A Review on the Artificial Intelligence Algorithms for the Recognition of Activities of Daily Living Using Sensors in Mobile Devices

Chapter · February 2020

DOI: 10.1007/978-3-030-40305-8_33

Ivan Miguel Pires
Universidade da Beira Interior

Nuno Garcia
Universidade da Beira Interior

Nuno Pombo
Universidade da Beira Interior

Francisco Flórez-Revuelta
University of Alicante

A Review on the Artificial Intelligence Algorithms for the Recognition of Activities of Daily Living Using Sensors in Mobile Devices

Ivan Miguel Pires[1,2,3], Gonçalo Marques[1,4](✉), Nuno M. Garcia[1,5], Nuno Pombo[1], Francisco Flórez-Revuelta[6], Eftim Zdravevski[7], and Susanna Spinsante[8]

[1] Instituto de Telecomunicações, Universidade da Beira Interior, Covilhã, Portugal
impires@it.ubi.pt, goncalosantosmarques@gmail.com, {ngarcia,ngpombo}@di.ubi.pt
[2] Altranportugal, Lisbon, Portugal
[3] Polytechnic Institute of Viseu, Viseu, Portugal
[4] Polytechnic Institute of Guarda, Guarda, Portugal
[5] Universidade Lusófona de Humanidades e Tecnologias, Lisbon, Portugal
[6] Department of Computer Technology, Universidad de Alicante, San Vicente del Raspeig, Spain
francisco.florez@ua.es
[7] Faculty of Computer Science and Engineering, University Ss Cyril and Methodius, Skopje, Macedonia
eftim.zdravevski@finki.ukim.mk
[8] Department of Information Engineering, Marche Polytechnic University, Ancona, Italy
s.spinsante@univpm.it

Abstract. Smart environments and mobile devices are two technologies that when combined may allow the recognition of Activities of Daily Living (ADL) and its environments. This paper focuses on the literature review of the existing machine learning methods for the recognition of ADL and its environments, by means of comparison jointly with a proposal of a novel taxonomy in this context. The sensors used for this purpose depends on the nature of the system and the ADL to recognize. The available in the mobile devices are mainly motion, magnetic and location sensors, but the sensors available in the smart environments may have different types. Data acquired from several sensors can be used for the identification of ADL, where the motion, magnetic and location sensors handle the recognition of activities with movement, and the acoustic sensors handle the recognition of activities related with the environment.

Keywords: Activities of Daily Living · Mobile devices · Pattern recognition · Sensors · Methods · Review

P. K. Singh et al. (Eds.): *Handbook of Wireless Sensor Networks: Issues and Challenges in Current Scenario's*, AISC 1132, pp. 685–713, 2020.
https://doi.org/10.1007/978-3-030-40305-8_33

1 Introduction

The recognition of ADL is of great importance for a number of reasons, among which one can find the need to monitor the activities of an elderly or a diseased person, as to allow the definition of adequate therapies not only as an improvement of that person's health, but also as an improvement to her/his wellbeing or quality of life. In addition, these features may be included for the development of a personal digital life coach (Garcia 2016), extending the identification of ADL.

An ADL (Foti and Koketsu 2013) may be identified with several types of sensors, including the motion, magnetic, vision, acoustic and location sensors usually found in off-the-shelf devices such as smartphones, allowing this identification to be performed in uncontrolled environments. While the recognition of ADL in controlled environments is related to the activities performed in smart environments equipped with several sensors, the recognition of ADL in uncontrolled environments is related to the use of several sensors attached to the subject's body or carried by the subject during the ADL. In this last scenario, the sensors used can be the ones that are widely available in a variety of off-the-shelf mobile devices such as smartwatches and smartphones. Several studies have been performed using the imaging sensors for the recognition of ADL, as presented in (Aggarwal and Ryoo 2011), but the main focus of this paper consists in the use of the sensors available in the mobile devices in order to promote the recognition of ADL in mobility.

The review of the methods for the development of an approach for the framework for the recognition of the ADL (Foti and Koketsu 2013) was started in the previous studies (Pires, Garcia et al. 2015, Pires, Garcia et al. 2016a, b, c, Pires, Garcia et al. 2016a, b, c, Pires, Garcia et al. 2018a, b, c, Pires, Garcia et al. 2018a, b, c, Pires, Garcia et al. 2018a, b, c, Pires, Santos et al. 2018, Pires, Teixeira et al. 2018), and the proposed framework includes the research of methods on data acquisition, data processing, data fusion and artificial intelligence methods for the recognition of ADL. The study (Pires, Garcia et al. 2016a, b, c) presented the review of the methods related to data acquisition, data processing and data fusion methods. However, the study (Pires, Garcia et al. 2016a, b, c) extends the research about data processing, including the research of methods about data cleaning and data imputation.

This paper present a review of the artificial intelligence methods for the recognition of ADL, published between 2007 and 2017, starting with the research of the methods used in smart environments, and, finally, the implemented in mobile devices for the recognition of ADL, where the most used sensors is the accelerometer for the recognition of simple activities, such as walking, running, walking on stairs, jumping, among others.

The remaining sections of this paper are organized as follows: Sect. 2 presents the methods for the recognition of ADL in smart environments. The methods for the recognition of ADL using mobile devices are presented in the Sect. 3. Section 4 presents the applicability of these methods and the results of the researched methods. Finally, the discussion and conclusions of this study are presented in the Sect. 5.

2 Background of the Recognition of Activities of Daily Living Using Sensors

The recognition of ADL was studied with the use of several types of sensors placed in the body of the individuals or available in smart environments. The authors of (Chernbumroong, Atkins et al. 2011) used Artificial Neural Networks (ANN) and decision tree for the recognition of simple activities, such as walking, running, standing, sitting and lying based on the data acquired from a single wrist-worn sensor, reporting an accuracy of 94.13%.

In (Bao and Intille 2004), a single wrist-worn sensor is also used for the recognition of several activities, including walking, sitting, working on computer, standing, eating, drinking, watching TV, reading, running, cycling, stretching, vacuuming, folding laundry, lying, brushing teeth, walking on stairs and riding an elevator, using decision tables, Instance-based learning (IBL), C4.5 decision tree and Naïve Bayes with reported accuracy of 84%.

Related to the recognition of ADL in smart environments, the Radio-frequency identification (RFID) sensors in different placements are used. The authors of (Naeem and Bigham 2007) used the RFID sensors for the recognition of making a tea, making a toast, drinking water, making coffee, warming a meal, washing dishes, using a dishwasher, and having a snack activities with Hidden Markov Model (HMM).

The Adaptive Learning Hidden Markov Model (ALHMM) was used with the data acquired from RFID sensors for the recognition of several activities, including making a tea, using the bathroom, phone calling, making a meal, taking out the trash, making soft-boiled eggs, setting the table, preparing orange juice, eating, making coffee and clearing the table (Cheng, Tsai et al. 2009).

The authors of (Hoque and Stankovic 2012) used the RFID sensors' data applied to HMM and Naïve Bayes for the recognition of sleeping, eating, preparing a breakfast, preparing a dinner, getting a drink, getting a snack, using a dishwasher, using a washing machine, taking a shower, using toilet, brushing teeth, leaving house and receiving guest.

In (Danny, Matthai et al. 2005), the C4.5 decision tree, Naïve Bayes and Support Vector Machine (SVM) are implemented with the data acquired from the RFID sensors, recognizing several activities with an accuracy around 42%, these are using a microwave, adjusting the thermostat, boiling a pot of tea, boiling water, brushing hair, brushing teeth, cleaning a toilet, cleaning the kitchen, doing laundry, drinking water, using a dishwasher, making a snack, reading, shaving face, using microwave, phone calling, vacuuming, using toilet, washing hands and watching TV.

The accelerometer is another sensor used for the recognition of ADL in smart environments. The authors of (Liming, Hoey et al. 2012) used several methods, including HMM, Dynamic Bayesian Network (DBN), SVM, Conditional random field (CRF), ANN, Logical formula, Naïve Bayes and decision tree, for the recognition of making coffee, brushing teeth and boiling water with accelerometer.

In (Wang, Chen et al. 2012), a method using the accelerometer data for the recognition of standing, walking, running, jumping, falling and sitting activities using Gaussian Mixture Model (GMM), HMM, and SVM was presented, reporting an accuracy between 96.43% and 98.21%.

The lying, sitting, standing, walking, cycling and running activities may be recognized with the accelerometer data, implementing the SVM, feed-forward neural network and decision tree (Gyllensten and Bonomi 2011). The eating and drinking activities may be recognized with the Extended Kalman Filter (EKF) applied to the accelerometer data (Zhang, Ang et al. 2009).

Only with the accelerometer data, the authors of (Khan, Lee et al. 2010) implemented the ANN and autoregressive (AR) model for the recognition of lying, sitting, standing, walking, walking on stairs and running activities, reporting an average accuracy of 97.9%.

The cameras are also used in smart environments for the recognition of ADL. The authors of (Botia, Villa et al. 2012) used the data retrieved from camera with the HMM for the recognition of movements in home office, kitchen, living room and outdoors, and activities, such as walking on stairs, making coffee and working on computer. Based on the use of cameras, the authors of (Aggarwal and Ryoo 2011) proposed a taxonomy for the recognition of ADL, separated in two different approaches, such as single-layered approaches and hierarchical approaches. The single-layered approaches can be Space-time approaches and Sequential approaches. Firstly, the space-time approaches are the Space-time volume, Trajectories and Space-time features. Secondly, the sequential approaches are the Exemplar-based and State-based. Finally, the hierarchical approaches are the Statistical, Syntactic and Description-based.

Other authors used the cameras for the recognition of several ADL, such as combing hair, making up, brushing teeth, washing hands, washing dishes, making a tea, making coffee, drinking, making a snack, vacuuming, watching TV, using a computer and using a smartphone, implementing SVM (Ramanan 2012).

The remaining studies related to the recognition of ADL presented in this section use a combination of sensors. The authors of (Szewcyzk, Dwan et al. 2009) used the data acquired from the accelerometer, camera and RFID sensors with the Naïve Bayes for the recognition of preparing dinner, working on computer, sleeping and watching TV activities, reporting an accuracy of 73.6%.

In (Chikhaoui, Wang et al. 2011), the authors used motion (e.g., accelerometer) and RFID sensors in different placements (i.e., door, light, temperature and item) for the recognition of several activities, such as having breakfast, waking up, preparing breakfast, toileting and preparing tea, with HMM, reporting a lowest accuracy of 86.08%.

The accelerometer and RFID sensors are also used for the recognition of several activities, such as making cereals, making a sandwich, making coffee, reading a book, watching TV, cleaning windows, using telephone, brushing teeth and sleeping, implementing HMM (Buettner, Prasad et al. 2009).

The authors of (Stikic, Huynh et al. 2008) used the accelerometer and RFID sensors for the recognition of dusting, ironing, vacuuming, brooming, mopping, cleaning windows, making the bed, watering plans, washing dishes and setting table activities, implementing HMM, Naïve Bayes and Joint Boosting.

In (Chernbumroong, Cang et al. 2013), the authors implemented the recognition of feeding, brushing teeth, dressing, walking, walking on stairs, sleeping, lying, washing dishes, ironing, sweeping and watching TV activities with the acquisition of data from the temperature, altimeter and accelerometer sensors, reporting an accuracy of 90% with SVM and ANN.

The authors of (Banos, Damas et al. 2012) implemented some variants of HMM, i.e., Two-level hierarchical HMM (HHMM), Bottom-level HMM and Top-level HMM, for the recognition of hoovering, sweeping, washing clothes, serving, making coffee, making a snack, brushing hair, phone calling, watching TV, knitting, listening music, brushing teeth and washing dishes activities with the data acquired from accelerometer and cameras.

In (Maurer, Smailagic et al. 2006), the implementation of the C4.5 decision tree reported an accuracy around 92.5% for the recognition of running, walking, walking on stairs, standing and sitting activities with data acquired from accelerometer, light, temperature and microphone sensors.

The combination of the accelerometer and the Global Positioning System (GPS) receiver for the recognition of lying, sitting, standing, walking, using a mouse, typing on a keyboard, flipping a page and eating activities with ANN and Bayesian networks (Zhu, Chen et al. 2010, Zhu and Sheng 2012). In (Libal, Ramabhadran et al. 2009), the GMM was used with data acquired from microphones and cameras in order to recognize eating, drinking, ironing, cleaning, phone calling and watching TV, reporting an accuracy of 57.64%.

According to (Tolstikov, Biswas et al. 2008), the eating activity may be recognized with camera, pressure, ultrasound and accelerometer sensors, implementing DBN and HMM. In (Kasteren and Krose 2007), the DBN is also used for the recognition of eating, bathing and toileting activities, using contact switches, pressure sensors and accelerometers. In (Suryadevara, Quazi et al. 2012), the authors used ZigBee wireless sensors with Naïve Bayes for the recognition of preparing a meal, watching TV and preparing tea.

The authors of (Ueda, Tamai et al. 2015) used the SVM with data acquired from power meters, ambient sensors, ultrasonic positioning sensor, door sensors and faucet sensors, reporting an accuracy of 82% in the recognition of several activities, such as watching TV, taking a meal, cooking, reading a book and washing dishes.

Based on the recognition of ADL with sensors available in smart environments and off-the-shelf mobile devices, the authors of (Hong, Kim et al. 2008) used the accelerometer and RFID sensors for the recognition of sitting, pushing a shopping cart, standing, phone calling, walking, taking picture, lying, put on skin conditioner, running, wiping, hand shaking, jumping, reading, hair brushing and cutting activities, reporting an accuracy of 84.36% with the decision tree.

The smart environments may have several types of sensors, where the authors of (Fulk, Edgar et al. 2012) used the accelerometer and the pressure sensor for the recognition of sitting, standing and walking activities, reporting an accuracy higher than 95% with the ANN.

Other authors (Ordonez, de Toledo et al. 2013) used the sensors available in smart environments, i.e., cameras and RFID sensors, and sensors available in off-the-shelf mobile devices for the recognition of leaving, toileting, sleeping, eating and drinking activities, implementing ANN, HMM and SVM.

Tables 1 and 2 summarize the ADL recognized in the literature and the methods used for the recognition of the ADL, concluding that the most recognized ADL are making a meal, eating, watching TV, brushing teeth, standing, sitting, lying, making coffee, running, drinking, making a tea, washing dishes, phone calling, walking on stairs and cleaning, and the methods with best accuracy are the ANN and HMM.

Based on the methods presented in Table 2 and the analysis of the methods presented in (Pires, Garcia et al. 2016a, b, c, Pombo, Garcia et al. 2017), the methods used for the recognition of ADL can be grouped in Neural Networks, Reinforcement Learning, Decision, Bayesian and Instance-based methods, where the methods that report better accuracy and performance than others are the ANN.

Table 1. ADL recognized with the methods available in the literature.

ADL	Number of studies	Studies
Making a meal; eating; walking	11	Chernbumroong, Atkins et al. 2011; Bao and Intille 2004; Wang, Chen et al. 2012; Gyllensten and Bonomi 2011; Khan, Lee et al. 2010; Botia, Villa et al. 2012; Chernbumroong, Cang et al. 2013; Maurer, Smailagic et al. 2006; Zhu, Cheng et al. 2010, Zhu and Sheng 2012; Hong, Kim et al. 2008; Fulk, Edgar et al. 2012
Watching TV; standing; sitting	10	Bao and Intille 2004; Danny, Matthai et al. 2005; Ramanan 2012; Szewcyzk, Dwan et al. 2009; Buettner, Prasad et al. 2009; Chernbumroong, Cang et al. 2013; Banos, Damas et al. 2012; Libal, Ramabhadran et al. 2009; Suryadevara, Quazi et al. 2012; Ueda, Tamai et al. 2015
Brushing teeth	9	Bao and Intille 2004; Hoque and Stankovic 2012; Danny, Matthai et al. 2005; Liming, Hoey et al. 2012; Ramanan 2012; Buettner, Prasad et al. 2009; Chernbumroong, Cang et al. 2013; Banos, Damas et al. 2012; Hong, Kim et al. 2008
Lying	8	Chernbumroong, Atkins et al. 2011 Bao and Intille 2004; Zhang, Ang et al. 2009; Khan, Lee et al. 2010; Chernbumroong, Cang et al. 2013; Zhu, Cheng et al. 2010, Zhu and Sheng 2012; Hong, Kim et al. 2008
Making coffee; running; drinking; phone calling	7	Naeem and Bigham 2007; Cheng, Tsai et al. 2009; Liming, Hoey et al. 2012; Botia, Villa et al. 2012; Ramanan 2012; Buettner, Prasad et al. 2009; Banos, Damas et al. 2012

(*continued*)

Table 1. (*continued*)

ADL	Number of studies	Studies
Making a tea; washing dishes	6	Naeem and Bigham 2007; Ramanan 2012; Stikic, Huynh et al. 2008; Chernbumroong, Cang et al. 2013; Banos, Damas et al. 2012; Ueda, Tamai et al. 2015
Walking on stairs; cleaning; reading; sleeping	5	Bao and Intille 2004; Khan, Lee et al. 2010; Botia, Villa et al. 2012; Chernbumroong, Cang et al. 2013; Maurer, Smailagic et al. 2006
Working on computer; vacuuming; using toilet	4	Bao and Intille 2004; Botia, Villa et al. 2012; Ramanan 2012; Szewcyzk, Dwan et al. 2009
Using a dishwasher; ironing	3	Stikic, Huynh et al. 2008; Chernbumroong, Cang et al. 2013; Libal, Ramabhadran et al. 2009
Cycling; making a toast; having a snack; using the bathroom; using a microwave; Brushing hair; washing hands; sweeping; using a mouse; typing on a keyboard; flipping a page; leaving house; jumping	2	Bao and Intille 2004; Zhang, Ang et al. 2009
Stretching; folding laundry; riding an elevator; taking out the trash; making soft-boiled eggs; setting the table; preparing orange juice; clearing the table; getting a drink; getting a snack; using a washing machine; taking a shower; receiving guest; adjusting the thermostat; doing laundry; falling; combing hair; making up; waking up; dusting; brooming; mopping; making the bed; watering plants; setting table; feeding; dressing; hoovering; washing clothes; serving; knitting; listening music; pushing a shopping cart; taking picture; put on skin conditioner; wiping; hand shaking; hair brushing; cutting; toileting	1	Chernbumroong, Cang et al. 2013; Hoque and Stankovic 2012; Danny, Matthai et al. 2005; Wang, Chen et al. 2012; Gyllensten and Bonomi 2011; Aggarwal and Ryoo 2011; Chikhaoui, Wang et al. 2011; Buettner, Prasad et al. 2009; Banos, Damas et al. 2012; Tolstikov, Biswas et al. 2008; Kasteren and Krose 2007; Hong, Kim et al. 2008; Fulk, Edgar et al. 2012

Table 2. Methods implemented in the studies available in the literature.

Method	Number of studies	Average of the accuracy reported	Studies
Artificial Neural Networks (ANN)	9	94.13%	Chernbumroong, Atkins et al. 2011; Liming, Hoey et al. 2012; Gyllensten and Bonomi 2011; Khan, Lee et al. 2010; Chernbumroong, Cang et al. 2013; Zhu, Cheng et al. 2010, Zhu and Sheng 2012; Fulk, Edgar et al. 2012; Ordonez, de Toledo et al. 2013
Hidden Markov Model (HMM)	12	91.43%	Naeem and Bigham 2007; Cheng, Tsai et al. 2009; Hoque and Stankovic 2012; Liming, Hoey et al. 2012; Wang, Chen et al. 2012; Botia, Villa et al. 2012; Chikhaoui, Wang et al. 2011; Buettner, Prasad et al. 2009; Stikic, Huynh et al. 2008; Banos, Damas et al. 2012; Tolstikov, Biswas et al. 2008; Ordonez, de Toledo et al. 2013
Decision tables	1	84.00%	Bao and Intille 2004
Instance-based learning (IBL)	1	84.00%	Bao and Intille 2004
Gaussian Mixture Model (GMM)	2	77.93%	Wang, Chen et al. 2012; Libal, Ramabhadran et al. 2009
Decision tree (i.e., J48 and C4.5)	6	74.75%	Chernbumroong, Atkins et al. 2011; Bao and Intille 2004; Chetty and White 2016; Liming, Hoey et al. 2012; Gyllensten and Bonomi 2011; Maurer, Smailagic et al. 2006
Support Vector Machine (SVM)	8	74.07%	Danny, Matthai et al. 2005; Liming, Hoey et al. 2012; Wang, Chen et al. 2012; Gyllensten and Bonomi 2011; Ramanan 2012; Chernbumroong, Cang et al. 2013; Ueda, Tamai et al. 2015; Ordonez, de Toledo et al. 2013
Naïve Bayes	7	66.53%	Bao and Intille 2004; Hoque and Stankovic 2012; Danny, Matthai et al. 2005; Liming, Hoey et al. 2012; Szewcyzk, Dwan et al. 2009; Stikic, Huynh et al. 2008; Suryadevara, Quazi et al. 2012

3 Methods for the Recognition of Activities of Daily Living Using Mobile Devices

Mobile devices are equipped with several sensors (Pires, Garcia et al. 2016a, b, c) that are able to acquire data related to the ADL and handle the recognition of ADL using lightweight methods, because these devices have low memory and processing power. Most common sensors embedded on these devices are the accelerometer, the gyroscope, the magnetometer, the microphone and the GPS receiver (Salazar et al. 2013).

According to the previous studies in the literature, the accelerometer is the most used sensor for the recognition of ADL, because it allows the acquisition of the data related to the movement. The authors of (Vilarinho et al. 2015) implemented the Phone Acceleration Threshold (PAT), the Phone Pattern Recognition (PPR) and the Watch Threshold and Pattern Recognition (WTPR) for the recognition of different patterns of falling activities as well as the walking, sitting, walking on stairs, trying shoes and jogging activities with the use of accelerometer data, reporting a recognition accuracy of 63% for the recognition of falling activities, and 78% for the recognition of other activities.

Falling activities and ADL are also recognized in (Ivascu, Cincar et al. 2017), including the recognition of several types of falls and walking on stairs, sitting, standing, lying, getting up, jumping, walking and running activities with the accelerometer sensor, reporting an accuracy of 91.3% with decision tree, 95.96% with SVM, 86.54% with Naïve Bayes, 96.21% with Random Forest, 94.44% with Adaboost, 95.95% with k-Nearest Neighbour (k-NN), and 96.56% with Deep Neural Networks (DNN).

The authors of (Tsai, Yang et al. 2015) also used the accelerometer data for the recognition of several types of falls and other ADL, including walking, jogging, sitting, standing and lying activities, and, based on the placement of the smartphone, the results obtained using ANN are around 84.29%. In (Mashita, Komaki et al. 2012), the accelerometer sensor was also used for the recognition of standing, walking and running activities, implementing SVM.

The sports activities, *e.g.,* running, volleyball, handball, basketball and futsal, can be also identified with the accelerometer sensor, reporting an accuracy of 42.3% with the Multilayer Perceptron (MLP), 53.8% with the k-NN, 38.4% with the Naïve Bayes, 38.4% with the J48 decision tree and 50% with the SVM (Costa, Fazendeiro et al. 2016). In (Okour, Maeder et al. 2015), the recognition of sitting, walking, standing, sleeping and falling activities were also performed with a rule-based classifier applied to the accelerometer data, reporting an accuracy of 87.7%.

The authors of (Kelly and Caulfield 2012) implemented the C4.5 decision tree, MLP, Logistic Regression, Bayesian Networks and SVM for the recognition of standing, sitting, walking on stairs, and walking using the accelerometer sensors, and they reported an accuracy around 88.2%.

In (Büber and Guvensan 2014), the study recognizes walking, sitting, standing, walking on stairs, jogging, cycling and jumping with the implementation of several methods with the accelerometer data acquired, these are the J48 decision tree with an accuracy of 91.01%, the k-Start with an accuracy of 93.35%, the Naïve Bayes with an accuracy of 80.55%, the Bayesian Network with an accuracy of 88.20%, the Random Forest with an accuracy of 93.13%, and the k-NN with an accuracy of 93.84%.

The authors of (Alam and Roy 2014) implemented the C4.5 decision tree for the recognition of talking, coughing, deglutition, silence and yawning, reporting an accuracy of 94.8% using accelerometer data. In the study (Khalifa, Lan et al. 2017), the rowing, cycling, running, walking, jumping, standing, sitting and walking on stairs activities were recognized with the accelerometer data, reporting an accuracy of 80.96% with the C4.5 decision tree, 61.27% with IBk Nearest Neighbour, 67.14% with Naïve Bayes, and 55.64% with SVM.

The authors of (Kilinc, Dalzell et al. 2015) used the ANN applied to the accelerometer data in order to recognize walking on stairs, drinking, getting up, sitting, standing and walking activities with a reported accuracy of 91%.

In (Nurwanto, Ardiyanto et al. 2016), the k-NN and Dynamic Time Warping Algorithm were implemented with accelerometer data for the recognition of pushing up, sitting, squatting and jumping activities, reporting an average accuracy around 84%.

The accelerometer sensor was also used for the recognition of walking and sitting activities in the study (Prabowo, Mutijarsa et al. 2016), reporting 87.29% with Bayesian networks, 87.86% with MLP, 88.26% with C4.5 decision tree, and 89.48% with k-NN.

The walking, standing, sitting and walking on stairs activities were also recognized with several methods applied to the accelerometer data, which reported 97.08% with decision tree, 93.53% with Bayesian networks, 93.03% with Naïve Bayes, 99.27% with k-NN and 92.54% with a rule based learner (Lau and David 2010).

In (Shen, Li et al. 2013), the SVM reports an accuracy around 95.8% for the recognition of sitting, standing and walking activities using the accelerometer data. The use of the J48 decision tree with the accelerometer data for the recognition of walking, walking on stairs, sitting, standing and lying activities reports an accuracy of 86% (Silva 2013). Recognizing eating, shopping, entertainment and recreational activities, the authors of (Phithakkitnukoon, Horanont et al. 2010) implemented the Naïve Bayes to the data acquired from the accelerometer sensor, but its accuracy is not mentioned. The authors of (Bujari, Licar et al. 2012) used the ANN for the recognition of the walking pattern with accelerometer data, reporting an accuracy between 75% and 98%.

In (Saponas, Lester et al. 2008), the Naïve Bayes classifier was used for the recognition of walking, running, cycling and sitting activities based on the accelerometer data, reporting an accuracy around 97%. Additionally, in (Kuspa and Pratkanis 2013), the recognition of walking on stairs, jogging, sitting, standing and walking activities was performed with the application of the Principal Component Analysis (PCA) and Gaussian Discriminant Analysis (GDA) to the accelerometer data, reporting an accuracy around 92%.

The standing, walking, cycling, driving and running activities were recognized by the authors of (Siirtola and Röning 2012) with the accelerometer data, applying the k-NN, Quadratic Discriminant Analysis (QDA) and SVM and reporting an average accuracy of 90%.

The accelerometer sensor was also used in (Kmiecik 2013) for the recognition of jogging, walking and walking on stairs, implementing Naïve Bayes classifier. The k-NN was used for the recognition of sitting and standing, reporting an accuracy of 100% with the accelerometer data (Kaghyan and Sarukhanyan 2012).

Based on the accelerometer data, the authors of (Anguita, Ghio et al. 2012) implemented the SVM for the recognition of standing, walking, laying and walking on stairs activities. In (Awan, Guangbin et al. 2013), the authors used the accelerometer data for the implementation of the J48 decision tree, the logistic regression and the Naïve Bayes, recognizing the sitting, standing, walking and jogging activities with an accuracy around 96%. In another study (Lara and Labrador 2012), the C4.5 decision tree was implemented for the recognition of running, walking and sitting activities, reporting an accuracy of 92.6% with the accelerometer data.

A system named Centinela, described in (Lara, Pérez et al. 2012), is a system that implements the Naïve Bayes for the recognition of walking, running, sitting and walking on stairs activities, reporting an accuracy up to 95.7%.

For the recognition of simple activities, *i.e.,* walking, running, standing and walking on stairs, and complex activities, *i.e.,* cooking and cleaning, another implementation of the ANN was presented in (Dernbach, Das et al. 2012), reporting an accuracy of 93% in the recognition of simple activities, and 50% in the recognition of complex activities. The authors of (Zhu and Sheng 2010) also used the accelerometer sensor for the recognition of sitting, standing, walking and lying activities, implementing the HMM that reports an accuracy of 60%.

For the recognition of lying, sitting, standing and walking activities, the authors of (Zhu and Sheng 2011) implemented the Viterbi algorithm, HMM and Bayesian filter, reporting an accuracy of 85% with the use of the accelerometer data. In (Huynh 2008), the SVM and HMM were implemented for the recognition of shopping, doing housework, bathing, dressing, toileting, feeding, walking, sitting, vacuuming, standing, eating and washing dishes activities with the accelerometer data, reporting an accuracy higher than 90%.

Using only the accelerometer sensor, the authors of (Jie, Shuangquan et al. 2010) used the k-NN one-class classifier, Support Vector Data Description (SVDD) one-class classifier and Gauss one-class classifier in order to recognize standing, walking, running and walking on stairs activities.

In (Zhang and Sawchuk 2013), the accelerometer data was used with Linear Description Analysis (LDA) and PCA for the recognition of walking, running, walking on stairs, standing, jumping and sitting activities with a reported accuracy of 96.1%. The authors of (Allen, Roozbeh et al. 2009) implemented the distributed sparsity classifier (DSC) for the recognition of standing, sitting, lying, kneeling, bending, jumping and walking on stairs activities, using the accelerometer data.

The previous studies analysed only used the accelerometer sensor, but other combinations of sensors have been studied in the last years. The authors of (Chetty and White 2016) used the accelerometer and gyroscope sensors for the recognition of walking, walking on stairs, sitting, standing and lying activities, reporting an accuracy of 79% with the Naïve Bayes classifier, 60% with the k-Means Clustering, 94% with J48 decision tree, 96.3% with Random Forest Classifier, 96.9% with Random Committee Classifier, and 97.89% with Lazy IBk Classifier.

In (Rasheed, Javaid et al. 2015), the Signal Magnitude Vector (SMV) algorithm was used for the recognition of standing, sitting, walking and running activities with accelerometer and gyroscope data. The lying and sitting activities were also recognized with the accelerometer and gyroscope sensors, reporting and accuracy of 80% with

Naïve Bayes, 87.5% with k-NN, 75.43% with Least Squares Method (LSM), 85.87% with ANN and 86.75% with SVM (Vallabh, Malekian et al. 2016).

The authors of (Roy, Misra et al. 2013) recognized the sitting, standing, walking, running, lying, walking on stairs, cleaning, cooking, taking medication, sweeping, washing hands and watering plants activities with the accelerometer and gyroscope sensors, reporting an accuracy between 50% and 85% with the HMM.

The ANN was also used to recognize the walking pattern with the accelerometer and gyroscope sensors, reporting an accuracy of 95.6% (Lorenzi, Rao et al. 2016). In (Shen, Chen et al. 2016), the accelerometer and gyroscope sensors are also used for the recognition of walking on stairs, walking, running and jumping activities, reporting an accuracy of 90.65% with Random Forest, 85.14% with SVM, 85.83% with ANN and 79.42% with k-NN.

The walking on stairs, walking, jogging and jumping activities are also recognized in (Chen and Shen 2017) with the accelerometer and gyroscope data, implementing several methods, such as the k-NN, which reports a minimum accuracy of 73.94%, the Random Forest, which reports a minimum accuracy of 83.59%, and the SVM, which reports a minimum accuracy of 69.21%.

The accelerometer and the gyroscope sensors are also used with SVM for the recognition of walking, running, and walking on stairs activities, reporting an accuracy of 92.5% (Hsu, Chu et al. 2015). The authors of (Anguita, Ghio et al. 2013) implemented the SVM for the recognition of walking, walking on stairs, sitting, standing and laying with the accelerometer and gyroscope data. An implementation of the SVM for the recognition of walking, standing, writing, smoking and jogging activities with accelerometer and gyroscope data was analysed in (Varkey, Pompili et al. 2011), reporting an accuracy of between 80 and 91%.

Another combination of sensors used for the recognition of ADL consists on the use of the accelerometer and the GPS receiver. The authors of (Fortino, Gravina et al. 2015) implemented the k-NN for the recognition of sitting, standing, walking, lying and falling activities with the accelerometer and the GPS receiver, reporting an accuracy of 96%.

In (Kwapisz, Weiss et al. 2011), the authors used the accelerometer and the GPS receiver for the recognition of walking, jogging, walking on stairs, sitting and standing activities with the J48 decision tree, logistic regression and MLP, reporting an accuracy of 90%. The walking, cycling, running and standing activities are recognized by the authors of (Chiang, Yang et al. 2013), which implemented the decision tree, k-NN, Naïve Bayes and SVM with the data acquired from the accelerometer and GPS receiver.

The authors of (Hong, Ramos et al. 2013) recognized the lying, sitting, standing, walking, walking on stairs and taking an elevator, implementing a system with ANN, SVM, GMM, HMM, k-NN, Random Forest and k-Means clustering with a reported accuracy of 90.4% using the accelerometer and GPS receiver. In (Ermes, Parkka et al. 2008), the ANN and decision tree were implemented for the recognition of lying, sitting, standing, walking, running, cycling, rowing and playing football based on the accelerometer and the GPS data, reporting an accuracy of 89%.

Another combination of sensors used for the recognition of ADL consists on the use of the accelerometer and the microphone. The authors of (Nishida, Kitaoka et al. 2014) implemented the GMM for the recognition of cycling, cleaning table, shopping, toileting, cooking, watching TV, eating, working on a computer, reading, using a smartphone, driving and sleeping, reporting an accuracy of 76.9% with the accelerometer and microphone data.

The ANN was implemented with the use of the accelerometer and the microphone data for the recognition of walking, working on a computer, driving, cycling, running, jumping and watching TV (Bieber, Luthardt et al. 2011). The HMM also used with the accelerometer and the microphone data for the recognition of walking, running, cooking, reading, driving, eating, washing dishes, brushing teeth and watching TV activities (Ganti, Srinivasan et al. 2010).

The accelerometer and the camera is another combination of sensors used for the recognition of ADL, where the authors of (Zhan, Faux et al. 2014) implemented the LogitBoost and the SVM for the recognition of walking, walking on stairs, drinking, standing, sitting, reading, watching TV, writing and washing hands, reporting an accuracy of 77.4% with LogitBoost and 68.91% with SVM. Using also the accelerometer and the camera, the authors of (Nam, Rho et al. 2013) implemented the SVM for the recognition of walking, running, walking on stairs, taking an elevator, sitting and standing activities, reporting an accuracy of 92.78%.

Another combination of sensors is composed by the data acquired from the accelerometer and the digital compass, where the authors of (Cruz-Silva, Mendes-Moreira et al. 2013) recognized the walking on stairs, taking an elevator, running, walking and sitting reported on the Naïve Bayes, k-NN and Random Forest.

The accelerometer and the magnetometer sensors available in off-the-shelf mobile devices may be also used for the recognition of walking and running activities, where the authors of (Maekawa, Kishino et al. 2012) implemented the HMM. The eating activity was recognized by the accelerometer, light, temperature and barometer sensors by the authors of (Kim and Cho 2015) that implemented the Bayesian network, reporting an accuracy of 94.57%.

The accelerometer, light, temperature and microphone sensors were used by the authors of (He and Bai 2014), which implemented the HMM for the recognition of standing, running and walking activities with a reported accuracy higher than 80%. In (Eskaf, Aly et al. 2016), the authors used the accelerometer, gyroscope, gravity and rotational vector sensors for the recognition of walking, standing, sitting and bowing activities, reporting an accuracy of 83% with the J48 decision tree, 90% with the k-NN and 79% with the Naïve Bayes.

The gyroscope, accelerometer and magnetometer sensors available in off-the-shelf mobile devices may be used for the recognition of travelling by public transport, running, running, cycling and walking activities, where the authors of (Ravì, Lo et al. 2015) reported a minimum accuracy of 84.97% with the SVM.

The gyroscope, accelerometer and magnetometer sensors were also used in (Shoaib 2013) for the recognition of cycling, travelling by car, smoking, eating and taking an elevator activities with the use of the k-NN, the J48 decision tree, the rule based classifier and the SVM.

The authors of (Das, Green et al. 2010) used the accelerometer, GPS, gravity and communication sensors for the recognition of standing, walking, running, jumping and walking on stairs activities, reporting an accuracy of 93% with the 1-Nearest Neighbour classification algorithm.

The standing, walking and jogging activities may be recognized with accelerometer, gyroscope and GPS receiver, where the authors of (Fitz-Walter and Tjondronegoro 2009) reported an accuracy of 86.53% with ANN. The authors of (Gafurov, Snekkenes et al. 2007) also implemented the ANN and J48 decision tree for the recognition of jogging, walking on stairs and walking with the use of accelerometer, GPS receiver, camera, microphone, light, temperature and altitude sensors.

In (Kazushige and Miwako 2012), the implementation of the ANN reported an accuracy of 85% in the recognition of standing, walking, running, boarding, vacuuming and brushing teeth with the accelerometer, the microphone and the GPS receiver.

Table 3. Studies analysed.

Paper	Year of Publication	Number of ADL recognized	ADL	Sensors	Methods
Ivascu et al. (2017)	2017	9	Falling; walking on stairs; sitting; standing; lying; getting up; jumping; walking; running	Accelerometer	J48 decision tree; SVM; Naïve Bayes; Random Forest; Adaboost; k-NN; DNN
Khalifa et al. (2017)	2017	8	Rowing; cycling; running; walking; jumping; standing; sitting; walking on stairs	Accelerometer	C4.5 decision tree; IBk Nearest Neighbour; Naïve Bayes; SVM
Chen et al. (2017)	2017	4	Walking on stairs; walking; jogging; jumping	Accelerometer; Gyroscope	k-NN; Random Forest; SVM
Chetty et al. (2016)	2016	5	Walking; walking on stairs; sitting; standing; lying	Accelerometer; Gyroscope	Naïve Bayes; k-Means Clustering; J48 decision tree; Random Forest Classifier; Random Committee Classifier; Lazy IBk Classifier
Costa et al. (2016)	2016	5	Running; volleyball; handball; basketball; futsal	Accelerometer	ANN; k-NN; Naïve Bayes; J48 decision tree; SVM
Eskaf et al. (2016)	2016	4	Walking; standing; sitting; bowing	Accelerometer; gyroscope; gravity; rotational vector	J48 decision tree; k-NN; Naïve Bayes
Nurwanto et al. (2016)	2016	4	Pushing up; sitting; squatting; jumping	Accelerometer	k-NN; Dynamic Time Warping Algorithm
Shen et al. (2016)	2016	4	Walking on stairs; walking; running; jumping	Accelerometer; Gyroscope	Random Forest; SVM; ANN; k-NN

(continued)

Table 3. (*continued*)

Paper	Year of Publication	Number of ADL recognized	ADL	Sensors	Methods
Prabowo et al. (2016)	2016	2	Walking; sitting	Accelerometer	Bayesian network; ANN; C4.5 decision tree; k-NN
Vallabh et al. (2016)	2016	2	Lying; sitting	Accelerometer; Gyroscope	Naïve Bayes; k-NN; LSM; ANN; SVM
Lorenzi et al. (2016)	2016	1	Walking	Accelerometer; Gyroscope	ANN
Kilinc et al. (2015)	2015	6	Walking on stairs; drinking; getting up; sitting; standing; walking	Accelerometer	ANN
Fortino et al. (2015)	2015	5	Sitting; standing; walking; lying; falling	Accelerometer; GPS receiver	k-NN
Okour et al. (2015)	2015	5	Sitting; walking; standing; sleeping; falling	Accelerometer	rule-based classifier
Ravì et al. (2015)	2015	5	Travelling by public transport; running; running; cycling; walking	Accelerometer; gyroscope; magnetometer	SVM
Tsai et al. (2015)	2015	5	Walking; jogging; sitting; standing; lying	Accelerometer	ANN
Vilarinho et al. (2015)	2015	5	Walking; sitting; walking on stairs; trying shoes; jogging	Accelerometer	PAT; PPR; WTPR
Rasheed et al. (2015)	2015	4	Standing; sitting; walking; running	Accelerometer; Gyroscope	SMV algorithm
Hsu et al. (2015)	2015	3	Walking; running; walking on stairs	Accelerometer; Gyroscope	SVM
Kim et al. (2015)	2015	1	Eating	Accelerometer; light; temperature; barometer	Bayesian network
Nishida et al. (2014)	2014	12	Cycling; cleaning table; shopping; toileting; cooking; watching TV; eating; working on a computer; reading; using a smartphone; driving; sleeping	Accelerometer; Microphone	GMM
Zhan et al. (2014)	2014	9	Walking; walking on stairs; drinking; standing; sitting; reading; watching TV; writing; washing hands	Accelerometer; Camera	LogitBoost; SVM

(*continued*)

Table 3. (*continued*)

Paper	Year of Publication	Number of ADL recognized	ADL	Sensors	Methods
Büber et al. (2014)	2014	7	Walking; sitting; standing; walking on stairs; jogging, cycling; jumping	Accelerometer	J48 decision tree; k-Start; Naïve Bayes; Bayesian Network; Random Forest; k-NN
Alam et al. (2014)	2014	5	Talking; coughing; deglutition; silence; yawning	Accelerometer	C4.5 decision tree
He et al. (2014)	2014	3	Standing; running; walking	Accelerometer; light; temperature; microphone	HMM
Roy et al. (2013)	2013	12	Sitting; standing; walking; running; lying; walking on stairs; cleaning; cooking; taking medication; sweeping; washing hand; watering plants	Accelerometer; Gyroscope	HMM
Hong et al. (2013)	2013	6	Lying; sitting; standing; walking; walking on stairs; taking an elevator	Accelerometer; GPS receiver	ANN; SVM; GMM; HMM; k-NN; Random Forest; k-Means clustering
Nam et al. (2013)	2013	6	Walking; running; walking on stairs; taking an elevator; sitting; standing	Accelerometer; Camera	SVM
Zhang et al. (2013)	2013	6	Walking; running; walking on stairs; standing; jumping; sitting	Accelerometer	LDA; PCA
Anguita et al. (2013)	2013	5	Walking; walking on stairs; sitting; standing; laying	Accelerometer; Gyroscope	SVM
Cruz-Silva et al. (2013)	2013	5	Walking on stairs; taking an elevator; running; walking; sitting	Accelerometer; Digital compass	Naïve Bayes; k-NN; Random Forest
Kuspa et al. (2013)	2013	5	walking on stairs; jogging; sitting; standing; walking	Accelerometer	PCA; GDA
Shoaib (2013)	2013	5	Cycling; travelling by car; smoking; eating; taking an elevator	Accelerometer; gyroscope; magnetometer	k-NN; J48 decision tree; rule based classifier; SVM
Silva (2013)	2013	5	Walking; walking on stairs; sitting; standing; lying	Accelerometer	J48 decision tree

(*continued*)

Table 3. (*continued*)

Paper	Year of Publication	Number of ADL recognized	ADL	Sensors	Methods
Awan et al. (2013)	2013	4	Sitting; standing; walking; jogging	Accelerometer	J48 decision tree; logistic regression; Naïve Bayes
Chiang et al. (2013)	2013	4	Walking; cycling; running; standing	Accelerometer; GPS receiver	J48 decision tree; k-NN; Naïve Bayes; SVM
Kmiecik (2013)	2013	3	Jogging; walking; walking on stairs	Accelerometer	Naïve Bayes
Shen et al. (2013)	2013	3	Sitting; standing; walking	Accelerometer	SVM
Dernbach et al. (2012)	2012	6	Walking; running; standing; walking on stairs; cooking; cleaning	Accelerometer	ANN
Kazushige et al. (2012)	2012	6	Standing; walking; running; boarding; vacuuming; brushing teeth	Accelerometer; microphone; GPS receiver	ANN
Siirtola et al. (2012)	2012	5	Standing; walking; cycling; driving; running	Accelerometer	k-NN; QDA; SVM
Kelly et al. (2012)	2012	4	Standing; sitting; walking on stairs; walking	Accelerometer	C4.5 decision tree; ANN; Logistic Regression; Bayesian Network; SVM
Anguita et al. (2012)	2012	3	Standing; walking; laying; walking on stairs	Accelerometer	SVM
Lara et al. (2012)	2012	3	Walking; running; sitting; walking on stairs	Accelerometer	Naïve Bayes
Lara et al. (2012)	2012	3	Running; walking; sitting	Accelerometer	C4.5 decision tree
Mashita et al. (2012)	2012	3	Standing; walking; running	Accelerometer	SVM
Kaghyan et al. (2012)	2012	2	Sitting; standing	Accelerometer	k-NN
Maekawa et al. (2012)	2012	2	Walking; running	Accelerometer; Magnetometer	HMM
Bujari et al. (2012)	2012	1	Walking	Accelerometer	ANN
Bieber et al. (2011)	2011	7	Walking; working on a computer; driving; cycling; running; jumping; watching TV	Accelerometer; Microphone	ANN

(*continued*)

Table 3. (*continued*)

Paper	Year of Publication	Number of ADL recognized	ADL	Sensors	Methods
Kwapisz et al. (2011)	2011	5	Walking; jogging; walking on stairs; sitting; standing	Accelerometer; GPS receiver	J48 decision tree; logistic regression; ANN
Varkey et al. (2011)	2011	5	Walking; standing; writing; smoking; jogging	Accelerometer; Gyroscope	SVM
Zhu et al. (2011)	2011	4	Lying; sitting; standing; walking	Accelerometer	Viterbi algorithm; HMM; Bayesian filter
Ganti et al. (2010)	2010	9	Walking; running; cooking; reading; driving; eating; washing dishes; brushing teeth; watching TV	Accelerometer; Microphone	HMM
Das et al. (2010)	2010	5	Standing; walking; running; jumping; walking on stairs	Accelerometer; GPS receiver; gravity; communication	1-Nearest Neighbour
Jie et al. (2010)	2010	4	Standing; walking; running; walking on stairs	Accelerometer	k-NN one-class classifier; SVDD one-class classifier; Gauss one-class classifier
Lau et al. (2010)	2010	4	Walking; standing; sitting; walking on stairs	Accelerometer	J48 decision tree; Bayesian network; Naïve Bayes; k-NN; rule based classifier
Zhu et al. (2010)	2010	4	Sitting; standing; walking; lying	Accelerometer	HMM
Phithakkitnukoon et al. (2010)	2010	3	Eating; shopping; entertainment and recreational activities	Accelerometer	Naïve Bayes
Allen et al. (2009)	2009	7	Standing; sitting; lying; kneeling; bending; jumping; walking on stairs	Accelerometer	DSC
Fitz-Walter et al. (2009)	2009	3	Standing; walking; jogging	Accelerometer; gyroscope; GPS receiver	ANN
Huynh (2008)	2008	12	Shopping; doing housework; bathing; dressing; toileting; feeding; walking; sitting; vacuuming; standing; eating; washing dishes	Accelerometer	SVM; HMM

(*continued*)

Table 3. (*continued*)

Paper	Year of Publication	Number of ADL recognized	ADL	Sensors	Methods
Ermes et al. (2008)	2008	8	Lying; sitting; standing; walking; running; cycling; rowing; playing football	Accelerometer; GPS receiver	ANN; J48 decision tree
Saponas et al. (2008)	2008	4	Walking; running; cycling; sitting	Accelerometer	Naïve Bayes
Gafurov et al. (2007)	2007	3	Jogging; walking on stairs; walking	Accelerometer; GPS receiver; camera; microphone; light; temperature; altitude	ANN; J48 decision tree

Table 4. Summary of the methods and accuracies reported.

Method	Average of the accuracy reported
Random Committee Classifier	96.90%
DNN	96.56%
LDA	96.10%
Adaboost	94.44%
PCA	94.05%
k-Start	93.35%
1-Nearest Neighbour	93.00%
GDA	92.00%
Random Forest	91.71%
Logistic Regression	91.40%
ANN	91.12%
Bayesian Network	90.36%
Rule-based classifier	90.12%
QDA	90.00%
k-NN	87.40%
Decision trees (i.e., J48 and C4.5)	86.56%
Viterbi algorithm	85.00%
Bayesian filter	85.00%
Dynamic Time Warping Algorithm	84.00%
GMM	83.65%
SVM	82.27%
HMM	81.73%
Naïve Bayes	81.12%
IBk Nearest Neighbour	79.58%

(*continued*)

Table 4. (*continued*)

Method	Average of the accuracy reported
LogitBoost	77.40%
LSM	75.43%
k-Means Clustering	75.20%
PAT	70.50%
PPR	70.50%
WTPR	70.50%

Tables 3 and 4 present the summary of the studies analysed related to the recognition of the ADL.

4 Applicability and Results

The recognition of ADL (Foti and Koketsu 2013) is included on the research of the development of Ambient Assisted Living (AAL) systems (Garcia and Rodrigues 2015, Dobre, Mavromoustakis et al. 2016) that can be performed with the framework proposed in (Pires, Garcia et al. 2015, Pires, Garcia et al. 2016a, b, c, Pires, Garcia et al. 2016a, b, c, Pires, Garcia et al. 2016a, b, c), where the concepts related to data acquisition, data processing and data fusion were analyzed in (Pires, Garcia et al. 2016a, b, c), consisting this research in the last stage of the development of the framework for the automatic recognition of ADL, which can be included the development of a Personal Digital Life Coach (Garcia 2016).

The automatic recognition of ADL may be used for several purposes, including the prediction of the functional capacity in healthy adults and elderly people, the training of the lifestyle with the relation between the environment and the physical activities, the identification of some diseases (*e.g.,* low cognitive impairment, neurobehavioral dysfunction and/or other neurological disorder), the compensation of some disabilities (*e.g.,* helping the memory), the detection of harmful situations (*e.g.,* fall), the measurement of the levels of activity, the identification of needed emergency medicine with the identification of the patterns of ADL, and the identification of emergency situations (Vacher, Fleury et al. 2010; Urwyler, Rampa et al. 2015; Zdravevski, Lameski et al. 2017).

When compared with the use of the smart environments for the monitoring of ADL and its environments, the use of the mobile devices allows the creation of solutions to help the monitoring of several situations with low cost equipments, but it has some constraints and problems previously studied (Pires, Garcia et al. 2018a, b, c).

Following the studies related to the recognition of ADL using sensors available in off-the-shelf mobile devices, we analyzed 65 studies, where the major part of the studies have been performed between 2012 and 2017 with a total of 49 studies (75%), where 3 studies in 2017 (5%), 8 studies in 2016 (12%), 9 studies in 2015 (14%), 5 studies in 2014 (8%), 13 studies in 2013 (20%) and 11 studies in 2012 (17%).

Regarding the number of ADL recognized in each study analyzed, all studies recognized between 1 and 12 ADL, where 3 studies recognized 12 ADL (5%), 3 studies recognized 9 ADL (5%), 2 studies recognized 8 ADL (3%), 3 studies recognized 7 ADL (5%), 6 studies recognized 6 ADL (9%), 17 studies recognized 5 ADL (26%), 13 studies recognized 4 ADL (20%), 11 studies recognized 3 ADL (17%), 4 studies recognized 2 ADL (5%) and 3 studies recognized 1 ADL (5%), concluding that the major part of the studies analyzed recognize between 3 and 5 ADL (63%).

Related to the ADL recognized in the studies analyzed, several ADL were recognized, where the patterns related to the walking activity was recognized in 55 studies (85%), the standing activity was recognized in 41 studies (63%), the sitting activity was recognized in 37 studies (57%), the walking on stairs activity was recognized in 29 studies (45%), the running activity was recognized in 27 studies (42%), the lying activity was recognized in 12 studies (18%), the jogging activity was recognized in 11 studies (17%), the jumping and cycling activities were recognized in 10 studies (15%), the eating activity was recognized in 6 studies (9%), the driving, cooking, taking an elevator and watching TV activities were recognized in 4 studies (6%), the shopping, reading and falling activities were recognized in 3 studies (5%), the working on a computer, sleeping, drinking, rowing, toileting, washing hands, washing dishes, brushing teeth, vacuuming, writing, laying, smoking, travelling and cleaning activities were recognized in 2 studies (3%), and the remaining ADL were recognized only in 1 study (2%).

Related to the sensors used in the studies analyzed, the accelerometer was used in all studies analyzed (100%), but another sensors available in off-the-shelf mobile devices were used, including the gyroscope used in 14 studies (22%), the GPS receiver used in 9 studies (14%), the microphone used in 6 studies (9%), the magnetometer, light sensor, temperature sensor and camera used in 3 studies (5%), the gravity sensor used in 2 studies (3%), and the digital compass, rotational vector sensor, altitude sensor, barometer and communication sensor used in 1 study (2%).

Related to the methods with the best average accuracies reported presented in Table 4, these studies are used in 31 studies (48%) of studies analyzed, were 17 studies used the ANN (26%), 8 studies used the Random Forest (12%), 5 studies used the Bayesian Network (8%), 3 studies used the rule-based classifier and Logistic Regression (5%), 2 studies used the PCA (3%), and 1 study used the Random Committee Classifier, DNN, LDA, k-Start, 1-Nearest Neighbour, GDA, QDA and Adaboost (1%).

The solutions developed with the sensors available in the mobile devices allows the recognition of ADL. On the other hand, the processing and memory capabilities of these devices are very limited. Considering the use of the smart environments, the methods that reported higher accuracy than others are ANN (94.13%) and HMM (91.43%), where the most used sensors are the motions sensors and RFID sensors. However, considering the use of the mobile devices, the ANN and its variants, *i.e.,* DNN (96.56%) and ANN (91.12%) also reported some of the best accuracies, but the best accuracy was reported by the Random Committee Classifier (96.90%). All of the architectures have several limitations, such as limited power and processing capabilities of the mobile devices, and dependence of the constant network connection in smart environments. Regarding the costs of the different solutions, the use of mobile devices has lower costs in the implementation and maintainability.

5 Discussion and Conclusions

The recognition of ADL using mobile devices is a subject that has been researched in the last years with the recognition of simple and complex activities, including walking, running, jumping, standing, walking on stairs and others. This review is included in the conception of a new approach for the development of a framework for the recognition of ADL and their environments. The sensors available in off-the-shelf mobile devices are capable to acquire data related to the physical and physiological parameters of people, as well as data related to the environment, where the most used sensors are the motion, magnetic, acoustic and location sensors, handling the recognition of ADL only with a single mobile device and with commodity and non-invasive methods.

Based in the taxonomy proposed in (Aggarwal and Ryoo 2011) and the machine learning methods found in the literature, this paper proposes a new taxonomy for the recognition of ADL (see Fig. 1), whose the most used sensors are the accelerometers, cameras, and the RFID sensors. The sensors can be used alone and combined with

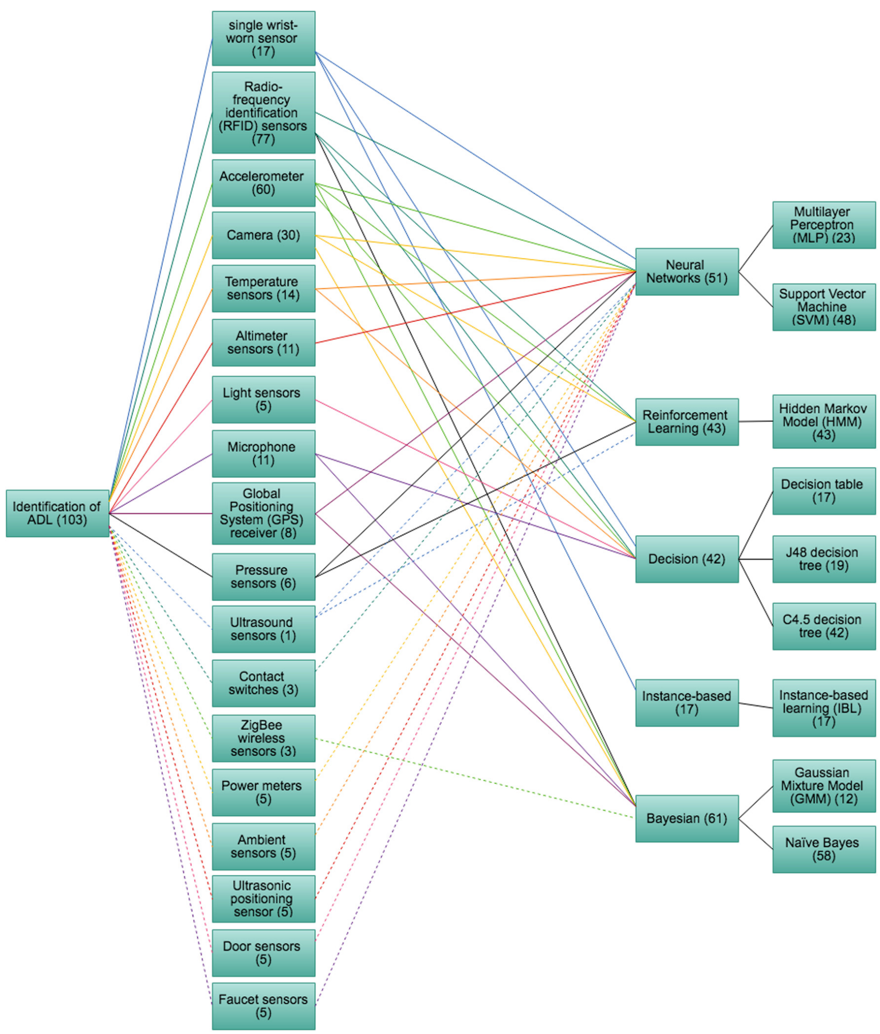

Fig. 1. Taxonomy proposed for the identification of ADL.

others, where the most used types of methods are the neural networks, reinforcement learning, decision, and the Bayesian methods.

Due to the high memory and power processing capabilities needed for the execution of the reinforcement learning methods, it is not adapted to the mobile devices. Related to the remaining methods, the neural networks show better accuracy than other methods. Using the sensors available in the mobile devices, the types of methods used are similar, where the neural network reported better results than others and the number of ADL recognized are higher with the ANN.

The most recognized ADL with mobile devices in the literature are the walking, standing, sitting, walking on stairs, running, lying, jogging, jumping and cycling activities, which are recognized in more than 10 studies analysed in this research. Therefore, the most implemented method in the literature is the ANN method, with is implemented in 17 studies and reported an average accuracy of 91.12%, but the three methods that report an average accuracy higher than 95% are the Random Committee Classifier, the DNN and the PCA.

The field related to the recognition of ADL has several purposes, including the training and monitoring of the lifestyles and people health.

Acknowledgments. This work is funded by FCT/MCTES through national funds and when applicable co-funded EU funds under the project UIDB/EEA/50008/2020 (Este trabalho é financiado pela FCT/MCTES através de fundos nacionais e quando aplicável cofinanciado por fundos comunitários no âmbito do projeto UIDB/EEA/50008/2020). This article/publication is based on work from COST Action IC1303 - AAPELE - Architectures, Algorithms and Protocols for Enhanced Living Environments and COST Action CA16226 - SHELD-ON - Indoor living space improvement: Smart Habitat for the Elderly, supported by COST (European Cooperation in Science and Technology). More information in www.cost.eu.

References

Aggarwal, J.K., Ryoo, M.S.: Human activity analysis: a review. ACM Comput. Surv. **43**(3), 1–43 (2011)

Alam, M.A.U., Roy, N.: GeSmart: a gestural activity recognition model for predicting behavioral health. In: 2014 International Conference on Smart Computing (SMARTCOMP) (2014)

Allen, Y.Y., et al.: Distributed recognition of human actions using wearable motion sensor networks. J. Ambient Intell. Smart Environ. **1**(2), 103–115 (2009). %@ 1876-1364

Anguita, D., et al.: Human activity recognition on smartphones using a multiclass hardware-friendly support vector machine. In: International Workshop of Ambient Assited Living (IWAAL 2012), Vitoria-Gasteiz, Spain (2012)

Anguita, D., et al.: A public domain dataset for human activity recognition using smartphones. In: European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, ESANN (2013)

Awan, M.A., et al.: A dynamic approach to recognize activities in WSN. Int. J. Distrib. Sens. Netw. **2013**, 1–9 (2013)

Banos, O., et al.: Daily living activity recognition based on statistical feature quality group selection. Expert Syst. Appl. **39**(9), 8013–8021 (2012)

Bao, L., Intille, S.S.: Activity Recognition from user-annotated acceleration data. In: Pervasive Computing, vol. 3001, pp. 1–17. Springer Heidelberg (2004)

Bieber, G., et al.: The hearing trousers pocket – activity recognition by alternative sensors. In: PETRA. ACM (2011)

Botia, J.A., et al.: Ambient assisted living system for in-home monitoring of healthy independent elders. Expert Syst. Appl. **39**(9), 8136–8148 (2012)

Büber, E., Guvensan, A.M.: Discriminative time-domain features for activity recognition on a mobile phone. In: 2014 IEEE Ninth International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP) (2014)

Buettner, M., et al.: Recognizing daily activities with RFID-based sensors. In: Ubicomp 2009 Proceedings of the 11th International Conference on Ubiquitous Computing. ACM, New York (2009)

Bujari, A., et al.: Movement pattern recognition through smartphone's accelerometer. In: 2012 IEEE Consumer Communications and Networking Conference (CCNC). IEEE, Las Vegas (2012)

Chen, Y., Shen, C.: Performance analysis of smartphone-sensor behavior for human activity recognition. IEEE Access **5**, 3095–3110 (2017)

Cheng, B.-C., et al.: HMM machine learning and inference for Activities of daily living recognition. J. Supercomput. **54**(1), 29–42 (2009)

Chernbumroong, S., et al.: Activity classification using a single wrist-worn accelerometer. In: 2011 5th International Conference on Software, Knowledge Information, Industrial Management and Applications (SKIMA). IEEE (2011)

Chernbumroong, S., et al.: Elderly activities recognition and classification for applications in assisted living. Expert Syst. Appl. **40**(5), 1662–1674 (2013)

Chetty, G., White, M.: Body sensor networks for human activity recognition. In: 2016 3rd International Conference on Signal Processing and Integrated Networks (SPIN) (2016)

Chiang, J.-H., et al.: Pattern analysis in daily physical activity data for personal health management. Pervasive Mob. Comput. **13**, 13–25 (2013)

Chikhaoui, B., et al.: A Frequent pattern mining approach for ADLs recognition in smart environments. In: 2011 IEEE International Conference on Advanced Information Networking and Applications (AINA). IEEE, Biopolis (2011)

Costa, J., et al.: A mobile application to improve the quality of life via exercise. In: 2016 IEEE 12th International Conference on Intelligent Computer Communication and Processing (ICCP) (2016)

Cruz-Silva, N., et al.: Features Selection for Human Activity Recognition with iPhone Inertial Sensors. In: 16th Portuguese Conference on Artificial Inteligence. Advances in Artificial Intelligence. APPIA, Angra do Heroísmo (2013)

Danny, W., et al.: Unsupervised activity recognition using automatically mined common sense. In: Proceedings of the 20th National Conference on Artificial Intelligence – vol. 1, pp. 21–27. AAAI Press, Pittsburgh (2005). %@ 1-57735-236-x

Das, S., et al.: Detecting user activities using the accelerometer on Android smartphones (2010)

Dernbach, S., et al.: Simple and Complex activity recognition through smart phones. In: 2012 8th International Conference on Intelligent Environments (IE). IEEE, Guanajuato (2012)

Dobre, C., et al.: Ambient Assisted Living and Enhanced Living Environments: Principles, Technologies and Control. Butterworth-Heinemann, Oxford (2016)

Ermes, M., et al.: Detection of daily activities and sports with wearable sensors in controlled and uncontrolled conditions. Trans. Info. Tech. Biomed. **12**(1), 20–26 (2008)

Eskaf, K., et al.: Aggregated activity recognition using smart devices. In: 2016 3rd International Conference on Soft Computing and Machine Intelligence (ISCMI) (2016)

Fitz-Walter, Z., Tjondronegoro, D.: Simple classification of walking activities using commodity smart phones. In: OZCHI 2009 Proceedings of the 21st Annual Conference of the Australian Computer-Human Interaction Special Interest Group: Design: Open 24/7. ACM, New York (2009)

Fortino, G., et al.: Activity-aaService: cloud-assisted, BSN-based system for physical activity monitoring. In: 2015 IEEE 19th International Conference on Computer Supported Cooperative Work in Design (CSCWD) (2015)

Foti, D., Koketsu, J.S.: Activities of daily living. Pedretti's Occup. Ther.: Pract. Skills Phys. Dysfunct. **7**, 157–232 (2013)

Fulk, G.D., et al.: Identifying activity levels and steps of people with stroke using a novel shoe-based sensor. J. Neurol. Phys. Ther. **36**(2), 100–107 (2012)

Gafurov, D., et al.: Gait authentication and identification using wearable accelerometer sensor. In: 2007 IEEE Workshop on Alghero Automatic Identification Advanced Technologies. IEEE (2007)

Ganti, R.K., et al.: Multisensor fusion in smartphones for lifestyle monitoring. In: 2010 International Conference on Body Sensor Networks (2010)

Garcia, N.M.: A roadmap to the design of a personal digital life coach. In: ICT Innovations 2015. Springer (2016)

Garcia, N.M., Rodrigues, J.J.P.: Ambient Assisted Living. CRC Press, Boca Raton (2015)

Gyllensten, I.C., Bonomi, A.G.: Identifying types of physical activity with a single accelerometer: evaluating laboratory-trained algorithms in daily life. IEEE Trans. Biomed. Eng. **58**(9), 2656–2663 (2011)

He, Z., Bai, X.: A wearable wireless body area network for human activity recognition. In: 2014 Sixth International Conference on Ubiquitous and Future Networks (ICUFN) (2014)

Hong, J.-H., et al.: An activity recognition system for ambient assisted living environments. In: Evaluating AAL Systems Through Competitive Benchmarking, vol. 362, pp. 148–158. Springer, Heidelberg (2013)

Hong, Y.-J., et al.: Activity recognition using wearable sensors for elder care. In: Second International Conference on Future Generation Communication and Networking, FGCN 2008. IEEE, Hainan Island (2008)

Hoque, E., Stankovic, J.: AALO: activity recognition in smart homes using active learning in the presence of Overlapped activities. In: 2012 6th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth) (2012)

Hsu, H.H., et al.: Two-phase activity recognition with smartphone sensors. In: 2015 18th International Conference on Network-Based Information Systems (2015)

Huynh, D.T.G.: Human activity recognition with wearable sensors. Fachbereich Informatik, Darmstadt. Technische Universitat Darmstadt. Doktor-Ingenieur (Dr.-Ing.) (2008)

Ivascu, T., et al.: Activities of daily living and falls recognition and classification from the wearable sensors data. In: 2017 E-Health and Bioengineering Conference (EHB) (2017)

Jie, Y., et al.: Wearable accelerometer based extendable activity recognition system. In: 2010 IEEE International Conference on Robotics and Automation (ICRA). IEEE, Anchorage (2010)

Kaghyan, S., Sarukhanyan, H.: Activity recognition using K-nearest neighbor algorithm on smartphone with tri-axial accelerometer. In: International Journal of Informatics Models and Analysis (IJIMA), 146–156. ITHEA International Scientific Society, Bulgaria (2012)

Kasteren, T.V., Krose, B.: Bayesian activity recognition in residence for elders. In: 3rd IET International Conference on Intelligent Environments, IE (2007)

Kazushige, O., Miwako, D.: Indoor-outdoor activity recognition by a smartphone. In: Proceedings of the 2012 ACM Conference on Ubiquitous Computing, pp. 537–537. ACM, Pittsburgh (2012). %@ 978-1-4503-1224-0

Kelly, D., Caulfield, B.: An investigation into non-invasive physical activity recognition using smartphones. In: 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (2012)

Khalifa, S., et al.: HARKE: Human activity recognition from kinetic energy harvesting data in wearable devices. IEEE Trans. Mob. Comput. **PP**(99), 1 (2017)

Khan, A.M., et al.: A triaxial accelerometer-based physical-activity recognition via augmented-signal features and a hierarchical recognizer. IEEE Trans. Inf. Technol. Biomed. **14**(5), 1166–1172 (2010)

Kilinc, O., et al.: Inertia based recognition of daily activities with ANNs and spectrotemporal features. In: 2015 IEEE 14th International Conference on Machine Learning and Applications (ICMLA) (2015)

Kim, K.H., Cho, S.B.: A dining context-aware system with mobile and wearable devices. In: 2015 IEEE International Conference on Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing (2015)

Kmiecik, L.S.: Cloud centered, smartphone based long-term human activity recognition solution (2013)

Kuspa, K., Pratkanis, T.: Classification of mobile device accelerometer data for unique activity identification (2013)

Kwapisz, J.R., et al.: Activity recognition using cell phone accelerometers. ACM SIGKDD Explor. Newsl. **12**(2), 74 (2011)

Lara, Ó.D., et al.: Centinela: a human activity recognition system based on acceleration and vital sign data. Pervasive Mob. Comput. **8**(5), 717–729 (2012)

Lara, S.D., Labrador, M.A.: A mobile platform for real-time human activity recognition. In: CCNC IEEE Consumer Communications and Networking Conference, pp. 667–671 (2012)

Lau, S.L., David, K.: Movement recognition using the accelerometer in smartphones. In: 2010 Future Network and Mobile Summit (2010)

Libal, V., et al.: Multimodal classification of activities of daily living inside smart homes. In: Distributed Computing, Artificial Intelligence, Bioinformatics, Soft Computing, and Ambient Assisted Living, vol. 5518, pp. 687–694. Springer, Heidelberg (2009)

Liming, C., et al.: Sensor-based activity recognition. IEEE Trans. Syst. Man Cybern. Part C (Appl. Rev.) **42**(6), 790–808 (2012)

Lorenzi, P., et al.: Mobile devices for the real-time detection of specific human motion disorders. IEEE Sens. J. **16**(23), 8220–8227 (2016)

Maekawa, T., et al.: Activity recognition with hand-worn magnetic sensors. Pers. Ubiquit. Comput. **17**(6), 1085–1094 (2012)

Mashita, T., et al.: A content search system for mobile devices based on user context recognition. In: 2012 IEEE Virtual Reality Workshops (VRW) (2012)

Maurer, U., et al.: Activity recognition and monitoring using multiple sensors on different body positions. In: International Workshop on Wearable and Implantable Body Sensor Networks, BSN 2006. IEEE, Cambridge (2006)

Naeem, U., Bigham, J.: A comparison of two hidden markov approaches to task identification in the home environment. In: 2nd International Conference on Pervasive Computing and Applications, ICPCA 2007, pp. 383–388. IEEE, Birmingham (2007)

Nam, Y., et al.: Physical activity recognition using multiple sensors embedded in a wearable device. ACM Trans. Embed. Comput. Syst. **12**(2), 1–14 (2013)

Nishida, M., et al.: Development and preliminary analysis of sensor signal database of continuous daily living activity over the long term. In: 2014 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA) (2014)

Nurwanto, F., et al.: Light sport exercise detection based on smartwatch and smartphone using k-Nearest neighbor and dynamic time warping algorithm. In: 2016 8th International Conference on Information Technology and Electrical Engineering (ICITEE) (2016)

Okour, S., et al.: An adaptive rule-based approach to classifying activities of daily living. In: 2015 International Conference on Healthcare Informatics (2015)

Ordonez, F.J., et al.: Activity recognition using hybrid generative/discriminative models on home environments using binary sensors. Sens. (Basel) **13**(5), 5460–5477 (2013)

Phithakkitnukoon, S., et al.: Activity-aware map: identifying human daily activity pattern using mobile phone data. In: Human Behavior Understanding, vol. 6219, pp. 14–25. Springer, Heidelberg (2010)

Pires, I., et al.: From data acquisition to data fusion: a comprehensive review and a roadmap for the identification of activities of daily living using mobile devices. Sensors **16**(2), 184 (2016a)

Pires, I.M., et al.: Multi-sensor data fusion techniques for the identification of activities of daily living using mobile devices. In: Proceedings of the ECMLPKDD 2015 Doctoral Consortium, European Conference on Machine Learning and Principles and Practice of Knowledge Discovery in Databases, Porto, Portugal (2015)

Pires, I.M., et al.: Identification of activities of daily living using sensors available in off-the-shelf mobile devices: research and hypothesis. In: Ambient Intelligence-Software and Applications–7th International Symposium on Ambient Intelligence (ISAmI 2016). Springer, Cham (2016b)

Pires, I.M., et al.: Limitations of the use of mobile devices and smart environments for the monitoring of ageing people. In: ICT4AWE 2018 4th International Conference on Information and Communication Technologies for Ageing Well and e-Health, Madeira, Portugal (2018a)

Pires, I.M., et al.: Validation techniques for sensor data in mobile health applications. J. Sens. **2016**, 1687–1725 (2016c)

Pires, I.M., et al.: Approach for the development of a framework for the identification of activities of daily living using sensors in mobile devices. Sensors (Basel) **18**(2), 640 (2018b)

Pires, I.M., et al.: Identification of activities of daily living through data fusion on motion and magnetic sensors embedded on mobile devices. Pervasive Mob. Comput. **47**, 78–93 (2018c)

Pires, I.M., et al.: Recognition of activities of daily living based on environmental analyses using audio fingerprinting techniques: a systematic review. Sensors (Basel) **18**(1), 160 (2018a)

Pires, I.M., et al.: Android library for recognition of activities of daily living: implementation considerations, challenges, and solutions. Open Bioinf. J. **11**(1), 61–88 (2018b)

Pombo, N., et al.: Classification techniques on computerized systems to predict and/or to detect apnea: a systematic review. Comput. Methods Programs Biomed. **140**, 265–274 (2017)

Prabowo, O.M., et al.: Missing data handling using machine learning for human activity recognition on mobile device. In: 2016 International Conference on ICT For Smart Society (ICISS) (2016)

Ramanan, D.: Detecting activities of daily living in first-person camera views. In: Proceedings of the 2012 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 2847–2854. IEEE Computer Society (2012)

Rasheed, M. B., et al.: Evaluation of human activity recognition and fall detection using android phone. In: 2015 IEEE 29th International Conference on Advanced Information Networking and Applications (2015)

Ravì, D., et al.: Real-time food intake classification and energy expenditure estimation on a mobile device. In: 2015 IEEE 12th International Conference on Wearable and Implantable Body Sensor Networks (BSN) (2015)

Roy, N., et al.: Infrastructure-assisted smartphone-based ADL recognition in multi-inhabitant smart environments. In: 2013 IEEE International Conference on Pervasive Computing and Communications (PerCom) (2013)

Salazar, L.H.A., et al.: A systematic literature review on usability heuristics for mobile phones. Int. J. Mob. Hum. Comput. Interact. **5**(2), 50–61 (2013)

Saponas, T., et al.: ilearn on the iphone: real-time human activity classification on commodity mobile phones. University of Washington CSE Tech Report UW-CSE-08-04-02 (2008)
Shen, B., et al.: Motion intent recognition for control of a lower extremity assistive device (LEAD). In: 2013 IEEE International Conference on Mechatronics and Automation (2013)
Shen, C., et al.: On motion-sensor behavior analysis for human-activity recognition via smartphones. In: 2016 IEEE International Conference on Identity, Security and Behavior Analysis (ISBA) (2016)
Shoaib, M.: Human activity recognition using heterogeneous sensors. In: Adjunct Publication of the 2013 ACM Conference on Ubiquitous Computing, UbiComp 2013 Adjunct. ACM, Zurich (2013)
Siirtola, P., Röning, J.: Recognizing human activities user-independently on smartphones based on accelerometer data. Int. J. Interact. Multimed. Artif. Intell. **1**(5), 38 (2012)
Silva, J.R.C.D.: Smartphone based human activity prediction. Faculdade de engenharia, Universidade do Porto, Master in Bioengineering, Porto (2013)
Stikic, M., et al.: ADL recognition based on the combination of RFID and accelerometer sensing. In: 2008 Second International Conference on Pervasive Computing Technologies for Healthcare (2008)
Suryadevara, N.K., et al.: Intelligent sensing systems for measuring wellness indices of the daily activities for the elderly. In: 2012 8th International Conference on Intelligent Environments (IE) (2012)
Szewcyzk, S., et al.: Annotating smart environment sensor data for activity learning. Technol. Health Care **17**(3), 161–169 (2009)
Tolstikov, A., et al.: Eating activity primitives detection - a step towards ADL recognition. In: 10th International Conference on e-health Networking, Applications and Services, HealthCom (2008)
Tsai, P.Y., et al.: Gesture-aware fall detection system: design and implementation. In: 2015 IEEE 5th International Conference on Consumer Electronics - Berlin (ICCE-Berlin) (2015)
Ueda, K., et al.: A method for recognizing living activities in homes using positioning sensor and power meters. In: 2015 IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops) (2015)
Urwyler, P., et al.: Recognition of activities of daily living in healthy subjects using two ad-hoc classifiers. Biomed. Eng. Online **14**, 54 (2015)
Vacher, M., et al.: Complete sound and speech recognition system for health smart homes: application to the recognition of activities of daily living (2010)
Vallabh, P., et al.: Fall detection using machine learning algorithms. In: 2016 24th International Conference on Software, Telecommunications and Computer Networks (SoftCOM) (2016)
Varkey, J.P., et al.: Human motion recognition using a wireless sensor-based wearable system. Pers. Ubiquit. Comput. **16**(7), 897–910 (2011)
Vilarinho, T., et al.: A combined smartphone and smartwatch fall detection system. In: 2015 IEEE International Conference on Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing (2015)
Wang, J., et al.: Generative models for automatic recognition of human daily activities from a single triaxial accelerometer. In: The 2012 International Joint Conference on Neural Networks (IJCNN). IEEE, Brisbane (2012)
Zdravevski, E., et al.: Improving activity recognition accuracy in ambient-assisted living systems by automated feature engineering. IEEE Access **5**, 5262–5280 (2017)
Zhan, K., et al.: Multi-scale conditional random fields for first-person activity recognition. In: 2014 IEEE International Conference on Pervasive Computing and Communications (PerCom) (2014)

Zhang, M., Sawchuk, A.A.: Human daily activity recognition with sparse representation using wearable sensors. IEEE J. Biomed. Health Inf. **17**(3), 553–560 (2013)

Zhang, S., et al.: Detection of activities by wireless sensors for daily life surveillance: eating and drinking. Sensors (Basel) **9**(3), 1499–1517 (2009)

Zhu, C., et al.: Human activity recognition via motion and vision data fusion. In: 2010 Conference Record of the Forty Fourth Asilomar Conference on Signals, Systems and Computers (ASILOMAR). IEEE, Pacific Grove (2010)

Zhu, C., Sheng, W.: Recognizing human daily activity using a single inertial sensor. In: 2010 8th World Congress on Intelligent Control and Automation (WCICA), pp. 282–287. IEEE, Jinan (2010)

Zhu, C., Sheng, W.: Realtime recognition of complex daily activities using dynamic Bayesian network. In: 2011 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, San Francisco (2011)

Zhu, C., Sheng, W.: Realtime recognition of complex human daily activities using human motion and location data. IEEE Trans. Biomed. Eng. **59**(9), 2422–2430 (2012)