# Human Activity Recognition from Triaxial Accelerometer Data
## *Feature Extraction and Selection Methods for Clustering of Physical Activities*

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Abstract: The demand for objectivity in clinical diagnosis has been one of the greatest challenges in Biomedical Engineering. The study, development and implementation of solutions that may serve as ground truth in physical activity recognition and in medical diagnosis of chronic motor diseases is ever more imperative. This paper describes a human activity recognition framework based on feature extraction and feature selection techniques where a set of time, statistical and frequency domain features taken from 3-dimensional accelerometer sensors are extracted. In this paper, unsupervised learning is applied to the feature representation of accelerometer data to discover the activities performed by different subjects. A feature selection framework is developed in order to improve the clustering accuracy and reduce computational costs. The features which best distinguish a particular set of activities are selected from a $180^{th}$- dimensional feature vector through machine learning algorithms. The implemented framework achieved very encouraging results in human activity recognition: an average person-dependent Adjusted Rand Index (ARI) of $99.29\% \pm 0.5\%$ and a person-independent ARI of $88.57\% \pm 4.0\%$ were reached.

# 1 INTRODUCTION

The constant concern with the human physical and psychological well-being has been the drive for research studies that have led to a promising evolution of medicine and engineering. The study, development and implementation of solutions that may serve as ground truth in physical activity recognition and in medical diagnosis of chronic motor diseases is ever more imperative. In this paper, a Human Activity Recognition (HAR) framework is developed using a wearable 3-dimensional accelerometer sensor. The main focus of this paper is to understanding the signals produced by a Triaxial Accelerometer (TA), interpreting them in the context of human movement and identifying relevant parameters from the data. The versatility of the algorithm enables the identification of relevant features able to recognize simple daily activities. We obtain a $180^{th}$- dimensional feature vector from statistical, time and frequency domains. The dimensionality of the feature vector should be as small as possible by reducing the amount of irrelevant and redundant information in the data, not only to reduce the computation complexity, but also to obtain better clustering performance. The remainder of the paper is organized as follows: Section 2 describes the background and related work. The importance of objective monitoring human movement is discussed. That section also presents an overview on other studies about HAR with wearable sensors. Section 3 explains the composition of the TA signal. The signal is made up of several components, and each of these is examined. The difficulties in distinguish between the different signal components are discussed. Section 4 describes the proposed methodology used in this work to extract and select features based on motion data. Section 5 describes the architecture of the acquisition system and the obtained results. Section 6 presents the conclusions obtained from the investigation and some future research directions.

# 2 BACKGROUND

In recent decades, there has been an increasing interest in the use of Accelerometry (ACC) to moni-

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tor human behaviour. Monitoring human movement can provide valuable information on a patient and some parameters of movement can provide information of health status, rate of rehabilitation and other potentially useful clinical data. The advance of technology has helped the development of accelerometers of small size and low cost, making them a very convenient tool for monitoring subjects. One of the key point is the diversity of areas where ACC has been used in the past. The most studied have being: metabolic energy expenditure, Physical Activity (PA), balance and postural sway, sit-to-stand transfers (which is an important indicator for postural instability) and detection of falls. The use of accelerometers has also allowed to help on diagnose of a number of diseases such as Parkinson's Disease (Palmerini et al., 2013), Autism Spectrum Disorder, (Bandini et al., 2013) and Depression (Phillips and McAuley, 2013).

## 3 TRIAXIAL ACCELEROMETER SIGNAL

The signal measured by each fixed-body accelerometer is a linear sum of, approximately, three components (Mathie, 2003):

- Body Acceleration Component: acceleration resulting from body movement;
- Gravitational Acceleration Component: acceleration resulting from gravity;
- Noise intrinsic to the measurement system.

The first two components provide different information about the wearer of the device: the Gravitational Acceleration (GA) provides information about the space orientation of the device, and the Body Acceleration (BA) provides information about the movement of the device. The separation of the information regarding the movement of the device - Body Acceleration Component - is important, however these two components have overlapping frequency spectra. The BA component ranges from above 0 Hz to possibly up 20 Hz, but is mostly contained in the range above 0 and below 3 Hz. This range overlaps the area covered by the GA component, which goes from 0 to several Hertz. It is possible to approximately separate the BA and the GA components with some filtering. A wide range of different filters types with different characteristics and different windowing percentages were tested in previous studies, as in (Mathie, 2003), in order to determine their ability to differentiate the components of the acceleration signal. In the presented study, a cut-off frequency of 0.25 Hz was chosen, as it is consistent with the frequencies used in other research works. (Smeja and Muller, 1997) and (Foerster and Fahrenberg, 2000) choose to use 0.5 Hz, while (Khan et al., 2010) choose 0.1 Hz. In the presented study, in order to isolate the BA component, a second-order Butterworth High-Pass filter with cut-off frequency of 0.25 Hz is used. Figure 1 illustrates each component of a typical recording from the accelerometer showing seven minutes of motion data where the subject is asked to perform seven specific tasks.

The placement of the accelerometer is another important point of discussion. A device that is to be worn over extended periods must be designed to be as simple to put on and comfortable to wear in order to encourage compliance of patients. General body motion can be measured with a single accelerometer placed close to the body's center of mass, which is located within the pelvis (Liu, 2013). The advantage of placing the accelerometer attached to the waist is that it allows the monitoring of accelerations near the center of mass. Any movement of the body will cause the center of mass to shift. This study aims to develop a HAR framework, for a waist mounted accelerometer based system.

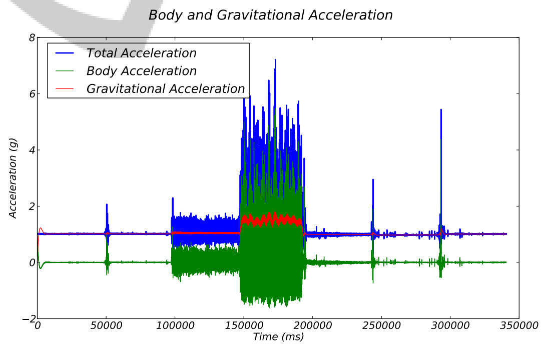


Figure 1: Body and Gravitational Acceleration for each axis of accelerometer sensor.

## 4 PROPOSED METHODS

Different segmentation methods can be applied to time-series data which enhance signal behaviour and enable the gather of useful information from continuous stream of data such as timing and sliding windows. For activity recognition, where accelerometer data is windowed, the choice of the number of frames is guided by a trade-off between information and resolution. The accelerometer data was collected, cleaned, and preprocessed to extract features that characterize different samples data windows. Clustering mechanisms separate and organize unlabeled data into different groups whose members are similar to each other in some metric. Different approaches generally lead to different clusters. Even for the same algorithm, the parameter identification or the sequence of input patterns may affect the final results. These assessments should be unbiased. In this work, the K-Means Clustering Algorithm (Lloyd, 1982) and a squared Euclidean distance metric were used.

## 4.1 Feature Design

The HAR strategy depends essentially on the set of features that are extracted from the signal. TA are made up of three separated accelerometer data time series, one time series for acceleration on each orthogonal axis $ACC_x$, $ACC_y$ and $ACC_z$. Complementary to the three axes data, an additional time series, $ACC_{tot}$, have been obtained by computing the magnitude of the acceleration, Equation 1:

$$ACC_{tot} = \sqrt{ACC_x^2 + ACC_y^2 + ACC_z^2} \quad (1)$$

Each time series $ACC_i$, with $i = x, y, z$ has been filtered with a second-order Butterworth High-Pass filter with cut-off frequency of 0.25 Hz in order to separate low frequencies component and high frequencies component as suggested in (Mathie, 2003) and (Mannini and Sabatini, 2010). This way, for each time series, three extra time series $BA_i$ are obtained, with $i = x, y, z$, representing the time series with body acceleration component. Finally, features from each one of the time series are extracted.

## 4.2 Accelerometer Signal Annotation

In unsupervised learning, the motion data has to be annotated to compute the performance of the algorithm. If true class labels are known, the validity of a clustering can be verified by comparing the predicted labels and the true labels. An aspect of activity recognition that has been greatly explored is the method of annotating sample data that can be used to compute the performance of the clustering method. Many experiments use unsupervised learning methods and apply manually annotated test data to evaluate their performances. In other cases, the experimenters told the participants in which order the specified activities should be performed, so the correct activity labels were identified before the sensor data was even collected. Still in other studies, the raw sensor data is manually inspected in order to annotate it with a corresponding activity label (Wren and Tapia, 2006). In the presented study, participants were continuously observed during experiments and an observer was stating starting/ending time of each activity. The subjects know in which order the specified activities should be performed and latter, raw sensor data was manually inspected in order to annotate it with a corresponding activity label. For each signal, an annotation, in *JavaScript Object Notation* (JSON) (Crockford, 2006) is created, with $i$ the number of activities, Scheme 2:

$$\begin{aligned} &"Labels" : [l_1, , \ldots, l_i], \\ &"Initial\_Times" : [init_1, \ldots, init_i] \\ &"End\_Times" : [end_1, \ldots, end_i] \end{aligned} \quad (2)$$

The dictionary has information about the number and label of the movements that took place and the time intervals that delimit them. Each label corresponds to one, and only one, activity, regardless of the subject. The input is an array with the initial and final times of each activity. It also receives as input the window size and the considered overlap percentage.

## 4.3 Feature Extraction

Recognizing human activities depends directly on the features extracted for motion analysis. A set of features, which will most efficiently and meaningfully represent the information that is important for analysis and the clustering process, is performed. In this section, tests were made in order to assess the following parameters:

- The influence of the signal's window size on the clustering performance.
- The influence of the free parameters in that same performance.
- The best feature combination that leads to a better performance of the implemented algorithm.

A dictionary of the extracted features from the motion data, was created, in a JSON format (Crockford, 2006). For each feature, the following information was collected: Description, Imports, Use, Metric, Free Parameters, Parameters, Number of Features, Function, Source and Reference. Table 1 shows the high level list of features considered in the presented study. The implemented dictionary divides the features into statistical, temporal and spectral domains. By manipulating this dictionary, the clustering algorithm can be easily tested with a different combination of features. To compute the feature vector the following inputs are needed: motion data, window length of the signal, sampling frequency of the data

Table 1: Statistical, Temporal and Spectral Domain Features.

| | |
|---|---|
| **Statistical Domain** | Kurtosis<br>Skewness<br>Mean<br>Standard Deviation<br>Interquartile Range<br>Histogram<br>Root Mean Square<br>Median Absolute Deviation |
| **Temporal Domain** | Zero Crossing Rate<br>Pairwise Correlation<br>Autocorrelation |
| **Spectral Domain** | Maximum Frequency<br>Median Frequency<br>Cepstral Coefficients<br>Power Spectrum<br>MFCC<br>Fundamental Frequency<br>Power Bandwidth |

acquisition, a feature's dictionary, a matrix of free parameter combinations and the considered overlap percentage. For each ACC axis, this function goes through each window of the signal, with the considered window length and overlap percentage and computes a feature matrix with $n$-samples by $m$-features dimension. For each signal, three new files were created: one with the features information per window, one with the names of the features that were extracted for the respective clustering test and another with the label of the activity corresponding to each window. The sensor acceleration signal is made up of three separated accelerometer data time series and complementary to the three axes data, an additional time series have been obtained by computing the magnitude of the acceleration, so four signal vectors are considered. From each window, a vector of features is obtained by calculating features from the statistical, time and frequency domain. This way, a $180^{th}$ - dimensional feature vector is obtained: from each one of the four signal vectors, we compute fifteen features with only one output and three features (histogram, cepstral coefficients and mel-frequency cepstral coefficients (MFCC)) with ten outputs each.

Because the scale factors and units of the features described above are different, all the features must be normalized to zero mean and unit variance, before proceed to the feature selection stage.

## 4.4 Feature Selection for Motion Data

A large number of features can usually be measured in many pattern recognition applications. However, not all features are equally important for a specific task. For each signal, different combinations of features, free parameters of these features and window size of the signal can be tested, in order to evaluate the performance of the implemented clustering algorithm. Optimal features are identified depending on the resulting clustering accuracies for each feature subset.

### 4.4.1 Free Parameters of Features Set

In order to make the implemented code versatile and the least subjective as possible, a matrix with the values of all the possible combinations that these parameters can take, was created. No window size value was stipulated, but a combination of different values from a growing logarithmic scale can be tested. According to Table 2, tests were made in which the window size ranged from 1000 to 4000 samples, in a log scale. For each window size, different performances were obtained. Tests were made to determine the free parameters in each activity, that allow a better activity recognition performance. Examples of free parameters are the number of bins or the range of the implemented histogram. The values given to these parameters will dictate the performance obtained by the clustering algorithm. In this way, a 486-dimensional free parameter combinations vector was obtained.

Table 2: Possible combinations of free parameters and window size values.

| Free Parameter | Range | Combinations |
|---|---|---|
| Window Size | [1000 ; 4000] | 3 |
| Bins of Histogram | [10 ; 20] | 3 |
| Range of Histogram | [1 ; 3] | 2 |
| Cepstral C. | [1 ; 11] | 3 |
| MFCC | [10 ; 20] | 3 |
| Power Bandwidth | [10 ; 20] | 3 |

### 4.4.2 Graphical Perception of Features Visualizations

A technique for the visualization of time series data and evaluate their effect in value comparison tasks was described in (Heer et al., 2009). In order to visually analyse each feature's behaviour throughout different activities, horizon graphs are used. This procedure ensures a visual perception of the features that better separate certain activities, those which do not change their value between activities and those which only add redundant information. Figure 2 shows an example of a horizon graph generated for a matrix of features, resulting from an ACC signal composed by seven distinct activities. Each activity lasts about one minute and we consider 4000 samples for the window size of the signal. It is possible to quantitatively compare the behaviour of each feature in each activity. First, the area between data curve and zero y-axis is filled in so that dark reds are very negative and dark blues are very positive. Then, negative values are flipped and coloured red, cutting the chart height by half. Finally, the chart is divided into bands and overlaid, again halving the height.

### 4.5 Unsupervised Learning

Machine learning algorithms based on the feature representation of accelerometer data have become the most widely used approaches in PA prediction (I. H. Witten, E. Frank and Hall, 2011). In this work, unsupervised learning is used to distinguish different activities. Clustering mechanisms separate and organize unlabeled data into different groups whose members are similar to each other in some metric. This method receives the number of clusters to form as well as the number of centroids to generate. In the presented study, the number of clusters was defined, a priori, a priori, from the designed protocol of the performed activities. A good clustering methodology will produce clusters in which the intra-class similarity is high and the inter-class similarity is low. The K-Means Clustering Algorithm (Lloyd, 1982) gives a single set of clusters, with no particular organization or structure within them.

## 5 DATA ACQUISITION AND RESULTS

The experiments have been carried out with a group of 8 volunteers within an age range of 16-44 years. The test consists in performing of a gym circuit. Each person performs seven activities in sequence lasting about one minute each - standing, sitting, walking, running, lying down (belly up), lying down (right side down) and lying down (left side down), wearing an accelerometer on the waist. Using this system, data with 3-axial acceleration at a constant rate of 800 Hz and 12 bits of resolution was acquired. The data acquisition was performed with OpenSignals platform (Gomes et al., 2012) and saved in a h5 format. The collected data was processed offline using Python Programming Language (Oliphant, 2006). Clustering tests are performed, individually, for each subject and with the respectively concatenated data: in a subject-dependent and a subject-independent context. To evaluate the subject-dependent accuracy of the proposed algorithm, the K-Means Clustering Algorithm (Lloyd, 1982) was performed for each subject data. Given the knowledge of the ground truth class assignments (labels true) and the clustering algorithm assignments of the same samples (predicted labels), the adjusted Rand index (ARI) is a function that measures the similarity of the two assignments, ignoring permutations and with chance normalization. The ARI was calculated to obtain the performance of the clustering method. An average person-dependent accuracy of 99.29% and standard deviation of 0.5% were obtained, with a window size of 4000 samples and the best set of features: mean, autocorrelation, root mean square and MFCC. High accuracies are reached for all subjects. The subject-independent performance was also evaluated with K-Means Clustering Algorithm (Lloyd, 1982). A person-independent accuracy of 88.57% and standard deviation of 4.0% were obtained, with a window size of 4000 samples and the best set of features: mean, autocorrelation, root mean square and MFCC.

Table 3: Clustering Performance (mean value) as a function of different window length extracted from the best set of features.

| **Window Size** | **Adjusted Rand Index (%)** |
|---|---|
| 1000 samples | 89.73% ±0.4% |
| 2000 samples | 97.42% ±0.9% |
| 4000 samples | 99.29% ±0.5% |

Table 3 shows the obtained performance for each value of window size, considering the best implemented set of features: mean, autocorrelation, root mean square and MFCC. An average of the performances obtained for the 8 subjects was calculated. Based on these results, the HAR system reaches an accuracy between 89.73% ±0.4% and 99.29% ±0.5%, with 1000 and 4000 samples, respectively.

### 5.1 Classification-based Evaluation: Proposed Metric

A new metric for assessing the obtained results from unsupervised techniques, a classification-based evaluation metric, was developed. Initially, a confusion matrix that contains information about true and predicted labels done by a clustering method was constructed. Once the clustering algorithm randomly associates the clustering results to non-annotated groups, the **Algorithm**, *Best Cluster Permutation*, that links these groups to their corresponded activity, was implemented. The presented **Algorithm** receives the confusion matrix with a random assignment and goes through each row of the matrix and stores the

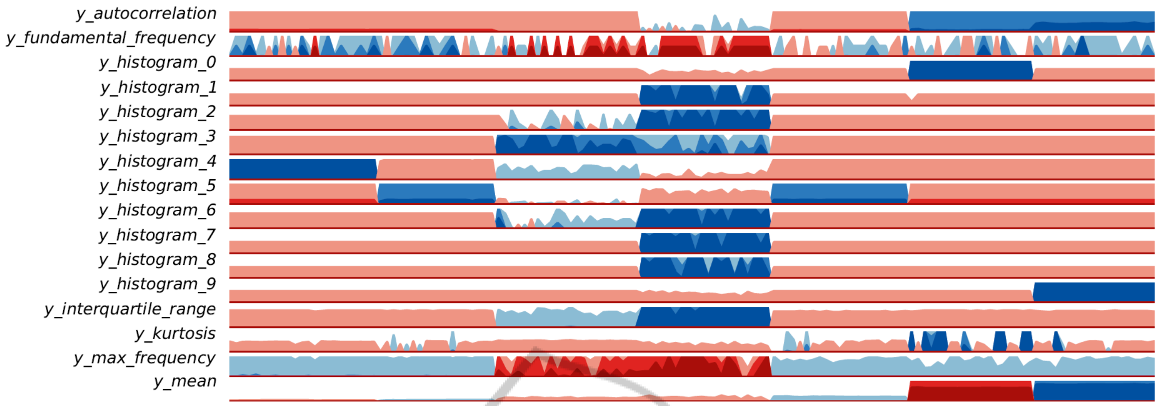


Figure 2: Horizon Graph - Time Series Visualization Technique.

index that contains the maximum value of each row.

**Algorithm**: `Best Cluster Permutation.`
`Input: Input: confusion matrix with a random assignment.`
`Output: confusion matrix correctly assigned.`

It is checked whether the index is unique throughout the matrix. If the index is unique, it makes the direct correspondence between the vector of true and predicted labels. Otherwise, it checks the index with the maximum value, and assigns it. The process is recursively repeated. After obtaining the swap vector, the matrix with the labels already associated is reconstructed. Table 4 shows the confusion matrix for this study where label $i$, with $i = \{1, 2, ..., 7\}$, corresponds respectively to: standing, sitting, walking, running, lying down (belly up), lying down (right side down) and lying down (left side down). For the concatenated data, the algorithm successfully distinguish all activities.

## 6 CONCLUSIONS AND FUTURE WORK

The continuously need to obtain more information, more efficient, more quickly and with less intervention from an expert has led to a growing application of signal processing techniques to motion data. During the experiment, acceleration signals were collected from a waist mounted accelerometer based framework. In the presented study, a methodology to search for the best features able to classify different physical activities was presented. The techniques that operate on the statistical, time and frequency domains, as well as on data representations that can be used to discriminate between user activities such as Horizon Plot were described. The obtained results in clustering accuracy of HAR were very encouraging: an average person-dependent ARI (Santos and Embrechts, 2009) of 99.29% and a person-independent ARI of 88.57% were reached. The major achievements of the current work, compared to the state of the art are: the presented study performs tests in intra and inter subject context; a set of 180 features was implemented, which are easily selected to test different groups of subjects and different activities and the implemented algorithm does not stipulate, a priori, any value for window length of the signal or overlap percentage, but performs a search to find the best parameters that define the specific data. A clustering metric based on the construction of the data confusion matrix was also proposed. The presented research leaves a few opened questions, to be explored in the future:

- **Bigger Timespan.** Week Long Acquisitions of Movement.
- **More Data.** Increase the Number of Subjects and Applications.
- **More Computing Power.** Use Parallel Computing Infrastructures on the Data Collected.
- **More Discoveries.** Detect the Behaviour changes and annotate those changes.

In the future, this framework should be tested on other intensity varying activities and across more subjects. For example, test it on individuals running and walking at a greater range of intensity levels. ACC data obtained from wearable accelerometers can be synchronized with the activity of daily living data recorded by such monitoring systems to better describe the information of human mobility, behavioural pattern and functional ability that encompass the important parameters regarding the overall health status of an individual.

Table 4: Confusion Matrix, in percentage, for concatenated data, where Lying Down$^{(1)}$ is lying down (belly up), Lying Down$^{(2)}$ is lying down (right side down) and Lying Down$^{(3)}$ is lying down (left side down).

| | **Standing** | **Sitting** | **Walking** | **Running** | **Lying Down$^{(1)}$** | **Lying Down$^{(2)}$** | **Lying Down$^{(3)}$** |
|---|---|---|---|---|---|---|---|
| **Standing** | **92.1±3.2** | 0.0±0.0 | 0.0±0.0 | 0.0±0.0 | 5.4± 2.3 | 1.3±0.9 | 1.1±0.8 |
| **Sitting** | 28.3±6.9 | **68.0±5.9** | 1.1±0.6 | 0.3±0.7 | 0.1± 0.3 | 1.6±0.7 | 0.6±1.3 |
| **Walking** | 0.0±0.0 | 0.4±0.5 | **99.5±0.5** | 0.1±0.3 | 0.0±0.0 | 0.0±0.0 | 0.0±0.0 |
| **Running** | 0.0±0.0 | 0.0±0.0 | 0.3±0.4 | **99.4±0.7** | 0.3±0.4 | 0.1±0.3 | 0.0±0.0 |
| **Lying Down$^{(1)}$** | 0.9±0.6 | 2.0±1.1 | 0.1±0.3 | 0.0±0.0 | **82.1±1.9** | 7.5±1.4 | 7.4±1.3 |
| **Lying Down$^{(2)}$** | 0.0±0.0 | 0.0±0.0 | 0.1±0.3 | 0.5±1.0 | 1.1±0.0 | **90.4±0.9** | 8.0±1.3 |
| **Lying Down$^{(3)}$** | 0.0±0.0 | 0.0±0.0 | 0.0±0.0 | 0.0±0.0 | 0.1±0.3 | 0.4±0.5 | **99.5±0.5** |

The main challenge for future work in this area will be the development of features and recognition strategies that can work in an ambient assisted living under a wide variety of environmental conditions.

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