Features Selection for Human Activity Recognition with iPhone Inertial Sensors

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Abstract. The recognition of human activities through sensors embedded in smart-phone devices, such as iPhone, is attracting researchers due to its relevance. The advances of this kind of technology are making possible the widespread and pervasiveness of sensing technology to take advantage of multiple sources of sensing to enrich users experience or to achieve proactive, context-aware applications and services. Human activity recognition and monitoring involves a continuing analysis of large amounts of data so, any increase or decrease in accuracy results in a wide variation in the number of activities correctly classified and incorrectly classified, so it is very important to increase the rate of correct classification. We have researched on a vector with 159 different features and on the vector subsets in order to improve the human activities recognition. We extracted features from the Magnitude of the Signal, the raw signal data, the vertical acceleration, the Horizontal acceleration, and the filtered Raw data. In the evaluation process we used the classifiers: Naive Bayes, K-Nearest Neighbor and Random Forest. The features were extracted using the java programming language and the evaluation was done with WEKA. The maximum accuracy was obtained, as expected, with Random Forest using all the 159 features. The best subset found has twelve features: the Pearson correlation between vertical acceleration and horizontal acceleration, the Pearson correlation between x and y, the Pearson correlation between x and z, the STD of acceleration z, the STD of digital compass y, the STD of digital compass z, the STD of digital compass x, the mean between axis, the energy of digital compass x, the mean of acceleration x, the mean of acceleration z, the median of acceleration z.

Keywords: Activities Recognition, Machine Learning, Data Analysis, Health Systems, Context-Aware

1 Introduction

The new generation of mobile devices with embedded sensors has created opportunities for exploring new context-aware services. This kind of data can be useful in many different areas: health care, sports, merchandising, among others.

Some of the available sensors in smart phone devices are: assisted GPS, digital-compass, accelerometer, three-axis gyro sensor and ambient light sensors. As these devices can make use of 4G, Bluetooth 4.0 , Wi-Fi as other communication support, the sensor data can be transmitted to some surveillance facility. This makes possible to monitor patients with mental illnesses, such as Bipolar disorder [15], Parkinson's and Alzheimer's [3], obtain patterns of sports activity, inform people considering their geographical location, etc. Independently of the area, context-aware services, typically, need to recognize the activity being performed and/or the space where it is happening. However we only discuss the first issue: the recognition of activities.

In 2004 Bao & Intile [2] did research to investigate wire-free accelerometers on 20 activities. A successful and exhaustive work was carried out. In their experiments they use 5 biaxial accelerometers on different parts of the body and then collect data from activities like walking, sitting, standing still, watching TV, running, stretching, scrubbing, folding laundry, climbing Stairs, etc. They used the data collected to train the classifiers C4.5 decision tree, decision table, k-nearest neighbor (K-NN) and Naive Bayes (NB), all of them part of WEKA [21]. The classifiers were tested with the following features: standard deviation, energy distribution, DC component, Entropy, and correlation coefficients. The best overall accuracy of 84 % was obtained with the C4.5 classifier.

In 2005 Ravi et al. tested the recognition of activities using an ensemble of classifiers [16]. They concluded that simple activities like standing, walking, running, going up and downstairs, can be recognized with fairly high accuracy using a single triaxial accelerometer, but it is hard to detect brushing with a single accelerometer worn near the pelvic region.

Other studies focused their work on the combination of sensors for activity recognition. Maurer et al., [13] used the Watch sensing platform. Sensors were placed on the belt, shirt pocket, trouser pocket, backpack and neck. They used Decision trees, K-Nearest Neighbor, Naive Bayes and Bayesian Networks for classification. It was concluded that the activity recognition can be done in real time using multiple sensors. Another interesting conclusion was drawn by Tapia et. al., [20], showed that, the area under the curve of acceleration and the mean features are very dependent on the magnitude of the signal and sensor orientation. Consequently they are not adequate for activity recognition based on sensors. In this study the best set of features found was: the average distance between axes, variance, energy of the signal and correlation coefficients. They tested the increase of accuracy by incorporating heart rate data.

Mannini et al., [12] used 5 accelerometers to detect 7 activities (lying, sitting, standing, walking, stair climbing, running and cycling), performed by 30 users. Kwapisz et al., showed the relevance of research about the recognition of activity in the area of WISDM - (Wireless Sensor Data Mining) [11]. Despite a good accuracy some of the characteristics are not independent of orientation. They over 90% of recognition. On the other hand, Siirtola et al., [19] did a study on human activity recognition based on sensor independent orientation. A 95,8 % accuracy was reached with the classifiers Quadratic Discriminant Analysis

(QDA) and 93,9 % with K-NN, they used data from eight individuals performing 5 activities.

In this work the authors made a performance evaluation of the classifiers, Naive Bayes (NB), Random Forest (RF) and k-nearest neighbor (K-NN) with the most common features for activity recognition, including features extracted from both the vertical and horizontal acceleration. We extracted the vertical reference from gravity, and the vertical and horizontal accelerations. We have researched on a vector with 159 different features and on the vector subsets in order to improve the human activities recognition.

Sect. 2 describes how the data set was collected and the data transformation task. The assessment is made in Sect. 3 and Sect. 4 provides the conclusion of this paper.

2 Data Collection and Features Extraction

Data collection was carried out with an application created by us for the iPhone 4. This mobile device has large sensory and computational capabilities: assisted GPS, digital compass, accelerometer, three-axis gyro sensor and ambient light sensors. The iPhone 4 uses the LIS302DL microelectromechanical systems (MEMS) motion sensing piccolo accelerometer [6].

The accelerometer and digital compass RAW data was collected at a 60Hz frequency. We collected data from five male individuals aged between 22 and 41, who weighed between 63 and 92 Kg. The people involved performed eight different activities with the mobile phone placed in the front pocket of their trousers without the supervision of investigators. The activities selected were: walking, running, climbing stairs, going down stairs, sitting, standing up, up on elevator and down on elevator. We selected these activities because they are common in everyday life.

Our data set have 28780 instances of climbing stairs, 28873 instances of down stairs, 2497 instances of down in the elevator, 1876 instances of rise on elevator, 53950 instances of running, 39068 instances of walking, 11574 instances of sit and rise, 13448 instances of sitting and 34 of mixed data.

The collected data was manually labeled in order to apply supervised learning.

Some authors extract features based on mean, standard deviation, median, dynamic time warping, mean between axis, energy, characteristic frequencies, pearson correlation and magnitude [19, 11, 12, 20, 13, 2, 16, 5, 17]. In this work we have researched on a vector with 159 different features, (as described in Table 1) and on the vector subsets in order to improve the human activities recognition. We extracted features from the raw signal data, from the vertical acceleration, and from the Horizontal acceleration. We applied to the extracted time series the Dynamic Time Warping (DTW), the Median, the Mean, the Mean between axis, the Standard Deviations (STD), the Energy, the FFT principal components and Pearson correlation.

To calculate the characteristics for the time series classification a sliding window with 128 readings was used. The reading was performed at a rate (frequency) of 60 Hz with a sliding window of 128 readings, corresponding to 2.1333 seconds time window. The size of the segments and features was chosen based on the results of previous works and because of the FFT usage, the number of samples must be a power of 2.

2.1 Dynamic Time Warping

Dynamic Time Warping (DTW) Eq. 1 [18] is an algorithm for measuring similarity between two sequences which may vary in time or speed.

DTW is based on the idea of non-linear alignments between time series. Non-linear alignments has been used in bioinformatics and speech recognition communities [7]. DTW can deal with distortion on the time axis of the time series [4].

The Euclidean distance generates a pessimistic dissimilarity measure, DTW already produces a dissimilarity measure due to the more intuitive nonlinear alignments [10].

$$DTW(S,T) = \frac{1}{k} \cdot \sqrt{\sum_{i=1}^{k} W_k} \tag{1}$$

2.2 Horizontal and Vertical Acceleration

The acceleration readings (a) are taken with the iPhone containing the gravity vector (g) plus the Linear acceleration (l), Equation (2).

$$\overrightarrow{a} = \overrightarrow{g} + \overrightarrow{l} \tag{2}$$

Thus it is clear that to obtain the acceleration of the gravity, we have to separate these two forces. This can be done by applying a low-pass filter like the one in Equation (3).

$$\overrightarrow{g}_{t+1} = \alpha \cdot \overrightarrow{g}_t + (1-\alpha) \cdot \overrightarrow{a} \tag{3}$$

As shown in eq. (2), the linear acceleration equals to the gravitational acceleration plus linear acceleration. So to obtain the linear acceleration we have to remove the acceleration of gravity Eq. 4.

$$\overrightarrow{l} = \overrightarrow{a} - \overrightarrow{g} \tag{4}$$

The value of vertical acceleration (av) may be obtained by scalar multiplication between the gravitational vector and the acceleration measures Equation (5).

$$a_v = \overrightarrow{g} \cdot \overrightarrow{a} \tag{5}$$

With the vertical acceleration and the measure of acceleration, we can obtain the magnitude of horizontal acceleration by using the Pythagorean theorem, Equation (6).

$$h = \sqrt[2]{|\overrightarrow{a}|^2 - a_v^2} \tag{6}$$

3 Evaluation and Results

This section describes the experimental setup used in the experiments. Three different experiments were done.

First experiment: The features are ranked using as criterion the information gain [21]. The rank is done according to the individual evaluation of the features (Sect. 1).

Second experiment: feature subset selection algorithms were used in order to select the most adequate set of feature for each classification algorithm used, Naive Bayes, K-NN and Random Forest. Since we have a 159-size vector of features, an exhaustive search, the only one that can guarantee that the best subset is found, would be too slow. Consequently we decided to use greedy forward search [9, 14]. It starts with no attributes and stops when the addition of any remaining attribute results in a decrease in evaluation [9, 14]. This is a wrapper approach. It uses 90% of the dataset for training and the remainder 10% for validation.

Third experiment: with the same classification algorithms previously described, different features were tested:

- Median of Raw data;
- Dynamic Time Warping (DTW) of Raw data;
- Standard deviation (STD) of Raw data;
- 65 features from Raw data;
- 65 features from filtered data;
- 11 features from magnitude;
- 22 features from V. and H;
- All 159 features;
- Best set of features found by Tapia[20], the average distance between axes, STD, energy peaks of the FFT and correlation coefficients;
- Best set of features found by us, Pearson correlation between vertical acceleration and horizontal acceleration, Pearson correlation between x and y, Pearson correlation between x and z, STD of acceleration z , STD of digital compass y, STD of digital compass z,STD of digital compass x, mean between axis, energy of digital compass x, mean of acceleration x, mean of acceleration z, median of acceleration z.

This experiment used the 90% part of the dataset used in the previous experiment. This was done with 5-fold cross validation (Sect. 3.1).

The second and the third experiments are presented in figure 1.

All experiments use the WEKA software [21], and the classification algorithms Naive Bayes, K-NN and Random Forest. Cross Validation (Sect. 3.1) and Greedy Stepwise (Sect. 3.2) are used respectively in the experimental setup and in the wrapper approach for feature selection.

3.1 Cross Validation

Is a nested operator. It has two subprocesses: a training subprocess and a testing subprocess. The training subprocess is used for training a model. The trained

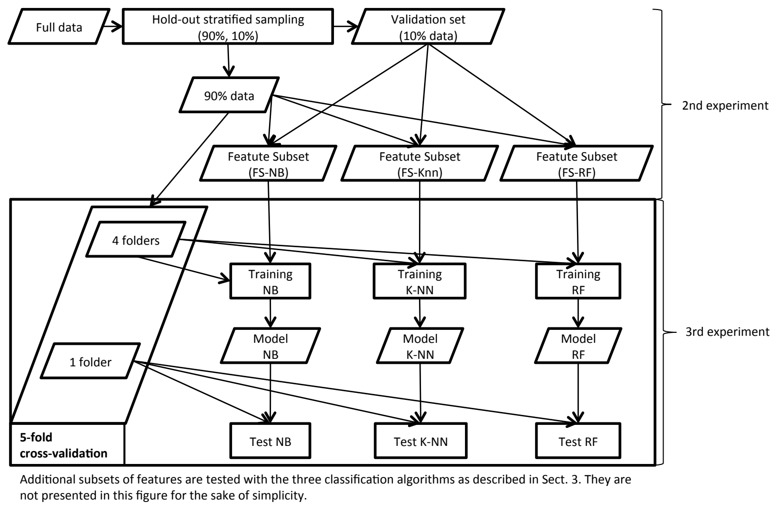

Fig. 1. features selection experimental setup

model is then applied in the testing subprocess. The performance of the model is also measured during the testing phase.

The input ExampleSet is partitioned into K subsets of equal size. Of the K subsets, a single subset is retained as the testing data set, and the remaining k subsets are used as training data set. The cross-validation process is then repeated K times, with each of the k subsets used exactly once as the testing data. The K results from the K iterations then can be averaged to produce a single estimation. The value K can be adjusted using the number of validations parameter.

The learning processes usually optimize the model to make it fit the training data as well as possible. If we test this model on some independent set of data, mostly this model does not perform that well on testing data as it performed on the data that was used to generate it. This is called 'over-fitting'. The Cross-Validation operator predicts the fit of a model to a hypothetical testing data. This can be especially useful when separate testing data is not present [21, 1].

3.2 Greedy Stepwise

Performs a greedy forward or backward search through the space of attribute subsets. May start with no/all attributes or from an arbitrary point in the space. Stops when the addition/deletion of any remaining attributes results in a decrease in evaluation. Can also produce a ranked list of attributes by traversing the space from one side to the other and recording the order that attributes are selected [21].

3.3 Results

We analyzed the results obtained in Tables 1 (first experiment), 3 (second experiment) and 2 (third experiment). The best result was obtained with the classifier Random Forest with all features which allowed to reach maximum accuracy of 99.97 % (Table 2). The behaviour of Random Forest according to the addition of more features is different comparing to Naive Bayes and K-NN. Indeed, Random Forest accommodates a kind of feature selection due to the CART induction algorithm. This does not happens in the other two algorithms used in these experiments. Consequently, the best feature subset for K-NN and Naive Bayes was found with greedy search (Table 3). The best set of features found was, the Pearson correlation between vertical acceleration and horizontal acceleration, the Pearson correlation between x and y, the Pearson correlation between x and z, the STD of acceleration z, the STD of digital compass y, the STD of digital compass z, the STD of digital compass x, the mean between axis, the energy of digital compass x, the mean of acceleration x, the mean of acceleration z, the median of acceleration z.

Table 1: Average Merit (AM), Average Rank (AR),Attribute Number(AN). Top 20 features description and Information Gain Ratio. The table with all 159 features is available at http://db.tt/5UprjG97

Features / Function	**AM**	**AR**	**AN**	**attribute**
STD of acceleration magnitude	0.380	1.0	65	Mag.STD.Accel
STD of vertical acceleration	0.360	2.6	86	Ver.STD.Accel
Mean of horizontal acceleration	0.359	3.2	84	Hor.Mean.Accel
DTW of vertical acceleration	0.359	3.4	87	Ver.DTW.Accel
DTW of horizontal acceleration	0.345	5.4	77	Hor.DTW.Accel
STD of raw acceleration y	0.339	6.4	100	Raw.STD.Accel.Y
STD of filtered acceleration y	0.338	6.4	5	Filtred.STD.Accel.Y
DTW of acceleration magnitude	0.331	7.8	66	Mag.DTW.Accel
STD of horizontal acceleration	0.326	8.8	76	Hor.STD.Accel
STD of filtered acceleration x	0.309	10.0	4	Filtred.STD.Accel.X
STD of raw acceleration x	0.308	11.0	99	Raw.STD.Accel.X
DTW of filtered acceleration x	0.297	12.2	10	Filtred.DTW.Accel.X
DTW of Raw acceleration x	0.294	12.8	105	Raw.DTW.Accel.X
Mean of magnitude acceleration	0.285	14.0	73	Mag.Mean.Accel
Mean of raw acceleration z	0.274	15.4	150	Raw.Mean.Accel.Z
Mean of Filtered acceleration z	0.273	15.6	55	Filtred.Mean.Accel.Z
STD of raw acceleration z	0.265	17.2	101	Raw.STD.Accel.Z
STD of filtered acceleration z	0.263	17.8	6	Filtred.STD.Accel.Z

Continued on next page

Table 1 – *Continued from previous page*

Features / Function	**AM**	**AR**	**AN**	**attribute**
Pearson y.z of filtered acceleration	0.254	19.4	3	Filtred.PearsonYZ
Pearson y.z of raw acceleration	0.255	19.6	98	Raw.PearsonYZ

Table 2: True positives rate (TP), False positives rate (FP), Precision (P), Recall (R), F-Measure(F-M) and accuracy. Evaluating pre-defined feature subsets using Random Forest, Naive Bayes and K-NN, trained and validated with 5-fold cross validation

Classifier	**Feature**	**TP**	**FP**	**P**	**R**	**F-M**	**ROC**	**Accuracy**
NB	Median of Raw data	0.556	0.096	0.653	0.556	0.518	0.862	55.60%
	DTW of Raw data	0.689	0.058	0.782	0.689	0.671	0.94	68.89%
	STD of Raw data	0.773	0.043	0.788	0.773	0.775	0.948	77.33 %
	65 features from Raw data	0.739	0.046	0.818	0.739	0.74	0.956	73.91%
	65 features from filtered data	0.74	0.046	0.818	0.74	0.741	0.956	73.95%
	11 features from magnitude	0.679	0.06	0.689	0.679	0.67	0.923	67.88%
	22 features from V. and H.	0.708	0.051	0.726	0.708	0.703	0.933	70.79%
	All 159 features	0.784	0.037	0.842	0.784	0.79	0.96	78.37%
	Features found by Tapia[20]	0.806	0.038	0.827	0.806	0.802	0.955	80.57%
	Best set of features found by us	0.93	0.012	0.94	0.93	0.933	0.987	93.00%
K-NN (k=5)	Median of Raw data	0.881	0.029	0.881	0.881	0.881	0.973	88.07%
	DTW of Raw data	0.999	0	0.999	0.999	0.999	1	99.92%
	STD of Raw data	0.998	0	0.998	0.998	0.998	1	99.77%
	65 features from Raw data	0.999	0	0.999	0.999	0.999	1	99.93%
	65 features from filtered data	0.999	0	0.999	0.999	0.999	1	99.92%
	11 features from magnitude	0.849	0.032	0.849	0.849	0.848	0.963	84.94%
	22 features from V. and H	0.922	0.016	0.923	0.922	0.922	0.987	92.21%
	All 159 features	0.999	0	0.999	0.999	0.999	1	99.87%
	Features found by Tapia[20]	0.995	0.001	0.995	0.995	0.995	0.999	99.49%
	Best set of features found by us	1	0	1	1	1	1	99.97%
RF	Median of Raw data	0.954	0.012	0.953	0.954	0.954	0.995	95.35%
	DTW of Raw data	0.999	0	0.999	0.999	0.999	1	99.93%
	STD of Raw data	0.997	0.001	0.997	0.997	0.997	1	99.73%
	65 features from Raw data	1	0	1	1	1	1	99.97%
	65 features from filtered data	1	0	1	1	1	1	99.97%
	11 features from magnitude	0.89	0.023	0.89	0.89	0.889	0.981	88.96%
	22 features from V. and H	0.967	0.006	0.967	0.967	0.967	0.998	96.72%
	All 159 features	1	0	1	1	1	1	99.97%
	Features found by Tapia[20]	0.999	0	0.998	0.999	0.999	1	99.86%
	Best set of features found by us	1	0	1	1	1	1	99.97%

The null hypothesis of equal performance between classifiers is rejected according to the Friedman Rank Test [8] for $\alpha = 0.05$ with a p-value of 0.00043. All pairwise comparisons is done using the Shaffer's static procedure [8]. It rejects

Table 3. Features selection with forward Stepwise search and 5 Fold Cross Validation

Algorithm	Feature	Correctly Classified	Incorrectly Classified	Accuracy
Naive Bayes	Filtred.PearsonXY, Filtred.PearsonXZ, Filtred.STD.Accel.Z, Filtred.STD.Comp.Y, Filtred.STD.Comp.Z, Filtred.DTW.Comp.X, Filtred.meanAxis, Filtred.Ener.Comp.X, Filtred.Mean.Accel.X, Filtred.Mean.Accel.Z, Filtred.Median.Accel.Z, Mag.STD.Accel, Mag.Mean.Accel, pearson.V.H, Raw.PearsonXY, Raw.PearsonXZ, Raw.meanAxis, Raw.Mean.Accel.X	167082	13018	92.77 %
k-NN (K=5)	MeanH, MeanV, MeanAcellz, STDAcellY, DTWAcellx, DTWv, MeanAcelly, freq4H, STDAcellX	179830	270	99.85 %

those hypotheses from Table 4 that have a p-value $\leq 0.016(6)$, i.e., there is a meaningfull difference between NB and RF, and between NB and KNN.

Table 4. Shaffer Table for $\alpha = 0.05$

$algorithms$	$p - value$
NB vs. RF	0.0001
NB vs. KNN	0.0133
KNN vs. RF	0.1573

4 Conclusion

We researched the performance of 159 features described in Table 1 with three classifiers, Naive Bayes, K-NN and Random Forest, for classifying 8 human activities. The best result was obtained using 12 features: Pearson correlation between vertical acceleration and horizontal acceleration, Pearson correlation between x and y, Pearson correlation between x and z, STD of acceleration z , STD of digital compass y, STD of digital compass z,STD of digital compass x, mean between axis, energy of digital compass x, mean of acceleration x, mean of acceleration z, median of acceleration z. With this set of features we achieve the accuracy of 99%. This set of features giver us, very good accuracy results and have low computational cost.

Wrapper approach with the search method Forward Greedy Stepwise is an simpler and relatively faster way to find a good features subset for activity recognition.

As we can see in Table 2, apply a noise filter didn't improve the activity recognition task, so, in our future work we will not dispense computational power on that task. In our future works we intend to explore new techniques for semi-supervised learning for data streams and apply to activity recognition.

Human activity recognition and monitoring involves a continuing analysis of large amounts of data. Any increase or decrease in accuracy, results in a wide variation in the number of activities correctly classified and incorrectly classified so it is very important to increase the rate of correct classification. This work provide a very accurate set of features for activity recognition and an efficient process to research accurate features for time series classification based on features.

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