ABSTRACT

This paper presents the main features and architecture of MHARS (Mobile Human Activity Recognition System), a pervasive system for monitoring the daily movement activities of patients in the context of Ambient Assisted Living. MHARS is based on smartphones, and allows data gathering from the different sensors usually available on this class of devices, as well as from external sensors, either the ones comprising a body sensor network as well as from ambient deployed sensors. MHARS uses accelerometer data for inferring the patient performed activity and her/his heart rate for computing its intensity. It also allows to correlate the inferred data with other context data (such as altitude, body and environment temperature, etc) for detecting user defined situations related with the patient current health status and provides a decision making engine for defining an action plan (set of actions) that must be executed whenever relevant health situations are detected. This paper emphasizes the MHARS service responsible for inferring the patient movement activity. We present a comprehensive set of experiments used for building the movement activity classifier and the evaluation of its performance.

1. INTRODUCTION

In health care, the term Ambient Assisted Living (AAL) has been used to designate a multidisciplinary research field, whose major efforts focus on developing intelligent systems for monitoring the daily activities of patients living or transiting in smart environments, such as smart homes [1]. AAL systems allow physicians, caregivers and family members to monitor a patient health status at distance, providing to her/him more autonomy and mobility during treatment. In this way, AAL systems promotes a transition from the traditional model of health care organizations to a patient-centered model, in which predominate individual monitoring services at home or even in other mobile scenarios, such as taking a walk in a city park or even traveling.

One of the most important components of an AAL system is the HAR (Human Activity Recognition), whose task is to recognize patterns of human movement activity (e.g. walking, running, sitting) from various types of low-level sensor data. Among the variety of sensors that can be applied in AAL systems, there are the wearable medical sensors, able to collect data from physiological signals (e.g. ECG, EMG, heart rate, oxygen consumption) or data reflecting the body movement (e.g. acceleration). Personal mobile devices, such as smartphones, are also usually equipped with motion and location sensors (e.g. accelerometer, GPS) that are also usually applied in AAL systems, among with environmental sensors, as they collect information that help determine if environmental conditions (temperature, luminosity, humidity, carbon dioxide levels) favor or not the patient’s health. The hit rate of the movement activity recognition and its respective intensity measurement varies according to several
Movement activity recognition is desirable in several types of treatment of chronic diseases, especially for heart (e.g. hypertension, heart failure, atrial fibrillation) and respiratory (e.g. chronic bronchitis, emphysema, asthma) problems. It allows to find out if the patient is doing the physical activity routine recommended by health professionals. For example, it is possible to infer whether the patient does walks or jogging frequently or if he/she has a more sedentary living style. In some situations it is important to check how the patient is responding to the performed physical activities, and detect whether the level of effort of doing them is compatible with the patient’s current physical capacity, imposed by her/his chronic condition, age, weight and other factors. This is called intensity measurement or measurement of body stress. If the values measured are not following the recommended intensity patterns, the activity detection system must decide the actions to be taken, such as to issue a warning to the health professional taking care of the patient, or ask the patient to increase or decrease the intensity of the physical activity being performed in order to better suit the activities’ defined limits.

Because of its recognized importance, monitoring the physical activity of patients and identifying its intensity using mobile devices is an active research area [3]. Movement activity Recognition can also be applied in several other domains, such as safety and sports.

A common approach used for classifying activities based on sensor data that can be related to the body movement is based on the use of machine learning algorithms. The choice of which technique is better suited for a given application may depend on the set of activities to be inferred, the available computational resources for running the algorithm and the size of the base training sets. A key problem addressed in this paper is whether the process of inferring the user movement activity should be carried out at a cloud/server infrastructure or solely at a mobile device, such as a smartphone. Arguments in favor of the first option include the little utilization of the mobile device’s resources and the ability to execute sophisticated algorithms that require much computing power. On the other hand, performing the activity detection at a cloud/server requires the transfer of the raw sensor data to the server or cloud, leading to higher bandwidth consumption and imposing a delay as a result of the network latency. In addition, the dependence of accessing an infrastructure imposes the need for continuous connectivity, which can limit the user mobility since a network coverage with the required quality may not be available in all the places he/she visits. In this paper we present a system that performs the activity recognition entirely at the mobile device. However, systems that execute computing-intensive algorithms on the mobile devices must be carefully designed and implemented so as to save as much as possible its computing resources.

In this context, this paper presents MHARS (Mobile Human Activity Recognition System), an activity recognition system, designed for running on mobile personal devices. This system was developed by the Distributed Systems Laboratory (LSD) at the Federal University of Maranhão (UFMA) in collaboration with the UFMA University Hospital (HU-UFMA) in order to support the monitoring of patients with chronic diseases. MHARS allows data gathering from sensors usually available on mobile personal devices (such as smartphones), as well as from external sensors, including both wearable health sensors and ambient sensors, i.e. sensors collecting data from the patient’s environment. MHARS uses accelerometer data for inferring the patient’s performed activity and her/his heart rate for computing its intensity. It allows to correlate the inferred activity and intensity with other context data (such as altitude, body and environment temperature, etc) for detecting user defined situations somehow related with the patient’s current health status. It also provides a decision making engine for defining an action plan (set of actions) that must be executed whenever relevant health situations are detected. This paper emphasizes the MHARS service responsible for inferring the patient movement activity, called HURS (Human Activity Recognition Service). We present a comprehensive set of experiments used for building the classifier used by HURS and the evaluation of its performance.

This paper is organized as follows: Section 2 describes main features and architecture of MHARS. Section 3 presents the methodology and experimental results used for building HURS classifier and performing its evaluation. Section 4 describes relevant related work and compares them with the system presented in this paper. Finally, in Section 5 we give our conclusions remarks and present the future directions of this research.

2. MHARS
MHARS (Mobile Human Activity Recognition System) is an AAL system that runs on mobile personal devices, performs the recognition of the user daily movement activity patterns, and measures the intensity with which these activities are conducted. It is currently able to recognize the following movement activities: walking, running, jumping, standing, lying down, walking up and down stairs. The activity intensity is related to the physiological effects (e.g. fatigue, stress, muscle fatigue, lactic acid) of the activity being performed, considering the health condition and the physical limits of each patient. The intensity is usually mapped to a scale comprising a set of ranges called intensity zones[4].

The following requirements were established for the system development: 1) Support for sensors heterogeneity: it should be able to interact with different types of sensors (wearable, portable or embedded in smart environments), making it possible to obtain different types of information about the patient (e.g. physiological, body movement and location), as well as sensing the environment in which he/she is in (e.g. light, temperature, air quality); 2) Activity Recognition: it should be able to group, process and classify the obtained sensor data automatically and in real time; 3) Intensity Measurement: it should be able to gauge the intensity of the user performed movement activities; 4) Situation Inference: it should be able to infer the situation in which the patient is in (e.g. running with moderate intensity at an altitude of 1800 meters at 15.00 having atrial fibrillation), through the specification of rules that allow the system to infer different situations based on the combination of sen-
sensor data, the activity being executed and its corresponded intensity, taking also into account the specific treatment being followed by the user. 5) Decision Making: it should be able to execute a set of user defined actions for dealing with the inferred situation of the patient in order to try to improve or maintain the user health condition.

MAHRS implementation is based on the Android platform. Figure 1 illustrates MAHRS architecture, showing the main components that are responsible for achieving the established requirements, as described below.

**Figure 1: MAHRS Main Components**

SDAS (Sensor Data Acquisition Service) is the component responsible for sensor data acquisition. If the sensor to be used is embedded in the mobile device (i.e., is an internal sensor), data acquisition is implemented through the Android sensor API. Only the required sensors are initialized, if available. For data acquisition from external sensors (body sensor network or environmental sensors), MAHRS uses short range wireless communication technologies, such as Bluetooth, NFC, WiFi Direct, or ANT+. The current MAHRS prototype supports only Bluetooth Classic and BLE. This service is responsible for the following actions: 1) discovery of, and connection to sensors, 2) discovery of the services provided by each sensor, 3) read and write of service attributes (e.g., sensor values, and actuator commands) and 4) notifications about sensors disconnection.

HURS (Human Activity Recognition Service) is the component responsible for carrying out the recognition of the activity being performed by the user. For this, HURS receives the data collected by SDAS and executes a pre-processing step that carries out conversion, filtering and refinement of the raw sensor signal required for transforming it to the input format requested by the classifier. The signals obtained from the accelerometer are pre-processed to extract a reduced set of numeric values that represent certain characteristics related to acceleration (e.g., standard deviation, highest/lowest value of the acceleration, signal entropy, signal energy). We adopted widely used pre-processing techniques [5],[6] that require low processing power and, therefore, are more suitable for being executed on mobile devices.

Classification is performed by machine learning techniques in order to recognize the actual activity patterns based on the values previously processed. There must be a prior training phase for the service to work. This training is based on data sets that contain labeled activities. The classification step may use various machine learning algorithms. Most of them are already provided by the WEKA library [7], which is specific for pattern recognition problems. HURS incorporates this library.

IMS (Intensity Measurement Service) is the component responsible for measuring the intensity of the user movement activity, inferred by HURS. In general, the computation of the activity intensity can take into consideration several parameters, including the ECG, heart rate and the volume of oxygen consumed. The choice of which is the best parameter varies with the monitoring requirements, such as the pretended monitoring environment and the availability, degree of intrusiveness and portability of the sensors that will be used. The dominant methodology found in the literature for measuring the movement activity intensity is based on a periodic analysis of the patient heart rate [8]. The closer one is of her/his maximum heart rate, the greater the activity intensity will be. IMS adopts this methodology.

SAS (Situation-Aware Service) is the component responsible for inferring different situations experienced by the patient during the course of an activity. In general, every situation is characterized by the correlation of the following data: ongoing activity, its intensity, the patient chronic condition and physical limits, and other context data gathered from internal or external sensors (e.g., temperature, location, altitude, humidity). The SAS has an intrinsic relationship with the DMS (Decision Making Service), the component responsible for the definition and execution of the actions necessary to react to the inferred situation. Situations, decisions to be made and actions to be performed are computationally represented through the use of Event-Condition-Action (ECA) rules. For example, for a patient with a chronic cardiovascular disease it is possible to characterize a hazardous situation when she/he runs over a long period of time with an intensity level not compatible with the medical recommendations. In this situation, examples of actions to be triggered can be to warn the patient about the risk of continuing with the activity and/or inform the physician in charge via SMS, so she/he will be aware of the patient’s situation.

NCS (Network Connection Service) is the component responsible for establishing connections through 3G/4G or WiFi networks, allowing customers to send data to a remote server as soon as there is an available connectivity. In the case of a network disconnection, the data is locally stored in a database for future forwarding. The remote server maintains a database related to the patient that stores all detected activities and their intensities, which are enhanced with context meta-data such as their timestamp and the user geographic location when the detection was made. This database is also used to store other higher-level information, such as the history of experienced situations and the records of the decisions and actions taken for reacting to the identified situations. The database can be accessed remotely by physicians, caregivers and family members in a controlled environment.

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manner (considering the user privacy requirements) through a Web system.

3. EVALUATION OF HURS

3.1 Materials and Methods

For evaluating HURS, a core component of MHARS, we adopted a methodology based on case studies. It consisted of experiments involving the monitoring of volunteers during the following movement activities: walking up stairs, walking down stairs, normal walking, running, sitting, standing and lying. The definition of the activities was done in conjunction with health-care professionals of HUUFMA. The main objective of the evaluation is to analyze the accuracy, i.e. the system’s ability to correctly recognize different activities using the data from acceleration sensors attached to different parts of the body: waist, chest, and on the right pocket of the user, what we will refer to from now on just as “leg”.

More specifically, we are interested in three evaluation aspects: i) to assess the relative performance of machine learning algorithms when applied to the recognition of human movement activities, in order to make an informed decision regarding the best algorithms for building the HURS classifier; ii) to identify the most appropriate position to place the accelerometer on the user’s body; iii) to estimate the accuracy of the correct recognition of each activity.

In the experiments, we used a Motorola Moto G II Smartphone\textsuperscript{2} with Android OS 4.4.2 KitKat and a Zephyr BioHarness 3 wearable device\textsuperscript{3}.

For the recognition of the movement activities, two accelerometers were used: one internal to the smartphone, and the other embedded in the wearable device. The smartphone was carried in two different positions on the user’s body (leg and waist). Regarding the wearable device, it is designed to be used only in the chest. With this, it is possible to analyze the variation of accuracy for different positions of the accelerometer. Both sensors were configured to operate at a frequency of 50Hz. In the literature this value is commonly used and it is considered suitable for the detection of stationary activities (e.g., standing and lying) and mobile activities (e.g. running, walking, climbing stairs and down stairs) \cite{9}. Furthermore, the frequency of 50Hz is considered acceptable with regard to the battery consumption of mobile devices.

Data was collected by monitoring 10 volunteers while performing an activity protocol in the following order: lying down, sitting, standing up, walking, climbing stairs, walking down stairs, and running, each activity for a maximum of five minutes. The volunteers were 19 to 51 years and had no physical disabilities able to hinder their locomotion. The acceleration data (acceleration values in the X, Y and Z axis) collected from the sensors placed in three distinct positions: waist, leg and chest. The sampling rate was 2.58 seconds. This means that at a frequency of 50 Hz, a total of 128 samples of acceleration data were collected to form an instance of the corresponding activity. This time window and respective number of samples are considered sufficient for the detection of activities that are performed repeatedly \cite{9}. For example, it is known that a person walking performs between 90 and 130 steps per minute, corresponding respectively to 1.5 and 2.7 steps per second. Thus, the 2.58 seconds time window is large enough to characterize a walking activity.

At the end of collection, the activity instances were labeled and split into three datasets, one dataset for each accelerometer position (waist, leg and chest). Each dataset has approximately 3,000 labeled instances comprising the seven aforementioned activities. These datasets were used for training and testing of the machine learning classifiers.

For the training and test of classifiers, it was adopted the following strategy: of all samples collected, 70\% were allocated to training, and the 30\% remaining were separated for estimating the accuracy of the obtained classifier. This is a common practice that leads to good empirical estimate of the accuracy independent of training data \cite{7}. In the training process, we used the Cross Validation technique with 10-folds \cite{10}. Before training and test, a pre-processing step is done. The raw (X,Y,Z) acceleration data of each instance is summarized in seven representative values: the mean value and standard deviation of the acceleration in the axis X, Y and Z, and the square root of the average obtained from the mean acceleration values in all the axis. This approach is widely adopted for Activity Detection via sensors and does not require much computational resources, which is extremely important when using mobile devices \cite{5}, \cite{6}. Other pre-processing methods could be adopted, but in general they require higher consumption of computing resources, making them less suitable for the recognition of movement activities through personal mobile devices that have limited processing capability and memory \cite{6}.

Regarding machine learning algorithms, we have conducted experiments with three decision tree algorithms (J48, RepTree, Random Forest and Random Tree), one neural network algorithm (Multilayer Perceptron), one instance-based algorithm (IBK), and one rule induction algorithm (JRIP). These seven algorithms were chosen because of their knowledge relevance to the recognition of human activities \cite{2}, \cite{11}.

Given the machine learning algorithms, a major challenge in obtaining good classifiers is to find an appropriate set of (hyper)parameter values. In general, the algorithms need to be configured with specific values (such as the number of instances per node, learning rate, or number of epochs). These values are called (hyper)parameters and directly affect the training and overall quality of the classifiers produced by the learning algorithms.

In order to find appropriate values for (hyper)parameters, the AutoWeKA tool was used. AutoWeka is a tool designed to search for the best set of (hyper)parameters values for a given learning algorithm when used to train classifiers from a given labeled dataset \cite{12}. AutoWEKA has a sophisticated mechanism to seek the best parameters for machine learning algorithm without the need to test all possible parameters.
for each algorithm.

By means of AutoWEKA, the seven chosen learning algorithm were used to find appropriate (hyper)parameters with which to train good classifiers from the three pre-processed activity datasets. In each run, AutoWeka was configured to evaluate one of the seven learning algorithms over one of the three datasets. Each run took 8 hours and was performed on desktop machines with an Intel I7 processor, 8 GB of RAM, running the Ubuntu Linux version 14.04 LTS. This evaluation gave the accuracy of the best classifier produced and the (hyper)parameters used to infer this best classifier.

### 3.2 Results and Discussion

This section describes and discusses the results of the experiments. Figure 2 summarizes the results in terms of mean accuracy estimations for the best classifiers produced by AutoWEKA. The estimations were obtained by testing the best classifiers on the test datasets and taking the mean over all activities. Table 1 provides detailed results by stratifying mean accuracy for each activity.

![Figure 2: Average accuracy (for all activities) for each ML algorithm and accelerometer position](image)

Regarding the position of the accelerometers, it is possible to observe that mean accuracy is higher when the accelerometer is located at the waist and leg, rather than at the chest position (see Figure 2). These results can be attributed to the fact that, when positioned at the waist or leg, accelerometers are able to detect the user’s movement with higher precision, since parts of the body suffer larger impact while performing the activity.

As can be seen in Table 1, stationary activities (with low variation of acceleration) have higher accuracy values when compared to the mobile activities (with high variance in acceleration). Most of the activities have accuracy values higher than 80%, with the exception of walking up and down stairs, that obtained values slightly lower. These results are attributed to the fact that the recognition of dynamic activities require more robust pre-processing methods. Depending on the sensor, the data obtained for training the machine learning algorithm may not be the most representative for the activity performed, causing the algorithm to become misled with data from another activity. The calibration of sensors also tends to interfere with the collected data, affecting the accuracy of the final classifier.

With respect to the learning algorithms used, in Table 1 it can be seen that the IBK and Random Forest algorithms produced classifiers with higher accuracies for all the positions of the accelerometer. For example, regarding the walking activity, IBK obtained the best mean accuracy values; while Random Forest produced the best accuracy estimate for the standing activity. Considering the sensor position, IBK produced higher accuracy values for the recognition of activities when the accelerometer was at the chest; while the Random Forest algorithm, on the other hand, obtained better results when the accelerometer was in the leg.

To build the HURS classifier we applied the IBK algorithm, recommending the user to place the mobile device at his/her waist. As can be seen by analyzing the results obtained with this configuration, HURS can reach an accuracy close to 83%. This result is quite satisfactory, an analysis reinforced by data found in literature that reports that an activity recognition system with accuracy higher than 70% can be considered a satisfactory system for most of the activities and applications [2].

We have also run a set of experiments with the objective of analyzing MHARS resources consumption running on a middle range smartphone, the Motorola Moto G II with Android OS 4.4.2 KitKat. The objective of the performed tests was to evaluate the MHARS CPU, memory, and battery usage stratified by the following functionalities: gathering of sensor data; preprocessing; and activity inference. The results indicated an average value of less than 4.5% of CPU utilization and less than 30 MB of RAM, which represents only 3% of the RAM available on the device used in the experiments. The battery level of the mobile device declined 8% during a one hour period and, therefore, we can estimate that the system can be used for more than 12 hours without the need to recharge the device battery. The results can be considered satisfactory, since the system can be run on middle range smartphones without compromising the device performance for a long period. The full description of MHARS performance evaluation is available in [13].

### 4. Related Work

This section briefly describes relevant work related to the recognition of human movement activities. The comparison between them and the approach proposed in this paper was based on the following criteria: I) the set of used sensors; II) the set of activities that are recognized; III) which techniques were used in the inference model; IV) the accuracy
obtained for the measured activities; V) the set of features provided besides the activity recognition.

It is worth to mention that the comparison of the provided accuracy described in each work is only relative and should be interpreted with restrictions, since the set of the detected activities differs, as well as the methodology and the dataset used for computing the provided accuracy.

In [14], Yang presents a classification model for six activities which are: standing, running, walking, biking, driving and sitting, using the accelerometer data provided in a smartphone. Fifteen preprocessing techniques are applied and the SVN algorithm is used to perform the activity classification. The provided accuracy is 86% for the proposed activities. This work assumes that the accelerometer can be attached to various positions at the body of the person. The set of recognized activities is different from MHARS, as it includes biking and driving but, on the other hand, leaving up and down stairs and lying outside of its scope. While the accelerometer data is collected at the mobile device, the inference engine runs at a server. In our proposal, the inference is done locally, providing a faster response time and giving support for handling eventual network disconnections, which are typical for mobile and wireless environments. This related work does not provide the correlation of contextual data for the detection of user situations and the support for automatically reacting to potential harmful ones, as provided by MHARS.

Carvalho et al. [15] present a system for monitoring patients at their homes that recognizes the degree of intensity of activities (low, moderate or intense) based on the use of accelerometer data. The sensor is attached to the user’s wrist in the evaluation experiments. However, unlike the MHARS, this system does not perform the activity recognizing process on mobile devices, but on a server in the patient’s home. Therefore, this system does not support the monitoring of patient activity in mobility scenarios (e.g., walking on the street or in a park). No information about the system’s activity recognition accuracy is provided. This system also has the ability to make decisions according to the patient’s situation and also stores the patient’s data on a remote server for further analysis.

On [5], Kwapisz et al. propose a system for detecting six types of activities: walking, jogging, walking upstairs, downstairs, sitting and standing, using accelerometers available on mobile devices. This work uses the following preprocessing techniques: average, standard deviation, and time between peak binned distribution. The MLP algorithm is used to perform the activity classification. The presented hit rate was 91% for the proposed activities. This article assumes that the accelerometer sensor is placed in the person’s leg. The set of recognized activities is almost identical that of MHARS, except for lying. It also collect the accelerometer data and send it to a server, where the activity detection engine is executed. It only provides activity detection, while MHARS provides a much richer set of features, that include the detection of user defined situations and provides a decision making engine for defining an action plan (set of actions) that must be executed whenever relevant health situations are detected.

The description of these related work highlighted that MHARS main contributions are the fact that all the activity inference process is performed on the user’s mobile device, which provides a greater degree of user mobility and the support of eventual network disconnections. The fact that the inference is held locally lead to design decisions for ensuring low consumption of computing resources, such as the use of simple

### Table 1: Average accuracy for each ML algorithm and sensor position for each user activity

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Position</th>
<th>Running</th>
<th>Upst.</th>
<th>Downst.</th>
<th>Walking</th>
<th>Standing</th>
<th>Sitting</th>
<th>Lying</th>
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preprocessing techniques. Nevertheless, MAHRS accuracy is above 80%, which can be considered quite satisfactory. In addition, MHARS also performs the inference of the activity intensity level and provides a rich set of features.

5. CONCLUSION

This work is about MHARS, a mobile client-server AAL system for the monitoring of patients, which supports the recognition of human activities, performs measurement of their intensity through heart rate sensors, and checks the patient’s general health situation through body and ambient sensors. MHARS’ mobile client executes HURS, a service that employs Machine Learning algorithms to detect the patient’s physical activity using accelerometer sensors embedded in smartphones and chest-worn wearable devices.

After an overview of the MHARS client architecture and main components, we evaluated seven candidate Machine Learning algorithms for HURS. The algorithms were evaluated for seven different physical activities and three different places of the body where the sensors were carried. The results indicate that for sensors placed at the waist, the IBK algorithm achieves a mean average accuracy of 83.3%, which is quite satisfactory for the activity recognition task. Therefore, we decided to use IBK as MHARS’ activity recognition algorithm.

MHARS also stands out by not only providing a movement activity detection engine, but also by providing a much richer set of features, that include the detection of user defined situations and a decision making engine for defining an action plan (set of actions) that must be executed whenever relevant health situations are detected.

The accuracy of the activity recognition may be improved through the use of more accurate sensors, larger sets of activity instances used for training, employment of hybrid machine learning through combination of several ML algorithms, as well as other accelerometer data pre-processing techniques such as signal energy and signal entropy analyses, all of which we want to test. As future work, we also plan to test MHARS in a real-world use case, measure the accuracy of the combined activity, intensity and situation inference, and measure the overall resource consumption of the entire of MHARS system during operation.

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6. REFERENCES