On the Development of A Real-Time Multi-Sensor Activity Recognition System

Oresti Banos[1], Miguel Damas[2], Alberto Guillen[2], Luis-Javier Herrera[2], Hector Pomares[2], Ignacio Rojas[2], Claudia Villalonga[2], and Sungyoung Lee[1]*

[1] Ubiquitous Computing Lab, Kyung Hee University
Yongin-si, Korea
{*oresti,sylee*}*@oslab.khu.ac.kr*

[2] Department of Computer Architecture and Computer Technology,
University of Granada, Granada, Spain
{*mdamas,aguillen,jherrera,hector,irojas,cvillalonga*}*@ugr.es*

Abstract. There exist multiple activity recognition solutions offering good results under controlled conditions. However, little attention has been given to the development of functional systems operating in realistic settings. In that vein, this work aims at presenting the complete process for the design, implementation and evaluation of a real-time activity recognition system. The proposed recognition system consists of three wearable inertial sensors used to register the user body motion, and a mobile application to collect and process the sensory data for the recognition of the user activity. The system not only shows good recognition capabilities after offline evaluation but also after analysis at runtime. In view of the obtained results, this system may serve for the recognition of some of the most frequent daily physical activities.

Keywords: Activity recognition, Wearable sensors, mHealth

1 Introduction

The identification of human activities has attracted very much attention lately. Typically, wearable sensors are used to register body motion signals that are analyzed by following a set of signal processing and machine learning steps to recognize the activity performed by the user [1]. Most of the existing works in this area contribute with diverse models that normally yield very high recognition capabilities [7, 2]. However, a major part of these solutions have only been validated in controlled environments and through offline evaluations. More importantly, there is a lack of papers covering the whole design process for the development of a system that can actually recognize human activity in realistic settings. This paper aims to help filling this gap by contributing with a detailed description of the steps required to develop a fully functional activity recognition system for the real-world.

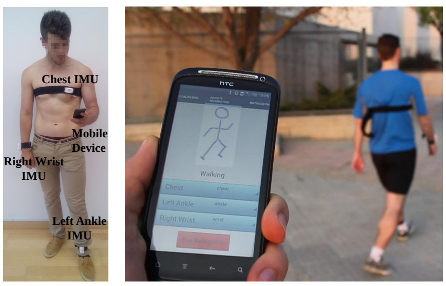
* Corresponding author.

2 Sensing Infrastructure and Processing Hub

The use of single-sensor recognition systems has predominantly been fostered in the past [4, 2]. However, multi-sensor configurations have recently been shown to be required when dealing with real-world technological and practical issues [12, 8, 11]. Likewise, dedicated systems have been used to gather and process the data coming from multiple sensors to estimate the user activity. Nevertheless, this trend has lately shifted towards the use of mobile devices since they offer higher computational power and memory capacity among other features. Accordingly, the system proposed here consists of three wearable inertial sensors (Fig. 1(a)), which are used for registering the user body motion, and a mobile application (Fig. 1(b)), devoted to collecting and processing the sensory data for the recognition and visualization of the user activity. Shimmer2 wearable sensors are used given the high reliability yielded by these commercial devices. The sensors are respectively placed on the subject's chest, right wrist and left ankle and attached through elastic straps. These placements cover most body movements assuming that the activities involve a symmetrical execution. The sensors measure the acceleration, rate of turn and magnetic field orientation of the body parts they are fastened to. The sampling rate used for all sensing modalities is of 50 Hz, enough for capturing human activity. The sensors are Bluetooth interfaced with the mobile device, which hosts an application built for the aggregation and processing of the data based on a given activity recognition model.

3 Activity Recognition Model Design

The process of designing an activity recognition model involves three steps: 1) collection of a dataset; 2) definition of candidate models; and 3) evaluation and selection of the most reliable model. The dataset used here comprises body motion recordings for ten volunteers wearing the inertial sensors as depicted in Fig. 1(a), while executing a set of regular activities (Table 1) in an out-of-lab environment. A detailed description of the dataset can be found in [10].



(a) (b)

Fig. 1. (a) Study setup and sensor deployment. (b) Running application.

Table 1. Activity set.

L1: Standing still (1 min)	L7: Frontal elevation of arms (20×)
L2: Sitting and relaxing (1 min)	L8: Knees bending (crouching) (20×)
L3: Lying down (1 min)	L9: Cycling (1 min)
L4: Walking (1 min)	L10: Jogging (1 min)
L5: Climbing/descending stairs (1 min)	L11: Running (1 min)
L6: Waist bends forward (20×)	L12: Jump front & back (20×)

Standard recognition models are built then for evaluation. All models use triaxial acceleration data since it is the most prevalent sensor modality in wearable activity recognition [5]. The signals are segmented through a 2-seconds non-overlapping sliding window approach, which proves a good trade-off between recognition speed and accuracy for the activities of interest [9]. Three incremental feature sets are considered for their discrimination potential and easy interpretation in the acceleration domain [4]: FS1 = "mean and standard deviation", FS2 = FS1 + "maximum, minimum and mean crossing rate" and FS3 = FS2 + "mode, median and kurtosis". Likewise, four of the most common machine learning techniques are used for classification: decision trees (DT), k-nearest neighbors (KNN), naive Bayes (NB) and nearest centroid classifier (NCC). The k-value for the KNN model is empirically set to three.

The resulting models are evaluated through a 10-fold cross validation process, which is repeated 100 times to ensure statistical robustness [3]. The F_1-*score* is used to measure the performance of each candidate model. The results obtained after evaluation are shown in Fig. 2. Those models utilizing DT for the classification process are clearly the most accurate among considered for all feature sets. Moreover, the feature set that leads to the best results is FS2. Thus, the model considered for implementation builds on the triaxial acceleration collected from the three wearable sensors; partitions these signals into data windows of two seconds; extracts the "mean, standard deviation, maximum, minimum and mean crossing rate" from every data window; and inputs these features to a DT classifier trained on all the dataset.

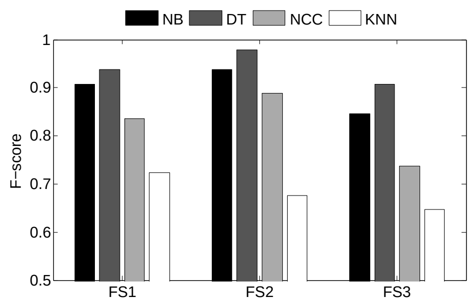


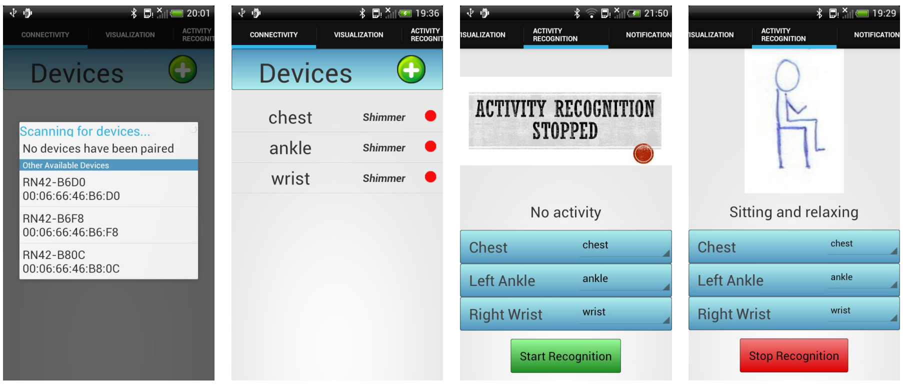
Fig. 2. Results from the offline evaluation of standard activity recognition models.

4 Activity Recognition Application Development

The activity recognition process is performed on a mobile device. Concretely, an intuitive app is developed to continously gather the data from the wearable sensors and process it according to the model described before. During the very first configuration of the app, the sensors must be Bluetooth paired with the mobile device (Fig. 3(a)). Each sensor is labeled to correctly match each data stream to the corresponding input of the recognition model (Fig. 3(b)). Thereafter, the user can start the activity recognition process by clicking on the corresponding start button (Fig. 3(c)), which also triggers the streaming of the wearable sensors to the mobile device. From then on, the app shows the recognized activity based on the analysis of the movements performed by the user (Fig. 3(d)).

The application has been implemented using the mHealthDroid framework [10]. This open source framework is devised to support the agile and easy development of mHealth applications on Android. The communication functionality relies on the mHealthDroid Communication Manager, which abstracts the underlying mobile and wearable devices, makes the communication transparent to the application and provides a unified and interpretable data format. Concretely, the mHealthDroid Adapters for Shimmer2 wearable devices are used for these devices to communicate with the mobile phone and to map their data to the proprietary format. In this manner, the registered triaxial acceleration samples are made available to the diverse components of the application.

A major interest in using mHealthDroid comes from the functionalities it provides for implementing a full recognition model. The Segmentation, Feature Extraction and Classification functionalities of the mHealthDroid Data Processing Manager are used here, some of which build on a stripped version of the



(a) (b) (c) (d)

Fig. 3. Snapshots from the activity recognition application: (a) scan process for discovering the sensors; (b) wearable sensors are paired and further labeled according to their placement; (c) sensors are matched to the corresponding inputs of the recognition model; (d) the application recognizes the activity performed by the user.

popular WEKA Data Mining Software [6]. Thus, to realize the designed recognition model, a 2-seconds windowing process is generated, the required statistical features are instantiated and the trained DT model is implemented.

The sensory data collected during the execution of the system can also be stored on a local database. Although this is not required for the recognition of the user activity, it is considered here for a potential inspection and review of the collected data at the point of need. The mDurance storage functionality builds on top of the mHealthDroid Storage Manager, which provides a high level of abstraction from the underlying storage technology and enables data persistence, both locally and remotely. In the current implementation, the app stores data locally on a SQLite database deployed on the mobile phone SD card.

5 Real-Time Evaluation

The developed recognition system is validated at runtime in realistic conditions. To that end, five independent volunteers were asked to perform the complete activity set (Table 1). Both user's activity and smartphone's screen were recorded on video for the evaluation of the system performance. The results of the evaluation are shown in Fig. 4. In broad strokes, it can be said that the system shows good recognition capabilities. Only a few misclassifications are observed. For example, during the identification of "sitting and relaxing", the model sometimes interprets that the users are bending their waist forward or elevating their arms. This is explained by some abrupt movements observed during the execution of this activity for some of the participants. Similarly, some errors are found for the detection of "knees bending or crouching", which is confused here again with "waist bend forwards". This is a consequence of some difficulties encountered by part of the users while performing this exercise, which translated into a moderate sway back and forth. Finally, a few misclassifications are observed among "walking", "jogging" and "running", which are basically originated from the varying cadence with which these activities were executed by the subjects.

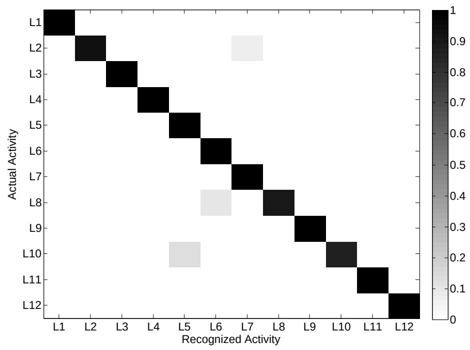


Fig. 4. Confusion matrix obtained from the online evaluation of the activity recognition model. Activities are identified through the labels used in Table 1.

6 Conclusions

This work has summarized the complete process for the realization of a multi-sensor activity recognition system for real-time applications. The system employs various wearable inertial sensors attached to different body parts to register a wide-spectrum of regular movements. The recorded data is transmitted to a mobile application that processes the information for the recognition of the user activity. This application develops on a recent mHealth framework that provides several functionalities significantly reducing the implementation time. Future extension of this work includes the incorporation of healthy physical lifestyles recommendations based on the analysis of the user activity patterns.

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