UNIVERSIDADE DE SÃO PAULO

Instituto de Ciências Matemáticas e de Computação

Elderly activity recognition using smartphones and wearable devices

Larissa Cardoso Zimmermann

Dissertação de Mestrado do Programa de Pós-Graduação em Ciências de Computação e Matemática Computacional (PPG-CMC)

SERVIÇO DE PÓS-GRADUAÇÃO DO ICMC-USP

Data de Depósito:

Assinatura: _____

Larissa Cardoso Zimmermann

Elderly activity recognition using smartphones and wearable devices

Master dissertation submitted to the Institute of Mathematics and Computer Sciences – ICMC-USP, in partial fulfillment of the requirements for the degree Master Program in Computer Science and Computational Mathematics. *FINAL VERSION*

Concentration Area: Computer Science and Computational Mathematics

Advisor: Profa. Dra. Maria da Graca Campos Pimentel

USP – São Carlos
April 2019

Ficha catalográfica elaborada pela Biblioteca Prof. Achille Bassi
e Seção Técnica de Informática, ICMC/USP,
com os dados inseridos pelo(a) autor(a)

C268e Cardoso Zimmermann, Larissa
Elderly activity recognition using smartphones
and wearable devices / Larissa Cardoso Zimmermann;
orientadora Maria da Graça Campos Pimentel. -- São
Carlos, 2019.
134 p.

Dissertação (Mestrado - Programa de Pós-Graduação
em Ciências de Computação e Matemática
Computacional) -- Instituto de Ciências Matemáticas
e de Computação, Universidade de São Paulo, 2019.

1. Human Activity Recognition. 2. Mobile
Computing. 3. Context Awareness. 4. Ubiquitous
Computing. I. Campos Pimentel, Maria da Graça,
orient. II. Título.

Larissa Cardoso Zimmermann

Reconhecimento de atividades de pessoas idosas com
integração de sensores de *smartphones* e dispositivos
vestíveis

Dissertação apresentada ao Instituto de Ciências
Matemáticas e de Computação – ICMC-USP,
como parte dos requisitos para obtenção do título
de Mestra em Ciências – Ciências de Computação e
Matemática Computacional. *VERSÃO REVISADA*

Área de Concentração: Ciências de Computação e
Matemática Computacional

Orientadora: Profa. Dra. Maria da Graca
Campos Pimentel

USP – São Carlos
Abril de 2019

Este trabalho é dedicado à minha família que sempre me apoia nas minhas decisões. À minha mãe Eliana, por me ouvir e ter paciência comigo. Ao meu pai Paulo, por me incentivar profissionalmente e pelas orientações. À minha irmã Mariana, por revisar meus textos e trabalhos. Ao meu cachorrinho Bidu, por me fazer companhia em diversas tardes de estudos e de trabalhos. À minha orientadora Maria da Graça, por todo apoio e suporte com sua sabedoria e seus conhecimentos e por ser um exemplo inspirador de mulher na tecnologia.

ACKNOWLEDGEMENTS

Special thanks for all my colleagues and professors of the University of São Paulo. I also thank CAPES for financial support to develop this research project.

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance Code 001.

*“If I have seen further, it is by standing
on the shoulders of giants.”
(Isaac Newton)*

ABSTRACT

ZIMMERMANN, L. C. **Reconhecimento de atividades de pessoas idosas com integração de sensores de *smartphones* e dispositivos vestíveis**. 2019. 134 p. Dissertação (Mestrado em Ciências – Ciências de Computação e Matemática Computacional) – Instituto de Ciências Matemáticas e de Computação, Universidade de São Paulo, São Carlos – SP, 2019.

Research that involves human-beings depends on the data collection. As technology solutions become popular in the context of healthcare, researchers highlight the need for monitoring and caring patients *in situ*. Human Activity Recognition (HAR) is a research field that combines two areas: Ubiquitous Computing and Artificial Intelligence. HAR is daily applied in several service sectors including military, security (surveillance), health and entertainment. A HAR system aims to identify and recognize the activities and actions a user performs, in real time or not. Ambient sensors (e.g. cameras) and wearable devices (e.g. smartwatches) collect information about users and their context (e.g. localization, time, companions). This data is processed by machine learning algorithms that extract information and classify the corresponding activity. Although there are several works in the literature related to HAR systems, most studies focusing on elderly users are limited and do not use, as ground truth, data collected from elder volunteers. Databases and sensors reported in the literature are geared towards a generic audience, which leads to loss in accuracy and robustness when targeted at a specific audience. Considering this gap, this work presents a Human Activity Recognition system – and corresponding database – focusing on the elderly, raising requirements and guidelines for supportive HAR system and the selection of sensor devices. The system evaluation was carried out checking the accuracy of the activity recognition process, defining the best statistical features and classification algorithms for the Elderly Activity Recognition System (EARS). The results suggest that EARS is a promising supportive technology for the elderly, having an accuracy of 98.37% with KNN ($k = 1$).

Keywords: Human Activity Recognition, Mobile Computing, Context Awareness, Ubiquitous Computing.

RESUMO

ZIMMERMANN, L. C. **Reconhecimento de atividades de pessoas idosas com integração de sensores de *smartphones* e dispositivos vestíveis**. 2019. 134 p. Dissertação (Mestrado em Ciências – Ciências de Computação e Matemática Computacional) – Instituto de Ciências Matemáticas e de Computação, Universidade de São Paulo, São Carlos – SP, 2019.

Pesquisas e serviços no campo da saúde se valem da coleta, em tempo real ou não, de dados de ordem física, psicológica, sentimental, comportamental, entre outras, de pacientes ou participantes em experimentos: o objetivo é melhorar tratamentos e procedimentos. As soluções tecnológicas estão se tornando populares no contexto da saúde, pesquisadores da área de saúde destacam a necessidade de monitoramento e cuidado dos pacientes *in situ*. O campo de pesquisa de Reconhecimento de Atividade Humana (sigla em inglês HAR, *Human Activity Recognition*) envolve as áreas de computação ubíqua e de inteligência artificial, sendo aplicado nos mais diversos domínios. Com o uso de sensores como câmeras, microfones e acelerômetros, entre outros, um sistema HAR tem por tarefa identificar as atividades que uma pessoa realiza em um determinado momento. As informações coletadas pelos sensores e os dados do usuário são processados por algoritmos de aprendizado de máquina para identificar a atividade humana realizada. Apesar de existirem vários trabalhos na literatura de sistemas HAR, poucos são voltados para o público ancião. Bases de dados e sensores reportados em trabalhos relacionados são voltadas para um público genérico, perdendo precisão e robustez quando se trata de um público específico. Diante dessa lacuna, este trabalho propõe um sistema de Reconhecimento de Atividade Humana voltado para o idoso, levantando requisitos para o sistema HAR assistido e selecionando os dispositivos sensores. Um banco de dados HAR com dados coletados de voluntários mais velhos também é fornecido e disponibilizado. A avaliação do sistema foi realizada verificando a acurácia do processo de reconhecimento da atividade, definindo as melhores características estatísticas e algoritmos de classificação para o sistema de reconhecimento de atividades do idoso. Os resultados sugerem que esse sistema é uma tecnologia de suporte promissora para idosos, tendo uma acurácia de 98.37% com KNN ($k = 1$).

Palavras-chave: Reconhecimento de Atividade Humana, Computação Móvel, Sensibilidade ao Contexto, Computação Ubíqua.

LIST OF FIGURES

Figure 1 – General Architecture of Human Activity Recognition Systems	32
Figure 2 – HAR Learning and Inference process: Training and Testing	33
Figure 3 – Number of articles identified per Digital Library after executing search string	41
Figure 4 – Number of Articles per year, describing Human Activity Recognition systems	41
Figure 5 – Description of the phases of studies selection	42
Figure 6 – Number of articles selected and accepted per Digital Library	43
Figure 7 – Target audience of Human Activity Recognition systems applied in elder-care	44
Figure 8 – Smart Home Perspective	46
Figure 9 – Body-worn Sensor Network Perspective	47
Figure 10 – Number of Articles per HAR system perspective	48
Figure 11 – Classification Algorithms used and their frequency in the selected articles	50
Figure 12 – Main Requirements for the design of an Elderly Activity Recognition system	65
Figure 13 – Four basis to have an EARS	68
Figure 14 – The volunteers wore the Smartwatch on their right hand	72
Figure 15 – Volunteers' Gender	74
Figure 16 – Volunteers' Education	75
Figure 17 – BMI Category of the Volunteers	76
Figure 18 – Percentage of the Volunteers per BMI Category	76
Figure 19 – Alcohol Consumption	77
Figure 20 – Frequency of Alcohol Consumption	77
Figure 21 – Percentage of Smokers among the Volunteers	78
Figure 22 – Percentage of Volunteers that practice Physical Activities	78
Figure 23 – Frequency of the Practice of Physical Activities	79
Figure 24 – Percentage of volunteers with abnormal physiological indexes	79
Figure 25 – Percentage of volunteers with Difficulty when they move	80
Figure 26 – Body part in which volunteers usually feel pain and difficulty when moving	80
Figure 27 – Evaluation of Satisfaction with Health	81
Figure 28 – Evaluation of Quality of Life	81
Figure 29 – Yes-Answer: Note for Satisfaction with Health	82
Figure 30 – No-Answer: Note for Satisfaction with Health	82
Figure 31 – Yes-Answer: Note for Satisfaction with Quality of Life	83
Figure 32 – Logo of the Move It application	84
Figure 33 – Move It: Sequence of screens of Adding a Research Project	84

Figure 34 – Move It: Sequence of screens of Adding Activities to the Project	85
Figure 35 – Move It: Sequence of screens of Adding Volunteers to the Project	85
Figure 37 – Move It: smartwatch app	86
Figure 36 – Move It: Sequence of screens of Collecting the data of a specific Activity . .	86
Figure 38 – LG Watch Urbane – Android Operating System	87
Figure 39 – Position of the Body-Worn Device and Orientation of 3-axes Accelerometer	88
Figure 40 – Architecture of the Elderly Activity Recognition System	90
Figure 41 – Elderly Activity Recognition application	93
Figure 42 – Performance of the 31 GoFs after the execution of Decision Tree	96
Figure 43 – Performance of the 31 GoFs after the execution of KNN, $k = 1$	96
Figure 44 – Performance of the 31 GoFs after the execution of KNN, $k = 3$	97
Figure 45 – Performance of the 31 GoFs after the execution of KNN, $k = 5$	97

LIST OF TABLES

Table 1 – Main simple human activities recognized by HAR system in the literature . . .	34
Table 2 – Target Audience of HAR systems	45
Table 3 – Architecture of HAR systems	49
Table 4 – Classification Algorithms used and their reported Accuracy	50
Table 5 – MIT PlaceLab Dataset	53
Table 6 – WARD Berkeley Dataset	54
Table 7 – CMU-MMAC Dataset	54
Table 8 – OPPORTUNITY Dataset	55
Table 9 – Van Kasteren Dataset	55
Table 10 – CASAS Multiresident Dataset	56
Table 11 – CASAS Kyoto Dataset	56
Table 12 – USC-HAD Dataset	57
Table 13 – WISDM Dataset	57
Table 14 – mHealth Dataset	58
Table 15 – MobiAct Dataset	58
Table 16 – DaLiAc Dataset	59
Table 17 – Mobility Tests Protocols	71
Table 18 – Volunteers’ Age	74
Table 19 – Volunteers’ Height	75
Table 20 – Volunteers’ Weight	75
Table 21 – Sampling rates provided by Android SDK	93
Table 22 – Elderly Activity Recognition System: overview and ML algorithms	93
Table 23 – Groups of Features (GoF)	95
Table 24 – Overview about the evaluation of Statistical Features	98
Table 25 – KNN ($k = 1$) Classification Analysis by WEKA	100
Table 26 – KNN ($k = 1$) – Confusion Matrix	100
Table 27 – Decision Tree (J48) – Classification Analysis	101
Table 28 – Decision Tree (J48) – Confusion Matrix	101
Table 29 – Brief Overview about the Elderly Activity Recognition System.	102
Table 30 – Digital Libraries visited	122
Table 31 – Evaluation of Quality of the selected Studies	125

LIST OF ABBREVIATIONS AND ACRONYMS

30CST	30 second Chair Stand Test
AAL	Ambient Assisted Living
Acc	Acceleration module
ADL	Activities of Daily Living
Amazon S3	Amazon Simple Storage Service
BMI	Body Mass Index
BWSN	Body-Worn Sensor Network
CAAE	Certificate of Presentation for Ethical Appreciation, in portuguese <i>Certificado de Apresentação para Apreciação Ética</i>
Diff	Difference to the gravity on y-axis
DTW	Dynamic Time Warping
EACH	School of Arts, Sciences and Humanities, in portuguese <i>Escola de Artes, Ciências e Humanidades</i>
EARDB	Elderly Activity Recognition Database
EARS	Elderly Activity Recognition System
FP	False Positive
GAFW	Genetic Algorithm-based Fusion Weight
GoF	Groups of Features
GPS	Global Positioning System
HAR	<i>Human Activity Recognition</i>
IBGE	Instituto Brasileiro de Geografia e Estatística
IMWUT	Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies
IoT	<i>Internet of Things</i>
IT	Information Technology
KNN	k-Nearst Neighbors
MCC	Matthews Correlation Coefficient
MeanXYZ	Mean of the acceleration components in each axis
ML	Machine Learning
MLP	Multilayer Perceptron
MMR	<i>Motion Mode Recognition</i>
OS	Operating System

PIR	Passive Infrared
PRC	Precision Recall Curve
RBF	Random Bits Forest
RFID	Radio-Frequency Identification
RmsXYZ	Root Mean Square of the acceleration components in each axis
ROC	Receiver Operating Characteristics
SDK	Software Development Kit
SPWT	Self-Paced Walk Test
StdXYZ	Standard deviation of the acceleration components in each axis
SVM	Support Vector Machine
TCLE	Term of Free and Clarified Consent, in portuguese <i>Termo de Consentimento Livre e Esclarecido</i>
TP	True Positive
TUDS	Timed Up and Down Stairs
TUG	Timed Up & Go
USP	University of São Paulo
WEKA	Waikato Environment for Knowledge Analysis

CONTENTS

1	INTRODUCTION	25
1.1	Context and Motivation	25
1.2	Objectives	27
1.3	Document Structure	27
2	THEORETICAL FOUNDATION	29
2.1	Ubiquitous Computing	29
2.2	Internet of Things	30
2.3	Supportive Technologies for Gerontology	31
2.4	Human Activity Recognition Systems	32
2.4.1	<i>Guidelines for the Design of a Human Activity Recognition System</i>	35
2.5	Final Considerations	36
3	LITERATURE REVIEW	39
3.1	Research Questions and Objectives	39
3.2	Search Methodology	40
3.3	Search Results	43
3.3.1	<i>Target audience</i>	44
3.3.2	<i>Elderly activities and behaviors</i>	45
3.3.3	<i>System architecture and algorithms used</i>	46
3.3.4	<i>Datasets for HAR systems</i>	52
3.3.4.1	<i>MIT PlaceLab Dataset</i>	53
3.3.4.2	<i>WARD Berkeley Dataset</i>	53
3.3.4.3	<i>CMU-MMAC Dataset</i>	54
3.3.4.4	<i>OPPORTUNITY Dataset</i>	54
3.3.4.5	<i>Van Kasteren Dataset</i>	55
3.3.4.6	<i>CASAS Multiresident Dataset</i>	55
3.3.4.7	<i>CASAS Kyoto Dataset</i>	56
3.3.4.8	<i>USC-HAD and WISDM Datasets</i>	56
3.3.4.9	<i>mHealth Dataset</i>	57
3.3.4.10	<i>MobiAct Dataset</i>	58
3.3.4.11	<i>DaLiAc Dataset</i>	58
3.3.5	<i>Contexts in which HAR systems are applied</i>	59

3.4	Final Considerations	61
4	AN ELDERLY ACTIVITY RECOGNITION SYSTEM	63
4.1	Elderly centered Human Activity Recognition system	63
4.1.1	Study methodology	64
4.1.2	Guidelines for an Elderly Activity Recognition system	64
4.1.2.1	Cost	64
4.1.2.2	Acceptance	65
4.1.2.3	Privacy	66
4.1.2.4	Accuracy	67
4.1.2.5	Elderly Activity Recognition System	68
4.2	EARDB: Database for Elderly Activity Recognition	68
4.2.1	Methodology	69
4.2.1.1	Academic Partnership	69
4.2.1.2	Ethics Committee	69
4.2.1.3	Elderly Daily Activities	69
4.2.1.4	Mobility Tests Protocols	70
4.2.1.5	Recruiting Process	71
4.2.1.6	Wearable Device's Position	72
4.2.1.7	Data Collection Process	72
4.2.2	Volunteers	73
4.2.2.1	Gender	74
4.2.2.2	Age	74
4.2.2.3	Education	74
4.2.2.4	Height and Weight	75
4.2.2.5	Body Mass Index	76
4.2.2.6	Alcohol Consumption and Smoking	76
4.2.2.7	Physical Activities	78
4.2.2.8	Physiological indexes and common Health Problems	79
4.2.2.9	Mobility	80
4.2.2.10	Satisfaction with Life and Quality of Life	80
4.2.2.11	Volunteers' Profile	82
4.2.3	Data Collector Application	83
4.3	Architecture of the Elderly Activity Recognition System	87
4.3.1	Wearable and Mobile Devices	87
4.3.2	Devices' Position and Sensors used	88
4.3.3	Target Audience	89
4.3.4	Elderly Activities and Behaviors	89
4.3.5	EARDB Dataset	90
4.3.6	Elderly Activity Recognition System	90

4.3.6.1	<i>Definitions of the Elderly Activity Recognition System</i>	91
4.3.6.2	<i>Elderly Activity Recognition application</i>	93
4.4	Elderly Activity Recognition System: Evaluation	94
4.4.1	<i>Evaluation of the Statistical Characteristics</i>	94
4.4.2	<i>Evaluation of the Classification Algorithm</i>	98
4.4.2.1	<i>KNN ($k = 1$) and GoF_{20}</i>	98
4.4.2.2	<i>Decision Tree (J48) and GoF_3</i>	100
4.4.2.3	<i>Elderly Activity Recognition System</i>	102
4.5	Final Considerations	102
5	CONCLUSION	105
5.1	Contributions	105
5.2	Limitations and Future Work	106
5.3	Final remarks	108
	BIBLIOGRAPHY	109
	APPENDIX A COMPLETE SYSTEMATIC REVIEW PROTOCOL	121
A.1	Procedure	121
A.2	Review Objectives	121
A.3	Research Questions	122
A.4	Research Process	122
A.4.1	<i>Search String</i>	122
A.4.2	<i>Digital Libraries</i>	122
A.5	Selection Criteria of the Studies	122
A.6	Study Selection Procedure	123
A.7	Quality Evaluation	123
A.8	Data Analysis	124
A.9	Synthesis of the Data Analysis	124
A.10	Conclusion	126
	APPENDIX B ETHICS COMMITTEE	127
B.1	Ethics Committee	127
B.2	Term of Free and Clarified Consent	127
B.3	Survey – Elderly	130

INTRODUCTION

This chapter presents the contextualization and the motivation behind a human activity and behavior recognition system specifically for elderly, using wearable and mobile devices, as smartphones and smartwatches. Aside from that, it is also introduced the main goals of this project, as well the structure and organization of this document.

1.1 Context and Motivation

Researches that involve human-beings depend on the data collection of physical, psychological, sentimental, behavioral orders, among others (CONNER *et al.*, 2009). Technology solutions are becoming popular in the context of healthcare, researchers from health area highlight the necessity of patients monitoring and caring *in situ* (CSIKSZENTMIHALYI; LARSON, 2014). Others researchers share also the same vision: Kleiman *et al.* (2017), Bedard *et al.* (2017), Serre *et al.* (2017), Nguyen, Dev and Eyler (2017), Labrique *et al.* (2017) and Wen *et al.* (2017).

According to data from World Population Prospects: the 2017 Revision, the number of elder people — those aged 60 years or over — is expected to more than double by 2050 and more than triple by 2100. Globally, population aged 60 or over is growing faster than all younger age groups (ECONOMIC; NATIONS, 2017). In Brazil, the Instituto Brasileiro de Geografia e Estatística (IBGE) reveals that the number of elderly in the Brazilian population has increased substantially in past years due to the rapid increase in the life expectancy of the Brazilians. The IBGE (2017) predicts in 2050 the number of elderly will represent circa 30% of the Brazilian population.¹

The rapid increase of the elderly population presents critical social perspectives on pension, health and caregiver policies. In fact, the number of diseases, mobility and health problems due to the aging process is increasing, sometimes occasioning partial or total dependence of the

¹ As highlighted on the reporting Estadão (2016).

elderly, who need special care (DOLL, 2017).

For example, researchers from health area have investigated several issues associated with elderly dependency and care: Luchesi *et al.* (2016) highlight the impact of stress on elderly caregivers during work time, Bombardelli *et al.* (2017) show its effects in the quality of life of older people, Cruz *et al.* (2017) provide risk factors associated with the care process of some diseases, and Santos *et al.* (2017) present some undesired conditions related to the hospitalization of elderly with cognitive and behavioral impairments.

Considering this, it is necessary to investigate computational methods, platforms and software solutions that assist elder patients and provide healthcare solutions and tools, not only to help health professionals and caregivers but also to afford improvements in the quality of life of the elderly, in a particular way. To illustrate it, the studies reported by Bal *et al.* (2011), Chaudhuri, Demiris and Thompson (2017), Tapia, Intille and Larson (2004), Kientz *et al.* (2008) and Stanford (2002) examine plenty ways of technological approaches in the context of smart-homes, in order to promote independent and healthy aging for the elderly.

Human Activity Recognition (HAR) system is a promising technology to support the elderly audience. HAR systems can provide technological approaches in order to minimize common affections and problems related to the aging process. For example, falls (ARAÚJO *et al.*, 2018; CHATZAKI *et al.*, 2017; BOJANOVSKY *et al.*, 2017) and abnormal behaviors detection (ZHAO *et al.*, 2014), elderly activities monitoring, and surveillance (TAHAVORI *et al.*, 2017; CHERN-BUMROONG *et al.*, 2013).

Although the researches in the HAR field justify their importance and motivation focusing on the elderly audience, most of them don't consider the elderly as main user, are limited and don't use, as ground truth, data collected from elder volunteers (Section 3.3.4). Some researches aren't based on well-defined guidelines and requirements for supportive technologies user-centered on the elderly, even though providing a technological solution for this audience. Hence, it is important to raise and highlight the main requirements and guidelines for supportive technologies having an elderly user-centered approach.

Another issue is the absence of public databases for HAR systems that use data collected from the elderly. Makihara, Mannami and Yagi (2011) evaluate the human motion in a wide diversity of gender and age (88 males and 80 females between 4 and 75 years old), and they reported that there are different patterns of motion among people regarding age and gender. Thus, there is the necessity to have a representative public dataset for HAR systems, considering people with diverse profiles.

Considering these gaps, this research aimed to present a HAR system user-centered on the elderly, raising and highlighting guidelines to design supportive technologies applied to older people, as well as collecting data from the elderly activities, and providing a database for HAR systems.

1.2 Objectives

The main goal of this research project was the design, the development and the evaluation of a Human Activity Recognition system with the purpose of providing an elderly user-centered approach. Thereunto, studies and requirements for Elderly Activity Recognition systems were raised by literature review process and followed by professionals of gerontology area. The author was also supported by these health professionals to highlight the most common activities performed by the elderly, that are important and should be recognized by the HAR system, providing a tool to analyze the routine of activities an elder person performs.

Wearable and mobile devices were used in this project, specifically smartphones and smart-watches. Monitoring and following the actions of the elderly through the process of activity recognition are the main purposes of this project, as well providing a diary about the Activities of Daily Living (ADL) of an elder person to health professionals and relatives. Thus, abnormal situations or behaviors that decrease the quality of life of the elderly can be identified by these professionals and family.

Another contribution of this research project is the design, the development and the provision of a public database specific for the recognition of activities performed by older people, recruiting elderly volunteers in order to collect data from sensors while they perform Activities of Daily Living. All the process and methods are defined and described in order to have a reproducible work, as well the wearable devices and sensors defined.

In Section 3.3.4, the public databases for Human Activity Recognition (HAR) systems found in the literature are presented and it is possible to notice that most of the data isn't collected from elder participants. As remarked by [Makihara, Mannami and Yagi \(2011\)](#), there are different patterns of motion among people regarding age and gender. Thus, it is important to have a HAR database including data from the elderly, in order to identify and establish the motion patterns of this audience.

Therefore, concerning the global scenario of population aging, the design and the development of a Human Activity Recognition system focused on the ADL of the elderly will be a contribution in short, medium and long term. This technological support can provide a better quality of life for the current and future elderly population.

1.3 Document Structure

This document is structured in the following way: Chapter 2 introduces the fundamental concepts to design and develop this research project. Ubiquitous Computing, Internet of Things, supportive technologies applied to Gerontology and Human Activity Recognition are the main topics presented in this chapter. Chapter 3 presents a systematic review of the literature, as well the criteria of the literature review process and its results. After, Chapter 4 shows the research project,

methodology and results, as well the partnerships established with researchers in the area of gerontology and health. Finally, Chapter 5 highlights the main requirements and guidelines to design a Elderly Activity Recognition system, discussion and conclusion.

THEORETICAL FOUNDATION

This chapter introduces the fundamental concepts and topics for the design and preparation of this research project. The concepts of Ubiquitous Computing, Internet of Things, supportive technologies for Gerontology and, finally, the fundamentals of Human Activity Recognition systems are presented in the following sections.

2.1 Ubiquitous Computing

“The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it.” (WEISER, 1999, p. 3)

Ubiquitous Computing is frequently described as the opposite of Virtual Reality. Virtual Reality is defined as the human-being immersion into the virtual world. While Ubiquitous Computing differs by being the immersion of computational systems in the real world. The progress of Information Technology area can be noticed by the process of rendering computing as an inseparable part of our daily routine experiences, i.e. the presence of computing is becoming more omnipresent from the perspective of human-being (ESPINILLA; LIU; GARCÍA-CHAMIZO, 2017).

Weiser (1999), in his classical paper named "The computer for the 21st century", predicts the ubiquitous computers, i.e. those computer that are embodied in real world and their presences are invisible, natural and integrated into the environment. In his prediction, computers become part of the human-being world and the people don't need anymore to get used to them, because the computers will belong to the human reality. At first, the computers would be noticed and change the way that human-beings interact with the world. However, as Weiser also observed, whenever people learn something sufficiently well, they cease to be aware of it. It means that, as time goes by, the human-beings would no longer notice the computer's presence in daily life.

The infrastructure behind the Information Technology (IT) is ever more projected and based on the Ubiquitous Computing concept. The Ubiquitous Computing is extensively spreading and integrating an increasing number of heterogeneous computational devices in the human daily routine. These devices are normally mobiles and embedded into the ambient and they cooperate and communicate with each other, in order to provide intelligent services to users (SRIVASTAVA, 2018).

For sure, Ubiquitous Computing is providing the transparent use of computational applications, which differ from the limited user experience proposed by the conventional computers. It is possible to see the Ubiquitous Computing as a tendency in the current mobile technologies and in the architecture and devices composing the smart home and cities perspectives. For example, those perspectives provide a natural user experience, through the touch, voice commands and sensors capable of identify the necessity and will of the user. They also do invisible connections between several systems, making transparently available a wide range of functions and services.

Currently, some mobile and wearable devices, as smartphones and smartwatches, are gradually becoming more popular and familiar to users, who interact with these devices in a natural and instinctive way, without marking that they are connected to several systems and services. The supportive technologies apply and integrate more than never the concepts of Ubiquitous Computing, in order to monitor, observe and follow patients, reporting all the information to health professional and relatives. After all, Weiser's predictions may not be entirely true, but its essence defines the current reality of computing applications.

2.2 Internet of Things

The concept of Internet of Things (*Internet of Things* (IoT)) was coined by the technological visionary Kevin Ashton during a presentation in 1999, in order to describe a network connecting objects in the physical world with the Internet. In general, the term of Internet of Things defines an interconnection through the network of daily objects. In general, ubiquitous intelligence is frequently embedded in these objects (XIA *et al.*, 2012).

The main idea behind the concept of IoT is the ubiquitous and pervasive presence of several things and objects in people's daily life – like Radio-Frequency Identification (RFID) tags, sensors, actuators, mobile and wearable devices, among others. In the survey, Atzori, Iera and Morabito (2010) highlight that the strength supporting the concept of IoT comes from the application of Ubiquitous Computing paradigm in several aspects of daily living of many potential users. Domotics, supportive technologies, e-health, industrial automation are some examples of the power of the computational applications in the IoT scenario.

The design of computational applications in the IoT context can provide numerous solutions that promise to improve the people's quality of life. Few of them are available to the society, but many can still be explored and improved, as asserted by Al-Fuqaha *et al.* (2015). IoT application

can be applied in the following areas:

- Transportation and Logistics: traffic detection, vehicles tracking, cars with smart brakes;
- Healthcare: elderly monitoring, controlling the physiological levels of patients;
- Smart Environments (homes, offices, smart cities): smart refrigerators, power and water consumption calculator;
- Personal and social domains: automatic meeting and activities reminder, recommendation systems, a system for automatic detection of symptoms of depression.

Considering this perspective raised by the concept of the Internet of Things, it is possible to notice that people rely more than ever on technology to improve their quality of life and the intelligent automation has become part of the people's daily life. As time goes by, new technologies and devices will become popular and familiar to the society, making possible computational application entirely ubiquitous in people's lives.

2.3 Supportive Technologies for Gerontology

Technology for supporting people in their activities of daily living such as personal assistance and smart homes carry great potential for making their lives more connected, healthy, efficient and safe by executing tasks on their behalf and guiding their actions (GARCIA; LARA, 2018).

New challenges are faced due to the rapid increase of the elderly population. For example, Doll (2017) asserts about the necessity and the importance of elderly care politics and the suitability of supportive ambient for them, addressing respect and solidarity among different generations. Considering this, supportive technologies can provide and pursue new solutions and approaches to handle issues due to this aging process, as well improve the quality of life of the elderly.

In this context, supportive technologies can have an interdisciplinary approach, involving and combining two areas: the Gerontology and the Information Technology, aiming at researching and developing products, services, solutions and strategies capable of support older people in their daily living. In other words, supportive technologies can address the development of applications for healthcare, mobility, education, communication, leisure, residence and work of older people (DOLL, 2017).

Supportive technologies can also be applied to elderly monitoring and surveillance, fall detection, identifying the elderly daily routine, checking for habits changes and early detection of common diseases among the elderly. For example, geofencing is a technology that uses Global Positioning System (GPS) tracking to put a virtual fence around an area that a person (e.g., a child or dementia patient) should stay. To support safety of the person being monitored, parents or caregivers should be notified immediately if the person leaves the area (RIEMSDIJK; JONKER; LESSER, 2015).

The combination of supportive technologies and Gerontology can provide improvements in

diverse matters, not only providing safety but also supporting an independent life for the elderly. Better quality of life, confidence, security, efficiency, and well-being of older people are some examples of the effects provided by the application of technology to solve the issues raised by the aging population.

Therefore, the supportive technologies applied to gerontology area is fundamental for the aging population process. The development of these technologies in the healthcare domain can avoid cognition impairments, identifying declines and losses, maintaining functional abilities, reestablishing autonomy and having an active, engaged, integrated and independent elderly. After all, everybody wants an aging process with quality of life, health, comfort, and safety.

2.4 Human Activity Recognition Systems

Human Activity Recognition (HAR) is a research field that combines two areas of computing: Ubiquitous Computing and Artificial Intelligence. HAR is daily applied in several service sectors: military, security (surveillance), health and entertainment – as observed by [Lara and Labrador \(2013\)](#). A Human Activity Recognition system aims to identify and recognize the activities and actions a user is performing, in real time or not.

In a HAR system, ambient sensors (e.g. cameras) and wearable devices (e.g. smartwatches) collect information about the user and the context involving him/her (e.g. localization, time, companions). All this data are processed by machine learning algorithms that are able to extract information and, at last, identify the human activity performed, one example is the work presented by [Intille et al. \(2016\)](#)). The challenges of HAR systems include the development of algorithms that aim to recognize the activities performed by the user with accuracy and reliability, taking into account the computational resources constraint and power limitation of mobile devices ([DAO; NGUYEN-GIA; MAI, 2017](#)).

Figure 1 – General Architecture of Human Activity Recognition Systems

Adapted from [Lara and Labrador \(2013, p. 1194\)](#)

Figure 1, adapted from the survey presented by [Lara and Labrador \(2013\)](#), shows the general architecture, normally deployed in Human Activity Recognition systems. The components of this architecture are:

Figure 2 – HAR Learning and Inference process: Training and Testing

Adapted from [Lara and Labrador \(2013, p. 1193\)](#)

- Sensors: accelerometer, GPS, heart rate monitor, luminosity sensor, temperature sensor, among others;
- Gateway Devices: smartphones, computers, among others;
- Communication: routers, cellphone networks, among others;
- Storage and Processing: local (in Gateway devices) or remote (in servers).

This architecture allows the developers and engineers to establish and define sensors and other devices specific to the information that is needed to be extracted and monitored. Considering this, all the information obtained can be stored and processed not only in the gateway device but also in a remote server. Or the data can be transmitted through the gateway device and redirected to a remote server, to be processed and stored.

After the data was collected and the storage and processing places were defined, the next step is the recognition of activities performed by the person being monitored. Figure 2, also adapted from the survey presented by [Lara and Labrador \(2013\)](#), shows all the learning and inference process behind a Human Activity Recognition system. As can be seen, the training and testing processes describe the learning mechanism done by a supervised machine learning algorithm. Therefore, there is the necessity of a pre-established and labeled dataset.

The human activity recognition process occurs in the following way: after the data was collected

Table 1 – Main simple human activities recognized by HAR system in the literature (LARA; LABRADOR, 2013) (WEISS *et al.*, 2016) (ELHOUSHI *et al.*, 2017)

Group	Activities
Ambulation Activities	Walking, Running, Sitting, Standing, Lying, Going upstairs, Going downstairs, Jumping, Falling, Riding escalator and elevator
Transportation	Riding a bus, Cycling and Driving
Phone usage	Text messaging, Making a call
Daily Activities	Eating, Drinking, Working at PC, Watching TV, Reading, Brushing teeth, Stretching, Scrubbing and vacuuming
Exercises/fitness	Rowing, Lifting weights, Spinning, Walking and Running on treadmill, Doing push ups
Military	Crawling, Kneeling, Opening a door
Upper Body	Chewing, Speaking, Swallowing, Sighing and Moving the head

(localization, physiological data, acceleration, among others), the characteristics extraction of this data is done. There are two types of characteristics extraction: structural and statistical. From the set of extracted characteristics, it is possible to learn with a labeled dataset and to infer the activity or action the user is performing.

The structural characteristics extraction process takes into account the inter-relation between the data, i.e., there is a lot of information coming from diverse types of sensors, providing a different correlation between them. So this process aims to obtain the correlation between the data coming from different sensors, summarizing them into characteristics and identifying patterns. Unlike the structural, the statistical characteristics extraction process uses quantitative aspects of the data, such as mean, standard deviation, Fourier and Wavelet transform (WEISS *et al.*, 2016).

There are two types of learning approach: supervised learning and unsupervised learning, which deal with labeled and non-labeled data, respectively (JORDAN; MITCHELL, 2015). In the case of HAR systems, the learning, inference and classification processes are achieved through supervised machine learning algorithms, recognizing patterns in the labeled training dataset (FRANK *et al.*, 2009). The classification algorithms frequently used in the literature are: Decision Tree, KNN, Support Vector Machine (SVM), Bayesian Network, among others (LARA; LABRADOR, 2013) (RONAO; CHO, 2016) (WEISS *et al.*, 2016).

The most common activities recognized by HAR systems in the literature are highlighted in Table 1 and labeled as ambulation activities, transportation, activities of daily living, military activities and physical exercises. Considered *simple* activities, they include walking, running, chewing, sitting, lying and standing, or urination activity (EUN *et al.*, 2017). Complex activities are composed by a set of simple activities having temporal and logical sequence – examples include the recognition of playing tennis (walking, running, movements of arms) (LARA; LABRADOR, 2013). As remarked by Dao, Nguyen-Gia and Mai (2017), the recognition of complex activities is still a challenge for HAR system, having low accuracy, performance, and reliability.

2.4.1 Guidelines for the Design of a Human Activity Recognition System

[Elhoushi et al. \(2017\)](#) show that a *Motion Mode Recognition* (MMR) system, which is categorized as a subset of HAR systems, must fill the usability and accessibility requirements, not to mention the acceptance of the system. From the standpoint of the authors, a HAR system shall be flexible, non-intrusive and manager the power consumption and computational resources constraints.

Other authors highlight some points that must be considered when it is desired to design and develop a Human Activity Recognition system, especially focused on the health area:

- **Selection of the sensors that will be used in the system:** the researcher must analyze the requirements and the functionalities of the system. He/she shall consider the activities that must be recognized by the system, in order to decide which sensor and wearable devices are more appropriate to collect the data. Besides that, it is a best practice that the users of HAR system shall not wear plenty of devices and not interact often with the application, in order to have a smooth, non-intrusive and comfortable user experience. The users' life and daily routine should not be modified in any circumstance by the presence of mobile and wearable devices ([DAO; NGUYEN-GIA; MAI, 2017](#)).
- **Defining a data collection protocol:** the researcher must be aware that a HAR system can have numerous users with different characteristics (in a matter of gender, age, weight, height and health conditions) and this wide range of end users may influence the accuracy, performance, and reliability of the system. Therefore, a HAR system must be designed for a generic way, i.e. not specific to an exclusive user type, having flexibility and supporting new users profiles anytime ([LARA; LABRADOR, 2013](#)).
- **Analysis the accuracy and performance of the activity recognition process:** the performance of a HAR system relies on several aspects – the set of activities that the system can recognize, the characteristics extraction method and the machine learning algorithm. In the first place, each set of activities presents specific issues related to its pattern recognition. For example, identifying simple activities like walking, running and lying is easier than the recognition of complex activities like watching TV, playing tennis, among others. In the second place, the training dataset must be generic and not focus in specific users' profiles. Finally, a comparative evaluation of the machine learning algorithms is necessary, since each dataset has its own distinction and characteristics. Hence, it is hard to define the correlation between the dataset, the machine learning algorithm, and the recognition performance in a theoretical way, it is necessary the empirical and experimental analysis, in order to raise the best machine learning method to the HAR system ([REYES-ORTIZ et al., 2015](#)) ([LARA; LABRADOR, 2013](#)).
- **Analysis the power consumption of the HAR system:** in general, HAR systems rely on a technological infrastructure composed by mobile and wearable devices, such as smart-phones and smartwatches, but these devices have power constraints due to their mobility.

These limitations of power consumption have become an issue in HAR system and it is a best practice to optimize the lifetime of batteries via software or hardware, especially in situations when the system works with critical data transmissions. The communication and processing procedures are the ones that have more power consumption (WEISS *et al.*, 2016).

- **Checking the real-time processing demand:** as said before, HAR systems, in general, depend on the infrastructure of mobile and wearable devices. In some case, some devices have computational and power consumption constraints, thus it is not desired to destine all the processing workload during activity recognition process to only one device. In most cases, the activity recognition procedure is performed in servers, which have more resources related to the storage, processing and power capacities. Without resources constraints, these servers can run robust algorithms, computationally expensive and more complex, providing a HAR system with higher performance and reliability. Although due to the communication with servers, the mobile and wearable devices still have the energy expenditure on data transmission. Hence, the researchers must always be aware of the HAR system architecture and try to optimize its solution in order to obtain the best of it: reliability, accuracy, and performance during the activity recognition process (RONAO; CHO, 2016).
- **Privacy issues in HAR systems:** this is a concern that happens in every Ubiquitous Computing system. As a HAR system is based on the Ubiquitous Computing guidelines, privacy is also an issue for it. For example, in the health area, there is the data collection related to the activities and health conditions of the patients. The system must have the total control about this information and provide a reliable user experience, i.e. only the patient can allow the access to her/him information, sharing with health professionals and relatives. After all, privacy is an individual right and the control, sharing, and usage of the data depend on the patient (HOYLE *et al.*, 2014) (AVANCHA; BAXI; KOTZ, 2012).

2.5 Final Considerations

Based on the main concepts briefly presented in this chapter, it is possible to notice that HAR systems fit in both context: Ubiquitous Computing and Internet of Things. HAR systems consist in applications that are embedded into the real world, non-intrusive and, besides that, are composed by several sensors that communicate with each other, providing intelligent services to the end-user.

Considering the context of global aging population, there is an increasing demand for supportive technologies applied to the elderly population. HAR systems can be a tool for health and gerontology professionals, monitoring the elderly activities, recognizing abnormal behaviors, detecting falls, as well as providing early diagnoses of common affections and diseases in older population. Although its great potential, having a HAR system for the elderly, but not considering

databases collected from them can impact the performance of activity recognition process.

Additionally, some requirements and guidelines for supportive technologies applied to the elderly must be raised and followed in order to provide an appropriated user experience and support the design of an elderly user-centered HAR system. Once again through technology, it is possible to improve the quality of life of the elderly, supporting this population and make the society aware about the aging process. After all, everyone will get older and it is necessary to have healthy and inclusive aging politics.

LITERATURE REVIEW

This chapter introduces the methodology used during the literature review process, as well as the selection criteria of the bibliography and its results. This study has an exploratory character and aims to briefly analyze the related works proposed by the scientific community, focusing on systems that recognize the activities performed by the elderly, using wearable and mobile devices.

Therefore, the systematic review process of the scientific literature, due to its methodological, systematic and reproducible aspects, can contribute to a succinct overview about HAR systems, highlighting their structure, architecture, sensors, devices, and the state-of-art of an elderly activity recognition system.

3.1 Research Questions and Objectives

In order to review systematically the literature, the main objectives of this process were defined and described below:

- **Primary Objective:**
 - Define the state-of-art and the approach of HAR systems focused on the elderly.
- **Secondary Objectives:**
 - Quantify and summarize pieces of evidence of HAR systems applied in older people monitoring and surveillance.
 - Mapping the context and the studies in which HAR systems are applied.
 - Raise the sensors, mobile and wearable devices, and algorithms used in HAR systems.
 - Define the activities that are recognized by HAR systems focused on the elderly, as well the sensors and devices used for it.
 - Identify the main audience of a HAR system: healthy or in-care elderly.

By means of the research objectives defined above, the following research questions were raised

in order to guide the literature review process:

Question 1: What are the context and the target audience of HAR systems applied on the elderly care?

Question 2: What are the activities and the behaviors of the elderly are recognized by the literature?

Question 3: What sensors and classification algorithms are applied on HAR systems that aim to monitor elderly people?

The following search process (Section 3.2) was executed up till November 28th 2018 on five scientific digital libraries: Springer Link, Scopus, Science@Direct, IEEE Digital Library and ACM Digital Library.

3.2 Search Methodology

First of all, only peer-reviewed, English, Portuguese and German language studies were considered relevant. Studies that reported HAR systems exclusively for elderly – those aged 60 years or over –, and using mobile and wearable devices were included. Five research bases were considered: Springer Link, Scopus, Science@Direct, IEEE Digital Library and ACM Digital Library. Therefore, a search in these bases were performed up till November 28rd 2018, applying terms that were combined to accomplish the search: 'mobile', 'wearable', 'smartphone', 'elder', 'older', 'elderly', 'activity recognition', and 'behavior recognition'. The complete search protocol is defined in [Appendix A](#).

The following search string was defined to be executed on the five research bases:

("elder" OR "elderly" OR "older") AND ("activity recognition" OR "behavior recognition") AND ("wearable" OR "mobile" OR "smartphone")

The original distribution of the number of articles per each digital library can be observed in [Figure 3](#).

[Figure 4](#) shows the number of articles about HAR systems per year, starting from 2004. As can be observed, there was a considerable growth of the number of papers related to this research field from 2007 on, that is the reason why the search in the digital libraries was restricted to studies published from 2007 on. Although any restriction related to the research field of the study wasn't applied and used as exclusion criteria.

The articles were selected through the following selection criteria:

- **Inclusion Criteria**

Figure 3 – Number of articles identified per Digital Library after executing search string.

Source: Elaborated by the author.

Figure 4 – Number of Articles per year, describing Human Activity Recognition systems

Graph from the *Engineering Village* platform ¹.

1. The primary studies must include only the Human Activity Recognition systems designed specifically to monitor, follow or observe the elderly.

- **Exclusion Criteria**

1. The studies that are not primary.
2. Only the English, Portuguese and German language studies were considered relevant.
3. Only full-text papers were selected.
4. Primary studies that present inconclusive results and lack of contributions to Computer Sciences area.
5. Primary studies that don't have the elderly as end-user of the HAR system.
6. Primary studies that don't concern about the privacy of the users and don't consider it as requirement of the system.
7. Short and repeated versions of the same study.
8. Primary studies without full-text available.

All the selection process was performed on the Parsifal tool. Parsifal is an online tool designed to support researchers to perform systematic literature reviews within the context of Software Engineering ² (PERFORM. . . ; KITCHENHAM; CHARTERS, 2007).

Selection Process

Figure 5 – Description of the phases of studies selection.

Source: Elaborated by the author.

Figure 5 shows the process of articles selection. To check whether or not the articles met the inclusion criteria, in the first place, the author selected researches by the title, excluding those that

² Parsifal can be accessed in <<https://parsif.al/>>

didn't match the main goal of the review. In second place, the author read the abstracts of selected articles and chosen those that matched the main objective of the review, excluding articles that propose the elderly care and monitoring only to show the importance of HAR systems. At last, only articles that propose a HAR system user-centered on elderly were selected and the author took part in the full text review.

Considering this, the search string were executed on the five research databases and there were identified 2712 articles. It is possible to see the distribution of articles per digital library in Figure 3. Some of the studies were duplicated, remaining only 2298. As defined in the inclusion criteria, all the studies that don't fit it were put away.

After reading the title and the abstract of 2298 studies and checking for inclusion criteria, 2030 articles were excluded. Figure 6 shows the distribution of the eligible 268 full-text papers accepted per digital library due to inclusion criteria applied on title and the abstract. At last, after full-text reading and applying the inclusion criteria, only 55 studies were included in qualitative synthesis.

Figure 6 – Number of articles selected and accepted per Digital Library (Research database).

Source: Elaborated by the author.

3.3 Search Results

The process of articles selection identified 55 relevant studies that met the inclusion criteria in the Section 3.2. After reading the full-text of these relevant articles, it was possible to extract the main information and characteristics of Human Activities Recognition system applied in elder care. In this section, it will be shown a brief discussion about the target audience of HAR systems for elderly (Section 3.3.1), the elderly activities and behaviors recognized by the literature (Section 3.3.2), the HAR system architecture, mobile and wearable devices used, algorithms applied, sensors and its positions (Section 3.3.3). Also it will raise the databases used in HAR systems for elderly (Section 3.3.4) and the context where HAR systems are applied – abnormal activities detection, activities monitoring (Section 3.3.5).

3.3.1 Target audience

The recognition of activities that are performed by elder people can be applied in a variety of ways in the context of *in-situ* elder-care and Ambient Assisted Living (AAL), reducing healthcare costs and providing infrastructure and care while keeping the elderly happy, independent, and socially connected. From the literature, it is possible to identify two groups of users: healthy and in-care elderly.

Figure 7 – Target audience of Human Activity Recognition systems applied in elder-care.

Source: Elaborated by the author.

Figure 7 shows that only 20% of the selected articles present a HAR system having as target audience the elderly in-care: cognition and memory impairment, Parkinson disease, mobility problems, and stroke patients. The other 80% focus on the activity monitoring and recognition from healthy elderly. It shows that most approaches of HAR systems are for elder people that aren't diagnosed with any disease and have able-body, without any mobility restriction. In this case, the HAR system aims to avoid future health problems, like falls and cognitive impairments, and to monitor the physical and physiological state of the elderly, prompting messages and alerts to health professionals and relatives.

For example, Zhao *et al.* (2014) provide a HAR system focused on elderly with physical and cognitive impairment, in order to reduce the potential risks associated with these impaired ability of the elderly living alone. Thus, it aims to provide a service that can automatically detect abnormal signs in the elderly ADLs (Activities of Daily Living), preventing it from becoming worse and providing the elderly with real-time support services (ZHAO *et al.*, 2014). Ugulino *et al.* (2012) and Taati *et al.* (2010) designed a HAR system to support people with Alzheimer's disease. Haescher *et al.* (2018), Chigateri *et al.* (2018) and Bravo *et al.* (2011) present a HAR system for frail elderly, whose aren't independent and in special need. Capela, Lemaire and Baddour (2015) provide a HAR solution for stroke patients. Summarizing, the articles presented in Table 2 represents the target audience of HAR systems. The elderly in-care are composed of elder people who aren't independent and have health problems as dementia, Alzheimer, Parkinson, physical and cognitive impairments, epilepsy, frailty, and stroke patients.

Table 2 – Target Audience of HAR systems

Target Audience	Articles
Healthy Elderly	Taraldsen <i>et al.</i> (2012), Tan <i>et al.</i> (2018), Meng, Miao and Leung (2017), Zhu, Sheng and Liu (2015), Moshtaghi, Zukerman and Russell (2015), Wang <i>et al.</i> (2012), Araújo <i>et al.</i> (2018), Chatzaki <i>et al.</i> (2017), Kozina <i>et al.</i> (2013), Mellone <i>et al.</i> (2012), Popescu <i>et al.</i> (2012), Fontecha <i>et al.</i> (2013), Pogorelc, Bosnić and Gams (2012), Mitas <i>et al.</i> (2014), Caroux <i>et al.</i> (2014), Liu, Hsieh and Chan (2018), Ouchi and Doi (2013), Tirkel <i>et al.</i> (2018), Scheurer <i>et al.</i> (2017), Chen <i>et al.</i> (2018), Mahitha <i>et al.</i> (2017), Soraya <i>et al.</i> (2017), Sebestyen, Stoica and Hangan (2016), Alam and Roy (2014), Chernbumroong, Cang and Yu (2015), Capela, Lemaire and Baddour (2015), Ge and Xu (2014), Chernbumroong <i>et al.</i> (2013), Cherian <i>et al.</i> (2017), Zeng, Chiu and Chang (2015), Hong <i>et al.</i> (2008), Ranasinghe, Torres and Wickramasinghe (2013), Mannini and Sabatini (2015), Rosero-Montalvo <i>et al.</i> (2017), Morales and Akopian (2017), Benmansour, Bouchachia and Feham (2015), Ruan (2016), Medjahed <i>et al.</i> (2009), Sansrimahachai and Toahchoodee (2016), Song, Jang and Park (2008), Lim <i>et al.</i> (2008), Fareed (2015), Janjua, Riboni and Bettini (2016), Rafael-Palou <i>et al.</i> (2015)
Elderly in-care	Zhao <i>et al.</i> (2014), Osmani, Zhang and Balasubramaniam (2009), Ugulino <i>et al.</i> (2012), Taati <i>et al.</i> (2010), Bojanovsky <i>et al.</i> (2017), Haescher <i>et al.</i> (2018), Chigateri <i>et al.</i> (2018), Bravo <i>et al.</i> (2011), Tahavori <i>et al.</i> (2017), Capela, Lemaire and Baddour (2015), Virone (2009)

3.3.2 Elderly activities and behaviors

As presented previously, a HAR system aims to recognize, in real-time or not, the activity a person is performing. Analyzing the selected literature and the target audience, each HAR system establishes the activities that will be recognized according to the system's goals and peculiarities.

For example, the study presented by Cherian *et al.* (2017) shows a HAR system that aims to recognize personal care activities, such as brush teeth, brush hair, take medicines. The main purpose is to avoid that the elderly with cognitive impairment forget to brush the teeth, preventing from cancer, cardiac problems, and other serious diseases caused by the absence of personal care.

Thus, the elderly activities recognized by the selected literature can be classified in five types: ambulation, transportation, daily activities, fall detection and prediction, and speech and guttural sounds. The activities for each classifier are detailed below:

- Ambulation activities: walking, running, sitting, standing, going downstairs, going upstairs;
- Transportation activities: cycling and driving;
- Daily activities: eating, drinking, watching TV, taking medicine, drinking, cooking, brushing hair, brushing teeth, washing dishes, sleeping, talking on the phone, dressing, leaving/entering home, doing exercises;
- Fall detection and prediction;
- Speech and guttural sounds: silence, coughing, yawning, deglutition, talking.

3.3.3 System architecture and algorithms used

In the selected studies, there are two possible approaches of the HAR systems' architecture. First, the sensors and mobile devices are distributed around the environment, in the context of smart homes. Second, the elderly monitoring is done through wearable and ubiquitous devices, as smartwatches, fitness wristband, smartphones, smart earrings, among others body-worn devices.

Figure 8 – Smart Home Perspective

Source: Elaborated by the author.

In the first perspective, the HAR system's architecture is based on a sensor network in the ambient, with a gateway device and a central processing server, as in Figure 8. This way, plenty of sensor and mobile devices are spread around the environment and located on objects and furniture, in order to identify which objects are manipulated by the user, which furniture the user interacts with and in which environment the user is. With this information, it is possible to define the activity the user is performing and his or her location in the house.

The sensor types applied in this approach are usually binary sensors, presence sensor, switches, pressure sensors, among others. For example, [Janjua, Riboni and Bettini \(2016\)](#) proposes a HAR system's architecture in the context of smart homes. In this work, the kitchen is instrumented with several types of sensors, capturing the actions involved in the activity. Temperature sensors to detect when the stove is turned on/off; RFID tags and readers to identify when medicines and food items are moved; presence sensors to capture the presence of person inside the dining room; and pressure sensors to identify the "sitting on the kitchen chair" event. With it, it is possible to recognize the activities of cooking, eating and taking medicine.

The smart home approach has its advantages and disadvantages. This solution doesn't require a high computational capacity, because it doesn't often use machine learning algorithms, having a low computational cost. Although, the necessity of plenty of sensors and mobile devices distributed on the environment turns the infrastructure expensive. Besides that, another disadvantage is that the sensor devices are normally embedded on objects, furniture and in the AAL, having the difficulty of mobility and maintenance of the sensor devices. The projects reported by [Medjahed](#)

et al. (2009) and *Osmani, Zhang and Balasubramaniam* (2009) are examples of a HAR system's smart home architecture that doesn't make use of machine learning algorithms.

Figure 9 – Body-worn Sensor Network Perspective

Source: Elaborated by the author.

In the second approach, the HAR system's architecture is based on Body-Worn Sensor Network (BWSN), with ubiquitous devices as wearable sensors. It's also common to have a gateway device – usually it is a smartphone –, and a central server, as can be seen in Figure 9. The ubiquitous devices – normally body-worn devices – communicate with the gateway device. All data provided by the sensors are executed and processed on this gateway, i.e. the recognition is done inside of it. After that, the processed information is logged on the central server, where more information can be extracted from the activity diary of the user.

The devices used in this approach must present an ubiquitous user experience. In other words, the sensors must be embedded on devices that elderly usually use and wear, being transparent and not intrusive in elder people's life. In this way, wearable devices as smartwatches, smart earrings are good examples for this perspective. Smartphone is another option that is becoming more popular in people's life, thus less intrusive (*MORALES; AKOPIAN, 2017*).

About the sensors, in body-worn devices, sensors that capture the movements and directions are used, for example: accelerometers (*ZHU; SHENG; LIU, 2015; UGULINO et al., 2012; CHATZAKI et al., 2017; KOZINA et al., 2013; CONCEPCIÓN et al., 2017; HAESCHER et al., 2018*), gyroscope and magnetometer (*MELLONE et al., 2012; TAHAVORI et al., 2017; MITAS et al., 2014; LIU; HSIEH; CHAN, 2018*). A heart rate sensor is also common to monitor vital signals (*CHERNBUMROONG; CANG; YU, 2015; MEDJAHED et al., 2009*).

Wearable devices are always fixed on the body. The most common positions of these devices are: right and left wrist, right and left thigh, waist, right and left ankle, chest and ear. Each position can improve the recognition accuracy of specific activities. For example, wearable devices positioned on chest or waist have a higher accuracy to detect falls and lying-standing movements. [Fontecha et al. \(2013\)](#) place the smartphone on waist and uses it only to detect falls. [Mellone et al. \(2012\)](#) also present a smartphone located on waist, in order to detect falls and prevent them. Another example of the relation between sensor position and the recognition of a specific activity is present by [Alam and Roy \(2014\)](#). In this work, it is used a smart earring – a earring with accelerometer – in order to recognize activities like: silence, coughing, yawning, deglutition and talking.

The fusion of sensors' position is a good approach for those works that want to minimize the influence of the position of sensors on the activity recognition process. [Ouchi and Doi \(2013\)](#) place wearable devices on three different positions: chest, wrist and on pants. [Mannini and Sabatini \(2015\)](#) also use the fusion of sensors' position to recognize the activity (wrist, ankles and chest). Both works have shown higher accuracy than those with device located on only one spot.

The main advantage of this approach is: it doesn't require a high number of sensor and mobile devices, in order to recognize the activity, thus the costs with sensors are not expensive. Another positive point is the transparency of the system, using wearable sensors and unobtrusive devices, but it also brings concerns about privacy that will be discussed later. Despite this, the body-worn sensor network perspective also has disadvantages. The high computational cost due to activity recognition algorithms applied in this approach is the main disadvantage. Although the microelectronics evolution in the past years, we still have concerns and issues about memory, battery and processing constrains.

Figure 10 – Number of Articles per HAR system perspective

Source: Elaborated by the author.

Table 3 – Architecture of HAR systems

Architecture	Articles
Smart Home	Tan <i>et al.</i> (2018), Meng, Miao and Leung (2017), Moshtaghi, Zukerman and Russell (2015), Zhao <i>et al.</i> (2014), Wang <i>et al.</i> (2012), Osmani, Zhang and Balasubramaniam (2009), Taati <i>et al.</i> (2010), Popescu <i>et al.</i> (2012), Caroux <i>et al.</i> (2014), Chen <i>et al.</i> (2018), Zeng, Chiu and Chang (2015), Virone (2009), Benmansour, Bouchachia and Feham (2015), Ruan (2016), Medjahed <i>et al.</i> (2009), Lim <i>et al.</i> (2008), Janjua, Riboni and Bettini (2016), Rafael-Palou <i>et al.</i> (2015)
Body-worn Sensor Network	Taraldsen <i>et al.</i> (2012), Zhu, Sheng and Liu (2015), Ugulino <i>et al.</i> (2012), Araújo <i>et al.</i> (2018), Chatzaki <i>et al.</i> (2017), Kozina <i>et al.</i> (2013), Bojanovsky <i>et al.</i> (2017), Concepción <i>et al.</i> (2017), Haescher <i>et al.</i> (2018), Mellone <i>et al.</i> (2012), Fontecha <i>et al.</i> (2013), Chigateri <i>et al.</i> (2018), Bravo <i>et al.</i> (2011), Tahavori <i>et al.</i> (2017), Pogorelc, Bosnić and Gams (2012), Mitas <i>et al.</i> (2014), Liu, Hsieh and Chan (2018), Ouchi and Doi (2013), Scheurer <i>et al.</i> (2017), Mahitha <i>et al.</i> (2017), Soraya <i>et al.</i> (2017), Alam and Roy (2014), Chernbumroong, Cang and Yu (2015), Capela, Lemaire and Baddour (2015), Chernbumroong <i>et al.</i> (2013), Cherian <i>et al.</i> (2017), Ranasinghe, Torres and Wickramasinghe (2013), Mannini and Sabatini (2015), Rosero-Montalvo <i>et al.</i> (2017), Morales and Akopian (2017), Sansrimahachai and Toahchoodee (2016), Song, Jang and Park (2008), Fareed (2015)
Intersection of both perspectives	Tirkel <i>et al.</i> (2018), Sebestyen, Stoica and Hangan (2016), Ge and Xu (2014), Hong <i>et al.</i> (2008)

Figure 10 shows the distribution of articles per HAR system perspective. As can be seen, 40% of the selected articles have the BWSN approach, circa 32% are applied on the smart home perspective and 7% have the fusion of both perspectives. In Table 3, it is possible to see the distribution of the selected articles into the HAR architecture classification. In addition, considering the evolution and the increasing popularity of wearable and mobile devices in the past years, it is possible to notice that most of the works applying the body-worn sensor network were reported from 2013 onwards. Those articles that present HAR systems based on smart home perspectives are more popular before 2013. Thus, there is a tendency of HAR system architecture migrating to the use of body-worn and mobile devices.

Algorithms

Only studies that have a body-worn sensor network or mixed approach were analyzed. Reviews and surveys were also excluded during this analysis. Figure 11 shows the classification algorithms used and their frequency in the literature. It is possible to observe that the Decision Tree algorithm is the algorithm with higher frequency, followed by SVM, Naive Bayes and Random Forest.

Table 4 summarizes all the classification algorithms used in the literature, as well their accuracy in the process of activities recognition. It is possible to notice that the Decision Tree are the most popular algorithm for HAR systems and it also has one of the highest accuracy. KNN, SVM and Naive Bayes also present great performance. Another point that should be raised is that the accuracy varies a lot for the same classification algorithm. It happens because there are a lot

of factors the accuracy depends on, for example, the processing platform – usually servers and computers have less resources constraint than smartphones. Another aspect is the dataset used, that also will influence in the process of activities recognition.

Figure 11 – Classification Algorithms used and their frequency in the selected articles

Source: Elaborated by the author.

Table 4 – Classification Algorithms used and their reported Accuracy

Articles	Classification Algorithms	Processing Platform	Accuracy
Zhu, Sheng and Liu (2015)	SVM	Smartphone	96.07%
Ugulino <i>et al.</i> (2012)	SVM, Voted Perceptron, MultiLayer Perceptron, Decision Tree (C4.5)	Smartphone	Decision Tree (C4.5) -> 98,10%
Araújo <i>et al.</i> (2018)	Threshold-based Algorithms	Smartphone& Smartwatch	94.20%
Chatzaki <i>et al.</i> (2017)	Decision Tree (J48)	Smartphone	96.80%
Kozina <i>et al.</i> (2013)	Decision Tree, Naive Bayes, Random Forest, EvAAL AR	Computer	Decision Tree-> 93.53%, Naive Bayes -> 97.75%, Random Forest-> 97.90%, EvAAL AR-> 98.85%

Bojanovsky et al. (2017)	Adaptive Boosting, Decision Tree (C4.5), k-Nearest Neighbors (k-NN), Naïve Bayes, Neural Networks, Random Forest and SVM	Smartphone& Smartwatch	Adaptive Boosting-> 96.70%, Decision Tree (C4.5)-> 96.40%, k-Nearest Neighbors (k-NN)-> 95.80%, Naïve Bayes-> 91.90%, Neural Networks-> 96.70%, Random Forest-> 97.70% and SVM-> 96.80%
Concepción et al. (2017)	Ameva	Smartphone	95.00%
Haescher et al. (2018)	Decision Tree (C4.5)	Smartphone& Smartwatch	—
Mellone et al. (2012)	—	Smartphone	—
Fontecha et al. (2013)	Affinity Tree	Smartphone	—
Chigateri et al. (2018)	—	Computer	92.80%
Bravo et al. (2011)	Dynamic Time Warping (DTW)	Smartphone	—
Tahavori et al. (2017)	Naives Bayes, LogitBoost, Random Forest, SVM	Server	Naives Bayes-> 81.24%, LogitBoost-> 89,69%, Random Forest-> 92,29%, SVM-> 84,17%
Pogorelc, Bosnić and Gams (2012)	SVM, Decision Tree, KNN, Naive Bayes, Random Forest, Neural Network	Server	SVM-> 97.90%, Decision Tree-> 90.10%, KNN-> 100.00%, Naive Bayes-> 97.20%, Random Forest-> 99.30%, Neural Network-> 100.00%
Liu, Hsieh and Chan (2018)	SVM	Server	81.63%
Ouchi and Doi (2013)	SVM	Smartphone	Chest pocket: 93.80%, Wrist: 91.00%, Pants pocket: 89.50%
Mahitha et al. (2017)	Naive-Bayes, KNN, SVM	—	Naive-Bayes-> 98.80%, KNN-> 99.47%, SVM-> 97.67%
Soraya et al. (2017)	Decision Tree (C4.5) and Random Forest for drinking activities; REP Tree and HMM for bathroom activities	Server & Smartphone	Drinking activities => Random Forest: 85.00%; Bathroom activities => HMM: 79,30%
Sebestyen, Stoica and Hangan (2016)	HMM	Smartphone, Galileo board	—
Alam and Roy (2014)	Decision Tree (C4.5)	Computer	94.80%

Chernbumroong, Cang and Yu (2015)	Genetic Algorithm-based Fusion Weight (GAFW)	—	98.00%
Capela, Lemaire and Baddour (2015)	Naives Bayes, SVM, Decision Tree (C4.5)	Smartphone	Naives Bayes-> 65.08%, SVM-> 88.42%, Decision Tree-> 94.78%
Chernbumroong <i>et al.</i> (2013)	Multilayer Perceptron (MLP), Random Bits Forest (RBF), SVM	Local Computer	MLP-> 81.52%, RBF-> 72.18%, SVM-> 90.43%
Cherian <i>et al.</i> (2017)	Decision Tree(C4.5), MLP, KNN (K=5), Random Tree, Random Forest	Smartwatch	Decision Tree-> 93.60%, MLP-> 90.50%, KNN-> 90.50%, Random Tree-> 77.60%, Random Forest-> 91.70%
Hong <i>et al.</i> (2008)	Decision Tree (C4.5)	Smartphone	95.00%
Mannini and Sabatini (2015)	SVM	Smartphone	95.00%
Rosero-Montalvo <i>et al.</i> (2017)	KNN (K=1, 3 e 5)	Arduino Nano	K=1-> 87.00%, K=3-> 95.00%, K=5-> 92.00%
Sansrimahachai and Toahchoodee (2016)	Decision Tree(C4.5)	Server	93.50%

3.3.4 Datasets for HAR systems

As contributions for Human Activity Recognition systems, public databases and frameworks are provided by researchers including Intille *et al.* (2005), Yang *et al.* (2009), Kwapisz, Weiss and Moore (2011), Zhang and Sawchuk (2012), Torre *et al.* (2008), Vavoulas *et al.* (2016), Roggen *et al.* (2010), Leutheuser, Schuldhaus and Eskofier (2013), Kasteren *et al.* (2008), Cook *et al.* (2013). From the literature review, the author identified 12 public databases for HAR systems, among which only one includes data from an older person – one individual over 60 years old (WARD dataset (YANG *et al.*, 2009)).

In this section, a brief analysis of these databases is shown in Tables from 5 to 16, and include database source, participant number and demographics, sensors used and their positioning, sample rate, among others.

Tables 9, 10 and 11 show databases that represent volunteers performing activities of daily living in a smart home scenario, where sensors were placed on the environment, objects and furniture.

3.3.4.1 MIT PlaceLab Dataset

In the case of MIT PlaceLab (Table 5), a dataset is provided to recognize daily activity as cooking, washing dishes, talking on the phone, answering e-mails. The data was collected from 3 volunteers, a man and a woman in their mid fifties, and a semi-retired woman in her late fifties – i.e. neither of them is 60 or over. A wearable device with 3-axis accelerometer is placed on five possible spots: right and left arms, waist, right and left leg. Notice that the number of participants is very small in order to have a good sample. Not to mention the lack of information about the way the activities were performed by the volunteers during the data collection of movements and the sampling rate.

Table 5 – MIT PlaceLab Dataset (INTILLE *et al.*, 2005)

	Information
Year	2006
Perspective	Body-Worn Sensor Network
Link	http://web.mit.edu/cron/group/house_n/data/PlaceLab/PlaceLab.htm
Participants	3 individuals: first participant was a man in his mid fifties who was working at home. The second participant was a semi-retired woman in her late fifties. The third participant was a woman in her mid-fifties who worked part-time (INTILLE <i>et al.</i> , 2005)
Recognized Activities	Cooking, do laundry, wash dishes, talking on the phone, answering e-mails
Sensors	3-axis accelerometer
Sensors Position	Five lightweight and wireless body limb acceleration sensors: right and left arms, waist, right and left leg

3.3.4.2 WARD Berkeley Dataset

With regard to WARD Berkeley dataset (Table 6), there is a good sample of volunteers, ranging on gender and age. However, the protocol to construct WARD database is not well defined and each activity is performed for only 10 seconds by each participant. Concerning the position of sensors on body, it is considered intrusive and doesn't provide an ubiquitous user experience, because it is placed on five spots along the participants' body. There are 20 volunteers – 7 women and 13 men – with age ranging from 18 to 70, but the number of volunteers aged 60 or over is not defined.

Table 6 – WARD Berkeley Dataset (YANG *et al.*, 2009)

	Information
Year	2009
Perspective	Body-Worn Sensor Network
Link	https://people.eecs.berkeley.edu/~yang/software/WAR/
Participants	7 female and 13 male human subjects (in total 20 subjects) with age ranging from 18 to 70 – it is not defined the number of subjects aged 60 or over
Recognized Activities	Stand, Sit, Lie down, Walk forward, Walk left-circle, Walk right-circle, Turn left, Turn right, Go upstairs, Go downstairs, Jog, Jump, Push wheelchair
Sensors	Wearable motion sensor consisting of 3-axis accelerometer and 2-axis gyroscope
Sensors Position	Five wearable motion sensors: right and left wrist, waist, right and left ankle
Sampling Rate	20Hz

3.3.4.3 CMU-MMAC Dataset

In Table 7, the CMU-MMAC dataset presents a hybrid approach, mixing both perspectives – smart home and body-worn sensor network. Despite the relevant number of participants, the authors didn't describe characteristics of them, like age, gender, height, and others. Besides that, the dataset is limited to activities performed only in the kitchen, as preparing meal, pizza, sandwich, eggs and salad.

Table 7 – CMU-MMAC Dataset (TORRE *et al.*, 2008)

	Information
Year	2009
Perspective	Smart Home and Body-Worn Sensor Network
Link	http://kitchen.cs.cmu.edu/
Participants	43 – nothing about the participants is defined, e.g. age, height, weight, others
Recognized Activities	Preparing meal: pizza, sandwich, salad, eggs
Sensors	Camera, microphone, RFID, 3-axis accelerometer and 3-axis gyroscope, temperature sensor, motion sensor
Sensors Position	Wearable sensors located on right and left arms, right and left wrists, right and left thigh, ankles, waist. Cameras, microphones, RFID, motion sensor located around in the AAL
Sampling Rate	60Hz

3.3.4.4 OPPORTUNITY Dataset

The project OPPORTUNITY provides a database (Table 8) only for morning activities (get up, prepare coffee, eat sandwich, cleanup). In order to construct this dataset, 15 networked sensor systems were deployed, with 72 sensors of 10 modalities, integrated in the environment, in objects, and on the body. Hence it is a hybrid perspective, involving smart home and Body-Worn Sensor Network approach, and a high number of sensors is required on body and on environment, having a scenario not only expensive, but also hard to reproduce.

Another negative point is the lack of description of the participants' profiles. It is only known that there are 12 volunteers, but their profiles aren't described – nothing about their age, height, weight, gender, others.

Table 8 – OPPORTUNITY Dataset (ROGGEN *et al.*, 2010)

	Information
Year	2013
Perspective	Smart Home and Body-Worn Sensor Network
Link	https://archive.ics.uci.edu/ml/datasets/opportunity+activity+recognition
Participants	12 – the authors don't provide any information about the participants
Recognized Activities	Morning activities in the kitchen: get up, prepare coffee, prepare sandwich, eat sandwich, cleanup and break
Sensors	3-axis accelerometer, gyroscope, magnetometer, microphone, camera
Sensors Position	Wearable sensors located on arms, wrists, knees, ankles, shoulders, waist
Sampling Rate	5Hz

3.3.4.5 Van Kasteren Dataset

In the dataset presented by KASTEREN *et al.* (Table 9), there are few volunteers, only three, all men under 60 years old, two of them in their 20s and the third one is 57 years old. This dataset presents a smart-home approach with door and cupboard switches spread in the house, pressure sensors on the couch and bed, some Passive Infrared (PIR) sensors to detect motion in a specific area, among others sensors. Thus, this approach requires a high number of devices in order to identify activities.

Table 9 – Van Kasteren Dataset (KASTEREN *et al.*, 2008)

	Information
Year	2010
Perspective	Smart Home
Link	https://sites.google.com/site/tim0306/datasets
Participants	3 men: 26, 28, 57 years old
Recognized Activities	Open or Close doors and cupboards, Sitting on a couch, Lying in bed, Detect the movement of objects, Motion detection, Flushing toilet
Sensors	Wireless network kits: Binary sensors
Sensors Position	Reed switches to measure whether doors and cupboards are open or closed; pressure mats to measure sitting on a couch or lying in bed; mercury contacts to detect the movement of objects (e.g. drawers); passive infrared (PIR) to detect motion in a specific area; float sensors to measure the toilet being flushed.

3.3.4.6 CASAS Multiresident Dataset

In CASAS Multiresident dataset (Table 10), the collected data represents two participants in the apartment at the same time performing fifteen ADLs. The biggest contribution is that the HAR system is able to recognize the activities performed by both volunteers simultaneously.

To provide physical training data for our algorithms, 40 volunteer participants were recruited to perform ADLs in the smart apartment. The smart space was occupied by two volunteers at the same time which performed the assigned tasks concurrently, making it a multiresident environment. The collected sensor events were manually labeled with the activity ID and the person ID, but the profiles of volunteers were not described.

Table 10 – CASAS Multiresident Dataset (SINGLA; COOK; SCHMITTER-EDGEcombe, 2010)

	Information
Year	2009
Perspective	Smart Home
Link	http://casas.wsu.edu/datasets/
Participants	40 participants. The data represents two participants at the same time performing fifteen ADLs in the apartment. The profile of participants is not described.
Recognized Activities	Activities of Daily Living can be performed by both participants at the same time. The system is able to recognize two different activities performed concurrently by each participant
Sensors	Motion sensors, Item sensors, Medicine container sensor, Pot sensor, Phone sensor, Cabinet sensor, Water sensor, Burner sensor, Temperature sensor
Sensors Position	Sensors located on objects and furniture

3.3.4.7 CASAS Kyoto Dataset

In CASAS Kyoto dataset (Table 11), the data was collected in the same apartment as CASAS Multiresident, but one volunteer at a time. This work focus on ADLs performed by person with cognitive impairment like dementia. Although this dataset aims to provide a healthcare solution for elderly with cognitive impairment, the volunteers who have provided the data are not well defined, i.e. it is not described their age, gender and other information about them.

Table 11 – CASAS Kyoto Dataset (COOK *et al.*, 2013)

	Information
Year	2013
Perspective	Smart Home
Link	http://casas.wsu.edu/datasets/
Participants	30 individuals
Recognized Activities	Activities of Daily Living and Memory in Older Adulthood and Dementia: make a phone call, wash hands, cook, eat, clean
Sensors	Motion sensors; Item sensors for oatmeal, raisins, brown sugar, bowl, measuring spoon; Medicine container sensor; Pot sensor; Phone book sensor; Cabinet sensor; Water sensor; Burner sensor
Sensors Position	Sensors located on objects and furniture

3.3.4.8 USC-HAD and WISDM Datasets

The datasets summarized on Tables 12 and 13 present data provided by wearable devices placed on front right hip. There are some small differences among them, for example, the wearable device used on USC-HAD dataset was composed with 3-axis accelerometer and 3-axis gyroscope,

in the other hand WISDM used a wearable device only with 3-axis accelerometer. They also provide similar ADLs, focusing on ambulation activities: walking, running, sitting, standing still, lying, climbing stairs, descending stairs, riding escalator, and riding elevator (LARA; LABRADOR, 2013). Moreover the USC-HAD dataset offers data collected from 14 volunteers, 7 men and 7 women, including plurality and diversity in the sample of participants. Although the WISDM dataset presents data collected from 29 volunteers, it is not defined nor described their profiles and the selection criteria of the sample of participants.

Table 12 – USC-HAD Dataset (ZHANG; SAWCHUK, 2012)

	Information
Year	2012
Perspective	Body-Worn Sensor Network
Link	http://sipi.usc.edu/had/
Participants	14 (7 male, 7 females), age range between 21 and 49, height range 160-185 cm, and weight range 43-80 kg
Recognized Activities	Walking forward, left, and right; Going upstairs and downstairs, Jumping, Sitting, Standing, Sleeping, Elevator up and down
Sensors	3-axis accelerometer and 3-axis gyroscope
Sensors Position	Wearable sensor located on front right hip
Sampling Rate	100Hz

Table 13 – WISDM Dataset (KWAPISZ; WEISS; MOORE, 2011)

	Information
Year	2011
Perspective	Body-Worn Sensor Network
Link	http://www.cis.fordham.edu/wisdm/
Participants	29
Recognized Activities	Walking, Jogging, Upstairs, Downstairs, Sitting, Standing
Sensors	3-axis accelerometer
Sensors Position	Wearable sensor located on front pants pocket
Sampling Rate	20Hz

3.3.4.9 mHealth Dataset

The mHealth collected dataset comprises body motion and vital signs recordings for 10 volunteers while performing 12 physical activities (BANOS *et al.*, 2014). The profile of volunteers is not described.

In Table 14, it is possible to observe the activities' data provided by this dataset. In the same way that the WARD dataset is considered intrusive and doesn't provide an ubiquitous user experience due to the position of sensors on body, the same situation happens to the mHealth dataset. The sensors were respectively placed on the subject's chest, right wrist and left ankle and attached by using elastic straps. In spite of the intrusive user experience, the use of multiple sensors permits us to measure the motion experienced by diverse body parts, thus better capturing the body dynamics.

Table 14 – mHealth Dataset (BANOS *et al.*, 2014)

	Information
Year	2014
Perspective	Body-Worn Sensor Network
Link	http://archive.ics.uci.edu/ml/datasets/mhealth+dataset
Participants	10 – the profile of participants is not defined
Recognized Activities	Standing still (1 min), Sitting and relaxing (1 min), Lying down, Walking (1 min), Climbing stairs (1 min), Waist bends forward (20x), Frontal elevation of arms (20x), Knees bending (crouching) (20x), Cycling (1 min), Jogging (1 min), Running (1 min), Jump front and back (20x)
Sensors	3-axis accelerometer, gyroscope, magnetometer
Sensors Position	Sensors placed on the subject's chest, right wrist and left ankle
Sampling Rate	50Hz

3.3.4.10 MobiAct Dataset

MobiAct is a dataset for HAR systems having the highest number of participants – 57 volunteers (42 men and 15 women), age between 20 and 47, height ranged from 160 to 189 cm and the weight is between 50 and 120 kg. Although the profiles of participants are different, it doesn't include the elderly among them.

Table 15 – MobiAct Dataset (VAVOULAS *et al.*, 2016)

	Information
Year	2016
Perspective	Body-Worn Sensor Network
Link	http://www.bmi.teicrete.gr/
Participants	57 subjects (42 men and 15 women) were recorded while performing the predefined activities. The subjects' age spanned between 20 and 47 years (average: 26), the height ranged from 160 cm to 189 cm (average: 175), and the weight varied from 50 kg to 120 kg (average: 76)
Recognized Activities	Falls, Standing, Standing with subtle movements, Walking, Jogging, Jumping, Stairs up, Stairs down, Sit chair, Car step in, Car step out
Sensors	Data were recorded from the accelerometer, gyroscope and orientation sensors of a Samsung Galaxy S3 smartphone with the LSM330DLC inertial module (3-axis accelerometer and 3-axis gyroscope)
Sensors Position	Trousers' pocket
Sampling Rate	200Hz

3.3.4.11 DaLiAc Dataset

At last, DaLiAc dataset also has a wide variety of participants, with different gender, age, weight and height. Although, as happened to MobiAct dataset, it doesn't consider the elder population. Table 16 shows that DaLiAc provides data from the activities related to mobility and transportation, such as sitting, lying, walking, cycling, among others. In the same way that MIT PlaceLab, WARD and mHealth datasets place multiple body-worn sensors, in DaLiAc there are four spots in volunteers' body where the sensor nodes are placed. This approach can increase the performance of the recognition process, but it usually provides an uncomfortable and intrusive user experience.

Table 16 – DaLiAc Dataset (LEUTHEUSER; SCHULDHAUS; ESKOFIER, 2013)

	Information
Year	2013
Perspective	Body-Worn Sensor Network
Link	https://www.mad.tf.fau.de/research/activitynet/daliac-daily-life-activities/
Participants	19 subjects (8 female and 11 male, age 26 ± 8 years, height 177 ± 11 cm, weight 75.2 ± 14.2 kg)
Recognized Activities	Sitting, Lying, Standing, Washing dishes, Vacuuming, Sweeping, Walking outside, Ascending stairs, Descending stairs, Treadmill running, Bicycling, Rope jumping
Sensors	Four SHIMMER (Shimmer Research, Dublin, Ireland) sensors were used for data acquisition. Each sensor node was equipped with a 3-axis accelerometer and a 3-axis gyroscope
Sensors Position	Four sensor nodes were placed on right hip, chest, right wrist and left ankle
Sampling Rate	200Hz

Therefore, in the context of the increasing aging population, these 12 datasets show that the HAR systems designed in the literature consider the elderly as common end-users and they don't achieve improvements in the elderly user experience. The main reason is that the researchers don't focus on older people and don't consider the requirements for this audience. For example, between 12 public databases specific for HAR system, only one includes data from people over 60 years old (WARD dataset). In spite of this, WARD dataset has an intrusive approach, with multiple body-worn devices. Thus, it is possible to observe that even considering the elderly as main users, the HAR systems aren't entirely designed for this audience. Not having a good user experience for the elderly may lead to usability and acceptance issues of the HAR system.

3.3.5 Contexts in which HAR systems are applied

Regarding the context that HAR systems are applied, two questions are usually raised:

1. How are HAR systems designed to the elderly usually approached?
2. When are HAR systems designed to the elderly usually approached?

How are HAR systems designed to the elderly usually approached?

According to the selected articles, HAR systems aim to provide mainly elderly-care services, such as the elderly monitoring and surveillance, the prevention of diseases and abnormal behaviors, falls detection, among others that focus on the improvement of elderly quality of life and their independence.

Some HAR systems designed for the elderly are applied to prevent diseases and abnormal behaviors, like the works related by Cherian *et al.* (2017) and Zhao *et al.* (2014) respectively. In the first one, the HAR system checks if the older person performs in a proper frequency the personal care activities, such as brushing teeth. The personal hygiene habits, when performed

adequately, may prevent from health problems and serious diseases, from periodontal disease to heart problems and pancreatic cancer. In the second one, HAR system is responsible for checking abnormal patterns of the elderly activities, in order to reduce the potential risks associated with physically and cognitively impaired ability of the elderly living alone.

The work described by [Janjua, Riboni and Bettini \(2016\)](#) is also an example of HAR system applied for prevention. This system checks for abnormal behavior performed by the user, aiming to detect initial symptoms of cognitive and memory impairment. In other hand, the HAR system proposed by [Sansrimahachai and Toahchoodee \(2016\)](#) follows the user's activities, trying to identify immobility situations and/or detecting early the mobility limitation of the elderly.

Besides that, HAR systems centered on the elderly can also provide the functionality of monitoring elderly, who have some disease, following the symptoms and reporting them to health and gerontology professionals. For example, the paper related by [Fareed \(2015\)](#) proposes multiple sensor fusion, in order to monitor the activities, and provides an adequate diagnosis to a person who suffers from cardiac insufficiency. The study presented by [Capela, Lemaire and Baddour \(2015\)](#) also introduces the monitoring of stroke patients, aiming to follow her/his vital signals and to provide the ideal diagnosis.

Another purpose of HAR systems centered on the elderly user is to provide an independent life, without the need for constant care of relatives and/or caregivers. Through the remote monitoring of the patient's health and behaviors by health and gerontology professionals, HAR systems contribute with significant improvements in the quality of life of the elderly ([MORALES; AKOPIAN, 2017](#)).

Although all these contexts are important, few studies use data collected from the elderly volunteers, as can be seen in Section 3.3.4. Therefore, it is necessary to design and develop Human Activity Recognition systems centered on the elderly user. Thus, HAR systems designed to the elder population must also consider privacy concerns. [Chernbumroong et al. \(2013\)](#), among others researchers, recommend the use of non-intrusive systems in the life of the elderly, e.g. avoiding the monitoring using cameras and microphones. Another concern that elderly users usually have is about the sharing of personal information. For that, the study must ask for the elderly and their relatives permission in order to share or make the data collected available.

When are HAR systems designed to the elderly usually approached?

Observing the selected articles and the Figure 4 (page 41), it is possible to notice that the HAR studies increased significantly in number from 2007 on. With the increasing life expectancy of the global population and the aging process, there is a concern about how the quality of life of the elderly will be in the future, and how the dependent elder people will be handled ([NATIONS; DESA, 2017](#)).

Considering this, HAR systems have become an attractive application to provide better quality

of life and independence to elderly through technology and assistive ambient. In spite of this, few HAR articles are, in fact, focused and/or centered on the elderly user. This situation can affect the elderly user experience of the HAR system, thinking about the acceptance and usability issues of the HAR application.

The public databases for HAR systems actually don't consider elderly users (Intille *et al.* (2005), Yang *et al.* (2009), Torre *et al.* (2008), Roggen *et al.* (2010), Zhang and Sawchuk (2012), Kwapisz, Weiss and Moore (2011), Kasteren *et al.* (2008), Cook *et al.* (2013), Singla, Cook and Schmitter-Edgecombe (2010), Banos *et al.* (2014), Vavoulas *et al.* (2016), Leutheuser, Schuldhaus and Eskofier (2013)). In this way, it doesn't motivate studies centered on the elderly in Human Activity Recognition research field, not presenting improvements and contributions to the area.

From this time, it is necessary to establish an Elderly Activity Recognition research field, in order to have more real and relevant contributions to HAR systems centered on the elderly users, because, more than never, systems that provide elderly assistance and monitoring will have high demands in the future. The technology and the computing, together with gerontology, can contribute in a constructive and relevant way for better quality of life of the elderly.

3.4 Final Considerations

By means of the systematic review of the literature, it was possible to answer the research questions and raise the state-of-art of Human Activity Recognition systems designed for the elderly. In this way, through the selected works, HAR systems applied for the older population were mapped, described and the main points were highlighted, such as the sensors and algorithms used, the accuracy and the activities recognized by the literature.

Although, thinking about the aging population process and the increasing demand of applications focused on the elderly, many HAR systems use this audience as an excuse exclusively, in order to justify the importance of their application, not worrying about the requirements and the real necessity of the elderly users. Few works bother about it and grab the responsibility of considering the elderly well-being.

Therefore, there is an increasing necessity of computational applications for assistive ambient, whose demand can be supplied by HAR systems applications centered on the elderly user. The availability of a public databases with data collected from the elderly volunteers would be a relevant contribution to Human Activity Recognition research field. These databases can work as an evaluation benchmark of HAR systems centered on the elder users, resulting in improvements and evolution of these systems.

AN ELDERLY ACTIVITY RECOGNITION SYSTEM

In this chapter, a proposal of Elderly Activity Recognition System (EARS) is presented. A HAR system entirely focused and centered on the elderly was designed. For this, literature review and studies analysis were performed by the researcher, in order to afford an appropriate HAR architecture for the elderly, considering requirements of usability and acceptance. In the following sections, the methodology of the research, the architecture and the database are presented and described.

4.1 Elderly centered Human Activity Recognition system

The increasing number of elder people and the lack of infrastructure to provide quality of life and independence of the elderly have motivated progressively the interdisciplinary studies and researches between two areas: computing and gerontology. In this context, Human Activity Recognition systems present important and great applicability.

Human Activity Recognition systems propose an architecture including wearable and mobile devices, basing on the concepts of Ubiquitous Computing and Internet of Things, and aiming to monitor and follow, in a non-intrusive way, the user and the activities performed by her/him.

Briefly, HAR systems are important to elderly care applications, because they have a lot of utility and applicability, solving common problems in the elderly daily living, for example:

- fall detection;
- elderly daily routine monitoring;
- abnormal behaviors detection;
- early detection of cognitive and memory impairments, facilitating the treatment in early states;

- following the mobility capacity of the elderly;
- assisting and supporting the elderly with mobility problems or with some problems due to any clinical condition, such as stroke patients;
- among others.

Then it is possible to notice that HAR systems centered on the elderly user are very important and present great contributions for supportive technologies in Gerontology area. Although, as can be seen in Section 2.4.1 (page 35), most of the studies only use the elderly as motivation, not really focusing on the elderly user experience.

Considering this, HAR systems for the elderly, that don't really center all the requirements on this audience, present issues with performance, accuracy, acceptance and usability (CHERNBUMROONG *et al.*, 2013). Hence, it is necessary to establish requirements and guidelines for the development of a HAR system centered on the elderly user.

4.1.1 Study methodology

First of all, it was performed the literature analysis, looking for the best practice of supportive technologies and focusing on Human Activity Recognition systems centered on the elderly. For this, the author has read all the selected papers and summarized the main concerns and best practices that should be considered and followed during the design of an Elderly Activity Recognition system. The author also had the support and the advice of health and gerontology professionals during this process. These professionals are part of the research group headed by Professor Maria da Graça Campos Pimentel. Finally, in the Section 4.1.2, the guidelines for an Elderly Activity Recognition system is presented, highlighting the main points and concerns.

4.1.2 Guidelines for an Elderly Activity Recognition system

Besides the guidelines for the design of a HAR system, presented in Section 2.4.1 (page 35), there are specific requirements of the supportive technologies and their applications, in order to obtain accuracy and great performance, taking into account the user's acceptance and privacy, usability and the cost of the system (infrastructure and sensors) (CHERNBUMROONG *et al.*, 2013; RAFAEL-PALOU *et al.*, 2015; TARALDSEN *et al.*, 2012).

Figure 12 the main points that should be considered during the outline of a Human Activity Recognition system for elderly: the cost with sensors, devices and the application's infrastructure, the user acceptance and privacy, the usability and, at last, the accuracy of the system (RAFAEL-PALOU *et al.*, 2015; TARALDSEN *et al.*, 2012; MAHITHA *et al.*, 2017).

4.1.2.1 Cost

To project and develop systems and application of Human Activity Recognition, in general, the computational, power and financial cost must be considered. The financial cost is related to the

Figure 12 – Main Requirements for the design of an Elderly Activity Recognition system

Adapted from Chernbumroong *et al.* (2013)

number of mobile and wearable devices used in the application. For a HAR system, there are two HAR architecture perspectives: Smart-home and Body-Worn Sensor Network (Section 3.3.3). The smart-home perspective is more expensive than the body-worn sensor network approach, because the first one needs more devices spread around the environment in order to have a good performance. In the perspective of body-worn sensors, usually they are embedded into wearable pieces, normally worn in the daily routine, such as watches, cellphones, earrings, among others. Both perspectives aim to be less intrusive as possible, although the smart-home approach demands more number of sensors and devices, consequently increasing the cost and the difficult of implementation and reproducibility for the test, evaluation and maintenance of the HAR system applied in the AAL. About the power consumption, it is related to the energetic self-sufficiency of the sensors and devices used. Solutions and applications must have a balanced energy consumption, without compromise the services provided by the system and their performance.

From the standpoint of computational cost, it is directly related to the system's architecture and its feature extraction and classification algorithms used to recognize the activities. It is also a good practice to note the processing platform, which resources are available, if they are enough to provide the desired performance of the system.

4.1.2.2 Acceptance

The proposal of a system that aims to recognize the activities the elderly perform is extremely attractive to health area due to its applicability and importance. Human Activity Recognition systems applied to gerontology area can influence in a constructive and positive way the quality

of life of the elderly, not to mention the independence.

However, all these advantages and applicability don't make sense if the system is not used neither accepted by the elder user. Hence, it is necessary that HAR systems present the usability and acceptance by the elderly audience. But how is it possible to guarantee these features for the EARS?

According to [Chernbumroong et al. \(2013\)](#), the selected devices and sensors must be wearable, unobtrusive and non-intrusive in the elders life. In this way, HAR systems centered on the elderly can establish the monitoring process in a ubiquitous way, ideally without interfering in the user's life, and being present and pervasive in daily routine of the elderly.

The study presented by [Kanis et al. \(2011\)](#) conducted interviews with elderly users about supportive and monitoring ambient, in order to define the requirements and guidelines for this kind of systems. Some of the questions are: What activities would the elderly users like to be monitored? With whom could the information be shared? How should monitoring systems be designed?

Most of the elderly were aware of the monitoring and supportive ambient and didn't enjoy the idea of the monitoring process using cameras and microphones, they consider the audio and video recording very invasive and worry about their privacy. Besides that, the elder people judge the supportive ambient necessary and very useful, because it can provide reminders to take medicine, identification of the motion and recognition of abnormal situations, such as mobility issues, falls and heart attacks. Regarding the privacy and the information sharing issues, the elderly feel comfortable only with sharing their information strictly with health and gerontology professionals and relatives.

Therefore, it is possible to conclude that the design of Human Activity Recognition system should be entirely focused on the elderly, in order to have a great acceptance of the application. The end users must be involved during all the development process of the supportive systems, taking into account their values, requirements, and opinions. In this way, applying the participatory design of HAR systems, it will be possible the creation of technologies more useful, appropriated for the target audience, and, therefore, having acceptance and usability by the elder users.

4.1.2.3 Privacy

The privacy of the Human Activity Recognition systems focused on the elderly users is closely related to the acceptance and usability of the application by older users. Thus, the privacy, well-being, and confidence of the elderly must be considered in the design of monitoring and supportive systems.

As addressed by the researchers [Kanis et al. \(2011\)](#), the elderly care about their privacy in the AAL through cameras and microphones. They don't feel comfortable with the idea of being monitored through videos and audios. The HAR system for elder users proposed by [Sebestyen,](#)

[Stoica and Hangan \(2016\)](#) also considers the user's intimacy, not being invasive and not violating the private life of the elderly. For it, cameras and audio recorders weren't used and applied in the HAR system. HAR systems must detect and monitor the activities without invasive procedures and not collecting personal data.

In order to establish a Human Activity Recognition system specific for the elderly, applying an elder user-centered approach, cameras, microphones, video and audio recorders must be avoided in the data collection process and the data storage. Therefore, the priority of a HAR system is to guarantee the well-being and trust of the elderly, providing the privacy of the users.

4.1.2.4 Accuracy

The accuracy of Human Activity Recognition systems for the elder users is the resulting of several choices made during the design process: the sensors and devices used, processing platforms defined, feature extraction and classification algorithms and, at last, the database used for the system training.

All these questions, when inadequately defined, can compromise the accuracy of the whole solution and, consequently, cause the rejection of the HAR system as a supportive application for the elderly. So that this does not happen, it is necessary to define sensors and devices that don't include high cost to the system, guarantee the privacy and the acceptance of the system, and, at last, provide the desired data, in order to recognize the activity effectively. Concerning the processing platform, it should have the enough computational power and resources to not compromise the performance of the HAR system, however, this should not mean the increasing of costs.

The feature extraction and classification algorithms are also very important for the evaluation of the system's accuracy. They shouldn't present a computational consumption higher than the processing platform's capacity and must be sufficiently efficient and effective to provide the best accuracy to the HAR system. The data used in the HAR system's training are also fundamental to guarantee the accuracy, hence the wrong choice of a dataset that doesn't match appropriately the devices used can bring serious accuracy issues. Besides that, a dataset that represents all the end users of the HAR system must be selected, in order to have HAR system centered on the target audience and, consequently, having the best recognition performance.

Therefore, the accuracy is an example of trade-off questions. The best scenario must be decided and defined in order to obtain an Elderly Activity Recognition system not only with acceptance and usability but also having affordable costs and respect for the privacy issues raised by the elderly, at last guaranteeing the appropriated performance.

Figure 13 – Four basis to have an EARS

Source: Elaborated by the author.

4.1.2.5 Elderly Activity Recognition System

In summary, the combination of these four points – acceptance, cost, accuracy and privacy – may provide to the elderly users a great user experience. As can be seen in Figure 13, the central area of the diagram represents the best scenario for EARSs, optimizing the four points that must be considered during the design of this kind of applications involving supportive technology.

4.2 EARDB: Database for Elderly Activity Recognition

Another important point raised in the Section 3.3.4 (page 52) is that most of the public databases for HAR systems don't provide any data from the elderly. For example, between 12 public databases specific for HAR system, only one includes data from people over 60 years old (WARD dataset). Although, WARD dataset doesn't follow the guidelines presented early in Section 4.1.2, having an intrusive approach, with multiple body-worn devices.

Considering this, in order to have the representation of the elderly in Human Activity Recognition systems, the author has performed a data collection of the elderly volunteers and provided the Elderly Activity Recognition Database (EARDB). In the next sections, it will be introduce the procedures, methodology and characteristics of the volunteers during the data collection, as well as the technological infrastructure.

4.2.1 Methodology

In order to design an Elderly Activity Recognition System, a database for HAR systems consisting of data from the daily activities of the elderly is needed. For it, some methodologies were established to recruit the elder volunteers, to define the mobility tests protocols and to collect the data.

4.2.1.1 Academic Partnership

First of all, the author was supported by health professionals in the academic environment:

- Professor Ruth Caldeira de Melo: lecturer in the Gerontology course at School of Arts, Sciences and Humanities – University of São Paulo. Professor de Melo has supported the author establishing the mobility tests protocols, in order to collect data from the elder volunteers, avoiding the fatigue and discomfort. She has also helped the author defining the daily activities that an Elderly Activity Recognition system should identify.
- Gerontologist Brunella Della Maggiori Orlandi: graduated in Gerontology – Federal University of São Carlos. She has supported the author during all the data collection process, guiding the elderly in the execution of the activities composing the motion protocols.

4.2.1.2 Ethics Committee

In order to recruit elderly volunteers, the project was submitted to the Brazilian Ethics Committee, the process of research project is described below:

- **Project Type:** P - Project of Coordinating Center (in portuguese, *Projeto de Centro Coordenador*);
- **Certificate of Presentation for Ethical Appreciation, in portuguese *Certificado de Apresentação para Apreciação Ética* (CAAE):** 57875016.3.0000.5390;
- **Responsible Researcher:** Isabela Zaine ¹;
- **Ethics Committee:** School of Arts, Sciences and Humanities, in portuguese *Escola de Artes, Ciências e Humanidades* (EACH) from University of São Paulo (USP)

The Term of Free and Clarified Consent, in portuguese *Termo de Consentimento Livre e Esclarecido* (TCLE) of the elder volunteer and the survey are shown in [Appendix B](#).

4.2.1.3 Elderly Daily Activities

In second place, it was necessary to define the activities that should be recognized by the EARS. In order to build a database base on the elderly daily activities, with the support of the health professionals, the author has defined the activities considering the public databases presented in Section 3.3.4 (page 52).

¹ More information in <http://lattes.cnpq.br/0665572503019533>

The author focused on ambulation activities (Section 3.3.2, page 45) and the main goal is to provide a public database only with data collected from elder volunteers, basing on existing public databases – WISDM (KWAPISZ; WEISS; MOORE, 2011) (Table 13 - page 57) and MobiAct (VAVOULAS *et al.*, 2016) (Table 15 - page 58). The selected daily activities is listed below:

- Standing
- Sitting
- Walking
- Going Upstairs
- Going Downstairs
- Running – the health professionals included it, just in case of elderly that have the habit of running, but they don't advise collecting data from elder volunteers that aren't used to run.
- Transition states: Sitting-to-Standing and Standing-to-Sitting.

Therefore, with an elderly-specific database, it is possible to train supervised machine learning algorithms and, at last, have a Human Activity Recognition system centered on the elderly.

4.2.1.4 Mobility Tests Protocols

With the support of health professionals, in special Professor de Melo's guidance, the author defined four Mobility Tests Protocols to collect the motion data from the elderly activities. These protocols are important because they establish a pattern during the data collection process, avoiding noises and inappropriate motions (FONTECHA *et al.*, 2013).

Four Mobility Tests Protocols were used to collect the motion data from the elderly and are described below:

- **Timed Up & Go (TUG):** the TUG assesses basic mobility skills as well as strength, balance, and agility. The TUG test consists on the following sequence of motions: to rise from sitting in a chair, walk 3 meters, turn, walk back to the chair, then sit down using regular footwear and a walking aid if required (BENNELL; DOBSON; HINMAN, 2011).
- **30 second Chair Stand Test (30CST):** the 30CST assesses to be performed for evaluating physical fitness in elderly. The subject is asked to stand up and sit down on the chair as fast as possible during a 30 seconds period (KATO *et al.*, 2014).
- **Self-Paced Walk Test (SPWT):** the SPWT assesses the time it takes to walk short distances (usually up to 50 meters). Different distances have been reported for the SPWT, e.g. 6 meters, 13 meters, or 40 meters. The SPWT is used to evaluate problems such as hip and knee osteoarthritis, rheumatoid arthritis, and also the mobility of older adults and children. Individuals are asked to walk quickly and safety without overexerting themselves, no matter how long it takes, time is recorded in seconds (BENNELL; DOBSON; HINMAN, 2011).

- **Timed Up and Down Stairs (TUDS):** the TUDS assesses the functional mobility of a person, also contributes to the control of posture. The subject is asked to stand 30 cm from the bottom of a 14-step stairs. The participant is instructed to go up stairs quickly, but safely, turn around on the top step (landing) and come all the way down until both feet land on the bottom step (landing). There are some variations of this test, the number of steps can change according to the stairs' availability (NICOLINI-PANISSON; DONADIO, 2013).

The Mobility Tests Protocols above were used in order to establish a pattern during the data collection, although they were in some situations adapted for the purpose of the work, Table 17 shows all the needed adaptations. Beyond that, in order to collect data from the standing and sitting activities, the author and the health professional asked the subjects to stand up for 1 minute period, and then to sit for 1 minute.

Table 17 – Mobility Tests Protocols

	Information
TUG	The subjects were instructed to perform this test as many times as needed to complete 2 minute period
30CST	The subjects were instructed to perform this test two times, in order to complete 1 minute period
SPWT	The subjects were instructed to walk the distance of 50 meters
TUDS	The subjects were instructed to perform this test as many time as needed to complete 1 minute period
Standing	The subjects were instructed to stand for 1 minute period
Sitting	The subjects were instructed to sit for 1 minute period

All the Mobility Tests Protocols were conducted by the gerontologist. The volunteers were instructed to perform the activities in a safe and comfortable way. All the data was collected by the author using the **Move It** application described in Section 4.2.3.

4.2.1.5 Recruiting Process

The recruiting process was performed in the community surrounding the University of São Paulo, campus São Carlos. Normally the elderly selected always visit the campus, are volunteers in others research projects or work at the University. It was desired a heterogeneous group, trying to reach several profiles, different genders, a wide range of age, healthy and in-care elderly without mobility impairment. In order to successfully select a wide range of volunteers, the University of São Paulo and Professor Maria da Graça Campos Pimentel helped with the communication process. Both disclosed several informative and recruiting e-mails and used the University's connections and projects to achieve a heterogeneous group of elderly.

The profile of volunteers desired is:

- Brazilian people older than or equal to 60 years ²
- Equal numbers of men and women
- Wide range of age
- Health or in-care elderly without mobility impairment

4.2.1.6 Wearable Device's Position

The volunteers were asked to wear the smartwatch on their right hand. Figure 14 shows how the elderly wore the wearable device.

Figure 14 – The volunteers wore the Smartwatch on their right hand

Source: Elaborated by the author.

4.2.1.7 Data Collection Process

After the recruiting process, 32 elder volunteers were selected and interviewed. The Move It application (Section 4.2.3 - page 83) was very important to collect and save the data. The data collection process took one week and was performed by the author and the gerontologist Brunella Della Maggiori Orlandi.

After selecting all the volunteers, the author scheduled an individual meeting with each of them. The meeting was programmed to take only one hour. First the individuals were interviewed by the author, answering questions about their health, physiological factors, personal perception of

² In Brazil, the definition of the elderly is a person older than or equal to 60 years old. This information can be accessed in http://www.planalto.gov.br/ccivil_03/LEIS/2003/L10.741.htm

their quality of life, their weight and height, as well their address, phone number, among other information. The interview was performed in Brazilian portuguese and the details can be seen in the Apendice –

The academic environment was prepared to execute the four Mobility Tests Protocols described early. A balance, an armless chair, a 28-step stairs with handrail and a 50 meters corridor were used with all volunteers. The sequence of the Mobility Tests Protocols and activities is highlighted below:

1. **TUG:** an armless chair was positioned in a way that the volunteer can stand up, walk for 3 meters, walk back and then sit again. In this protocol, the following activities were recorded: Sitting-to-Standing, Standing-to-Sitting, Walking and Sitting. The volunteers were asked to perform the TUG protocols as many time as needed to complete 1 minute period.
2. **Standing and Sitting:** the volunteers were requested to standing still for 1 minute period and then sitting still for another 1 minute period. The activities recorded here were Standing and Sitting.
3. **30CST:** with an armless chair, the volunteers were required to perform this protocol 2 times, consisting of 1 minute recording the following activities: Sitting, Standing, Sitting-to-Standing and Standing-to-Sitting.
4. **SPWT:** the volunteers were asked to walk safely and quickly through the 50 meters corridor, always respecting their mobility capacity, without overexerting themselves, no matter how long it takes. With this protocol, it was possible to record the Walking activity.
5. **TUDS:** in a 28-step stair with handrail, the volunteers were asked to go up and down the stairs as many times as needed to complete 1 minute period. They were advised to only use the handrails in case of necessity, even so, they must use the handrail on the opposite side of the smartwatch.

During all the data collection, the author and the gerontologist followed the volunteers and guided them through the tests. Any question or discomfort that they may have, they were oriented to ask or stop the activities and tests.

4.2.2 Volunteers

The volunteers selected for the data collection are Brazilian people older than or equal to 60 years old. The selection process was performed in the community surrounding the University of São Paulo, in the city of São Carlos. It was desired a heterogeneous group, trying to reach several profiles, different genders, a wide range of age, healthy and in-care elderly. At last, 32 elder volunteers were selected and interviewed. Following the elderly group selected will be described.

4.2.2.1 Gender

It was possible to recruit 32 elder volunteers in the community, 15 women and 17 men, corresponding to 46.90% and 53.12%, respectively. The gender proportion can be seen in Figure 15 and provides a great representation of both of them.

Figure 15 – Volunteers' Gender

Source: Elaborated by the author.

4.2.2.2 Age

Among the 32 elder volunteers in the community, the range of age is between 60 and 75 years old. The average age is 67 years old. Considering only the women, the range of age is between 61 and 73 years old. The female average age is also 67 years old. Only looking at the male part, the range of age is between 60 and 75 years old. The male average age is 66 years old. All this information can be seen in Table 18.

Table 18 – Volunteers' Age

	Average	Minimum	Maximum	Mode
All	67	60	75	68
Female	67	61	73	69
Male	66	60	75	68

4.2.2.3 Education

About 56.30% of the volunteers have concluded a college degree. Almost half of the volunteers have only the basic education. Figure 16 shows this education proportion among the 32 elder volunteers. For this population, the number of older people that has a college degree is high, considering it in Brazil.

Volunteers' Education

Figure 16 – Volunteers' Education

Source: Elaborated by the author.

4.2.2.4 Height and Weight

All the 32 volunteers were measured and weighed. The range of height in all of them is between 1.49 and 1.82 meters, the average height is 1.68 meters. In Table 19, it is possible to see that men are higher than women and the height variation of the volunteers.

Table 19 – Volunteers' Height

	Average (meters)	Minimum (meters)	Maximum (meters)
All	1.68	1.49	1.82
Female	1.60	1.49	1.70
Male	1.72	1.65	1.82

Regarding the weight, Table 20 shows the weight range between all the volunteers. In general, the average weight is 82.10 kg and the range of range is between 38.60 and 118.10 kg. As common sense, women are lighter than men. Following, it is presented the Body Mass Index (BMI).

Table 20 – Volunteers' Weight

	Average (kg)	Minimum (kg)	Maximum (kg)
All	82.10	38.60	118.10
Female	72.80	38.60	96.00
Male	90.30	62.90	118.10

4.2.2.5 Body Mass Index

Body Mass Index, or BMI, is used to determine whether you are in a healthy weight range for your height. BMI compares your weight to your height, and is calculated by dividing your weight (in kilograms) by your height (in square meters). It categorizes the person in 'underweight', 'normal weight', 'overweight' and 'obesity'. BMI is one type of tool to help health professionals assess the risk for chronic disease.

Figure 17 – BMI Category of the Volunteers

Source: Elaborated by the author.

Figure 18 – Percentage of the Volunteers per BMI Category

Source: Elaborated by the author.

Figures 17 and 18 show that most of the elderly are categorized in obesity state and circa 1/3 of the volunteers are in overweight. This is a very alarming situation, since the elderly must always be aware of their health state.

4.2.2.6 Alcohol Consumption and Smoking

The consumption of alcoholic drinks among the 32 elderly are not a habit, more than half of the volunteers declare they don't consume alcoholic beverages. Figure 19 shows that 43.80% of

the elderly drink alcohol. In Figure 20, it is possible to see that only 14.30% of the elderly that consume alcohol drink it everyday.

Figure 19 – Alcohol Consumption

Source: Elaborated by the author.

Figure 20 – Frequency of Alcohol Consumption

Source: Elaborated by the author.

Only 12.50% of the elder volunteers are smokers and they declare the desire to stop smoking. Figure 21 shows the percentage of smokers among the elderly.

Figure 21 – Percentage of Smokers among the Volunteers

Source: Elaborated by the author.

4.2.2.7 Physical Activities

The practice of physical activities is important to prevent diseases and heart problems and also to improve physiological index, such as cholesterol and triglyceride rates and glycemic index world2003health. Among the 32 volunteers, 65.60% declare to practice physical activities, as can be observed in Figure 22. Among them, only 4.80% say that do physical activities everyday,.

Figure 22 – Percentage of Volunteers that practice Physical Activities

Source: Elaborated by the author.

Figure 23 – Frequency of the Practice of Physical Activities

Source: Elaborated by the author.

Figure 23 shows the percentage of the elderly that practice physical activities and their frequency.

4.2.2.8 *Physiological indexes and common Health Problems*

Cholesterol and triglyceride rates, blood pressure, sugar level and cardiac evaluation are some common routine exams that every elder person must do. Considering the 32 elder volunteers, Figure 24 shows the percentage of volunteers having abnormal indexes among the cited above. It is possible to notice that the most common health problems are high cholesterol rate and hypertension.

Figure 24 – Percentage of volunteers with abnormal physiological indexes

Source: Elaborated by the author.

Figure 25 – Percentage of volunteers with Difficulty when they move

Source: Elaborated by the author.

Figure 26 – Part of the Body that usually the volunteers feel pain and difficulty when they move

Source: Elaborated by the author.

4.2.2.9 Mobility

Regarding the mobility, Figure 25 shows that 9 elder people (28.10%) feel pain when they are moving. Among them, they declare to feel pain on the knee, back, legs, hips and feet. Figure 26 shows the most common part of the body where volunteers who have difficulty of moving feel pain. Most of the them say they have fragility in the knee, feeling discomfort when moving.

4.2.2.10 Satisfaction with Life and Quality of Life

All the 32 volunteers answered questions about their satisfaction with their health and also about the quality of life. The definition of quality of life involves how an individual measures and evaluates the 'goodness' of multiple aspects of their life. There evaluations include the person's emotional reactions to life occurrences, disposition, sense of life fulfilment, work and personal relationships (THEOFILOU, 2013). The term 'quality of life' is frequently referred to well-being

Figure 27 – Evaluation of Satisfaction with Health

Source: Elaborated by the author.

Figure 28 – Evaluation of Quality of Life

Source: Elaborated by the author.

of the individual.

In order to measure the volunteers sense of their quality of life, they have to answer two questions:

- Are you happy/satisfied with your health?
- Are you happy/satisfied with your quality of life?

They are yes-or-no questions, followed by quantifying question. The volunteers had to classify their satisfaction with their health and their quality of life into a range of 1 to 10. Figures 27 and 28 show the answers of the 32 volunteers. Regarding the satisfaction with health, all the volunteers, that have answered Yes to the question, presented a range of evaluation between 6 and 9, the average answer is 7.96. In other hand, the volunteers that have answered No for the same question presented a range of evaluation between 4 and 7, the average answer is 6. Thus, in general, the elderly are satisfied with their health. Figures 29 and 30 shows the frequency of the notes for the volunteers' satisfaction with health.

Figure 29 – Yes-Answer: Note for Satisfaction with Health

Source: Elaborated by the author.

Figure 30 – No-Answer: Note for Satisfaction with Health

Source: Elaborated by the author.

Considering now only the quality of life, all the volunteers, that have a positive answer, presented a range of evaluation between 6 and 10, the average answer is 8.24. In other hand, only 3 volunteers aren't satisfied with their quality of life, evaluating it as 5. Figure 31 shows the Yes-answers and the volunteers' quality of life evaluation.

Therefore, most of the elderly are living happily and satisfied with their life and health, although the common health problems and natural pains of the aging process.

4.2.2.11 Volunteers' Profile

Observing all the information presented above, it is possible to notice that the volunteers can represent healthy and independent elderly. Some of them have locomotion issues (e.g. reduced movement speed, musculoskeletal disorders) but they don't interfere in their moving abilities, they can live independently even with their pains.

Figure 31 – Yes-Answer: Note for Satisfaction with Quality of Life

Source: Elaborated by the author.

Another point is: some of them support each other in daily living activities. The author has interviewed some siblings and married couples that live together and help each other in the difficulties due to the aging process.

Summarizing briefly, there is a good proportion of men and women, which is practically the same. The range of age is wide, varying between 60 and 75 years old. More than half of volunteers have a high level of education. The height and weight are diverse, but most of them are obese and overweight – which is something that demands attention.

In general, they don't have an exaggerated lifestyle, most of them don't drink alcohol and don't smoke. More than half of the volunteers practice physical activities 3 days a week and complain only about common issues in the aging process. At last, they are happy with their life and health.

4.2.3 Data Collector Application

In this section, the data collector application used to build the EARDB is presented. First of all, the name of the application is **Move It**. It is an Android application developed by the author, that connects the smartphone and the smartwatch. There are two apps, one for the smartphone and the other for the smartwatch, both must be synchronized in order to communicate.

The Move It application provides a handheld solution to create databases collecting data from the users' motion. On it, the researcher can add projects and manager all the activities and volunteers. It is generic application to create databases for Human Activity Recognition systems, using accelerometer and gyroscope. Figure 32 show the logo of the Move It application. This application will be publish in the Google Play Store ³.

This smartphone application present this functions:

³ Access the Google Play Store here: <https://play.google.com/store>

Figure 32 – Logo of the Move It application

Source: Elaborated by the author.

- **Add Project:** the researcher can add the research project that she/he is involved. Figure 33 shows the sequence of screens of the adding project functionality.

Figure 33 – Move It: Sequence of screens of Adding a Research Project

Source: Elaborated by the author.

- **Add Activities:** the researcher can add how many activities as needed. This is the flexible part of the Move It. It doesn't have a set of predetermined activities. Figure 34 shows the sequence of screens when adding a new activity.

Figure 34 – Move It: Sequence of screens of Adding Activities to the Project

Source: Elaborated by the author.

- **Add Volunteers:** the researcher can add how many volunteers as needed to the research project. Figure 34 shows the sequence of screens when adding a new volunteer.

Figure 35 – Move It: Sequence of screens of Adding Volunteers to the Project

Source: Elaborated by the author.

- **Data Collection:** the researcher can control how long the data will be collect and also set the activity that the volunteer is performing at the moment. Figure 36 shows how the data is collected, using the Move It application.

Figure 37 – Move It: smartwatch app

Source: Elaborated by the author.

Figure 36 – Move It: Sequence of screens of Collecting the data of a specific Activity

Source: Elaborated by the author.

In Figure 37, it is the interface of the Move It app. This smartwatch version is controlled by the smartphone app. When the researcher starts collecting the data, a service is initialized on the smartwatch and the app pop up a notification, reporting the Move It status.

In summary, the Move It application is a very useful and applied tool. This tool integrating smartwatch and smartphone can motivate and encourage the construction of databases for Human Activity Recognition systems, including a big variety of volunteers' profiles. Besides that, researchers can use these new databases as benchmarks of HAR systems, that can provide future improvements in the HAR research area.

4.3 Architecture of the Elderly Activity Recognition System

To begin with, the architecture of an Elderly Activity Recognition System is presented considering the guidelines in Section 4.1.2. During all this section, all the decisions and definitions are based on the four points – acceptance, cost, accuracy and privacy – in order to achieve a great elder user experience. Others determinations of the systems, that aren't related to the elderly experience, are based on the literature review and the information extracted from the selected articles.

4.3.1 Wearable and Mobile Devices

Considering the guidelines, the chosen devices for the activity recognition were:

- **Smartphone or Tablet as processing platform:** the author has selected a smartphone or tablet with Android operating system. The reasons behind this choice were: the author has already worked with Android platform and the research group has several Android smartphones and tablets.
- **Smartwatch as collector device:** the smartwatch selected here was the LG Watch Urbane⁴. Figure 38 shows the wearable device with Android Operating System (OS). The main reasons for this choice were: it is wearable and fancy device, it isn't heavy and it is easily integrated with Android smartphones and tablets. The researcher doesn't have to build a communication protocol, the Android Software Development Kit (SDK) provides everything to turn the software development process easy.

Figure 38 – LG Watch Urbane – Android Operating System

Image from [LG \(2018\)](#)

⁴ It is possible to read more about the LG Watch Urbane in [LG \(2018\)](#).

Figure 39 – Position of the Body-Worn Device and Orientation of 3-axes Accelerometer

Source: Elaborated by the author.

Besides that, the fact of using a smartwatch as collector and monitoring device complies with the requirements proposed in Section 4.1.2. A watch is a common wearable object in the elderly daily living, making it non-intrusive nor annoying in the user's life and filling the requirements of acceptance and privacy, since there aren't any camera and microphones. The price of a smartwatch is not low as desired, but also not expensive as a smart-home approach can be. The Android OS also provides the resources management - optimizing the power consumption and the use of computational resources, without harming any services.

4.3.2 *Devices' Position and Sensors used*

According to the guidelines for an Elderly Activity Recognition system presented in Section 4.1.2, the device must be non-intrusive in people's life and have privacy safety. For it, the Body-Worn Sensor Network perspective (Section 3.3.3 – page 46) has advantages. Therefore, the author has define a smartwatch as body-worn device to be positioned on the right wrist of the user, as can be seen in Figure 39.

The sensor used to collect data from the activities performed by the elderly was the 3-axis accelerometer. Its orientation can also be seen in Figure 39. Because of performance purposes and the sampling rate provided by the Android Operating System, only the accelerometer sensor is used to recognize activities. Briefly, the main reason for it is: when the software developer configures a sampling rate in the Android application, using more then one sensor, the Android

OS shares this sampling rate among the sensor and decreases performance of the system.

Thus, in order to have a dedicated sampling rate to only one sensor and avoiding the decline of performance, the author chose only to work with accelerometers. Some of the articles in the literature reported HAR systems identifying activities only with accelerometer and they also presented good accuracy and performance (TARALDSEN *et al.*, 2012; CHATZAKI *et al.*, 2017; KOZINA *et al.*, 2013; FONTECHA *et al.*, 2013; CHIGATERI *et al.*, 2018; SONG; JANG; PARK, 2008).

4.3.3 Target Audience

As the profile of the elder volunteers defined in the Section 4.2.2, the EARS proposed in this work aims to have an supportive application for healthy and independent elderly. Some of them has locomotion issues, but they don't interfere in the elder volunteers' life and moving abilities, they still can live independently even with their pains. Section 4.2.2.11 summarized the profile of the recruited volunteers.

4.3.4 Elderly Activities and Behaviors

In order to design an EARS, the author had to investigate the daily activities performed by the elderly and that are interesting for health professionals to follow the activities of their patients. For it, the author was supported by two health professional described in Section 4.1. Besides that, the author also based the selection of the activities in the public database presented in Section 3.3.4 (page 52).

The author focused on the ambulation activities (Section 3.3.2, page 45) and relied on the existing public databases – WISDM (KWAPISZ; WEISS; MOORE, 2011) (Table 13 - page 57) and MobiAct (VAVOULAS *et al.*, 2016) (Table 15 - page 58). The selected daily activities are:

- Standing
- Sitting
- Walking
- Walking Upstairs
- Walking Downstairs
- Running – the health professionals included it, just in case of elderly that have the habit of running.
- Transition states: Sitting-to-Standing and Standing-to-Sitting.

Therefore, the EARS, for now, is able to recognize these 8 activities described above.

Figure 40 – Architecture of the Elderly Activity Recognition System

Source: Elaborated by the author.

4.3.5 *EARDB Dataset*

As asserted in Section 3.3.4 (page 52), even in the context of the increasing aging population, among 12 public datasets for HAR systems compiled by the author, only one includes data from people over 60 years old (WARD dataset). Although the WARD dataset provide data from the elderly, it has an intrusive approach with multiple body-worn devices.

Considering this, the EARS includes the EARDB – database collected and presented by the author in Section 4.2 (page 68), because it provides data from the daily activities of the elderly, has a non-intrusive perspective, only using one wrist-worn sensor, and consequently it is more appropriated for the aging process, allowing an elderly centered approach.

4.3.6 *Elderly Activity Recognition System*

EARS is a HAR system centered on the elderly, focusing on the user experience and the guidelines for a comfortable and unobtrusive supportive application. In order to achieve this goal, the author has established the guidelines for a Human Activity Recognition centered on the elderly (Section 4.1, page 63) and also a database collected from activities performed by the elderly (Section 4.2, page 68). With them, it is possible to design a Elderly Activity Recognition System.

The architecture of the EARS is based on the general architecture of HAR systems presented in Figure 1 (page 32), but also introduces some differences due to the guidelines for elder-care applications. Figure 40 shows the architecture of the EARS.

First of all, there is the collector device. In this case, it is the LG Watch Urbane⁵. Smartwatch is responsible for getting all the data and send it to the processing platform. This communication is done via Bluetooth, providing all the data needed to the activity recognition process.

The processing platform, in this work, is a smartphone. There isn't any model or brand defined, since the Android application of the EARS isn't model-specific. Considering this, the smartphone runs the classification algorithm to identify the activity based on the training database. The classification process can be seen in Figure 2 (page 33). The classification algorithm used and others system's specification are defined below.

After processing the data collected on the smartwatch, the smartphone provides the daily activities performed by the elder user to a server, which stores them as a life logging or a diary. This communication is done through Internet connection and the author uses the Amazon Simple Storage Service (Amazon S3)⁶.

4.3.6.1 Definitions of the Elderly Activity Recognition System

According the surveys and systematic reviews presented on the literature (TARALDSEN *et al.*, 2012; LARA; LABRADOR, 2013; MORALES; AKOPIAN, 2017), there are some important points that must be defined on the EARS using mobile and wearable devices in the context of Body-Worn Sensor Network.

Observing again Figures 1 (page 32) and 40, the author must define the processing platform and collector device. In the data collection process, the sensor used, its sampling rate and time window must be described as pattern of the HAR system.

Finally, in the process of activity recognition, a supervised machine learning algorithm must be defined, as well the training dataset of the system (see Figure 2, page 33) and the features that are extracted and applied to the supervised machine learning algorithm.

Thus, the following items summarizes the authors definition for the EARS:

- **Processing Platform:** the author defined a smartphone or tablet as processing platform.
- **Collector Device:** the author selected a wearable device to collect data from the activities performed by an elder end-user. The wearable device can be a smartwach (LG Watch Urbane - more information in Section 4.3.1) or even a smartphone (it usually accumulates two functions: processing platform and collector device).
- **Sensor:** the author defined a 3-axis accelerometer sensor to collect data from the ambulation activities. This sensor is embedded in the collector device (it can be a smartwatch or a smartphone).
- **Sampling rate:** Android OS controls everything in the devices: when the sensors are

⁵ It is possible to read more about the LG Watch Urbane in LG (2018)

⁶ Amazon Simple Storage Service: <https://docs.aws.amazon.com/pt_br/AmazonS3/latest/dev/Welcome.html>

turned on for example, the software developer must send a request to the Android OS to turn on the desired sensor. This is not different for the sampling rates. Android OS provides pre-defined sampling rates and the software developer must choose the one that suits better to the application. In this case, the author defined the constant **SENSOR_DELAY_UI** as the sampling rate of the EARS. Even the database provider by the author is collect in this frequency of 16 Hz. Table 21 shows all the sampling rates provided by Android ⁷. The survey presented by Morales and Akopian (2017) shows that a good sampling rate for HAR systems is between 20 Hz and 50 Hz, although there are some articles using sampling rates around 10 Hz and presenting a good accuracy (CHATZAKI *et al.*, 2017; ARAÚJO *et al.*, 2018; CONCEPCIÓN *et al.*, 2017; HAESCHER *et al.*, 2018; MELLONE *et al.*, 2012; FAREED, 2015).

- **Time windows:** the surveys presented by Lara and Labrador (2013) and CHATZAKI *et al.* show the time windows that provide the best accuracy in HAR systems are between 1 and 2 second. The author has defined a time window of 2 seconds.
- **Supervised Machine Learning Algorithms:** the most used machine learning algorithms in the HAR literature that presents the best accuracy are: k-Nearest Neighbors (KNN) and Decision Tree (J48), according to Table 4 (page 50). The author has defined to validated the system with both algorithms and, specially for KNN, it was established the K values 1, 3 and 5, because, according to Morales and Akopian (2017) and Chatzaki *et al.* (2017), these K values present best accuracy for HAR systems among others.
- **Feature Extraction:** for the feature extraction, the author selected the most common and with best performance statistical characteristics from the literature (KWAPISZ; WEISS; MOORE, 2011).
 - Difference to the gravity on y-axis (Diff): (y gravity - z gravity - x gravity);
 - Mean of the acceleration components in each axis (MeanXYZ): mean_Ax, mean_Ay, mean_Az;
 - Standard deviation of the acceleration components in each axis (StdXYZ): std_Ax, std_Ay, std_Az;
 - Root Mean Square of the acceleration components in each axis (RmsXYZ): rms_Ax, rms_Ay, rms_Az;
 - Acceleration module (Acc).

Thus, there are 5 set of features that were selected in order to extract information of the labeled databases.

Summarizing all this important information in Table 22, it is possible to have a brief overview about the Elderly Activity Recognition system.

⁷ The information about the sensors' sampling rates and guidelines can be found in <https://developer.android.com/guide/topics/sensors/sensors_overview>

Table 21 – Sampling rates provided by Android SDK

Constants	Delay (microseconds)	Frequency (Hz)
SENSOR_DELAY_NORMAL	200000	5
SENSOR_DELAY_UI	60000	16
SENSOR_DELAY_GAME	20000	50
SENSOR_DELAY_FASTEST	0	200

Table 22 – Elderly Activity Recognition System: overview and alternative ML algorithms

	Information
Processing Platform	Smartphone
Collector Device	Smartwatch
Sensor	3-axis accelerometer
Sampling Rate	16 Hz (SENSOR_DELAY_UI)
Time Window	2 seconds
Machine Learning Algorithms	Decision Tree (C4.5) and KNN (K = 1, 3, 5)
Feature Extraction	Diff, MeanXYZ, StdXYZ, RmsXYZ, and Acc

4.3.6.2 Elderly Activity Recognition application

The Android application developed for the EARS is an app that runs in both devices – smartwatch and smartphone. The communication process among them is very similar to the Move It application (Section 4.2.3, page 83).

In Figure 41, the author has defined a testing user interface for the smartphone, just with 2 buttons – start and stop. When the user presses start, it sends a message to the smartwatch to start the collecting service. When the service is up and collecting data, it prompts a notification for the elder user similar to Figure 37.

Figure 41 – Elderly Activity Recognition application

Source: Elaborated by the author.

During the collecting process, the smartphone receives the accelerometer data from smartwatch with sampling rate of 16 Hz, as defined in Section 4.3.6.1. With a time window of 2 seconds, the set of data is process by a classification algorithm, which returns the activity that the user is performing.

The smartphone app stores locally the activities, logging it on a file only when the user's activity changes, saving the date, time and name of the activity. Periodically, smartphone sends all the information to the Amazon S3 each 1 hour or when the Internet connection is up.

4.4 Elderly Activity Recognition System: Evaluation

Regarding the computing system's performance, the Elderly Activity Recognition System was evaluated according to the best set of features among the ones established on Section 4.3.6.1, the accuracy of the classification algorithms, highlighting the best ones, and at last there is the comparison of the EARS's accuracy with other HAR systems presented in the literature.

4.4.1 Evaluation of the Statistical Characteristics

According to Table 22 and Section 4.3.6.1, the statistical characteristics extracted from the literature were:

- Difference to the gravity on y-axis (Diff);
- Mean of the acceleration components in each axis (MeanXYZ);
- Standard deviation of the acceleration components in each axis (StdXYZ);
- Root Mean Square (RMS) of the acceleration components in each axis (RmsXYZ);
- and Acceleration module (Acc).

Considering this, the author has performed the combination of these five groups of statistical characteristics, resulting in 31 Groups of Features (GoF) described in following Table 23. In fact, the evaluation of these 31 GoFs is done by running the Decision Tree (J48) and KNN (k = 1, 3 and 5) algorithms over the database established by the author.

Figure 42 shows the execution of Decision Tree algorithm over the author's database considering all these 31 GoFs of the original statistical features (Table 22). It demonstrates that the GoF_3 , GoF_{19} , GoF_4 , GoF_{20} present the best performances, respectively 98.47%, 98.46%, 98.44% and 98.39%. The others' performances decrease considerably. Thus, the best Group of Features for the Decision Tree algorithm is GoF_3 : Diff, MeanXYZ, StdXYZ, Acc.

Table 23 – Groups of Features (GoF)

GoF	Statistical Characteristics
1	Diff, MeanXYZ, StdXYZ, RmsXYZ, Acc
2	Diff, MeanXYZ, StdXYZ, RmsXYZ
3	Diff, MeanXYZ, StdXYZ, Acc
4	Diff, MeanXYZ, StdXYZ
5	Diff, MeanXYZ, RmsXYZ, Acc
6	Diff, MeanXYZ, RmsXYZ
7	Diff, MeanXYZ, Acc
8	Diff, MeanXYZ
9	Diff, StdXYZ, RmsXYZ, Acc
10	Diff, StdXYZ, RmsXYZ
11	Diff, StdXYZ, Acc
12	Diff, StdXYZ
13	Diff, RmsXYZ, Acc
14	Diff, RmsXYZ
15	Diff, Acc
16	Diff
17	MeanXYZ, StdXYZ, RmsXYZ, Acc
18	MeanXYZ, StdXYZ, RmsXYZ
19	MeanXYZ, StdXYZ, Acc
20	MeanXYZ, StdXYZ
21	MeanXYZ, RmsXYZ, Acc
22	MeanXYZ, RmsXYZ
23	MeanXYZ, Acc
24	MeanXYZ
25	StdXYZ, RmsXYZ, Acc
26	StdXYZ, RmsXYZ
27	StdXYZ, Acc
28	StdXYZ
29	RmsXYZ, Acc
30	RmsXYZ
31	Acc

Figure 42 – Performance of the 31 GoFs after the execution of Decision Tree

Source: Elaborated by the author.

Figures 43, 44 and 45 show the execution of KNN ($k = 1, 3, 5$ respectively) algorithm over the author's database considering all these 31 GoFs of the original statistical features (Table 22).

Regarding the KNN with $k = 1$ (Figure 43), the subsets that have best performance are GoF_{20} , GoF_3 , GoF_{19} and GoF_4 , with accuracy of 98.63%, 98.46%, 98.39% and 98.37% respectively. Note that it resulted on the same subsets presented by the Decision Tree, the only difference is, in this case, the best Group of Features is GoF_{20} : MeanXYZ and StdXYZ.

Looking at the results of KNN with $k = 3$ (Figure 44), the GoFs with best performance are GoF_{20} , GoF_{18} , GoF_3 and GoF_2 , with accuracy of 97.92%, 97.91%, 97.87% and 97.80% respectively. In this case, the set of the best 4 feature subsets changes, excluding GoF_{19} and GoF_4 , and including GoF_{18} and GoF_2 . The KNN, $k = 3$ doesn't have a good performance as the KNN with $k = 1$, slowly decreasing the accuracy of the GoF_{20} , which is the best Group of Features for this classification algorithm.

Figure 43 – Performance of the 31 GoFs after the execution of KNN, $k = 1$

Source: Elaborated by the author.

Figure 44 – Performance of the 31 GoFs after the execution of KNN, $k = 3$

Source: Elaborated by the author.

Figure 45 – Performance of the 31 GoFs after the execution of KNN, $k = 5$

Source: Elaborated by the author.

Looking at the results of KNN with $k = 5$ (Figure 45), the GoFs with best performance are GoF_4 , GoF_3 , GoF_{19} and GoF_{20} , with accuracy of 89.90%, 89.51%, 89.07% and 88.80% respectively. Although the set of the best 4 GoFs is the same, as shown in Decision Tree and KNN ($k = 1$), the best GoF of KNN with $k = 5$ differs from both of them, it is the GoF_4 : Diff, MeanXYZ, StdXYZ.

Finally, it also is possible to notice that the KNN with $k = 1$ has the best performance among the others KNNs and the Decision Tree. Table 24 summarizes all these information, sorting the algorithms in order of best performance.

Table 24 – Overview about the evaluation of Statistical Features

Classification Algorithm	Best Group of Features	Accuracy
KNN ($k = 1$)	GoF_{20}	98.63%
Decision Tree	GoF_3	98.47%
KNN ($k = 3$)	GoF_{20}	97.92%
KNN ($k = 5$)	GoF_4	89.90%

4.4.2 Evaluation of the Classification Algorithm

Regarding the performance of the activity recognition process, the author used the Waikato Environment for Knowledge Analysis (WEKA) workbench to analysis the performance of the two first algorithms and subsets shown in Table 24. Thus, the author evaluates in this Section the classification accuracy of Decision Tree (J48) and KNN ($k = 1$), having the subsets 3 and 20 respectively.

WEKA⁸ is a collection of machine learning algorithms for data mining tasks. It contains tools for data preparation, classification, regression, clustering, association rules mining, and visualization (WITTEN; FRANK; HALL, 2011). In this case, it is used only for the activity classification process.

In order to evaluate both algorithms cited early, the author has prepared the elderly database extracting the features established in both GoFs (GoF_3 and GoF_{20} – see Table 23, page 95). The evaluation technique used here was 10-fold cross validation. Briefly, the cross-validation is a technique to evaluate predictive models by partitioning the original sample into a training set to train the model, and a test set to evaluate it. In the next two sections, it is shown the results of the evaluation process.

4.4.2.1 KNN ($k = 1$) and GoF_{20}

Running the KNN ($k = 1$) over the training dataset and applying the technique of 10-fold cross validation, the WEKA returned the accuracy of 98.37%. Considering Table 24, it is a little lower than the expected – it was expected an accuracy of 98.63%, although the error here is very small, around 0.26%.

Also, WEKA returned the following information:

- Correctly Classified Instances: 98.37%
- Incorrectly Classified Instances: 1.63%
- Relative absolute error: 1.9962%
- Total Number of Instances: 5644

Thus the 0.26% error agrees with the relative absolute error reported by WEKA. Table 25 shows some measures used to evaluate the performance of the classification algorithm. For it, the

⁸ More information can be accessed on <https://www.cs.waikato.ac.nz/ml/index.html>

definition of terms shown in this table is presented below:

- **True Positive (TP) Rate:** rate of true positives, those instances that were correctly classified as a given class.
- **False Positive (FP) Rate:** rate of false positives, those instances that were falsely classified as a given class.
- **Precision:** proportion of instances that are truly of a class divided by the total instances classified as that class.
- **Recall:** proportion of instances classified as a given class divided by the actual total in that class (equivalent to TP rate).
- **F-measure:** a combined measure for precision and recall calculated as

$$\frac{2 \times Precision \times Recall}{Precision + Recall}$$

- **Matthews Correlation Coefficient (MCC):** is used in machine learning as a measure of the quality classifications. A MCC of +1 represents a perfect prediction, 0 no better than random prediction and -1 indicates total disagreement between prediction and observation.
- **Receiver Operating Characteristics (ROC) Area:** one of the most important values output by WEKA, it shows the percentage of the area above line shown in the graphic FP (x-axis) X TP (y-axis). It is desired to have a ROC Area of 1.
- **Precision Recall Curve (PRC) Area:** shows the percentage of the area above line shown in the graphic Recall (x-axis) X Precision (y-axis). It is desired to have a PRC Area of 1.

Finally, observing Table 25, it is possible to see that KNN ($k = 1$) provides a good precision for every activity, its MCCs are very close to +1, which represents an excellent prediction. Looking at the ROC and PRC areas, it is possible to note that the values are very close to 1 and shows an excellent classification performance of the KNN ($k = 1$).

Table 26 shows the Confusion Matrix of KNN classification. In the problem of statistical classification, a confusion matrix allows the visualization of the performance of an algorithm. It is also known as an error matrix, because it is possible to see how many instances were falsely classified, the diagonal from left to right, top to bottom shows the number of instances that were correctly classified.

Analyzing the Confusion Matrix of KNN, it is possible to observe that there is a confusion among the Standing-to-Sitting and Sitting-to-Standing classification process, although it is not a representative number.

Therefore, the algorithm KNN ($k = 1$) presents an excellent performance and accuracy and certainly is a very good candidate and eligible to be the classification algorithm of the Elderly Activity Recognition system.

Table 25 – KNN (k = 1) Classification Analysis by WEKA

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0,975	0,003	0,982	0,975	0,979	0,975	0,989	0,969	Standing-to-Sitting
0,964	0,002	0,980	0,964	0,972	0,969	0,982	0,952	Upstairs
0,996	0,003	0,989	0,996	0,993	0,991	0,997	0,989	Walking
0,995	0,001	0,996	0,995	0,996	0,995	0,997	0,992	Standing
0,974	0,004	0,969	0,974	0,971	0,967	0,988	0,949	Sitting-to-Standing
0,990	0,001	0,996	0,990	0,993	0,992	0,994	0,983	Sitting
0,977	0,003	0,975	0,977	0,976	0,973	0,989	0,968	Downstairs
0,967	0,001	0,937	0,967	0,952	0,951	0,976	0,872	Running
1,000	0,001	0,960	1,000	0,980	0,979	0,999	0,934	Fast-walking
0,984	0,002	0,984	0,984	0,984	0,981	0,991	0,972	Weighted Avg.

Table 26 – KNN (k = 1) – Confusion Matrix

Classified as	a	b	c	d	e	f	g	h	i
a = Standing-to-Sitting	774	0	0	1	17	0	2	0	0
b = Upstairs	0	530	11	0	0	0	5	3	1
c = Walking	0	1	1201	0	0	0	3	1	0
d = Standing	0	0	0	833	3	1	0	0	0
e = Sitting-to-standing	13	0	2	2	677	1	0	0	0
f = Sitting	0	0	0	0	2	781	2	4	0
g = Downstairs	1	10	0	0	0	0	541	0	2
h = Running	0	0	0	0	0	1	2	119	1
i = Fast-walking	0	0	0	0	0	0	0	0	96

4.4.2.2 Decision Tree (J48) and GoF₃

Running the Decision Tree (J48) over the training dataset and applying the technique of 10-fold cross validation, the WEKA returned the accuracy of 95.24%. Considering Table 24, it is lower than the expected – it was expected an accuracy of 98.47%, the error is around 3.27%.

Also, WEKA returned the following information:

- Correctly Classified Instances: 95.2339%
- Incorrectly Classified Instances: 4.7661%
- Relative absolute error: 6.1396%
- Total Number of Instances: 5644

As happened with KNN, the 3.27% error agrees with the relative absolute error reported by WEKA. Table 27 shows some measures used to evaluate the performance of the classification

Table 27 – Decision Tree (J48) – Classification Analysis

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0,935	0,012	0,929	0,935	0,932	0,920	0,980	0,944	Standing-to-Sitting
0,913	0,009	0,916	0,913	0,914	0,905	0,977	0,924	Upstairs
0,978	0,010	0,965	0,978	0,972	0,964	0,992	0,974	Walking
0,983	0,004	0,979	0,983	0,981	0,978	0,997	0,981	Standing
0,919	0,007	0,947	0,919	0,933	0,924	0,984	0,951	Sitting-to-standing
0,966	0,004	0,976	0,966	0,971	0,966	0,997	0,985	Sitting
0,940	0,008	0,930	0,940	0,935	0,928	0,991	0,954	Downstairs
0,935	0,000	0,991	0,935	0,962	0,962	0,971	0,943	Running
0,948	0,002	0,901	0,948	0,924	0,923	0,999	0,939	Fast-walking
0,952	0,007	0,952	0,952	0,952	0,945	0,989	0,961	Weighted Avg.

Table 28 – Decision Tree (J48) – Confusion Matrix

Classified as	a	b	c	d	e	f	g	h	i
a = Standing-to-Sitting	742	3	5	6	26	5	7	0	0
b = Upstairs	2	502	19	0	0	4	20	0	3
c = Walking	6	9	1180	3	4	1	2	0	1
d = Standing	6	1	6	823	1	0	0	0	0
e = Sitting-to-standing	34	2	7	6	639	6	1	0	0
f = Sitting	5	7	3	3	3	762	2	0	4
g = Downstairs	2	23	3	0	0	2	521	1	2
h = Running	2	1	0	0	0	1	4	115	0
i = Fast-walking	0	0	0	0	2	0	3	0	91

algorithm.

Observing Table 27, it is possible to see that Decision Tree (J48) also provides a good precision for every activity, its MCCs are very close to +1, presenting an excellent prediction. Looking at the ROC and PRC areas, it is possible to note that the values are very close to 1 and shows an excellent classification performance of the Decision Tree (J48). Although the accuracy presented in Section 4.4.2.1 by the KNN algorithm is better than the Decision Tree.

Table 28 shows the Confusion Matrix of Decision Tree classification. The diagonal from left to right, top to bottom shows the number of instances that were correctly classified. It is possible to notice that there are confusions among the Standing-to-Sitting and Sitting-to-Standing classification, and also among the Downstairs and Upstairs. Although it is not a representative number, the KNN only have a little confusion among Standing-to-Sitting and Sitting-to-Standing, which demonstrates better accuracy.

Table 29 – Brief Overview about the Elderly Activity Recognition System.

	Information
Processing Platform	Smartphone
Collector Device	Smartwatch
Sensor	3-axis accelerometer
Sampling Rate	16 Hz (SENSOR_DELAY_UI)
Time Window	2 seconds
Machine Learning Algorithms	KNN (k = 1)
Feature Extraction	MeanXYZ and StdXYZ

Therefore, the algorithm KNN ($k = 1$) and the GoF_{20} were chosen by the author to be officially applied in the Elderly Activity Recognition system, because they present better performance in the simulations, having an accuracy of 98.37%.

4.4.2.3 Elderly Activity Recognition System

The analysis performed in Sections 4.4.2.1 and 4.4.2.2 identified the machine learning algorithms and the statistical features to be deployed in the EARS. As a result, the overview and alternative Machine Learning (ML) algorithms presented in Table 22 (page 93) is updated in Table 29 to reflect KNN ($k=1$) as the selected algorithm.

The author compared the accuracy of the EARS with the Table 4 (page 50) that shows the performance of the selected articles, and it is possible to conclude that the EARS has a great accuracy and performance, sometimes higher than some HAR systems presented in the literature review. As said before, these systems don't use data collected from elder volunteers, and when they do, or a public database is not provided, or it is not a considerable amount of data collected from the elderly.

Therefore, the Elderly Activity Recognition System is a HAR system using a training dataset collected from the elder volunteers – EARDB – and the design process was focused and centered on the elderly user. The EARS provides an accuracy of 98.37% through KNN ($k = 1$) and is a promising supportive technology that can help the elder people's life, providing them independence and quality of life.

4.5 Final Considerations

In this section, the author proposed the guidelines for a Human Activity Recognition system centered on the elderly end-user, as well as a database consisting of data collected from elder volunteers is described and available. With them, the Elderly Activity Recognition System (EARS) is proposed and designed, aiming to provide to the elderly a better quality of life and independence. Besides that, the design of the Elderly Activity Recognition system may contribute

to the increase in the number of researches in the area of Human Activity Recognition focused on the elderly audience.

CONCLUSION

The United Nations remarks¹ that *Population ageing is poised to become one of the most significant social transformations of the twenty-first century, with implications for nearly all sectors of society*. In this context, supportive technologies may provide services, solutions, and strategies to support older people in daily living, facilitating life in domestic tasks and providing monitoring and surveillance, to name a few. This chapter summarizes the main contributions of the work by the author, and discusses limitations and future works.

5.1 Contributions

The author's work contributes to the area of Human Activity Recognition centered on the elderly, offering researches and practitioners a suite comprised of guidelines, dataset and software infrastructure.

- The guidelines for the EARS presented in the Section 4.1.2 (page 64) establish the main points to be considered during the design of a HAR system focused on the elderly. Software developers, collaborating with gerontology professionals, must take into account the requirements related to cost, accuracy, acceptance, and privacy a proposed solution. This is a difficult task because of the underlying trade-off questions. Ideally the best scenario must be investigated so as to define EARS with suitable acceptance, usability and respect for privacy issues raised by the elderly, as well as affordable costs – besides guaranteeing the proper accuracy.
- The database EARDB contains data collected from 32 elder volunteers age 60-75 years old – annotated with respect to 8 activities: standing, sitting, walking, going upstairs, going downstairs, running, sitting-to-standing and standing-to-sitting. As highlighted in the Section 3.3.4 (page 52), the author's research identified 12 public datasets used for HAR, from which only one includes data from people – in fact, one individual – over

¹ <http://www.un.org/en/sections/issues-depth/ageing/>

60 years old (WARD dataset). The WARD dataset was built using an intrusive approach which deployed multiple body-worn devices. The EARDB tackles the need for a public database with data collected from the older population.

- Another contribution for the research field of Human Activity Recognition is the Move It application presented in Section 4.2.3 (page 83). This application provides a technological infrastructure to collect data from several activities and construct databases for HAR systems. With the MOVE IT Android app, the researcher can create projects and define the activities she/he wants to collect data, and make the new database for HAR systems public.
- An Elderly Activity Recognition System was designed and developed, the best set of features was investigated, as well as the machine learning algorithms with best accuracy. Thus, this work provides as contribution the evaluation of the EARS, raising the classification algorithm and the statistical features with best performance.

These results are reported in manuscripts as follows:

- An article is in preparation to be submitted to the Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies (IMWUT), intitled: “Elderly Activity Recognition using wearable and mobile device”. This article reports mainly the contents presented in Chapter 4.
- An article summarizing the literature review about HAR systems focusing on the elderly is in preparation to be submitted to Computer Surveys. This article reports the contents presented in Chapter 3.
- Article published in WebMedia 2018 – Proceedings of the 24th Brazilian Symposium on Multimedia and the Web, title: “Recording Maybe?: Location-Based Application for Detection and Capture of Ad-hoc Meetings”. This article describes a context-aware system recognizing when a person is in a meeting. Through location sensors of the users’ smartphone and an Android app called *inMeeting*, it is possible to recognize when a group of pre-registered people is in a meeting. Upon recognition, the Android app sends a notification to all members involved, offering them the opportunity to pervasively record the current meeting, with audio or video and along with the corresponding metadata (VIEL *et al.*, 2018).

5.2 Limitations and Future Work

During the research reported in this dissertation, the author followed methodologies of scientific research for the area of Computer Science. The results, summarized in the previous section, present limitations which lead to future works as follows:

- **Extension of set of simple activities recognized.** In the current version of EARS, the author, with the support of health professional, defined the activities recognized by the system as a subset of the simple ambulation activities presented in Table 1 (page 34), in

order to establish a delimitation of the research project. However, the system has been designed so that the set of activities recognized can be extended as follows: (i) the Move It app (Section 4.2.3, page 83) is used to collect data from different volunteers' profiles while performing the targeted activities; (ii) after the data collection, the Move It app provides a labeled database and a new activity classification model must be generated in order to include the different volunteers' profiles and the targeted activities; (iii) finally, this activity classification model is include in the EARS application.

- **Recognition of complex activities.** The definition of simple and complex activities is described in Section 2.4 (page 32). In the case of the Elderly Activity Recognition System, only simple activities are identified. As complex activities are composed of a set of simple activities, the difficulty is to identify more than one activity at the same time and to check their correlation and if they define a complex activity. The recognition of complex activities has been discussed as future work by many researchers (LARA; LABRADOR, 2013; ELHOUSHI *et al.*, 2017; CHATZAKI *et al.*, 2017): one possible approach to detect complex activities is the fusion of sensors and their data. In particular in the context of older adults, researchers must take into account guidelines for HAR systems centered on elder users – such as those compiled by the author (Section 4.1.2, page 64).
- **Recognition of interaction with other persons.** Elder persons who live alone may or not keep contact with family, friends or health professionals. A HAR system able to detect the user interaction with other persons may monitor the existence or absence of such interaction, since older people are more vulnerable to loneliness and social isolation, as observed by Dury (2014). An application such the *inMeeting* (VIEL *et al.*, 2018), which identifies when pre-registered people meet as observed in the previous section, can be integrated to EARS so as to support the collection of context-aware information about elder users' social activities.
- **Benchmark to evaluate the HAR system's accuracy and performance in the real world.** There are several tools to evaluate a HAR system in simulated environments, but there is a lack of tools to evaluate the performance and accuracy of a HAR system in the real world, monitoring real users. The work reported in this dissertation may contribute to provide such benchmark by extending the methodology adopted in the design, construction and evaluation of EARS.
- **Create new databases including other audiences.** In general, HAR systems focus on a generic public, usually young and without any mobility impairments and health problems – there is a demand for the development of databases with other people profiles. Considering this, Move It app can facilitate making new databases for HAR systems available for the academic community.

5.3 Final remarks

The work reported in this dissertation developed an infrastructure to Human Activity Recognition system centered on the elderly. The adopted methodology along with the resulting software platform may motivate and contribute to new advances in the area.

The materials and documents used in the research are available in the Appendices. The software and database will be made available to the community.

BIBLIOGRAPHY

AL-FUQAHA, A.; GUIZANI, M.; MOHAMMADI, M.; ALEDHARI, M.; AYYASH, M. Internet of things: A survey on enabling technologies, protocols, and applications. **IEEE Communications Surveys Tutorials**, v. 17, n. 4, p. 2347–2376, Fourthquarter 2015. ISSN 1553-877X. Citation on page 30.

ALAM, M. A. U.; ROY, N. Gesmart: A gestural activity recognition model for predicting behavioral health. In: **2014 International Conference on Smart Computing**. [S.l.: s.n.], 2014. p. 193–200. Citations on pages 45, 48, 49, 51 e 125.

ARAÚJO, L. de; DOURADO, L.; FERNANDES, L.; ANDRADE, R. M. d. C.; AGUILAR, P. A. C. An algorithm for fall detection using data from smartwatch. In: **2018 13th Annual Conference on System of Systems Engineering (SoSE)**. [S.l.: s.n.], 2018. p. 124–131. Citations on pages 26, 45, 49, 50, 92 e 125.

ATZORI, L.; IERA, A.; MORABITO, G. The internet of things: A survey. **Computer Networks**, v. 54, n. 15, p. 2787 – 2805, 2010. ISSN 1389-1286. Available: <<http://www.sciencedirect.com/science/article/pii/S1389128610001568>>. Citation on page 30.

AVANCHA, S.; BAXI, A.; KOTZ, D. Privacy in mobile technology for personal healthcare. **ACM Computing Surveys**, v. 45, n. 1, p. 54, 2012. Citation on page 36.

BAL, M.; SHEN, W.; HAO, Q.; XUE, H. Collaborative smart home technologies for senior independent living: A review. **IEEE - Proceedings**, p. 481–488, 2011. Citation on page 26.

BANOS, O.; GARCIA, R.; HOLGADO-TERRIZA, J. A.; DAMAS, M.; POMARES, H.; ROJAS, I.; SAEZ, A.; VILLALONGA, C. mhealthdroid: A novel framework for agile development of mobile health applications. In: PECCHIA, L.; CHEN, L. L.; NUGENT, C.; BRAVO, J. (Ed.). **Ambient Assisted Living and Daily Activities**. Cham: Springer International Publishing, 2014. p. 91–98. ISBN 978-3-319-13105-4. Citations on pages 57, 58 e 61.

BEDARD, C.; KING-DOWLING, S.; MCDONALD, M.; DUNTON, G.; CAIRNEY, J.; KWAN, M. Understanding environmental and contextual influences of physical activity during first-year university: The feasibility of using ecological momentary assessment in the movingu study. **JMIR Public Health and Surveillance**, JMIR Publications Inc., Toronto, Canada, v. 3, n. 2, p. e32, 2017. Citation on page 25.

BENMANSOUR, A.; BOUCHACHIA, A.; FEHAM, M. Human activity recognition in pervasive single resident smart homes: State of art. In: **2015 12th International Symposium on Programming and Systems (ISPS)**. [S.l.: s.n.], 2015. p. 1–9. Citations on pages 45, 49 e 125.

BENNELL, K.; DOBSON, F.; HINMAN, R. Measures of physical performance assessments: Self-paced walk test (spwt), stair climb test (sct), six-minute walk test (6mwt), chair stand test (cst), timed up & go (tug), sock test, lift and carry test (lct), and car task. **Arthritis Care & Research**, v. 63, n. S11, p. S350–S370, 2011. Available: <<https://onlinelibrary.wiley.com/doi/abs/10.1002/acr.20538>>. Citation on page 70.

BOJANOVSKY, V.; BYRNE, S.; KIRWAN, P.; CLELAND, I.; NUGENT, C. Evaluation of fall and seizure detection with smartphone and smartwatch devices. In: OCHOA, S. F.; SINGH, P.; BRAVO, J. (Ed.). **Ubiquitous Computing and Ambient Intelligence**. Cham: Springer International Publishing, 2017. p. 275–286. ISBN 978-3-319-67585-5. Citations on pages 26, 45, 49, 51 e 125.

BOMBARDELLI, C.; ROSA, L. H. T. d.; KELLER, K. D.; KLAHR, P. d. S.; ROSA, P. V. d.; PERES, A. Quality of life of elderly people living in a municipality with rural characteristics in the countryside of rio grande do sul, brazil. **Revista Brasileira de Geriatria e Gerontologia**, SciELO Brasil, v. 20, n. 1, p. 85–90, 2017. Citation on page 26.

BRAVO, J.; FONTECHA, J.; NAVARRO, F. J.; HERVAS, R. A mobile proposal for frailty monitoring by rehabilitation and physical daily activity. In: **2011 IEEE International Conference on Consumer Electronics -Berlin (ICCE-Berlin)**. [S.l.: s.n.], 2011. p. 176–180. ISSN 2166-6814. Citations on pages 44, 45, 49, 51 e 125.

CAPELA, N. A.; LEMAIRE, E. D.; BADDOUR, N. Feature selection for wearable smartphone-based human activity recognition with able bodied, elderly, and stroke patients. **PLOS ONE**, Public Library of Science, v. 10, n. 4, p. 1–18, 04 2015. Available: <<https://doi.org/10.1371/journal.pone.0124414>>. Citations on pages 44, 45, 49, 52, 60 e 125.

CAROUX, L.; CONSEL, C.; DUPUY, L.; SAUZÉON, H. Verification of daily activities of older adults: A simple, non-intrusive, low-cost approach. In: **Proceedings of the 16th International ACM SIGACCESS Conference on Computers & Accessibility**. New York, NY, USA: ACM, 2014. (ASSETS '14), p. 43–50. ISBN 978-1-4503-2720-6. Available: <<http://doi.acm.org/10.1145/2661334.2661360>>. Citations on pages 45, 49 e 125.

CHATZAKI, C.; PEDIADITIS, M.; VAVOULAS, G.; TSIKNAKIS, M. Human daily activity and fall recognition using a smartphone's acceleration sensor. In: RÖCKER, C.; O'DONOGHUE, J.; ZIEFLE, M.; HELFERT, M.; MOLLOY, W. (Ed.). **Information and Communication Technologies for Ageing Well and e-Health**. Cham: Springer International Publishing, 2017. p. 100–118. ISBN 978-3-319-62704-5. Citations on pages 26, 45, 47, 49, 50, 89, 92, 107 e 125.

CHAUDHURI, S.; DEMIRIS, G.; THOMPSON, H. Translating smart home research into practice. **Handbook of Smart Homes, Health Care and Well-Being**, Springer, p. 555, 2017. Citation on page 26.

CHEN, Y.; YU, L.; OTA, K.; DONG, M. Robust activity recognition for aging society. **IEEE Journal of Biomedical and Health Informatics**, v. 22, n. 6, p. 1754–1764, Nov 2018. ISSN 2168-2194. Citations on pages 45, 49 e 125.

CHERIAN, J.; RAJANNA, V.; GOLDBERG, D.; HAMMOND, T. Did you remember to brush?: A noninvasive wearable approach to recognizing brushing teeth for elderly care. In: **Proceedings of the 11th EAI International Conference on Pervasive Computing Technologies for Healthcare**. New York, NY, USA: ACM, 2017. (PervasiveHealth '17), p. 48–57. ISBN 978-1-4503-6363-1. Available: <<http://doi.acm.org/10.1145/3154862.3154866>>. Citations on pages 45, 49, 52, 59 e 125.

CHERNBUMROONG, S.; CANG, S.; ATKINS, A.; YU, H. Elderly activities recognition and classification for applications in assisted living. **Expert Systems with Applications**, v. 40, n. 5, p. 1662 – 1674, 2013. ISSN 0957-4174. Available: <<http://www.sciencedirect.com/science/article/pii/S0957417412010585>>. Citations on pages 26, 45, 49, 52, 60, 64, 65, 66 e 125.

CHERNBUMROONG, S.; CANG, S.; YU, H. Genetic algorithm-based classifiers fusion for multisensor activity recognition of elderly people. **IEEE Journal of Biomedical and Health Informatics**, v. 19, n. 1, p. 282–289, Jan 2015. ISSN 2168-2194. Citations on pages 45, 47, 49, 52 e 125.

CHIGATERI, N. G.; KERSE, N.; WHEELER, L.; MACDONALD, B.; KLENK, J. Validation of an accelerometer for measurement of activity in frail older people. **Gait Posture**, v. 66, p. 114 – 117, 2018. ISSN 0966-6362. Available: <<http://www.sciencedirect.com/science/article/pii/S0966636218314383>>. Citations on pages 44, 45, 49, 51, 89 e 125.

CONCEPCIÓN, M. Ángel Álvarez de la; MORILLO, L. M. S.; GARCÍA, J. A. Álvarez; GONZÁLEZ-ABRIL, L. Mobile activity recognition and fall detection system for elderly people using ameva algorithm. **Pervasive and Mobile Computing**, v. 34, p. 3 – 13, 2017. ISSN 1574-1192. Pervasive Computing for Gerontechnology. Available: <<http://www.sciencedirect.com/science/article/pii/S1574119216300505>>. Citations on pages 47, 49, 51, 92 e 125.

CONNER, T. S.; TENNEN, H.; FLEESON, W.; BARRETT, L. F. Experience sampling methods: A modern idiographic approach to personality research. **Social and Personality Psychology Compass**, v. 3, n. 3, p. 292–313, 2009. Citation on page 25.

COOK, D. J.; CRANDALL, A. S.; THOMAS, B. L.; KRISHNAN, N. C. Casas: A smart home in a box. **Computer**, v. 46, n. 7, p. 62–69, July 2013. ISSN 0018-9162. Citations on pages 52, 56 e 61.

CRUZ, M. F. d.; RAMIRES, V. V.; WENDT, A.; MIELKE, G. I.; MARTINEZ-MESA, J.; WEHRMEISTER, F. C. Simultaneity of risk factors for chronic non-communicable diseases in the elderly in pelotas, rio grande do sul state, brazil. **Cadernos de Saúde Pública**, SciELO Brasil, v. 33, n. 2, 2017. Citation on page 26.

CSIKSZENTMIHALYI, M.; LARSON, R. Validity and reliability of the experience-sampling method. In: **Flow and the foundations of positive psychology**. [S.l.]: Springer, 2014. p. 35–54. Citation on page 25.

DAO, M.-S.; NGUYEN-GIA, T.-A.; MAI, V.-C. Daily human activities recognition using heterogeneous sensors from smartphones. **Elsevier**, p. 323–328, 2017. Citations on pages 32, 34 e 35.

DOLL, J. Gerontecnologia: Pesquisa e inovação para uma humanidade sustentável. **Anais do II Congresso Brasileiro de Gerontecnologia - Medicina (Ribeirão Preto. Online) 2017; 50(Supl.3)**, p. 42–46, 2017. Citations on pages 26 e 31.

DURY, R. Social isolation and loneliness in the elderly: an exploration of some of the issues. **British Journal of Community Nursing**, MA Healthcare London, v. 19, n. 3, p. 125–128, 2014. Citation on page 107.

ECONOMIC, D. of; NATIONS, S. A. U. **World Population Prospects: the 2017 Revision**. 2017. Available: <https://esa.un.org/unpd/wpp/Publications/Files/WPP2017_KeyFindings.pdf>. Citation on page 25.

ELHOUSHI, M.; GEORGY, J.; NOURELDIN, A.; KORENBERG, M. J. A survey on approaches of motion mode recognition using sensors. **IEEE Transactions on Intelligent Transportation Systems**, v. 18, n. 7, p. 1662–1686, July 2017. ISSN 1524-9050. Citations on pages 34, 35 e 107.

ESPINILLA, M.; LIU, J.; GARCÍA-CHAMIZO, J. M. Special issue on “recent advancements in ubiquitous computing”. **Journal of Ambient Intelligence and Humanized Computing**, v. 8, n. 4, p. 467–468, Aug 2017. ISSN 1868-5145. Available: <https://doi.org/10.1007/s12652-017-0476-6>. Citation on page 29.

ESTADÃO. População idosa vai triplicar entre 2010 e 2050, aponta publicação do ibge. **Estadão**, 2016. Available: <http://brasil.estadao.com.br/noticias/geral, populacao-idosa-vai-triplicar-entre-2010-e-2050-aponta-publicacao-do-ibge,10000072724>. Accessed: 12/12/2017. Citation on page 25.

EUN, S.-J.; WHANGBO, T.-K.; PARK, D. K.; KIM, K.-H. Development of personalized urination recognition technology using smart bands. **International neurourology journal**, Korean Continence Society, v. 21, n. Suppl 1, p. S76, 2017. Citation on page 34.

FAREED, U. Smartphone sensor fusion based activity recognition system for elderly healthcare. In: **Proceedings of the 2015 Workshop on Pervasive Wireless Healthcare**. New York, NY, USA: ACM, 2015. (MobileHealth '15), p. 29–34. ISBN 978-1-4503-3525-6. Available: <http://doi.acm.org/10.1145/2757290.2757297>. Citations on pages 45, 49, 60, 92 e 125.

FORTECHA, J.; NAVARRO, F. J.; HERVÁS, R.; BRAVO, J. Elderly frailty detection by using accelerometer-enabled smartphones and clinical information records. **Personal and Ubiquitous Computing**, v. 17, n. 6, p. 1073–1083, Aug 2013. ISSN 1617-4917. Available: <https://doi.org/10.1007/s00779-012-0559-5>. Citations on pages 45, 48, 49, 51, 70, 89 e 125.

FRANK, E.; HALL, M.; HOLMES, G.; KIRKBY, R.; PFAHRINGER, B.; WITTEN, I. H.; TRIGG, L. Weka-a machine learning workbench for data mining. In: **Data mining and knowledge discovery handbook**. [S.l.]: Springer, 2009. p. 1269–1277. Citation on page 34.

GARCIA, A. C.; LARA, S. M. A. de. Enabling aid in remote care for elderly people via mobile devices: The mobicare case study. In: **Proceedings of the 8th International Conference on Software Development and Technologies for Enhancing Accessibility and Fighting Info-exclusion**. New York, NY, USA: ACM, 2018. (DSAI 2018), p. 270–277. ISBN 978-1-4503-6467-6. Available: <http://doi.acm.org/10.1145/3218585.3218671>. Citation on page 31.

GE, Y.; XU, B. Elderly personal intention recognition by activity and context recognition in smart home. In: **2014 9th International Conference on Computer Science Education**. [S.l.: s.n.], 2014. p. 347–350. Citations on pages 45, 49 e 125.

HAESCHER, M.; MATTHIES, D. J.; SRINIVASAN, K.; BIEBER, G. Mobile assisted living: Smartwatch-based fall risk assessment for elderly people. In: **Proceedings of the 5th International Workshop on Sensor-based Activity Recognition and Interaction**. New York, NY, USA: ACM, 2018. (iWOAR '18), p. 6:1–6:10. ISBN 978-1-4503-6487-4. Available: <http://doi.acm.org/10.1145/3266157.3266210>. Citations on pages 44, 45, 47, 49, 51, 92 e 125.

HONG, Y.; KIM, I.; AHN, S. C.; KIM, H. Activity recognition using wearable sensors for elder care. In: **2008 Second International Conference on Future Generation Communication and Networking**. [S.l.: s.n.], 2008. v. 2, p. 302–305. ISSN 2153-1447. Citations on pages 45, 49, 52 e 125.

HOYLE, R.; ANTHONY, D.; TEMPLEMAN, R.; ARMES, S.; CRANDALL, D.; KAPADIA, A. Privacy behaviors of lifeloggers using wearable cameras. **ACM**, p. 571–582, 2014. Citation on page 36.

IBGE. Projeção da população do brasil e das unidades da federação. **Instituto Brasileiro de Geografia e Estatística**, 2017. Available: <<https://ww2.ibge.gov.br/apps/populacao/projecao/index.html>>. Accessed: 12/12/2017. Citation on page 25.

INTILLE, S.; HAYNES, C.; MANIAR, D.; PONNADA, A.; MANJOURIDES, J. μ ema: Microinteraction-based ecological momentary assessment (ema) using a smartwatch. In: **ACM. Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing**. [S.l.], 2016. p. 1124–1128. Citation on page 32.

INTILLE, S. S.; LARSON, K.; BEAUDIN, J. S.; NAWYN, J.; TAPIA, E. M.; KAUSHIK, P. A living laboratory for the design and evaluation of ubiquitous computing technologies. In: **CHI '05 Extended Abstracts on Human Factors in Computing Systems**. New York, NY, USA: ACM, 2005. (CHI EA '05), p. 1941–1944. ISBN 1-59593-002-7. Available: <<http://doi.acm.org/10.1145/1056808.1057062>>. Citations on pages 52, 53 e 61.

JANJUA, Z. H.; RIBONI, D.; BETTINI, C. Towards automatic induction of abnormal behavioral patterns for recognizing mild cognitive impairment. In: **Proceedings of the 31st Annual ACM Symposium on Applied Computing**. New York, NY, USA: ACM, 2016. (SAC '16), p. 143–148. ISBN 978-1-4503-3739-7. Available: <<http://doi.acm.org/10.1145/2851613.2851687>>. Citations on pages 45, 46, 49, 60 e 125.

JORDAN, M. I.; MITCHELL, T. M. Machine learning: Trends, perspectives, and prospects. **Science**, American Association for the Advancement of Science, v. 349, n. 6245, p. 255–260, 2015. ISSN 0036-8075. Available: <<http://science.sciencemag.org/content/349/6245/255>>. Citation on page 34.

KANIS, M.; ALIZADEH, S.; GROEN, J.; KHALILI, M.; ROBBEN, S.; BAKKES, S.; KRÖSE, B. Ambient monitoring from an elderly-centred design perspective: What, who and how. In: KEYSON, D. V.; MAHER, M. L.; STREITZ, N.; CHEOK, A.; AUGUSTO, J. C.; WICHERT, R.; ENGLEBIENNE, G.; AGHAJAN, H.; KRÖSE, B. J. A. (Ed.). **Ambient Intelligence**. Berlin, Heidelberg: Springer Berlin Heidelberg, 2011. p. 330–334. Citation on page 66.

KASTEREN, T. V.; NOULAS, A.; ENGLEBIENNE, G.; KRÖSE, B. Accurate activity recognition in a home setting. In: **Proceedings of the 10th International Conference on Ubiquitous Computing**. New York, NY, USA: ACM, 2008. (UbiComp '08), p. 1–9. ISBN 978-1-60558-136-1. Available: <<http://doi.acm.org/10.1145/1409635.1409637>>. Citations on pages 52, 55 e 61.

KATO, D.; FUEKI, M.; ENDO, Y.; UGA, D.; DOBASHI, K.; NAKAZAWA, R.; SAKAMOTO, M. 30-second chair-stand test is a valuable evaluation in chronic respiratory diseases. **European Respiratory Journal**, European Respiratory Society, v. 44, n. Suppl 58, 2014. ISSN 0903-1936. Available: <https://erj.ersjournals.com/content/44/Suppl_58/P4286>. Citation on page 70.

KIENTZ, J. A.; PATEL, S. N.; JONES, B.; PRICE, E.; MYNATT, E. D.; ABOWD, G. D. The georgia tech aware home. In: **CHI '08 Extended Abstracts on Human Factors in Computing Systems**. New York, NY, USA: ACM, 2008. (CHI EA '08), p. 3675–3680. ISBN 978-1-60558-012-8. Available: <<http://doi.acm.org/10.1145/1358628.1358911>>. Citation on page 26.

KITCHENHAM, B.; CHARTERS, S. **Guidelines for performing Systematic Literature Reviews in Software Engineering**. 2007. Citations on pages 42 e 123.

KLEIMAN, E. M.; TURNER, B. J.; FEDOR, S.; BEALE, E. E.; HUFFMAN, J. C.; NOCK, M. K. Examination of real-time fluctuations in suicidal ideation and its risk factors: Results from two ecological momentary assessment studies. **Journal of abnormal psychology**, American Psychological Association, v. 126, n. 6, p. 726, 2017. Citation on page 25.

KOZINA, S.; GJORESKE, H.; GAMS, M.; LUŠTREK, M. Efficient activity recognition and fall detection using accelerometers. In: BOTÍA, J. A.; ÁLVAREZ-GARCÍA, J. A.; FUJINAMI, K.; BARSOCCHI, P.; RIEDEL, T. (Ed.). **Evaluating AAL Systems Through Competitive Benchmarking**. Berlin, Heidelberg: Springer Berlin Heidelberg, 2013. p. 13–23. ISBN 978-3-642-41043-7. Citations on pages 45, 47, 49, 50, 89 e 125.

KWAPISZ, J. R.; WEISS, G. M.; MOORE, S. A. Activity recognition using cell phone accelerometers. **SIGKDD Explor. Newsl.**, ACM, New York, NY, USA, v. 12, n. 2, p. 74–82, Mar. 2011. ISSN 1931-0145. Available: <<http://doi.acm.org/10.1145/1964897.1964918>>. Citations on pages 52, 57, 61, 70, 89 e 92.

LABRIQUE, A.; BLYNN, E.; AHMED, S.; GIBSON, D.; PARIYO, G.; HYDER, A. A. Health surveys using mobile phones in developing countries: Automated active strata monitoring and other statistical considerations for improving precision and reducing biases. **J Med Internet Res**, v. 19, n. 5, p. e121, May 2017. Available: <<http://www.jmir.org/2017/5/e121/>>. Citation on page 25.

LARA, O. D.; LABRADOR, M. A. A survey on human activity recognition using wearable sensors. **IEEE Communications Surveys Tutorials**, v. 15, n. 3, p. 1192–1209, Third 2013. ISSN 1553-877X. Citations on pages 32, 33, 34, 35, 57, 91, 92 e 107.

LEUTHEUSER, H.; SCHULDHAUS, D.; ESKOFIER, B. M. Hierarchical, multi-sensor based classification of daily life activities: Comparison with state-of-the-art algorithms using a benchmark dataset. **PLOS ONE**, Public Library of Science, v. 8, n. 10, p. 1–11, 10 2013. Available: <<https://doi.org/10.1371/journal.pone.0075196>>. Citations on pages 52, 59 e 61.

LG. Lg urbane watch. **LG**, 2018. Available: <<https://www.lg.com/br/wearables/lg-W150>>. Accessed: 16/12/2018. Citations on pages 87 e 91.

LIM, J.-H.; JANG, H.; JANG, J.; PARK, S. Daily activity recognition system for the elderly using pressure sensors. In: **2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society**. [S.l.: s.n.], 2008. p. 5188–5191. ISSN 1094-687X. Citations on pages 45, 49 e 125.

LIU, K.; HSIEH, C.; CHAN, C. Transition-aware housekeeping task monitoring using single wrist-worn sensor. **IEEE Sensors Journal**, v. 18, n. 21, p. 8950–8962, Nov 2018. ISSN 1530-437X. Citations on pages 45, 47, 49, 51 e 125.

LUCESI, B. M.; SOUZA Érica N.; GRATÃO, A. C. M.; GOMES, G. A. de O.; INOUE, K.; ALEXANDRE, T. da S.; MARQUES, S.; PAVARINI, S. C. I. The evaluation of perceived stress and associated factors in elderly caregivers. **Archives of Gerontology and Geriatrics**, v. 67, n. Supplement C, p. 7 – 13, 2016. ISSN 0167-4943. Available: <<http://www.sciencedirect.com/science/article/pii/S0167494316301182>>. Citation on page 26.

MAHITHA, G.; SWARNA, N.; MURALIDHARAN, V.; AMUTHA, R. Medical activity monitoring for elderly people using wearable wrist device. In: **2017 International Conference on Communication and Signal Processing (ICCSP)**. [S.l.: s.n.], 2017. p. 2016–2020. Citations on pages 45, 49, 51, 64 e 125.

MAKIHARA, Y.; MANNAMI, H.; YAGI, Y. Gait analysis of gender and age using a large-scale multi-view gait database. In: KIMMEL, R.; KLETTE, R.; SUGIMOTO, A. (Ed.). **Computer Vision – ACCV 2010**. Berlin, Heidelberg: Springer Berlin Heidelberg, 2011. p. 440–451. ISBN 978-3-642-19309-5. Citations on pages 26 e 27.

MANNINI, A.; SABATINI, A. A smartphone-centered wearable sensor network for fall risk assessment in the elderly. In: . [S.l.]: ACM, 2015. Citations on pages 45, 48, 49, 52 e 125.

MEDJAHED, H.; ISTRATE, D.; BOUDY, J.; DORIZZI, B. Human activities of daily living recognition using fuzzy logic for elderly home monitoring. In: **2009 IEEE International Conference on Fuzzy Systems**. [S.l.: s.n.], 2009. p. 2001–2006. ISSN 1098-7584. Citations on pages 45, 47, 49 e 125.

MELLONE, S.; TACCONI, C.; SCHWICKERT, L.; KLENK, J.; BECKER, C.; CHIARI, L. Smartphone-based solutions for fall detection and prevention: the farseeing approach. **Zeitschrift für Gerontologie und Geriatrie**, v. 45, n. 8, p. 722–727, Dec 2012. ISSN 1435-1269. Available: <<https://doi.org/10.1007/s00391-012-0404-5>>. Citations on pages 45, 47, 48, 49, 51, 92 e 125.

MENG, L.; MIAO, C.; LEUNG, C. Towards online and personalized daily activity recognition, habit modeling, and anomaly detection for the solitary elderly through unobtrusive sensing. **Multimedia Tools and Applications**, v. 76, n. 8, p. 10779–10799, Apr 2017. ISSN 1573-7721. Available: <<https://doi.org/10.1007/s11042-016-3267-8>>. Citations on pages 45, 49 e 125.

MITAS, A. W.; RUDZKI, M.; WIECLAWK, W.; ZARYCHTA, P.; PIWOWARSKI, S. Wearable system for activity monitoring of the elderly. In: PIĘTKA, E.; KAWA, J.; WIECLAWK, W. (Ed.). **Information Technologies in Biomedicine, Volume 4**. Cham: Springer International Publishing, 2014. p. 147–160. ISBN 978-3-319-06596-0. Citations on pages 45, 47, 49 e 125.

MORALES, J.; AKOPIAN, D. Physical activity recognition by smartphones, a survey. **Bio-cybernetics and Biomedical Engineering**, v. 37, n. 3, p. 388 – 400, 2017. ISSN 0208-5216. Available: <<http://www.sciencedirect.com/science/article/pii/S020852161630314X>>. Citations on pages 45, 47, 49, 60, 91, 92 e 125.

MOSHTAGHI, M.; ZUKERMAN, I.; RUSSELL, R. A. Statistical models for unobtrusively detecting abnormal periods of inactivity in older adults. **User Modeling and User-Adapted Interaction**, v. 25, n. 3, p. 231–265, Aug 2015. ISSN 1573-1391. Available: <<https://doi.org/10.1007/s11257-015-9162-6>>. Citations on pages 45, 49 e 125.

NATIONS, U.; DESA. World population prospects: The 2017 revision. **United Nations**, 2017. Available: <<https://esa.un.org/unpd/wpp/>>. Accessed: 20/12/2017. Citation on page 60.

NGUYEN, T.; DEV, S.; EYLER, L. 535-self-reported eating and exercise behaviors are related to mood and cognition in bipolar disorder: An ecological momentary assessment study. **Biological Psychiatry**, Elsevier, v. 81, n. 10, p. S217, 2017. Citation on page 25.

NICOLINI-PANISSON, R. D.; DONADIO, M. A. V. A.-c. F. Timed "Up Go" test in children and adolescents. **Revista Paulista de Pediatria**, scielo, v. 31, p. 377 – 383, 09 2013. ISSN 0103-0582. Available: <http://www.scielo.br/scielo.php?script=sci_arttext&pid=S0103-05822013000300377&nrm=iso>. Citation on page 71.

OSMANI, V.; ZHANG, D.; BALASUBRAMANIAM, S. Human activity recognition supporting context-appropriate reminders for elderly. In: . [S.l.: s.n.], 2009. Citations on pages 45, 47, 49 e 125.

OUCHI, K.; DOI, M. Smartphone-based monitoring system for activities of daily living for elderly people and their relatives etc. In: **Proceedings of the 2013 ACM Conference on Pervasive and Ubiquitous Computing Adjunct Publication**. New York, NY, USA: ACM, 2013. (UbiComp '13 Adjunct), p. 103–106. ISBN 978-1-4503-2215-7. Available: <http://doi.acm.org/10.1145/2494091.2494120>. Citations on pages 45, 48, 49, 51 e 125.

PERFORM Systematic Literature Reviews. Available: <https://parsif.al/>. Citations on pages 42 e 123.

POGORELC, B.; BOSNIĆ, Z.; GAMS, M. Automatic recognition of gait-related health problems in the elderly using machine learning. **Multimedia Tools and Applications**, v. 58, n. 2, p. 333–354, May 2012. ISSN 1573-7721. Available: <https://doi.org/10.1007/s11042-011-0786-1>. Citations on pages 45, 49, 51 e 125.

POPESCU, M.; HOTRABHAVANANDA, B.; MOORE, M.; SKUBIC, M. Vampir - an automatic fall detection system using a vertical pir sensor array. In: . [S.l.]: IEEE, 2012. Citations on pages 45, 49 e 125.

RAFAEL-PALOU, X.; ZAMBRANA, C.; VARGIU, E.; MIRALLES, F. Home-based activity monitoring of elderly people through a hierarchical approach. In: HELFERT, M.; HOLZINGER, A.; ZIEFLE, M.; FRED, A.; O'DONOGHUE, J.; RÖCKER, C. (Ed.). **Information and Communication Technologies for Ageing Well and e-Health**. Cham: Springer International Publishing, 2015. p. 145–161. ISBN 978-3-319-27695-3. Citations on pages 45, 49, 64 e 125.

RANASINGHE, D. C.; TORRES, R. L. S.; WICKRAMASINGHE, A. Automated activity recognition and monitoring of elderly using wireless sensors: Research challenges. In: **5th IEEE International Workshop on Advances in Sensors and Interfaces IWASI**. [S.l.: s.n.], 2013. p. 224–227. Citations on pages 45, 49 e 125.

REYES-ORTIZ, J.-L.; ONETO, L.; SAMÁ, A.; PARRA, X.; ANGUITA, D. Transition-aware human activity recognition using smartphones. **Elsevier**, n. 171, p. 754–767, 2015. Citation on page 35.

RIEMSDIJK, M. B. van; JONKER, C. M.; LESSER, V. Creating socially adaptive electronic partners: Interaction, reasoning and ethical challenges. In: **Proceedings of the 2015 International Conference on Autonomous Agents and Multiagent Systems**. Richland, SC: International Foundation for Autonomous Agents and Multiagent Systems, 2015. (AAMAS '15), p. 1201–1206. ISBN 978-1-4503-3413-6. Available: <http://dl.acm.org/citation.cfm?id=2772879.2773303>. Citation on page 31.

ROGGEN, D.; CALATRONI, A.; ROSSI, M.; HOLLECZEK, T.; FÖRSTER, K.; TRÖSTER, G.; LUKOWICZ, P.; BANNACH, D.; PIRKL, G.; FERSCHA, A.; DOPPLER, J.; HOLZMANN, C.; KURZ, M.; HOLL, G.; CHAVARRIAGA, R.; SAGHA, H.; BAYATI, H.; CREATURA, M.; MILLÀN, J. d. R. Collecting complex activity datasets in highly rich networked sensor environments. In: **2010 Seventh International Conference on Networked Sensing Systems (INSS)**. [S.l.: s.n.], 2010. p. 233–240. Citations on pages 52, 55 e 61.

RONAO, C. A.; CHO, S.-B. Human activity recognition with smartphone sensors using deep learning neural networks. **Elsevier - Expert Systems with Applications**, n. 59, p. 235–244, 2016. Citations on pages 34 e 36.

ROSETO-MONTALVO, P. D.; PELUFFO-ORDÓÑEZ, D. H.; GODOY, P.; PONCE, K.; ROSETO, E. A.; VÁSQUEZ, C. A.; CUZME, F.; FLORES, S. C.; MERA, Z. A. Elderly fall detection using data classification on a portable embedded system. In: **2017 IEEE Second Ecuador Technical Chapters Meeting (ETCM)**. [S.l.: s.n.], 2017. p. 1–4. Citations on pages 45, 49, 52 e 125.

RUAN, W. Unobtrusive human localization and activity recognition for supporting independent living of the elderly. In: **2016 IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops)**. [S.l.: s.n.], 2016. p. 1–3. Citations on pages 45, 49 e 125.

SANSRIMAHACHAI, W.; TOAHCHOODEE, M. Mobile-phone based immobility tracking system for elderly care. In: **2016 IEEE Region 10 Conference (TENCON)**. [S.l.: s.n.], 2016. p. 3550–3553. ISSN 2159-3450. Citations on pages 45, 49, 52, 60 e 125.

SANTOS, V. C.; ANJOS, K. F. d.; BOERY, R. N. S. d. O.; MOREIRA, R. M.; CRUZ, D. P.; BOERY, E. N. Hospitalization and hospital mortality of elderly people with mental and behavioral disorders in brazil, 2008-2014. **Epidemiologia e Serviços de Saúde**, SciELO Public Health, v. 26, n. 1, p. 39–49, 2017. Citation on page 26.

SCHEURER, S.; TEDESCO, S.; BROWN, K. N.; O'FLYNN, B. Sensor and feature selection for an emergency first responders activity recognition system. In: **2017 IEEE SENSORS**. [S.l.: s.n.], 2017. p. 1–3. Citations on pages 45, 49 e 125.

SEBESTYEN, G.; STOICA, I.; HANGAN, A. Human activity recognition and monitoring for elderly people. In: **2016 IEEE 12th International Conference on Intelligent Computer Communication and Processing (ICCP)**. [S.l.: s.n.], 2016. p. 341–347. Citations on pages 45, 49, 51, 67 e 125.

SERRE, F.; FATSEAS, M.; SWENDSEN, J.; AURIACOMBE, M. How psychiatric comorbidity and mood states influence craving and substance use in daily life? an ecological momentary assessment study in patients with alcohol, tobacco, cannabis and heroin use disorders. v. 171, p. e187, 02 2017. Citation on page 25.

SINGLA, G.; COOK, D. J.; SCHMITTER-EDGECOMBE, M. Recognizing independent and joint activities among multiple residents in smart environments. **Journal of Ambient Intelligence and Humanized Computing**, v. 1, n. 1, p. 57–63, Mar 2010. ISSN 1868-5145. Available: <<https://doi.org/10.1007/s12652-009-0007-1>>. Citations on pages 56 e 61.

SONG, S.-k.; JANG, J.; PARK, S. An efficient method for activity recognition of the elderly using tilt signals of tri-axial acceleration sensor. In: HELAL, S.; MITRA, S.; WONG, J.; CHANG, C. K.; MOKHTARI, M. (Ed.). **Smart Homes and Health Telematics**. Berlin, Heidelberg: Springer Berlin Heidelberg, 2008. p. 99–104. ISBN 978-3-540-69916-3. Citations on pages 45, 49, 89 e 125.

SORAYA, S. I.; CHIANG, T.; CHAN, G.; SU, Y.; YI, C.; TSENG, Y.; CHING, Y. Iot/m2m wearable-based activity-calorie monitoring and analysis for elders. In: **2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)**. [S.l.: s.n.], 2017. p. 2390–2393. ISSN 1558-4615. Citations on pages 45, 49, 51 e 125.

SRIVASTAVA, A. **UBIQUITOUS COMPUTING**. Phd Thesis (PhD Thesis) — Sungkyunkwan University, 2018. Citation on page 30.

STANFORD, V. Using pervasive computing to deliver elder care. **IEEE Pervasive Computing**, v. 1, n. 1, p. 10–13, Jan 2002. ISSN 1536-1268. Citation on page 26.

TAATI, B.; SNOEK, J.; GIESBRECHT, D.; MIHAILIDIS, A. Water flow detection in a hand-washing task. In: **2010 Canadian Conference on Computer and Robot Vision**. [S.l.: s.n.], 2010. p. 175–182. Citations on pages 44, 45, 49 e 125.

TAHAVORI, F.; STACK, E.; AGARWAL, V.; BURNETT, M.; ASHBURN, A.; HOSEINITA-BATABAEI, S. A.; HARWIN, W. Physical activity recognition of elderly people and people with parkinson's (pwp) during standard mobility tests using wearable sensors. In: **2017 International Smart Cities Conference (ISC2)**. [S.l.: s.n.], 2017. p. 1–4. Citations on pages 26, 45, 47, 49, 51 e 125.

TAN, Z.; XU, L.; ZHONG, W.; GUO, X.; WANG, G. Online activity recognition and daily habit modeling for solitary elderly through indoor position-based stigmergy. **Engineering Applications of Artificial Intelligence**, v. 76, p. 214 – 225, 2018. ISSN 0952-1976. Available: <<http://www.sciencedirect.com/science/article/pii/S0952197618301726>>. Citations on pages 45, 49 e 125.

TAPIA, E. M.; INTILLE, S. S.; LARSON, K. Activity recognition in the home using simple and ubiquitous sensors. In: SPRINGER. **Pervasive**. [S.l.], 2004. v. 4, p. 158–175. Citation on page 26.

TARALDSEN, K.; CHASTIN, S. F.; RIPHAGEN, I. I.; VEREIJKEN, B.; HELBOSTAD, J. L. Physical activity monitoring by use of accelerometer-based body-worn sensors in older adults: A systematic literature review of current knowledge and applications. **Maturitas**, v. 71, n. 1, p. 13 – 19, 2012. ISSN 0378-5122. Available: <<http://www.sciencedirect.com/science/article/pii/S0378512211003690>>. Citations on pages 45, 49, 64, 89, 91 e 125.

THEOFILOU, P. Quality of life: Definition and measurement. **Europe's Journal of Psychology**, v. 9, n. 1, p. 150 – 162, 2013. ISSN 18410413. Available: <<http://search.ebscohost.com/login.aspx?direct=true&AuthType=ip,shib,sso,uid&db=aph&AN=85822093&lang=pt-br&site=eds-live&scope=site>>. Citation on page 80.

TIRKEL, T.; EDAN, Y.; KHVOROSTIANOV, N.; BAR-HAIM, S. Sit less: A prototype home-based system for monitoring older adults sedentary behavior. **Assistive Technology**, Taylor Francis, v. 0, n. 0, p. 1–13, 2018. PMID: 29944466. Available: <<https://doi.org/10.1080/10400435.2018.1493707>>. Citations on pages 45, 49 e 125.

TORRE, F. D. L.; HODGINS, J.; BARGTEIL, A. W.; MARTIN, X.; MACEY, J.; COLLADO, A.; BELTRAN, P. Guide to the carnegie mellon university multimodal activity (cmu-mmact) database. In: . [S.l.: s.n.], 2008. Citations on pages 52, 54 e 61.

UGULINO, W.; FERREIRA, M.; VELLOSO, E.; FUKS, H. Virtual caregiver: A system for supporting collaboration in elderly monitoring. In: **2012 Brazilian Symposium on Collaborative Systems**. [S.l.: s.n.], 2012. p. 43–48. ISSN 2326-2826. Citations on pages 44, 45, 47, 49, 50 e 125.

VAVOULAS, G.; CHATZAKI, C.; MALLIOTAKIS, T.; PEDIADITIS, M.; TSIKNAKIS, M. The mobiaact dataset: Recognition of activities of daily living using smartphones. In: INSTICC. **Proceedings of the International Conference on Information and Communication Technologies for Ageing Well and e-Health - Volume 1: ICT4AWE, (ICT4AGEINGWELL 2016)**.

[S.I.]: SciTePress, 2016. p. 143–151. ISBN 978-989-758-180-9. Citations on pages 52, 58, 61, 70 e 89.

VIEL, C. C.; ZIMMERMANN, L. C.; RODRIGUES, K. R. H.; PIMENTEL, M. G. C. Recording maybe?: Location-based application for detection and capture of ad-hoc meetings. In: **Proceedings of the 24th Brazilian Symposium on Multimedia and the Web**. New York, NY, USA: ACM, 2018. (WebMedia '18), p. 53–60. ISBN 978-1-4503-5867-5. Available: <<http://doi.acm.org/10.1145/3243082.3243102>>. Citations on pages 106 e 107.

VIRONE, G. Assessing everyday life behavioral rhythms for the older generation. **Pervasive and Mobile Computing**, v. 5, n. 5, p. 606 – 622, 2009. ISSN 1574-1192. Available: <<http://www.sciencedirect.com/science/article/pii/S1574119209000571>>. Citations on pages 45, 49 e 125.

WANG, J.; CHENG, Z.; ZHANG, M.; ZHOU, Y.; JING, L. Design of a situation-aware system for abnormal activity detection of elderly people. In: HUANG, R.; GHORBANI, A. A.; PASI, G.; YAMAGUCHI, T.; YEN, N. Y.; JIN, B. (Ed.). **Active Media Technology**. Berlin, Heidelberg: Springer Berlin Heidelberg, 2012. p. 561–571. ISBN 978-3-642-35236-2. Citations on pages 45, 49 e 125.

WEISER, M. The computer for the 21st century. **SIGMOBILE Mob. Comput. Commun. Rev.**, ACM, New York, NY, USA, v. 3, n. 3, p. 3–11, Jul. 1999. ISSN 1559-1662. Available: <<http://doi.acm.org/10.1145/329124.329126>>. Citation on page 29.

WEISS, G. M.; LOCKHART, J. W.; PULICKAL, T. T.; MCHUGH, P. T.; RONAN, I. H.; TIMKO, J. L. Actitracker: A smartphone-based activity recognition system for improving health and well-being. **IEEE International Conference on Data Science and Advanced Analytics**, p. 682–688, 2016. Citations on pages 34 e 36.

WEN, F. C. K.; SCHNEIDER, S.; STONE, A. A.; SPRUIJT-METZ, D. Compliance with mobile ecological momentary assessment protocols in children and adolescents: A systematic review and meta-analysis. **J Med Internet Res**, v. 19, n. 4, p. e132, Apr 2017. Available: <<http://www.jmir.org/2017/4/e132/>>. Citation on page 25.

In: WITTEN, I. H.; FRANK, E.; HALL, M. A. (Ed.). **Data Mining: Practical Machine Learning Tools and Techniques (Third Edition)**. Third edition. Boston: Morgan Kaufmann, 2011, (The Morgan Kaufmann Series in Data Management Systems). p. 587 – 605. ISBN 978-0-12-374856-0. Available: <<http://www.sciencedirect.com/science/article/pii/B9780123748560000237>>. Citation on page 98.

XIA, F.; YANG, L. T.; WANG, L.; VINEL, A. Internet of things. **Int. J. Commun. Syst.**, John Wiley and Sons Ltd., Chichester, UK, v. 25, n. 9, p. 1101–1102, Sep. 2012. ISSN 1074-5351. Available: <<http://dx.doi.org/10.1002/dac.2417>>. Citation on page 30.

YANG, A. Y.; JAFARI, R.; SASTRY, S. S.; BAJCSY, R. Distributed recognition of human actions using wearable motion sensor networks. **J. Ambient Intell. Smart Environ.**, IOS Press, Amsterdam, The Netherlands, The Netherlands, v. 1, n. 2, p. 103–115, Apr. 2009. ISSN 1876-1364. Available: <<http://dl.acm.org/citation.cfm?id=1735835.1735838>>. Citations on pages 52, 54 e 61.

ZENG, Y.; CHIU, Y.; CHANG, W. Activity recognition and its applications for elder care based on mono-type sensor network. In: **2015 IEEE 4th Global Conference on Consumer Electronics (GCCE)**. [S.l.: s.n.], 2015. p. 44–47. Citations on pages 45, 49 e 125.

ZHANG, M.; SAWCHUK, A. A. Usc-had: A daily activity dataset for ubiquitous activity recognition using wearable sensors. In: **ACM International Conference on Ubiquitous Computing (Ubicomp) Workshop on Situation, Activity and Goal Awareness (SAGAware)**. Pittsburgh, Pennsylvania, USA: [s.n.], 2012. Citations on pages [52](#), [57](#) e [61](#).

ZHAO, T.; NI, H.; ZHOU, X.; QIANG, L.; ZHANG, D.; YU, Z. Detecting abnormal patterns of daily activities for the elderly living alone. In: ZHANG, Y.; YAO, G.; HE, J.; WANG, L.; SMALHEISER, N. R.; YIN, X. (Ed.). **Health Information Science**. Cham: Springer International Publishing, 2014. p. 95–108. ISBN 978-3-319-06269-3. Citations on pages [26](#), [44](#), [45](#), [49](#), [59](#) e [125](#).

ZHU, C.; SHENG, W.; LIU, M. Wearable sensor-based behavioral anomaly detection in smart assisted living systems. **IEEE Transactions on Automation Science and Engineering**, v. 12, n. 4, p. 1225–1234, Oct 2015. ISSN 1545-5955. Citations on pages [45](#), [47](#), [49](#), [50](#) e [125](#).

COMPLETE SYSTEMATIC REVIEW PROTOCOL

A.1 Procedure

The systematic review protocol was conducted under the supervision of Professor Maria da Graça Campos Pimentel in second semester 2018. The research questions and objectives raised were established from the pre-established readings of papers and studies about Human Activity Recognition systems, which is the subject of the author's interest.

A.2 Review Objectives

- **Primary objective:**

- Establish the state-of-art and the approach of Human Activity Recognition systems focused on the elderly.

- **Secondary objectives:**

- Quantify and summarize pieces of evidence of HAR systems applied in older people monitoring and surveillance.
- Mapping the context and the studies in which HAR systems are applied.
- Raise the sensors, mobile and wearable devices, and algorithms used in HAR systems.
- Define the activities that are recognized by HAR systems focused on the elderly, as well the sensors and devices used for it.
- Identify the main audience of a HAR system: healthy or in-care elderly.

A.3 Research Questions

Question 1: What are the context and the target audience of HAR systems applied on the elderly care?

Question 2: What are the activities and the behaviors of the elderly are recognized by the literature?

Question 3: What sensors and classification algorithms are applied on HAR systems that aim to monitor elderly people?

A.4 Research Process

A.4.1 Search String

("elder" OR "elderly" OR "older") AND ("activity recognition" OR "behavior recognition") AND ("wearable" OR "mobile" OR "smartphone")

A.4.2 Digital Libraries

Table 30 – Digital Libraries visited

Digital Libraries	
ACM Digital Library	http://portal.acm.org
IEEE Digital Library	http://ieeexplore.ieee.org
Science@Direct	http://www.sciencedirect.com
Scopus	http://www.scopus.com
Springer Link	http://link.springer.com

A.5 Selection Criteria of the Studies

The articles were selected through the following selection criteria:

- **Inclusion Criteria**

1. The primary studies must include only the Human Activity Recognition systems designed specifically to monitor, follow and observe the elderly.

- **Exclusion Criteria**

1. The studies that are not primary.
2. Only the English, Portuguese and German language studies were considered relevant.
3. Only full-text papers were selected.
4. Primary studies that present inconclusive results and lack of contributions to Computer Sciences area.

5. Primary studies that don't have the elderly as end-user of the HAR system.
6. Primary studies that don't concern about the privacy of the users and don't consider it as requirement of the system.
7. Short and repeated versions of the same study.
8. Primary studies without full-text available.

The search in the digital libraries was restricted to studies published from 2007 on. Any restriction related to the research field of the study wasn't applied and used as exclusion criteria.

A.6 Study Selection Procedure

All the selection process was performed on the Parsifal tool. Parsifal is an online tool designed to support researchers to perform systematic literature reviews within the context of Software Engineering ([PERFORM...](#), ; [KITCHENHAM; CHARTERS, 2007](#)).

During the analysis of the studies, the following parameters were considered:

- Number of studies per year and per digital library.
- Number of candidate studies per year and per digital library.
- Number of selected studies per year and per digital library.
- The relevant and selected studies were defined by only one researcher.
- A list of the rejected studies with the rejection reasons was defined.

A.7 Quality Evaluation

The literature systematic review process aims to evaluate the research field of Human Activity Recognition, raising the frontier of knowledge of this area, as well as defining gaps – delimiting what is known and what is unknown.

The planning review starts with the following question:

- Why does this research area have a lack of publications?

This is an exploratory question because there isn't enough information to answer it at the moment. Although, it is desired to have a question more specific and well defined from the moment that the research field is defined and there is evidence of works and studies. After the literature systematic mapping, the quality evaluation of the studies is planned and performed.

The evaluation of quality took into account the aspects:

1. Is there a clear statement of research goals?
2. Is there an adequate description of the context in which the research was carried out?
3. Did the data analysis process follow any scientific guidelines?
4. Were the results reported in a clear way?

5. What is the maturity level of the study?

The answers for each question were quantified according the following criteria:

- Yes (Y) – 1 point;
- Maybe Yes (MY) – 0,66 points;
- Maybe Not (MN) – 0,33 points;
- No (N) – 0 points.

Therefore, the levels of quality range between 0 points (minimum) and 5 points (maximum). In Table 31, there are all the selected studies and their level of quality based on the criteria above.

A.8 Data Analysis

The data analysis was performed according to the topics:

1. Citation of the study (BibTex).
2. Study type: Quantitative? / Qualitative?
3. Does the study show evidence of a Human Activity Recognition system applied to elderly users? If yes, how is it?
4. Does the study show evidence of a Human Activity Recognition system applied to elderly users? If yes, when is it?
5. Does the study propose something new? If yes, what is it?
6. What is the target audience of the HAR system: healthy or in-care elderly?
7. What are the activities recognized by the system?
8. What devices and sensors were used? Where were they positioned?
9. Where was the data processed: in a local device or a remote server?
10. Does the training database provide data from elder volunteers?
11. Which machine learning algorithms were applied? What was the accuracy reported by the HAR study?

Considering the answers, the author was able to distinguish the articles and define how the studies of HAR systems for elderly were approached, designed and developed. The main goal is the present a general overview about HAR system for elderly.

A.9 Synthesis of the Data Analysis

Analysing the data extracted from the selected studies, the author has pooled the information according to the contexts: how, when and where. These contexts were quantified and clustered by similarity. At last, the author reported the conclusions about the selected studies.

Table 31 – Evaluation of Quality of the selected Studies

Study	Level of Quality
Taraldsen <i>et al.</i> (2012)	4.66
Tan <i>et al.</i> (2018)	3.64
Meng, Miao and Leung (2017)	4.32
Zhu, Sheng and Liu (2015)	3.98
Moshtaghi, Zukerman and Russell (2015)	1.98
Zhao <i>et al.</i> (2014)	4.32
Wang <i>et al.</i> (2012)	4.66
Osmani, Zhang and Balasubramaniam (2009)	3.98
Ugulino <i>et al.</i> (2012)	2.31
Taati <i>et al.</i> (2010)	1.98
Araújo <i>et al.</i> (2018)	2.98
Chatzaki <i>et al.</i> (2017)	5.00
Kozina <i>et al.</i> (2013)	4.66
Bojanovsky <i>et al.</i> (2017)	3.98
Concepción <i>et al.</i> (2017)	4.32
Haescher <i>et al.</i> (2018)	3.30
Mellone <i>et al.</i> (2012)	1.98
Popescu <i>et al.</i> (2012)	1.98
Fontecha <i>et al.</i> (2013)	3.98
Chigateri <i>et al.</i> (2018)	4.32
Bravo <i>et al.</i> (2011)	4.66
Tahavori <i>et al.</i> (2017)	4.66
Pogorelc, Bosnić and Gams (2012)	1.98
Mitas <i>et al.</i> (2014)	5.00
Caroux <i>et al.</i> (2014)	4.66
Liu, Hsieh and Chan (2018)	4.32
Ouchi and Doi (2013)	4.66
Tirkel <i>et al.</i> (2018)	1.98
Scheurer <i>et al.</i> (2017)	2.98
Chen <i>et al.</i> (2018)	3.30
Mahitha <i>et al.</i> (2017)	4.32
Soraya <i>et al.</i> (2017)	4.32
Sebestyen, Stoica and Hangan (2016)	5.00
Alam and Roy (2014)	1.98
Chernbumroong, Cang and Yu (2015)	4.32
Capela, Lemaire and Baddour (2015)	2.97
Ge and Xu (2014)	5.00
Chernbumroong <i>et al.</i> (2013)	4.66
Cherian <i>et al.</i> (2017)	3.98
Zeng, Chiu and Chang (2015)	1.98
Hong <i>et al.</i> (2008)	4.66
Virone (2009)	2.97
Ranasinghe, Torres and Wickramasinghe (2013)	4.32
Mannini and Sabatini (2015)	4.66
Rosero-Montalvo <i>et al.</i> (2017)	4.66
Morales and Akopian (2017)	5.00
Benmansour, Bouchachia and Feham (2015)	4.32
Ruan (2016)	4.66
Medjahed <i>et al.</i> (2009)	3.98
Sansrimahachai and Toahchoodee (2016)	3.98
Song, Jang and Park (2008)	3.98
Lim <i>et al.</i> (2008)	1.98
Fareed (2015)	5.00
Janjua, Riboni and Bettini (2016)	4.32
Rafael-Palou <i>et al.</i> (2015)	4.32

A.10 Conclusion

This systematic review is used to present an overview of Human Activity Recognition systems applied to the elderly. The systematic review protocol is available and the results are reported in this work and aim to contribute to the scientific community of Ubiquitous Computing, besides the contribution to the society, providing technological solutions for the Gerontology area.

ETHICS COMMITTEE

B.1 Ethics Committee

In order to recruit elderly volunteers, the project was submitted to the Brazilian Ethics Committee, the process of this research project is described below:

- **Project Type:** P - Project of Coordinating Center (in portuguese, *Projeto de Centro Coordenador*);
- **Certificate of Presentation for Ethical Appreciation, in portuguese *Certificado de Apresentação para Apreciação Ética*:** 57875016.3.0000.5390;
- **Responsible Researcher:** Isabela Zaine ¹;
- **Ethics Committee:** School of Arts, Sciences and Humanities, in portuguese *Escola de Artes, Ciências e Humanidades* (EACH) from USP

B.2 Term of Free and Clarified Consent

The Term of Free and Clarified Consent (in portuguese, *Termo de Consentimento Livre e Esclarecido – TCLE*) is an agreement term to participate in an academic research. This term was approved by the Brazilian Ethics Committee and is specific for elderly volunteers.

¹ More information in <http://lattes.cnpq.br/0665572503019533>

ANEXO 9

Termo de Consentimento Livre e Esclarecido (TCLE) - Idosos (Estudo 5.4)

Você está sendo convidado(a) como voluntário(a) a participar da pesquisa intitulada “*Método para amostragem de experiências e intervenção programada*”.

Objetivo: O principal objetivo é a coleta de dados provenientes de atividades físicas realizadas por idosos através de celulares inteligentes (*smartphones*) e relógios inteligentes (*smartwatches*), com a finalidade de desenvolver um sistema que realize o reconhecimento dessas atividades realizadas por idosos. Esse sistema de reconhecimento de atividades será integrado ao sistema ESPIM e também será avaliado e validado diante da sua perspectiva como usuário. Um sistema de reconhecimento de atividades humanas tem por objetivo identificar, com precisão, as atividades e as ações que uma pessoa em observação realiza.

Procedimentos: Sua participação será realizada em duas etapas. Na primeira, você terá acesso a um dispositivo vestível chamado *smartwatch*. Com esse dispositivo você será orientado a vesti-lo em seu pulso dominante, ou seja, o pulso do lado que você tem facilidade para realizar tarefas, como escrever. A partir desse momento, o pesquisador responsável irá lhe perguntar sobre quais atividades físicas você se sente confortável em realizar, por exemplo: andar, correr, sentar, levantar, subir e descer escada, entre outras atividades desempenhadas por você no cotidiano. Dentre as atividades que você se sentir confortável, o pesquisador pedirá que você realize cada atividade em um certo intervalo de tempo (por exemplo, de 1 a 5 minutos). A realização de cada atividade poderá ter intervalos de descanso, caso você prefira ou se sinta mais confortável. Durante esses intervalos, não haverá coleta de dados pelo *smartwatch*, apenas quando você estiver desempenhando alguma atividade estabelecida pelo pesquisador.

Na segunda etapa, você será convidado a utilizar a aplicação móvel chamando SENSEM. Especialistas e profissionais da área da saúde irão planejar programas de monitoração de atividades para você, e você terá acesso a um dispositivo vestível chamado *smartwatch* e a um *smartphone*. Com esse dispositivo você será orientado a vesti-lo em seu pulso. Com o programa estabelecido pelo especialista, o sistema coletará informações sobre as atividades que você realiza. Não se preocupe, as informações não serão divulgadas publicamente. Serão coletadas apenas para avaliação e validação do sistema. Por fim, você será convidado a validar o sistema da sua perspectiva como usuário, respondendo a um questionário e/ou a uma entrevista.

Desconforto e Riscos: Apesar da natureza do estudo não envolver procedimentos invasivos, pode haver algum desconforto em realizar algumas das atividades físicas e também em relação ao uso do *smartwatch*. Poderá haver alguma frustração por não conseguir realizar as atividades de acordo com suas expectativas individuais. Faremos o possível para minimizar tais desconfortos, e caso eles ocorram, você poderá interromper sua participação a qualquer momento.

Possíveis Benefícios: Participando deste estudo você poderá ser beneficiado pelo uso do sistema e também contribuirá para que sistemas computacionais sejam cada vez mais voltados e centrados em usuários idosos. Além disso, através do questionário e/ou da entrevista realizadas durante os estudos, você fornecerá suas impressões sobre a coleta e o sistema que nos ajudarão a modificar o mesmo para melhorá-lo em versões posteriores.

Acompanhamento e Assistência: Você receberá orientações específicas de como o pesquisador realizará a coleta de dados. Esse pesquisador estará disponível a qualquer momento para te orientar e esclarecer dúvidas que possam ocorrer no decorrer desta pesquisa. Os resultados da coleta e da pesquisa estarão à sua disposição quando finalizada.

Liberdade de participação: Sua participação é voluntária e você tem total liberdade para recusar este convite ou desistir da participação a qualquer momento sem que essa decisão acarrete qualquer prejuízo. A sua participação na primeira etapa não o obriga a participar da segunda etapa, caso não deseje ou não tenha disponibilidade.

Sigilo de identidade: Sua identidade será mantida em sigilo absoluto, sem que haja divulgação de seu nome e imagem ou de outros materiais que potencialmente o identifiquem como participante.

Ressarcimento de despesas e indenização: Todos os procedimentos envolvidos nesta pesquisa são gratuitos, não acarretando qualquer ônus financeiro de sua parte. Os dispositivos móveis e vestíveis serão disponibilizados pelos pesquisadores responsáveis durante a coleta, sem custo para você. A sua participação é voluntária. Você tem direito ao ressarcimento e cobertura de eventuais despesas decorrentes da participação nesta pesquisa e garantia de indenização diante de eventuais danos decorrentes da mesma.

Este documento encontra-se impresso em duas vias. Uma via deverá ser assinada e devolvida às pesquisadoras responsáveis, para fins de documentação e arquivamento no Instituto de Ciências Matemáticas e de Computação da Universidade de São Paulo - São Carlos (ICMC-USP). Uma segunda via

será fornecida a você, para que você tenha acesso aos objetivos da pesquisa e ao contato das pesquisadoras responsáveis.

Eu, _____, declaro que entendi os objetivos, procedimentos, riscos e benefícios da minha participação nesta pesquisa e concordo em participar. Declaro também que recebi uma cópia deste Termo de Consentimento Livre e Esclarecido e que me foi dada a oportunidade de lê-lo e esclarecer minhas dúvidas. Fui informado que o projeto foi aprovado¹ pelo Comitê de Ética em Pesquisa Envolvendo Seres Humanos da Escola de Artes, Ciências e Humanidades da Universidade de São Paulo - CEP EACH-USP².

São Carlos, _____ de _____ de 20 ____.

Assinatura do Participante

Assinatura Testemunha

Pesquisadora Responsável:

Larissa Cardoso Zimmermann

Mestranda no Instituto de Ciências Matemáticas e de Computação da
Universidade de São Paulo - São Carlos (ICMC-USP)

email: larissacazi91@gmail.com

tel: (16) 99152-3766/(19)99608-2323

Pesquisadora Coordenadora:

Profa. Dra. Maria da Graça Campos Pimentel

Profa. titular do Instituto de Ciências Matemáticas e de Computação
da Universidade de São Paulo - São Carlos (ICMC-USP)

email: mgp@icmc.usp.br

tel: (16) 3373-9668/(16) 3373-9657

¹ Número de Processo: 57875016.3.0000.5390

² Endereço: Av. Arlindo Bértio, 1000 Ermelino Matarazzo, São Paulo - SP CEP: 03828-000, sala T13 - I1;
Telefone: (11) 3091-1046; e-mail: cep-each@usp.br; Horário de atendimento: Segunda a Sexta-feira, das
10h às 12h e das 14h às 16h.

B.3 Survey – Elderly

This survey aims to define the profile of the elderly volunteers. The author asks questions about the volunteers' personal and professional information, as well as their birthplace and current city, height and weight, questions about health, habits, and behaviors. These questions were elaborated by the author with the support of health professionals.

Questionário para coleta de dados relativos à mobilidade com smartwatch

**Obrigatório*

1. Nome: *

2. Sexo: *

Marcar apenas uma oval.

☐ Mulher

☐ Homem

3. Data de nascimento: *

Exemplo: 15 de dezembro 2012

4. Cidade Natal:

5. Endereço:

6. Celular:

7. Telefone:

8. Ocupação: *

Informe se aposentado(a).

Passe para a pergunta 9.

25/01/2019

Questionário para coleta de dados relativos à mobilidade com smartwatch

Informações Médicas

9. **Peso:** *

10. **Altura:** *

11. **Você consome bebida alcóolica?** *

(cerveja, destilados, outros)

Marcar apenas uma oval.

☐ Sim

☐ Não

12. **Caso você tenha respondido "Sim" para a questão anterior, informe-me nos com que frequência você bebe.**

Marcar apenas uma oval.

☐ Somente em reuniões sociais

☐ Nos finais de semana

☐ Diariamente

☐ Prefiro não responder

☐ Outra: _____

13. **Você é fumante?** *

Marcar apenas uma oval.

☐ Sim

☐ Não

14. **Caso você tenha respondido "Sim" na questão anterior, diga-nos se você tem vontade de parar de fumar.**

Marcar apenas uma oval.

☐ Sim

☐ Não

☐ Talvez

☐ Prefiro não responder

15. **Caso você tenha respondido "Não" na questão anterior, diga-nos, você já fumou antes?** *

Marcar apenas uma oval.

☐ Sim

☐ Não

☐ Prefiro não responder

25/01/2019

Questionário para coleta de dados relativos à mobilidade com smartwatch

16. Você pratica alguma atividade física? **Marcar apenas uma oval.*

- ☐ Sim
- ☐ Não
- ☐ Muito raramente

17. Caso você tenha respondido "Sim" na questão anterior, diga-nos, com qual frequência você realiza atividade física?*Marcar apenas uma oval.*

- ☐ Menos de 3 vezes por semana
- ☐ Somente nos finais de semana
- ☐ 3 ou mais vezes por semana
- ☐ Outra: _____

18. Se você realiza atividades físicas, diga-nos qual atividade você realiza.

19. Você tem alguma dificuldade de locomoção? **Marcar apenas uma oval.*

- ☐ Sim
- ☐ Não

20. Caso tenha respondido "Sim" à questão anterior, por favor, diga-nos qual a dificuldade e o que ocasionou a mesma.

21. Informações sobre a saúde geral **Marcar apenas uma oval por linha.*

	Sim	Não
Já sofreu algum problema no coração?	☐	☐
Taxa de colesterol é alta?	☐	☐
Taxa de triglicérides é alta?	☐	☐
É hipertenso?	☐	☐
É diabético?	☐	☐
Sofreu algum AVC?	☐	☐

25/01/2019

Questionário para coleta de dados relativos à mobilidade com smartwatch

22. Você tem alguma doença diagnosticada por um médico?

Exemplo: Doenças respiratória (asma, bronquite); depressão; câncer; Parkinson, Alzheimer, entre outras.

23. Você está satisfeito com sua saúde? *

Marcar apenas uma oval.

☐ Sim☐ Não**24. Que nota você daria para a sua saúde atualmente? ***

Marcar apenas uma oval.

0 1 2 3 4 5 6 7 8 9 10

☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐**25. Você está satisfeito com sua qualidade de vida? ***

Marcar apenas uma oval.

☐ Sim☐ Não**26. Que nota você daria para a sua qualidade de vida atualmente? ***

Marcar apenas uma oval.

0 1 2 3 4 5 6 7 8 9 10

☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐**27. Tem alguma informação adicional sobre a sua saúde que você gostaria de nos contar?**

Com tecnologia