Human Activity Recognition Based on Novel Accelerometry Features and Hidden Markov Models Application

Ana Luísa Gomes[1], Vítor Paixão[3] and Hugo Gamboa[1,2]
[1]*Universidade Nova de Lisboa Faculdade de Ciências e Tecnologias, FCT-UNL, Lisbon, Portugal*
[2]*PLUX - Wireless Biosignals, Lisbon, Portugal*
[3]*Champalimaud Neuroscience Programme, Champalimaud Centre for the Unknown, Lisbon, Portugal*

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Abstract: The Human Activity Recognition (HAR) systems require objective and reliable methods that can be used in the daily routine and must offer consistent results according to the performed activities.
In this work, a framework for human activity recognition in accelerometry (ACC) based on our previous work and with new features and techniques was developed. The new features set covered wavelets, the CUIDADO features implementation and the Log Scale Power Bandwidth creation. The Hidden Markov Models were also applied to the clustering output. The Forward Feature Selection chose the most suitable set from a 423^{th} dimensional feature vector in order to improve the clustering performances and limit the computational demands. K-means, Affinity Propagation, DBSCAN and Ward were applied to ACC databases and showed promising results in activity recognition: from $73.20\% \pm 7.98\%$ to $89.05\% \pm 7.43\%$ and from $70.75\% \pm 10.09\%$ to $83.89\% \pm 13.65\%$ with the Hungarian accuracy (HA) for the FCHA and PAMAP databases, respectively. The Adjust Rand Index (ARI) was also applied as clustering evaluation method. The developed algorithm constitutes a contribution for the development of reliable evaluation methods of movement disorders for diagnosis and treatment applications.

1 INTRODUCTION

Over time, the increasingly demand for objectivity in clinical diagnosis and the continuous pursuit for human wellbeing led to the development of enginery for healthcare. The combined efforts of medicine and engineering created and developed techniques that provide large amounts of information and simultaneously allow to interpret the generated data. According to different studies and our previous work, accelerometry is a reliable system for monitoring and evaluate daily physical activities over time(Inês Prata Machado, 2014), (Nishkam Ravi and Littman, 2005), (A. M. Khan and Kim, 2010). In this study, a framework for HAR systems was developed and tested with different accelerometry databases acquired with a triaxial accelerometer.

Biosignal processing requires an acquisition stage and a transformation with conversion, filtering and extraction of the useful features, which will depend on the aim of the investigation. The feature extraction step becomes very important for activity recognition because it defines what information we will cluster with. The selected features are directly related with the information extracted from the ACC signals which allows data organization inside each cluster by clustering algorithms. The clustering organization must show a lower variation between similar activities than between different activities (Lin and Chen, 2005), (Nishkam Ravi and Littman, 2005).

1.1 Unsupervised Learning Methods

Several techniques for data acquisition and processing have been developed to improve the early diagnosis and to aid clinical treatment of various diseases. ACC signals processing shows the importance of objective monitoring human locomotion through movement quantification when the medical diagnosis of pathologies is subjective and hard to trace such as Parkinson's disease and Cerebrovascular Accident (CVA).

U. Maurer and coworkers (Uwe Maurer and Deisher, 2006) and our group (Inês Prata Machado, 2014) concluded that four features from time and frequency domains can achieve high activity recogni-

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tion accuracy (about 99%). The work developed in (Inês Prata Machado, 2014) also contributed for the physical activity (PA) recognition in accelerometry with the K-means technique and also inferred that one waist-worn accelerometer can identify the physical activities in an adequate manner. Furthermore, (Adrian Ball and Velonaki, 2011) states that not only k-means clustering has a good performance but also the spectral clustering and the affinity propagation approaches show high accuracy results.

In the K-means method, the k value (number of clusters) is defined and k points are chosen randomly as cluster centers (Ittay Eyal and Rom, 2011),(Ghahramani, 2004), (Liao, 2005). Besides the K-means method, other clustering methods were applied in the present work such as Affinity Propagation (Walter, 2007), DBSCAN and Ward (Liao, 2005). The Affinity Propagation clusters dataset sending messages between pairs of samples until they converge. These messages represent the suitability for one data point to be the exemplar (similar) of the other, which is updated in response to the values from other pairs (Walter, 2007). In the DBSCAN method, clusters are areas of high density, separated by regions of low density, while the Ward method is based on the minimal variance criterion where two clusters will be agglomerated into one when a defined value is not achieved. Otherwise, both clusters will be apart (Liao, 2005).

Clustering techniques applied to biosignals morphology knowledge allows the detection and classification of different physical positions and everyday movements. The clustering stage is crucial for pathology detection and abnormal behavior evaluation (Nunes, 2011) due to changes that can be detected in the morphology of the accelerometry signal. Therefore, it is mandatory to acquire enough knowledge and data in order to be able to distinguish between normal movement patterns and those of certain pathologies.

1.2 Hidden Markov Models

The Hidden Markov Models (HMM) are statistical models where the observation is a probabilistic function of the state. In this case, the observation task is made by inference and the training set will determine the transition probabilities between the existing states (Ping Guo and Wang, 2012),(Fosler-Lussier, 1998).

In (Trabelsi et al., 2013) the HMM were used to identify the sequence corresponding to 12 physical activities and the final results lead to 91.4 % as a mean correct classification rate averaged over all observations. They also concluded that the HMM application leads to a better classification rate (84 %) and with k-means algorithm (60 %). This fact highlights the potential benefit of automatic identification of human activity with the HMM approach.

1.3 Clustering Performance Evaluation

After the clustering and HMM application, it is possible to assess if the separation of the data is similar to the available ground truth set. In an unsupervised learning context, it is important to create a data annotation as a ground truth (A. M. Khan and Kim, 2010).

In the present work, two clustering performance evaluation methods were used:

1. Hungarian Accuracy - With two solution sets, the predicted labels and the ground truth set, it is possible to measure the distance between both sets. The labeling of the predicted clusters must correspond to the ground truth available. However, if two partitions of the dataset are equivalent but its labelings are represented with different labels, there will be an ambiguity. To overcome this ambiguity the labelled indices in one predicted solution are permuted in order to increase the agreement between the two solution sets under comparison. This ambiguity can be minimized through the Hungarian method with a matrix construction based on the predicted labels and the ground truth similarity. This performance evaluation method measures the fraction of disagreement between both labels sets through the diagonal of the resulting matrix (Kuhn, 2009).
2. Adjust Rand Index - No conjecture is performed on the cluster arrangement and this technique measures the similarity between the predicted labels and the ground truth set, ignoring permutations. The ARI accuracy ranges from 0.0 (0%) to 1.0 (100%), for a perfect score (Clu, 2014).

It is proposed in the present work a framework implementation for activity recognition through new features and techniques application, presented in figure 1.

New features applied to accelerometry, instead of audio signal alone, might contribute for the discovery of important movement characteristics never detected before, such as the CUIDADO features and wavelets. A new feature inspired in the Mel scale is created and implemented, called Log Scale Power Bandwidth.

The HMM are also applied to the clustering output to improve the final results of the developed framework.

Section 2 describes the materials and methods adopted in this work to extract the ACC data for motion analysis. Section 3 describes the implementation

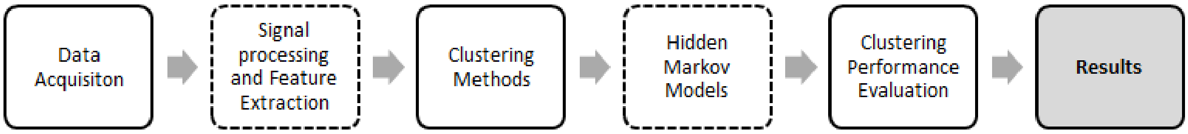

Figure 1: Overall structure of the framework developed for HAR systems. After the ACC data acquisition, the signal processing and the feature extraction stages are carried out and its results are used in clustering methods and in the HMM application. Finally, the clustering performance evaluation is applied. The hatched blocks show novel approaches for activity recognition.

of some algorithms that form the developed framework, including the feature selection method and the Log Scale Power Bandwidth implementation. Section 4 shows the results and respective discussion. Section 5 presents the main conclusions and the take home message obtained with this work.

2 METHODOLOGY AND MATERIALS

Two databases were analyzed in the present work: the online available PAMAP database (PAM, 2014) and the Foundation Champalimaud Human Activity (FCHA) database, described in the following subsections.

2.1 FCHA Database

Seven tasks were carried out by 9 volunteers with an age range from 23 to 44 years old: standing, sitting, lying down, walking, running, and ascending and descending stairs. All activities were performed with a predefined order and time, excluding the ascending and descending stairs tasks. The walking and running activities were carried out in a exercise treadmill with predefined velocities (4 km/h and 10 km/h respectively).

A triaxial accelerometry sensor was located on the waist with an acquisition frequency sampling of 800 Hz and a resolution of 16 bits. The ACC data acquired in this protocol formed the FCHA database. Data acquisition was carried out in the Champalimaud Centre for the Unknown with the OpenSignals software (Ricardo Gomes and Gamboa, 2012).

2.2 PAMAP Database

The PAMAP database is available at (PAM, 2014) and was also analyzed alongside the FCHA database in order to verify that the framework created in this work may suggest encouraging performances even from acceleration data with different resolutions. The PAMAP signals were acquired with a sampling frequency of 100 Hz and a resolution of 13 bits. The PAMAP signals show several physical activities and nine were selected: standing, sitting, lying down, walking, running, ascending and descending stairs, jumping and cycling. The data was acquired from 8 volunteers within an age range 25-31 years and the 3D-accelerometer sensor used was placed in the chest. All movement tasks were performed at a variable rhythm, according with each subject in order to acquire data in the most realistic conditions as possible.

2.3 Annotation Stage

The annotation document concerns all the labels and times of each activity performed by a given volunteer. The initial and final time of each activity was annotated in a JSON file created for each acquired signal. In addition to the annotation task adopted, the present work added an extra stage where motion series of all volunteers were videotaped in order to avoid erroneous times or labels and for ground truth validation (Figure 2).

Figure 2: Frames of the subject08's videotape, performing four tasks from the protocol: running, lying down, climbing stairs and cycling.

3 PROPOSED FRAMEWORK

Several algorithms were implemented in this work, including new previously unused features and the feature selection method. Algorithms such as the segmentation process and the feature design stage, used in the present work, were developed previously by our group (Inês Prata Machado, 2014).

3.1 Feature Implementation

There are several features already suggested in other studies and applied to accelerometry, such as the Mean and Standard Deviation (Adrian Ball and Velonaki, 2011),(Ittay Eyal and Rom, 2011), (Godfrey and ÓLaighin, 2008), listed in Table 1 with [1].

It is possible to group features according to different parameters, such as time, statistical and frequency domains. However, in the frequency spectrum analysis, the FFT does not provide information about the time at which these frequency components occur, which leads to the need for a tool that allows us to analyze the signal on both domains. A wavelet is a specific technique for the time-frequency domain and allows the visualization of the frequency content over time and consequently a better transient event description of an accelerometry signal (Godfrey and ÓLaighin, 2008), (Jani Mantyjarvi and Seppanen., 2001). The approximation coefficients from wavelets decomposition reflect the main characteristics of the signal and these values are used as feature coefficients in this work (Demetrio Labate and Wilson, 2013), (Galka and Ziólko, 2008).

There are other features, called the "CUIDADO features", applied for the first time for audio signals by G. Peeters in (Peeters, 2004) and can be applied and useful for accelerometry studies. Some from the CUIDADO features, shown in the Table 1 with [2], were used in this work. For more information about these, see (Peeters, 2004).

Table 1 shows all features from the four domains analyzed in this work.

3.1.1 Log Scale Power Bandwidth

In the present work, the lower frequencies were studied in more detail than higher frequencies through logarithmic scales in order to analyze meticulously the frequency domain. This study was inspired by the audio spectrum and the Mel scale which ultimately lead to the feature Log Scale Power Bandwidth creation.

The Log Scale Power Bandwidth coefficients are computed and its input is the motion data. This algorithm concerned five stages:

1. The first stage was the pre-emphasizing of the signal in the time domain. This stage filters a data sequence (the input segment signal) using a digital filter which emphasizes the energy of the signal at high frequencies with a pre-emphasis factor of 0.97;
2. The second step refers to the framing which divides the input data into a set of 3 (M) frames, each of these with 256 (N) samples;
3. Next, the conversion of the signal segment into the frequency domain is carried out through the Fast Fourier Transform application. However, whenever a finite Fourier Transform is applied and if the start and end of the finite data do not match, there will be a discontinuity in the signal. In this case, there will show up nonsense and undesirable high-frequencies in the Fourier transform. Therefore, a windowing stage was computed to the data sample with a Hamming window to make sure

Table 1: List of all features used in the present work and respective domains and number of output coefficients for each acceleration component: x, y, z, and total acceleration. [1] Refers to all traditional features already applied in accelerometry (Inês Prata Machado, 2014); [2] Refers to the CUIDADO features used in audio recognition; [3] Refers to the new feature type created and implemented in this work.

Feature Type	Number of Output Coefficients (for each acceleration component)
Statistical	
Skewness [1]	1
Kurtosis [1]	1
Histogram [1]	10
Mean[1]	1
Standard Deviation[1]	1
Interquartile Range[1]	1
Time	
Root Mean Square[1]	1
Median Absolute Deviation[1]	1
Zero Crossing Rate[1]	1
Pairwise Correlation[1]	3 (in total)
Autocorrelation[1]	1
Temporal Centroid[2]	1
Variance[2]	1
Frequency	
Maximum Frequency[1]	1
Median Frequency[1]	1
Power Spectrum[1]	2
Fundamental Frequency[1]	1
Power Bandwidth[1]	10
Log Scale Power Bandwidth[3]	40
Total Energy[2]	1
Spectral Centroid[2]	1
Spectral Spread[2]	1
Spectral Skewness[2]	1
Spectral Kurtosis[2]	1
Spectral Slope[2]	2
Spectral Decrease[2]	1
Spectral Roll-off [2]	1
Time-Frequency	
Wavelets [2]	20

that the ends match up;

4. A set of triangular overlapping windows in the range 133-3128 Hz was created. This set of triangular filters was spaced linearly at lower frequency, below 199 Hz, and logarithmic spaced above 199 Hz;

5. The triangular filter bank was applied to the resulting data from the step 3 which gives the powers at each frequency. Finally, the algorithm computes the log (in base 10) of the powers at each frequency and returned the Log Scale Power Bandwidth coefficients as the amplitudes of the resulting spectrum.

3.2 Feature Selection

Feature normalization to zero mean and unit variance is adopted before creating any feature selection. Next, the most suitable features for activity recognition were identified once the feature computation is a time consuming and computationally heavy task.

The protocol for feature selection is based on the Forward Feature Selection protocol and aims to select 10 features at most for each clustering method used. This study may be described by the following steps:

1. Elimination of the redundant information: Correlation between all features and removal of the redundant features. The second feature is removed when two features show correlation values greater than or equal to 0.98. The resulting set from this correlation and elimination stage is called A;

2. Selection of the best fitting features: 20 features with the highest ARI value are chosen among the set A, named set B. From the new set formed by 20 features types, B, the feature type with the highest ARI performance is collected to the set C, which leaves the original set B with only 19 features. Next, the algorithm combines the set C with the existing feature types from the set B. The combination with the highest ARI value and the corresponding set are identified. The new feature belonging to B and to the identified set is collected by C. In each iteration, a new feature is deleted from B and is collected to C. This iterative procedure repeats until C shows the best combination of 10 features;

3. Saving the final results: The algorithm finishes the procedure and saves the name and ARI performance of the 10 features set.

3.3 Hidden Markov Models Application

HMM were applied to the clustering results to achieve higher ARI accuracies in activity recognition. Its application was formed by the training and testing stages.

The implemented algorithm uses the ground truth (true labels) by collecting frequencies of the transitions between all different activities/states and also defines the initial state of a given sequence of activities through the most frequent initial state. The frequencies recorded are then converted to the probabilities of the existing symbols and state sequences. Finally, the testing stage estimates the most probable sequence of hidden states based in the trained model and with the Viterbi algorithm.

In the present work, the HMM topology is a completely connected structure of an ergodic model and it uses the labels from the clustering methods as test set and the annotation data (ground truth) as training set. Finally, the HMM output is used in the clustering performance evaluation stage.

4 RESULTS AND DISCUSSION

All studies here presented used defined parameters according to the highest ARI accuracy for each of these, such as: window segmentation, filtering stage and wavelet level decomposition. Segments with time duration of 5 seconds were used as window segmentation. The 8^{th} level was selected as the best level decomposition for the wavelets algorithm and the filtering stage was eliminated from the signal processing stage. The referred parameters were used in all studies presented in the following sections, 4.1, 4.2 and 4.3.

Clustering methods were also selected according to the ARI performances in order to improve the clustering accuracy. The K-means, Affinity Propagation, DBSCAN and Ward showed the highest ARI for ACC data. In parallel to the unsupervised learning techniques, three classification methods were used: K-Nearest Neighbors, Random Forest and Linear Discriminant Analysis (LDA).

4.1 Best set of Features

Feature selection is formed by two stages. The first part aims to find the best number of feature types for activity recognition and second stage aims to identify which feature types must be used.

The best 10 features were computed from the Forward Feature Selection Algorithm, for each subject and clustering method. Figure 3 shows the ARI performance (%) for each number of features and for each clustering method in order to select the best number of features to use in ACC recognition. This study used as ACC data the FCHA database and all implemented features from four domains: statistical, time, frequency and time-frequency, presented in Table 1.

Figure 3 suggests higher ARI percentages in 4 to 7 features. For a more detailed analysis, table 2 shows the ARI performances achieved with different clustering methods when the framework uses the best 4 to 7 feature types (sets A, B, C and D respectively) and all features.

From table 2, it can be concluded that the set B is the best set for K-means and Ward performances with $89.97\% \pm 9.97\%$ and $88.56\% \pm 11.72\%$, respectively. On the other hand, the set C showed higher performance for the DBSCAN method with $80.43\% \pm 6.29\%$ while the set D showed best performance for the Affinity Propagation with $81.19\% \pm 5.99\%$. For this reason, any choice from set B, C and D is acceptable. For K-means, Affinity Propagation, DBSCAN and Ward, the clustering performance values are $84.54\% \pm 9.23\%$,$81.19\% \pm 5.99\%$, $79.84\% \pm 10.75\%$ and $84.73\% \pm 9.00\%$ for set D, $89.97\% \pm 9.97\%$, $76.85\% \pm 10.30\%$, $78.12\% \pm 10.95\%$ and $88.56\% \pm 11.72\%$ for set B. Overall, sets B and D showed similar computing times (with difference of approximately 13 seconds) and the best accuracy values. In the present study set D is the set of the best 7 features and it was chosen for the formed framework.

After selecting the best number as 7 features, the best group of features was found through a histogram, where the occurrences of each feature type were represented. The 10 most used features in each clustering method were pooled, some of them belonging to the same feature type, presented in the figure 4.

The histogram shown in figure 4 suggested that the Forward Feature Selection algorithm used with a higher frequency the Log Scale Power Bandwidth, Root Mean Square, Total Energy, Autocorrelation, Variance, Wavelet Coefficients and the Mean for HAR systems. Therefore, these feature types are the most used and promising features for the developed framework.

Furthermore, figure 4 suggested that the Log Scale Power Bandwidth occurs more frequently (over 20%) than all the other types of features (with less than 20% in all occurrences). The Log Scale Power Bandwidth algorithm involved complex stages and offered a wide number of coefficients as output. The resulting data from those 40 output coefficients are complementary. One particular coefficient tended to be more sensible in activity distinction due to the variation in behavior over time while the other coefficient may identify better other different tasks. Thus, by using this type of feature, all these coefficients are used together and there will be more information related to the activity distinction compared with other type of features with fewer information and lower number of coefficients.

Moreover, the Log Scale Power Bandwidth feature considered data from the lower frequencies. A detailed analysis in this frequency range suggested that there was important information for activity recognition in accelerometry.The information located at low frequencies was preserved due to the elimination of the filtering step in the signal processing stage. Therefore, no information was lost and the GA component was maintained in the ACC data.

It was possible to observe from figure 5, and in opposition to others features, that each Log Scale Power Bandwidth coefficient showed an overall distinction for all activities carried out by the volunteers. Therefore the choice of this type of feature from the Forward Feature Selection as the best feature is justified for its greater ability for activity recognition.

Some difficulties referred in (Inês Prata Machado, 2014) such as the hard discrimination between sitting and standing positions and between walking and running activities were also identified in this work. These difficulties were subdued due to the presence of the GA component in the processed data and the use of the Log Scale Power Bandwidth and Wavelet coefficients as features. The Horizon Plot in figure 5 showed the variation of six Log Scale Power Bandwidth coefficients, six Wavelet coefficients and one coefficient of the Autocorrelation, Mean, Root Mean Square, Total Energy and the Variance from the x-axis component over time. It is possible to observe that feature types such as Log Scale Power Bandwidth and Wavelets are important for the standing and sitting positions distinction as well in many other tasks.

4.2 Hidden Markov Models Application

All the existing transitions in the test set (predicted labels from the clustering algorithms) with lower probability of occurrence may be a consequence of cluster miscalculation. These transition probabilities were gathered from the ground truth (train data) and all transitions with low probability of occurrence are avoided and replaced by a more likely transition.

The influence of the Hidden Markov Model application and its improvement (in %) is presented in figure 6 and in table 3. All implemented features were used in this study and only the FCHA database was analyzed. The improvement values shown in the

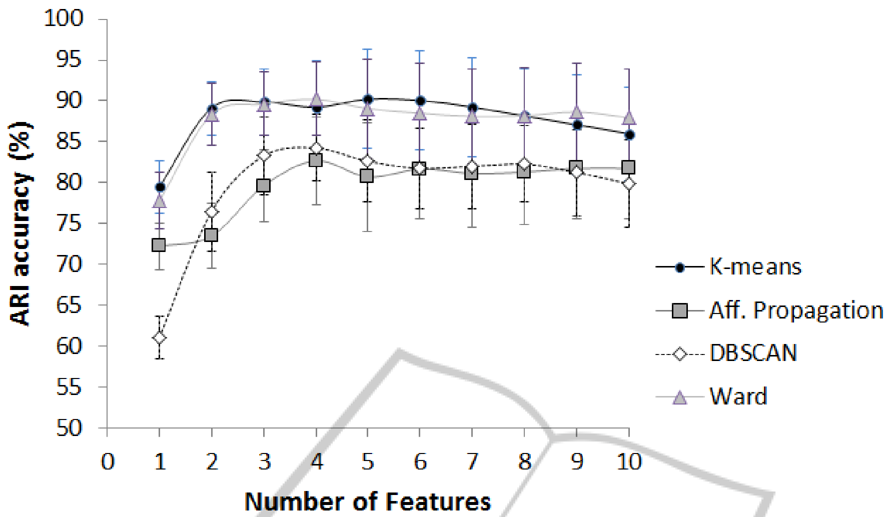

Figure 3: ARI performances (%) as a function of different numbers of features (from 1 to 10 features) and according to different clustering techniques: K-means, Affinity Propagation, DBSCAN and Ward.

Table 2: ARI performances for all features (first column) and for the best 4 to 7 features (set A-second, set B-third, set C-fourth and set D-fifth columns). The last row refers to the time interval used to compute each set of features.

	ARI (%)				
Clustering Methods	All Features	Set A	Set B	Set C	Set D
K-means	87.69 ± 5.56	87.37 ± 12.78	89.97 ± 9.97	84.52 ± 7.56	84.54 ± 9.23
Affinity Propagation	$78.41 \pm 6,86$	76.85 ± 10.30	76.85 ± 10.30	78.33 ± 6.48	81.19 ± 5.99
DBSCAN	78.36 ± 6.96	74.18 ± 9.67	78.12 ± 10.95	80.43 ± 6.29	79.84 ± 10.75
Ward	86.31 ± 8.68	85.96 ± 13.93	88.56 ± 11.72	84.73 ± 9.00	84.73 ± 9.00
Time Response	**347.16**	**107.46**	**132.13**	**142.25**	**145.05**

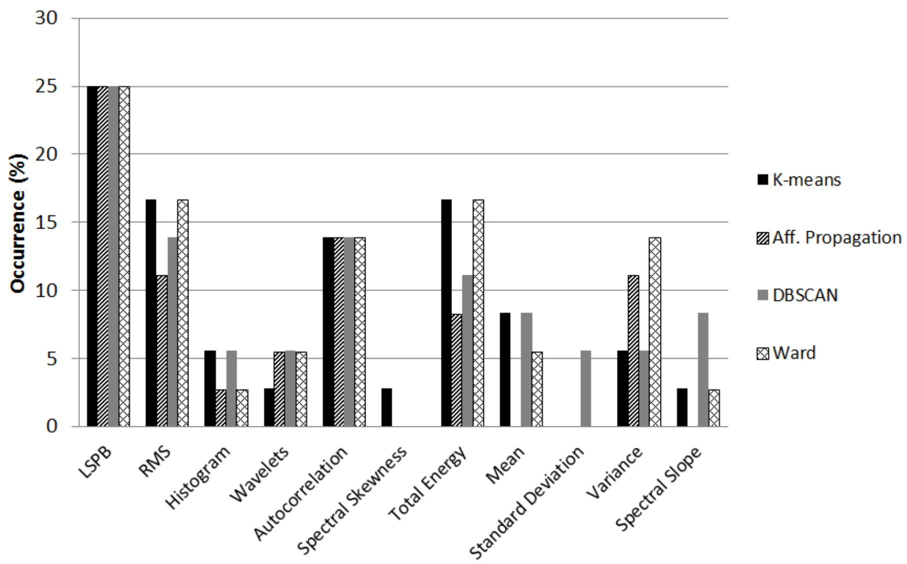

Figure 4: Representation of the Forward Feature Selection results. The algorithm outputted the set of the best 10 features for each clustering method. Each column corresponds to all occurrences of each feature type in all resulting sets for each clustering method.

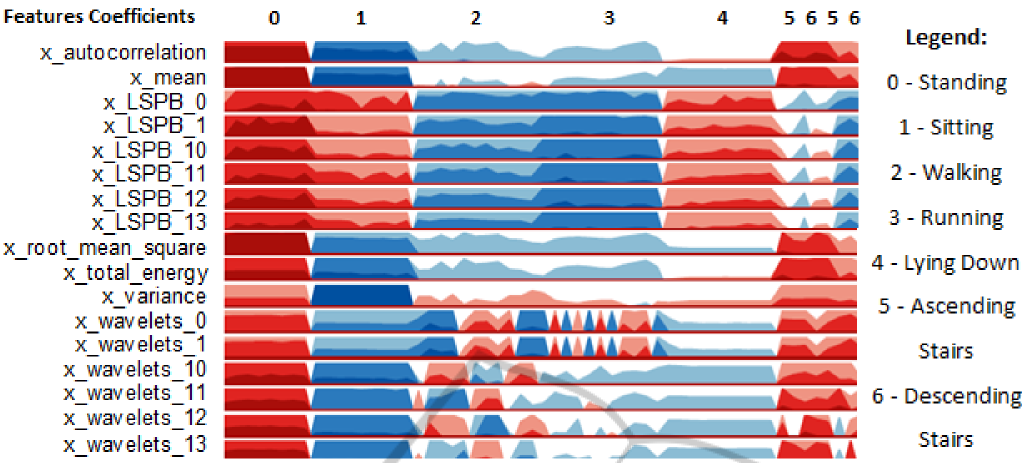

Figure 5: Horizon Plot with some feature coefficients from the X-axis acceleration component which vary over time according to the activity type performed.

Table 3: Clustering performances through ARI without and with the HMM application and its improvement.

Clustering Methods	ARI(%) without HMM application	ARI(%) with HMM application	Improvement (%)
K-means	81.37 ± 9.83	87.69 ± 5.56	33.92
Affinity Propagation	78.02 ± 9.90	78.41 ± 6.86	1.76
DBSCAN	73.89 ± 12.98	78.36 ± 6.96	17.10
Ward	84.82 ± 8.17	86.31 ± 8.68	9.81

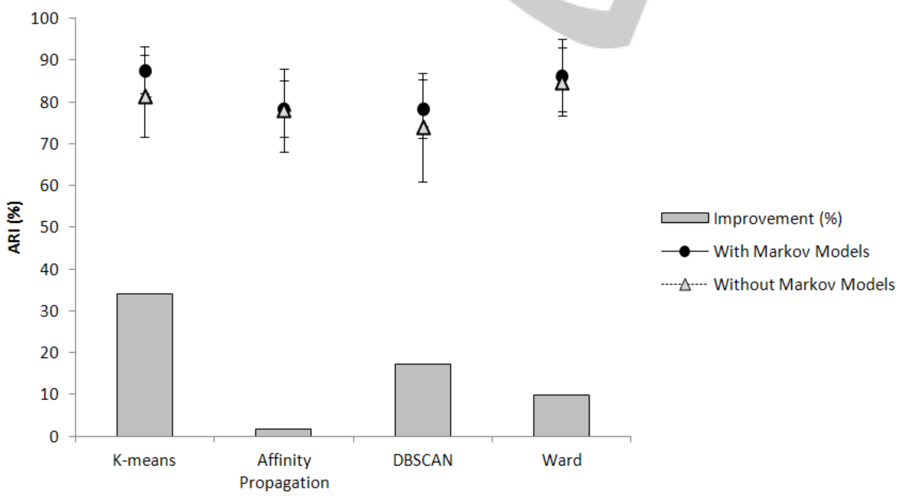

Figure 6: Clustering performances through ARI with and without the HMM application (%) and its performances improvement (%) in bars shown in table 3.

present section is represented by:

$$Improvement(\%) = \frac{100(x_2 - x_1)}{100 - x_1} \quad (1)$$

where:
x_1 - ARI accuracy value without HMM application
x_2 - ARI accuracy value with HMM application

The obtained improvement values were 33.92%, 1.76%, 17.10% and 9.81%, for K-means, Affinity Propagation, DBSCAN and Ward method, respectively. These results deserve a special attention because there is a significant improvement for certain clustering methods such as the K-means. Thus, it is important to take into account the HMM application together with the adopted unsupervised learning method. All improvement values were positive and in this case the HMM algorithm does not provide heavy computational demands hence it may be applicable to all demonstrated situations.

4.3 Evaluation of the Performance of the Framework

After the framework construction, the FCHA database and the PAMAP database were applied to the developed algorithms set. In this study, unsupervised and supervised learning approaches were applied. The tables 4 and 5 showed all results achieved with the ARI and the HA application and with classification methods: Random forest, LDA and K-Nearest Neighbors, which K value equals the number of activities carried out. The accuracy score method was used in classification techniques in which the ground truth was used as training set and the clustering output as test set.

The PAMAP signals were acquired with a frequency sampling of 100 Hz while the FCHA database is formed by ACC signals acquired with 800 Hz. Thus, this data showed different resolutions which influence the amount of information available for the clustering and classification methods.

Table 4: Clustering evaluation with the ARI and the HA (in %) for K-means, Affinity Propagation, DBSCAN and Ward.

Clustering (ARI %)		
Databases	FCHA	PAMAP
K-means	84.54 ± 9.23	61.56 ± 13.93
Affinity Propagation	81.19 ± 5.99	63.00 ± 0.19
DBSCAN	79.84 ± 10.75	74.26 ± 16.06
Ward	84.73 ± 9.00	60.53 ± 13.70
Clustering (HA %)		
Databases	FCHA	PAMAP
K-means	89.05 ± 7.43	74.47 ± 8.35
Affinity Propagation	73.20 ± 7.98	83.89 ± 13.65
DBSCAN	76.62 ± 9.68	70.75 ± 10.09
Ward	87.10 ± 8.87	71.13 ± 10.37

Table 5: Classification accuracy (in %) with K-Nearest Neighbors, Random Forest and LDA methods.

Classification (Accuracy %)		
Databases	FCHA	PAMAP
K-Nearest Neighbors	97.78 ± 6.67	99.40 ± 1.19
Random Forest	95.39 ± 12.64	97.89 ± 3.89
LDA	98.57 ± 4.30	98.03 ± 2.37

The results obtained within the ARI accuracy ranged from $79.84\% \pm 10.75\%$ to $84.73\% \pm 9.00\%$ and from $60.53\% \pm 13.70\%$ to $74.26\% \pm 16.06\%$ for the FCHA and PAMAP databases, respectively. On the other hand, the Hungarian accuracy results ranged from $73.20\% \pm 7.98\%$ to $89.05\% \pm 7.43\%$ and from $70.75\% \pm 10.09\%$ to $83.89\% \pm 13.65\%$ for the same databases. The main cause of the difference between the two databases may be related to the large difference in resolution, since the sampling frequencies for the FCHA base and the PAMAP database are 800 and 100 Hz, respectively. The FCHA data shows eight times more information than PAMAP data, which leads to a higher accuracy values. Unlike clustering, classification uses the ground truth for training and also showed high results: from $95.39\% \pm 12.64\%$ to $99.40\% \pm 1.19\%$ for both databases.

More than 85% of the presented results showed an accuracy higher than 70% which revealed the frameworks robustness and versatility for activity recognition with ACC signals, acquired with different sensors and different resolutions.

4.4 Conclusions

This work aimed to create and develop a novel gesture recognition system based on the consulted literatures concepts and presented in (Inês Prata Machado, 2014).

In the present work and in addition to those used in our previous work new features were implemented, such as the Log Scale Power Bandwidth coefficients. Other features previously used in audio recognition were also used in ACC data such as the CUIDADO features and wavelets coefficients. This work offered a set of 423 feature types for machine learning techniques which provide more and new information regarding the performed movement tasks compared to the literature (Ghahramani, 2004),(Jani Mantyjarvi and Seppanen., 2001), (Nishkam Ravi and Littman, 2005).

The Forward Feature Selection aimed to reduce the undesirable redundancy between features and to select the set of features that may lead to the best frameworks performance. The chosen features selected as the most suitable feature types for HAR systems are the Log Scale Power Bandwidth, Root Mean Square, Total Energy, Autocorrelation, Variance, Wavelet Coefficients and Mean coefficients.

The achieved results also suggested that it is important not to waste any information regarding to movement. The presence of the information located in lower frequencies, such as the GA component, and the Log Scale Power Bandwidth implementation may lead to better static activity distinction.

The obtained results with the FCHA database and PAMAP database showed that the developed framework is suitable for activity recognition even for ACC data with a large difference in resolution.

The major achievements of the current work allowed to construct a novel HAR system with HMM which may lead to better performances in activity recognition. The created framework with a small number of feature types also ensure high machine learning results without heavy computational demands. Therefore, as expected accelerometry is a suitable technique for monitoring movement patterns in free-living subjects over long periods of time. The knowledge acquired over this thesis may be applied into the clinical setting for the diagnosis and physiotherapy fields.

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