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International Electronic Conference on Sensors and Applications
1 - 16 June 2014

www.mdpi.com/journal/sensors

Conference Proceedings Paper – Sensors and Applications

Dynamic Activity Recognition using Smartphone Sensor Data

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Published: 1 June 2014

Abstract: Smartphones equipped with various sensors provide sufficient sensor data and computation power to enable daily activity detection for applications such as u-healthcare, elderly monitoring, sports coaching and entertainment. Instead of applying multiple sensor devices, as observed in many previous investigations, this work proposes the use of a smartphone with its built-in accelerometer as an unobtrusive sensor device for real time activity recognition of basic daily activities. The proposal is tested experimentally through evaluations on real data collected from 50 participants. A prototype application is developed to demonstrate and evaluate the selected classification methods for the designated recognition tasks. The results indicates that the J48 classifier using a window size of 512 samples with 50% overlapping obtained the highest accuracy (i.e., up to 96.02%). To measure the actual classification accuracy, a 5×10-fold cross validation with different random seeds was performed on the dataset using WEKA. Finally, to determine whether a classifier is superior to another, 5×2 fold cross validation along with a paired *t*-test was subsequently performed on the results using J48 as the baseline scheme with the other classification algorithms being compared to it. A value of $p < 0.05$ was considered statistically significant.

Keywords: activity recognition; smartphone; accelerometer data; WEKA; machine learning

1. Introduction

Activity recognition is simply continuous monitoring of physical activity in a free living environment for prolonged periods. HAR (human activity recognition) provides new opportunities for context aware applications in various areas including healthcare [1,2], assisted living, sports coaching [3], security [4], virtual reality and wearable computing. Such systems can improve the quality of life, health, security, freedom and safety of the elderly population at home [5].

The task of achieving the goal of recognizing the daily activities starts with sensing the physical world. This has been approached in two different ways, namely external and wearable sensors. Smart homes [6,7] embedded with sensors in everyday objects are a typical example of external sensors. The foremost problem with using the external approach is its lack of pervasiveness, i.e. it forces the user to stay within a perimeter defined by the position and the capabilities of the sensors. The majority of approaches in HAR has relied on the latter case where multiple wearable sensors are attached at different locations of the body to detect everyday tasks such as sitting, walking, and running, using stairs and jogging [8,9]. Although this provides sufficient contextual information, placing sensors at multiple locations can become cumbersome for the wearer. This solution is obtrusive and many people may not like to have sensors attached to their bodies, clothes, or belts for that purpose. Therefore, the focus of this research is on activity recognition using smartphone as an unobtrusive sensor device that can be easily carried around by the users.

Nowadays, smartphones are equipped with multiple sensors, including accelerometers, gyroscopes, magnetometers, proximity, light, pressure, GPS and camera. This makes smartphones to serve as an unobtrusive device to collect data as compared to custom tracking systems. Furthermore, software creation and distribution are easier because open source tools allow anyone to create applications and deploy them on smartphones. Thus, smartphones conveniently contain all of the hardware and software capabilities required to create a stand-alone activity tracking system, with the practical benefit that people wear them every day. Although, HAR has been studied extensively in the previous works, implementing HAR system where the entire recognition process is done on a smartphone is a relatively new area. Recently, many studies have incorporated smartphones accelerometer for human activity recognition, such as [2,10-13]. However, most of the previous works have used smartphones as mere data collection devices, which sent data to an accompanying device (such as PC/server) for further processing. Performing real-time activity recognition locally on a smartphone is beneficial in terms of scalability, reliability, and energy consumption. However, it becomes challenging since smartphones are still constrained in terms of storage, processing and communication capabilities.

This paper reports an investigation on how we can empower users with unobtrusive context aware devices and proposes a design and implementation of a human activity and context recognition system that uses a smartphone. Analysis and system evaluations are carried out using both offline and online settings, for subject-dependent and subject-independent scenarios using data collected from the subjects.

2. Methods

2.1. Data Collection

For this study, activity data were collected from 50 healthy subjects (30 males and 20 females) between the ages of 21 and 35 years old, with an average height of 172cm and average weight of 67 kg. Six common dynamic activities were selected: walking, jogging, using stairs, sitting, standing and lying down. A custom build application was used for data collection and annotation. This application, through a simple graphical user interface, permitted to record the user's ID, start and stops the data collection, and label the activity being performed. The subjects carried the Android phone in their front trouser leg pocket for recording of the acceleration data. The data was collected in a *naturalistic* fashion, thus, no specific instructions were given to the participants on how to perform the activities except how to use this data collection application. The acceleration signals were sampled at 20 Hz and stored on a SD (Secure Digital) card in the smartphone. This sampling frequency is sufficient to capture most everyday activities [14]. Another reason to use lower sampling when possible is to reduce the load of the smartphone. The more data to be measured, the more resource will be needed for either storage, transmission or processing.

2.2. Feature Extraction

Standard classification algorithms cannot be directly applied to raw time-series accelerometer data. Hence, features must be extracted from the raw time series data. For this study, simple time domain statistical features were extracted from smartphone raw acceleration data using a window size of 512 samples with 256 samples overlapping between consecutive windows. Feature extraction on sliding windows with a 50% overlap has demonstrated reasonable results in previous works [8,15]. The choice of simple statistic features is due to the simplicity and low computational cost. Five features have been selected to be evaluated. These are: mean, standard deviation, MAD (mean absolute deviation), time between peaks and the resultant magnitude. Five features were extracted from each window, giving a total of 13 attributes. These features are then used as an input for WEKA (Waikato Environment for Knowledge Analysis) [16] data mining software to train and build the classifiers.

2.3. Classification Models

Various classification models have been applied in the field of human activity recognition. However, there is no universally accepted method of recognizing a particular set of activities and all approaches have associated limitations and benefits. For this study, in order to identify which machine learning algorithm provided the most accurate activity detection, eight different classification algorithms were applied to the data. These include: BN (Bayesian Network), MLP (Multilayer Perceptron), NB (Naïve Bayes), J48 (C4.5 Decision Tree), RT (Random Tree), RBFNet (Radial Basis Function Network), SMO (Sequential Minimal Optimization) and Logistic Regression.

To determine whether a classifier is superior than another, a 5×2 fold cross validation was performed using the WEKA experimenter. A paired t-test was subsequently performed on the results to identify if the percentage of correctly classified instances was significantly different using the J48 as the baseline scheme, with the other seven algorithms being compared to it. A value of less than $p = 0.05$ was considered statistically significant. To further evaluate the performance of our approach we have employed conventional metrics including the precision, the recall rate, the F-measure, FPR (false positive rate) and FNR (false negative rate).

3. Results and Discussion

3.1. Offline Analysis using WEKA (subject-independent)

In total eight classifiers were evaluated with five different random seeds $s_i \in \{1, 128, 255, 1023, 4095\}$. Table 1 shows the results of the 5×2-fold cross validation for the accelerometer dataset. To find the best classifier for the dataset, a paired two-tailed *t*-test was performed between the J48 and all other classifiers with a significance level $\alpha = 0.05$. Since all the *p*-values are below the significance level, there is strong statistical evidence that J48 is more accurate than all other classifiers in the tested dataset.

Table 1: Percentage Classification accuracy given by the 5×2-fold cross validation

	s_1	s_2	s_3	s_4	s_5	**Avg.**	***p*-value**
BN	76.8211	77.8112	77.1924	77.3868	77.2984	77.302	<0.001
MLP	93.9003	94.4484	93.8649	93.8649	94.1478	94.045	0.001
NB	58.0622	57.6025	57.4257	57.7086	56.4887	57.457	<0.001
J48	**94.9788**	**95.1556**	**95.0318**	**95.4031**	**95.2086**	**95.156**	-
RT	93.6704	94.4031	94.4837	94.6782	94.5191	94.351	0.004
RBFNet	72.0297	71.7999	71.0396	73.0375	72.7723	72.136	<0.001
SMO	89.4802	89.7808	90.1167	90.2758	89.71	89.872	<0.001
Logistic	91.9024	92.6096	92.4505	92.7157	91.7786	92.291	<0.001

Since, 2-fold cross validation takes into account only half of the dataset during training, it is essential to point out that a 5×2-fold cross validation is not performed to measure the classification accuracy but to rather find differences in the overall accuracy of the classifiers. To measure the actual classification accuracy, a 5×10-fold cross validation was performed on the dataset. After evaluating the best classifiers in each dataset for all five random seeds, the overall accuracy for J48 classifier reached 96.02% (see Table 2). A more detailed analysis was carried out for each activity by calculating a number of performance metrics.

Table 2: Evaluation metrics for the best classifier: precision, recall, F-measure, FPR, FNR for J48.

Overall Accuracy: 96.0219%						
J48	**Walking**	**Jogging**	**Stairs**	**Sitting**	**Standing**	**LyingDown**
Precision	0.971	0.92	0.851	0.967	0.957	0.964
Recall	0.98	0.875	0.845	0.958	0.973	0.948
F-measure	0.975	0.897	0.848	0.963	0.965	0.956
FPR	0.019	0.003	0.007	0.012	0.008	0.004
FNR	0.020	0.125	0.155	0.041	0.027	0.052

3.2. Online Recognition via two new subjects (subject-dependent)

In order to generate predictions on the user's activity, the alphanumeric representation of the Decision Tree model, as given by the WEKA output, was implemented in Java. Thus, the results presented here are more realistic. For this experiment, two individuals *A* and *B* who were new to the system were employed. During training mode, each user used the smartphone HAR application for annotating the activity they were performing for a certain amount of time. Meantime, the smartphone activity recognition application directly computes the classified activity using J48 algorithm, the confusion matrices and displayed on the phone. Table 3 (A) and (B) display the confusion matrices for J48 classifier for both individuals.

Table 3: Confusion matrix for Individuals *A* and *B*

		Individual A-Predicted Class (Overall Accuracy: 92.36%)					
		Walking	Jogging	Stairs	Sitting	Standing	LyingDown
Actual Class	Walking	30	0	1	0	0	0
	Jogging	0	19	0	0	0	0
	Stairs	0	1	39	0	0	0
	Sitting	1	0	0	7	5	0
	Standing	0	0	0	3	62	0
	LyingDown	0	0	0	2	0	0

		Individual B- Predicted Class (Overall Accuracy 97.30%)					
		Walking	Jogging	Stairs	Sitting	Standing	LyingDown
Actual Class	Walking	60	0	0	0	0	1
	Jogging	0	12	0	1	0	0
	Stairs	0	0	4	0	0	0
	Sitting	0	0	0	18	0	0
	Standing	0	0	0	0	0	0
	LyingDown	0	0	0	1	0	14

The confusion matrices show that the overall accuracy for individual *A* is quite lower (92.36%) than individual *B* (97.30%). However, the accuracies achieved show encouraging results even though these two individuals were not part of the training phase. The discrepancies in the results can be inferred that the gait and the intensity at which activities are performed are individual specific. Also, individuals *A* and *B* were of different physical characteristics than the participants who collected training data for offline analyses.

4. Conclusions

This work proposes the idea of online Human Activity Recognition system that focuses on using unobtrusive devices and services for the designated context aware features. The evaluation indicates that the J48 classifier using a window size of 512 samples with 50% overlapping yields the highest accuracy (i.e., up to 96.02%). To achieve this peak accuracy, time domain features were extracted from raw accelerometer data using smartphone. This system partially integrates the WEKA API in the Android Platform to enable the recognition of different activities. The system does not require a server for feature extraction and processing, thus, reducing the energy expenditures and making it more robust and responsive. The mobile HAR system is flexible, as performing the recognition and feature extraction computations locally on the smartphone mitigates the server load.

Acknowledgments

This work was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (NRF-2009-0093828) and the Woojung Education & Culture Foundation of Korea.

Conflicts of Interest

"The authors declare no conflict of interest".

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