From fall detection to stress pattern using smart devices

THÈSE

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Résumé

Les services pour smartphones et les applications sont omniprésents dans nos vies. La prise de mesures médicales préventives ou nécessaires pour améliorer le bien-être d'une personne est appelée «soins médicaux ». L'utilisation de dispositifs intelligents accorde plus d'attention aux soins médicaux jour après jour. Les applications médicales rendent les smartphones utiles dans la pratique de la médecine factuelle, en plus de leur utilisation dans la communication clinique mobile.

À mesure que les gens vieillissent, ils ont tendance à devenir de plus en plus vulnérables aux handicaps physiques et aux maladies mentales. Afin d'éviter la détérioration de leur qualité de vie, nous avons inventé des applications qui aident les personnes âgées à continuer leurs activités quotidiennes (ADL). Plus précisément, nous avons réalisé des recherches dans deux domaines importants de la cybersanté, qui sont la détection des chutes et la détection du stress. Les chutes et le stress sont deux des principaux problèmes de santé auxquels les personnes âgées sont confrontées aujourd'hui. Ces deux graves problèmes de santé peuvent causer un large éventail d'autres conséquences liées à la santé qui détériorent la qualité de vie des personnes âgées et les rendent vulnérables à divers problèmes liés à la santé et donc aux problèmes.

Le but de cette thèse est la description de la contribution d'un système de détection des chutes et d'un système de détection de stress dans la vie quotidienne des personnes âgées. Tout d'abord, nous présentons un système pratique de détection des chutes en temps réel sur une smartwatch appelé F2D. Les chutes parmi les personnes âgées restent une question de santé publique très importante. Dans la majorité des cas de chutes, un soutien externe est impératif pour éviter d'importantes conséquences. Par conséquent, la capacité à détecter automatiquement ces événements d'automne pourrait contribuer à réduire le temps de réponse et à améliorer considérablement le pronostic des victimes de chute. Dans F2D, les données de l'accéléromètre sont collectées, en passant par un algorithme adaptatif basé sur le seuil qui détecte des motifs correspondant à une chute. Un module de décision prend en compte le mouvement résiduel de l'utilisateur, qui fait le lien entre le motif de chute détecté et une chute réelle. Contrairement aux systèmes traditionnels qui nécessitent une station de base et une centrale d'alarme, F2D fonctionne complètement indépendamment. À notre connaissance, c'est le premier système de détection d'automne qui fonctionne sur une smartwatch, moins stigmatisant pour l'utilisateur final. L'algorithme de détection des chutes a été testé par la Fondation Suisse pour les Téléthèses (FST), le partenaire du projet responsable de la commercialisation de notre système. De plus, en testant avec des données réelles, nous disposons d'un système de détection d'automne prêt à être déployé sur le marché. Enfin, le dernier module de F2D est le module de localisation qui rend notre système très utile pour les maisons de soins infirmiers qui accueillent des personnes âgées.

Grâce à la connaissance que nous avons acquise en extrayant des informations utiles à partir des capteurs des périphériques intelligents et plus particulièrement en détectant les chutes à partir d'une smartwatch, nous avons amélioré notre

savoir-faire en analysant et en extrayant les modèles à partir des données de capteurs brutes. La prochaine mise en œuvre de notre expertise et deuxième élément principal de cette thèse est la détection de modèles de stress en analysant les données des smartphones.

Par conséquent, nous présentons dans un deuxième temps un nouveau système de détection de stress qui vise à détecter les risques de stress et de burn-out en analysant les comportements des utilisateurs via leur smartphone. Le principal objectif de notre système de détection du stress repose sur l'utilisation des capteurs mobiles pour détecter le stress. En particulier, nous recueillons des données provenant de l'utilisation quotidienne des personnes, rassemblant des informations sur le mode de sommeil, l'interaction sociale et l'activité physique de l'utilisateur. Nous combinons l'information recueillie à partir de ces dimensions principales du bien-être et nous fournissons un score de relaxation à l'utilisateur final, ce qui lui fait prendre conscience de son niveau de stress. À notre connaissance, c'est le premier système qui calcule un score de stress basé sur différentes dimensions du bien-être humain. L'innovation principale de ce travail repose sur la façon dont le niveau de stress est calculé, par une méthode la moins invasive possible. Notre solution repose uniquement sur l'usage quotidien du téléphone. De plus, nous acquérons la donnée fondamentale, celle qui sera considéré comme vérité, pour chaque dimension du bien-être, pour chaque individu en demandant aux utilisateurs directement. Cela nous conduit à un modèle personnalisé qui se concentre sur la personnalité de chaque utilisateur. Notre algorithme de détection de stress a été l'élément clé d'un projet Active and Assisted Living (AAL) appelé StayActive et a été évalué dans un environnement réel avec des personnes travaillant dans la compagnie de transport public de Genève (Transports Public Genevois).

Les deux systèmes présentés dans cette thèse ont été utilisés dans des applications qui seront disponibles sur le marché, en transférant directement la recherche scientifique sur un produit commercial. De plus, les deux systèmes ont été testés avec de vrais utilisateurs finaux et, par conséquent, la recherche a été un peu plus loin, au-delà des essais en laboratoire.

Enfin, la communauté de recherche et celle du monde industriel ont montré un grand intérêt pour nos résultats de recherche. Par conséquent, nos résultats de recherche ont abouti à deux nouveaux projets de la Commission pour la technologie et l'innovation (CTI). Nous collaborons avec l'un des plus grands groupes de cliniques en Suisse, Hirslanden, travaillant sur un projet appelé Recover@home. L'idée principale de ce projet est de construire une solution pour surveiller un patient à la maison. De plus, nous collaborons avec Hirslanden dans un projet intitulé Stress and Burnout (SaB). L'innovation principale de SaB sera un algorithme permettant de calculer un niveau de stress en combinant les signaux biologiques enregistrés par un dispositif portatif, l'information comportementale d'un smartphone, ainsi que des réponses subjectives aux questionnaires médicaux standards.

Pour récapituler, dans cette thèse, nous présentons deux applications de cybersanté. Nous commençons par un système de détection des chutes et nous continuons avec un système de détection du stress. Enfin, nous présentons les nouvelles orientations de recherche et les projets qui ont été créés en fonction de notre expertise de détection de modèles à partir de données de capteurs brutes, collectées grâce à des périphériques intelligents.

Abstract

Smart mobile services and applications are ubiquitous in our lives. The act of taking preventative or necessary medical procedures to improve a person's wellbeing is called healthcare. The use of smart devices is getting more attention in healthcare day by day. Medical applications make smartphones useful tools in the practice of evidence-based medicine at the point of care, in addition to their use in mobile clinical communication.

As people get older, they tend to become more and more vulnerable to physical disabilities and mental illnesses. In order to prevent the deterioration of their quality of life we have invented applications that help elderly to sustain their activities of daily living (ADL). More specifically, we have made research in two important domains of e-health which are the fall detection and the stress detection. The falls and the stress are two of the main health problems that elderly people are facing nowadays. These two serious health problems can cause a wide spectrum of other health related consequences that deteriorate the quality of life of elderly people and make them vulnerable to various health related and so problems.

The purpose of this thesis is the description of the contribution of a fall detection system and a stress detection system in the daily life of elderly people. Firstly, we present a practical real time fall detection system running on a smartwatch called F2D. Falls among older people remain a very important public healthcare issue. In the majority of fall events external support is imperative in order to avoid major consequences. Therefore, the ability to automatically detect these fall events could help reduce the response time and significantly improve the prognosis of fall victims. In F2D data from the accelerometer is collected, passing through an adaptive threshold-based algorithm which detects patterns corresponding to a fall. A decision module takes into account the residual movement of the user, matching a detected fall pattern to an actual fall. Unlike traditional systems which require a base station and an alarm central, F2D works completely independently. To the best of our knowledge, this is the first fall detection system which works on a smartwatch, being less stigmatizing for the end user. The fall detection algorithm has been tested by Fondation Suisse pour les Téléthèses (FST), the project partner who is responsible for the commercialization of our system. Moreover by testing with real data we have a fall detection system ready to be deployed on the market. Finally, the last module of F2D is the location module which makes our system very useful for nursing homes that host elderly people.

Thanks to the knowledge that we acquired by extracting useful information from the sensors of smart devices and more specifically by detecting falls from a smartwatch, we enhanced our know-how analyzing and extracting patterns from raw sensor data. The next implementation of our expertise and second main element of this thesis is the detection of stress patterns by analyzing smartphone data.

Therefore, secondly we present a novel stress detection system which aims to detect stress and burn-out risks by analyzing the behaviors of the users via their smartphone. The main purpose of our stress detection system is the use of the mobile sensor technology for detecting stress. In particular, we collect data from

people's daily phone usage, gathering information about the sleeping pattern, the social interaction and the physical activity of the user. We combine the information gathered from these main dimensions of wellbeing and we provide a relaxation score to the end-user, making him aware about his stress level. To the best of our knowledge, this is the first system that computes a stress score based on different dimensions of human wellbeing. The main innovation of this work is addressed in the fact that the way the stress level is computed is as less invasive as possible. Our solution relies only on the daily phone usage of people. Also we acquire the ground truth for the importance of each dimension of wellbeing for each individual by asking the users. This leads us to a personalized model which focuses on the personality of each individual user. Our stress detection algorithm was the key element of an Active and Assisted Living (AAL) project called StayActive as well and it has been evaluated in a real world environment with people working in the public transportation company of Geneva (Transports Publics Genevois).

Both of the systems that are presented in this thesis have been used in applications that will be available on the market, transferring directly the scientific research into a commercial product. Also both of the systems have been tested with real end-users and therefore the research has gone one step further, beyond the lab trials.

Finally, people coming from the research community and the industrial world have shown great interest in our research results. Therefore, our research results led to two new Commission for Technology and Innovation (CTI) projects. We collaborate with one of the biggest clinic groups in Switzerland, Hirslanden, working on a project called Recover@home. The main idea of this project is to build a solution to monitor a patient while at home. Moreover we collaborate with Hirslanden for extending our stress detection system in a project called Stress and Burnout (SaB). The main innovation of SaB will be an algorithm computing a stress level by combining biosignals from a wearable device, behavioral information from a smartphone, as well as subjective answers to standard medical questionnaires.

To recapitulate, in this thesis we present two e-health applications. We begin with a fall detection system and we continue with a stress detection system. Last but not least we present the new research directions and projects that have been created based on our expertise of detecting patterns from raw sensor data, collected from smart devices.

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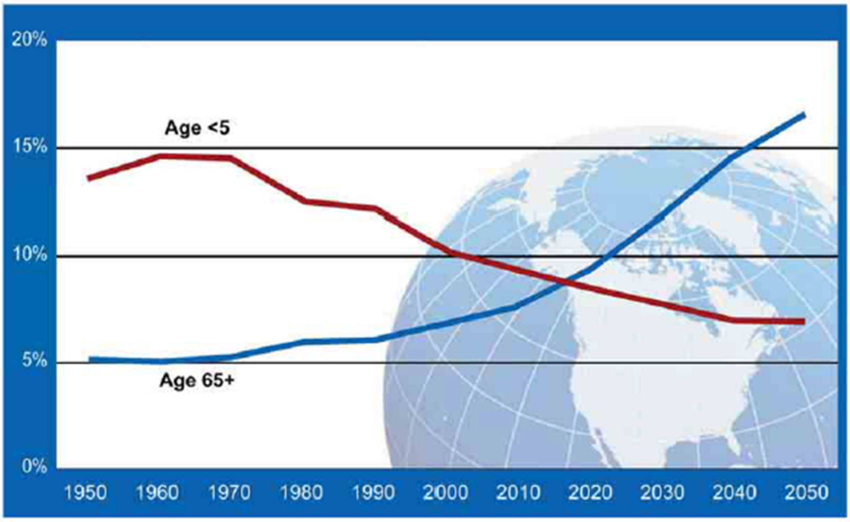
Acronyms

Acronym	Full text
ADL	Activities of Daily Living
ANS	Autonomic Nervous System
API	Application Programming Interface
CTI	Commission for Technology and Innovation
ECG	Electrocardiography
FST	Fondation Suisse pour les Téléthèses
F2D	Fall Detection Device
GDP	Gross Domestic Product
GPS	Global Positioning System
GSR	Galvanic Skin Response
HR	Heart Rate
HRV	Heart Rate Variability
IMU	Inertial Measurement Unit
LASA	Longitudinal Aging Study Amsterdam
ML	Machine Learning
PANAS	Positive and Negative Affect Schedule
PDR	Pedestrian Dead Reckoning
PNS	Parasympathetic Nervous System
SCL	Skin Conductance Level
SCR	Skin Conductance Response
SDK	Software Development Kit
SE	Sensitivity
SNS	Sympathetic Nervous System
SP	Specificity

1. Introduction

Ageing is a natural process, which presents a unique challenge for all sections of the society. Although the exact definition of elderly age group is controversial, it is defined as people with a chronological age of 65 years and above [1].

As people get older they become vulnerable to various illnesses that deteriorate their quality of life. It is very important for the evolution and the sustainability of our society to improve the conditions that the elderly people live. Especially nowadays that the population aging accelerates more and more (Figure 1) the demand of applications related to the improvement of health of elderly people becomes necessary.



Source: United Nations. *World Population Prospects: The 2010 Revision.*
Available at: http://esa.un.org/unpd/wpp.

Figure 1: Children and elderly as percentage of global population: 1950-2050.

Nowadays, thanks to the evolution of the medications, people are living longer. However, as they get older, their bodies change and new health issues arise. Many health issues, both genetic and environmental, affect how they age.

The most widespread conditions affecting those 65 and older include arthritis, heart disease, stroke, cancer, pneumonia and the flu. Accidents, especially falls that result in hip fractures, are also unfortunately common in the elderly [2].

1.1 Elderly and health problems

Healthy ageing is one of the most important parameters of elderly people’s lives. When elderly people have a good health, they can be an active part of the society and they can live independent enjoying their lives [1].

The main health problems that elderly people are facing nowadays can be summarized as follows: dementia, including Alzheimer’s disease, depression, arthritis, osteoporosis, diabetes, breathing problems, frequent falls, which can lead to fractures, Parkinson's disease, sleep problems, eye problems (cataracts, glaucoma, Macular Degeneration) and weight loss [2].

The main research question that this thesis tries to answer is how elderly people could be able to sustain their well-being and their activities of daily living by using smart devices. Nowadays elderly people use more and more smart devices like smartphones and smartwatches. We take advantage of this evolution and we provide them with applications that can be used in their daily life without being invasive and at the same time help them to sustain their quality of life.

During the last few years has been observed an increased adoption of smartphones by healthcare professionals as well as the general public. The smartphones and in general the smart devices like smartwatches and bracelets are a new technology that combines mobile communication and computation in a handled-size device making it very comfortable and not invasive for the end-user. In this context we have created two e-health applications that help elderly people to sustain their daily life activities and improve their autonomy for daily activities.

Dealing with technical challenges related to the extraction of useful patterns from raw sensors of smart devices we have created innovative algorithms and e-health applications that help elderly people to sustain their well-being and avoid a wide spectrum of potential health issues. We have taken into account that most adults prefer to age in place. That is: to remain in the home of their choice as long as possible. These older adults have a determination to live in their homes and enjoy living in their homes for as long as they can.

We are confident that the e-heath applications we have developed in this thesis will help older adults engage with their community, peers and families both socially and through active skill based engagement. They will retain their dignity and individuality, whilst engaging in a secure way with those in the community that they want to catch up with. This will increase the individual's self-esteem, confidence and positive sense of well-being. Thus delaying the need for some professional care and the associated costs and impact on resources, for both the individual and the community.

In this thesis we focus our attention on two problems that are very crucial for the quality of life of elderly people [3]. More specifically we concentrate on fall and stress detection. Elderly people that are vulnerable to falling are not able to live independently. At first we present an innovative fall detection system (F2D), which gives the opportunity to elderly people that suffer from falling to feel safer. By using F2D they feel very confident for themselves and they are able to perform their activities of daily living (ADL) without any assistance. Then we present a stress detection system (StayActive) which gives the opportunity to people with ages between 55-70 years to live without stress about stress. Therefore the main purpose of this thesis is to provide help to elderly people that are vulnerable to falls and to stress-related problems.

1.2 Falls and elderly people

In this thesis we will concentrate at first on the problem of falling. The latter is one of the most serious problems for the elderly people [3]. By definition, a fall is an event which results in a person coming to rest inadvertently on the ground or other lower level, as a consequence of the following: sustaining a violent blow, loss of consciousness, sudden onset of paralysis, or an epileptic seizure [3]. Falls are a major concern specifically for the elderly people [4]. Several studies have shown that falls are a main reason for hospitalizations for injuries for people with special needs like elderly people, disabled, overweight and obese [4]. Each year, millions of older people older than 65 years fall. More specifically, more than one out of four older people falls each year, but less than half tell their doctor [5].

Moreover, falls can also lead to disability and decreased mobility which often results in increased dependency on others and, hence, an increased need of being admitted to an institution. Finally, one other serious consequence of falling is the "long-lie" condition where a falling person remains on the ground or floor for more than an hour after a fall. The "long-lie" is a sign of weakness, illness and social isolation and is associated with high mortality rates among the elderly. Time spent on the floor can be associated with a fear of falling, muscle damage, pneumonia, pressure sores, dehydration and hypothermia [16, 17].

Moreover, the fear of falling is one major issue as people are getting older. A possible serious fall can lead to an injury and therefore the loss of independence for elderly people. By losing their independence they will need a person to take care of them and therefore they will not be able to perform all the activities that they were doing as they were younger and independent. This chain leads to the deterioration of their quality of life. These reasons, combined with the vast evolution of the smart-devices (e.g. smartphones, smartwatches) and the increasing accessibility and miniaturization of sensors, is leading to the development of fall detection systems.

Therefore, we present an innovative fall detection system (F2D) which takes into account the residual movement of the user after falling and contextual data information into account. As context we mean the behavior of the user right after his fall and the location that the fall event took place. By taking into account the residual movement of the user and the context we are able to overcome the main challenges of the fall detection. The first main challenge is that several everyday fall-like activities are difficult to distinguish from a fall. Most of the current approaches define a fall as having greater accelerations than normal daily activities [18]. However, if we focus our attention only in this characteristic of a fall event we will have as a result a lot of false alarms. There are a lot of activities of daily living (ADL) e.g. going up the stairs, sitting on a sofa, which are characterized from a fast acceleration as well. The two main characteristics of a robust fall detection system are firstly the accurate detection of the fall events and secondly the minimization of the false alarms [34]. More specifically a successful fall detection system should achieve high sensitivity and specificity. No one will accept to use a fall detection system that does not detect all the fall events since it can lead in serious mistakes. Moreover it will be disturbing for the end-users to use a fall detection system that creates a lot of false positives and triggers many false alarms. F2D is a complete fall detection system since it meets these two above mentioned requirements. Moreover the third main characteristic of a fall detection system is the ease of installation. People and especially elderly will not accept to wear devices which are difficult to be installed. In F2D we meet this third requirement because the fall detection algorithm runs on a smartwatch. The user wears his smartwatch as usual and in the background our fall detection system is able to detect the fall events, making it as less stigmatizing as possible.

Finally, the context awareness that the location module has added to F2D is very important for the final scope of our fall detection system. Since we are targeting the care of elderly people who are in a nursing home, knowing the location of the user after a fall is very important. The caretakers will know in which room the elderly has fallen and therefore they will be able to immediately provide the help that this person needs. Since minimal cost and setup process for the end user were the requirements of the localization system, we used the minimum amount of Bluetooth beacons, that is one Bluetooth beacon per room, and we opted to develop a more sophisticated algorithm for room detection.

1.3 People, smartphones and stress

Stress is a pervasive part of the modern fast-paced life. The problem of job stress is widely recognized as one of the major factors leading to a spectrum of health problems [48]. By definition stress is the wear and tear on the body caused by constant adjustment to an individual's changing environment. Anything that causes change in our life causes stress. There are many changes going on in the lives of the elderly [8].

Stress can be short-term (acute) or long-term (chronic). Acute stress is the reaction to an immediate threat. This is commonly known as the "fight or flight" response. The threat can be any situation that is experienced, even subconsciously, as a danger. Under stress, a person's heart rate and breathing rate increase. His or her muscles become tense. A person's stress level increases when there are multiple stressors present. A person's body needs relief from stress to re-establish balance. As people age, the ability to achieve a relaxation response after a stressful event becomes more difficult. Aging may simply wear out the systems in the brain that respond to stress [9].

Stress detection remains one of the main research topics of affective computing [10]. However, the attention has shifted from controlled experiments to real-life scenarios out of the lab. Along this direction smart phones have become the main tools for analysis [11].

Nowadays mobile smart devices and mobile internet are changing the way people do things in their daily life. The average time people spend on their mobile devices daily is 3 hours and 40 minutes (Figure 2) and that amount of time does not include the time we spend doing actual phone calls.

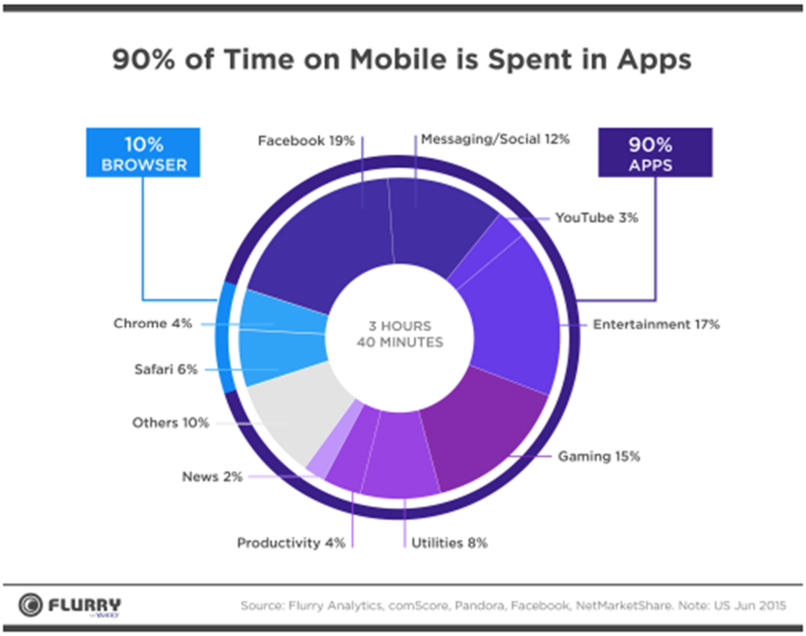


Figure 2: Time on mobile spent in apps.

According to the participants that took part in a survey of Bank of America [12], they could not last a day without their smartphones [13]. By taking into account the necessity of smartphones in the daily life of people nowadays we are able to collect important information about their daily habits and more specifically different factors of their wellbeing, like their physical activity, their social interaction and their sleeping habits as well.

In this thesis we focus on the problem of stress detection and more specifically on how it does affect the lives of people. Combining all the above mentioned parameters of the daily life of people we have built a sophisticated mathematical algorithm that provides a stress level for the users. The idea behind our stress detection system (StayActive) compared to others is that it tries to be as less invasive as possible. We inform the user for his stress level by using only information which comes from his smartphone. Then the user can take a break or another relaxation activity in order to reduce his stress level if it is high.

We present a stress detection system which validates the results of stress that provides through self-assessment questionnaires. The participants of our study who were middle age people working for the public transportation company of Geneva (TPG) tested our stress detection module and provided their feedback evaluating the accuracy of stress detection. Based on the feedback that we acquired from the testers coming from TPG we conclude that we have created an accurate enough, not invasive stress detection system. Unlike other stress detection systems [46, 48, 61] StayActive uses information that comes from the daily phone usage of the end-users being as less invasive as possible for them. After our experience with end-users and of course after the discussions in the panels of the conferences that we have presented our work it has become pretty clear that the end-users will not accept to use an invasive wearable device (e.g. a t-shirt or a chest-band) in a daily basis. Even if you can ensure them that their stress detection will be pretty accurate they will not be willing to use an invasive device for a long period of time. This is the main vulnerability of such stress detection systems which are using wearable devices to measure the HRV and the GSR of the user and combine them with other features in a machine learning model in order to predict stress.

1.4 Solutions

People as they become older start having serious health problems which deteriorate the quality of their life. The scientific community tries the last decades to improve the quality of life of elderly people by assisting them with applications and digital tools that they can use in their daily life.

In this thesis we focus on two of the main problems of elderly people which are the falls and the stress. We provide concrete solutions for detecting both of these problems. The solutions are two e-health applications. A fall detection system that helps elderly people when they have a fall accident and a stress detection system which measures and provides support to people that are stressed. Both of the systems have as ultimate goal to improve the quality of life of elderly people and make them live independent as long as possible. Independence is really important for everyone. Especially for the elderly people, the feeling of being independent makes them happy and it motivates them to continue their social lives and activities.

Falls and the stress are two of the main problems that elderly people are facing nowadays. These two serious problems can cause a wide spectrum of other health related consequences that deteriorate the quality of life of elderly people and make them vulnerable to various health related and so problems.

In this thesis we provide two innovative solutions. The first one is a fall detection system called F2D and the second one is a stress detection system called StayActive.

2. Fall detection

Falls among older people remain a very important public issue [15]. In the majority of fall events external support is imperative in order to avoid major consequences. Therefore, the ability to automatically detect these fall events could help reducing the response time and significantly improve the prognosis of fall victims [73].

Despite extensive preventive efforts, falls continue to be a major source of morbidity and mortality among older adults. Yearly, more than 11 million falls are registered in the U.S. alone [14], leading to a wide spectrum of injuries for this age group. Aside from causing physical injuries, falls can also have dramatic psychological consequences that reduce elderly people's independence [15]. It has been found that after falling, 48% of older people report a fear of falling and 25% report curtailing activities.

Moreover, falls can also lead to disability and decreased mobility which often results in increased dependency on others and, hence, an increased need of being admitted to an institution. Finally, one other serious consequence of falling is the "long-lie" condition where a falling person remains on the ground or floor for more than an hour after a fall. The "long-lie" is a sign of weakness, illness and social isolation and is associated with high mortality rates among the elderly. Time spent on the floor can be associated with a fear of falling, muscle damage, pneumonia, pressure sores, dehydration and hypothermia [16, 17].

According to the World Health Organization [18] approximately 28-35% of people aged 65 and over fall each year increasing to 32-42% for those over 70 years of age. The frequency of falls increases with age and frailty level. In fact, falls exponentially increase with age-related biological changes, which is leading to a high incidence of falls and fall related injuries in the ageing societies. If preventive measures are not taken in the immediate future, the number of injuries caused by falls is projected to be a 100% higher in 2030. In this context, assistive devices that could help to alleviate this major health problem are a social necessity. Indeed, fall detectors are being actively investigated.

2.1 State of the art

A fall detection system can be defined as an assistive device whose main objective is to alert when a fall event has occurred. In a real-life scenario, they have the potential to mitigate some of the adverse consequences of a fall. Specifically, fall detectors can have a direct impact on the reduction of the fear of falling and the rapid provision of assistance after a fall. In fact, falls and fear of falling depend on each other: an individual who falls may subsequently develop fear of falling and, vice versa, the fear of falling may increase the risk of suffering from a fall [20]. Fear of falling has been shown to be associated with negative consequences such as avoidance of activities, less physical activity, falling, depression, decreased social contact and lower quality of life [21]. The effect of automatic fall detection units on the fear of falling has been studied by Brownsel et al. [22]. They conducted a study with community alarm users who had experienced a fall in the previous six months. At the end of the study, those who wore the fall detector appropriately reported that they felt more confident and independent, and considered that the detector improved their safety. One of the conclusions of the study was that the fear of falling is likely to be substantially affected by user perception of the reliability and accuracy of the fall detector.

If a fall event occurs and the system does not detect it, the consequences can be dramatic: the person can remain lying on the floor for a long time with all that this implies. In addition, the loss of confidence in the system may eliminate the benefits of the detector on the fear of falling. By contrast, if the system reports an excessive number of false activations, caregivers may perceive it as ineffective and useless, which may lead to device rejection. But robustness is not easy to achieve. Although several commercial products are available on the market, the fact is that they are not widely used and do not have a real impact on the elders' lives yet [23, 24]. Besides, the vast majority of their potential users do not know of their existence. However, when the concept of fall detection is presented, they find in it a great potential to improve their security and safety at home. For these and many more reasons, the number of studies on fall detection has increased dramatically over recent years. Unfortunately, there are not many reviews on fall detection. The work of Noury et al. [25], which appeared in 2008, can be considered the first one in this field. Shortly thereafter, Perry et al. [26] published a similar analysis. These studies provided a general overview of the fall detection status, but the latter has changed greatly since they were published, and the current fall detection trends have little in common with those of previous years. Mubashir et al. [27] is more recent, but it includes only 2 papers from 2011 and lacks later papers anyway, for instance many smartphone-based detectors. In this thesis we present a practical real time fall detection system which works on a smartwatch and it is tested with real data.

In an attempt to minimize the above mentioned serious consequences of falling, various fall detection systems were developed over the last decade. Also elderly people desire to live at home, so new technologies, such as automated fall detectors, become necessary to support their independence and security. These systems are mainly based on video-cameras [28-30], acoustic [31, 32] or inertial sensors [33] and mobile phone technology [34-37].

The main disadvantage of the fall detection systems based on video-cameras is the privacy issues that are triggered. People will not accept to be monitored because they consider it as something that invades in their personal life [29].

Specifying different types of falls help towards an understanding of the existing approaches. It also guides and contributes towards the design of new algorithms. Different scenarios should be considered when identifying different kinds of falls: falls from walking or standing, falls from standing on supports, (e.g., ladders, etc.), falls from sleeping or lying on the bed and falls from sitting on a chair. There are some common characteristics among these falls as well as significant different characteristics. It is also interesting to note that some characteristics of a fall also exist in normal actions, e.g., a crouch also demonstrates a rapid downward motion. Noury et al. [25] and Yu [39] reviewed principles and methods used in existing fall detection approaches. These are the only review papers on fall detection and their scope is limited, which prompts us to write a comprehensive survey of recent fall detection techniques. Existing fall detection approaches can be explained and categorized into three different classes to build a hierarchy of fall detection methods. Different methods under these categories are discussed further in the following sections. Fall detection methods can be divided roughly into three categories: wearable device based, ambience sensor based and camera (vision) based.

Common fall detection systems are based on a sensor detecting a strong vertical acceleration, launching an alarm when a fall event is recognized. More recent systems usually take into account other sensors able to detect the device's orientation in order to determine whether the user is lying or standing [34, 35].

In [34] the authors present a fall detection system called iFall which works on the smartphones of the users. They use a threshold-based algorithm. They use touch screen response and voice recognition providing a reliable interface with the user. iFall runs as discreetly as possible in a background service that constantly listens to the accelerometer. The activity is waking up only and only if a fall is detected and therefore other applications can run on top of iFall minimizing the memory consumption. A main advantage of iFall is the use of programmable cellular phones which is an existing technology. This choice reduces the cost for the patient and exploits the communication capabilities of the software features.

As every other fall detection algorithm iFall tries to make the distinction between ADLS's such as walking, running and standing and actual falls. By taking the root-sum-of-squares of the three axials of the accelerometer which is the most informative sensor regarding the fall detection, the authors are able to determine the acceleration. The thresholds that they are using are adaptive and based on user provided parameters such as: height, weight, and level of activity. If the acceleration amplitude crosses the lower and upper thresholds in a set duration period as seen in Figure 3 a fall is suspected. Moreover in order to reduce the false positives the authors take the position of the user into account. A fall is only suspected if both thresholds are crossed within a specific duration of time and the position is changed.

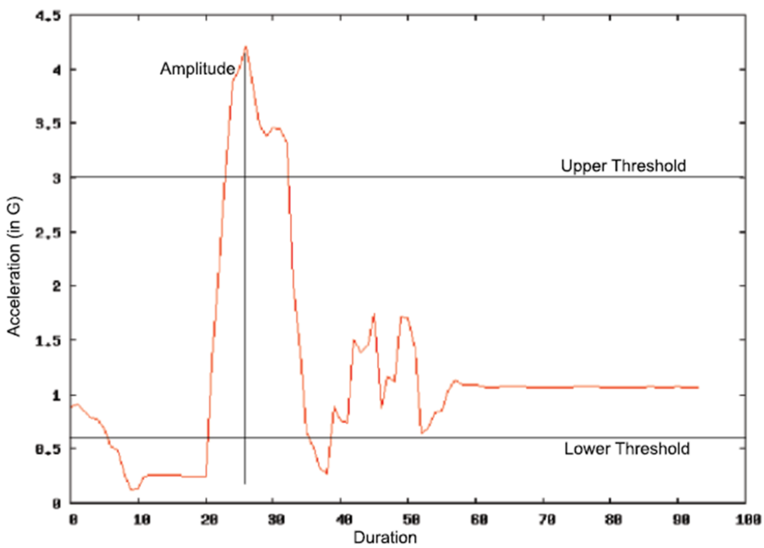


Figure 3: Example of a fall.

The procedure that takes place after a fall event is the following. Firstly, iFall tries to communicate with the user. If the user does not respond, iFall then attempts to contact members in his or her social network. If both of them fail or the social contact confirms a fall, the system alerts an emergency service. Finally the iFall application is designed to be simple to use. The number of buttons and options which are available to the user have been decreased as much as possible.

Also in [35] the authors present a fall detection system called PerFallD which works on the smartphones of the users utilizing them as the platform for pervasive fall detection development. They benefit from the advantage that the smartphones provide, which is the combination of the fall detection and the communication components. Mobile phone-based fall detection systems can function almost everywhere since mobile phones are highly portable, all necessary components are already integrated therein, and their communication services have vast coverage. It is an acceleration-based detection approach whose only requirement is that a mobile phone has an accelerometer.

The authors argue that elderly people may prefer to have a single phone with self-contained fall detection functionality than to carry a separate fall detection device on their bodies. The user interfaces of PerFallD have large, lit key buttons that make their usage easy. There are no confusing menus and the operation of the system is simple and straightforward.

The fall detection algorithm has been designed for the mobile phones that are equipped with an accelerometer. It is a threshold-based algorithm as well. They are using a combination of the acceleration of the phone combined with its orientation in a specific time window in order to detect a fall event. Firstly the application will load a profile for each individual user. The configuration of a user profile contains default sampling frequency, default fall detection algorithm and emergency contact list. Different profiles have varying degrees of rapidity. Then the main application works as a background daemon. If a fall is detected the phone iteratively calls and texts up to five contacts. The user is able to manually cancel the alarm as well. The thresholds of the algorithm have been set according to the training data obtained from extensive experiments. The thresholds are adjusted in order to reduce the false negatives and at the same time keep the false positive rate in an acceptable range.

For the evaluation of their fall detection system they have collected data of falls with different directions (forward, lateral and backward, different speeds (fast and slow) and in different rooms (living room, bedroom, kitchen and outdoor garden). Of course they have collected data of ADL including walking, jogging, standing and sitting. They conclude that PerFallD has different performances when the phone is placed at different positions and the waist is the best position to attach the phone, with the performance of average false negative value being 2.67% and false positive value being 8.7%.

In [36] the authors firstly focused on the data acquisition for building their fall detection algorithm. They constructed a mobile device that can send accelerometer data to a computer, using wireless communication. With this mobile device, 200 daily activities and 34 falls were simulated by one young subject, aged 25. The data resulted from simulations were analysed in order to design the fall detection system. The algorithm processes data from a triaxial accelerometer and computes the sum vector for the acceleration values on all the three spatial axes. They use 6 parameters in order to detect a fall. These parameters are the following. The first one, which is denoted as P is the acceleration sum vector (SV) peak value encountered during an ADL or a fall. The second parameter (B) is the base length of the triangle formed by the peak value and the 1000 mg horizontal axis. The third parameter is the ratio between the peak value and the base length and is denoted as $R_{1.}$ The fourth parameter is independent of the three mentioned before and it is the velocity after the impact, denoted as V. The fifth parameter is the ration between V and R_1 and it is denoted as R_2. The last parameter A is the activity level after the impact. The main idea behind their fall detection algorithm is that they are comparing the above presented six parameters with a threshold value. Based on this comparison the event is classified as a fall or as an ADL.

The logic behind the fall detection algorithm based on these parameters is the following. Since most of the falls have a higher SV value than daily activities, the SV peak is the starting point for the distinction between falls and ADL's. The overall accuracy of the system taking only this criterion into account was 51.28%. Therefore the second parameter, B is taken into account in order to achieve an increased accuracy of 71.37%. The way that the base length is taken into account is that it should be smaller in case of a fall compared to the case of ADL's, because when a fall occurs there is only a short-term impact and the shock is quickly absorbed by the human body.

Then the ratio between P and B increases more the accuracy of the fall detection system. Usually P is higher for falls and B is larger for daily activities. Therefore it means that R_1=P/B has a high value for falls and a small value for ADL's. A major improvement in the performance of the algorithm which is independent of three ones mentioned before is the post-impact velocity after a fall. The main difference between a fall and a daily activity like walking or running is the velocity after the impact should be small. By taking this metric into account the accuracy of the algorithm reached an accuracy of 97.86%.

Their basic principle for fall detection was the following: In case of a fall, the velocity after the impact should be small, as the body suddenly stops moving and it remains still for at least a few moments, even if the person is conscious after the fall and tries to get up. One aspect that is very important for a threshold-based algorithm like this is the robustness of the thresholds used. For this reason, it is very important to have tested the fall detection algorithm on a data set with as many simulated falls as possible.

Moreover they gave great attention in the response time after a fall event. They claim that this time can be improved with the help of an automatic fall detection system that could trigger an alarm whenever a fall is detected.

Also, Pierleoni and others in [92] present a fall detection system consisting of an inertial unit that includes triaxial accelerometer, gyroscope and magnetometer with efficient data fusion and fall detection algorithms. The algorithm defines a set of acceleration and orientation thresholds for the distinction of fall events and activities of daily living. The system has been tested with volunteers who performed simulated falls, simulated falls with recovery and activities of daily living. The orientation sensors are integrated within a compact module allowing the owner to move unrestricted.

As depicted in Figure 4 the acceleration changes can be summarized in the following four phases.

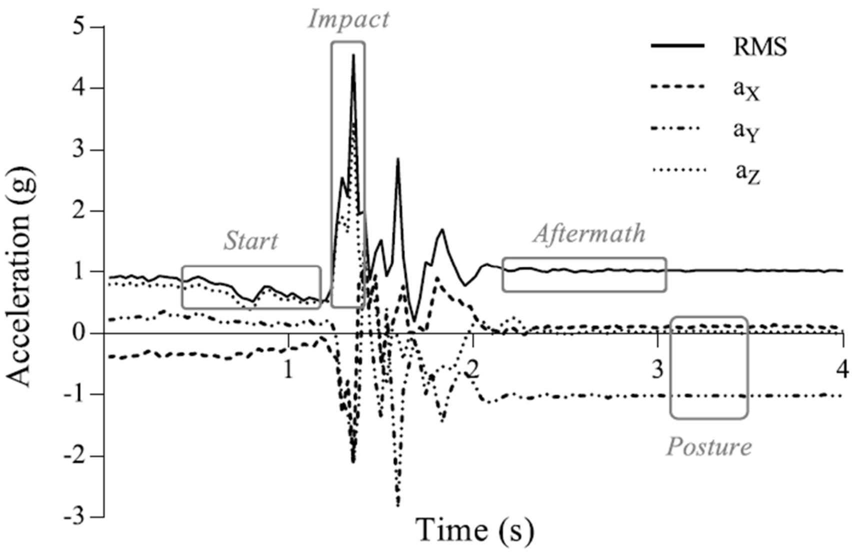


Figure 4: Acceleration changes during a fall event.

1) Start: This is the phase where the subject loses the contact with the ground.

2) Impact: The faller impacts the ground or other objects

3) Aftermath: After the impact the faller usually remains without any motion on the ground.

4) Posture: The body of the person that has fallen will be in a different orientation than before the impact.

The authors propose a wearable fall detection device which is incorporated a MARG (Magnetic, Angular Rate, and Gravity) sensor to increase the robustness of the fall detection algorithm.

The accurate measurement of orientation plays a critical role in human motion analysis. For the description of the posture of the human body they adopt Euler angles formalism [93], also known as Yaw, Pitch and Roll angles for representing the spatial orientation as depicted in Figure 5. The axes of fixed reference frame are denoted as X, Y, Z and are supposed to be rigidly attached to a rigid body. Yaw, Pitch and Roll angles are identified as the rotations around the Z, Y and X axis, respectively. Therefore they are used to represent the actual orientation of the human body. The orientation filter used in this fall detection algorithm combines accelerometer, gyroscope and magnetometer data obtained by the MARG sensor in order to provide a complete measurement of orientation relative to the direction of gravity and the Earth’s magnetic field.

The authors tested their algorithm with simulated falls and ADL's. The 6 categories of falls and activities that have been studied are backward fall, forward fall, lateral left fall, lateral right fall, syncope and ADL. The study involved 10 volunteers (8 male and 2 female) between 22 and 29 years old. Each of them repeated the scenarios by 18 times so that there are in total 540 tests. Their algorithm has an average accuracy of 90.37%, a sensitivity of 80.74% and a specificity of 100%.

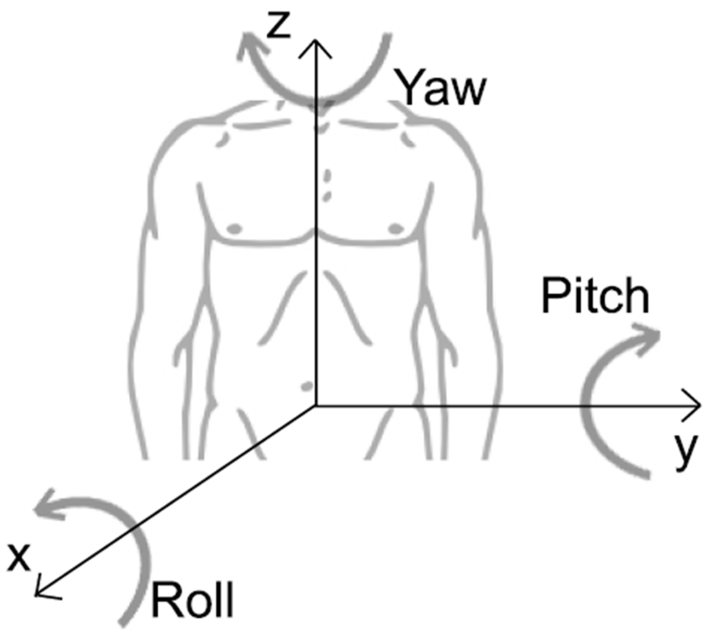


Figure 5: Spatial orientation.

Finally, Aguiar and Rocha in [37] describe the implementation and evaluation of a smartphone-based fall detection system. The system uses data from the smartphone built-in accelerometer as input in a state machine that recognizes the fall stages in a sequential order. The features and thresholds of the acceleration values have been determined using decision trees, after a comparison of diverse machine learning classifiers. The system was evaluated using a validation protocol framework proposed by Noury et al. [23], and estimating sensitivity and specificity.

More specifically their fall detection system has been designed to run as a background task in the smartphone in order to detect every possible fall event that will take place during the day. When a fall alarm is detected a sound alarm is automatically triggered. Moreover the system sends SMS and email notifications to the previously configured set of contacts. The flow of all the events that take place after the fall are depicted in Figure 6.

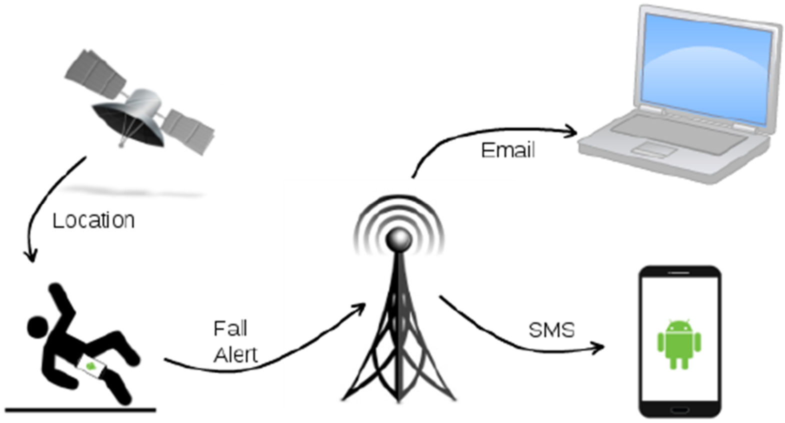


Figure 6: Application flow after falling.

Taking into account that the application is continuously running throughout the day, only the tri-axial accelerometer is collected for the fall detection. The main purpose of this decision is the concern for the battery life of the application. It is very inconvenient to ask people to charge during the day the device that they will be using for fall detection.

The authors present an algorithm based on a state machine which recognizes a fall only if all the stages of a fall event take place in the correct order as well. There are three states. The first one is the 'Stable' state where it is true when the user does not move at all. The second state is the 'Unstable' one which is true when the user is moving. If the user is in the 'Unstable phase' the system will check if the movement that he is doing causes a severe decrease of acceleration. If this is the case then it means that the user is starting a free fall movement which is one of the main stages of every fall event. Then the state of the user will change to 'Falling' and the system will be waiting for the impact on the ground. The phases of a fall event are given in the Figure 7.

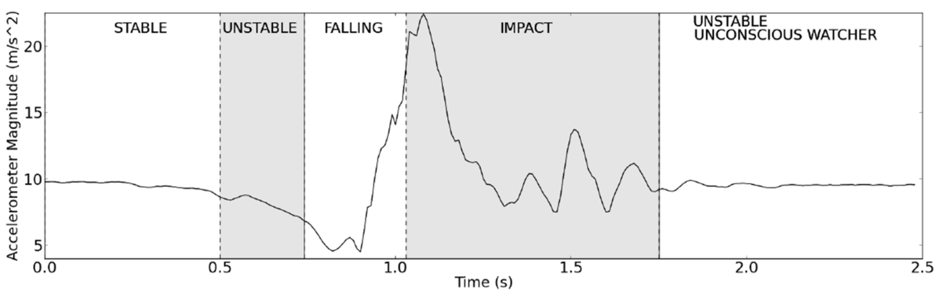


Figure 7: Fall stages.

When the 'Impact' is recognized the system will launch an 'Unconscious Watcher' and return to the 'Unstable' stage and therefore the analysis of events never stops as there could be two sequential events similar to falls. The 'Unconscious

Watcher' state runs in parallel and shows if the user has recovered from a fall. If the user does not move for 10 seconds then a fall alarm is triggered.

The validation of the algorithm took place through simulated falls and ADL's from two groups. The first group consists of healthy young subjects who were willing to simulate falls. The second group was consisting of young and elderly volunteers who could perform the ADL's. All the end-users had their smartphone in the trousers front pocket in a vertical position and/or hold to the belt (centrally or laterally).

Finally the ultimate goal of the proposed fall detection system is to monitor the user throughout the full day and so the battery consumption of the application is a very crucial issue. After testing with three different Android devices the results that the authors obtained are the following: A phone can last more than one day with the application fully active.

In [84] Li and others have designed a fall detection system for elderly people based on the Neyman-Pearson detection framework. An optimal detection threshold can be obtained which minimizes the false alarm rate and at the same time maximizes the fall detection rate. They use TeloW mote [85] with accelerometer as the detector, which is attached to the waist of the old people in order to capture the movement data. The accelerometer periodically samples the acceleration of the person and compares it to a predefined threshold. Once the threshold is exceeded an alert message will be delivered to the based station through multi-hops using 802.15.4/Zigbee network. For the fall detection the sampled acceleration data can either be processed locally at the sensor node or forwarded to the base-station where a more sophisticated analysis can take place.

In [83] Cheng and Jhan present a machine-learning based fall detection system. They first introduce the sensor board they use for detection and communication followed by the overview of the system architecture. They propose a cascade-AdaBoost support vector machine (SVM) classifier to complete the triaxial accelerometer-based fall detection procedure. Their method uses the acceleration signals of daily activities of volunteers from a database and calculates feature values in order to train their system. They used the UCI database for their experiments, in which the triaxial accelerometers are worn around the left and right ankles, on the chest and on the waist. The experimental results show that the tiaxial accelerometers around the chest and waist produce optimal results in terms of fall detection rate and the lowest false alarm rate.

Finally, Hou and Li in [43] present an automatic fall detection system consisting of a triaxial accelerometer and a smartphone is evaluated. The system classifies raw sensor data by using an online algorithm. Based on physical characteristics of activity, four time-domain features are abstracted, which are all independent of the sensor orientation with respect to the body. A decision tree is used as a classifier running on smartphone. In the meantime, permitting control is adopted to save power by reducing data traffic. The accelerometer and Bluetooth unit are bounded as a wearable unit and placed on the subject's waist/chest as seen in Figure 8. The accuracy of their algorithm is 92%.

Figure 8: Wearable unit placed on the chest.

2.2 Theoretical model and implementation

Nowadays, simple smartwatches are very powerful and have a set of sensors that can be used and diverted from their original intent. More computing power and storage on these devices offer greater opportunities. In F2D we use the accelerometer sensor in the smartwatch to feed the fall detection algorithm, considering also the residual movement after the fall. Our main concern is the battery consumption and therefore we designed a threshold-based algorithm which uses only the accelerometer which is the most informative sensor regarding the fall detection. F2D is designed to consume the less possible battery so that it can last as much as possible without charging the smartwatch.

F2D works on a smartwatch and therefore fixed on the wrist of the person. The fall detection algorithm is implemented in a background service and is running continuously. The user can operate his smartwatch as usual. F2D does not cause any interference with the normal usage of installed applications. The algorithm is threshold based like [36], relying on the captured data of the accelerometer of the smartwatch.

The main functionality of F2D is to distinguish daily activities from falls. Activities of Daily Living (ADL) are normal activities such as walking, standing or running. The pattern of a fall must be different from the patterns of these activities. Acceleration data is sampled at 40 Hz from the 3-axis accelerometer sensor embedded in the Android smartwatch. Specifically, the sensor which provides acceleration information (linear acceleration) is used. We calculate the norm of the acceleration for each moment as described in Equation 1.

$$acceleration = \sqrt{x^2 + y^2 + z^2} \quad (1)$$

We can observe the residual movement of the user right after falling as depicted in Figure 9. This movement is very crucial for the detection of a fall pattern in our fall detection algorithm as it is described in the fall pattern section. We have analyzed a set of data with 150 different simulated falls from different people involved in the experiments from our project partner FST. This company has a long experience in creating and using innovative products adapted to people with disabilities. Thanks to this data we have improved the detection of possible falls. We observed that all falls follow one of the three patterns which we have called smooth, strong and sharp. They are given in Figures 12, 13 and 14 respectively. The main difference between them is the time interval of the residual movement after the fall. The three possible values of the time interval are the following: smooth=100ms, strong=300ms, sharp=500ms. More specifically, when a fall takes place, the peak that exceeds the upper threshold of the acceleration corresponds to the hit. After this, the pattern of the fall has a second peak, lower than the first one and exceeding the lower threshold. Finally, the acceleration returns to normal values. This behavior of the acceleration after the first peak represents the residual movement, as seen in Figure 9, that we take into account in the decision module for the characterization of a possible fall event as a real fall.

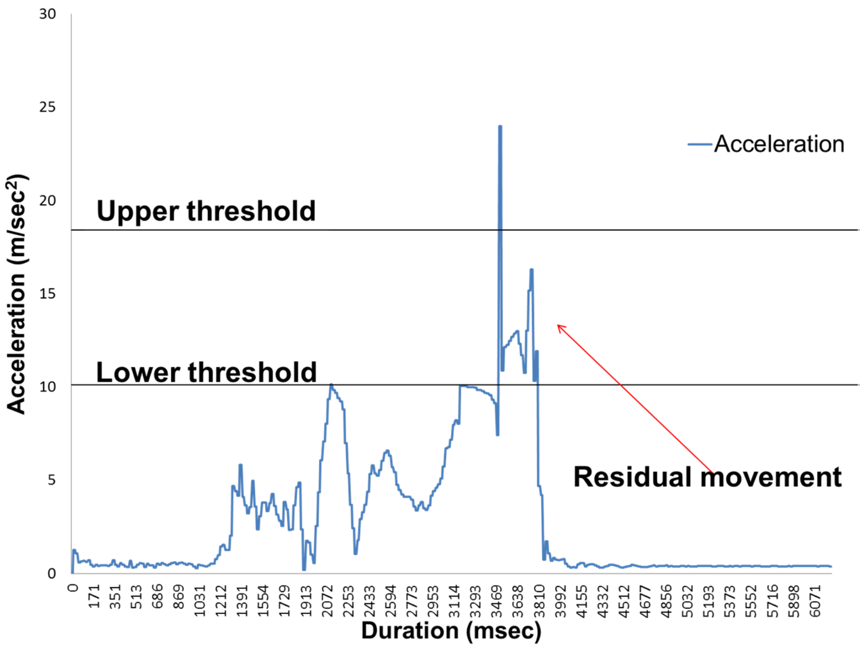


Figure 9: Analysis of residual movement.

Time window

The time window is an essential part of the fall detection algorithm. We have defined a time window in which we are able to recognize a fall pattern. This window is set to 6 seconds, a value which has been selected after conducting experiments, using the set of data from simulated falls mentioned above. The main goal of the algorithm is the detection of all falls and at the same time the elimination of false positives. Building and testing our system we concluded that less than 6 seconds is not enough for the detection of all different types of falls. However, setting the window to higher values creates a bigger occurrence of false positives.

Fall pattern

The next step of the algorithm is the detection of a possible fall. Although in our previous work [70] the acceleration thresholds were fixed, in this thesis the thresholds are flexible. We have received data for a large number of falls and ADL from our industrial partner (FST) in order to train our fall detection system and therefore find the best adaptive thresholds that will provide the best sensitivity and specificity of the algorithm. More specifically we have received 150 fall events simulated by experts in falling and 150 events of ADL from elderly people. The events of ADL have been extracted from hours of recordings of elderly people doing their normal daily activities. Our partner was selecting specific events (time windows) during these hours of recordings that represent ADL that have a strong acceleration and can be similar to fall events. For example walking, running, going up the stairs, going down the stairs. Moreover, we used experts in studying and repeating falls in order to simulate falls because it was impossible to ask elderly people to fall. But our project partner FST was responsible to make sure that the acceleration patterns of falling that we acquired from the experts are identical to real falls of elderly people. They are experts in studying falls because they work for many years with elderly people that are vulnerable in falling and they have watched hundreds of videos of real falls reproducing them in their labs. Therefore we can claim that we have simulated falls as close as possible to real ones.

By analyzing the real ADL from elderly people we were able to find a wide range of acceleration thresholds that keep F2D robust and therefore acceptable for the user. In order to consider an activity as a possible fall the two following conditions must be satisfied: 1) The acceleration must exceed an upper threshold which can take values from 10 to 18m/sec^2 depending on the profile of the user. 2) After a flexible time interval the acceleration must exceed a lower threshold which can take values from 2 to 7m/sec^2 depending again on the profile of the user. The time difference between the two peaks represents the rebound of the user after a fall. This rebound is very crucial for our adaptive threshold-based algorithm because the user wears the smartwatch on his wrist and therefore immediately after falling his wrist has a rebound that comes right after the big hit of falling. The intensity of this movement depends on the profile of the individual user. The time interval between the higher and the lower peak is flexible but cannot exceed the 0.5 seconds which is the maximum length of the rebound after a fall according to our experiments. Making the time interval flexible instead of giving it fixed values like in our previous work [70] has led to an increase of the specificity of the algorithm of 3%. The ranges of the two thresholds have been selected based on the basic trade-off between detecting all falls and avoiding false positives. To the best of our knowledge this is the very first fall detection system that takes into account the residual movement of the user right after falling [76].

If the two conditions are satisfied during the time window of 6 seconds then a possible fall is suspected. We can see in Figures 12 - 14 that this time window is sufficient for the satisfaction of the two conditions that should happen in order to detect a fall pattern. The full analysis of the fall pattern is given in the next flow chart (Figure 10).

As soon as we are in the time window of 6 sec which is the time window of a possible fall event we check the values of the acceleration. If the acceleration is higher than the upper threshold ($acceleration\_{t\text{-}interval}$ > upper threshold) then we check after the interval of the 0.5 sec if the acceleration is higher than the lower threshold ($acceleration\_{t}$ > lower threshold). This check represents the residual movement of the user right after falling. If these two checks are successful then we increase the possible fall counter (possible fall counter ++), otherwise if one of the two condition is not satisfied we do not increase the possible fall counter. And we repeat these checks while we are inside the time window of the 6 sec. In the end of the time window we have a value for the counter. The last step is the comparison of the value of the counter at the end of the time window with the X, Y which are the lower and the higher acceptable values, for detecting a fall, of the counter respectively. We keep repeating this procedure for the following time windows.

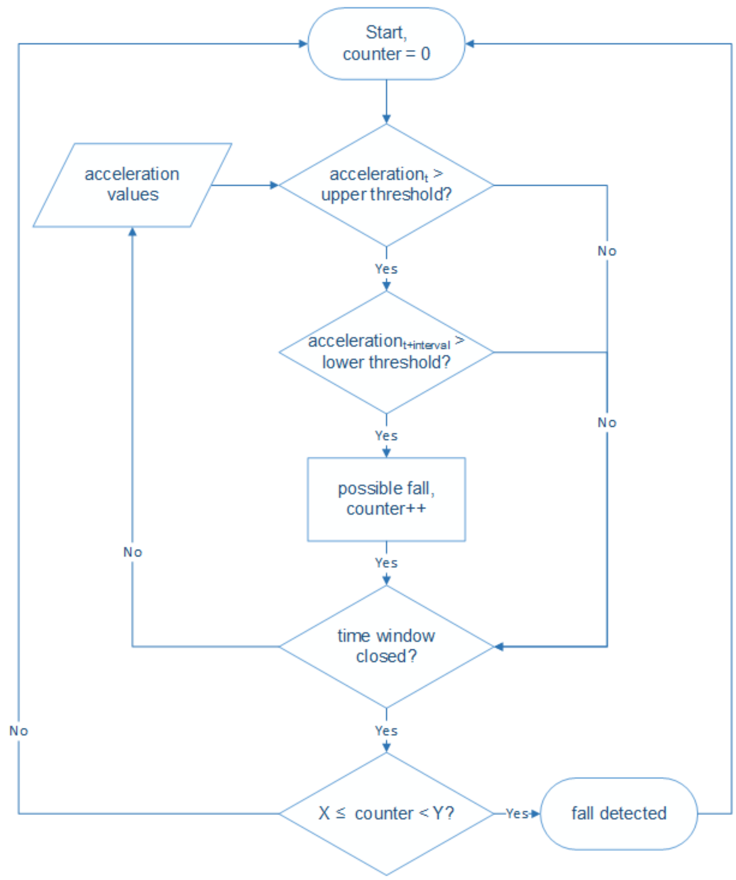


Figure 10: Fall detection algorithm.

Decision module

The final step of the fall detection algorithm is the classification of the fall pattern as real. In this decision module a counter increases every time that both conditions of exceeding the thresholds are satisfied. We define X and Y to be the lower and higher acceptable values of the counter respectively. The critical range of the values of the fall counter is (X ≤ counter < Y). If (counter ≥ Y), then it is due to another activity being performed (e.g., running) which gives the difference in the acceleration values as we can see in Figure 15. Based on the real ADL data that we processed from elderly people we concluded that the value Y that gives the best specificity lays between [5-10] and not 14 comparing to [70]. On the other hand, if (counter < X) where X = 1 it means the user at most did a sudden movement with his wrist and so the threshold conditions were not satisfied (e.g., when a user was going down the stairs). The graphical explanation and the structure of the fall detection algorithm are given in the flow chart of Figure 10.

Location

The last module of F2D is the location module. This module makes our fall detection system very useful for nursing homes that host elderly people. It includes two different scenarios. The first one is the scenario of the user being outdoors. Then the fall detection system will work without any further filtering, minimizing the probability that we miss any fall that can be dangerous for the end-user.

The second scenario is the case that the end-user is indoors. Then using the exact location of the user in the building (e.g. an apartment) we can further filter the fall detection events. We use the iBeacon technology for this scenario, placing one beacon in each room of the apartment. iBeacon uses Bluetooth low energy to transmit a universally unique identifier picked up by a compatible app or operating system. The use of the location as contextual information leads to an increase of the specificity of the algorithm. Although it is the user that cancels the alarm, it makes F2D more robust and reduces the probability of losing a fall event and put elderly's lives in danger. On top of this, knowing the precise location where the fall has occurred, it will decrease the reaction time of the caretakers. Therefore the fall detection system can work accurately and provide immediate help to elderly people and caretakers at nursing homes.

1) RSSI and propagation model: In RSSI-based localization, the packets sent from the anchor beacon to the mobile device are used to map the RSSI to a distance by means of a propagation model. The correct calibration of the propagation model is crucial, since the way RSSI is transformed into a distance significantly affects the accuracy of the positioning. Currently, the widely used model for wireless signal propagation loss [96] is given in Equation 2.

$$r_i = r_0 - 10nlog\left(\frac{d_i}{d_0}\right) + X\sigma \qquad (2)$$

where d_i and d_0 denote the real distance and the reference distance respectively, r_i and r_0 denote the received signal power in dBm at the real and at the reference distance respectively, $X\sigma$ is a random variable representing the noise in the measured r_i and n is the path loss exponent, that depends on the transmission channel, the transmitter and the receiver. Using d_0 =1 meter as the reference distance, and assuming $X\sigma$ to be a Gaussian distributed random variable with zero mean and variance σ^2 , the simplified model is used as follows:

$$r = p - 10nlog(d) \qquad (3)$$

where r is the received signal power at the distance d, *p* is the received signal power of the receiver from a transmitter one meter away and n is again the path loss exponent

2) Room dimensions and RSSI thresholds: Let S be the surface area of a room and h be the height of it. Assuming a square room as on Figure 11, the radii of the inner and the outer tangent circles are calculated with Equations 4 and 5 respectively.

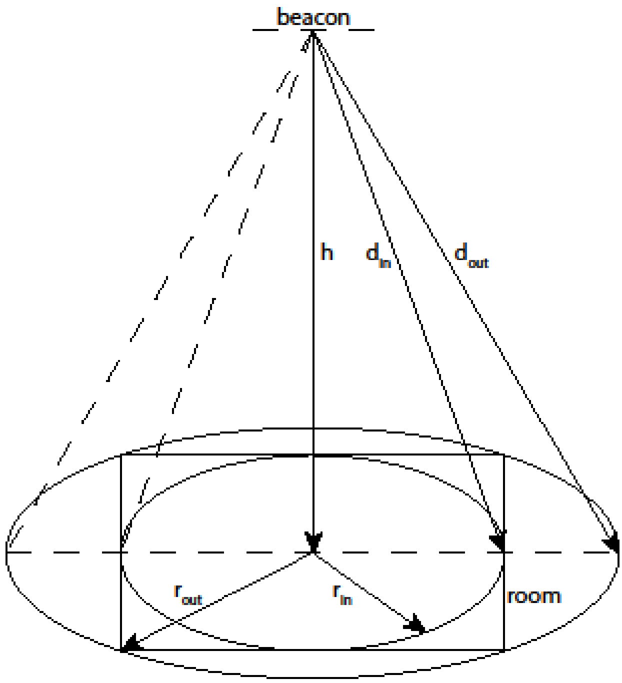


Figure 11: Square room.

$$r_{in} = \frac{\sqrt{S}}{2} \qquad (4)$$

$$r_{out} = \sqrt{\frac{S}{2}} \qquad (5)$$

Now using the Pythagorean theorem, the hypotenuses are calculated with Equations 6 and 7 respectively.

$$d_{in} = \sqrt{h^2 + \frac{S}{4}} \qquad (6)$$

$$d_{out} = \sqrt{h^2 + \frac{S}{2}} \qquad (7)$$

Eventually by substituting the calculated distances of the hypotenuses into the propagation model of Equation 3, the inner and the outer thresholds are calculated with Equations 8 and 9 respectively.

$$threshold_{in} = \mathrm{p} - 10nlog(\sqrt{h^2 + \tfrac{S}{4}}) \qquad (8)$$

$$threshold_{out} = \mathrm{p} - 10nlog\sqrt{h^2 + \tfrac{S}{2}} \qquad (9)$$

3) RSSI classification and localization algorithm: For every Bluetooth beacon placed in a room, the $threshold_{in}$ and $threshold_{out}$ are calculated as described previously. Based on their RSSI readings, they fall into one of the following categories. The Strong category (S) when RSSI $>threshold_{in}$, the Medium category (M) when $threshold_{in}$ > RSSI > $threshold_{out}$, the Weak category (W) when $threshold_{out}$ > RSSI and the Not found category (N) when there is no reading for a specific beacon. The ordering of those categories based on their significance is the following: S > M > W > N.

For any given moment, for each beacon, a set of its N latest RSSI readings is averaged, so that each beacon can be classified into one of the aforementioned categories. The most significant non empty category is then picked. If only one beacon falls into this category, then the procedure ends and presence is assumed in the room that this specific beacon was placed in. When multiple beacons fall into this category, then a score is calculated for each beacon that is equal to the difference between its measured RSSI and its lower threshold.

The lower threshold is equal to $threshold_{in}$ when S is the most significant non empty category, $threshold_{out}$ when M is the most significant non empty category and when W is the most significant non empty category it can be a global minimum of the RSSI readings (e.g. -100) selected by the user. Then the beacon with the highest score wins. In the final case of a draw, the beacon that is placed in the biggest room wins.

To summarize, the location approach described above is an easy to deploy Bluetooth-based indoor positioning system with room-level accuracy. The system only requires the sizes of the rooms and Bluetooth beacons placed in the center of each one of them. Then the presented algorithm computes two RSSI thresholds for each room, and based on them, categorizes the RSSI readings and finally estimates a room location.

Emergency actions

If the algorithm decides that a fall has happened then the background service notifies the main application, which in turn sends a message to the caretakers. The smartwatch communicates directly with the caretakers. In case of an alarm the loudspeaker of the watch is automatically turned on at a high volume and calls from caretakers are automatically answered. This allows the user to communicate even in uncomfortable positions that could result after a fall. One key innovation of F2D is the fact that it takes into account the behavior of the user after a fall event. Based on the residual movement of the user after the fall we categorize the falls in three types. B1: No movement at all, B2: Small amount of movement after the fall event, B3: Back to normal activity after the fall event. It is clear that, if after a fall the user does not move at all, then the caretakers should immediately be informed and therefore the alarm will be triggered directly. On the other hand, if the user is able to fully recover after a soft fall event, then he is able to cancel the alarm and therefore not disturb the caretakers for no reason. F2D will be released on the market and it requires the least possible false alarms.

There are two main advantages of using this categorization of fall types. The first one is the increase of the specificity of the algorithm and so it makes it the system more robust. The second one is linked to the first and comes as a result that F2D aims to be available on the market. After making tests with end-users from FST and taking into account their feedback, we concluded that giving the opportunity to the user to cancel the alarm in case of B3 type of fall will make F2D more user friendly.

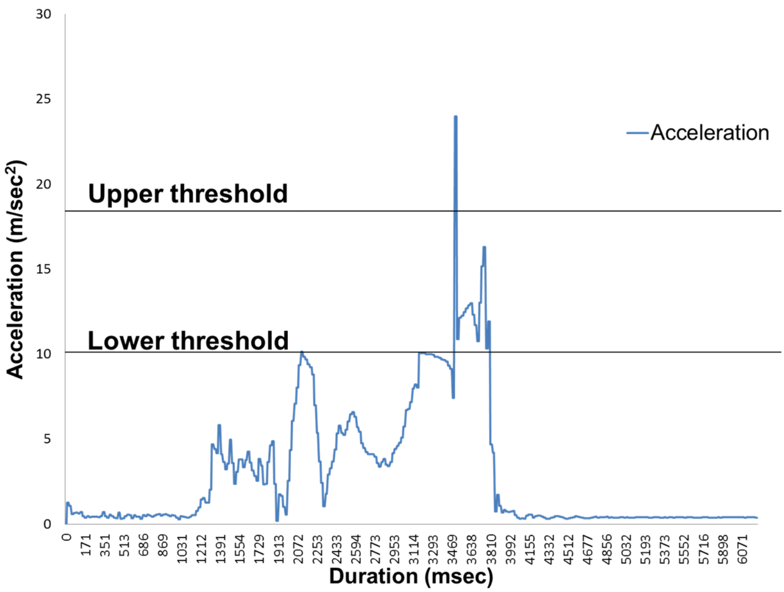


Figure 12: Smooth fall.

In Figure [12] we have a smooth fall which means that after the big hit of the fall event, the residual movement of the user comes 100_{msec} after the hit.

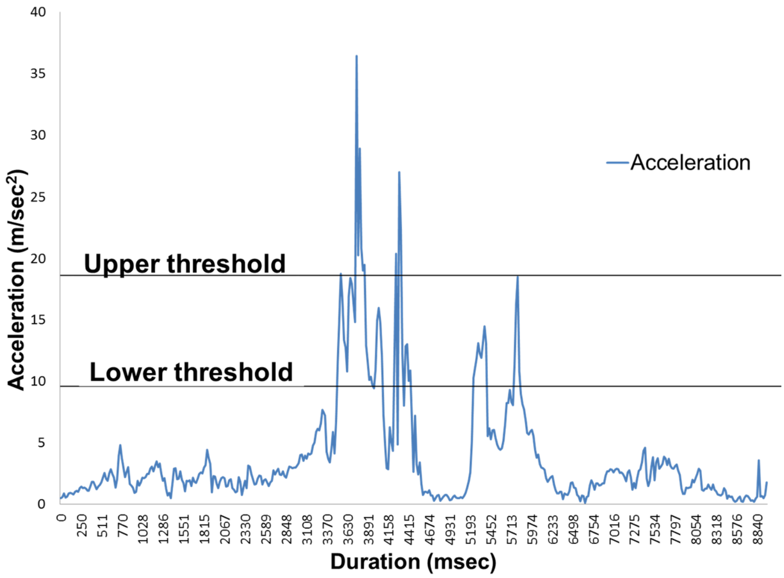


Figure 13: Strong fall.

In Figure [13] we have a strong fall which means that after the big hit of the fall event, the residual movement of the user comes 300_{msec} after the hit.

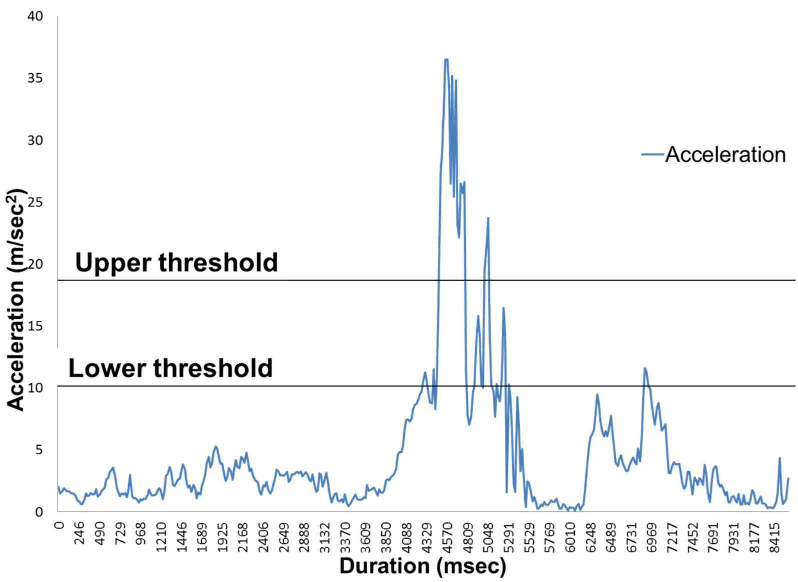


Figure 14: Sharp fall.

In Figure [14] we have a sharp fall which means that after the big hit of the fall event, the residual movement of the user comes 500_{msec} after the hit.

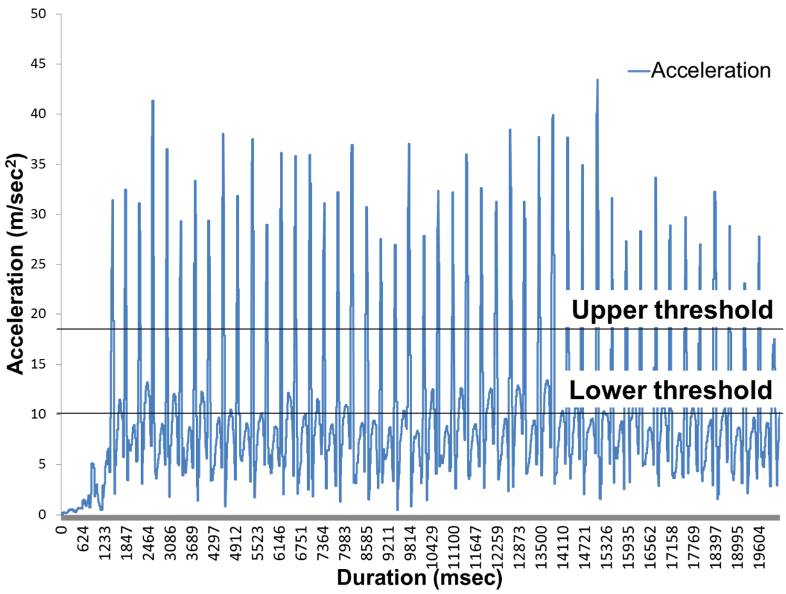


Figure 15: Running.

Using a single smartwatch as a device for running the F2D application satisfies the condition of ease of installation of the fall detection system. The context awareness that the location module added to the fall detection system is very important for the final scope of this application. Since we are targeting the care of elderly people who are in a nursing home, knowing the location of the user after a fall is very important. The caretaker will know in which room the elderly has fallen and therefore they will be able to immediately provide the help that this person needs. The latter has been achieved through the location module that has been included in F2D. By knowing the precise location where the fall has occurred, it will decrease the reaction time of the caretakers. Therefore the fall detection system can work accurately and provide immediate help to elderly people and caretakers at nursing homes. We use the iBeacon technology for this scenario, placing one beacon in each room of the apartment. iBeacon uses Bluetooth low energy to transmit a universally unique identifier picked up by a compatible app or operating system [47].

Finally, the main innovation of F2D is that we have used real Activities of Daily Living from elderly people, testing our system in real life situations. Also we used data with simulated falls from experts (FST) in reproducing falls simulated like coming from elderly people.

Evaluation

For the evaluation of the reliability of F2D we performed a series of experiments. We evaluated our fall detection algorithm using a set of falls recorded by experts in studying and repeating falls hired from our industrial partner FST. This set consists of 384 simulated falls. We should clarify that these falls have been simulated by experts and therefore they are as similar as possible to real falls from elderly people. As we already have highlighted, we used experts in studying and repeating falls in order to simulate realistic falls because it was impossible to ask elderly people to fall. These people were working under the guidance of our project partner. Therefore we can claim that we have falls as close as possible to real ones.

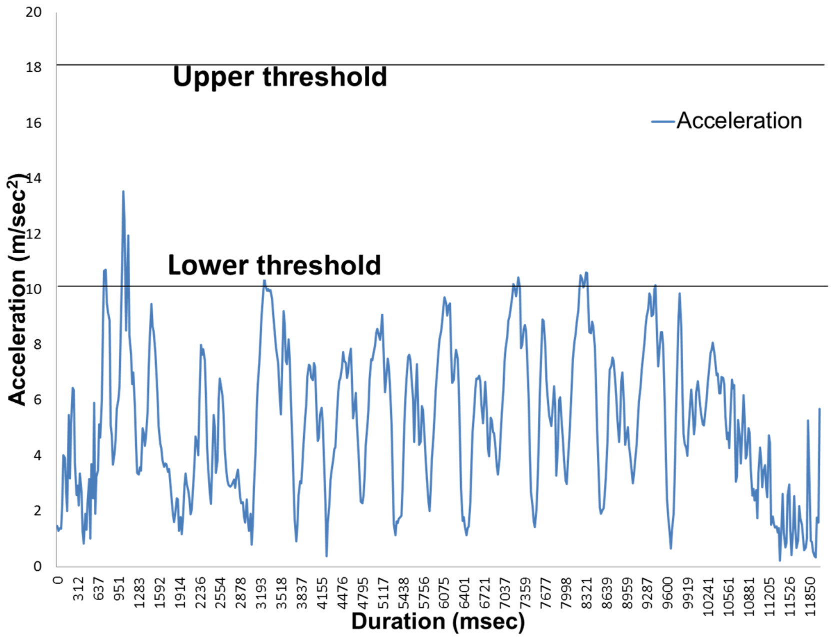


Figure 16: Walking.

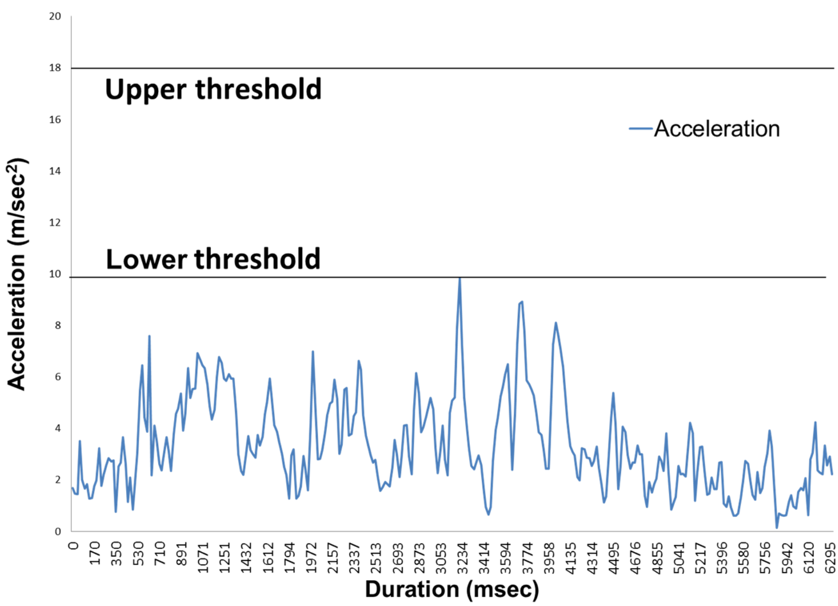


Figure 17: Going up the stairs.

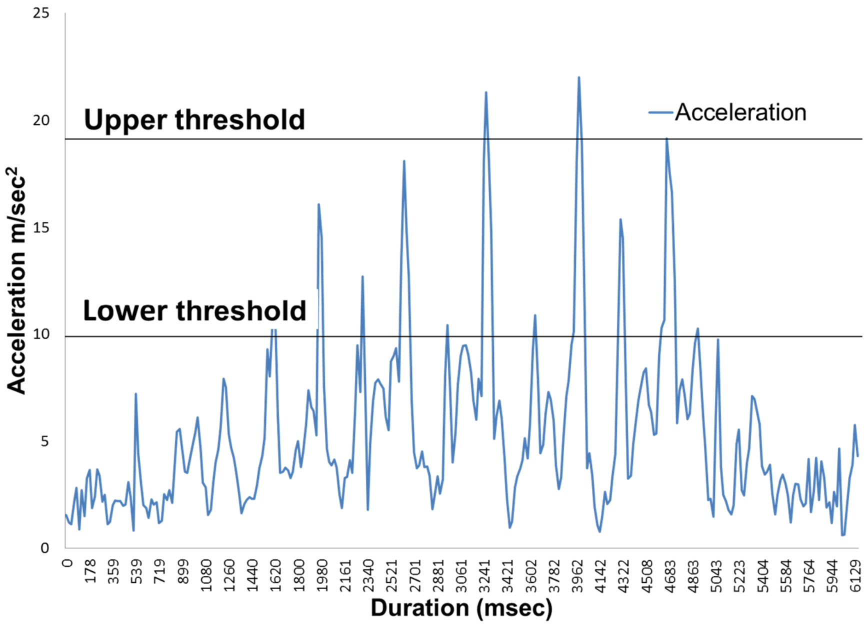


Figure 18: Going down the stairs.

The main innovation is that we evaluated F2D with real ADL from elderly people (412 files) which give us the opportunity to test our system in real life conditions of the target population group. These 412 files have been extracted after many hours of recordings, representing specific time windows from ADL that have similar acceleration patterns with falls. The set of data that we are using is much larger comparing with other systems [36] where only 34 simulated falls and 200 daily activities simulated by a single young person were used. Our real data has been collected from 6 elderly people with different profiles as reported in Table 2. We must highlight that the real data that we have received from our project partner FST are totally anonymous and therefore the anonymity and privacy of the people that were involved in the experiments is protected.

Age	Height (cm)	Weight (kg)
74	158	53
83	165	60
86	160	59
86	175	65
87	156	100
93	155	50

Table 1:Different profiles.

For the evaluation of the experiments, sensitivity and specificity measures that have been described by [97] are employed.

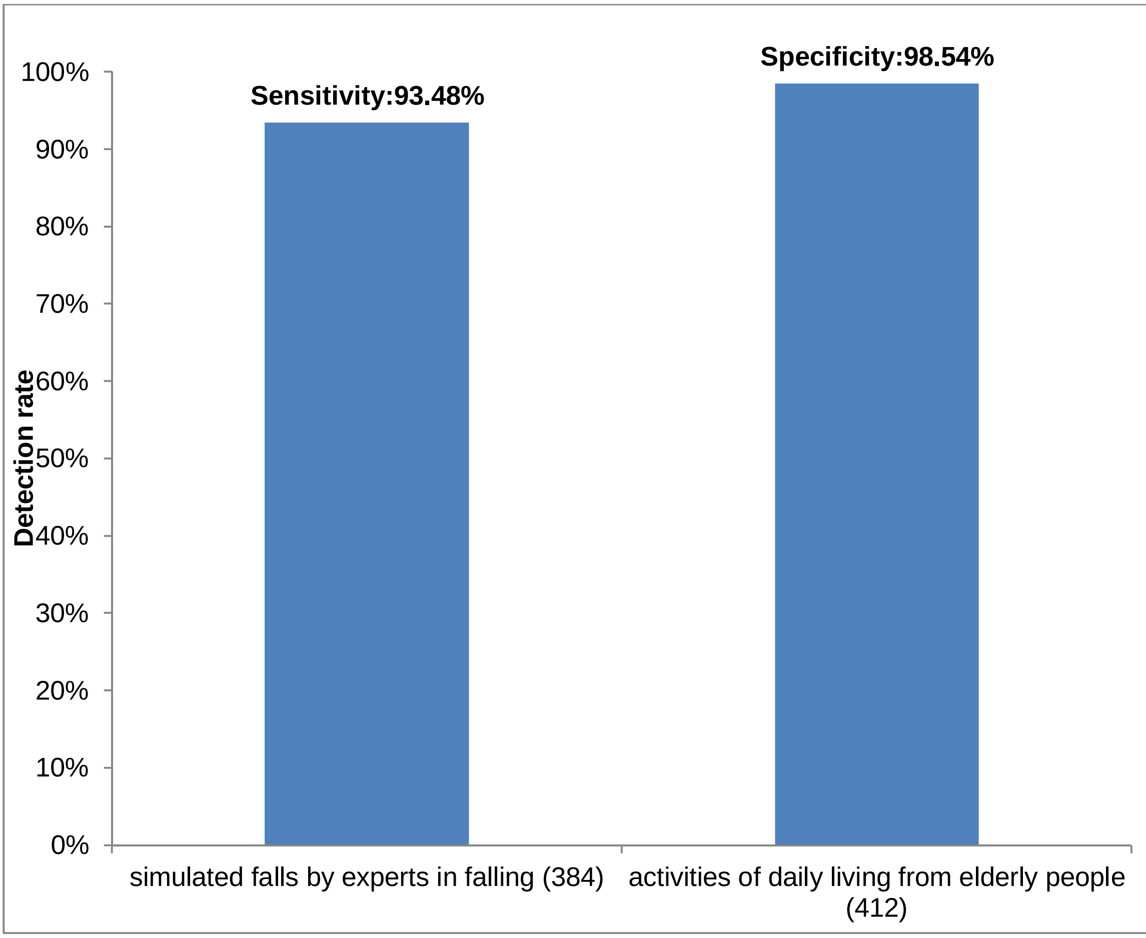


Figure 19: Sensitivity and specificity using real data from partner.

Sensitivity is defined as the portion of the falls that are detected as falls with the proposed algorithm. Specificity is the portion of the nonfall events (ADL) that do not lead to false alarms. $Sensitivity$ and $Specificity$ are given by

$$Sensitivity = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \qquad (10)$$

$$Specificity = \frac{\mathrm{TN}}{\mathrm{TN+FP}} \qquad (11)$$

where true positive (TP) is the detection of a fall by the system when it occurred, false positive (FP) is the detection of a fall when it did not occur, true negative (TN) is the system not detecting a fall when a fall did not occur, and false negative (FN) is the system not detecting a fall when it occurred.

The real ADL were the following: walking, going up the stairs, going down the stairs, as seen in Figures 15-18. Based on these facts, it can be noted that the accuracy of our algorithm is quite high. We achieved a true positive rate (sensitivity) of 93.48% for the set of simulated falls and a true negative rate (specificity) of 98.54% for detecting the real ADL from the elderly people. The average of sensitivity and specificity represents the accuracy of the system which is equal to 96.01%. The analytical results are presented in Figure 19.

For the quantitative results analysis, we have created a tool which gives us the opportunity to run the fall detection algorithm against the data that FST has provided. Based on this tool we had the opportunity to systematically test all the improvements made to the algorithm.

We conclude that the F2D system works reliably. Some false alarms were detected when the testers performed sudden movements with residual activity trying to simulate the same pattern of a fall event.

Based on the results that we have obtained by testing our fall detection system in real life scenarios, the commercial deployment of F2D is the natural next step. F2D will enlarge the product range the FST is currently providing to their users. Since they work directly with end-users and with end-user organizations, they are able to personalize the system according to the user profile and environment, thus providing a much more accurate and safe system than the generic solutions available in the market. The final application gives the opportunity to the user to select the parameters that correspond to their profile and trade-off between fall detection and false alarms as depicted in Figure 20.

More precisely if the user wants to detect a percentage of 99% of the falls, they are able to decrease the thresholds of the final application. This means that they will have some more false alarms and they should sometimes have to cancel the alarm. In the final application these settings will be abstracted to a single “sensitivity” control, which maps discrete sensitivity levels to particular settings of the thresholds and counters.

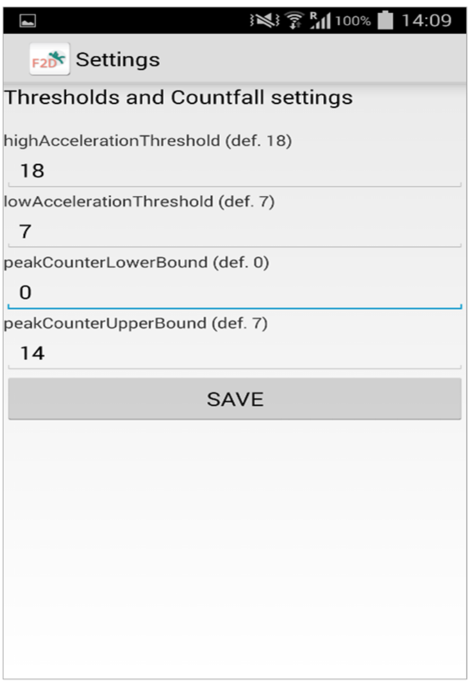


Figure 20: Settings.

Indoor localization evaluation

1) Experiment methodology: For our experiments we used the Kontact.io Smart Beacons, set in their default configuration settings (TX Power = 3 and Interval = 350 ms). We gathered RSSI readings at grid locations in each room throughout the floor. At each point, we collected a total of 209 RSSI readings for each beacon, one per second. The receiver was placed on a non-conducting surface at roughly 70 centimetres from the floor.

2) Propagation model calibration: In order to construct the specific propagation model for our application, we placed a Bluetooth beacon in the center of a corridor. Then we took multiple measurements at several points with a known distance from the beacon, ranging from 0.5 to 7 meters. By constructing the line of best fit described by Equation 3, the estimated values of the propagation model parameters were p = -70:09 and n = 1.95. For our tests we also have empirically set N = 10, where N is the size of the set of the latest RSSI readings of each beacon that is averaged.

3) Deployment in two locations: We have deployed our indoor positioning system in two different locations. The first is a typical office environment housing eight people (Figure 21), composed of three rooms. The area is divided by thick concrete walls and wooden doors. The second is a house environment composed of five rooms of different sizes and one corridor (Figure 23). Due to the corridor being oblong, we have divided its total area into two equal ones, so that we can abstractly consider that the house is composed of a total of seven rooms. The area is divided by thin concrete walls and wooden doors. In both figures the circles mark the locations where measurements were taken along with an ascending number. Each room is also represented by a letter.

4) Comparison: We compare the performance of our indoor positioning system with room-level accuracy with the one without thresholds. That is a system that only considers the magnitude of the RSSI readings and assumes presence in the room with the highest one.

5) Office environment: In this experiment RSSI readings were collected at 27 different points (9 for every room) as depicted by the circles in Figure 21. The green points are the ones for which the accuracy was improved, while for the red ones the accuracy was deteriorated. Table 3 presents the locations in the office for which accuracy has changed with the introduction of the localization algorithm and Table 4 presents the averaged accuracy per room. As seen in Figure 22, the average accuracy of the points of room B has increased by 1.89 % and the average accuracy of the points of room C has increased by 3.72 %.

Point	Accuracy change (%)
13	+13.5
15	+1
16	+2.5
19	+36.5

20	-3.5
25	+0.5

Table 2: Locations in the office with an accuracy change.

6) Home environment: In this experiment RSSI readings were collected at 63 different points (9 for every room) as depicted by the circles in Figure 23. Once more, the green points are the ones for which the accuracy was improved, while for the red ones the accuracy was deteriorated. Table 5 presents the specific locations in the house for which accuracy has changed with the introduction of the localization algorithm and Table 6 presents the averaged accuracy per room. As seen in Figure 24, the average accuracy of the points of room A has increased by 0.78 %, of room B by 1.56 %, of room E by 2.94 %, of room G by 1.67 %, while the average accuracy of the points of room D has deteriorated by 0.17 %.

Room	Accuracy without the algorithm (%)	Accuracy with the algorithm (%)	Accuracy change (%)
A	100	100	0
B	89.94	91.83	+1.89
C	87.94	91.67	+3.72

Table 3: Per room accuracy comparison in the office.

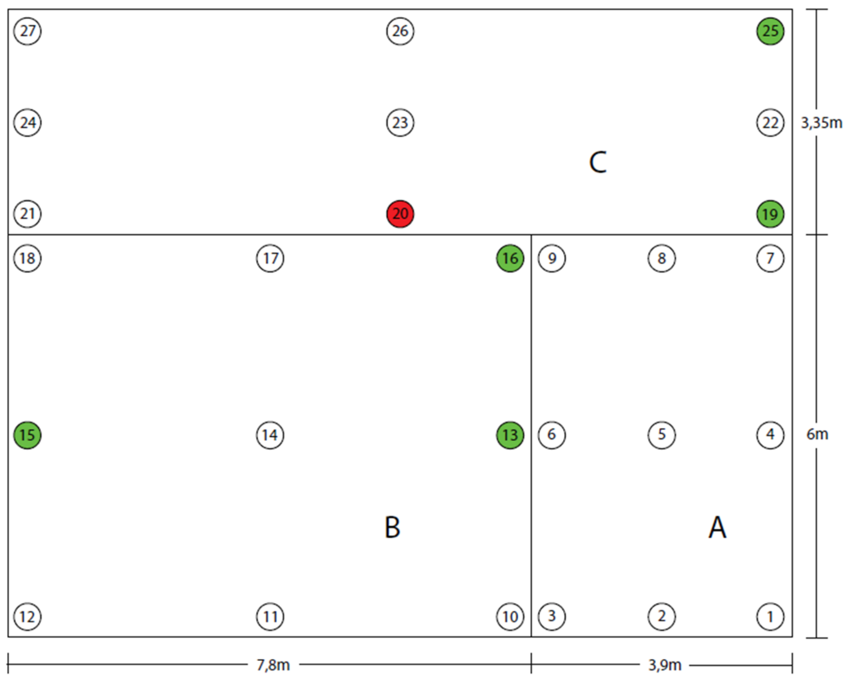


Figure 21: Office evaluation area and targeted locations.

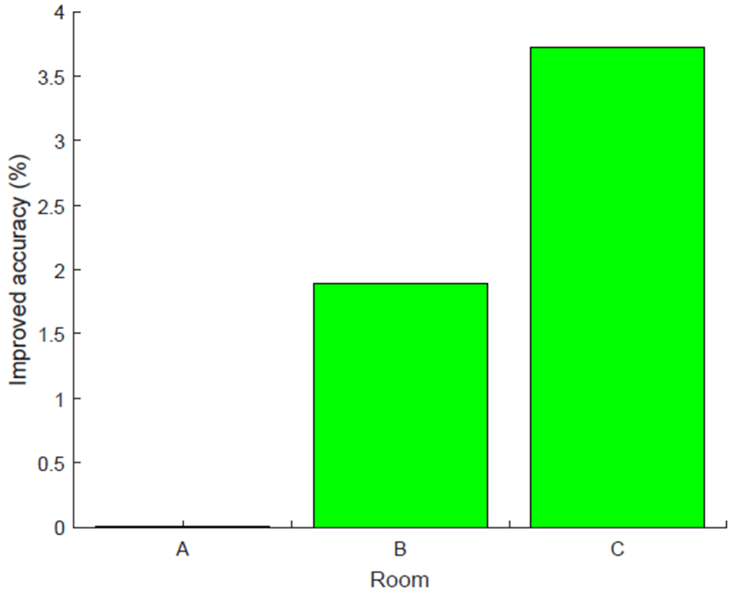


Figure 22: Improved accuracy in the office evaluation area.

To sum up, after comparing it with the no-threshold approach, we saw an average improvement of room estimation accuracy of 9% for the points that the accuracy was improved and an average deterioration of room estimation accuracy of 1.375% for the points that the accuracy was deteriorated.

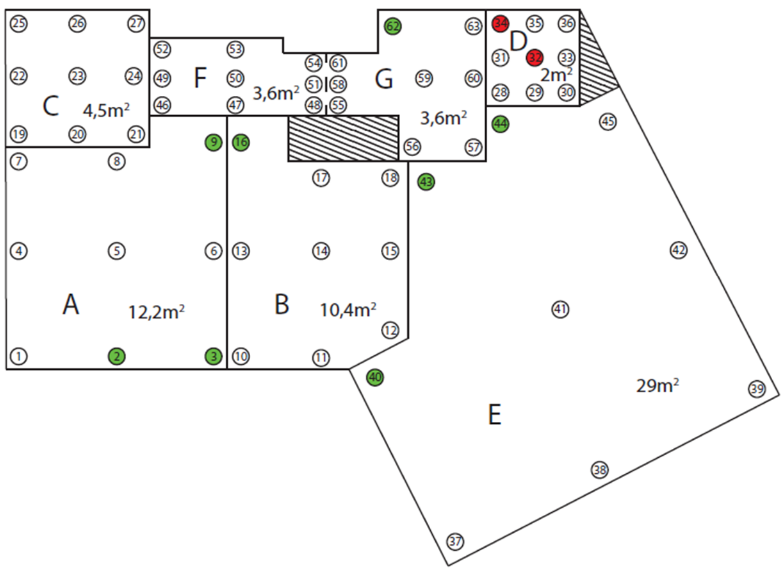


Figure 23: House evaluation area and targeted locations.

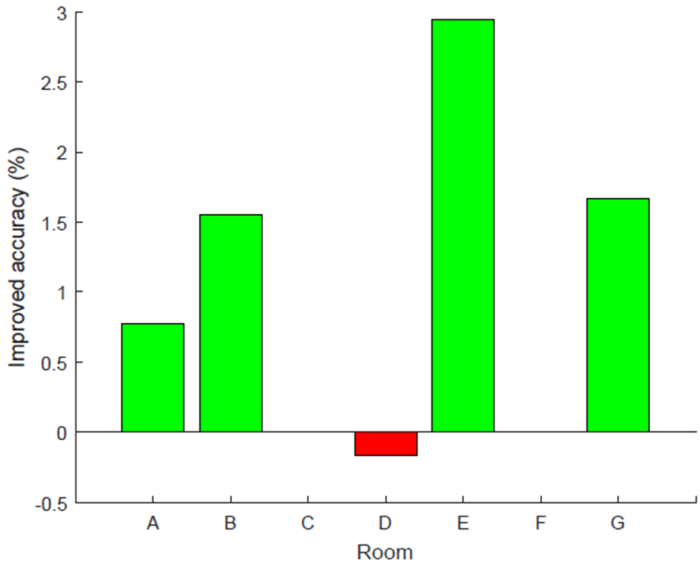


Figure 24: Improved accuracy in the house evaluation area.

Point	Accuracy change (%)
2	+0.5
3	+0.5
9	+6
11	-0.5
16	+14.5
32	-1
34	-0.5
40	+2
43	+21
44	+3.5
62	+15

Table 4: Locations in the house with an accuracy change.

Room	Accuracy without the algorithm (%)	Accuracy with the algorithm (%)	Accuracy change (%)
A	90.28	91.06	+0.78
B	91.78	93.33	+1.56
C	100	100	0
D	98.22	98.06	-0.17

E	78.22	81.17	+2.94
F	84.67	84.67	0
G	81.28	82.94	+1.67

Table 5: Per room accuracy comparison in the house.

2.3 Discussion and comparison

In this thesis we propose a fall detection system (F2D) which works on a smartwatch, therefore completely independent from a base station. Using such a device is less stigmatizing for the user. In addition, it can be offered for less than half of the cost of existing systems on the market. Our system meets the requirements of reliability, ease of installation and restriction of false positives [41] which are essential for a properly built fall detection system.

F2D works on a smartwatch and therefore fixed on the wrist of the person. We have avoided the disadvantages of He and Li at [42] where the solution of the waist-mounted smartphone they provide is not feasible for two reasons: 1) Normally people do not wear their phones on the waist but in their pockets. 2) The system will be working only when the smartphone is mounted on the waist and not at other times [42]. Other problems such as the usage of intrusive devices exist in [43] and [44], where the accelerometer and Bluetooth unit are bounded as a wearable unit and placed on the subject’s waist or chest.

We decided to use a threshold based algorithm and not a machine learning approach like [37] as it is less complex and therefore requires the lowest computational power [45]. In the typical scenario, the user will use the application on his smartwatch normally during the day without the requirement of charging it much more than usually. Since the fall detection system will run continuously, we should optimize the battery consumption of the device. Therefore, only the tri-axial accelerometer signal is used since it is the most informative sensor regarding the fall detection.

Unlike computer vision techniques, the privacy issues can be eliminated by the usage of ambient sensors. It is inexpensive and simple. In addition these types of sensors are more sensitive to noise. Thus, it is not suitable for living environments. Monitoring more number of people is also possible with this approach, but it requires an immense amount of domain research. It is well suited for indoor applications [38]. But a robust fall detection system should work indoors and outdoors as well. The fall detection system which is presented in this thesis, called F2D, works on an independent smartwatch and therefore it protects the users indoors and outdoors. The user is able to use normally his smartwatch and at the same time a possible fall event will be detected from F2D.

Even though fall detection has received significant attention in recent years, it still represents a challenging task for two reasons. First, there are several everyday fall-like activities that are hard to distinguish from strong falls. Most of the current approaches define a fall as having greater acceleration than normal daily activities. However, focusing only on a fast acceleration can result in many false alarms during fall-like activities, such as sitting down quickly or lying down on a bed quickly. The second reason is that not all falls are characterized by a fast acceleration of the wrist.

The detection of soft falls should be an intrinsic part of creating a successful fall-detection system. There are several approaches that can be used for fall-detection such as using the camera like the research done by Koray Ozcan [40]. In Ozcan's study the camera is attached to the body. So, if there is a change in the orientation of the camera it can be concluded that the person fell. His research obtained quite good results, that is 86.66% accuracy. Nevertheless, some improvements must be considered since there are still a lot of false positives.

Comparing F2D with iFall [34] the main advantage of our solution is that our fall detection algorithm works on a smartwatch that each end-user wears on his wrist. Therefore we have a consistent fall pattern. On the other side in [34] it is difficult to convince users to mount the phone to various body parts in order to improve fall detection rate. Instead, the software must dynamically adjust to different methods of carrying the phone (e.g., in the purse, pants or shirt pocket, or on a belt or neck clip). This requires the software to classify acceleration parameters of general use to identify the correct parameters for the fall detection logic. Moreover the authors of iFall do not provide any real data and the corresponding sensitivity and specificity of their algorithm so that we can compare it with our results.

Comparing F2D with PerFallD [35] the main advantage of our solution is like comparing with iFall that the fall detection algorithm is running on a smartwatch. The device is attached on the wrist of the person and therefore we have a consistent fall pattern. Moreover if we compare their best case scenario where the smart-phone of the user is attached on the waist they receive a percentage of 8.7% false negatives when we receive a percentage of 1.45%. Also although our false negative is higher (6.52%) than in PerfallD (2.67%) the balance between false positives and false negatives is better for F2D comparing with PerFallD. Also we should take into account that we compare their best case scenario and not the scenario where the phone is on the wrist of the user like in our case where the user wears his smartwatch. Moreover we have tested our system with elderly people whereas they have tested their system with young adults.

Comparing F2D with the machine-learning based approach of Cheng and Jhan at [86] using a self-constructing cascade Adaboost-SVM classifier we can make the following conclusions. Firstly F2D works on a smartwatch being as less invasive as possible for the end-users, whereas their solution forces the users to wear triaxial accelerometers around their ankles and around their chest and waist. Moreover as we have already mentioned a machine-learning based fall detection solution will destroy the battery of the smart device of the user forcing him to charge it during the day.

Comparing F2D with [84] we observe that F2D is a completely autonomous fall detection system whereas the Neyman-Pearson based system needs a base central for further analysis of the possible fall events. Moreover in [84] the testers were young adults from their lab whereas in our case the falls have been simulated from experts and the ADL data come from elderly people.

Finally comparing F2D with the fall detection system of Hou and Li [43] we make the following observations. F2D works on a smartwatch and therefore fixed on the wrist of the person instead of the waist-mounted smartphone solution they provide. Their solution is not feasible for two reasons: 1) Normally people do not wear their phones on the waist but in their pockets. 2) The system will be working only when the smartphone is mounted on the waist and not at other times. Moreover F2D achieves a higher accuracy of 96.01% comparing with their accuracy of 92%.

2.4 Personal contribution

In the first publication [70] related to the fall detection system is highlighted the innovative fall detection algorithm. The latter takes into account the residual movement of the user to increase the fall detection accuracy and summarizes the architecture and the implementation of the fall detection system working on a smartwatch. The user can operate his smartwatch as usual. F2D does not cause any interference with the normal usage of installed applications. The algorithm is threshold based like [29], relying on the captured data of the accelerometer of the smartwatch. We decided to use a threshold based algorithm and not a machine learning approach like [37] as it is less complex and therefore requires the lowest computational power [71]. In the typical scenario, the user will use the application on his smartwatch normally during the day without the requirement of charging it much more than usually. Since the fall detection system will run continuously, we should optimize the battery consumption of the device. Therefore, only the tri-axial accelerometer signal is used since it is the most informative sensor regarding the fall detection. Based on the reliability of the fall detection and the restriction of false positives, which are guaranteed by the fall detection algorithm, we have built a system which meets the requirements for deployment and use.

The second F2D publication [72] builds on top of the first one and takes into account the after falling activity and the location of the user as well. Based on the residual movement of the user after the fall we categorize the falls in three types. B1: No movement at all, B2: Small amount of movement after the fall event, B3: Back to normal activity after the fall event. It is clear that, if after a fall the user does not move at all, then the caretakers should immediately be informed and therefore the alarm will be triggered directly. On the other hand, if the user is able to fully recover after a soft fall event, then he is able to cancel the alarm and therefore not disturb the caretakers for no reason. F2D will be released on the market and it requires the least possible false alarms. This combination of the after fall activity and the location of the user after falling, it eliminates the false positives and gives a better accuracy to the algorithm.

Moreover, by testing with partially real data provided by our industrial partner FST, we present a fall detection system ready to be deployed on the market. To the best of our knowledge this is the first fall detection system which has been tested with real data of elderly people. This is a big innovation because the majority of the fall detection systems have been tested with simulated falls and ADL activities of young adults.

In our third publication related to the fall detection [73] the iBeacon technology is used in order to be able to know the precise location where the fall has occurred and therefore decreasing the reaction time of the caretakers. By being able to locate the user after falling with room-level accuracy makes our fall detection system very useful for nursing homes. The carers will know in which room the elderly has fallen and therefore they will be able to immediately provide the help that this person needs. Since minimal cost and setup process for the end user were the requirements of the localization system, we used the minimum amount of Bluetooth beacons, that is one Bluetooth beacon per room, and we opted to develop a more sophisticated algorithm for room detection.

The papers that compose this thesis are product of deep research in the field of fall detection. The author of this thesis was the first author in these papers. The innovative ideas and the algorithms that are presented in these papers have been developed from the author of the thesis. He has created all the models and has run all the experiments that had been described in the publications. Moreover he was the one that designed and tested all the innovative algorithms for the fall detection. He created the fall detection system and added all the components described above that enhanced the accuracy of the system. The co-authors of the papers were participating mostly in the coding support and in the quality of the English of the papers.

3. Stress detection

Thanks to the knowledge that we acquired by extracting useful information from the sensors of smart devices and more specifically by detecting falls from a smartwatch, we enhanced our know-how analyzing and extracting patterns from raw sensor data. The next implementation of our expertise and second main element of this thesis is the detection of stress patterns by analyzing smartphone data.

Stress is a mental condition that everybody experiences in his life, sometimes even daily. In today's society working environments are becoming more stressful and people working in these environments become prone to various illnesses. Stress symptoms may be affecting people's health, even though they might not realize it [48]. People may think illness is to blame for that nagging headache, their frequent insomnia or their decreased productivity at work. But stress may actually be the culprit. Due to all these negative effects, it can be assumed that early assessment of stress condition, and early suggestions on how to reduce it, may reduce its overall impact and lead to improved health state of individuals [49].

Stress, depression and anxiety are included into work-related health problem. In Europe, in 2007 those health problems where in the third rank after back pain problems and other muscular problems with a percentage of 14%. Data was collected in different European countries with survey addressed directly to worker aged from 15 to 64 years old [40].

The problem of stress detection has been tackled with different approaches. However, former works can be divided into two different groups, depending on the use of physiological signals or other behavioral characteristics.

3.1 State of the art

The autonomic nervous system (ANS) regulates the body's major physiological activities, including the heart's electrical activity, gland secretion, blood pressure, and respiration. The ANS has two branches: the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS). The SNS mobilizes the body's resources for action under stressful conditions. In contrast to the SNS, the PNS relaxes the body and stabilizes the body into steady state [82].

Cortisol, or as frequently called "the stress hormone", is released in response to fear or stress by the adrenal glands. This is the reason why, the obvious way to measure stress is by measuring the cortisol levels in the body. There have been many studies measuring the cortisol levels and some of them do so either in the saliva [46] or in the interstitial fluid [47]. The problem with those methods though, is that they are often invasive for the user and the used sensors are not most of the times commercially available in order for such a product to be useful to the general public. Other methods and studies for measuring emotions and stress are using electroencephalogram (EEG) bands [48], the respiration rate [49] or computer vision [50, 51].

Many technologies have been developed to measure or detect the stress level. Methods based on biological signals include blood pressure [52], heart rate [52], heart rate variability [53], skin conductance [54], cortisol [54] and pupil diameter [56].

In the work of Guo and others [86] is presented a pervasive and unobtrusive system for sensing human emotions which are inferred based on the analysis of the Galvanic Skin Response (GSR). They explore the characteristics of temporal variations of humans GSR signal that indicates different types of human emotions. They take into account that different people exhibit heterogeneous characteristics in their emotion patterns. Therefore they perform emotion classification for each experiment subject individually.

The basic idea of emotion sensing is to explore the characteristics of temporal variations of humans GSR signal. Figure 25 shows some examples of the GSR signals from various emotions.

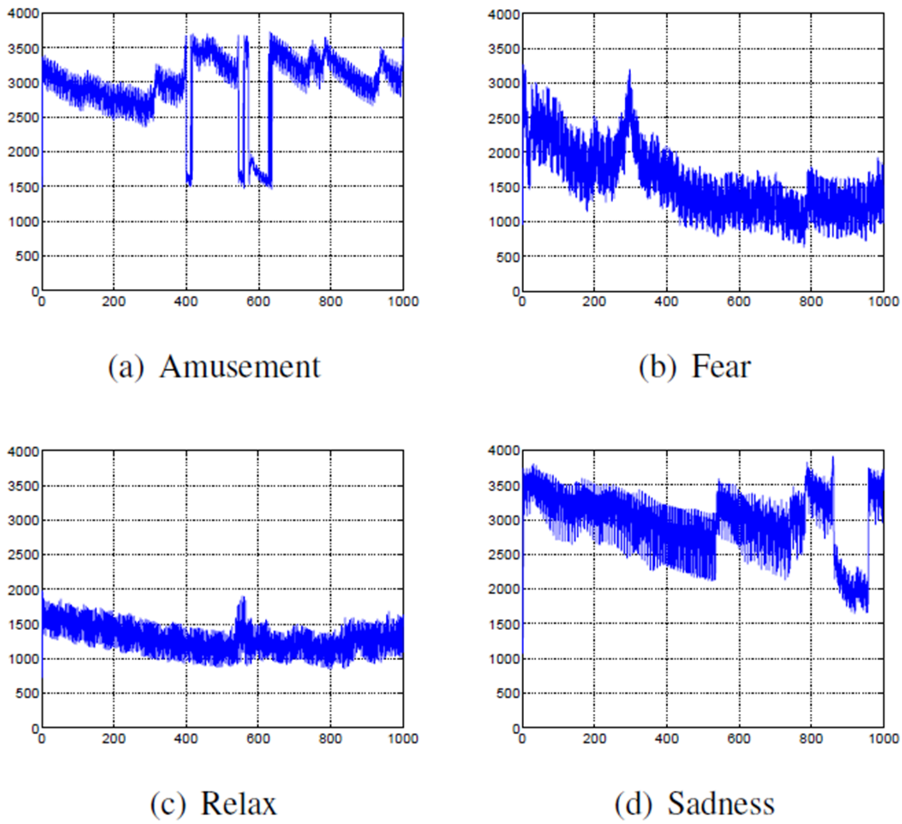


Figure 25: Raw GSR signals for human emotions.

The system architecture is the following. Firstly the authors propose a quadrant model to represent the four basic categories of emotions. These are amusement, fear, relax and sadness. Then they choose video clips of different themes from social media websites in order to arouse the human emotions. They have chosen 17 video clips for each category of emotions which include prank videos, thrilling trailers of movies, soft music and movies with bad ending. The ground truth comes from the labels of these movies. The next step is the removal of the noise from the GSR signals that have been collected in order to ensure high accuracy of emotion classification. Finally they rescale and resample the data into the same length so that they can perform comparison on top of them. Different methods of classification accuracy are tested and the overall classification accuracy is the average value of all the experimental subjects. The extracted features from the affective GSR signal sequence were verified to be effective in emotion classification within the subject-dependent context. The future work of the authors focuses on developing the subject-dependent mobile applications to monitor the personal emotion changes at real-time with an online learning strategy.

Moreover the analysis of the fluctuations in heartbeat intervals, which is known as heart rate variability (HRV) analysis, is a frequently studied physiological rhythm. Kumar and others at [87] have performed a stochastic fuzzy analysis method of heartbeat intervals in order to quantify the stress level of people. Their method has been implemented in a mobile telemedical application. They have included in their experiments 50 users whose stress scores were assessed at different times of the day. They evaluate their system by comparing predicted stress score values with the subjective rating scores coming from the users.

The main problem that the researchers of this study have addressed is how is it possible a given 5-minutes long series of heartbeat intervals to be evaluated for the estimation of stress of an individual on a numerical scale from 0 to 100. The analysis method should meet the following requirements:

1) handling the uncertainties in modeling complex relationships between observed heart rate signal and respective stress level

2) the analysis method should be robust against noise and missing physiological data

3) it should be suitable for a real-time operation in the stress telemonitoring system.

The authors consider a stochastic fuzzy modeling-based approach in order to solve the above mentioned problem. In general the stochastic fuzzy systems have been introduced to integrate randomness and fuzziness for the approximation of stochastic processes [94]. Their stress prediction model has been implemented on an e-health system called the eHealth–MV system developed jointly with Infokom GmbH, Germany. This eHealth-MV system provides mobile telemedical applications related to stress and fitness monitoring. The system that acquires the data is based on a mobile phone and a sensor electronic module with a special chest belt for acquiring as many as possible physiological parameters.

The experiments perform a 24-h monitoring of 50 subjects in e-health setting. The testers were asked at different times during the day to input on their phone their subjective stress score based on how they were feeling the last 5 minutes. The stochastic fuzzy analysis-based approach is general to evaluate any biomedical signal for functional state assessment.

In [91] Choi and Ahmed present a wearable sensor platform to monitor a number of physiological correlates of mental stress. They discuss tradeoffs in both system design and sensor selection to balance information content and wearability. They propose a new spectral feature that estimates the balance of the autonomic nervous system by combining information from the power spectral density of respiration and heart rate variability. For the assessment of the effectiveness of their solution they collected experimental data from two experimental conditions: mental stress and relaxation. The mental stress condition consisted of a number of tests. These were dual tracking, memory search, mirror tracing, Stroop color word test and public speech. On the other side the relaxation condition consisted of deep breathing exercise.

The authors of this study have developed a minimally invasive wearable sensor platform which allows monitoring a number of physiological indicators of stress. The system as seen in Figure 26 weights 277 grams and allows uninterrupted operation in excess of 13 hours. It can combine information from multiple physiological signals into a single index of stress. The logistic regression results prove that this HRV index has the highest predictive power.

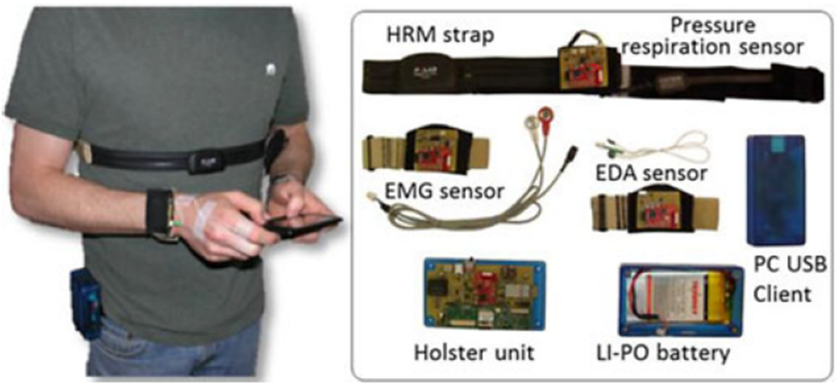


Figure 26: A tester wearing the full sensor suite.

Finally, Yoon and others at [88] present a human stress monitoring patch with small skin contact area and high flexibility to enhance wearing comfort of the patch. The stress monitoring patch consists of three layers: a skin contact layer, an insulation layer and a pulse wave sensing layer as depicted in Figure 27. The stress monitoring performance of the three individual sensors integrated in the patch are experimentally characterized in the human physiological ranges. The dimensions and the performance of the patch are designed to detect human physiological signals, including skin temperature, skin conductance and pulse wave. The authors have taken into account for the design of the patch that people feel the wearable devices are comfortable when they wear the less number of devices, small and light devices, and highly flexible devices. The described patch satisfies all these conditions since the three sensors are integrated in a single multi-layer structure the number of devices and the skin contact area of the patch.

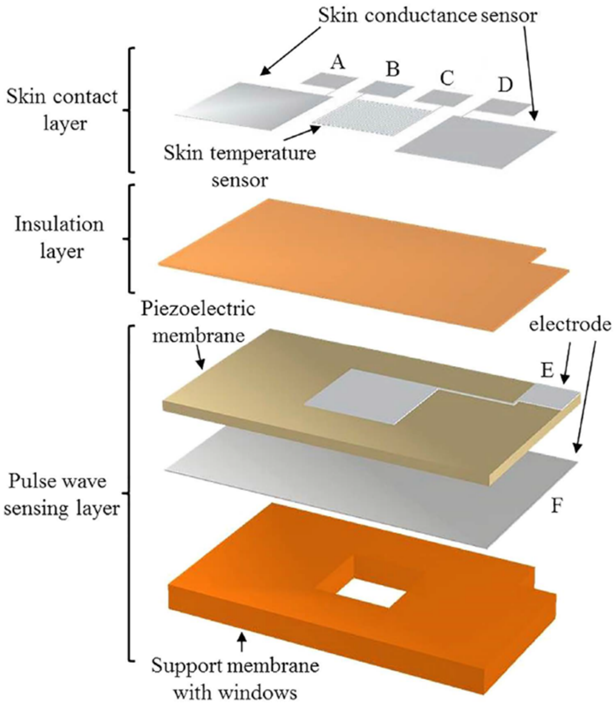


Figure 27: Three layers of flexible human stress monitoring patch.

Behavioral characteristics

On the other side, smartphones have become ubiquitous and are transforming every aspect of daily life, including the way people track their health. Currently there are many health applications available, running on mobile platforms, including some developed by major companies in the smartphone industry. Those applications either act as a diary, allowing users to manually enter data regarding the various aspects of their well-being, or actively record data from the smartphone itself and from electronic accessories and wearables.

Several researches have already been conducted to detect stress using biological signals. The vast majority of them have been conducted though in laboratory settings. This is the limitation that in our solution we overcome.

In the work of LiKamwa and others [79], their vision is a smartphone service, called MoodSense, which can infer its owner's mood based on information already available in today's smartphones. The service will fundamentally enhance context-awareness by providing clues about mobile users' mental states. They report early results from studying 25 iPhone users in the field and the correlation between their mood and phone usage. They show that user mood can be inferred into four major types with an average accuracy of 91%. This is achieved using only three weeks of training data and simple smartphone usage statistics. The results, though preliminary, strongly suggest the feasibility of mood inference without using the power hungry and socially invasive microphone and camera.

The authors conclude that smartphone usage indicates user mood. The users prefer different applications and communicate with different people depending on their mood. There are used six pieces of usage information (SMS, email, phone call, application usage, web browsing and location). They highlight that how the usage of the smartphone indicates the mood of the user is very personal and therefore the accuracy of mood classification is improved to 91% from 61% when it is based on the data of the same user. The classifier must be trained with the same user's data.

Before the field study the authors conducted a two-part focus group study with the participants in order to observe their intuition of automatic mood inference. The first part was to ask the users to report the way their smartphone usage changes depending on their mood. The second part was to ask the participants how they would share their mood. More specifically the users were invited to answer on how they would publish their mood, with whom they would share their mood, when they would like others to see their mood, whose moods they would be interested to see, how they would like their phone to automatically adapt to their mood and how sharing their mood would affect their life. All of the participants indicated that they would like to share their mood within certain social circles like their friends but they would not want people to see their current mood when they were in extremely bad moods and they did not want to talk about it. Moreover all of the participants were interested in seeing others' mood and especially the mood of their friends.

The next step is the field study where real-world data are collected for the study of the correlation between mood and smartphone interactions. The users are asked to input their mood at least four times a day into the mood input application running on their smartphones. At the same time the authors use the LiveLab iPhone Logger [95] to gather relevant information in order to form the mood models. Web browsing, application usage, phone calls, emails, messages, calendar entries and location changes are collected as user behavior features.

Types of stress

Nowadays we can categorize stress into three main types [80]:

1) Acute: stress caused by an acute short-term stress factor.

2) Episodic acute: acute stress that occurs more frequently and/or periodically.

3) Chronic: stress caused by long-term stress factors and can be very harmful in the long run.

Today we have many wearable devices, such as mobile phones and wearable sensors to measure physiological or behavioral data in our daily lives. In the work of Muaremi and others [11], the authors present a solution for assessing the stress experience of people, using features derived from smartphones and wearable chest belts. In particular, they use information from audio, physical activity, and communication data collected during workday and heart rate variability data collected at night during sleep to build multinomial logistic regression models.

In general, they follow the approach of estimating changes of subjective self-perception of stress using smartphone sensor measures and information derived for the HRV signal during night. From 8 a.m. to 8 p.m., the day is divided into four sections, and randomly within each section, a notification is shown which asks the user to fill in a self-assessment questionnaire as depicted in Figure 28. In parallel to that, smartphone data are being collected during the day in the background. Before going to sleep, the user answers an additional stress question and puts on the Wahoo chest belt (http://www.wahoofitness.com) which collects HRV data during night until the next morning. After getting up, a new cycle of data collection begins. The idea now is to use these smartphone and wearable device data to estimate the self-assessment stress score.

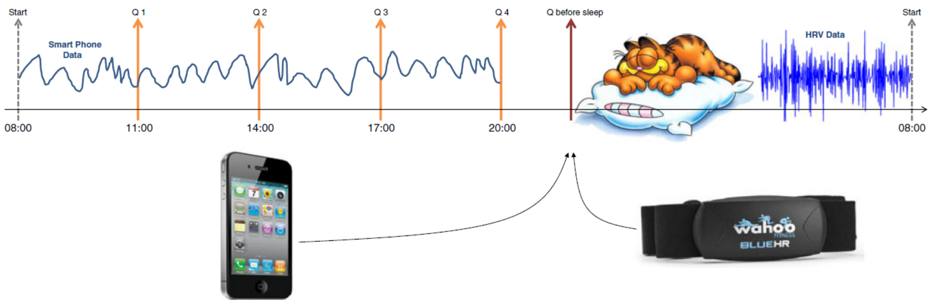


Figure 28: Cycle of data collection.

The authors conducted their evaluation experiment with 35 users working in three IT companies participated for 4 months. The ages of the participants were equally distributed from 25 to 62 years old. Regarding the selection of the features the procedure that they followed was to reduce their number using cross-correlation analysis and then to feed the remaining features into a sequential feature selection method to find the best subset in terms of classification accuracy. Finally they defined two different stress scores, the daily stress score estimating the acute stress level of the previous day and the long-term stress score which is the accumulated stress over the last days and estimates the chronic stress level of a person. Based on the cross-correlation analysis that they implemented they have estimated the best feature subset for each individual user. They highlight that the HRV features are in general more important than the smartphone features.

Another relevant study is the one of Sano and Picard [61] aims to use technology to recognize stress levels using data from the devices that users always carry and wear.

In Sano and Picard's study [61], the authors collected 5-day physiological and behavioral data including skin conductance which is considered as a stress measure as well as mobile phone usage data and subjective measures about general health, mood and stress from 18 subjects. They then investigated whether these data would allow them to recognize whether participants felt stressed or not. Note that this study is limited to stress that participants are able to perceive and report.

In the experiment participated 18 people who at first they had to fill out three pre-surveys and they were given the instructions on how to use the application. The main features coming from the wearable sensors are the following: three axis accelerometer data (ACC) and skin conductance (SC) a measure of sympathetic nervous activity. Then the main features coming from the mobile phone were:

calls, SMSs, location and screen on/off. Moreover surveys were filled out every morning and evening. The details of the questions are depicted in Figure 29.

Morning Survey	Evening Survey
Sleep time	Start and end time of nap
Wake time	# of cups of caffeinated beverages (6oz cups of coffee, soda, or others)
Last use your computer, tablet, mobile phone or TV	The time of the last cup
Sleep quality	# of alcoholic drinks (6oz cups)
General health when you woke up	The time of the last drink
Mood when you woke up	General health of the day
Alertness when you woke up	Mood of the day
Tiredness when you woke up	Alertness of the day
General stress level	Tiredness of the day
Things which affected sleep time last night	General Stress Level of the day

Figure 29: Mobile phone questions.

Their results show over 75% accuracy of low and high perceived stress recognition using the combination of mobile phone usage and sensor data. Although these are preliminary with limited number of participants and data, it promises that mobile phone usage and wearable sensor data include some features related to the stress level of the users.

In the work of Bakker and others [80] is considered a simplified setting assuming that a person is either in the normal state or in a stressed state. The change between the two states can be sudden or incremental, typically, arousal is more rapid and relaxation takes considerably longer. They have conducted a pilot case study aimed at the identification of likely challenges they need to address to make their approach work in practice. They focus only on the problem of detecting changes in the stress level from the GSR sensor data alone. They study the peculiarities of noise and disturbances in the signal and argue the need of the related contextual data for improving the quality of stress detection.

The principal task is to detect whether a person is stressed at a specific moment in time or not. The detector assigns a label ‘’stressed’’ or ‘’not stressed’’ based on the observed historic data. The four states that depict the inner process of stress are depicted in Figure 30.

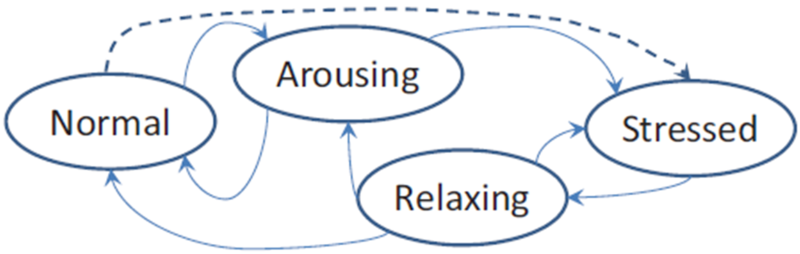


Figure 30: Four states depicting the inner process of stress.

The authors highlight that the changes in GSR data is not as straightforward as someone might think looking at the Figure 31. Different types of noise in the data and changes in GSR data due to other factors than stressors make it a non-trivial task.

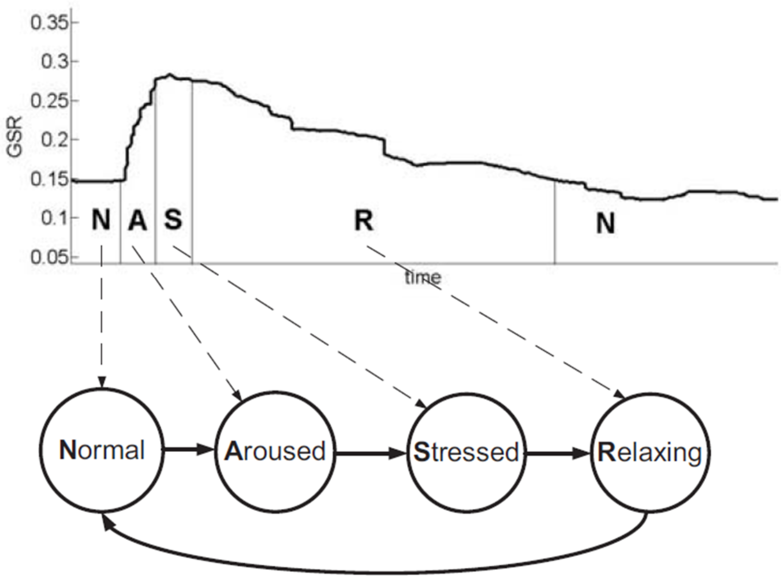


Figure 31: Acute stress pattern observed from GSR data.

The quality of the GSR signal depends primarily on the continuity of the contact between the device and the skin of the user. The skin conductance is measured by two electrodes that require skin contact in order to produce a reliable signal. However this contact is not the same for everyone.

Finally we should mention that there are some commercial solutions that aim to detect stress by using the above mentioned methods based on physiological signals [89, 90]. For example Emvio [89] is a new released bracelet that aims to measure the stress levels of the end-users. Emvio measures stress mainly through assessing the sympathetic component of the autonomic nervous system (ANS). It uses a heart rate variability index to calculate the stress level of the user in a fixed scale from 0 to 10. There are several commercial solutions that aim to detect stress but in reality they simply monitor physiological signals in real-time and they purely based on changes of the autonomic nervous system like in the above mentioned methods based on biological signals.

3.2 Theoretical model and implementation

During the design and test of the fall detection system described above, we acquired deep knowledge in processing raw sensor data from smart devices. Thanks to this knowledge we have created a mathematical model for detecting stress patterns based on the raw data of the sensors of the smart phones of the users.

We envision a new class of personal wellbeing applications for smartphones capable of monitoring multiple dimensions of human behavior, encompassing physical, mental and social dimensions of wellbeing. An important enabler of this vision is the recent advances in smartphones, which are equipped with powerful embedded sensors, such as an accelerometer, digital compass, gyroscope, Global Positioning System (GPS), microphone, and camera.

Smartphones present a programmable platform for monitoring wellbeing as people go about their lives. It is now possible to infer a range of behaviors on the phone in real-time, allowing users to receive feedback in response to everyday lifestyle choices that enables them to better manage their health. In addition, the popularity of smartphone application stores (e.g., the Apple App Store, Android Market) has opened an effective software delivery channel whereby a wellbeing application can be installed in seconds, further lowering the barrier to user adoption. We believe production-quality wellbeing applications will gain rapid adoption globally, driven by: i) near zero user effort, due to automated sensor based activity inference and ii) universal access, only requiring a single download from a mobile phone application store and installation on an off-the-shelf smartphone.

In this thesis we present a stress detection system which takes into account three main dimensions of wellbeing. The sleeping pattern, the physical activity of the users and their social interaction are accumulated with different weight factors and give an estimation of the daily stress level of the user. To the best of our knowledge, this is the first system that computes a stress score based on different dimensions of human wellbeing. The main innovation of this work is addressed in the fact that the way the stress level is computed is as less invasive as possible. Our solution relies only on the daily phone usage of people. Also we acquire the ground truth for the importance of each dimension of wellbeing for each individual by asking the users. This leads us to a personalized model which focuses on the personality of each individual user.

System design: The StayActive system provides an Android application running on a smart phone. We have chosen the Android based solution because it is an open source framework designed for mobile devices. The Android Software Development Kit (SDK) provides the Application Programming Interface (API) libraries and developer tools necessary to build, test and debug applications for Android. We implemented the prototype in Java using the Android SDK API 23. The idea of the full StayActive system is the following. There is a mathematical model which computes the stress level of the users. The mathematical model is running on the phone of the user being a light application with minimized battery consumption. The reason is that we want to make the users able to use the application for the biggest possible amount of time without needing to recharge their phone. The general architecture of our stress detection system is given in Figure 32.

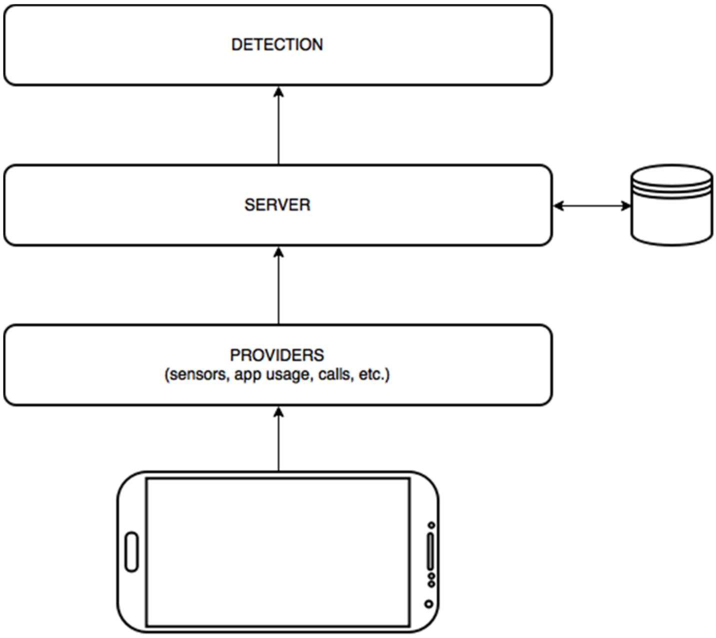


Figure 32: StayActive system architecture overview.

Providers: The first layer is the one that collects and provides the data to upper layers. The provider module contains all the implemented data providers, which are responsible for collecting a specific type of data from the device. They are free to implement the data monitoring behavior as they wish. The currently implemented providers collect the following type of data: type of physical activity, calls and SMS, ambient light and temperature, location, battery level, screen on/off intervals, Wi-Fi, step counter, number of screen touches and finally type of applications launched. We give some examples of the results of these providers in Figures 33 - 36.

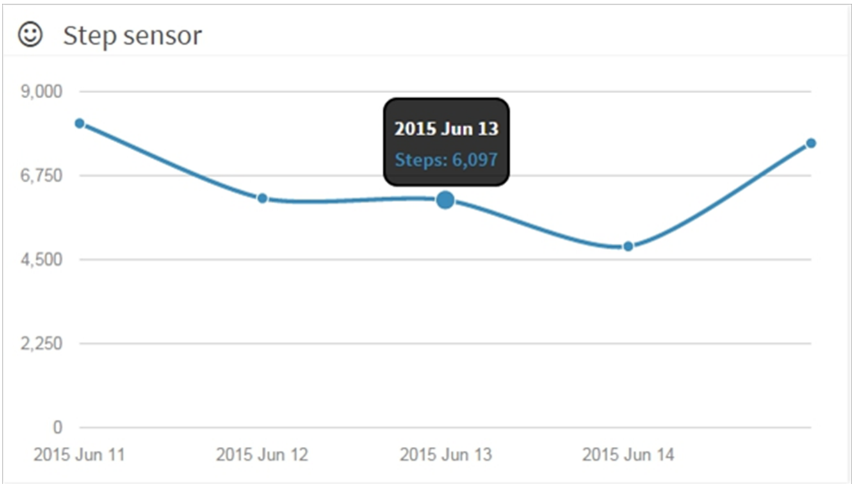


Figure 33: Visualization of data from the step counter provider.

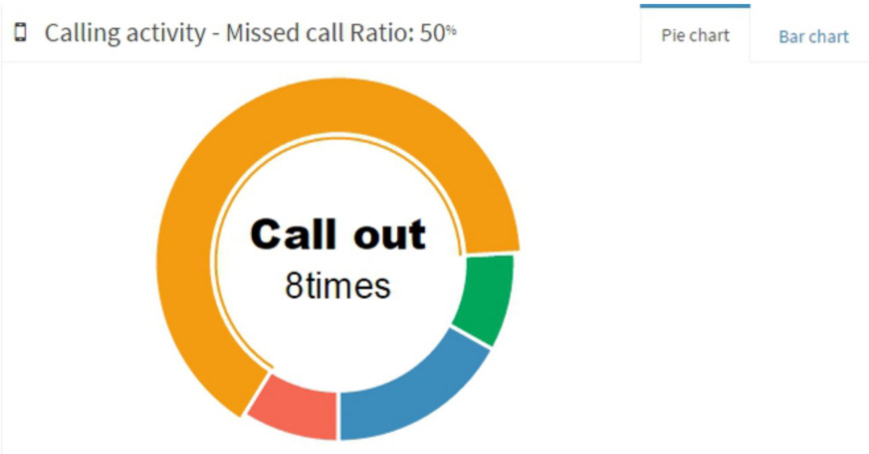


Figure 34: Visualization of data from the call provider.

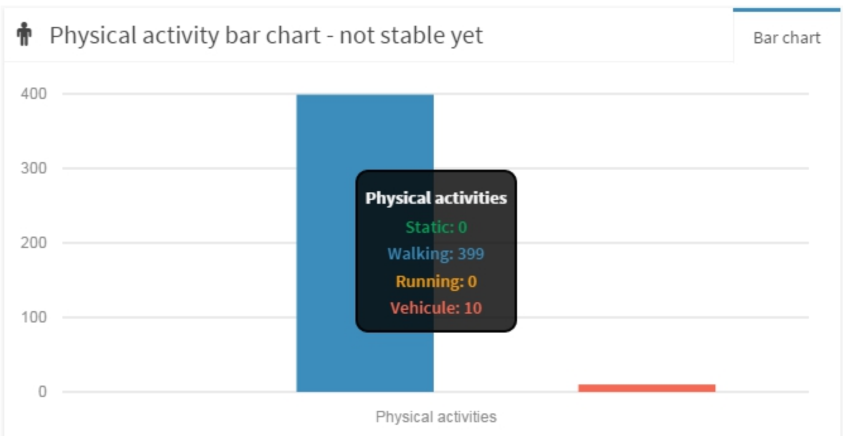


Figure 35: Visualization of data from the physical activity provider.

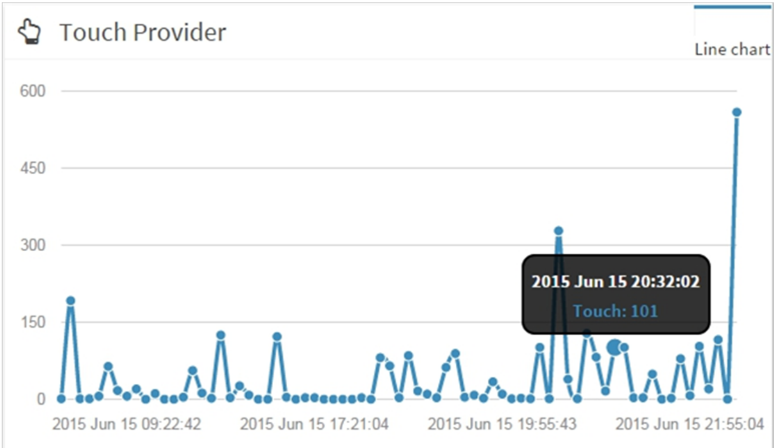


Figure 36: Visualization of data from the touch provider.

Server: The server module is responsible for receiving data from the mobile devices and storing it in a database. We aggregate all the data and we process it in order to extract a relaxation score for each user.

Detection: This module contains analyzers for each data provider, which extract useful information and patterns from the raw data to output a partial relaxation score. The relaxation score is the opposite of the stress score. We decided to use the relaxation score because it is more comfortable for the end-users. The relationship of the stress and the relaxation scores has been validated from our project partners at Ana Aslan Foundation (AAIF). The core detector module will aggregate the results of these individual analyzers and compute a final stress level, as explained in the next section.

Sleeping pattern: There is a large body of research work which analyzes the link between sleep hygiene and the mood of people [63, 64]. People usually exchange sleep for additional working hours as a coping mechanism for busy lifestyles. In our stress detection module we take into account the user's duration of sleep. We set the number of normal sleeping hours at 8 and penalize insufficient sleep and oversleeping. Between 6 p.m. and 10 a.m. we compute the biggest time interval that the user did not touch his screen and we infer the duration of his sleep. The function that computes the score for the sleeping pattern (as depicted in Figure 37) takes into account the daily sleeping hours to the perfect score of 8 hours (golden value), the mean of the sleeping history of the user to the golden value average and a consistency metric that takes into account the standard deviation of the sleeping hours values. Taking the standard deviation into account we compute a more accurate stress score that takes the past into account. For example the stress result for a person that slept the last month consistently 8 hours will be different and better than the one for a person that slept on average the last month 8 hours but was sleeping some days 10 hours and some days 6 hours. Also if a user sleeps a day more than 8 hours we will penalize his behavior in the sleep score.

$$sleep = \frac{(1-\sqrt{f(day)}) + (1-\sqrt{f(average)})}{2}(1-D_m)10$$

where,

$$f(x) = \begin{cases} \frac{8-x}{8} & x \leq 8 \\ \frac{x-8}{8} & 8 < x \leq 16 \\ 1 & x > 16 \end{cases}$$

$$D_m = \frac{\sum_{i=1}^{N} |x_i - average|}{Naverage}$$

Figure 37: Function for computation of sleeping hours.

We should clarify that we could have asked directly the user of the smartphone how many hours per day he was sleeping or to use existing apps that can calculate the amount of sleep of the people. However, we decided not to follow this approach because it was crucial for our stress detection system to be as less invasive as possible for the end-user. In order to validate our findings we compared the results of our sleeping algorithm with existing apps and with the feedback of the users we were able to validate the accuracy of our sleeping pattern prediction.

Social interaction: The daily social interaction of people has a serious impact on many dimensions of wellbeing [64]. People who maintain dense social connections are more likely to have resilient mental health. They tend to be able to cope with stress and often are better able to manage chronic illness. On the other hand regarding communication, researchers are hypothesizing that perhaps people become so used to and even dependent on receiving constant messages, emails, and tweets, that the moment they do not receive one, their anxiety increases. People feel compelled to check their phone constantly, which can then lead to disappointment when there are no new messages, and increased stress about why no one is messaging them, or when the next message might come.

However, repetitive checking of mobile phones is considered a compulsive behavior [65]. People who are highly dependent on the Internet for interaction act impulsively, avoid emotions, and fail to keep up a proper planning or time management [66]. We identify features which are relevant for detecting problematic phone usage and therefore increase the stress level of the user.

In our system we take into account the number of touches of the screen (quantifying the usage of applications on the phone), the number of calls and the number of SMSs as factors for the social interaction of the users using their smartphones, as seen in Figure 38. The accumulated result per day is multiplied with the corresponding weight factor and therefore it is accumulated in the total relaxation score.

Figure 38: Social interaction.

The accumulated result of the social interaction dimension is computed using weights. These weights of the subdimensions of the social pattern are computed by asking the users in the beginning of the experiment to prioritize the ways of social interaction. The idea of the scoring procedure is the following. We assign a weight factor to each of the three subdimensions of social interaction. This factor is based on the response of the participants to the following question which was asked in the beginning of the experiment. Which of the three subdimensions do they personally consider as the most important for their communication with other people? To the most important dimension we assign a weight of $w_1 = 0.4$ and to the rest we assign a weight of 0.3 respectively ($w_2 = w_3 = 0.3$), so that $w_1 + w_2 + w_3 = 1$.

Physical activity: Physical activity plays a key role in the control of neuroendocrine, autonomic, and behavioral responses to physical and phychosocial stress. Physical activity is commonly regarded as beneficial to both physical and psychological health, and is seen as an effective preventive measure and treatment for stress-related diseases. Physically active people show reduced reactivity to physical stressors as well as reduced susceptibility to the adverse influences of life stress [67]. Several studies have linked exercise to improved depression, self-esteem and stress [68], [69]. Our system monitors the physical activity of the user, making the distinction between the type of activity (e.g. walking, running, bicycling). We have also implemented a step counter which gives us the opportunity to find the number of steps that each user took per day. The American Heart Association uses the 10,000 steps metric as a guideline to follow for improving health and decreasing risk of heart disease, the leading cause of death in America. 10,000 steps a day is a rough equivalent to the Surgeon Generals recommendation to accumulate 30 minutes of activity most days of the week.

At first, in our model we assign the maximum value of wellbeing, and therefore the lowest stress level, when reaching the goal of 10,000 steps per day. If someone reaches less than this number we penalize (decrease relaxation score) with a weight factor per 1,000 steps. After the reception of the data for one month and based on the answers of the users to the Circumplex Model of Affect, we extract the pattern between the ideal physical activity of each individual user and his daily steps. Therefore extracting the personal pattern of the user we assign this value to the maximum value of wellbeing for this user. Then the comparison and the behavior of the user is compared with this personalized new value. The full analysis of the stress detection algorithm is given in the stress detection paper in Appendices.

Evaluation: The evaluation of our model has been divided in two phases. During the first phase we monitored the behavior of the users in the above mentioned three dimensions of well-being (sleeping pattern, social interaction, physical activity) collecting data for a month. The participants of this first phase were five young adults coming from our lab. We decided that at least in the beginning the end-users will be the members of our team. This made our plan more flexible to immediate feedback and changes to the StayActive application. The plan was to have four weeks of recordings where the end-users will use the StayActive application and they will give their input on how relaxed/stressed they feel with the questionnaire described above.

We computed a relaxation score for each individual user for every day of the monitoring month. In order to evaluate the accuracy of this relaxation score value we were asking the users two self-measure their relaxation level as depicted in Figure 39. Based on the feedback that we were taking from the users we were able to see how accurately we measure their relaxation level and accordingly adjust the weight factors of the sub dimensions.

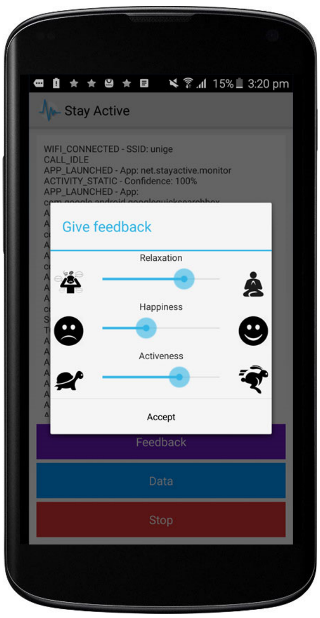


Figure 39: Self-assessment of relaxation level.

Besides gathering as many data as possible from the smartphone, the user had to fill a questionnaire with his subjective self-perception of his mood. First we researched several validated models that phycologists have proposed to measure and describe affect and emotion, including the “Positive and Negative Affect Schedule (PANAS)” one. We concluded to use the “Circumplex Model of Affect” as described by James A. Russell [78]. This model consists of 2 dimensions, the pleasure-displeasure and the arousal-sleep dimension. We chose to use this model because it can represent a wider range of mood states. In addition to that we have added another dimension, that is the relaxation-stress one, which may be finally used either on its own, or as a third dimension along with the other two and the one that is used for the evaluation of our predictions.

The plan was the following. For the first three weeks we were training the system with data that we were collecting from the 5 end-users. Taking into account their feedback regarding their relaxation level each day and the relaxation score that we were computing through StayActive. For the last week of the experiment we evaluated our stress detection system.

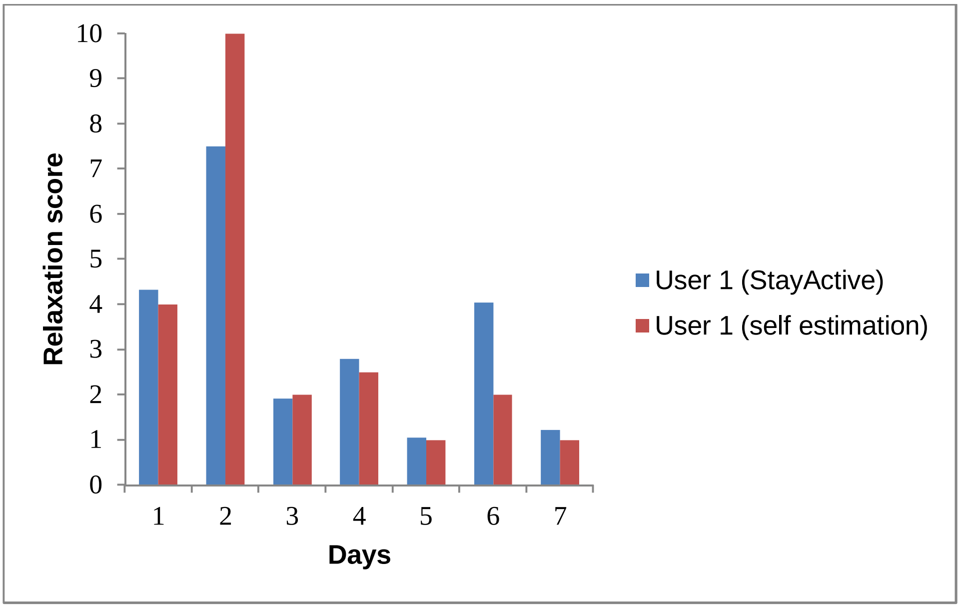


Figure 40: Relaxation score validation for user 1.

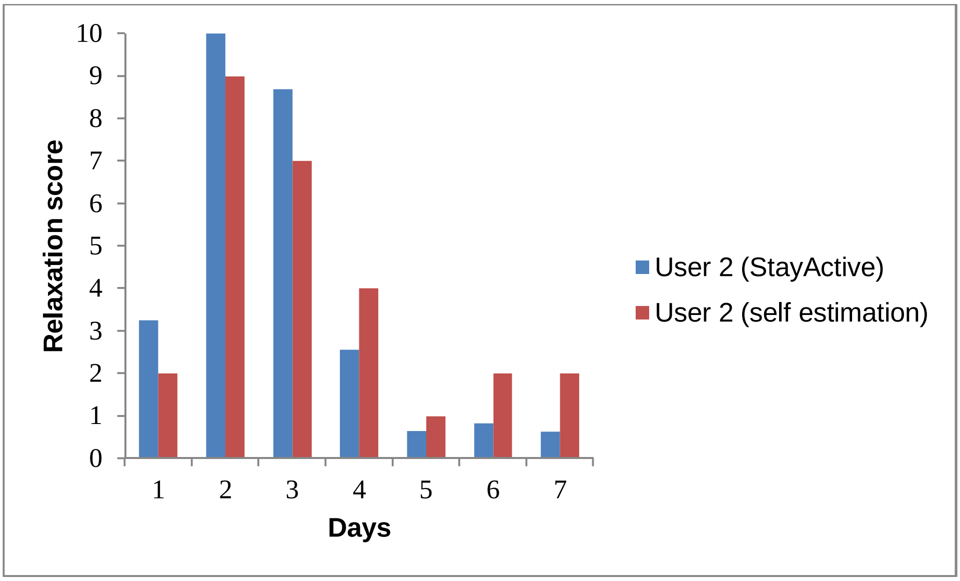


Figure 41: Relaxation score validation for user 2.

In the Figures 40-44 we can see the comparison of the relaxation score that our stress detection system computes for the last seven days of the experiment and the corresponding values of the user feedback for these days.

In order to evaluate the accuracy of the prediction of our model we have calculated the Root Mean Square Error (RMSE) for each user. We received the following values. $RMSE_1$=1.23, $RMSE_2$=1.247, $RMSE_3$=0.76, $RMSE_4$=2.17 and $RMSE_5$=2.06.

Three of the five participants were using their personal phones and therefore their computed relaxation level was consistent since we were able to accurately measure their sleeping pattern. The user 4 and the user 5 were using the application only during the working hours and therefore we were calculating their relaxation score based on the two of the three dimensions, the physical activity and the social interaction. We were not taking into account the sleeping pattern. We observe that the RMSE values for these two users were bigger that the other three users and this leads to the fact that each of the dimensions is very important for the correct estimation of the relaxation level of the user.

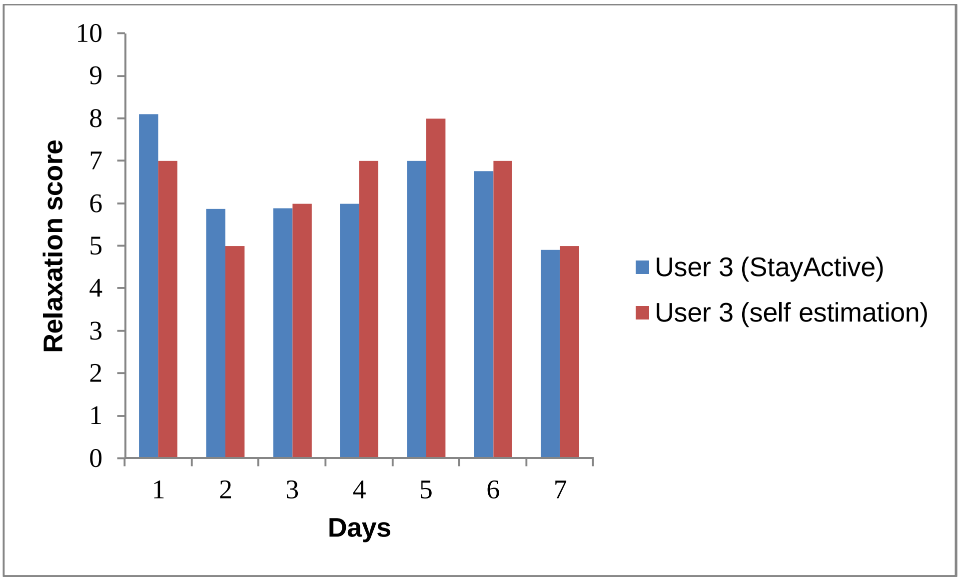


Figure 42: Relaxation score validation for user 3.

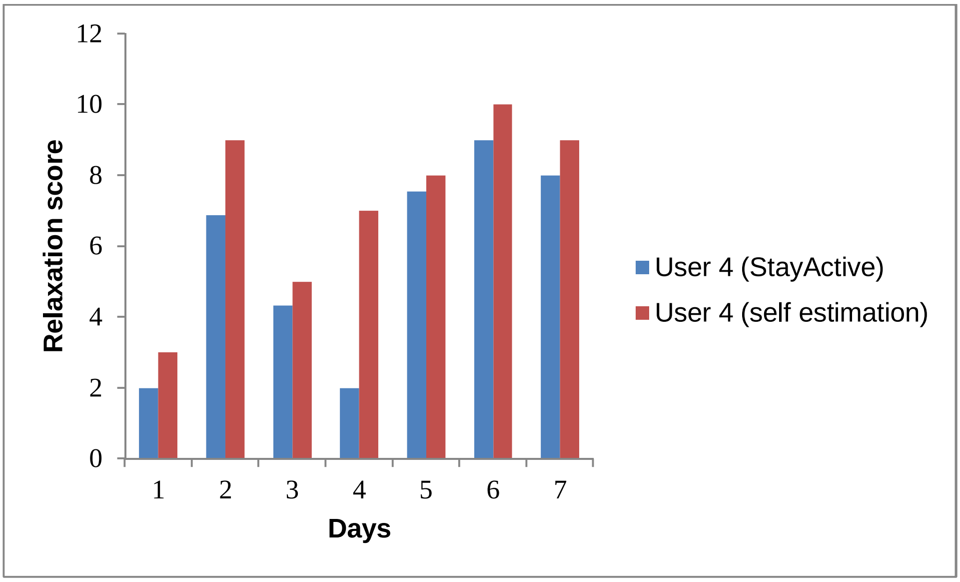


Figure 43: Relaxation score validation for user 4.

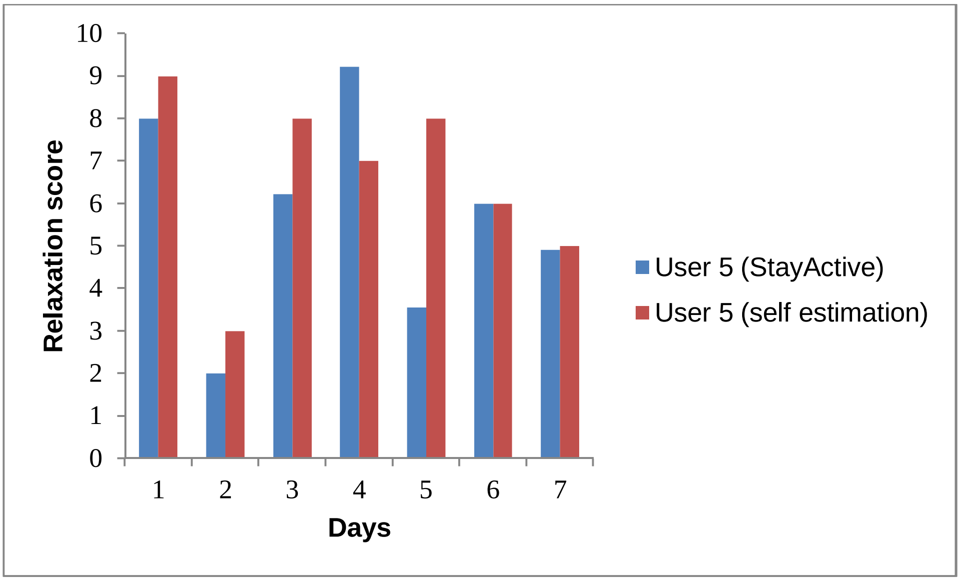


Figure 44: Relaxation score validation user 5.

We can see in the Figures 40-42 of the scores of the three users that the predicted values were close enough to the actual responses of the users. This means that our system has been trained in a way that the stress detection is accurate enough when we take into account all the dimensions of the stress detection algorithm.

Moreover it becomes clear the importance of taking into account all the dimensions of the algorithm. We observe that as soon as a dimension is not taken into account the predicted value of the relaxation score of the user has more uncertainty.

Modeling: Taking under consideration that the underlying objective is that of multiclass classification, a consideration should be made on the frame of reference upon which a measure of predictive improvement shall be taken.

Selection of modelling technique

The objective is the prediction of the psychic perception class “low”, “medium” or “high” for Relaxation. Therefore suitable classification techniques from the statistical and machine learning framework are employed to provide results. Despite the fact that a number of different techniques exist, we selected four techniques that belong to different modelling traditions. The selected techniques are the Partial Least Squares (PLS), the Random Forests (RF), the Gradient Boosting Machines (GBM) and the Support Vector Machines (SVM).

- **Partial least squares**

Partial least squares (PLS) is a statistical method that bears some relation to principal components regression; instead of finding hyperplanes of minimum variance between the response and independent variables, it finds a linear regression model by projecting the predicted variables and the observable variables to a new space [98]. It is very useful when we need to predict a set of independent variables from a large set of independent variables.

- **Random Forests**

Random forests (RF) is a notion of the general technique of random decision forests that are an ensemble learning method for classification, regression and other tasks, that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees [99].

- **Gradient Boosting Machines**

Gradient boosting is a machine learning technique for regression and classification problems, which produces a prediction model in the form of an ensemble of weak prediction models, typically decision trees [100]. It is quite powerful technique and has shown considerable success in a wide range of practical applications

- **Support Vector Machines**

In machine learning, support vector machines (SVMs, also support vector networks) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis [101].

Models comparison assessment (with respect to predictive capability)

All models shall be tested with respect to maximizing the “Accuracy” metric, under the resampling method of repeated cross validation. “Accuracy” is selected due to its simplicity of meaning. It refers directly to the model's capability of identifying correctly the estimated class.

"Cross-validation is a model validation technique for assessing how the results of a statistical analysis will generalize to an independent data set. The goal of cross validation is to define a dataset to "test" the model in the training phase (i.e., the validation dataset), in order to limit problems like overfitting, give an insight on how the model will generalize to an independent dataset (i.e., an unknown dataset, for instance from a real problem), etc. One round of cross-validation involves partitioning a sample of data into complementary subsets, performing the analysis on one subset (called the training set), and validating the analysis on the other subset (called the validation set or testing set) [102].

Predicting Relaxation

The following table summarizes the Accuracy results of the four different modeling approaches.

Model	Min	Mean	Max
PLS	0.4412	0.5889	0.8182
RF	0.4688	0.6313	0.7500
GBM	0.4848	0.6111	0.8182
SVM	0.3636	0.5488	0.7188

Table 6: Accuracy results

Besides the above seen results, the tests were performed on the models' performance in pairs. Based on the results it can be seen that PLS, RF and GBM outperform SVM. RF outperforms PLS, however no clear decision in a statistical significant way can be made on whether RF is better than GBM or if GBM is better than PLS.

Since a final model should be selected, the present study chooses based on just the mean Accuracy results to select RF as the one that delivers the best predictive performance. Comparing RF predictive performance against the naive model (that being that all predictions are “high”) where the prediction “Accuracy” is equal to 50.4%, one can observe that the machine learning approach provided with a lift of predictive performance equal to 63.13% - 50.4% ~ 12.7%.

The second phase of the evaluation of our stress detection system took place in Switzerland with the Public Transportation Company of Geneva (TPG) and in Romania with various end-users from the Bucharest Transportation Company (RATB), the Bucharest University and from a Clinical Hospital (admin staff). The 20 participants aged between 55 and 65 years old. The users used smartphones with the StayActive application installed in the phones for two weeks. Again the same procedure like in the first phase of the evaluation has been followed. The StayActive app was calculating a relaxation score for each individual user who was able to self-assess this score by the feedback depicted in Figure 39.

The focus of the second phase of the study was on the evaluation of how acceptable is our stress detection system from the end-users. The ultimate goal of our stress detection system was to be as less invasive as possible and therefore user-friendly. In the Figures 45, 46 we are able to see the acceptance of StayActive from the end-users. We can see that 75% of the end-users found the system easy to use and intuitive. Moreover 90% of the users wanted to be able to see a graph of their relaxation score in their StayActive mobile application.

As we already mentioned before we must highlight that the real data that we have received from our project partners are totally anonymous and therefore the anonymity and privacy of the people that were involved in the experiments is protected.

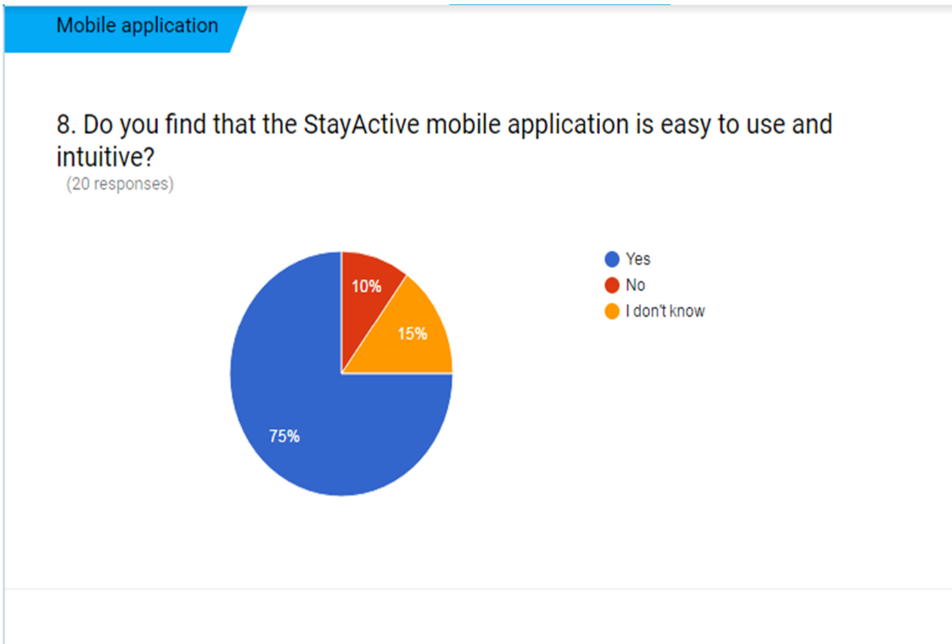


Figure 45: Acceptance of StayActive.

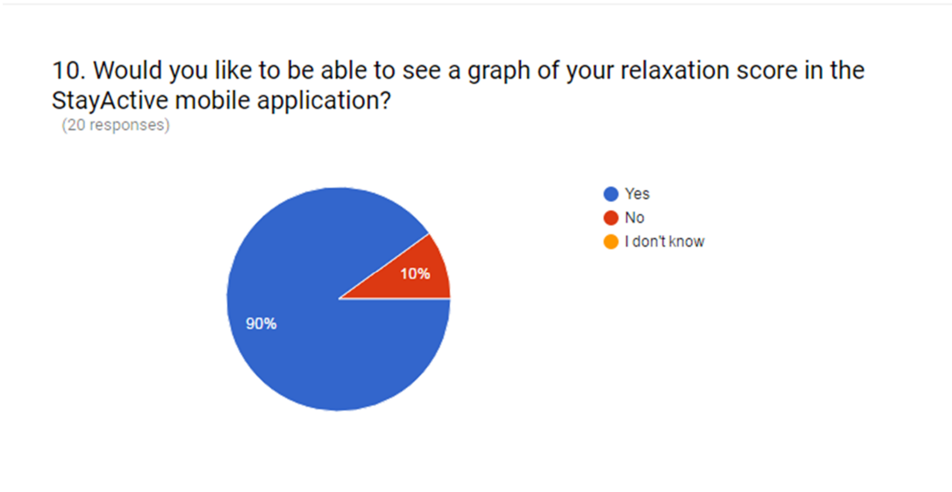


Figure 46: Acceptance of graphics of StayActive.

This leads to the conclusion that the end-users found the stress detection system comfortable and easy to use.

The main goal of our stress detection system compared to others is that we are trying to be as less invasive as possible. After our experience with end-users and of course after the discussions in the panels of the conferences that we have presented our work it has become pretty clear that the end-users will not accept to use an invasive wearable device (e.g. a t-shirt or a chest-band) in a daily basis.

Even if you can ensure them that their stress detection will be pretty accurate they will not be willing to use an invasive device for a long period of time. This is the main vulnerability of such stress detection systems which are using wearable devices to measure the HRV and the GSR of the user and combine them with other features in a machine learning model in order to predict stress.

In StayActive we use only smartphone data for detecting stress. This means that the user is not obliged to wear an uncomfortable device that will decrease his motivation to use the stress detection system. He can use his smartphone as usual and at the same time he will be able to measure his relaxation level.

3.3 Discussion and comparison

In this thesis we focus only on the chronic stress. Chronic stress is difficult to manage because it cannot be measured in a consistent and timely way. One current method to characterize an individual’s stress level is to conduct an interview or to administer a questionnaire during a visit with a physician or psychologist. This method provides only a momentary snapshot of the individual’s stress level, as most individuals cannot accurately recall the history of the ebb and flow of their stress symptoms [57]. Continuous monitoring of an individual’s stress levels is essential for understanding and managing personal stress. A number of physiological markers are widely used for stress assessment, including: galvanic skin response, several features of heart beat patterns, blood pressure, and respiration activity [58, 59]. Fortunately, miniaturized wireless devices are available to monitor these physiological markers. By using these devices, individuals can closely track changes in their vital signs in order to maintain better health.

The most common method to quantify stress is to simply ask people about their mood using questionnaires. There are standard methods for doing so like the Perceived Stress Scale questionnaire (PSS) [60]. Questions in the PSS assess to what degree a subject feels stressed in a given situation.

Nowadays wearable devices such as mobile phones and wearable sensors are ubiquitous in our lives. Several researchers have tried to understand personality from mobile phone usage [61]. Our stress detection system aims to use technology to recognize stress levels using data from the devices that users always carry and wear.

Sleeping patterns, social life and physical activity are connected with the presence of stress in people's lives [62]. We take into account these three dimensions for building our stress detection system. The motivation for creating a solution based only on the daily phone usage of people is based on the idea to be as less invasive as possible for the end-user.

Stress is an important aspect of well-being and it impacts mental health. Unlike sleeping hours, or activity time, stress is unfortunately more difficult to quantify in a non-intrusive way. The ability to detect stress in a continuous way is the motivation behind our research. Our target is to detect stress in a non-invasive way for the user. Information gathered from the smartphone will be utilized.

In this thesis we aim to find behavioral markers for stress. Although there are still several open questions regarding the links between the behavior of a person and their stress level, in our stress detection system called StayActive we take a pragmatic approach and build an initial stress detection module which can be extended and refined.

The main goal of our stress detection system compared to others is that we are trying to be as less invasive as possible. After our experience with end-users and of course after the discussions in the panels of the conferences that we have presented our work it has become pretty clear that the end-users will not accept to use an invasive wearable device (e.g. a t-shirt or a chest-band) in a daily basis. Even if you can ensure them that their stress detection will be pretty accurate they will not be willing to use an invasive device for a long period of time. This is the main vulnerability of such stress detection systems which are using wearable devices to measure the HRV and the GSR of the user and combine them with other features in a machine learning model in order to predict stress.

In StayActive we use only smartphone data for detecting stress. This means that the user is not obliged to wear an uncomfortable device that will decrease his motivation to use the stress detection system. He can use his smartphone as usual and at the same time he will be able to measure his relaxation level.

Simply collecting the patterns of people’s behavior is insufficient for helping them improve their personal wellbeing. It is important to use different dimensions of people’s wellbeing and compute their stress level. That way, we will be able to help them by giving advice for reducing their stress level and therefore improving their quality of life. Our stress detection system takes into account three main dimensions of wellbeing: the sleeping pattern of the users, their social interaction and their physical activity.

Comparing StayActive with the work of Muaremi [11] we observe that their stress detection system uses a chest belt which is uncomfortable for the end-users and there is the possibility that they will refuse to wear it. On the other side StayActive uses only data that come from the smart phones of the users and therefore it is a less invasive, easily acceptable solution.

Moreover, comparing StayActive with the work that researchers at MIT [61] have done there is again the advantage of StayActive in terms of acceptance of the end user. The number of people that they tested their stress detection system was 18, coming from their lab whereas in our case we evaluated the accuracy of our stress detection with 5 people and the acceptability of the system with 20 end-users that work for the public transportation company of Geneva and Romania.

Comparing StayActive with MoodSense [79] we can make the following statements. They have created an iPhone application that tries to infer it’s owners mood based on information already available in today’s smartphones. They report results from studying 25 iPhone users in the field and the correlation between their mood and phone usage. We observe that although they are not invasive since they use data coming from the smartphones of the users, they do not detect stress. On the other side we have created a model that is able to detect stress based on the data that we collect from the daily phone usage of the users. Therefore we go one step further and we have advanced the research of detecting mood and stress using the daily usage of the smart devices of the users.

To the best of our knowledge, StayActive is the very first stress detection system that takes into account only the usage of the smartphone of the end-user. Of course someone can argue that we can miss important information (extra dimensions) that come from wearable devices. This is an issue that we have taken into account creating the necessary engineering structure. Our solution is built in a way that it can easily add extra dimensions coming from wearable devices such as the heart rate, the heart rate variability and the galvanic skin response. Therefore it can detect stress in a non-invasive way and at the same time compare its performance with other stress detection systems that take different or more dimensions into account in order to extract a stress score. Finally the architecture of StayActive provides us the opportunity to include all the dimensions that can refine our stress detection score.

3.4 Personal contribution

In the research part of the stress detection system, in our first publication related to the stress detection [74] we present the architecture and the model of StayActive, a system which aims to detect stress and burn-out risks by analysing the behavior of the users via their smartphone. In particular, we collect data from people's daily phone usage gathering information about the sleeping pattern, the social interaction and the physical activity of the user. We assign a weight factor to each of these three dimensions of wellbeing according to the user's personal perception and build a stress detection system.

In the second publication related to stress detection [75] we evaluate our system in a real world environment with people working in the transportation company of Geneva. The main innovation of this work is addressed in the fact that the way the stress level is computed is as less invasive as possible for the users. The user is not obliged to wear an uncomfortable device that will decrease his motivation to use the stress detection system. He can use his smartphone as usual and at the same time being able to measure his relaxation level.

The papers that compose this thesis are product of deep research in the field of stress detection. The author of this thesis was the first author in these papers. The innovative ideas and the algorithms that are presented in these papers have been developed from the author of the thesis. He has created all the models and has run all the experiments that had been described in the publications. He was the main researcher of the StayActive AAL project starting from the analysis of the existing state of the art to the design and implementation of a promising with many future directions stress detection system. The co-authors of the papers were participating mostly in the coding support and in the quality of the English of the papers.

4. Discussion

In this thesis, two innovative e-health applications have been presented. The first one is a fall detection system called F2D which runs on an independent smartwatch. Thanks to the knowledge that has been acquired by building F2D, we were able to extract from the smartphones of the users useful data for detecting stress patterns. Therefore, the second application is a stress detection system called StayActive which uses information from the daily phone usage of the user.

4.1 Limitations

In order to conclude our work we have to discuss the design and implementation limitations of the presented fall and stress detection systems.

Fall detection

F2D works on a smartwatch, therefore completely independent from a base station. Using such a device is less stigmatizing for the user. In addition, it can be offered for less than half of the cost of existing systems on the market. Our system meets the requirements of reliability, ease of installation and restriction of false positives [41] which are essential for a properly built fall detection system.

We decided to use a threshold based algorithm and not a machine learning approach like [37] as it is less complex and therefore requires the lowest computational power [45]. In the typical scenario, the user will use the application on his smartwatch normally during the day without the requirement of charging it much more than usually. Since the fall detection system will run continuously, we should optimize the battery consumption of the device. Therefore, only the tri-axial accelerometer signal is used since it is the most informative sensor regarding the fall detection.

A main issue that came across while designing F2D was the after fall activity and more specifically what should happen as long as we detect a fall. For the moment we trigger an alarm and we inform a caretaker who can be a family member or another person like a nurse. But which should be the next step, if the caretaker is busy and he will not respond to the call or SMS that he will receive? This is a main issue that we should clarify in order to successfully transform our fall detection system to a service.

Moreover the transformation of the fall detection system to a service needs to identify in an accurate way the location that the fall has taken place. It is very crucial for the safety of the person that has fallen to know the exact position that the fall took place. The context awareness that the location module added to the fall detection system is very important for the final scope of this application. Since we are targeting the care of elderly people who are in a nursing home, knowing the location of the user after a fall is very important. The carertaker will know in which room the elderly has fallen and therefore they will be able to immediately provide the help that this person needs. This issue has already been discovered from our side and it is explained in more detail in the next section of the future work.

Also another limitation of F2D is that although the activities of daily living have been recorded from elderly people making our solution very innovative compared to others, still the falls have been simulated from experts of falling and not from elderly people. Of course this limitation exists in all the fall detection systems that have been reviewed because it is impossible to ask elderly people to fall just for testing purposes.

Finally, we should highlight the potential privacy issues of a fall detection system. We should highlight that not all types of sensors are equally vulnerable. Context-aware systems in general and video-based systems are much more prone to privacy concerns than a solution that works on a smartwatch like F2D. Therefore the end-user will accept to use our fall detection system since he does not feel to be monitorized.

Stress detection

In StayActive we use only smartphone data for detecting stress. This means that the user is not obliged to wear an uncomfortable device that will decrease his motivation to use the stress detection system. He can use his smartphone as usual and at the same time he will be able to measure his relaxation level.

Simply collecting the patterns of people's behavior is insufficient for helping them improve their personal wellbeing. It is important to use different dimensions of people's wellbeing and compute their stress level. That way, we will be able to help them by giving advice for reducing their stress level and therefore improving their quality of life. Our stress detection system takes into account three main dimensions of wellbeing: the sleeping pattern of the users, their social interaction and their physical activity.

We should highlight that stress is a subjective term. Therefore it is very challenging to predict it if you do not take into account the self-assessment of the end-users. This fact gives much more importance in the different dimensions that we take into account in order to evaluate the stress level of the end-users. The more the dimensions the better the assessment will be. In order to transform our stress detection system to a service we should add more dimensions in the algorithm that detects the stress. We will have the flexibility to discard the dimensions that have not been accurately measured. Like for example, in our case with the sleeping pattern dimension for the end-users that did not use their personal phone.

Another big challenge that we have to take into account is the user preference in the software of the smart devices. Nowadays some people use Android devices whereas some others iOS. For this reason our stress detection should not depend on any specific platform. Careful consideration should be given to the limitations imposed by both those mobile platforms. In other words, our system must be designed with enough flexibility so that it still works with specific platform-dependant limitations. For the moment we have tested our system only on Android smartphones but our service should be device independent.

Finally we should highlight the potential privacy issues. Firstly, all the users of the study were conscious about the data that were collected during the trials. There was a consent from created from our end-user partner in Romania (Ana Aslan Foundation) that the users had signed before starting the trials. Moreover each user had a unique identification number on the server that the data were collected for analysis. Therefore, the identification of the users was taken place by this identification number and not by name. It was only Ana Aslan Foundation that could make the link of the identification numbers to the names of the users.

In general, as Westin [81] pointed out, our participants' sample confirmed the existence of three main groups of privacy categories. We have users that tend not to delete any automatically shared data (privacy unconcerned). There are also other users that are more equilibrated, i.e., privacy pragmatists, who take different decisions, depending on context and kind of data shared. Finally, there are some that are privacy fundamentalists and tend always to delete content. This particular fact is known, and our results show that our sample has similar characteristics. Only privacy unconcerned participants are sharing significantly more when data is anonymous. At this stage, this fact implies that anonymity cannot, in theory, change the mind of users in our sample on how they make their sharing decisions. Privacy pragmatists are still pragmatist, and fundamentalists remain fundamentalists.

5. Conclusion and future work

Quality healthcare provisioning in Europe has become a major issue for the EU healthcare systems. The population growth and the increasing number of chronic patients have created a strong shift in creating applications for the improvement of daily lives of these people. In this context, innovation through the e-health industry will bring fruitful results to the demands of the elderly patients.

Older people, especially those who may have just left the working environment, can suffer a sense of loss, particularly of value, purpose, confidence. This can lead to mood swings, isolation and possibly depression.

In this thesis we have tried to show how elderly people could be able to sustain their daily life activities by using their smart devices (e.g. smartphones and smartwatches). There is no need for them to use invasive and uncomfortable devices that will be hard for them to use in the long-term. We provide them with e-health applications that run on the existing smart devices of people without any conflict with their other applications. Therefore without changing their daily habits they will be able at the same time to be protected and sustain their activities of daily living and feel confident and autonomous.

Two innovative e-health applications which will improve the quality of life of elderly people have been presented. The first one is a fall detection system which runs on an independent smartwatch. Thanks to the knowledge that we acquired by extracting useful information from the sensors of smart devices and more specifically by detecting falls from a smartwatch, we enhanced our know-how analyzing and extracting patterns from raw sensor data. The next implementation of our expertise and second main element of this thesis is the detection of stress patterns by analyzing smartphone data. We created a stress detection system which uses information from the daily phone usage of the user. StayActive takes into account three main dimensions of wellbeing: the sleeping pattern of the users, their social interaction and their physical activity, being as less invasive as possible for the end-user.

Both the fall detection system and the stress detection systems have as main technical characteristic the extraction of useful patterns from the raw sensor data of smart devices. We have acquired deep knowledge and we have developed different patterns for extracting useful information from the sensors that the typical smart devices like smartphone and smartwatches use. Based on these patterns we have created innovative algorithms that have led to the two e-health applications that have been analyzed.

Fall detection is a research field that has a big impact on the improvement of the daily life of elderly people. In this thesis we presented the first fall detection system designed to run on an independent smartwatch (F2D). There is no base station (which limits the range), no central alarm station (which is more difficult to manage) and it works on a standard smartwatch. It implies that it is less stigmatizing for the end user, removing the social stigma of wearing a medical device, quite cheap comparing to existing systems and it is easily extendable. F2D uses an innovative fall detection algorithm which takes into account the rebound after the fall, the residual movement and the location of the user in order to match a fall pattern to a real fall.

Nowadays, simple smartwatches are very powerful and have a set of sensors that can be used and diverted from their original intent. More computing power and storage on these devices offer greater opportunities. In F2D we use the accelerometer sensor in the smartwatch to feed the fall detection algorithm, considering also the residual movement after the fall. Using a single smartwatch as a device for running the F2D application satisfies the condition of ease of installation of the fall detection system. The context awareness that the location module added to the fall detection system is very important for the final scope of this application. Since we are targeting the care of elderly people who are in a nursing home, knowing the location of the user after a fall is very important. The carer will know in which room the elderly has fallen and therefore they will be able to immediately provide the help that this person needs.

Finally, the main innovation of F2D is that we have used real Activities of Daily Living from elderly people, testing our system in real life situations. Also we used data with simulated falls from experts (FST) in reproducing falls simulated like coming from elderly people. These experiments demonstrated that the fall detection system is robust and ready to be released on the market.

For the quantitative results analysis, we have created a tool with which we can run the fall detection algorithm against the data that FST has provided. Using this tool we could systematically test all the improvements made to the algorithm. Based on the results that we have obtained by testing our fall detection system in real life scenarios, the commercial deployment of F2D is the natural next step. F2D will enlarge the product range the FST is currently providing to their users. Since they work directly with end-users and with end user organizations, they are able to personalize the system according to the user profile and environment, thus providing a much more accurate and safe system than the generic solutions available on the market. The final application gives the opportunity to the user to select the parameters that correspond to their profile and trade off between fall detection and false alarms.

Based on the reliability of the fall detection and the restriction of false positives, which are guaranteed by the fall detection algorithm, we have built a system which meets the requirements for deployment and use.

Moreover, stress detection is a research field that can have a big impact on the improvement of people's daily life. In this thesis we presented a stress detection system which takes into account three main dimensions of wellbeing. The sleeping pattern, the physical activity of the users and their social interaction were accumulated with different weight factors and give an estimation of the daily stress level of the user. To the best of our knowledge, this is the first system that computes a stress score based on different dimensions of human wellbeing. The main innovation of this work is addressed in the fact that the way the stress level is computed is as less invasive as possible. Our solution relies only on the daily phone usage of people. Also we acquire the ground truth for the importance of each dimension of wellbeing for each individual by asking the users. This leads us to a personalized model which focuses on the personality of each individual user.

The main goal of our stress detection system compared to others is that we are trying to be as less invasive as possible. After our experience with end-users and of course after the discussions in the panels of the conferences that we have presented our work it has become pretty clear that the end-users will not accept to use an invasive wearable device (e.g. a t-shirt or a chest-band) in a daily basis. Even if you can ensure them that their stress detection will be pretty accurate they will not be willing to use an invasive device for a long period of time. This is the main vulnerability of such stress detection systems which are using wearable devices to measure the HRV and the GSR of the user and combine them with other features in a machine learning model in order to predict stress.

In StayActive we use only smartphone data for detecting stress. This means that the user is not obliged to wear an uncomfortable device that will decrease his motivation to use the stress detection system. He can use his smartphone as usual and at the same time he will be able to measure his relaxation level.

Also we acquire the ground truth for the importance of each dimension of wellbeing for each individual by asking the users. This leads us to a personalized model which focuses on the personality of each individual user.

To conclude, both of the systems that have been developed for this dissertation are very useful applications for the domain of healthcare. The ultimate goal of this thesis was to develop health care/monitoring systems and therefore help people by improving their quality of life. Both of the systems have been used in applications that will be available on the market, transferring directly the scientific research into a commercial product. Also both of the systems have been tested with real end-users and therefore the research has gone one step further, behind the lab trials. This was the main reason that our research had a great impact in academic and industrial partners as well, making them willing to create new research projects for applying and improving our innovative algorithms. The natural next steps after F2D and StayActive are Recover@home and SaB, two CTI projects which will go the research presented in this thesis one step further and make it applied on new markets.

Future work

For both of the systems that we have presented there is space for improvement and future directions. More specifically for the fall detection system the main innovation that can be further investigated is the test with real falls from elderly people. Although we have tested our system, compared with others, with ADL of elderly people, in order to make it even more robust we should test it with real falls of elderly people. We are in agreement with our industrial partner FST to provide the sooner possible our fall detection system to some elderly patients of a clinic to wear it for a month and therefore record their ADL's and possible falls that will happen as well.

Moreover, the context awareness that the location module added to the fall detection system is very important for the final scope of this application. Since we are targeting the care of elderly people who are in a nursing home, knowing the location of the user after a fall is very important. The carer will know in which room the elderly has fallen and therefore they will be able to immediately provide the help that this person needs. During the last decade, location based services have become very popular and the developed indoor positioning systems have reached centimeter level accuracy. The problem though is that even if the only requirement is room-level accuracy, those systems are most of the times not cost-efficient and not easy to set up. In the past two decades, there has been a continuous rise in interest in location-aware applications. After the invention of the Global Positioning System (GPS), more and more devices have included a GPS receiver and have been using this technology. Especially with the rise of the smartphones, these systems have become available on the market at low cost, and are nowadays ubiquitous. While the GPS is an exemplary solution for most outdoor applications, it is of little use in indoor environments. Therefore, researchers and engineers have invented new technologies and systems that can be used for indoor localization.

Our approach to indoor localization is based on the use of Bluetooth beacons. The important feature of our approach that distinguishes it from other systems based on Bluetooth is that it does not only rely on radio signal quantities. It also takes into account the geometry of the rooms the beacons are placed in, i.e. the height and the surface area. The measured radio signal quantities typically include the received signal strength indicator (RSSI), the link quality, the time of arrival, the angle of arrival and the time difference of arrival. In our work we only consider positioning based on the RSSI, since it is available in all standard wireless communication devices. Naturally in line of sight conditions the performance of such a system can be accurate. On the other hand, the RF signals indoors are prone to disturbances due to shadowing, fading and the multipath propagation phenomenon. These can lead to major errors when estimating distances based on the radio signal quantities, since these signals can significantly fluctuate.

Location information of the user is provided alongside their residual movement in order to improve the accuracy and to reduce the false positives of the system. Since minimal cost and setup process for the end user were the requirements of the localization system, we used the minimum amount of Bluetooth beacons, that is one Bluetooth beacon per room, and we opted to develop a more sophisticated algorithm for room detection.

Also there is enough space for improvement and future directions in our stress detection system. After testing it with the workers of the public transportation of Geneva (TPG) and after recording with questionnaires their feedback we have enough user data to take into account. As we have claimed in this thesis, to the best of our knowledge StayActive is the first stress detection system which tries to detect the relaxation levels of the user taking only smartphone data into account. More specifically by using three of the dimensions of wellbeing (sleeping pattern, physical activity, social interaction). This data give us enough information for the chronic stress level of the user. But in order to make our stress detection system more robust we plan to take biosignals (HRV, GSR etc) and therefore the acute stress into account. Combining the information for the chronic and the acute stress levels of the users we will be able to provide them with more accurate stress levels of their daily life.

More specifically, we have planned to use a non-invasive wearable device such as a bracelet in order to measure peaks of acute stress of the users and take them into account in the final prediction of the total stress level of the users. In this way, we will not be invasive at all and we will be able to combine the data coming from the smartphone usage and the biosignals coming from the non-invasive bracelet.

Based on the user data by testing our stress detection module with real end- users we are confident enough that this extra innovation will make StayActive an even more promising solution to the daily life problem of stress.

Research leads to new projects

Finally based on the scientific research that has been done for building a robust stress detection system, we acquired valuable knowledge and results which gave us the opportunity to create new research projects. The first one is called Recover@home and it is a CTI (Commission for Technology and Innovation) project. The main idea of this project is to build a solution to monitor a patient while at home. Technically, the idea is to build an algorithm able to define at what stage of the healing process a patient is. To do so, the system will take into account different dimensions. For this project, the dimensions we are going to work on are gait analysis, sleeping analysis, vital signals analysis and questionnaire feedback. The algorithm will be built to be evolutionary and allow the introduction of new dimensions at any time. This is a key element that will allow it to stay on the edge of what is feasible by taking into account new hardware/technologies available.

Scientifically, the main focus will be on the gait and sleeping dimensions, as well as on the algorithm that will put all the dimensions together (which will require real life data analysis).

The second research project is called SaB (Stress and Burnout) and it is a CTI project as well. SaB is a stress monitoring algorithm computing a stress level by combining biosignals from a wearable device, behavioral information from a smartphone, as well as subjective answers to standard medical questionnaires.

The goal of the project is to provide a device independent solution for stress detection. So the end user will be able to freely choose a wearable device that provides at least some specified biosignals (heart rate monitor, galvanic skin response). Technically, SaB will be able to identify the behavior and the activity level of the user, e.g. working in the office, standing, walking or running. Based on that, biosignals coming from the wearable device will be classified. The lifestyle choices of the user, the amount of sleep he gets and the way he responds to questionnaires will all be taken into account. The key innovation of SaB is the way those information from heterogeneous sources with differing conceptual and contextual representations will be fused in order to give an indication of the stress level of the user, based on a sophisticated algorithm. SaB will be able to identify stressful situations in daily life settings and not only in a laboratory environment.

Our target is to detect stress in a non-invasive way for the user. Information gathered from the smartphone will be utilized, but will not suffice for our goal. The alternative way to truly approach stress detection is by using biosignals. Bracelets and generally wearables have always been a great source of such input. The wearable market also saw a rise the last decade, analogous to that of the smartphone market, and currently there is a wide variety of sensors available. The first approach of our research focused on picking a bracelet that would fit our purpose. Generally, the more information the wearable device can provide, the better for the research that will take place. The bracelets that for the time being seems to be useful for our research is the Microsoft Band 2 (Figure 47) [77], since it includes, among others, galvanic skin response, skin temperature and heart rate sensors. It also includes an API to directly access the sensors, a functionality that will facilitate our experiments.

Figure 47: Microsoft band 2.

Since the use of a smartphone will be indispensable to our research, something not present in older researches, the users may be asked many questions from a predefined pool of questions many times during the day. The reason for this selected frequency is to quantify the stress caused by events still in the short-term memory of the subject, or ideally in the working memory. Another idea that differentiates our approach with the aforementioned questionnaires will be that the questions will be mostly delta ones, i.e. "Do you feel better compared to yesterday?", so that past and mostly short-term feelings are taken into account in a relative way. Sample questions that may be used include:

- Are you full of energy today?
- Do you have more time for yourself compared to yesterday?
- Do you feel tired during the last days?
- Do you have many worries the last week?
- Etc.

Although there is a considerable amount of health tracking applications, and an equally large amount of health tracking bracelets, very few of them approach the topic of stress detection and no solution to the best of our knowledge is accessible by everyone. This is exactly what our work is focused on and with our research and our experiments we target towards detecting stress in a continuous way. We believe that a feasible and non-invasive solution for quantifying stress can be achieved by using information coming from a smartphone and biosignals coming from a wearable device. With this project, we envision to progress beyond the state of the art in the areas of questionnaire designing and data fusing for stress detection.

In terms of research, healthcare is a trending topic. At UNIGE, there is a big focus towards using technology in support of healthcare. Our main target for this project is the innovation of a patent. We also expect to publish the main findings of the project in order to improve the current e-health state-of-the-art.

Some quantified goals of the project can be summarized as follows:

- The stress detection system should be designed and engineered to be platform independent in order to run on all major mobile operating systems.
- The input of the stress detection system should be the concerned sensors that should not depend on any specific wearable device.
- The algorithm should be able to identify if the variation of the physiological responses is caused by mental stress or by physical activity with an accuracy of more than 50%.
- The application should be able to combine objective data (biosignals, smartphone usage) with subjective feedback (questionnaires) to evaluate the stress level of the user.
- The stress detection system should be able to adapt itself to each specific user, or generally to the age group the user belongs to.

Expected results:

The main research direction of the entire project will be an innovative stress detection algorithm that allows to compute a stress level by combining biosignals from a wearable device, behavioral information from a smartphone, as well as subjective answers to standard medical questionnaires.. The client prototype will be designed for Android smartphones, but all the design will be done so that it can be easily translated for other devices, like iOS.

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