Wearable Computing: Accelerometers' Data Classification of Body Postures and Movements

Wallace Ugulino[1], Débora Cardador[1], Katia Vega[1],
Eduardo Velloso[2], Ruy Milidiú[1], and Hugo Fuks[1]

[1] Pontifical Catholic University of Rio de Janeiro, Informatics Department
[2] School of Computing and Communications, Lancaster University, UK
{wugulino,dcosta,kvega,milidiu,hugo}@inf.puc-rio.br,
e.velloso@lancaster.ac.uk

Abstract. During the last 5 years, research on Human Activity Recognition (HAR) has reported on systems showing good overall recognition performance. As a consequence, HAR has been considered as a potential technology for e-health systems. Here, we propose a machine learning based HAR classifier. We also provide a full experimental description that contains the HAR wearable devices setup and a public domain dataset comprising 165,633 samples. We consider 5 activity classes, gathered from 4 subjects wearing accelerometers mounted on their waist, left thigh, right arm, and right ankle. As basic input features to our classifier we use 12 attributes derived from a time window of 150ms. Finally, the classifier uses a committee AdaBoost that combines ten Decision Trees. The observed classifier accuracy is 99.4%.

Keywords: Human Activity Recognition, Wearable Computing, Machine Learning, Accelerometer.

1 Introduction

With the rise of life expectancy and ageing of population, the development of new technologies that may enable a more independent and safer life to the elderly and the chronically ill has become a challenge [1]. Ambient Assisted Living (AAL) is one possibility to increase independence and reduce treatment costs, but it is still imperative to generate further knowledge in order to develop ubiquitous computing applications that provide support to home care and enable collaboration among physicians, families and patients.

Human Activity Recognition (HAR) is an active research area, results of which have the potential to benefit the development of assistive technologies in order to support care of the elderly, the chronically ill and people with special needs. Activity recognition can be used to provide information about patients' routines to support the development of e-health systems, like AAL. Two approaches are commonly used for HAR: image processing and use of wearable sensors.

The image processing approach does not require the use of equipment in the user's body, but imposes some limitations such as restricting operation to the indoor environments, requiring camera installation in all the rooms, lighting and image quality concerns and, mainly, users' privacy [2]. The use of wearable sensors minimizes these problems, but requires the user to wear the equipment through extended periods of time. Hence, the use of wearable sensors may lead to inconveniences with battery charges, positioning, and calibration of sensors [3].

We performed a literature review on HAR using wearable accelerometers data, discussed in Section 2. This review unfolded an intense growth on the number of publications related to wearable accelerometers in the last 5 years. It was further observed that few works provide public datasets for benchmarking and there is no sufficient information on the specification and orientation of the sensors deployed. The absence of public datasets and information for the reproduction of the studies are evidences of the need for maturity within the area. In view of such results, it was decided for the investigation of activities recognition by means of wearable accelerometers approach.

In this project we built a wearable device with the use of 4 accelerometers positioned in the waist, thigh, ankle and arm. The design of the wearable, details on the sensors used, and other necessary information for the reproduction of the device are shown on Section 3. We collected data from 4 people in in different static postures; and dynamic movements with which we trained a classifier using the AdaBoost method and decision trees C4.5 [3, 5]. The design of the wearable, data collection, extraction and selection of features and the results obtained with our classifier are described in Section 4.   Conclusion and future work are discussed in Section 5.

2   Literature Review

The results presented in this section are part of a more comprehensive systematic review about HAR with wearable accelerometers. The procedures used for the results of this paper are the same used in a traditional systematic review: we defined a specific research question, used a search string in the database, applied exclusion criteria and reviewed resulting publications in qualitative and quantitative form. For the quantitative analysis, we collected metadata from articles and used descriptive statistics to summarize data. The method application is described as follows:

- Research Question: What are the research projects conducted in recognition of human activities and body postures with the use of accelerometers?
- Search string: (((("Body Posture") OR "Activity Recognition")) AND (accelerometer OR acceleration)). Refined by: publication year: 2006 – 2012;
- Results in IEEE database: 144 articles;
- Exclusion criteria:
  - Use of accelerometers in smartphones;
  - HAR by image processing;
  - Not related to human activity (robots, in general);

- Different task (composite activities, games, gesture input recognition, etc.);
- Researches in the area of sensors network, without development of predictors/classifiers;
- It was used the most recent publication when the same result was published in different moments;
- Research about energy consumption in wearable devices;
- Result: 69 articles for quantitative and qualitative analysis.

For the quantitative analysis the metadata drawn from the articles were as follows: research title, year, quantity of accelerometers, use of other sensors, accelerometers position, classes, machine learning technique (or threshold based algorithms), number of subjects and samples, test mode (training dataset + test dataset, cross-validation with modes: k-fold, leave-one-example-out, or leave-one-subject-out), percentage of correctly classified samples. It was observed in relation to the publication year, that there is a growing number of publications on HAR with Wearable Accelerometers, as shown in Figure 1, which shows evidence of the importance of the approach for the Human Activity Recognition community.
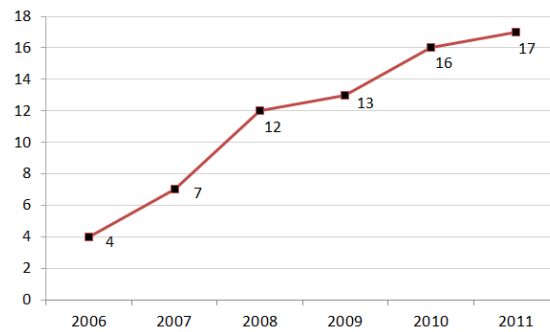

Fig. 1. IEEE publications based on wearable accelerometers' data for HAR

In the surveyed works, we observed the use of up to 4 accelerometers in the collection of data for the most part of the works. The most widely used test mode is the k-fold cross-validation; however, less-dependable tests and even non-standard tests were performed in some recent works. Another important data identified in the literature is that most works present a percentage starting at 90% of success rate in the activities' classification. However, in just 7 works it was informed the dataset size. A list of metadata drawn from the most recent publications (2012 and 2011) is shown on Table 1.

Table 1. HAR based on accelerometers' data from 2012 and 2011 (IEEE database)

Research	# of sensors	Accelerometers' position	Solution	# of users	Learning mode	Test mode	Correct (%)
Liu et. al. (2012) [6]	1	hip, wrist (no info about orientation)	SVM	50	Super-vised	leave-one-out	88.1
Yuting et al. (2011) [7]	3	chest and both thighs (no info about orientation)	Threshold-based	10	--	--	98.6
Sazonov et al. (2011) [8]	1	foot	SVM	9	Super-vised	4-fold cross validation	98.1
Reiss & Stricker (2011) [9]	3	lower arm, chest and foot	Boosted Deci-sion Tree	8	Super-vised	8-fold cross validation	90.7
Min et al., (2011) [10]	9	torso, arms and legs	Threshold-based	3	--	Comparison with k-means	96.6
Maekawa & Watanabe (2011) [11]	4	wrists of both hands, waist, and right thigh	HMM	40	Unsu-pervised	leave-one-out	98.4
Martin et al. (2011) [12]	2	hip, foot and chest	Threshold-based	5	--	--	89.4
Lei et al. (2011) [3]	4	waist, chest, thigh, and side of the body	Naive Bayes	8	Super-vised	Several, w/ no cross validation	97.7
Alvarez et al. (2011) [13]	1	centered in the back of the person	Genetic fuzzy finite state machine	1	Super-vised	leave-one-out	98.9
Jun-ki & Sung-Bae (2011) [14]	5	forehead, both arms, and both wrists	Naive Bayes and SVM	3	Super-vised	leave-one-out	**99.4**
Ioana-Iuliana & Rodica-Elena (2011) [15]	2	right part of the hip, lower part of the right leg	Neural Networks	4	Super-vised	66% trainning vs 33% test	**99.6**
Gjoreski et al. (2011) [2]	4	chest, waist, ankle and thigh	Naïve Bayes, SVM, C4.5, Random Forest	11	Super-vised	Leave-one-person-out	90.0
Feng, Meiling, and Nan (2011) [16]	1	Waist	Threshold-based	20	--	--	94.1
Czabke, Marsch, and Lueth (2011) [17]	1	Trousers' Pocket	Threshold-based	10	--	--	90.0
Chernbumroong, et al. (2011) [18]	1	Non-dominant wrist (watch)	C4.5 and Neural Networks	7	Super-vised	5-fold cross-vali-dation	94.1
Bayati & Chavarriaga (2011) [19]	--	Simulations instead of real accelerometers	Expectation Maximization	--	Unsuper-vised	Not mentioned	86.9
Atallah et al (2011) [20]	7	ear, chest, arm, wrist, waist, knee, and ankle	Feature Selection algorithms*	11	Super-vised	Not applied	--
Andreu et al. (2011) [21]	1	Not mentioned	fuzzy rule-based	--	Online learning	--	71.4

* This work is about sensor positioning and feature extraction

In the set of articles assessed, it was observed that the subject independent analysis has been less explored: just 3 out of 69 articles presented a subject independent analysis. The primary alternatives presented by the authors in order to improve the prediction performance in subject independent tests are: (1) increase of dataset, performing the data collection from subjects of different profiles; (2) adapting learning to a subject from data collected from subjects with similar physical characteristics [11]; and (3) investigation of subject independent features and more informative of the classes [22].

Among the articles assessed, we observed a discussion on the importance of the location of the accelerometers on the body. The positions in which wearable accelerometers most commonly mounted on are the waist, next to the center of mass, and chest. A research investigates specifically the development of classifiers adaptable to different amounts of accelerometers [20].

It was also observed that the main problematic issue found was the unavailability of the dataset, which restrains the comparison of results between researches. There is also a lack of information about the orientation of the sensors axis in most of the researches, although the location is usually well described. In some research it was not informed the model of sensor used. The absence of information about orientation and sensors model impairs the reproduction of the wearable devices.

As the area matures, it is imperative that datasets be published in order to enable comparison of results. The importance of disclosing datasets for benchmarking is also commented by Yang & Lianwen [23] as it acknowledges that "*the recognition algorithms rely heavily on the dataset*". The authors also verified the unavailability of datasets in the area and denounced the existence of unpublished proprietary datasets. As a form of contribution, the authors made available a dataset for benchmark in HAR, in addition to details on the location, orientation and model of sensors used. The dataset provided by the authors is small, with only 1278 samples, but it is an important step towards the maturity of this research area. It is necessary that more datasets are publicized, about different activities, and that accurate information on the model, positioning and orientation of sensors are provided in order to enable the comparison of research results in the HAR area by means of wearable accelerometers.

In order to enable the reproduction of the literature review discussed in this article, all publications assessed in this paper are available in RIS format, in the following web address: http://groupware.les.inf.puc-rio.br/har. In this research, the bibliographic management and publishing solution used was the EndNote X5™. The library in EndNote format is also available in this project web address.

3   Building Wearable Accelerometers for Activity Recognition

Our wearable device comprised 4 tri-axial ADXL335 accelerometers connected to an ATmega328V microcontroller. All modules were of the Lilypad Arduino toolkit. The wearable device and the accelerometers' positioning and orientation diagram are illustrated in Figure 2.
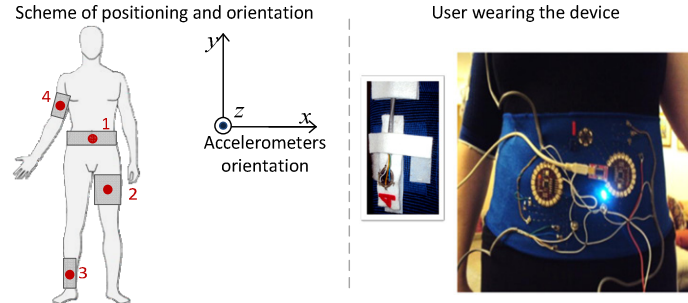
Scheme of positioning and orientation   User wearing the device

Accelerometers orientation

Fig. 2. Wearable device built for data collection

The accelerometers were respectively positioned in the waist (1), left thigh (2), right ankle (3), and right arm (4). All accelerometers were calibrated prior to the data collection. The calibration consists of positioning the sensors and the performance of the reading of values to be considered as "zero". From the calibration, the read values of each axis during data collection are subtracted from the values obtained at the time of the calibration.

The purpose of the calibration was to attenuate the peculiar inaccuracy issues of this type of sensor. Because of this, the sensors were calibrated on top of a flat table in the same position. Another regular type of calibration is the calibration by subject [3], in which the accelerometers are read and calibrated after positioned in the subjects' bodies. The calibration by subject may benefit the data collection provided that it enables the obtainment of more homogeneous data. However, it makes the use of the wearable after completion more complex.

Even though the Lilypad Arduino platform was design to be used with conductive thread, we used wired cablesin order to increase robustness, to enable on-the-fly changes in the circuit and to facilitate reprogramming the microcontroller. The assembly took into consideration the ease of move by the users. The source code (sketch in the *Arduino* Programming Language) is available at http://groupware.les.inf.puc-rio.br/har.

4   Building a Classifier for Wearable Accelerometers' Data

We took the following steps to develop a classifier for the data achieved from the 4 accelerometers: data collection, data pre-processing, feature extraction, feature selection, and 10-fold cross-validation type tests to assess the accuracy of the classifier developed.
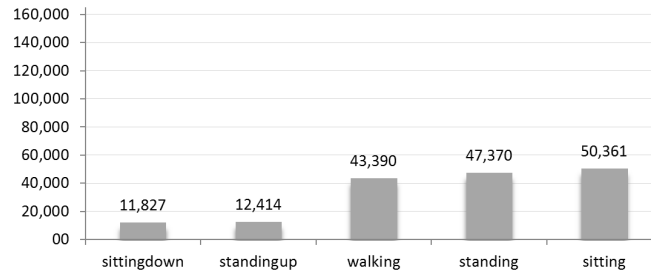
4.1   Data Collection

We collected data during 8 hours of activities, 2 hours with each one of the 4 subjects: 2 men and 2 women, all adults and healthy. The protocol was to perform each activity separately. The profile of each subject is shown in Table 2:

Table 2. Characteristics of the participants

Subject	Genre	Age	Height	Weight	Instances
A	Female	46 y.o.	1.62m	67kg	51,577
B	Female	28 y.o.	1.58m	53kg	49,797
C	Male	31 y.o.	1.71m	83kg	51,098
D	Male	75 y.o.	1.67m	67kg	13,161*

* A smaller number of observed instances because of the participant's age

Although the number of subjects is small, the amount of data collected is reasonable (2 hours for each subject) and the profile is diverse: women, men, young adults and one Elder. At total it was collected 165,633 samples for the study; the distribution of the samples between the classes is illustrated in Figure 3.

Fig. 3. Frequency of classes between collected data

4.2 Feature Extraction

From the data collected from the tri-axial accelerometers it was performed a data pre-processing, following some instructions from [24]. It was generated a 1 second time window, with 150ms overlapping. The samples were grouped and descriptive statistic was used for generating part of the derivate features. The derivate features of acceleration in axis x, y, and z and of the samples grouped are listed as follows:

- For each accelerometer: Euler angles of roll and pitch and the length (module) of the acceleration vector (called as total_accel_sensor_n);
- Variance of roll, pitch and module of acceleration for all samples in the 1 second window (approximately 8 reads per second), with a 150ms overlapping;
- A column discretizing the module of acceleration of each accelerometer, defined after a statistic analysis comparing the data of 5 classes;

The final dataset generated with all the derived features is available for public free use at http://groupware.les.inf.puc-rio.br/har.

4.3 Feature Selection

With the purpose of reducing the use of redundant features and select more informative features in relation to the classes, we used Mark Hall's selection algorithm based

on correlation [25]. The algorithm was configured to adopt the "Best First" method, which has a greedy strategy based on backtracking. The 12 features selected by through this procedure were: (1) Sensor on the Belt: discretization of the module of acceleration vector, variance of pitch, and variance of roll; (2) Sensor on the left thigh: module of acceleration vector, discretization, and variance of pitch; (3) Sensor on the right ankle: variance of pitch, and variance of roll; (4) Sensor on the right arm: discretization of the module of acceleration vector; From all sensors: average acceleration and standard deviation of acceleration.

4.4   Classifier for Activity Recognition

Ross Quinlan's [4] C4.5 decision tree was used in connection with the AdaBoost ensemble method [5] for classifying tasks. The C4.5 tree is an evolution proposed by Ross Quinlan to the ID3 algorithm (Iterative Dichotomiser 3) and its main advantage over the ID3 is a more efficient pruning. The boosting AdaBoost method "*tends to generate distributions that concentrate on the harder examples, thus challenging the weak learning algorithm to perform well on these harder parts of the sample space*" [5]. In a simplified manner, with the use of AdaBoost, the C4.5 algorithm was trained with a different distribution of samples in each iteration, thus favoring the "hardest" samples.

We used AdaBoost with 10 iterations and configured the C4.5 tree for a confidence factor of 0.25. The overall recognition performance was of 99.4% (weighted average) using a 10-fold cross validation testing mode, with the following accuracies per class: "sitting" 100%, "sitting down" 96.9%, "standing" 99.8%, "standing up" 96.9%, and "walking" 99.8%. The confusion matrix is presented in Table 3.

Table 3. Confusion Matrix

Sitting	Sitting down	Predicted class Standing	Standing Up	Walking		
50,601	9	0	20	1	Sitting	
10	11,484	29	297	7	Sitting down	Actual class
0	4	47,342	11	13	Standing	
14	351	24	11,940	85	Standing up	
0	8	27	60	43,295	Walking	

The results obtained in this research are very close to the top results of the literature (99.4% in [14], and 99.6% in [15]), even though, it is hard to compare them. Each research used a different dataset, a different set of classes, and different test modes.

5   Conclusion and Future Works

This work discussed a literature review on the recognition of activities using wearable accelerometers data obtained , a wearable device consisted of 4 accelerometers , and the data collection procedure, extraction and selection of features for the development of a classifier for human activities; The main contributions of this article are:

- A comparative table of the researches in the HAR from wearable accelerometers;
- A wearable device for data collection of human activities;
- The offer of a public domain dataset with 165,633 samples and 5 classes, in order to enable other authors to continue the research and compare the results.

In future works we want to include new classes in the dataset and investigate the classifier's performance with the use of accelerometers in different positions and in different quantities. Another future work is the qualitative recognition of activities, which consists in recognizing different specifications for the performance of the same activity, such as different specifications for weight lifting.

References

1. Yu-Jin, H., Ig-Jae, K., Sang Chul, A., Hyoung-Gon, K.: Activity Recognition Using Wearable Sensors for Elder Care. In: Proceedings of Second International Conference on Future Generation Communication and Networking, FGCN 2008, vol. 2, pp. 302–305 (2008), doi:10.1109/FGCN.2008.165
2. Gjoreski, H., Lustrek, M., Gams, M.: Accelerometer Placement for Posture Recognition and Fall Detection. In: 7th International Conference on Intelligent Environments, IE (2011)
3. Lei, G., Bourke, A.K., Nelson, J.: A system for activity recognition using multi-sensor fusion. In: Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC (2011)
4. Salzberg, S.L.: C4.5: Programs for Machine Learning by J. Ross Quinlan. Morgan Kaufmann Publishers, Inc. (1993) Machine Learning 16(3), 235–240 (1994) ISSN: 0885-6125, doi: 10.1007/bf00993309
5. Freund, Y., Schapire, R.E.: Experiments with a New Boosting Algorithm. In: International Conference on Machine Learning, pp. 148–156 (1996)
6. Liu, S., Gao, R.X., John, D., Staudenmayer, J.W., Freedson, P.S.: Multisensor Data Fusion for Physical Activity Assessment. IEEE Transactions on Biomedical Engineering 59(3), 687–696 (2012) ISSN: 0018-9294
7. Yuting, Z., Markovic, S., Sapir, I., Wagenaar, R.C., Little, T.D.C.: Continuous functional activity monitoring based on wearable tri-axial accelerometer and gyroscope. In: 5th International Conference on Pervasive Computing Technologies for Healthcare, PervasiveHealth (2011)
8. Sazonov, E.S., et al.: Monitoring of Posture Allocations and Activities by a Shoe-Based Wearable Sensor. IEEE Transactions on Biomedical Engineering 58(4), 983–990 (2011)
9. Reiss, A., Stricker, D.: Introducing a modular activity monitoring system. In: Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC (2011)

10. Min, X., Goldfain, A., Chowdhury, A.R., DelloStritto, J.: Towards accelerometry based static posture identification. In: IEEE Consumer Communications and Networking Conference, CCNC (2011)

11. Maekawa, T., Watanabe, S.: Unsupervised Activity Recognition with User's Physical Characteristics Data. In: 15th Annual International Symposium on Wearable Computers, ISWC (2011)

12. Martin, H., Bernardos, A.M., Tarrio, P., Casar, J.R.: Enhancing activity recognition by fusing inertial and biometric information. In: Proceedings of the 14th International Conference on Information Fusion, FUSION (2011)

13. Alvarez-Alvarez, A., Trivino, G., Cordon, O.: Body posture recognition by means of a genetic fuzzy finite state machine. In: IEEE 5th International Workshop on Genetic and Evolutionary Fuzzy Systems, GEFS (2011)

14. Jun-Ki, M., Sung-Bae, C.: Activity recognition based on wearable sensors using selection/fusion hybrid ensemble. In: IEEE International Conference on Systems, Man, and Cybernetics, SMC (2011)

15. Ioana-Iuliana, F., Rodica-Elena, D.: Detection of daily movements from data collected with two tri-axial accelerometers. In: 34th International Conference on Telecommunications and Signal Processing, TSP (2011)

16. Feng, W., Meiling, W., Nan, F.: Research on Classification of Human Daily Activities Based on a Single Tri-Axial Accelerometer. In: 1st International Workshop on Complexity and Data Mining, IWCDM (2011)

17. Czabke, A., Marsch, S., Lueth, T.C.: Accelerometer based real-time activity analysis on a microcontroller. In: 5th International Conference on Pervasive Computing Technologies for Healthcare, PervasiveHealth (2011)

18. Chernbumroong, S., Atkins, A.S., Hongnian, Y.: Activity classification using a single wrist-worn accelerometer. In: 5th International Conference on Software, Knowledge Information, Industrial Management and Applications, SKIMA (2011)

19. Bayati, H., Millan, J.d.R., Chavarriaga, R.: Unsupervised Adaptation to On-body Sensor Displacement in Acceleration-Based Activity Recognition. In: 15th Annual International Symposium on Wearable Computers, ISWC (2011)

20. Atallah, L., et al.: Sensor Positioning for Activity Recognition Using Wearable Accelerometers. IEEE Transactions on Biomedical Circuits and Systems 5(4), 320–329 (2011)

21. Andreu, J., Baruah, R.D., Angelov, P.: Real time recognition of human activities from wearable sensors by evolving classifiers. In: IEEE International Conference on Fuzzy Systems, FUZZ (2011)

22. Xu, S., Kashima, H., Tomioka, R., Ueda, N., Ping, L.: A New Multi-task Learning Method for Personalized Activity Recognition. In: IEEE 11th International Conference on Data Mining, ICDM (2011)

23. Yang, X., Lianwen, J.: A naturalistic 3D acceleration-based activity dataset & benchmark evaluations. In: IEEE International Conference on Systems Man and Cybernetics (SMC), pp. 4081–4085 (2010) ISSN: 1062-922X

24. Maziewski, P., Kupryjanow, A., Kaszuba, K., Czyzewski, A.: Accelerometer signal preprocessing influence on human activity recognition. In: Conference Proceedings of Signal Processing Algorithms, Architectures, Arrangements, and Applications (SPA), pp. 95–99 (2009) ISSN:978-83-62065-06-6

25. Hall, M.A.: Correlation-based Feature Subset Selection for Machine Learning. PhD thesis, Department of Computer Science, University of Waikato, Hamilton, New Zealand (April 1999)