HARDroid: Human Activity Recognition using a collaborative approach

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# ABSTRACT

Human Activity Recognition (HAR) is a research topic broadly covered in the last decade for its relevance in areas where the users’ context is important to build interactive applications. Smartphone applications have the capability to collect data from the environment and along with algorithms that take advantage of context-aware information becomes a powerful development platform. In this paper, we propose a HAR System denominated HARDroid that is specifically designed to detect common user activities. Furthermore, data collected from users on ground are taken into account to improve the activity recognition classifier. HARDroid is freely available as a library that may be included in Android applications. Finally, an evaluation that comparing the initial classifier with an improved classifier is presented, achieving a recall of 91% and a precision of 92%.

## Author Keywords

## Location-Aware/Contextual Computing; Collaboration; Mobile Devices: Phones/Tablets; Quantitative Methods; Prototyping/Implementation; Machine Learning; Sensors Wearable Computers; Contextual Inquiry; Survey; Artifact or SystemDataset.

## ACM Classification Keywords

H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous; See<http://acm.org/about/class/1998>for the full list of ACM classifiers. This section is required.

# INTRODUCTION

Human Activity Recognition (HAR) is a research topic in constant development for more than a decade and that covers the design of algorithms that collect data from people interacting with their environment to provide contextual information [1]. The common example of using these algorithms is to recognize basic ambulatory activities, which are, when an individual is walking, running, standing or sitting, all through some type of sensor or camera available for that purpose.

As smart mobile phones began to become more widespread, HAR-based applications have been propitious to be developed in order to determine user interactivity and interact with them. This allows the use of contextual information available for various purposes such as data mining and predicting activities for various types of intelligent applications in different fields, for example in medicine, security, entertainment or military use, etc. [2].

The usual sensors in a smartphone are varied and may include a GPS (for location), microphones, cameras, luxometer, thermometer, barometer, compass and accelerometer. There are also other sensors more varied depending on the model, manufacturer or accessories that can be paired with the device. The accelerometer is the most common sensor in these devices and can measure the movement in two or three axes as well as detect the orientation of the device. The main use of provided sensors information is the recognition of human activities.

Along with the above, there has also been a breakthrough in the state of the art for the human activities recognition with sensors. This includes recognition techniques, methods of data capture and signal processing, and the application of artificial intelligence techniques such as Machine Learning [3, 4].

On the other hand, despite the large amount of software and applications that have been developed in the field of human activities recognition, there is still a lack of a software HAR component that can be extensible and be available for free use or for its improvement. That is, without relying on private Application Programming Interfaces (APIs), Software as a Service (SaaS) platforms, or third-party applications of free use but of closed definition, such as Google Play Services and Apple Health Kit, among others.

This proposal contemplates the study of the human activity recognition techniques on smartphones with focus in provide a HAR system in the form of a library that is free to use or to improve. Moreover, interactive user participations are taken into account to do a collaborative improve of the recognition classifier. The generated components are validated through experimental tests and the collected data shows the effectiveness of the resultant library.

# STRUCTURE OF HAR SYSTEMS

As in other automated learning applications, the recognition process is divided into two well-known stages, training and testing (or evaluation).

The figure 1 shows the common phases of these two stages [2]. The training stage initially requires a set of data collected in a time series with the attributes measured from individuals performing each activity. The series are divided into time windows to apply sample extraction thereby filtering the relevant information from the raw signals.

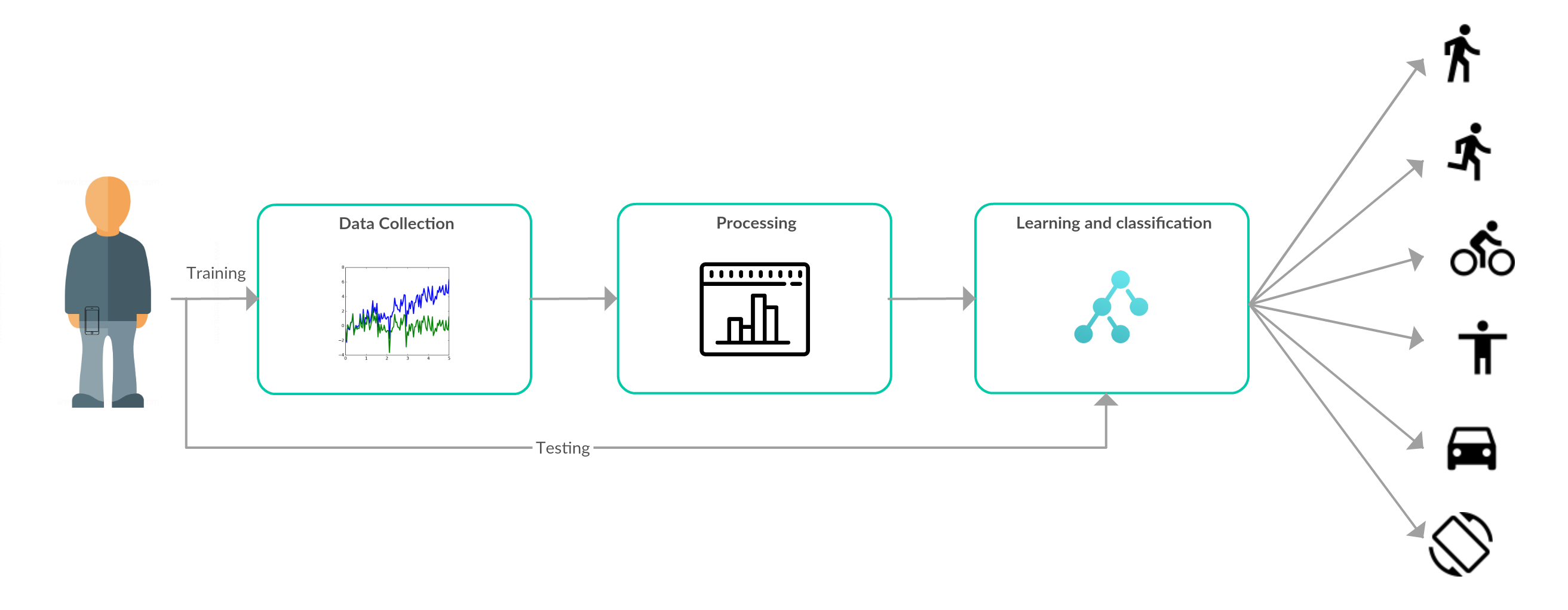


Figure . General structure of human activity recognition.

Later, learning methods are used to generate an activity recognition model from the data set collected through the calculated characteristics. Similarly, for the test or evaluation stage, data are collected during a time window, which is used to extract the same characteristics used in the model; these are evaluated in the previously trained learning model, generating a label of the predicted activity.

## Data collection

The definition of the data collection method is an important point in a HAR system, since an incorrect collection can add noise to the data causing models with bad precision.

The first step in the recognition process is to collect of signals obtained from sensors that continuously are sensing users; these are attached to the body; on the waist, wrist, breastplate, thighs or on the head. Also, the sensors could be carried by the user since they are commonly embedded in devices like modern mobile phones, in watches or smart lenses.

The recording method consists of capturing the signals from a sensor and separating the measurements into one or more variables depending on the type of sensor. The organization of the records is done with respect to time. The timestamp is usually measured milliseconds and depending of the sensor the interval between measurements can vary in the same order, for example an output rate of 60 Hz have 60 measurements in a second.

The sensor signals can be classified according to movement, position, environment and physiological:

### Motion Signals

Motion sensors provide highly informative signals for HAR system because they measure the acceleration and rotation forces on three axes when carried by their users. In this category of sensors are accelerometers and gyroscopes.

### Position Signals

Position sensors provide signals with additional information that can be used to HAR system and context applications with location-based services. In this category are orientation sensors (or compass), magnetometers and GPS.

### Environmental Signals

These sensors alone, though, might not provide sufficient information as individuals can perform each activity under diverse contextual conditions in terms of weather, audio loudness, or illumination. Therefore, environmental sensors are generally accompanied by accelerometers and other sensors.

### Physiological Signals

Physiological sensors provide signals of vital signs of an individual. Information on heart rate, respiration rate and body temperature could be combined to enrich the context during recognition in certain specific applications such as health-oriented.

## Processing

The next step in the recognition activities is the processing of the signals obtained by the sensors and extract relevant characteristics of the raw data. The recognition model is constructed from a sample assembly and compared using machine learning methods in the training scenario.

Sample processing relies on three distinct tasks that are performed automatically in both stages of the HAR process, in addition a manual task is performed during the training stage called labeling and then each task is detailed.

### Labeled

The automatic learning process requires a moderate amount of data collected from users while performing human activities at our study. These data should be collected and labeled using an application designed for the case, for example, in this work is used an Android phone and the application *SensorLog*.

The collection protocol consists of enlisting a group of people who carry a Smartphone while performing a specific set of activities and recording data through the application. The activities of interest described in Table 1 should be carried out by carrying the phone in the pocket where each individual takes a walk, run, bike or drive a vehicle for a period of 10 to 15 minutes.

| Activities | **Label** |
| --- | --- |
| ic_activity_walk.png | WALKING |
| ic_activity_run.png | RUNNING |
| ic_activity_still.png | STILL |
| ic_activity_tilt.png | TILTING |
| ic_activity_bike.png | ON\_BICYCLE |
| ic_activity_car.png | ON\_VEHICLE |

Table . Activities.

### Signal Filter

The electronic sensors can introduce some instability in the signal (known as jitter) causing a result in the readings due to errors in the measurement affecting the quality of the data. Therefore, even though a motion sensor device is completely stationary, the readings could record noise in the data, for example errors of the order of ±0.005.

Then, to reduce signal noise, one or more filters must be applied. The filter allows smoothing the signal by means of a simple function such as the moving average that is used in this work. There are also other methods such as Butterworth [5].

### Sampling

Human activities are performed for long periods of time, in the order of seconds or minutes. A simple measurement captured in an instant does not provide enough information to describe what activity a person is doing. Therefore, human activities must be recognized from samples drawn in time windows ***w*** rather than using a single instantaneous measure in ***t***.

Time windows cause signals to be segmented into discrete samples used as activity recognition units. To increase the number of samples, a 50% overlap with consecutive windows with a size of 2.56 seconds is used, as recommended by other HAR works such as [1,5]. Overlap prevents certain events from being lost and activities are truncated.

### Feature Extraction

The extraction process consists in extracting characteristic values ​​in each window by means of the relevant information display and the calculation of values ​​that identify in a certain way the signals. This translates into characteristic vectors (feature vectors) with relevant information that compose several metrics calculated based on windows in the time domain. Later also, the windows are transformed into the frequency domain with discrete Fourier methods using FFT algorithms with real numbers.

The statistical metrics with respect to time and frequency used in this work are shown in Table 2. [5]:

| Function | **Methods** |
| --- | --- |
| mean(s) | Mean |
| std(s) | Standard deviation |
| max(s) | Largest values |
| min(s) | Smallest value |
| skewness(s) | Frequency signal Skewness |
| kurtosis(s) | Frequency signal Kurtosis |
| energy(s) | Average sum of the squares |
| entropy(s) | Signal Entropy |
| irq(s) | Interquartile range |
| autoregression(s) | 4th order Burg  Autoregression coefficients |
| meanFreq(s) | Frequency signal weighted  average |

Table 2. Summary of feature extraction method for acceleration signals.

The processed signals of the set ***S*** correspond to the acceleration attribute.

In order to minimize such effects caused by orientation changes, is calculated the magnitude of a sensor, from de dimensions ***x***, ***y***, ***z***. This choice was motivated about orientation-independence in activity recognition, because the magnitude feature is less sensitive to orientation changes.

## Learning and classification

A HAR system is similar to any automatic learning application (Machine Learning, ML) where an algorithm is required to extract information from the data. The main purpose of the algorithm is to classify the unknown data.

The primary requirement for the learning task is to choose the appropriate algorithm for classification. There are many classification algorithms, such as Decision Trees, SVM, Bayes Classifiers, Markov Models, Neural Networks and others. This work classifies unknown instances by a model built with C4.5 algorithm based on the decision tree approach whose implementation is based on Java implementation J48.

One of the primary topics of ML algorithms is the way in which data are processed by classifying unknown data and used to construct an effective recognition model. In dealing with the data, it is a good strategy to divide the available input instances into a training set and a remnant known as a test set. The validation set allows evaluating the classifier by determining if the results are over-adjusted and with how accurate the model is.

# HARDROID

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# EVALUATION OF HAR SYSTEMS

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# Conclusion

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