Body Location Independent Activity Monitoring

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Abstract: Human Activity Recognition (HAR) is increasingly common in people's daily lives, being applied in health areas, sports and safety. Because of their high computational power, small size and low cost, smartphones and wearable sensors are suitable to monitor user's daily living activities. However, almost all existing systems require devices to be worn in certain positions, making them impractical for long-term activity monitoring, where a change in position can lead to less accurate results. This work describes a novel algorithm to detect human activity independent of the sensor placement. Taking into account the battery consumption, only two sensors were considered: the accelerometer (ACC) and the barometer (BAR), with a sample frequency of 30 and 5 Hz, respectively. The signals obtained were then divided into 5 seconds windows. The dataset used is composed of 25 subjects, with more than 7 hours of recording. Daily living activities were performed with the smartphone worn in 12 different positions. From each window a set of statistical, temporal and spectral features were extracted and selected. During the classification process, a decision tree was trained and evaluated using a leave one user out cross validation. The developed framework achieved an accuracy of 94.5 ± 6.8 %, regardless the subject and device's position. This solution may be applied to elderly monitoring, as a rehabilitation tool in physiotherapy fields and also to be used by ordinary users, who just want to check their daily level of physical activity.

1 INTRODUCTION

The interest in HAR has been growing in different areas, becoming an important issue of healthcare, fitness and safety. HAR can be used as a motivation tool to practice physical exercise, allowing to control the activities of daily living, as a way to monitor the elderly and detect possible falls, and also as a rehabilitation tool, performing movements analysis and helping doctors and their patients to execute the exercises needed in a more controlled and better way (Karantonis et al., 2006; Silva, 2013).

As almost all the existing HAR systems require firm attachment of the device to a specific body part, it would be desirable to become the activity monitoring independent of sensors position, not only in a matter of comfort, but also to avoid misplacement and, consequently, false results.

In this paper, a location independent algorithm for HAR using smartphones sensors is developed, using signals acquired with smartphones present in several positions (like right pocket or back pocket), tools to process and extract information from them and also classification algorithms to recognize the respective activity. We detained our attention in signals produced by the ACC and the BAR, extracting information on statistical, temporal and spectral domains and interpreting them in the context of human movement and activities recognition. Finally, using machine learning techniques, the identification of different activities was made. The developed system is based on an architecture of signal sensor processing, feature extraction and selection, classification algorithms and validation process.

2 BACKGROUND

Over the last years, several HAR systems have been proposed and studied. Nowadays, most of these studies based on wearable and smartphone's built-in sensors are made, placing them in different parts of the body.

From all the existing sensors, ACC is the most common choice to HAR. Despite its usefulness, there

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are still difficulties in the detection of vertical movements, like climbing stairs. Through the BAR sensor, the atmospheric pressure can be measured enabling to detect considerable variations in height. So, combining it with the ACC can lead to better accuracy results. (Bianchi et al., 2010) investigated the improvement of fall detection when using BAR and ACC sensors. Using a Decision Tree classifier, the proposed system obtained an accuracy of 96.9%, compared to 85.3% for the same measures when using ACC alone. On the other hand, (Muralidharan et al., 2014) used these sensors to successfully detect considerable variations in height, such as the ones that occur when a person moves from one building floor to another. Also (Moncada-Torres et al., 2014) shown that the use of a BAR increases the HAR performance for walking upstairs and downstairs by up to 20%.

In order to achieve a position-independent activity monitoring, a few studies were made, but a completely position-independent was not found, yet. Even though, in these studies the effects of changing position are minimized. One of the explored ways was to train a generalized classifier with data from several appropriate positions (Reddy et al., 2010). Similarly, (Anjum and Ilyas, 2013) create a smartphone application with a non-specific position and orientation classification system.

3 PROPOSED FRAMEWORK

The developed framework for HAR is based on the acquisition of 2 different sensors: the ACC, the most useful for this analysis, beyond its optimized battery usage, and the BAR, which helps in the discrimination of climbing stairs and walking.

3.1 Data Acquisition

The acquisition protocol followed was not overly specific, being the main concern to ensure that subjects keep doing the same activity during the entire sample without any interruption. Besides this, it was also important to save the subject's name, age, weight, height, gender, leg height and shoe size before any acquisition. The activities included and used in the considered dataset were walking, running, standing, sitting, upstairs and downstairs, while using the smartphones in several positions (like left or right pocket, for example).

3.2 Signal Processing

In the last years, an evolution in smartphones has been seen. Nowadays, many of its capabilities are possible due to the embedded sensors. In smartphones, most of the sensors are Micro-Electro-Mechanical-Systems (MEMS) based. These systems are very small chips composed by one or more sensors (Grankin et al., 2012). In this work ACC and BAR signals were processed and used.

3.2.1 Accelerometer

The use of ACC to characterize and recognize human movements has been increasing in the last years. This sensor provides qualitative and quantitative data that can be used to recognize users activities (Kavanagh and Menz, 2008).

ACC measures the acceleration force applied to the smartphone caused due to gravity or tilting action on tree physical axes (x, y and z).

While subjects move, the body acceleration components change, causing variations in the measured accelerations, regardless of its location. On the other hand, the acceleration is proportional to external forces and can also reflect the intensity and frequency of human movement (Gomes, 2014; Mathie et al., 2004; Xiao et al., 2014).

The triaxial ACC is composed by 3 data times series, one for each axis: ACC_x, ACC_y and ACC_z. Besides these 3 axes data, the magnitude of the acceleration was also computed, which is independent of the ACC orientation and measures the instantaneous intensity of the subject movement at time (t) (Machado, 2013; Li et al., 2013). This time series is calculated as represented in the following equation:

$$ACC_{mag}(t) = \sqrt{ACC_{x,t}^2 + ACC_{y,t}^2 + ACC_{z,t}^2} \quad (1)$$

The ACC signal is composed by the combination of the gravitational acceleration with the subject's body acceleration. So, the measured acceleration is always influenced by the gravitational acceleration of the earth ($g = 9.8m/s^2$). Therefore, to measure the real acceleration of the subject, the gravitational component must be isolated and removed. In order to do so a high-pass filter was used. In Figure 1 the magnitude of total acceleration, after the filtering process, is presented, i.e, the subject's acceleration for 6 different activities.

As can be seen in Figure 1, the upstairs, downstairs and walking ACC signals are very similar, which can lead to a confusion in the classification process.

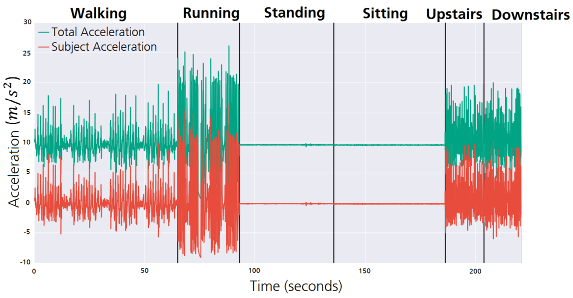

Figure 1: Magnitude of total acceleration and subject's acceleration for 6 different activities.

3.2.2 Barometer

Smartphones built-in MEMS BAR calculate pressure considering the piezo-resistive effect. The piezo-resistive pressure sensor is composed by a plurality of piezo-resistance elements arranged on a diaphragm on a silicon substrate, which bends with applied pressure. Because of that bending, a deformation in the crystal lattice of the diaphragm occurs. Then, this deformation causes a change in the band structure of the piezo-resistors that are placed on the diaphragm, leading to a variation of the resistance of piezo-resistance elements (Rodrigues, 2015; Cabuz et al., 2009)

The atmospheric pressure decreases as the altitude increases, so through the BAR signal it is possible to detect altitude changes and, consequently, infer if the subject was climb up or down the stairs. Figure 2 shows the barometer signal obtained from the same acquisition as Figure 1. As can be seen, the differences between walking, upstairs and downstairs are quite evident.

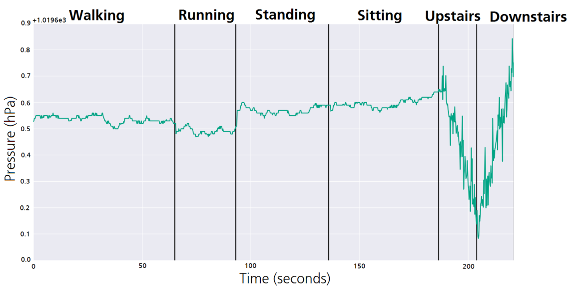

Figure 2: Pressure signal for 6 different activities.

3.3 Feature Extraction

In machine learning techniques, the choice of the features that will be extracted is essential to make the learning task more efficient and accurate. In the present work, the sensor signals extracted were divided into fixed length windows where all the information of each activity were extracted. Based on the new method of feature extraction developed in (Machado, 2013), this process was made using a JavaScript Object Notation (JSON) file, where a dictionary of features was created. The three sets of features that were considered are present in Figure 3.

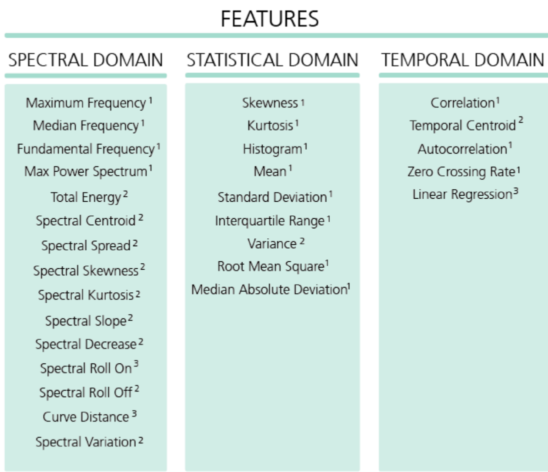

Figure 3: Spectral, Statistical and Temporal Domain Features used in the present work. [1] Features already used in accelerometer signals; [2] Features used in audio recognition (Peeters, 2004); [3] New features created and applied in the current work.

Afterwards, the extracted features are normalized and bounded within $[-1, 1]$, according to the equation:

$$f_{norm} = \frac{f - f_{min}}{f_{max} - f_{min}} \times 2 - 1 \quad (2)$$

Where f_{norm} is the feature normalized, f is the original feature and f_{max} and f_{min} are the maximum and minimum values of the feature f, respectively. This step is important to avoid a "preference" in features with higher magnitude by the classification algorithm.

3.4 Feature Selection

After features extraction, it is possible that many of them are either redundant or irrelevant, and can be removed without incurring much loss of information. Furthermore, features computation is time consuming and computationally heavy task. So, it is very important to keep the dimensionality of the feature data as small as possible, which can be obtained with a feature selection process. In feature selection is very important to take into account the type of data that is been used and the aim of the classification. A perfect feature type has a wide variation between different classes and a small one between the same class data (Gomes, 2014; Machado, 2013; Trier et al., 1996).

In this work was implemented a feature selection based on a wrapper approach and on the "Forward Feature Selection" algorithm, in which features are sequentially added to an candidate set until the addition of more features does not decrease the classification performance.

In order to visualize the behaviour of the best features throughout the performance of different activities, the Horizon Plot was considered, as shown in Figure 4. In this method the blue and red colors correspond to positive and negative values, respectively, and the color intensity increases with the respective absolute value. It was possible to observe that the features types Root Mean Square, Median Absolute Deviation and Standard Deviation (all from ACC signals) allowed the discrimination between running, walking, static and stairs activities. To distinguish between standing and sitting activities was important the extraction of the features Spectral Roll On, Mean and Max Power Spectrum, also from ACC signals. BAR signals can help to discriminate between upstairs, downstairs and walking activities, which was possible to confirm. Besides the ACC Spectral Centroid helped in upstairs and downstairs discrimination, the best results were obtained with features extracted from BAR signals. Firstly, BAR Spectral Roll Off differentiates walking and running from upstairs and downstairs. Then, BAR Centroid and Linear Regression, discriminate between upstairs and downstairs.

3.5 Supervised Learning

In this work, supervised learning techniques to discriminate between 6 different activities (walk, run, stand, sit, upstairs and downstairs) were used. Considering the gathered dataset and the respective features extracted and selected, a classification algorithm based on decision trees was trained. Then, in order to evaluate this classification algorithm, a leave one user out cross validation strategy was used.

3.5.1 Decision Tree and Rejection Class

A Decision Tree creates a model that predicts the value of a target variable by learning simple decision rules inferred from the data features. Each node is a choice between a limited number of alternatives and each branch a classification. There are several metrics for the choice of the feature that best splits the set of samples (Kotsiantis et al., 2007; Ture et al., 2009). In this work, the Gini impurity metric was considered. At node d, the Gini impurity index, $g(d)$, is defined as (Ture et al., 2009):

$$g(d) = \sum_{j \neq i} p(j|d)p(i|d) \tag{3}$$

Where i and j are the classes of the target variable. Setting k as the number of classes for a target variable (in this case the number of possible activities), when the cases in a node are evenly distributed across the classes, the Gini index takes its maximum value of $1-\left(\frac{1}{k}\right)$. On the other hand, when all cases in the node belong to the same class, the Gini index is 0 (Ture et al., 2009).

Beyond the Decision Tree based classifier, a Rejection Class was also considered. The main goal was to consider just the classification results that were made based in a high probability. With this, in case of the probability was less than a specific value, the result was rejected and was not considered in the overall classification performance. In the context of this work, it was considered that if the rejected data represents less than 5% of the total data, a very significant amount of data was not lost.

3.5.2 Leave One User Out Cross Validation

To validate the proposed model, a leave one user out cross validation algorithm was developed. As input it receives the data (the set of features extracted) and the correspondent labels and also the subjects names for each time window. After it divides the data into train and test sets and performs the feature selection, which gives the n best features and correspondent accuracy. In each iteration the resulting accuracy is saved into a list, which in the end has all the accuracies obtained. The final step consists in the calculation of the average value of this list.

For s subjects $s-1$ subjects are used to train the Decision Tree and 1 to validate it. This process is repeated s times, where each subject is used exactly once as the validation set. So, for the s subjects, there are s different training sets and s different test sets. With this cross validation technique we can ensure an independence of the subject.

4 PERFORMANCE EVALUATION

The performance of the proposed HAR system was validated in four approaches: Position Dependent (Pdep), Position Followed by Activity Recognition (Pact), Position Independent (Pindep), and Position Dependent and Independent Combination (Pdep+indep). This evaluation was also performed in a subject-independent condition. In order to reach a balanced result between the classification accuracy and battery consumption, a sampling frequency and

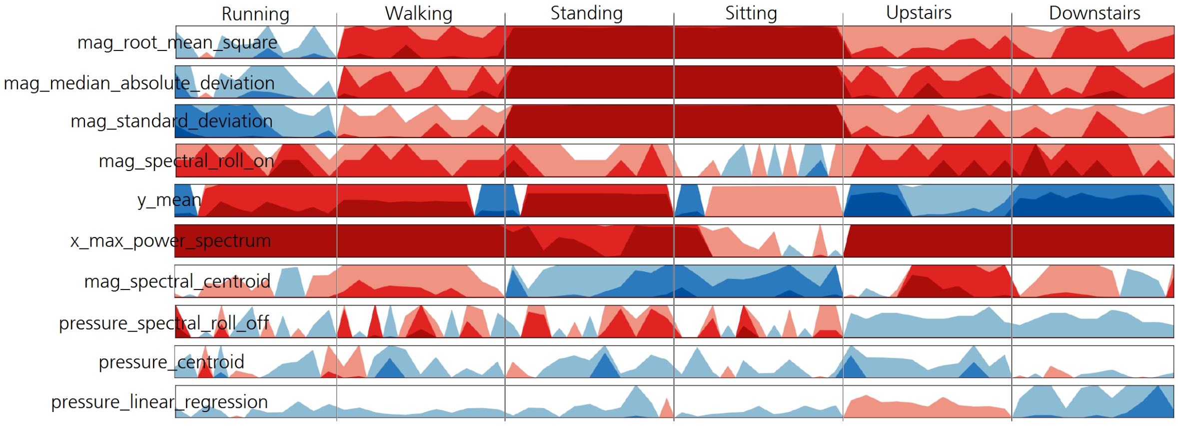

Figure 4: Horizon Plot with some of the most notable features extracted from the ACC and BAR sensors according to the activity performed. The *x_*, *y_*, *mag_* and *pressure_* indexes refer to the component where was extracted the respective feature: *x* and *y* axis of the ACC, ACC magnitude and BAR single axis, respectively.

time complexity analysis were performed. The combination of different features were also explored to improve the classification accuracy.

4.1 Activity Dataset

Daily life activities require many complex movements and their complexity diverge according to each subject. In this study, the analysed data is part of Fraunhofer AICOS dataset and is composed by 25 subjects, 7 males and 18 females, with an average age of 23 ± 4 years, average height of 169 ± 8 cm and an average weight of 61 ± 11 kg. Overall, more than 7 hours (5281 windows of 5 seconds duration) of data were recorded for 6 different activities (Walking, Running, Standing, Sitting, Upstairs and Downstairs) with the smartphone placed into 12 different positions (Table 1).

Table 1: Set of smartphone positions and the respective activities performed considered in this work. [1] Walking; [2] Running; [3] Standing; [4] Sitting; [5] Upstairs; [6] Downstairs.

Positions	Activities Performed
Calling	1, 2, 3, 4, 5, 6
Texting	1, 2, 3, 4, 5, 6
Left/Right/Back Pocket	1, 2, 3, 4, 5, 6
Front Pocket	2, 3, 4
Center/Left/Right Vest	1, 2
Belt	1, 2
Chest Attached	1, 2
Left Arm	2

Although there are positions that have been only used in just one activity, like Left Arm, they were also important to increase the variety of positions used in the Pindep approach, leading to a more comprehensive result.

4.2 Resampling and Time Windows

Due to the variability in sampling frequency of different smartphones, sensors signals were resampled to 30 Hz and 5 Hz for ACC and BAR, respectively. After this sampling frequency conversion, the next step was to split the signals into segments of 5 seconds (time windows), from which the features were extracted. Afterwards, the extracted features were normalized and bounded within $[-1, 1]$, according to the equation:

$$f_{norm} = \frac{f - f_{min}}{f_{max} - f_{min}} \times 2 - 1 \quad (4)$$

Where f_{norm} is the feature normalized, f is the original feature and f_{max} and f_{min} are the maximum and minimum values of the feature f, respectively. This step was important to avoid a “preference” in features with higher magnitude.

4.3 Results

As the features were extracted from ACC and BAR signals with a time window of 5 seconds and with a sampling frequency of 30 and 5 Hz, there were 150 and 25 samples for each window, respectively.

After feature extraction and selection, signal processing and classification, the performance results were obtained with leave one user out cross validation, where the accuracy value was calculated through the Equation:

$$A = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

Where TP are the True Positives, TN the True Negatives, FP the False Positives and FN the False

Negatives. All the results are also shown in a normalized confusion matrix format, where the percentage of classified samples are present in a table layout with size 6×6, for the 6 different classes available. Thereby, it is possible to easily compare the diagonal and the off-diagonal values obtained, where the higher the diagonal values the better, indicating many correct predictions.

Regarding to the rejection class, the lower probability considered was 40%, which represented about 3% of the total data, whereby it can be considered that was not lost a very significant amount of data.

In order to ascertain how much the classification accuracy improves with the usage of the BAR, the results obtained with a single sensor (the ACC) and with the two sensors are also present.

4.3.1 Position Dependent Approach

Despite the main objective of this work was to find a location independent algorithm for HAR, in a first stage we have tested the developed algorithm in a position dependent approach. Table 2 summarizes the results obtained. As can be observed, considering the positions which were used in all the possible activities (see Table 1), and using just the ACC, the results obtained range from $84.2 \pm 8.3\%$ to $95.0 \pm 3.6\%$. On the other hand, combining the ACC with the BAR, the results improved, ranging from $93.0 \pm 5.9\%$ to $98.4 \pm 2.5\%$, mainly due to the reduction of the existing confusion between upstairs, downstairs and walking.

Table 2: Accuracy obtained considering Pdep approach with just ACC signals (Single Sensing) and with ACC and BAR (Dual Sensing).

Position	Single Sensing Accuracy (%)	Dual Sensing Accuracy (%)
Back Pocket	95.0 ± 3.6	98.1 ± 3.1
Left Pocket	94.5 ± 6.0	98.4 ± 2.5
Right Pocket	92.3 ± 9.7	94.1 ± 8.1
Calling	92.1 ± 6.6	94.4 ± 5.4
Texting	84.2 ± 8.3	93.0 ± 5.9

4.3.2 Position Followed by Activity Recognition Approach

As shown in the previous approach, with the knowledge of the smartphone position a fairly accurate classification was obtained. So, in order to achieve an activity recognition independent of position, one possible approach consists in two fundamental steps: first the position recognition, followed by the activity recognition. Using the same methods than activity classification, the position classification was performed, obtaining an average accuracy of $70 \pm 21\%$, where Texting, Calling and Belt are the more accurately classified positions. Furthermore, the Center and Right Vest positions are mostly classified as Left Vest. With this, we decided to test the algorithm considering just 4 classes for the possible positions: Texting, Calling and Belt (the more accurately classified positions) and also Vest (which includes Center, Right and Left Vest). This way, we improved the position classification for $99.1 \pm 1.9\%$.

4.3.3 Position Independent Approach

To achieve the desirable position independent recognition, another approach can be followed, where it is not taken into account the smartphone position. For that, was given to the developed algorithm as data inputs the features extracted and selected from the 6 different activities performed with the smartphone into the 12 different positions, and as the desirable outputs, only the correspondent activity.

Using just the ACC, a classification with an accuracy of $82 \pm 11\%$ was performed. Similarly to what was shown in Pdep approach, and, once again, in agreement with the expected, by combining the 2 sensors the results are highly improved. In this case, the classification was performed with an accuracy of $92.3 \pm 5.8\%$, which corresponds to an increase of 10%. Although there is still some confusion between upstairs, downstairs and walking, it was quite decreased, where the worst classified activity was downstairs with 81.2% of data correctly identified (about 2 times better than the previous result). The correspondent normalized confusion matrix is present in Figure 5.

In order to simulate the arising of new positions and evaluate how the developed algorithm will responds, another evaluation test was made. For this purpose, the leave one position out cross validation was developed, which consists in a very similar version of the leave one user out, where instead of using the subjects is used the positions. In this conditions, an accuracy of $92.8 \pm 9.3\%$ was obtained.

4.3.4 Position Dependent and Independent Combination Approach

The last approach considered in this work was based in the combination of the Pdep and Pindep approaches, consisting in, at a first stage, classify the device position and then, considering the position obtained, classify the activity performed. If the position was classified based on a high accuracy, the Pdep approach was considered. Otherwise, was employed the

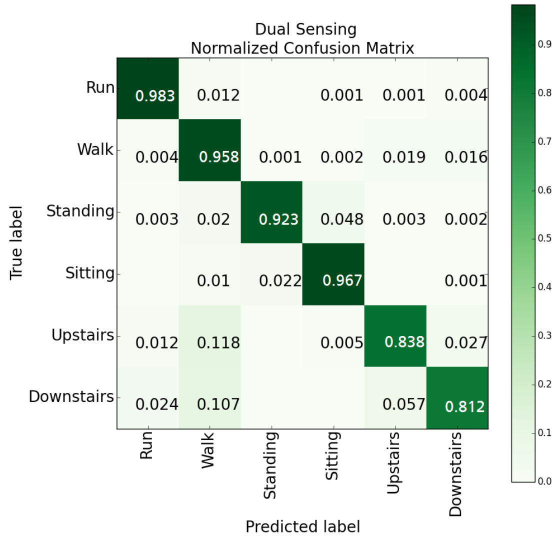

Figure 5: Normalized Confusion Matrix obtained for Pindep approach, using features extracted from ACC and BAR.

Pindep.

Overall, an accuracy value of $94.5 \pm 6.8\%$ was achieved, increasing about 2% than considering just the Pindep approach. The correspondent normalized confusion matrix is present in Figure 6.

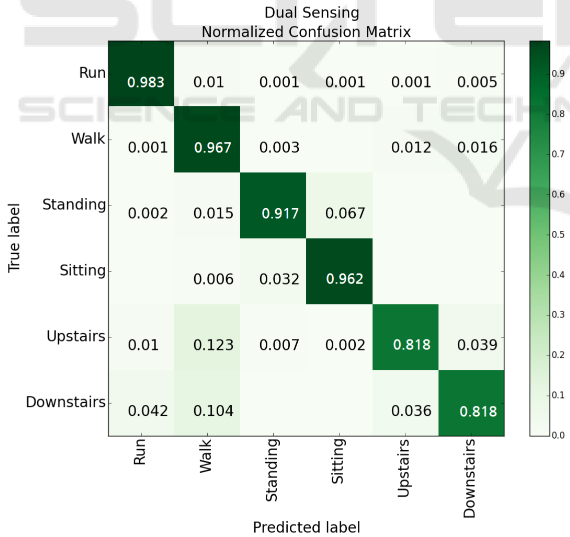

Figure 6: Normalized Confusion Matrix obtained for Pdep+indep approach, using features extracted from ACC and BAR.

4.4 Discussion

The system developed in this work aims to identify human activities, independently of the device's position. After sampling frequency reduction, features were extracted from signals. Using just the suitable number and combination of them, four approaches were studied. In every case a Decision Tree was used as classifier, evaluated with the developed leave one user out cross validation.

Firstly, we studied the system performance when was known the smartphone position, achieving an accuracy between $93.0 \pm 5.9\%$ to $98.4 \pm 2.5\%$, where the best result was obtained with Back Pocket and the worst with Texting position. Based on it, the first approach followed to reach the independence of position was Pact, where, considering all the possible positions, a low accuracy result was obtained ($70 \pm 21\%$). Taking into account just the best classified positions was possible to improve the previous results, but in everyday life the users do not use their smartphone only in those positions. With Pindep approach this problem was solved. Without knowing the smartphone position, an accuracy of $92.3 \pm 5.8\%$ was achieved. Finally, the best result was obtained through the Pdep+indep approach, where an accuracy value of $94.5 \pm 6.8\%$ was achieved, since Pdep was only used if the position classification result was based on a high accuracy (higher than 98%). Otherwise, was employed the Pindep.

5 CONCLUSIONS

The results obtained suggest that through ACC and BAR users' activities can be adequately identified independently of the smartphone position.

Comparing to the state of the art, despite (Anjum and Ilyas, 2013) achieved better accuracy results, we may consider that the developed work is broader, allowing to discriminate more activities independently of device's position. In (Anjum and Ilyas, 2013) were only tested 4 different positions, against the 12 that we had considered. Regarding to (Reddy et al., 2010), was not considered upstairs and downstairs, one of the most difficult activities to recognize. Even so, the accuracy obtained was about 0.9% lower than the achieved in this work.

The major achievement was to get a system which allows a smartphone to monitor users activities in a simple way, not requiring a specific position. There are many scenarios where the contributions of the present work may be applicable, such as to monitor the elderly, as a rehabilitation tool in physiotherapy fields and also to be used by ordinary users, who just want to check their daily level of physical activity. In all cases, the independence of position is a big concern, not only to provide more comfort and usability, but also to avoid misplacement and, consequently, false results.

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