Offline and Online Activity Recognition on Mobile Devices Using Accelerometer Data

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Abstract. This paper presents a process for extracting knowledge for physical activity recognition, from accelerometer data provided by mobile devices. Starting from a dataset collected by three different users, knowledge discovery is performed through a phase of feature extraction from raw data, minimizing the number of statistical features and optimizing the classification process. The development and comparison of classifying models over this new dataset, using both offline and online algorithms, is also described. Phases of data acquisition, pre-processing and classification are detailed, and experimental results for different machine learning algorithms are provided. For these results, different evaluation criteria are used, and the best algorithm is selected according to these criteria. Final results show success rates around 98%, while other similar works offer rates around 87%.

1 Introduction

Activity recognition on mobile devices is currently a widely explored field in data mining and artificial intelligence, due to the large range of technical possibilities that these devices offer to users and developers. The different types of sensors embedded into these devices, such as accelerometers, GPS, light and temperature sensors, and audio and image recorders, together with their small size and their computing power, make mobile devices one of the best tools for ubiquitous computing [11].

There are a large number of real applications for activity recognition in small mobile devices, such as patient monitoring [12], video surveillance [13] or smart-homes development [10].

In this work, a set of six different physical activities, regularly performed on a daily basis, is proposed to be classified, namely sitting, standing, walking, running, ascending stairs and descending stairs. For this aim, accelerometer from Android-based mobile phones will be used for recording data, since this sensor offers robust and reliable measurements for determining body-position and posture-sensing [7].

This paper is organized as follows: section 2 provides a discussion of the current state of the art, describing the previous work that has been developed in this field and the difference with the work presented in this paper. Section 3

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describes the materials and methods, detailing the acquisition of data, the structure of the dataset used for classification, and the different algorithms and techniques evaluated. Section 4 details the proposed evaluation criteria, and provides the obtained experimental results. Finally, conclusions and future work are presented in section 5.

2 Related Work

Many sensor-based activity recognition systems have been presented in the past years. However, the sensing process for obtaining data for classification can be performed in many ways. In [1], five different accelerometers are located in different body parts (ankle, knee, elbow, wrist and hip). [8], [5], [15] and [17] also propose approaches involving several sensors to cover up the maximum possible data from the environment, while [18] and [14] use ad-hoc designed sensors for receiving data. In this work, a reduction in the number of sensors is proposed, in order to take advantage of the wide extension of smart phones all over the world, which allows the development of applications that can be used by several millions of people.

Regarding the techniques for extracting information from raw data obtained by an accelerometer, most of the previous works on this topic propose feature extraction for knowledge discovery. However, the number of different statistical features used for creating data instances is usually high, such as in [11], where 6 different statistical markers are extracted, or in [20], where 22 features are initially extracted, and then reduced via feature selection algorithms. The use of a reduced set of statistical features (mean and standard deviation) proposed in this work, could lead to a lower consumption of resources from the mobile phone, a desirable condition due to the limitations of these devices.

In relation to the algorithms and techniques used in other works, most of the approaches propose supervised machine learning techniques, such as decision trees [5], Naive Bayes [18] or Nearest Neighbor algorithms [1], as well as artificial neural networks [11], although some approaches explore Hidden Markov Models [17] and SVM [9] for obtaining classifying models. In this work, a comparison between well known machine learning techniques is presented, and one of the algorithms is finally selected. Moreover, a comparison between the results from this work and those from similar works such as [11] and [20] will be performed.

Although some works treat the online classification approach [6], due to the nature of data used for activity recognition, and the characteristics of the data acquisition itself, comparison between offline and online classification is needed, in order to determine whether models regarding only a fixed number of past measurements are able to offer the same classification results as offline techniques.

3 Materials and Methods

This section introduces the proposed approach for activity recognition, dividing the development process into three different phases: data acquisition, related to the collection and labeling of data that will be used for training the different classifying models, data pre-processing, regarding the process of formatting the data in order to obtain reliable results, and data classification, this is, selection of the different algorithms and techniques used for recognizing activities.

3.1 Data Acquisition

For this purpose, an Android labeling application has been developed. In this application, the user can select, from a set of six different activities (sitting, standing, walking, running, ascending stairs and descending stairs), the activity he is going to perform, and then start recording data from the accelerometer. Thus, once the user has selected the activity, the acceleration experienced by each of the three axis of the mobile phone is stored into the database, as well as the class representing the type of activity being performed.

However, before data is collected by this application, two previous assumptions have to be taken into account:

- The mobile phone will be located inside the user's pocket.
- Frequency of sensing will be one second, i.e., every second the application will record a piece of data from the accelerometer.

The aim of the first assumption is to determine a concrete location and position of the device when data is being collected, in order to assure the congruence and robustness of the data used for classification. The sensing frequency is selected in order to reduce the consumption of resources from the mobile device, since the final classification model that will be developed in this process is thought to be implemented inside a mobile application for activity recognition.

3.2 Data Pre-processing

In this point of the knowledge discovery process, the problem to be solved is a sequential classification problem, which can be transformed into a classical classification problem through the use of a sliding window [4]. The size of the window will be 20 measurements, enough to capture activity intervals of 20 seconds, in which useful cycles and characteristics for classification could exist. Therefore, the window is slid along the data stream and every time that the 20 measurements inside the window belong to the same class, a new instance is extracted for classification.

A selection and extraction of statistical features is performed over data from the sliding-window. The extraction of statistical characteristics from the original instances is an important step for obtaining accurate classifiers in patter recognition problems [16]. Although the number of features that can be calculated is high, in order to maintain the aim of reducing the consumption of resources, in this work only two widely used statistical markers are extracted: mean and standard deviation [19], [1]. The difference of values between two consecutive data inside the window, in each of the three axis of the accelerometer, is also taken into account. Therefore, for each instance of the sliding window, an instance suitable to be used for classification is generated. This final instance is denoted by:

$$(M_x, M_y, M_z, M_{\Delta x}, M_{\Delta y}, M_{\Delta z}, SD_x, SD_y, SD_z, SD_{\Delta x}, SD_{\Delta y}, SD_{\Delta z}, Class)$$

It contains 12 attributes and the class representing the physical activity to which it refers, can be observed. M_x, M_y, M_z refer to the means of the values from the three axis (X, Y and Z) of the accelerometer, $M_{\Delta x}$, $M_{\Delta y}$, $M_{\Delta z}$ represent the means of the values of two consecutive measurements for the three axis, SD_x, SD_y, SD_z refer to the standard deviations of the values from the three axis, and $SD_{\Delta x}$, $SD_{\Delta y}$, $SD_{\Delta z}$ are the standard deviations of the values of two consecutives measurements, for the three axis.

3.3 Data Classification

Algorithms used for offline classification are divided into three main types, inside the field of supervised classification: lazy algorithms (K-Nearest Neighbor, with K=3, 5 and 11, and Nearest neighbor with generalization, NNge), decision trees (C4.5) and decision rules (RIPPER). Using 10-fold cross validation, these six algorithms have been tested over the dataset.

Online classification is performed using the same six algorithms, and 10-fold cross validation. However, some of the algorithms do not provide an incremental implementation, this is, the classifying model is not directly updateable, so a non-incremental approach is implemented to perform the online classification, building the complete classifying model each time a new instance is loaded from the training set, instead of updating the model.

4 Evaluation and Results

Data acquisition process was carried out by three different users, and 6.523 measurements were retrieved. After data pre-processing, a total of 5.714 instances are available for training the classifying models.

Table 1. Number of instances per class

	Sit	**Stand**	**Walk**	**Run**	**Ascend**	**Descend**	**Total**
Raw	767	346	1969	2804	321	316	6523
Final	677	308	1722	2636	188	183	5714

Table 1 shows the number of raw and final instances per class. It can be clearly observed that data used for classification are unbalanced, this is, there exists a high difference between the number of instances from classes "Standing", "Ascending stairs" or "Descending stairs", with less than a 10% of total instances, and classes "Walking", with 30% of the instances, and "Running", with almost half of the instances.

4.1 Evaluation Criteria

Success rate and Kappa coefficient [3] are used for evaluating the performance of the different algorithms over the dataset. However, since original data are unbalanced, success rate is not the most appropriate measure of performance. F-Measure is defined as a harmonic mean of precision (measurement of purity in retrieval performance) and recall (measurement of completeness in retrieval performance) [2], and will be used for testing the algorithms taking into account minority classes. Significance testing between algorithms is done at a confidence interval of 95% using a two-tailed student t-test and using matching paired data.

Differences between offline and online algorithms are also useful for understanding the problem. In this case, online experiments will show the performance of the algorithm as the size of the training dataset increases, over the same test dataset, while the size of the training dataset used by offline algorithms to build the model is always the same.

4.2 Offline Results

Table 2 shows the results for offline classification performed by the six algorithms. The algorithm that presents the best classification results, in terms of all the proposed evaluation criteria, is K-Nearest neighbor, with K = 3. The t-test also confirms that the difference between this algorithm and the rest is statistically significant in almost all cases. However, t-test indicates that 3-NN and 5-NN are equivalent in this case.

Table 2. Results for Offline Classification (expressed in %). Best results appear in boldface type.

	3-NN	**5-NN**	**11-NN**	**NNGE**	**C4.5**	**Ripper**
Success	**99.14**±**0.45**	98.95±0.40	98.20±0.53	98.08±0.39	98.16±0.45	97.58±0.79
Kappa	**98.73**±**0.67**	98.44±0.60	97.32±0.80	97.14±0.57	97.28±0.66	96.41±1.18
Precision	**97.87**±**1.71**	97.43±1.28	96.56±1.56	96.66±1.50	95.27±1.60	94.11±2.49
Recall	**96.19**±**1.94**	95.34±1.61	92.33±1.90	91.76±1.87	93.74±2.04	91.36±2.82
F-Measure	**97.02**±**1.72**	96.37±1.38	94.40±1.49	94.14±1.41	94.49±1.73	92.71±2.47

Table 3. Confusion Matrix for 3-NN Offline

	Inferred					
True	**Sit**	**Stand**	**Walk**	**Run**	**Ascend**	**Descend**
Sit	**68**	0	0	0	0	0
Stand	0	**31**	0	0	0	0
Walk	0	0	**171**	0	0	0
Run	0	0	0	**264**	0	0
Ascend	0	0	1	0	**17**	1
Descend	0	0	1	0	1	**16**

Table 3 shows the confusion matrix for the test set of algorithm 3-NN. It can be observed that the overall performance of the algorithm is quite good for all the classes.

4.3 Online Results

Table 4 shows the results of the online algorithms (both incremental and non-incremental). The percentages are slightly lower than for offline classification, although the algorithm that presents the best results is 3-NN again, except for precision. In this experiment, there is a statistically significant difference between 3-NN and the rest of the algorithms in all cases.

Table 4. Results for Online Classification (expressed in %). Best results appear in boldface type.

	Incremental				Non-Incremental	
	3-NN	**5-NN**	**11-NN**	**NNGE**	**C4.5**	**Ripper**
Success	**97.58±2.50**	97.09±3.39	96.07±4.15	96.57±2.14	96.33±3.21	95.26±3.75
Kappa	**96.38±3.83**	95.61±5.55	94.04±7.10	94.85±3.29	94.55±4.83	92.90±5.99
Precision	94.53±3.84	94.18±4.13	92.84±4.67	**94.97±2.00**	90.94±4.83	89.54±5.01
Recall	**89.77±8.02**	87.77±8.96	83.71±10.23	85.96±7.24	88.46±7.51	85.17±9.05
F-Measure	**92.00±6.25**	90.73±6.93	87.81±7.96	90.10±5.06	89.62±6.35	87.16±7.25

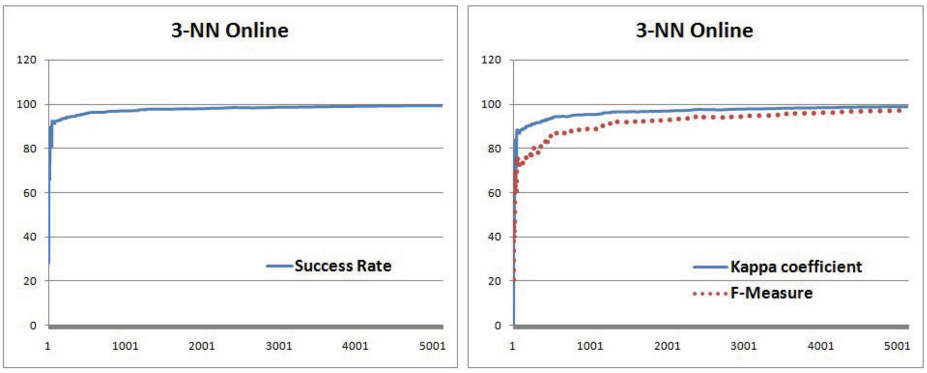

Fig. 1. Online Classification Performance for 3-NN

Fig 1 shows the evolution of the performance of algorithm 3-NN as the number of instances used for training the model increases. Convergence is fast, and success rate, Kappa coefficient and F-Measure reach acceptable values around instance 1000.

5 Discussion

In this work, a method for acquiring accelerometer data from mobile devices has been proposed. The data pre-processing includes the use of a sliding-window and feature extraction, allowing the transformation of a sequential classification problem into a classical classification problem. However, this feature extraction has been reduced to the minimum amount of statistical characteristics (mean and standard deviation), in order to minimize the consumption of resources of mobile devices. Future lines of work should cover the real impact of this reduction of statistical features, by implementing the classification model into a mobile device and extracting information about the use of resources. Several machine learning algorithms, such as K-Nearest Neighbor, C4.5 or RIPPER have been tested and their performance compared. After this comparison process, algorithm 3-NN has shown the best results for both offline and online classification, providing statistically significant differe nces with the other evaluated algorithms. New algorithms such as artificial neural networks could be applied to the dataset, and their performance compared to those already evaluated.

Regarding a direct comparison between different works, in [20] the experiments are performed over a dataset retrieved by four different users, and success rates of around 87% for the best algorithm (decision trees) are obtained, while [11] achieves 91.7% of success using the multilayer perceptron, over a dataset retrieved by twenty-nine users. The approach proposed in this work uses a dataset collected by three users, and obtains more than 99% of success through a 3-NN offline algorithm, and more than 97% through the online version of the same algorithm.

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