical **loss** versus **epoch** graph during the training of a DNN. The data has been split at (a) subject level or (b) sample level; loss is the training loss and val_loss is the validation loss. The gap between the training and validation loss indicates the amount of over-fitting.

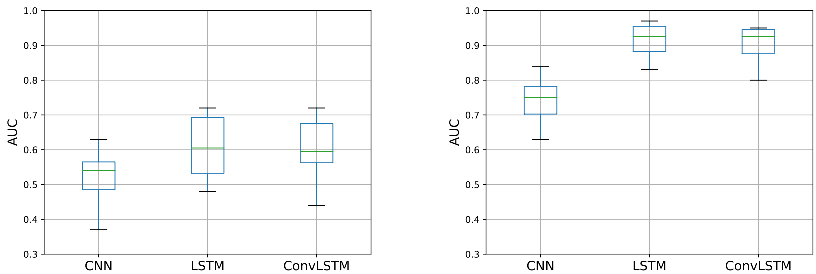


(a) subject level, AUC=0.65, chance=0.50 (b) sample level, AUC=0.94, chance=0.50

Figure 5.6: Examples of the ROC curves and their corresponding AUC values obtained using a ConvLSTM model. The dashed line represents the ROC for chance. The dataset was split at (a) subject level and (b) sample level.

layer index	**01**	**03**	**05**	**07**	**09**	**11**	**12**
type filter	CNN	CNN	CNN	CNN	CNN	LSTM	Dense
number filters	N	N	N	$\frac{3}{4}N$	$\frac{3}{4}N$	N	2

Table 5.2: The ConvLSTM architecture. To keep the architecture clear, we omitted the input-layer (layer 00) and the dropout layers (the even layer indices) applied after each CNN-layer. N is set to 128.



(a) Subject level

(b) Sample level

Figure 5.7: A boxplot of the AUC's of different DNN architectures. For the LSTM architecture at least two LSTM layers were involved, while for the ConvLSTM architecture, only one LSTM layer was involved. The dataset was split at (a) subject level and (b) sample level.

	AUC	
	average	**standard deviation**
subject level	0.65	0.09
sample level	0.94	0.07

Table 5.3: Comparison of the Average AUC and the corresponding standard deviation when splitting at sample or subject level.

	subject level AUC	time (hrs)	sample level AUC	time (hrs)
CNN	0.52 (0.07)	6	0.74 (0.07)	7
LSTM	0.61 (0.10)	160	0.91 (0.06)	180
ConvLSTM	0.60 (0.09)	35	0.90 (0.05)	40

Table 5.4: Average AUC (standard deviation) and corresponding average training time, per NN architecture type, for a subset of the data. The difference in training time between the ways of splitting the data is due to the slower convergence when splitting at the sample level.

	Dataset size in minutes 10	30	60	120	complete dataset
average AUC	0.61	0.63	0.65	0.65	0.65
training duration (Hrs)	35	90	150	250	350
number of folds	10	10	10	2	1

Table 5.5: Average AUC, training duration and number of folds obtained when applying the ConvLSTM model to different dataset sizes. The dataset was cut into three subsets at the subject level.

5.5.2 Experiment 2

For this experiment the complete dataset was randomly split into three subsets (training, validation and testing set) again but now at **sample level**. As a consequence, there was only a small chance that all the 10 seconds samples of a single subject were allocated to only one subset. As in the first experiment, we evaluated three DNN architectures to a small set of the data to identify the best performing architecture. The ConvLSTM architecture again resulted in the best trade-off between performance and training time (Figure 5.6(b) and Figure 5.7(b)). A t-test showed that both LSTM and ConvLSTM have a significantly better performance than CNN ($p < 0.002$) and no significant difference between LSTM and ConvLSTM(0.580). Furthermore, this experiment resulted in a better performance than the previous experiment as shown in Table 5.3.

The high AUC when splitting the data at sample level compared to subject level can be explained by the smaller within-subject, compared to between-subject, variability of gait. However, another explanation may be that the model learns to identify subjects better than it recognises characteristics indicating fall risk (since the same subjects were present in train and test set, the model could map their identity to fall risk). In the third experiment, we checked the model's ability to identify subjects' gait signatures.

5.5.3 Experiment 3

We again split the dataset into three subsets at **sample level**. To learn subject signatures together with their fall risk, we used multi-task learning (MTL): fall risk was the main task, while the identity of the subject was the auxiliary task. We used the same ConvLSTM architecture as in Table 5.2, because of its good trade-off between performance and learning time in the previous experiments, with an additional dense output layer (connected to layer 11) for the auxiliary task. The overall loss of the network is a weighted sum of the losses on the main and auxiliary tasks. Ten-fold cross validation was used to calculate the performance of both the main and auxiliary tasks. The performance of the auxiliary task, which identified the person out of the 296 in the dataset, was evaluated with a plot of the ROC for each subject in a one versus all approach. The ROC of the main task and, for clarity, a random sample of the ROCs for the auxiliary task are shown in Figure 5.8.

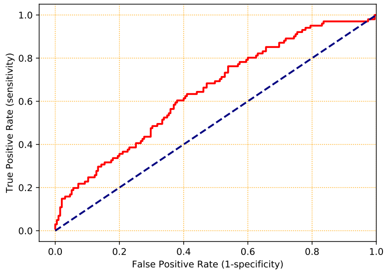
As we can see, when both tasks are given the same weight (Figures 5.8(a) and 5.8(b)), the network is exceedingly good at recognising identities, but not so much at predicting fall risk. The network has the information to learn the mapping from identity to risk, but not the information capacity to learn this mapping. So when we increase the weight of the main task, the network becomes better at predicting fall risk at the expense of the identification task (Figures 5.8(c) and 5.8(d)). From this, we can conclude that there are important differences between subjects, but that there are other informative patterns in the data, which leaded us to our next experiment.

5.5.4 Experiment 4

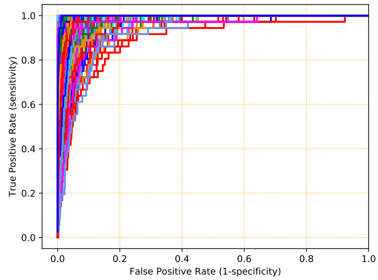
In this experiment, we investigated the effect of MTDL on the model performance. When we split the data at subject level, it makes no sense to use subject ID as the auxiliary task — since the IDs in the test set are never seen during training — but other subject characteristics can form an informative auxiliary task. The experimental setup is similar to the previous experiment, except that the data is split at the subject level and the auxiliary task is one of the following subject characteristics: *age*, *gender*, *weight* and *height*. Table 5.6 shows the average AUC and the corresponding standard deviation of the main task (fall status). We can conclude that MTDL consistently results in improved performance compared to the single-task learning used in the first experiment. The improvement, however, is not significant when compared to the base model.

5.5.5 Experiment 5

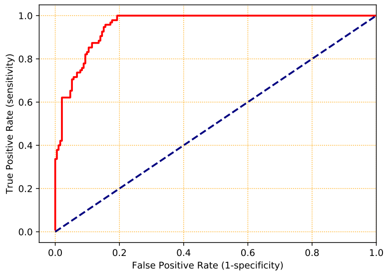
In the previous experiments, we used the exact same 10-second data segments as in van Schooten et al. (2016), which consists of samples of locomotion as identified by the accelerometer manufacturer's algorithm (Dijkstra et al., 2010). As the data were collected in a daily living environment, the locomotion bouts may contain some 'non-gait' data



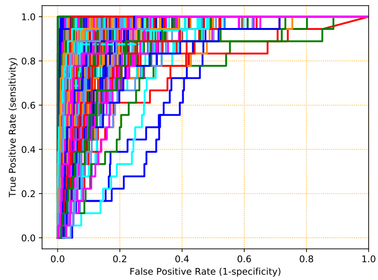
(a) Main task, AUC=0.63, chance=0.50



(b) Auxiliary task, average AUC=0.97



(c) Main task, AUC=0.96, chance=0.50

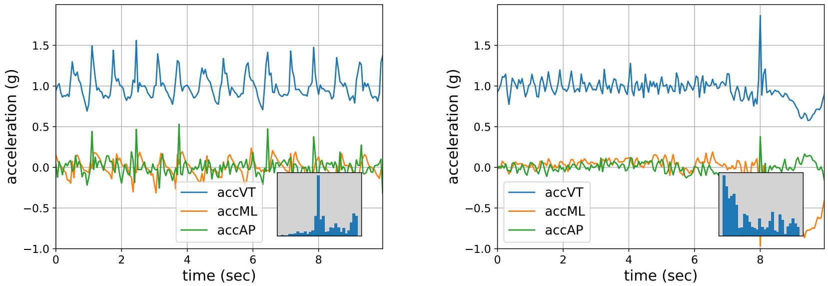


(d) Auxiliary task, average AUC=0.91

Figure 5.8: A sample of obtained ROCs for MTDL with fall status as main task and subject identity as auxiliary task. For the auxiliary task, the ROCs are computed using one-versus-all. The corresponding average AUC is reported. For Figures (a) and (b), the main and auxiliary losses are given the same weight ($1 : 1$); for Figures (c) and (d) the main loss function is given higher weight ($10^4 : 1$) than auxiliary loss function. The dashed line in Figures (a) and (c) represents the chance ROC.

Characteristic	**AUC main task (std dev)**		**p-value diff to base model**	
	Experiment 4	**Experiment 5**	**Experiment 4**	**Experiment 5**
Gender	0.70 (0.06)	0.75 (0.05)	0.070	<0.001
Age	0.70 (0.05)	0.74 (0.05)	0.082	<0.001
Weight	0.68 (0.05)	0.72 (0.05)	0.306	0.005
Height	0.63 (0.06)	0.65 (0.06)	0.987	0.897

Table 5.6: Average AUC and the corresponding standard deviation of the main task (fall status), obtained when the ConvLSTM is applied to the test set. The p-value is obtained using the z-test to test the difference in performance to the base model.



(a) gait (b) non-gait

Figure 5.9: (a) An example of a 10-seconds data sample included in the training and testing set and (b) an example of a data sample excluded in experiment 5 due to the low dominant frequencies in the VT-axis. In the bottom-right corners, histograms of the VT-frequencies up to 3 Hz are depicted. Both examples are included in the first 4 experiments.

samples, which may have negatively affected the performance of the DNNs. Visual inspection of the data indeed suggested the presence of such data samples. These data samples correspond to cyclic accelerations of the trunk without taking clear steps (such as when riding a bike) or involve only a few steps (such as when moving in the kitchen while preparing a meal). The objective of this experiment was to investigate the effect of conservatively selecting gait data samples on the performance of the models. To do so, 10-seconds data samples having a very low dominant frequency in the vertical direction (VT-axis) ($\leq$ 0.2 Hz) were removed from the data, resulting in approximately 20% discarded data. An example of such included and excluded samples is shown in Figure 5.9. A procedure similar to experiment 4 was followed to train, test and calculate the performance of the ConvLSTM model. Table 5.6 shows the obtained average AUC and the corresponding standard deviation of the main task. Notice that although different data were used for both training and testing, the results are per *subject*, for the same subjects: they are, therefore, comparable. Comparing these results with those of experiment 4, we may conclude that the excluded samples did have a negative effect on the performance of the DNNs. The obtained results of the z-test showed that this model resulted in a significant improvement compared to the performance of the base model. These results suggest that improvement in fall prediction based on accelerometry is not only warranted on the modeling side, but also on the input (or activity classification) side.

5.6 Discussion and conclusions

In this paper, we studied the use of deep learning neural networks to model fall risk on the basis of accelerometer data. Our aim was to compare the performance of deep learning on raw acceleration data with the performance of a base model that uses biomechanical features extracted from the data. For this comparison we used the same dataset. We did not compare our approach with other work done on different tasks such as activity recognition (Ordónez and Roggen, 2016) or age-related differences in walking (Hu et al., 2018).

In our first experiment, we selected the ConvLSTM neural model based on its trade-off between performance and training time. However, although we found that this architecture was best in modeling the training data, it generalized poorly over subjects. This was confirmed in experiment 2, where we achieved a very good performance ($AUC = 0.94$) when the training and validation sets contain data, split at samples, from all 296 subjects. The very good performance in this case may have been caused by the network learning identities of subjects from gait data and using these implicitly to model individual fall risk. In experiment 3 we studied an MTL network that simultaneously modeled fall risk and identity. We infer the need to control for subject-specific factors since training for both fall risk and identity improved the model's performance considerably. In experiment 4, we studied an MTL approach whereas auxiliary task we chose more general characteristics such as age or weight as secondary tasks that are still related to the subject, but is not the subject itself. We found an improvement of the performance of the ConvLSTM model on the validation set of new subjects if we use gender and age as auxiliary output. When we compare the performance of our MTL ConvLSTM with the base model of van Schooten et al. (2015) we saw a slightly higher performance, however, this was not significant. Nevertheless, our results indicate that deep learning methods provide similar high accuracy of fall risk prediction compared to biomechanical models, with the advantage that they do not require painstakingly-crafted features.

The performance of a model relies on the model architecture used and on the input data. In experiment 5, we, therefore studied an approach where we selectively ignored some of the data samples based on a spectral analysis. We found a significantly better performance. These results suggest that a stricter gait classification algorithm may result in more accurate identification of an individual's gait signature and therefore improve model performance. An other option is to use the dynamics in the data over periods longer than 10 seconds. This can be done by using the entire locomotion bout as input for the ConvLSTM network. Another method is adopting hierarchical methods (van Kasteren et al., 2011).

In conclusion, this work shows that machine learning on accelerometer data acquired in the home environment provides comparable accuracy to conventional models, with the advantage that they do not rely on handcrafted extracted features, in the assessment of fall risk of older adults. We believe that this approach will contribute to the societal challenge of healthy and active aging in the home environment.

6
General Conclusion

The population of older adults is set to increase worldwide due to declining total fertility rates and increasing life expectancy thanks to medical advances and lifestyle improvements. The process of ageing involves many unavoidable changes related to the decline of cognitive, mental and physical health in older adults. Ageing therefore has a major impact on healthcare services.
This thesis describes research on the use of sensor monitoring to detect changes in the functional health of older adults living alone. Functional health refers to the adults capability of performing various (daily) tasks independently, which is crucial for independent living. Early detection of a decline allows for timely intervention, which may contribute to healthy and active ageing in the home environment. Technology for ageing in a home environment is considered to be an emerging technology, because ageing in place offers a significant feeling of independence and autonomy and the presence of a social network for older adults. Ambient sensor networks and body-worn inertial sensors are used in many research studies for the ambulatory monitoring of humans in daily life, providing reliable insights into an individuals functional health. These sensors have low costs and pose fewer to no privacy issues in comparison to intrusive sensors such as cameras. These kinds of sensors are ever more incorporated in home environments and in the devices we use daily. Examples of such devices include wearables such as smart phones, smart watches and smart bracelets and ambient devices such as smart thermostats, motion detection devices and home automation.

The focus of this thesis is the on the development and use of machine-learning algorithms for the purpose of monitoring the functional health condition of older adults, in particular to detect change in functional health condition. The machine-learning algorithms used in this thesis are applied to sensor data collected in the daily-life environments of older adults (the wild). The sensors used to collect data are both ambient and wearable and generate data that is comparable with that generated by devices now used on a daily basis by many people. The machine algorithms used in this thesis can therefore be easily implemented in monitoring systems and incorporated into home environments. We have developed machine learning algorithms for a) the detection of visits to older adults, b) the continuous measurement of the indoor gait velocity and c) the prediction of fall risk.

The sensors used in this thesis do not record any audio or video. Therefore, it is important to know that the collected data comes from a single person, the resident. The first contribution of the thesis is in the detection of regular and irregular visits to older adults. We explored both supervised and unsupervised methods for the detection of visits, and a multidimensional Markov modulated non-homogenous Poisson process (M3P2) was described. This model is based on the Markov modulated Poisson process (MMPP), which allows the incorporation of multiple feature streams. The non-homogeneous property allows weekly and daily cycles to be modelled. As features, we used sensor-transitions, both general transitions and transitions with knowledge on sensor placement. Sensor transitions refer to sensor events that the resident can trigger in sequence without tripping a third sensor in between. To evaluate the performance of the M3P2 model, we conducted several experiments to test various aspects of the model, such as time discretization, the influence of meteorological seasons and the generalisation of the model. The experiments show that our model M3P2 significantly ($p < 0.05$) outperforms the standard MMPP model.
Detecting and analysing visits gives us insight into the social life of the resident. Many regular visits to the resident may be an indication of one or multiple chronic diseases, as the most regular visits are from (health) care professionals. Meanwhile, the absence of regular visits may be an indication of loneliness of the resident.
In summary, we are able to detect visits in a unsupervised manner using the M3P2 described in chapter 3. Not only does the detection make it possible to differentiate between the residents and the visitors data streams, but the detected type and frequency of visits are also important indicators of the social participation of older adults.

The second contribution of the thesis is the continuous measurement of the gait velocity (indoor walking speed) of older adults from unconstrained sensor data, because many studies have shown that gait velocity is an important predictor of functional health. We have developed a method to automatically collect walking trajectories and calculate their duration and length in a simultaneous manner. The duration of the walking trajectories was best estimated by fitting a mixture of a Poisson and a normal distribution on the collected data, because walking in the home seemed usually to be interwoven with other activities. The length of the trajectories was estimated by manually specifying the length of one single walking trajectory of the resident (e.g., extracted from the map of the apartment) and deriving other lengths from it. The developed methods were applied to multiple data sets collected over a period of 27 months to estimate the weekly gait velocity of the residents. The results showed the ability to discover clearer trends in the gait of the resident, which can be translated to clearer trends in the functional health of the older adults. Compared to controlled tests, such as timed up and go (TUG) and performance oriented mobility assessment (POMA), our method resulted in an estimated velocity based on a variety of walking trajectories and a variety of speeds in natural conditions, which makes it more representative of the functional health of the resident. The installation of the sensors does not involve any complicated placement requirements. The location of the sensors is chosen, so that all the important rooms in the apartment are covered without affecting the residents daily life.
The automatically collected walking trajectories can also be analysed to detect changes in the daily rhythm of the resident. By monitoring for a long period, the method makes

it possible to detect changes in the most frequent walking trajectories and discover new walking trajectories. These kinds of insight are valuable for different caregivers. For example, a shift of a frequent walking trajectory livingroom-bathroom–bedroom to livingroom-bedroom during some period of time may be a reason for a therapist to test the resident for the diagnosis of dementia. Another example may be the detection of a new walking trajectory bedroom-toilet-bedroom during the night, which may be an indication for a caregiver (or family member) to test the resident for an infection in the urinary system. The automatically collected walking trajectories can also be analysed to detect changes in the daily rhythm of the resident. By monitoring for a long term, the method makes it possible to detect Changes in the most frequently walking trajectories and discover new walking trajectories. These kind of insights are valuable for different caregivers. For example, a shift of a frequent walking trajectory livingroom–bathroom–bedroom to livingroom–bedroom during some period of time may be a reason for a therapist to test the resident for the diagnosis of dementia. Another example may be the detection of a new walking trajectory bedroom–toilet–bedroom during the night which may be an indication for a caregiver (or family member) to test the resident for an infection in the urinary system.
In summary, standard tests, such as TUG and POMA, evaluating mobility and walking abilities give a general insight into the physical abilities of a patient, but they may be affected by factors such as performance anxiety or pressure to perform in response to being watched. Continuous measurements in the home environment suffer much less from these limitations and provide an opportunity for more accurate assessment of the persons functional health.

Early detection of high fall risk is an essential component of fall prevention in older adults. Fall risk assessment is a process in which the probability of a future fall is estimated, usually within a time frame of six to twelve months. In many intervention programs proposed for fall prevention, fall risk assessment is performed as the initial step to identify persons at the highest risk. The third contribution of the thesis is the assessment of fall risk using state-of-the-art machine-learning models. We trained three deep learning model architectures: convolutional neural network (CNN), long short term memory (LSTM) and the combination of these two which is ConvLSTM and applied them to a dataset of 296 older adults. Deep learning allows the creation of computational models that are composed of multiple processing layers and learn representations of data with multiple levels of abstraction. This approach has resulted in more powerful models compared to the baseline model, because the complexity of the feature computations are dictated directly by the data and by the quality of the model predictions, rather than by preconceptions of the operator. The performance of these three deep learning architectures, without fine tunings, compared to a baseline model with biomechanical features showed comparable accuracy, with the advantage that they do not rely on handcrafted extracted features. Fine tuning these deep learning models using multi-task learning, with gender and age as auxiliary tasks, resulted in a significantly better performance than the baseline model. Further fine tuning of the approach by excluding the non-gait data samples resulted in even better performance of the DNNs. This suggests that improvement in fall prediction based on accelerometery data is warranted not only by fine tuning on the modelling side, but also by fine tuning on the input side. This suggests that the appli-

cation of these models on data subsets may result in good performance and new insights, for example, in the detection and analysis of detailed patterns of sleeping, standing up, sitting down or climbing stairs.
We also showed that the DNNs are able to recognize individuals based on their gait signature. As a consequence, it is possible to detect changes in the gait of older adults by monitoring their gait signature. A change in gait signature may be an indication of a change in their functional health.

This thesis has produced several insights with respect to continuous monitoring obtained by applying state-of-the-art machine-learning models to datasets collected in the wild for a long period of time. Different aspects of functional health can be measured using algorithms applied to data sets collected using both ambient and wearable sensors. Ambient sensors can be installed in a manner such that they do not affect the daily rhythm of the resident. Wearable sensors are powerful in capturing the movement characteristics of the resident. These two types of sensor are incorporated in a portable monitoring system for remote monitoring, providing information about how active the patient is and which activities he or she is performing (Nait Aicha et al., 2016). One example where this portable monitoring system has been applied is a rehabilitation program aiming to support older adults to remain living independently after a hip fracture (Pol et al., 2017). The occupational therapist used the monitoring system as support and feedback to coach the patient during the weekly rehabilitation sessions. Another example where sensor monitoring can be easily implemented in a real life situation is the early detection and diagnosis of Alzheimer (Robben et al., 2016). For this study, we have collected data using the portable sensor to show that regularity is a promising candidate feature for the purpose of early detection of Alzeheimer.

In summary, this thesis thoroughly investigated the possibility of continuously monitoring the functional health condition of older adults living alone by applying machine-learning algorithms to raw sensor data. The sensors used to collect data are simple ambient and wearable sensors, and the algorithms developed require little to no a priori knowledge. Some of the insights that were obtained have been implemented in a commercial monitoring system, and other insights require less to no effort to be implemented in real-life monitoring systems, which makes the gained knowledge applicable in practice.

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Summary

This thesis describes research on the use of sensor monitoring to detect changes in the functional health of older adults living alone. Functional health refers to the capability to perform activities that a person needs and wants to do without being limited by pain or injury. The ability to perform these activities is crucial for older adults living independently, because the process of ageing involves many unavoidable changes (usually a decline) related to mental and physical health. Early detection of a decline of functional health status allows for timely intervention, which may contribute to healthy and active ageing in the home environment.

To monitor functional health, we used sensor monitoring systems consisting of both ambient and wearable sensors. These sensors are comparable to sensors incorporated in devices used on a daily basis by many people nowadays. The focus of this thesis is on the development and use of machine-learning algorithms applied to sensor data collected in the daily-life environments of older adults (the wild). These algorithms can therefore be easily implemented in monitoring systems and incorporated in home environments. We have developed machine learning algorithms for a) the detection of visits to older adults, b) the continuous measurement of indoor gait velocity and c) the prediction of falls.

The first contribution of the thesis is the detection of regular and irregular visits to older adults. For the analysis of the functional health of the resident, it is important to know that the collected data originates from the resident and not from visitors. To this end, we developed a M3P2. The model is composed of a stochastic process component representing observed events over time (sensor transitions, in our case) and a latent component that modulates the observed process (visits, in our case). Furthermore, the model allows us to incorporate multiple feature streams, and its non-homogeneous property allows us to model weekly and daily cycles. The approach is fully unsupervised, with the advantage that the labelling of the data is not required. Especially when dealing with data collected in the wild, it is difficult to collect labels without affecting the daily routine or the privacy of older adults. The developed model makes it possible to filter out all data which do not originate from the resident, and in addition, the detected type and frequency of visits are important indicators of the social participation of older adults.

The second contribution of the thesis is the continuous measurement of the gait velocity (indoor walking speed) of the older adult from unconstrained ambient sensor data. Gait velocity is an important predictor of functional health in many research studies. We have developed a method to automatically collect indoor walking paths and calculate their duration and length in a simultaneous manner. A probabilistic model consisting of a mixture of a Poisson and a normal distribution is used to estimate the duration of the walking paths, because the analysis of the data showed that the majority of the walking paths of the resident are interwoven with some activity. Standard tests, such as TUG and POMA, evaluating mobility and walking abilities, give a general insight into the physical abilities of a patient, but they may be affected by factors such as performance anxiety or pressure to perform as a response to being watched. Compared to these standard tests, our method resulted in an estimated velocity based on a variety of walking trajectories

and a variety of speeds in natural conditions, which makes it more representative of the functional health of the resident. The automatically collected walking trajectories can also be analysed to detect changes in the daily rhythm of the resident.

The third contribution of the thesis is the assessment of fall risk using state-of-the-art machine-learning models. The assessment of fall risk is a process in which the probability of a future fall is estimated, usually within a time frame of six to twelve months. Fall assessment is an important predictor of functional health and is usually performed as the initial step to identify persons at highest risk of a fall. Early detection of high fall risk is an essential component of fall prevention in older adults.
The sensor data that we used came from a study of fall risk factors and consisted of a population of 296 older adults. Fall incidences and descriptions (labels) were monthly obtained during a six-month follow-up period (van Schooten et al., 2015). Because of the presence of labels, we trained three deep learning model architectures: CNN, LSTM and ConvLSTM which is a combination of these two architecures. Using deep learning techniques, the features were automatically distilled from raw sensor data, with the advantage that the likelihood of missing features is small compared to the way in which biomechanical features are selected. The performance of the three deep learning architectures compared to the strong baseline model with biomechanical features showed comparable accuracy. Fine tuning the deep learning models by using multi-task learning resulted in significantly better performance. Further fine tuning by excluding the non-gait data samples resulted in even better performance. We also showed that the DNNs are able to recognize individuals based on their gait signature. As a consequence, it is possible to detect changes in the gait of older adults by monitoring their gait signature. A change in the gait signature may be an indication of a change in their functional health.

In summary, this thesis thoroughly investigated the possibility of continuously monitoring the functional health condition of older adults living alone by applying machine-learning algorithms to raw sensor data. The sensors used to collect data are simple ambient and wearable sensors, and the algorithms developed require little to no a priori knowledge and can evolve in time.

Samenvatting

Dit proefschrift beschrijft onderzoek naar het gebruik van sensormonitoring teneinde veranderingen in de functionele gezondheid van zelfstandig wonende ouderen vroegtijdig te detecteren. Functionele gezondheid definiëren wij als de mate van uitvoering van de activiteiten die iemand moet of wil uitvoeren zonder te worden beperkt door pijn of letsel. Het vermogen om deze activiteiten uit te voeren is cruciaal voor zelfstandig wonende ouderen omdat het proces van ouder worden veel onvermijdelijke veranderingen met zich meebrengt. Deze veranderingen vertalen zich meestal in een achteruitgang van de mentale gesteldheid of van de fysieke gezondheidstoestand. Vroegtijdig detecteren van een achteruitgang in de functionele gezondheidstoestand kan zorgen voor tijdige interventie die wedereom kan bijdragen aan gezond en actief ouder worden. Voor het monitoren van functionele gezondheid gebruiken we sensor-monitoringssystemen bestaande uit zowel omgevings- als draagbare sensoren. Dit zijn sensoren die ingebouwd zijn in apparaten die we dagelijks gebruiken zoals een mobiele telefoon. De focus van dit proefschrift is het ontwikkelen van machine learning algoritmen en deze toepassen op sensordata. Deze data is verzameld in een realistische omgeving waar ouderen dagelijks verblijven (slimme huizen). De ontwikkelde algoritmen sluiten daarom dichter aan bij de werkelijkheid dan als de data in laboratoria verzameld was, en kunnen daarom sneller in praktijk worden toegepast. We hebben machine learning-algoritmen ontwikkeld voor het detecteren van bezoeken, voor het continu meten van de loopsnelheid in huis en voor het voorspellen van vallen in de nabije toekomst.

De eerste bijdrage van het proefschrift is het detecteren van (on)regelmatige bezoeken aan ouderen. De reden is dat het voor de analyse van de functionele gezondheid van de bewoner belangrijk is dat de genalyseerde gegevens afkomstig zijn van de bewoner en niet van de bezoekers. Hiervoor hebben we het M3P2 model ontwikkeld. Het model bestaat uit twee componenten: de eerste component is een een stochastisch proces dat de sensorwaarden modelleert in de tijd (sensorovergangen in ons geval) en de tweede component is een latente variabele die het waargenomen proces moduleert (bezoeken in ons geval). Het model stelt ons in staat om meerdere stromen van data op te nemen als kenmerk en de niet-homogene eigenschap stelt ons in staat om dagelijkse en wekelijkse cycli te modelleren. Deze aanpak is volledig autonoom, in de zin dat in de leerfase geen manuele annotatie van de bezoeken nodig is (hetgeen bij traditionele classificatie wel het geval is). Vooral als het gaat om sensordata die in de praktijk zijn verzameld, is het moeilijk om data-labels (annotatie) te verzamelen zonder beïnvloeding van de dagelijkse routine en de privacy van de oudere. Naast de mogelijkheid om de data van de bezoeker te filteren stelt het ontwikkelde model ons in staat om de type en de frequentie van de bezoeken te detecteren. Hiermee kan een indicatie van de sociale participatie van de oudere verkregen worden.

De tweede bijdrage van het proefschrift is het continu meten van de loopsnelheid van de oudere in huis op basis van algoritmen toegepast op omgevingssensordata. De reden is dat loopsnelheid in veel onderzoeken gezien wordt als een belangrijke voorspeller voor de functionele gezondheid. Hiervoor hebben we een methode ontwikkeld om automatisch looppaden te verzamelen en daar uit de duur en de lengte en daarmee de snelheid

te berekenen. Een probabilistisch model bestaand uit een mix van een Poisson en een normale verdeling werd gebruikt voor het schatten van de duur van de looppaden. Uit de analyse van de gegevens bleek namelijk dat de overgrote meerderheid van de verzamelde looppaden van de bewoner zijn verweven met een activiteit. Tests zoals TUG en POMA die gebruikt worden om de mobiliteit en loopvaardigheid van een persoon te evalueren, geven een algemene indruk van de fysieke toestand van de oudere. Deze tests kunnen echter beïnvloed worden door factoren zoals faalangst en prestatiedruk als gevolg van geobserveerd worden tijdens de test. Vergeleken met deze standaardtests resulteerde onze methode in een geschatte snelheid op basis van een verscheidenheid aan looppaden met verschillende snelheden in een natuurlijke woonomgeving. De omstandigheden zijn hierdoor veel meer representatief voor de functionele gezondheid van de oudere dan de omstandigheden waarin standaard tests uitgevoerd worden. De automatisch verzamelde looppaden kunnen bovendien worden geanalyseerd om veranderingen in het dagelijkse ritme van de inwoner te kunnen ontdekken.

De derde bijdrage van het proefschrift is het beoordelen van het valrisico van de oudere met behulp van moderne machine learning modellen. De valrisico-beoordeling is een proces waarbij de kans op een val binnen een tijdsbestek van zes tot twaalf maanden wordt geschat. Valrisico-beoordeling is een belangrijke voorspeller van de functionele gezondheid en wordt vaak uitgevoerd om personen met het hoogste risico te identificeren. Het identificeren van personen met een hoog valrisico is namelijk een essentieel onderdeel van valprentie bij ouderen. De in dit proefschrift gebruikte sensordata is afkomstig uit een onderzoek naar valrisicofactoren met een populatie van 296 ouderen (van Schooten et al., 2015). Valincidenten (de labels) waren maandelijks verkregen tijdens een followup-periode van zes maanden. Omdat we beschikten over labels hebben we drie deep learning-architecturen getraind: CNN, LSTM en een combinatie van deze twee (ConvLSTM). Met behulp van deep learning-technieken worden de kenmerken automatisch gedistilleerd uit ruwe sensordata. Dit heeft als voordeel een geringe kans om kenmerken te missen vergeleken met wanneer gebruikt wordt van bio-mechanische kenmerken. De nauwkeurigheid van de drie deep learning-architecturen in vergelijking met het basismodel met biomechanische kenmerken vertoonde vergelijkbare resultaten. Het verfijnen van deep learning-modellen door gebruik te maken van multi-task learning resulteerde in een significant betere nauwkeurigheid. Verdere verfijning door het uitsluiten van samples die geen bewegingsdata bevatten resulteerde in een nog betere nauwkeurigheid. Verder hebben we in deze bijdrage laten zien dat de deep learning-modellen individuen kunnen herkennen op basis van hun manier van bewegen. Logischerwijs zou het mogelijk zijn om veranderingen in het gedrag van ouderen te detecteren door hun manier van bewegen te monitoren. Een verandering in de manier van bewegen kan een indicatie zijn voor de verandering in hun functionele gezondheid.

Samenvattend hebben we in dit proefschrift grondig onderzoek gedaan naar de mogelijkheid om de functionele gezondheidstoestand van alleenstaande ouderen continu te monitoren door machine learning algoritmen toe te passen op sensordata. De gebruikte sensoren voor het verzamelen van data zijn eenvoudige sensoren die in talrijke hedendaagse apparaten zijn verwerkt. De ontwikkelde algoritmen kunnen daarom sneller in praktijk worden toegepast en bovendien kunnen ze in de tijd evolueren.

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