Robust smartphone-based human activity recognition using a tri-axial accelerometer

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***Abstract*—Mobile artifacts such as smartphones have made possible the development of wearable systems for user activity monitoring and recognition due to the synergy of communication, computation and sensing capabilities in battery-powered systems-on-chip. Due to user acceptability, smartphones are able to measure nonintrusively proprioceptive motion outside of a controlled environment for rather long periods of time using embedded inertial sensors. Though work has been done for accelerometer-based activity recognition, the portability of the smartphone to a single fixed tight position has been a major constraint to easy the interpretation of the collected data. In this paper, a human activity hierarchical recognition system based on time-domain features and neural networks without the need of the smartphone to be constrained to a single fixed body position is presented. Experimental results on Android-capable smartphones on four on-body locations show that the recognition system achieves high classification rates, above 92%, for five activities including static, walking, running, and up-down stairs walking, running continuously in near real-time with reduced power consumption.**

I. Introduction

Studies have shown that knowledge of human activities and behaviors are good indicators to assess human health status associated to sedentarism [1], and that activity recognition is a low-level enabler of mobile health (mHealth) systems whose purpose is to improve human health and well-being by continuously monitoring their status, rapidly diagnosing, recognizing behaviors and delivering just-in-time interventions in the mobile user environment [2]. Thanks to the advances in microelectromechanical (MEM) technologies, wearable inertial sensors directly attached to the human body or embedded into portable devices such as smartphones can be used to monitor human activity [3]. Due to their communication, computation and sensing capabilities, smartphones have become everyday devices that many people carry with them all day long, which facilitate both remote acquisition and on-device processing of personal, social or environmental data, captured through embedded physical sensors [4][5][6].

It is known that the acceleration, measured by inertial sensors, during human movement varies both across the body and upon the activity being performed; the acquired signals might be totally different for the same user activity with sensors placed on different locations. Generally, as the actual device location and orientation is not known a priori, a recognition system must solve the position dependency by imposing some placement constraints to reduce the problem complexity [7]. Yet, in practical applications, factors such as sensor sampling rate, processing time, memory size and power consumption, are particularly important for deployment of a given solution to a mobile device [8]. Although high-end smartphones are equipped with high performance microprocessors, activity recognition should not represent a computational overhead as other applications in the software stack run simultaneously on top of the operating system (OS) and the whole processing power is not fully available at any time for just a single task.

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Most accelerometer-based daily physical activity recognition systems use multiple accelerometers attached to different locations on a subject body [9][10], and fewer ones use a single accelerometer attached to a specific location [1][11][12][13]. Under such constrained scenarios, the solutions achieve good offline recognition results, i.e., activities are recognized outside the mobile device, using the device just as a wearable sensor for sampling and storing. For feature extraction, most works targeted to mobile devices use time domain features, but others have used frequency domain features employing the Fourier transform or the wavelet transform to improve precision at the cost of computational load. Several classification methods have been used for activity recognition ranging from heuristic classifiers to artificial neural networks (ANNs) combined with kernel discriminant analysis (KDA) and support vector machines (SVM), which must be carefully ported to battery-powered mobile devices. In [12] and [13], authors present a hierarchical scheme for accelerometer-based activity recognition using statistical signal features and ANNs. The upper level recognition uses coefficients of an autoregressive (AR) model of the acceleration vector along with the signal-magnitude area and tilt angle to form an augmented-feature vector, which is further processed by the linear-discriminant analysis. Such method recognizes 15 activities with an average accuracy of 97% using only a single triaxial accelerometer attached to the user body fixed to a single position, but their proposal is not validated in a smartphone device. In [14], authors extend their work to address position-independent recognition, but processing is still performed offline. Recall that the proposed work herein aims at position-independent activity recognition in a mobile device for continuous monitoring.

In this paper, a position-independent activity recognition system for continuous real-time monitoring to be used as stand-alone in a smartphone, based on a single embedded triaxial accelerometer, and that works naturally and unobtrusively for the user, at some extent, is presented. Some typical locations on the subject body were considered and no restriction is

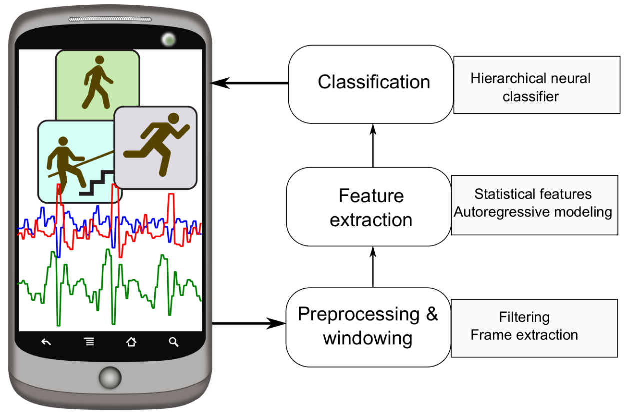

Fig. 1: Block diagram of the main processing steps for activity recognition from an accelerometer embedded in a smartphone.

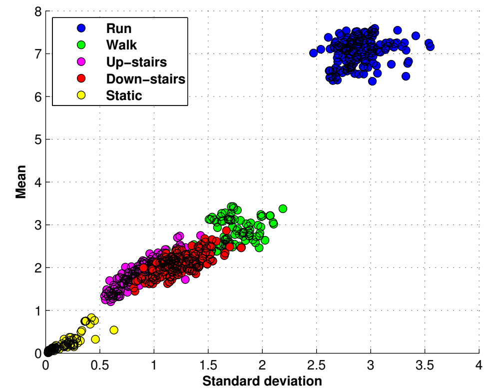

Fig. 2: Feature distribution for instances in the training dataset.

imposed on the orientation of the device; front and back trouser pockets when performing a set of daily routine activities (static, walking, running, upstairs and downstairs walking). The rest of this paper is organized as follows. Section II presents in detail the proposed hierarchical neural recognition system. Experimental results and analysis are provided in section III, as well as performance and power consumption of a proof-of-concept application ported to Android capable smartphones. Finally, concluding remarks and future work are presented.

II. Activity recognition system

Figure 1 shows a block diagram of the main processing steps of a typical accelerometer-based activity recognition system; the particularities for each step in the proposed approach are also outlined, and then described in more detail in the following subsections. In the preprocessing stage, redundancy and noise are minimized and then more computationally efficient representations of data, features, are extracted. The selected features are used as inputs to the classifier to determine the activity being performed. Lightweight feature extraction mechanisms well coupled with classifiers are required to better adapt to resource constraints of mobile platforms [4].

A. Preprocessing and windowing

To remove gravity, static acceleration, a first order high pass filter was applied on each acceleration component, and for noise reduction a three-point moving average filter was applied [15]; then the vector magnitude was used to reduce the effect of device orientation. According to experiments, accelerometers in Android devices are likely sampled irregularly because of the restricted sampling mechanism. Thus, linear interpolation was applied in order to estimate missing samples. A non-overlapping sliding window was used to segment the signal into small windows or frames. Note that the window size is a key parameter that affects both the computation and the power consumption of classifiers and must be taken into account when ported to a mobile device [16].

B. Feature extraction

The extracted time-domain statistical features [17] are summarized in Table I. Mean and standard deviation are commonly used to differentiate body postures and for activity intensity [4]. Figure 2 shows a typical class distribution of instances in the dataset, see details in section III; note the discriminative ability of standard deviation and median for static and run from other activities. An autoregressive model over the magnitude signal is performed as suggested in [12]. Principal components analysis (PCA) was applied to remove any correlation among features and to reduce further the feature vector dimensions.

C. Hierarchical neural classifier

Following the proposal in [13] and [18], a hierarchical neural recognition scheme, figure 3, is proposed in this work. The hierarchical structure is used as it has been shown that neural networks (NNs) perform well when a single activity needs to be detected instead of using a large network for the recognition of various activities [18]. The recognizer discriminates between physical activities ranging from coarse levels, such as moving or stationary, to finer levels of motion, such as down-stairs and upstairs walking. Static or dynamic recognition, is done at the first level in the hierarchy, L_1, using only statistical features and a simple perceptron as well as for the L_2 level. At lower levels from L_3 to L_4, as the interclass correlation increases, the number of features is augmented and larger multilayer feedforward NNs are employed. This hierarchy model is similar to decision trees, but training on each level is performed in supervised mode. A hierarchy of thresholds is a computationally efficient; once a NN has asserted a given class, the rest of the NNs are not computed and when the classifier is ported to a mobile device, timing and power consumption are improved in a mobile device.

III. Experiments and evaluation

A dataset was collected using an application on a Samsung Galaxy Ace GT-S5830M device, with the Android OS version 2.3.6, see figure 4 for some screenshots. The application can operate in three different modes: data acquisition, offline processing for debugging purposes, and real-time activity continuous background monitoring. The *game* sampling rate was used for data acquisition, which is around 40 Hz, but a constant sampling is not guaranteed as it depends on the computational load and the capabilities of the device. Data was collected for three subjects performing five different activities wearing the

TABLE I: Selected time-domain features used for accelerometer-based activity recognition.

Feature	Mean	Standar deviation	Percentiles	Coefficients AR modeling
Formula	$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i$	$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2}$	$P_k = k(n+1)/100$	$x(n) = \sum_{k=1}^{M} a_i x(n-k) + \varepsilon(n)$

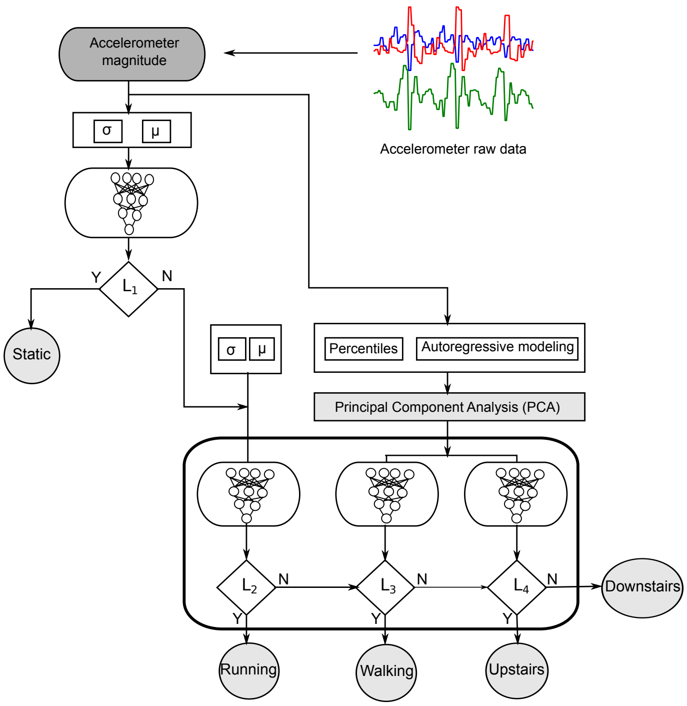

Fig. 3: Hierarchical neural activity classifier; the processing overhead increases from top to bottom, L_1 to L_4.

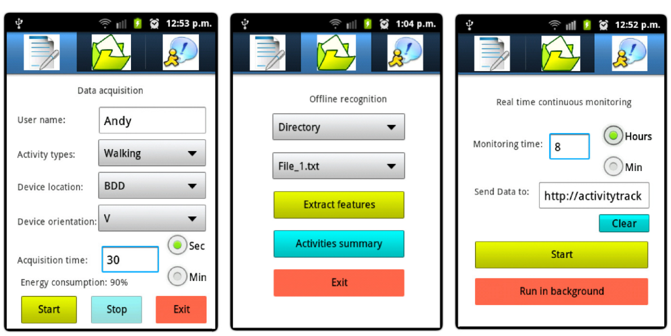

Fig. 4: Screenshots of the three main operation modes of the Android application: data acquisition (left), offline processing and debugging (middle), and real-time monitoring (right).

device at four different locations; two front pockets and two back pockets, without restriction in the device orientation. For each activity-location combination, each subject performed for 5 trials of one minute long.

TABLE II: Main characteristics of the NNs used in the different levels of the hierarchical neural classifier.

Level	Network	Input features	Transfer function
L_1	Perceptron	σ, μ	hard limit
L_2	Perceptron	σ, μ	hard limit
L_3	Feedforward (25-2-1)	$PCA_{25}(\sigma, AR_{Coeff})$	tangent sigmoid
L_4	Feedforward (25-2-1)	$PCA_{25}(P_{95}, AR_{Coeff})$	tangent sigmoid

TABLE III: Confusion matrix for the proposed recognition system using a single user dataset.

Class	Static	Run	Walk	US	DS	Overall	Precision
Static	**150**	0	0	0	0	150	**100%**
Run	0	**152**	0	0	0	152	**100%**
Walk	0	0	**148**	3	7	158	**93.6%**
US	0	0	6	**139**	18	163	**85.2%**
DS	0	0	7	11	**136**	154	**88.3%**
Total	150	152	161	153	161	**777**	
Recall	**100%**	**100%**	**91.9%**	**90.8%**	**84.4%**		**93.3%**

A. *Classification performance evaluation*

A time window of 5 seconds was used, i.e., around 200 samples per window, in the experiments for parameter tuning and to verify the system accuracy. For AR modeling, 50 coefficients were used to approximately recover the acceleration signal, and 25 coefficients from PCA were used (97% of the variance). An offline k-fold ($k = 10$) cross validation was used on the dataset; the NN parameters for each level in the hierarchy are shown in table II. Precision and recall for a single user data are shown in table III. The importance of the obtained results is that different smartphone locations were allowed. The user-specific trained classifier generalizes well on data from other three users, a precision over 86% was obtained. Other classifiers such as NB (Naïve Bayes), K-NN (k-nearest neighborhood), and SVM (Support Vector Machine) were implemented for comparison. The proposed solution average performance is better than the others as shown in table IV. The up-stairs (US) and down-stairs (DS) walking are the most difficult activities to be recognized accurately.

B. *Execution time and power consumption*

Three smartphones were used for evaluation; their main characteristics, the execution time and the power consumption results are summarized in table VI. A typical application power consumption profile, using the Android BatteryManager API, is shown in figure 5. The battery was fully charged, to ensure identical starting conditions, and then the application run in background until the battery was depleted (from 10 to 16 hours).

TABLE IV: Comparison with other classifiers. Acronyms: NB (Naïve Bayes), K-NN (k-nearest neighborhood), SVM (Support Vector Machine), P (Precision), R (Recall).

	NB		K-NN		SVM		Proposed	
Class	**P**	**R**	**P**	**R**	**P**	**R**	**P**	**R**
Static	100	99.3	100	99.3	100	99.3	**100**	**100**
Run	100	100	100	100	100	100	**100**	**100**
Walk	91.1	85.7	79.2	84.4	91.0	59.1	**93.6**	**91.9**
US	80.9	88.6	78.1	86.9	57.3	93.4	**85.2**	**90.8**
DS	82.2	79.2	79.4	65.8	57.5	39.6	**88.3**	**84.4**
Average	90.8	90.6	87.3	87.3	81.1	78.3	**93.4**	**93.4**

TABLE V: Timing (milliseconds) for the processing steps on three devices; time for AR model is enclosed in parenthesis.

Smartphone device	Preprocessing (ms)	Feature extraction (ms)	Classifier (ms)
Samsung Galaxy Ace ARM 11, 832 MHz, 278 MB Android 2.3.6, 1350 mAh	185	553 (550)	573
Samsung Galaxy S Cortex-A8, 1 GHz, 512 MB Android 2.1, 1500 mAh	56	161 (160)	195
Samsung Galaxy Note II Cortex-A9, 1.6 GHz, 2 GB Android 4.1.1, 3100 mAh	35	146 (145)	156

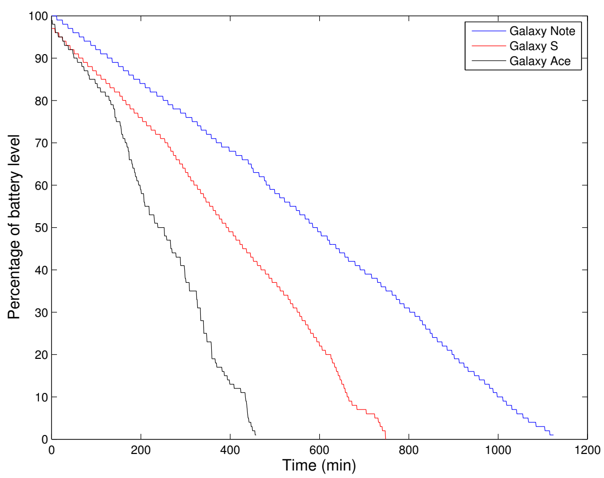

Fig. 5: Energy consumption profile of the activity recognition system on three different Android smartphones.

IV. Concluding remarks

In this paper a robust human activity recognition based on a single triaxial accelerometer has been proposed. It considers some typical locations where users carry out the smartphone without a firm attachment to the subject. A fully implementation on smartphones show near real-time performance and low power consumption thanks to the on-device lightweight processing. Experimental results show that the system performance compares favorably with previous works. Despite these encouraging results, further work is still needed to improve the system portability across individuals on larger datasets and to better identify new classes at run time.

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