Human Activity Recognition from Accelerometer Data Using a Wearable Device

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Human Activity Recognition from Accelerometer Data Using a Wearable Device

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Abstract. Activity Recognition is an emerging field of research, born from the larger fields of ubiquitous computing, context-aware computing and multimedia. Recently, recognizing everyday life activities becomes one of the challenges for pervasive computing. In our work, we developed a novel wearable system easy to use and comfortable to bring. Our wearable system is based on a new set of 20 computationally efficient features and the Random Forest classifier. We obtain very encouraging results with classification accuracy of human activities recognition of up to 94%.

Keywords: Physical Activity Recognition, Wearable Computing, Pervasive Computing.

1 Introduction

Activity Recognition is an emerging field of research, born from the larger fields of ubiquitous computing, context-aware computing and multimedia. Recognizing everyday life activities is becoming a challenging application in pervasive computing, with a lot of interesting developments in the health care domain, the human behavior modeling domain and the human-machine interaction domain [3]. Even if first works about activity recognition used high dimensional and densely sampled audio and video streams [9], in many recent works ([2],[1]), activity recognition is based on classifying sensory data using one or many accelerometers. Accelerometers have been widely accepted due to their compact size, their low-power requirement, low cost, non-intrusiveness and capacity to provide data directly related to the motion of people.

In recent years, several papers have been published where accelerometer data analysis has been applied and investigated for physical activity recognition [5]. Nevertheless, few of them override the difficulty to perform experiments out-of-the-lab. The condition to perform experiments out-of-the-lab creates the need to build easy to use and easy to wear systems in order to free the testers from the expensive task of labeling the activities they perform.

In our work, we propose a new set of features extracted from wearable data that are competitive from computational point of view and able to ensure high classification results comparable with the state of the art wearable systems. The

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features proposed can be computed in real-time and provide physical meaning to the quantities involved in classification. The new set of features has been validated by mean of a reliable analysis comparing the new features with the majority of all the features commonly used in physical activity recognition using accelerometer data. Based on these features, we show that Random Forest classifier is an optimal classifier that reaches classification performances between 90% and 94%.

Moreover, we present a custom wearable system for human action recognition, developed in our lab, that is based on the analysis of accelerometer data. The wearable system is easy to use–users need only to start-stop the device, and comfortable to bring, having a reduced form which does not prevent any type of movement. Acceleration data can be acquired in many different, non-controlled environments allowing to overpass the laboratory limitation setting. Five basic every-day life activities like walking, climbing stairs, staying standing, talking with people and working at computer are considered in order to show its performance and robustness.

The paper is structured as follows. After discussing related work in Section 2, we describe in Section 3 how we create the dataset using in Section 3 we provide the technical details about the best features extraction for classifing human activities. In Section 4, we present the results of the classification of the activities. Finally, Section 5 concludes the paper.

2 Related Works

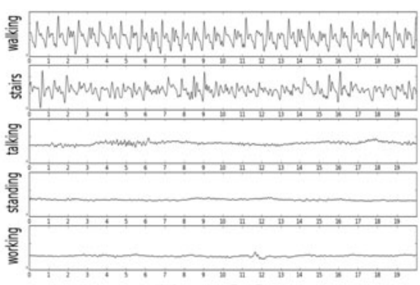
In [5], Mannini and Sabatini give a complete review about the state of the art of activity classification using data from one or more accelerometers. In their review, the best classification approaches are based on wavelet features using threshold classifiers. In their work, they separate high-frequency (AC) components, related to the dynamic motion the subject is performing from low-frequency (DC) components of the acceleration signal related to the influence of gravity and able to identify static postures. They extracted features from the DC components. The authors classify 7 basic activities and transitions between activities from data acquired in the lab, from 5 biaxial accelerometer placed in different part of the body, using a 17th-dimensional feature vector and a HMM-based sequential classifier, achieving 98.4% of accuracy.

Lester, Choudhury and Borriello in [4] summarize their experience in developing an automatic physical activities recognition system. In their work, they answer some important questions about where sensors have to be placed in a person, if variation across users helps to improve the accuracy in activity classification and which are the best modalities for recognizing activities. They reach the conclusion that it does not matter where the users place the sensors, variation across users do help improving accuracy classification and the best modalities for physical activities recognition are accelerometers and microphones. Again, human activities are acquired in a controlled environment.

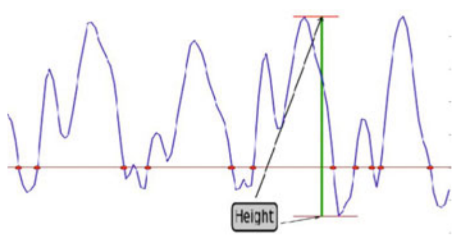
Our previous work in this research line [10], uses a prototype of wearable device completed by camera. Data of five everyday life activities have been collected from people acting in two circumscribed environments. A GentleBoost classifier has been used for classifying the five activities with 83% of accuracy for each activity. Using the combination of a physical activity classifier and a face detector, face-to-face social activities have been detected with high confidence. In contrast, in this work we question how far we can get in human activities recognition using only wearable data.

3 The Problem of Human Activity Recognition

Recognizing human activities depends directly on the features extracted for motion analysis. Accelerometers provide three separated accelerometer data time series, one time series for acceleration on each axis A_x,A_y,A_z. An example of accelerometer data for five different activities is shown in Figure 1(a). Activities refer to regular walking, climbing stairs, talking with a person, staying standing and working at computer. In the figure, one can appreciate a pattern arising from a walking activity. In climbing stairs, an activity similar to walking, the same pattern seems not to be present, even if some common components between the two activities can be noted. The rest of activities differ significantly from the previous ones specially in the waveform and in the acceleration intensities involved, although forming another group of similar dynamic patterns. Small differences in the variation of the acceleration can help to discriminate the three activities. Complementary to the three axes data, an additional time series, A_m, have been obtained computing the magnitude of the acceleration:$A_m = \sqrt{A_x^2 + A_y^2 + A_z^2}$.



(a)



(b)

Fig. 1. (a) Accelerometer Data for Five Different Activities..(b) Minmax sample in Accelerometer Data

3.1 Features Selection for Motion Data

Each time series A_i, with $i = \{x, y, z, m\}$ has been filtered with a digital filter in order to separate low frequencies components and high frequencies components as suggested in [5]. The cut-off frequency has been set to $1Hz$, arbitrarily. In this way, we obtain for each time series, three more time series A_{ij} with $j = \{b, dc, ac\}$, where b,dc,ac represent respectively the time series without filtering, the time series resulting from a low pass filtering and the time series resulting from a high pass filtering. Finally, we extract features from each one of the time series.

A successful technique for extracting features from sequential motion data has been demonstrated to be windowing with overlapping. We extract features from data using windows of 52 samples, corresponding to 1 second of accelerometer data, with 50% of overlapping between windows. From each window, we propose to extract the following features: root mean squared value of integration of acceleration in a window, and mean value of Minmax sums. In next section, we will show that these two features play important role being two of the most discriminant ones because they provide informations about the physical nature of the activity being performed. The integration of acceleration corresponds to the Velocity. For each window, the integral of the signal and the RMS value of the series are computed. The integral has been approximated using running sums with step equals to 10 samples. The physical meaning that this feature provides is evident. The Minmax sums are computed as the sum of all the differences of the ordered pairs of the peaks of the time series. Note that minmax sums can be considered as a naive version of standard deviation. In Figure 1(b), an example of minmax sample is shown.

Still, in order to complete the set of features we add features that have proved to be useful for human activity recognition [5] like: mean value, standard deviation, skewness, kurtosis, correlation between each pairwise of accelerometer axis (not including magnitude), energy of coefficients of seven level wavelet decomposition. In this way, we obtain a 319-dimensional feature vector.

3.2 Classification and Derivation of Importance Measurement

Random forest [6] is an ensemble classifier that, besides classifying data, can be used for measuring attribute importance. Random Forest builds many classification trees, where each tree votes for a class and the forest choose the classification having the most votes over all the trees. Each tree is built as follows:

- If the number of cases in the training set is N, N cases are sampled at random with replacement. This sample is the training set.
- If there are M input variables, a number $m \ll M$ of variables is selected at random and the best split on these m variables is used to split the node. The value of m is held constant during the construction of the forest.
- Trees are not pruned.

When the training set for the current tree is drawn with replacement, about one-third of the cases is left out of the sample. This Out-Of-Bag (OOB) data is used to get an unbiased estimate of the classification error as trees are added to the forest. Random Forest has the advantage to assign explicitly an information measurement to each feature. Measuring the importance of attributes is based on the idea that randomly changing an important attribute between the m selected variables for building a tree affects the classification, while changing an unimportant attribute does not affect it in a significant way. Importance of all attributes for a single tree are computed as: correctly classified OOB examples

Table 1. List of Features selected by Random Forest

Feature	**Importance**	**Feature**	**Importance**
Mean Value A_{zdc}	4.64	Mean Value A_{ydc}	3.86
MinMax A_{zdc}	4.61	Rms Velocity A_{ydc}	3.67
RMS Velocity A_{zdc}	4.23	Mean Value A_{zb}	3.59
RMS Velocity A_{mdc}	4.2	Mean Value A_{xdc}	3.57
RMS Velocity A_{xac}	4.14	MinMax A_{xdc}	3.52
Mean Value A_{mdc}	4.07	MinMax A_{zb}	3.51
MinMax A_{ydc}	3.92	Mean Value A_{yb}	3.33
Standard Deviation A_{xb}	3.9	Rms Velocity A_{xdc}	3.22
MinMax A_{mdc}	3.89	Rms Velocity A_{zb}	3.2
Standard Deviation A_{xdc}	3.87	MinMax A_{yb}	2.96

minus correctly classified OOB examples when an attribute is randomly shuffled. The importance measure is obtained dividing the accumulated attribute by the number of used trees and multiplying the result by 100.

Using Random Forest, an importance measure of the features has been obtained. In Table 1, the best 20 features obtained out of 319 are reported with their respective importance value.

4 Validation and Discussions

First we discuss the architecture of our wearable system and then discuss the obtained results.

System architexture: Our wearable system, shown in Figure 2(a), is based on a Beagleboard, a low-price board built around the TI OMAP system on chip. We use Linux as operating system on the board. A low-cost USB webcam and a Bluetooth accelerometer are connected with the board. The system is powered using a portable lithium battery able to power up to four hours the system. Users can wear the system as in Figure 2(b), where the directions of the acceleration axis are printed upon the picture. More specifically, Z-axis represents the axis concordant to the direction of movement and the plane defined by the X and Y axis lies on the body of the person. The system works with three modalities, video, audio and accelerometer data. It takes photos, grabs audio continuously applying a filter for voice removal and it receives via bluetooth data from the accelerometer. All the sensors can be localized in the same part of the body. In our setting, sensors are located on the breast.

Data acquisition: Data have been collected from fourteen testers, three women and eleven men with age between 27 and 35. For labeling activities, people were asked to annotate the sequential order of the activities they performed and restart the system. Every time the system starts, data are named with a serial number. Once the user presses the starting button, she/he can start to perform the activity. The system boots in less then 2 minutes and the acquisition automatically starts while the user is already performing the activity. In this way, there are no "border effects" due to starting. The user can stop the acquisition in

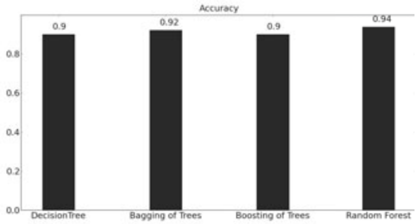
(a) (b)

Fig. 2. (a) The components of the wearable system, (b) The wearable system worn by an experimenter

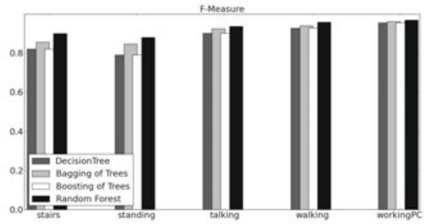
every moment pressing again the start button. The data set collected is composed by 33 minutes of walking up/down stairs, 82 minutes of walking, 115 minutes of talking, 44 minutes of staying standing and 86 minutes of working at computer.
Human activity classification: Random Forest selects really meaningful features for classifying activities. The most important features selected are related to the Z axis that is, the direction of the movements. The majority of the features are relative to the DC components of movements and only the RMS velocity feature relative to the X axis from the AC components has been selected. The information relative to the variation of movements on the X axis can help to discriminate between activities like staying standing, talking and working at PC. On the other side, features relative to the variation of movements on Y axis, can help to discriminate between activities like walking and walking up/down stairs. Mean value, minmax features and RMS velocity are selected for all the DC components of all the time series. Random Forest selects the best features but it is not able to discriminate between features bringing the same information. For example, all the features selected that have been extracted from the time series without filtering are also selected from the DC time series and, in all the cases, the features selected from the DC time series have an importance value bigger than the corresponding value from the series without filtering. Features derived from higher level statistics (skewness and kurtosis) and features relative to the correlation between axis are features with the lowest importance.

In order to verify if the features selected are really informative, we use different classification methods for classifying the five activities. We compare the classification results obtained using Decision Trees, Bagging of 10 Decision Trees, AdaBoost using Decision Trees as base classifiers and a Random Forest of 10 Decision Trees. All the results are validated by 5-fold cross validation. The data set D_m has been created using the 20 features selected by the Random Forest classifier. In Figure 3(a) we show the classification accuracy of the classifiers trained on D_m. In Figure 3(b) we show the F-Measure of each activity for every classifier.

As can be seen from the graphics, the best classification accuracy is obtained using Random Forest. The F-Measure obtained for each class shows how each



(a)



(b)

Fig. 3. (a) Classification Accuracy for Different Classifiers.(b) F-Measure for each Activity on the Motion Dataset.

activity can be classified with high precision and recall. In particular, activity with the best performances are walking and working at computer. Bagging and Random Forest are the classifier that give the best performances for each class. The confusion matrix obtained with the Random Forest classifier is reported in Table 2. Note how similar activity like walking and climbing stairs have some confusions between them. The biggest confusion in obtained between talking and standing, activity that can be easily confused from the perspective of motion. From Table 2 it can be concluded that all the classifiers have accuracy above

Table 2. Confusion Matrix of Random Forest trained on D_m

	stairs	walking	talking	standing	workingPC
stairs	**0.898**	0.029	0.004	0.002	0.001
walking	0.075	**0.959**	0.006	0.002	0.001
talking	0.015	0.007	**0.929**	0.093	0.012
standing	0.006	0.001	0.039	**0.888**	0.006
working	0.004	0.001	0.02	0.014	**0.977**

the 90% using only the motion modality. The Random Forest classifier trained on D_m shows confusions between similar activities like walking and walking up/down stairs, and between talking and standing. The F-Measure does not present significative differences between the classes that means that the five activities can be recognized with high confidence.

5 Conclusions

In this work, a study on the best features able to classify physical activities has been done. A new set of features has been taken into account and compared to the most commonly used features used for activity recognition in literature. The Random Forest classifier has been used to evaluate the informative measure of this new set of features. Results obtained show that the new set of features represent a very informative group of features for activity recognition. Using the features selected by Random Forest, different classifiers have been used for evaluating classification performances in activity recognition. Very high classification performances have been reached, obtained up to 94% of accuracy using Random Forest. State of the art classification performances ([5],[4]) ensures classification performances higher than 94% when two-stages classification pipeline are used.

The validation of the new set of features has been performed using data collected using a custom wearable system, easy to use and comfortable to bring. The custom wearable device allows to perform experiments in uncontrolled environment overpassing the laboratory setting limitation. Testers perform activities in the environment they selected without the effort of labeling activities.

Based on these results obtained using only the motion sensor, future works plan to add the other sensors to increase the classification performances. We expect that adding further information from the camera and the microphone can help considerably in discriminating between activities like “standing”, “talking” and “workingPC” or “walking” and “walking up/down stairs” activities where the biggest confusions are present. Moreover, we plan to extend the set of human activities in order to address the problem of short-term and long-term human behavior based on the accelerometer and video data.

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