Activity Recognition Using Smartphones and Wearable Wireless Body Sensor Networks

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Abstract. This paper explores automated activity recognition using a WIreless Sensor nEtwork (WISE) connected via Bluetooth to a smartphone. Automated activity recognition enables patients, such as diabetics, to keep more accurate logs of their activities (intensity and duration of the activity) and so to prevent short-terms complication, such as hypoglycaemias. We developed a platform records motion using two wearable sensory devices equipped with 3-axis accelerometers, worn on the waist and the shank, and a wireless heart rate monitor. Data are transmitted via Bluetooth to a smartphone, annotated and analyzed to recognize user activity. WISE platform architecture is described along with recognition accuracy performed by multiple classifiers.

Keywords: activity recognition, body sensor network, classification, chronic diseases.

1 Introduction

Technical advances in sensors miniaturization has extend their usage in various daily and medical applications, while most of the sensors tend to be wirelessly interconnected. Their small size enabled the development of wearable devices that can be used to create Body Sensor Networks (BSNs) to transmit medical data in real time. Our implementation targets to provide patients and health professionals with an innovative mechanism to easily and accurately recognize daily physical activities, in terms of type, duration and intensity. A smart and non invasive activity recognition mechanism provides objective quantification of user's locomotion, helping health professionals to have a better overview of their patient's daily habits and allowing them to modify their medication or educate them more effectively. Smartphones have been used to promote patients' self-management [1], although their usage will expand further as they are interconnected with wearable wireless sensors to transmit user's vital signals. Automated activity recognition enables patients suffering from chronic diseases (Diabetes, Parkinson's Disease, etc) to keep more accurate logs on their daily activities and help them maintain more stable blood glucose levels (diabetics), or monitor and classify objectively the severity of their disease induced movements (parkinsonians) [2].

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2 Related Work

A number of relate studies has been performed using five biaxial accelerometers placed on the right ankle, the left thigh, the waist, the left upper arm and right wrist, trying to distinguish whole body movements and activities involving partial body movement (standing still, folding laundry, brushing teeth, watching TV or reading) [3]. Lester used one board embedded with eight sensors on the shoulder to classify physical activities such as sitting, standing, walking etc [4]. Ravi *et al* proposed the usage of an accelerometer placed near the pelvic region to detect activities, demonstrating the ability of distinguishing daily physical activities with a single accelerometer [5]. Parkka *et al* performed measurements in free living conditions investigating various activities recognition, although, the devices used were quite bulky and heavy [8].

In contrast to the related work, our platform (sensors and smartphone application) targets to provide a versatile, compact, lightweight, low cost and power efficient platform for activity monitoring of patients and healthy individuals using mainly open-source hardware and software, with high accuracy.

3 Platform Description

Our target on the development of the WISE BSN was to provide both health professionals and patients with a comfortable, non invasive platform to monitor vital parameters and motion. In that sense, we developed two similar sensors to acquire the data and transmit them wirelessly to a smartphone via Bluetooth protocol.

Two versions of the WISE sensors were developed, a basic and an extended version. Both are equipped with 3-axis, low noise and low power, accelerometers (ADXL335) to record motion with a sampling rate of 20 samples per second. Sampling rate proved adequate to identify daily activities described below, while keeping power consumption at low levels. The extended sensor version is equipped additionally with Polar Heart Rate Module (RMCM01) to receive and parse data transmitted by a Polar, chest worn, heart rate monitor. The recorded data are transmitted via Bluetooth protocol to a smartphone running Android 2.2 operating system. Data are stored locally for further analysis.

The sensors are equipped with Li-Pol rechargeable batteries, power consumption of the devices is relatively low, and during our measurements we succeeded to acquire data for more than 8 hours in a row without recharging, proving that it can be used for daily monitoring purposes. This, along with the fact that the devices are equipped with a USB port to recharge the battery, seems to make the sensors adequate for medical applications where data should be collected for long periods of time. The size of the sensors is relatively small. Packaging dimensions are 6.8 x 3.0 x 1.0 cm, and the weight is 50 gram (battery included), making them fairly portable and lightweight for everyday usage, as they can be worn under the clothes. The packaging of the sensors consists of a belt-clip to attach the sensor around the waist and a stretching strap that allows the sensor to be attached on the shank. Both sensors are equipped with LEDs to provide their status (power, connected to the mobile, heart rate received etc).

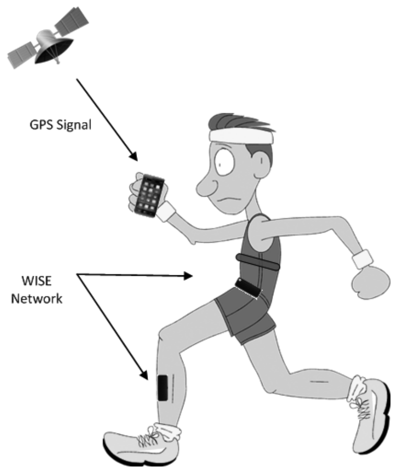

Fig. 1. Graphical representation of the *WISE Body Sensor Network*. One sensor is placed around the shank and the other one is placed around the waist. The heart rate monitor transmits the heart beat to the waist sensor and they both transmit the measurements via Bluetooth to the smartphone. GPS signal is also acquired to determine accurately the speed of the user.

4 Feature Extraction and Classification

4.1 Methodology

During our tests, healthy individuals, male and female, participated in data collection to train the classifiers. The average age of the participants was 28 ± 8 years old. We used both versions of WISE sensors, one place on the waist and one on the shank. Data collection performed following a predefined protocol, which included stair ascending and descending, standing, walking, jogging and running. Average recording time of all the individuals was almost 3 hours of data. The smartphone application developed and used for data annotation allowed the storage of speed and elevation data, acquired by the GPS receiver, embedded in the mobile phone. This information used to automatically discriminate activity intensity.

Data annotation performed by the users, using the prototype data collection mobile application. Upon data collection, raw accelerometer signal and heart rate were divided into epochs. We used half overlapping sliding window to classify the data. Window size selected to be 1 second long, allowing data identification of both rapid and slow movements. Each window includes 40 frames of data (20 samples per second per WISE sensor). The features we used to classify the recordings were mean, variance, energy and heart rate (19 features). Energy calculated as the sum of the absolute values of the FFT components. Data analysis performed using WEKA toolbox, an open source data analysis software developed by the University of Waikato [6]. The analysis performed using all the extracted features, but the primary results showed that by reducing the number of the features from 13 to 7, the results are better. Then, speed data provided by the GPS signal included as an extra feature, resulting to 14 features. The 10-folder cross-validation used to evaluate classification accuracy. All the test cases were put in one dataset and then randomly divided it into 10 equal-sized folders. Each time one folder used the test dataset and the rest the training dataset.

4.2 Classification and Results

The activities identified were: walking (various at speeds), jogging, running, ascending and descending stairs, standing or sitting and driving. Classification performed using Naive Bayes, Ensembles of Nested Dichotomies [10], Multilayer Perceptron with back-propagation (one hidden layer with 12 hidden nodes, learning rate 0.3 and momentum 0.2, 500 epochs sigmoid for activation), Decision Trees implementing C4.5 pruned algorithm, Random Forest of 10 trees considering 4 random features classifiers and Functional Trees [7] [9]. The results of the classification executed on the collected datasets are summarized in Tables 1 and 2.

4.3 Result Analysis

Examining the results shown in Tables 1 and 2, it can be assumed that WISE platform provides relatively accurate results, regarding activity recognition, especially when Functional Trees (FT) are used for data classification. Examining the confusion matrix of the FT classifier (Table 2), it is clear that most of the activities can be discriminated from the other and that the activities that cause misclassification errors are stairs versus walking. This can be explained due to the fact that annotation “walk” is given when there is absence of GPS signal (no speed data), something that also happens upon ascending/descending stairs because most of the times happens inside a building.

Table 1. Classification results using 14 features and various classifiers

Classifiers	**14 Features**			
	Correctly Classified	Precision	Recall	F-Measure
Naive Bayes	84.52%	85.30%	84.50%	83.70%
END	95.93%	96.10%	95.90%	95.90%
Multilayer Perceptron	95.99%	95.80%	96.00%	95.80%
Functional Trees	**97.28%**	97.20%	97.30%	99.10%
Random Forest	93.89%	94.30%	93.90%	98.90%
Decision Tree C4.5	94.84%	94.90%	94.80%	94.80%

Table 2. Confusion matrix of Functional Trees classifier

	Activity	a	b	c	d	e	f	g	h	i	j
a	Walk	2917	0	1	0	0	0	13	13	98	0
b	Walk ≤ 3 km/h	0	5502	2	0	0	0	3	0	16	0
c	Walk 3 ~ 5 km/h	2	3	5640	0	0	0	6	0	3	1
d	Walk 5 ~ 7 km/h	0	0	0	427	0	0	0	0	0	0
e	Walk 7 ~ 9 km/h	0	0	0	0	40	0	1	0	0	0
f	Running	1	2	2	0	0	536	77	10	1	0
g	Jogging	7	6	20	2	2	60	1318	0	11	0
h	Standing	6	0	0	0	0	6	3	3947	6	0
i	Stairs	152	29	4	0	0	0	35	22	747	0
j	Driving	0	0	1	0	1	0	0	3	1	1561

5 Conclusions – Future Work

Our first field tests of WISE platform prototype provided highly accurate activity recognition rates. The next steps of our research shall focus on testing the platform with a wider range of healthy individuals and people suffering from chronic diseases, so that to examine activity recognition accuracy in miscellaneous groups. We also work on extending the range of the activities recognized, covering a wider range of daily activities, while performing extended analysis on system accuracy under various circumstances (absence of GPS signal, no heart rate monitoring, loss of connection of one of the sensors etc).

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