Framework for the Recognition of Activities of Daily Living and Their Environments in the Development of a Personal Digital Life Coach

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Abstract: Due to the commodity of the use of the off-the-shelf mobile devices and technological devices by ageing people, the automatic recognition of the Activities of Daily Living (ADL) and their environments using these devices is a research topic were studied in the last years, but this project consists in the creation of an automatic method that recognizes a defined dataset of ADL using a large set of sensors available in these devices, such as the accelerometer, the gyroscope, the magnetometer, the microphone and the Global Positioning System (GPS) receiver. The fusion of the data acquired from the selected sensors allows the recognition of an increasing number of ADL and environments, where the ADL are mainly recognized with motion, magnetic and location sensors, but the environments are mainly recognized with acoustic sensors. During this project, several methods have been researched in the literature, implementing three types of neural networks, these are Multilayer Perceptron (MLP) with Backpropagation, Feedforward neural network (FNN) with Backpropagation and Deep Neural Networks (DNN), verifying that the neural networks that report highest results are the DNN method for the recognition of ADL and standing activities, and the FNN method for the recognition of environments.

1 INTRODUCTION

Mobile devices has several sensors embedded that are capable for the acquisition of physical and physiological parameters for the recognition of Activities of Daily Living (ADL) and their environments. The sensors commonly available in the off-the-shelf mobile devices are the accelerometer, the gyroscope, the magnetometer, the microphone, and the Global Positioning System (GPS) receiver. The use of these sensors in a system for the monitoring of the lifestyle and/or the elderly people, and the training of the lifestyles is included in the research about the Ambient Assisted Living (AAL) systems.

These sensors are available in the equipments used daily, but their capabilities are not widely explored, and this paper presents the development of a new framework for the recognition of ADL and their environments (Pires et al., 2016-a; Pires et al., 2015; Pires et al., 2016-b), taking in account the limitations of these devices, but achieving reliable results for further implementation in the development of a personal digital life coach (Garcia, 2016). As presented in the figure 1, this framework has several stages, such as data acquisition, data processing, data fusion, and classification methods. This project is already started and some results were achieved, exploring the use of several types of neural networks in the recognition of the ADL and their environments, these are the Multilayer Perceptron (MLP) with Backpropagation, the Feedforward neural network (FNN) with Backpropagation, and the Deep Neural Networks (DNN). The currently achieved results are available in (Pires et al., 2017 (In Review)-a; Pires et al., 2017 (In Review)-b; Pires et al., 2017 (In Review)-c; Pires et al., 2017 (In Review)-d) and the data acquired for the experiments are available in a free repository (ALLab, 2017).

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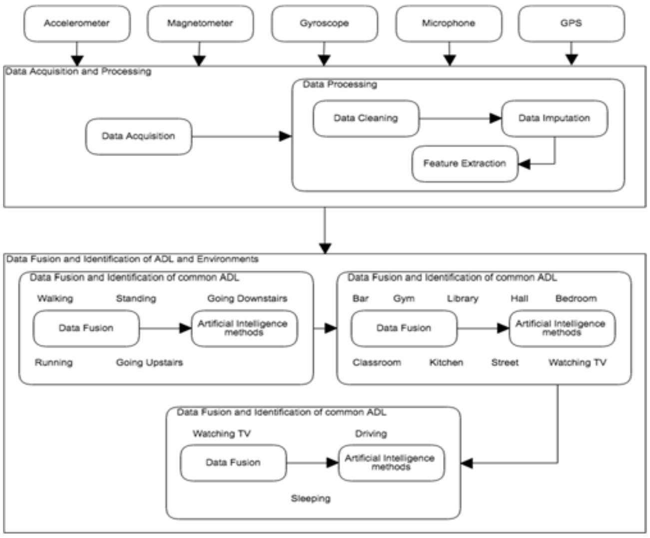

Figure 1: Workflow of the proposed framework for the recognition of ADL and their environments.

2 RELATED WORK

2.1 Data Acquisition and Processing

2.1.1 Data Acquisition

Data acquisition process using mobile devise is commonly performed without the use of frameworks, but there are some studies using frameworks, *e.g.*, Acquisition Cost-Aware QUery Adaptation (ACQUA) that performs dynamic modification in the order of the data acquisition and the streams requested from the different sensors (Lim et al., 2012). However, in the major part of the studies, the data acquisition does not use a framework for the data acquisition, reading directly the data from each sensor available (Scalvini et al., 2013).

2.1.2 Data Cleaning

The data cleaning is the process to filter the data acquired from the sensors in order to remove or fix the incorrect values commonly named as noise, using different types of filters based on the type of data acquired (Jeffery et al., 2006). Firstly, for the data acquired from the accelerometer, gyroscope and magnetometer sensors, the filter that is commonly applied are the low pass filter (Graizer, 2012). Finally, for the data acquired from the microphone, the filter that is commonly applied is the Fast Fourier Transform (FFT) (Rader and Brenner, 1976) for the extraction of the frequencies.

2.1.3 Data Imputation

During the data acquisition, several factors may cause the loss of the data, the hardware fails, the positioning of the mobile device, the different sampling rate between the several sensors used, and the number of sensors used (Bersch et al., 2014). Our previous study (Pires et al., 2016-a) presents several methods for the performance of the validation of the data acquired, that may have different types, these are Missing Completely At Random (MCAR), Missing At Random (MAR) and Missing Not At Random (MNAR) (Vateekul and Sarinnapakorn, 2009).

Based on the literature, the most used method for the imputation of the sensors' data is the K-Nearest Neighbor (k-NN) and their variants (García-Laencina et al., 2009), but there are other methods used for data imputation, these are mean imputation (MEI) (Rahman et al., 2015), multiple imputation (Ni et al., 2005), linear regression (D'Ambrosio et al., 2012), logistic regression (D'Ambrosio et al., 2012), among others.

2.1.4 Feature Extraction

There are several studies that uses different features, based on the purpose of the study and the sensors used, but the correct definition of the features is important to improve the accuracy of the methods for the recognition of the different ADL.

Related to the extraction of the features from the accelerometer, gyroscope and magnetometer sensors, the most extracted features are the mean (Liu et al., 2016), the variance (Liu et al., 2016), the maximum

(Liu et al., 2016), the minimum (Liu et al., 2016), the standard deviation (Liu et al., 2016), the average time between peaks (Kumar and Gupta, 2015), among others.

Related to the extraction of the features from the microphone data, the most extracted features are the average value (Hon et al., 2015), the threshold value (Hon et al., 2015), the minimum value (Hon et al., 2015), the maximum value (Hon et al., 2015), and Mel-frequency cepstrum coefficients (MFCC) (Sert et al., 2006)

Related to the extraction of the features from the GPS receiver, the most extracted features are the distance travelled (Shoaib et al., 2013), the speed (Shoaib et al., 2013), and the location (Shoaib et al., 2013; Zou et al., 2016).

2.2 Data Fusion and Classification

2.2.1 Recognition of Common ADL

After the extraction of several features from the accelerometer, magnetometer and gyroscope sensors, they need to be fused for the application of classification methods for the recognition of ADL. The authors of (Guo et al., 2016) recognized the sitting, standing, walking, walking on stairs, and running activities, using the accelerometer, gyroscope and magnetometer sensors' data and applying the Random Forest classifier with several features, such as the variance, the mean, the frequency of the point with maximum amplitude, the energy of the extremum value, the mean of the extremum value, the sum of the difference between extremum values, among others.

The authors of (Shoaib et al., 2013) used several methods, including Artificial Neural Networks (ANN), Support Vector Machine (SVM), Naïve Bayes, Logistic regression, decision tree, k-NN, and rule based classifiers, for the recognition of sitting, standing, walking, walking on stairs, and running activities, using the mean and the standard deviation as features extracted from the accelerometer, magnetometer and gyroscope sensors.

In (Elhoushi, Georgy, Wahdan, Korenberg, and Noureldin, 2014), several features were extracted from the accelerometer, magnetometer, and gyroscope sensors, including the mean, the median, the variance, the standard deviation, the inter-quartile range, the Zero-Crossing Rate and the number of peaks, and they implemented a decision tree method for the recognition of walking on stairs, walking on an escalator, standing and taking an elevator.

2.2.2 Recognition of Environments

After the extraction of several features from the microphone and other sensors, they need to be fused for the application of classification methods for the recognition of environments and other ADL. The authors of (Lane et al., 2011) extracted the spectral roll-off from the microphone data and other features extracted from the other sources used for the correct recognition of walking, sleeping, running, standing, and social interaction activities, based on the environment, using linear and logistic regression methods.

The authors of (Mengistu et al., 2016) used the Support Vector Machine (SVM) and Gradient Boosting Decision Tree methods with the zero-crossing rate, the total spectrum power, the sub-band powers, the spectral centroid, the spectral spread, the spectral flux, the spectral roll-off, and the Mel-Frequency Cepstral Coefficients (MFCC) as features extracted from the microphone and other features extracted from other sources for the recognition of standing, lying, walking, walking on stairs, jogging, drinking and running activities based on the environment.

In (Nishida et al., 2015), the Gaussian mixture model (GMM) was used with the log power and the MFCC as features extracted from the microphone for the recognition of cycling, cleaning table, shopping, travelling by car, going to toilet, cooking, watching television, eating, driving, working on a computer, reading, and sleeping activities based on the environment.

The accelerometer and the microphone was used by the authors of (Filios et al., 2015) for the recognition of several activities based on the environment, including shopping, waiting in a queue, driving, travelling by car, cleaning with a vacuum cleaner, cooking, washing dishes, working at a computer, sleeping, watching television, being a bar, sitting, walking, standing, lying, and standing, extraction the mean, the standard deviation, the range, the angular degree, and the MFCC as features for the application of decision tree methods and the IBk lazy algorithm.

2.2.3 Recognition of Standing Activities

After the extraction of several features from the GPS receiver and other sensors, they need to be fused for the application of classification methods for the recognition of ADL. The authors of (Shoaib et al., 2013) used several methods, including ANN, SVM, Naïve Bayes, Logistic regression, decision tree, k-NN, and rule based classifiers, for the recognition of sitting, standing, walking, walking on stairs, and running activities, using the distance, the location and the speed as features extracted from the GPS receiver, and other features extracted from other sensors.

The distance the location and the speed are also extracted from the GPS receiver by the authors of (Hung et al., 2014), and other features were extracted from other sensors in order to recognize walking, standing, walking on stairs, lying and running activities, using J48 decision tree, Logistic Regression, ANN, and SVM methods.

In (Altini et al., 2014), the SVM method was implemented with the altitude difference in meters and speed extracted as features from the GPS receiver and other features extracted from other sources, in order to recognize sitting, standing, washing dishes, walking on stairs, cycling, and running.

The authors of (Luštrek et al., 2015) extracted the distance between to access points was inputted as feature from the GPS receiver and other features were extracted from other sources, using the Naïve Bayes, C4.5 decision tree, RIPPER, SVM, Random Forest, Bagging, AdaBoost and Vote methods for the recognition of sleeping, standing, preparing food, eating, working, jogging, and travelling.

3 METHODS

3.1 Data Acquisition and Processing

3.1.1 Data Acquisition

This step includes the development of a mobile application that acquires the data from several sources available in the Android devices, these are accelerometer, gyroscope, magnetometer, microphone and GPS receiver. The data was acquired in a background process and in real life environment with the mobile device in the pocket for the recognition of the signal of the sensors. The population included in the experiments is aged between 16 and 60 years old, performing several activities and providing their feedback with the selection of the activity performed. The ADL included in this study are sleeping, walking on stairs, walking, running, standing and driving. In addition, the environments recognized are bar, gym, kitchen, classroom, library, hall, street, bedroom, and watching TV. The data acquired for this project is available in a free repository (ALLab, 2017).

3.1.2 Data Cleaning

The application of the data cleaning methods depends on the type of sensors used during the data acquisition method presented in the section 3.1.1. When the study is based on data acquired from the motion and magnetic sensors, *e.g.*, accelerometer, gyroscope and magnetometer sensors, the best method for the data cleaning process is the low pass filter (Graizer, 2012). However, when the study makes use of acoustic data, the best method for the data cleaning is based on the extraction of the relevant frequencies using the Fast Fourier Transform (FFT) (Rader and Brenner, 1976). Related to the location sensors' data, the data cleaning methods are not useful for the improvement of the recognition of ADL and their environments.

3.1.3 Data Imputation

The imputation of the sensors' data acquired with the mobile application may improve the reliability of the framework for the recognition of ADL and their environments. There are some problems that can be minimized with data imputation methods, where the most used methods are the mean imputation (MEI) (Rahman et al., 2015), and the K-Nearest Neighbor (k-NN) (García-Laencina et al., 2009).

3.1.4 Feature Extraction

After the application of the methods presented in the previous sections and based on the sensors used in the framework for the recognition of ADL and their environments, we are able to extract the different features, these are:

- *Accelerometer, gyroscope and magnetometer sensors' data (stage 1):* 5 greatest distances between the maximum peaks, average, standard deviation, variance and median of the maximum peaks, standard deviation, average, variance, maximum, minimum and median of the raw signal;
- *Microphone data (stage 2):* 26 MFCC coefficients, standard deviation, average, maximum, minimum, variance and median of the raw signal;
- *Accelerometer, gyroscope and magnetometer sensors' data, microphone data and GPS receiver data (stage 3):* 5 greatest distances between the maximum peaks, average, standard deviation, variance and median of the maximum peaks, standard deviation, average, variance, maximum, minimum and median of the raw signal for the accelerometer, gyroscope and magnetometer

sensors, the environment recognized, and the distance and location extracted from the GPS receiver.

3.2 Data Fusion and Classification

The proposed study includes the use of different types of neural networks in order to identify the best methods for each stage of the implementation of the framework for the recognition of ADL and their environments. The types of neural networks selected for the experiments are:

- MLP method, applied with Neuroph framework (Neuroph, 2017);
- FNN method, applied with Encog framework (Research, 2017);
- DNN method, applied with DeepLearning4j framework (Nicholson, 2017).

Table 1 summarizes the configurations of the neural networks studied for the development of the framework for the recognition of ADL and their environments, which all of the neural networks implemented use the Sigmoid as activation function and backpropagation.

Table 1: Configurations of the classification methods.

Parameters	MLP	FNN	DNN
Activation function	Sigmoid	Sigmoid	Sigmoid
Learning rate	0.6	0.6	0.1
Momentum	0.4	0.4	N/A
Maximum number of training iterations	4×10^6	4×10^6	4×10^6
Number of layers	1	1	3
Weight function	N/A	N/A	Xavier
Seed value	N/A	N/A	6
Backpropagation	Yes	Yes	Yes
Regularization	N/A	N/A	L_2

3.2.1 Recognition of Common ADL

This stage includes the use of accelerometer, magnetometer and gyroscope sensors for the recognition of the most common ADL, these are walking on stairs, running, walking and standing. For this research, we implemented the three types of neural networks presented in the section 3.2 with normalized and non-normalized data as well as with different sets of features. The normalization of the data depends on the type of neural network implements, and, for the implementation of the MLP and Feedforward networks with Backpropagation, the normalization method used was the MIN/MAX normalizer (Jain et al., 2005), and, for the implementation of the DNN method, the normalization with mean and standard deviation (Brocca et al., 2010) and the application of the L_2 regularization (Ng, 2004) were performed.

3.2.2 Recognition of Environments

This stage includes the use of the microphone data for the recognition of the environments, these are bar, gym, kitchen, classroom, library, hall, street, bedroom, and watching TV. For this research, we implemented the three types of neural networks presented in the section 3.2 with normalized and non-normalized data as well as with different sets of features. The normalization of the data depends on the type of neural network implements, and, for the implementation of the MLP and FNN methods, the normalization method used was the MIN/MAX normalizer (Jain et al., 2005), and, for the implementation of the DNN method, the normalization with mean and standard deviation (Brocca et al., 2010) and the application of the L_2 regularization (Ng, 2004) were performed.

3.2.3 Recognition of Standing Activities

This stage includes the use of accelerometer, magnetometer and gyroscope sensors' data, the environment recognized with the method implemented in the section 3.2.2, and the distance and location features extracted from the GPS receiver for the recognition of standing activities, these are sleeping, driving and watching TV. For this research, we implemented the three types of neural networks presented in the section 3.2 with normalized and non-normalized data as well as with different sets of features. The normalization of the data depends on the type of neural network implements, and, for the implementation of the MLP and FNN methods, the normalization method used was the MIN/MAX normalizer (Jain et al., 2005), and, for the implementation of the DNN method, the normalization with mean and standard deviation (Brocca et al., 2010) and the application of the L_2 regularization (Ng, 2004) were performed.

4 RESULTS

4.1 Recognition of Common ADL

For the development of the method for the recognition of the common ADL, the reported results with the different number of sensors allowed and with normalized and non-normalized data are presented in the tables 2 and 3.

Table 2: Classification accuracies with non-normalized data for common ADL.

	MLP	FNN	DNN
Accelerometer	34.76%	74.45%	80.35%
Accelerometer and Magnetometer	35.15%	42.75%	70.43%
Accelerometer, Magnetometer and Gyroscope	38.32%	76.13%	74.47%

As verified the best method for the different number of sensors is the DNN method with normalized data, where the reported results are highlighted in the table 3, and they are between 85.89% and 89.51%.

Table 3: Classification accuracies with normalized data for common ADL.

	MLP	FNN	DNN
Accelerometer	24.03%	37.07%	85.89%
Accelerometer and Magnetometer	24.93%	64.94%	86.49%
Accelerometer, Magnetometer and Gyroscope	37.13%	29.54%	89.51%

4.2 Recognition of Environments

For the development of the method for the recognition of the environments, the reported results with normalized and non-normalized data are presented in the table 4, verifying that the best results are achieved with the FNN method with non-normalized data, reporting an accuracy of 86.50%.

Table 4: Classification accuracies with acoustic data.

	MLP	FNN	DNN
Non-normalized	12.86%	86.50%	48.11%
Normalized	19.43%	82.75%	4.74%

4.3 Recognition of Standing ADL

The results of the recognition of the standing ADL depends on the correct recognition of the common ADL as standing, because, based on the environment recognized and/or the distance travelled, the standing ADL are recognized with a reported accuracy of 100%, based on the results of the DNN method with normalized data.

4.4 Overall Results

The development of the proposed framework for the recognition of ADL and their environments explored several scenarios, showing the accuracies reported by the selected method for each scenarios, where a scenario is a combination of sensors used. They are:

A. Use of the accelerometer;
B. Use of the accelerometer and the magnetometer;
C. Use of the accelerometer, the magnetometer and the gyroscope;
D. Use of the microphone;
E. Use of the environment recognized and/or the GPS receiver.

Table 5 shows the accuracies of the selected method, presenting the accuracy of the proposed framework that, based on the number of sensors available, is between 90.80% and 92%. Finally, the average accuracy of the framework is 91.27%.

Table 5: Classification accuracies of the proposed framework.

Stages	A / D / E	B / D / E	C / D / E	Average accuracy
Common ADL	85.89%	86.49%	89.51%	87.30%
Environments	86.50%	86.50%	86.50%	86.50%
Standing activities	100.00%	100.00%	100.00%	100.00%
Average accuracy	90.80%	91.00%	92.00%	91.27%

5 CONCLUSIONS

The recognition of ADL and their environments using the commodity off-the-shelf mobile is a project that allows the training and monitoring of lifestyles with reliable accuracy and the reducing costs in the monitoring of elderly people and/or the physical training as a personal trainer.

Several research have been performed using small sets of sensors, but the current state of this project probes that the use of a major number of sensors increases the number of ADL and environments recognized and the accuracy of the recognition.

The current development of this project using the data available in (ALLab, 2017) and neural networks reports an accuracy around 91.27%, complaining the several stages of the treatment and analysis of the sensors' data.

As future work, the implementation of data imputation methods and other classification methods, including Adaboost and Support Vector Machines (SVM), reveals important to attempt to increase the reliability of the framework, improving the quality of the data acquired. The development of the method should take in account the limitations of the mobile devices. However, the ongoing results proves that the combination of the different types of neural networks achieves reliable results in the recognition.

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