Low-power activity recognition from triaxial accelerometer data

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***Abstract*—In this work, a low power triaxial accelerometer data acquisition prototype is presented, which is used to derive physical activity recognition algorithms to be used for implantable or wearable applications. There different characterization methods were implemented and can predict the different activities with good accuracy (380 cases out of 386).**

***Keywords*—accelerometer - Low power – activity recognition**

I. Introduction

Determining the physical activity that a patient is doing is crucial for several implantable medical devices (IMD) as the response required in each case can be different. In particular, rate adaptive pacemakers change heart rate to track patient's need while performing different activities. Because it is a non-invasive sensor, traditional adaptive pacemakers mostly use an accelerometer to estimate physical activity; and since energy consumption is a major concern in implantable electronics, piezoelectric sensors were traditionally utilized because of their almost null self-power consumption (note physical activity estimation is an always-on circuit block). For example, in [1][2], the integrated signal conditioning of a single-axis piezoelectric accelerometer aimed at adaptive pacemakers is presented. The sensor's signal is amplified and filtered, and then turned into a quasi-DC output proportional to the last 5-seconds average of the acceleration's amplitude in the band from 0.5 to 15 Hz The analog circuits in [1][2] consume a few hundred nA which is almost insignificant for a pacemaker, but still present limitations, e.g. to identify stairs climbing which requires a greater effort and higher heart rate, or isometric exercises. But the most relevant limitation in the case of implantable medical products in the circuits in [1][2] are ASICs and the development of an ASIC is not always possible for an IMD where production series are most of the time limited to a few thousand devices.

But recent development of commercial micro power three axes accelerometers integrating the sensor and signal conditioning also at a low cost ([3] and [4]), and probably also gyroscopes in the near future, may allow to implement physical activity recognition aimed at IMDs using off-the-shelf ICs. Also 3-axis accelerometers/gyroscopes combined with an intelligent signal processing and pattern recognition as is now possible with modern low-power microcontrollers may allow for better physical activity recognition while maintaining the low power required for IMDs. In this work, a prototype system aimed at physical activity identification in IMDs using two different commercially available low power triaxial accelerometers is presented, and different techniques for determining the activity of the patient are evaluated as a proof of concept. While probably physical activity estimation circuit embodiments using standard micropower accelerometers and microcontrollers may consume several times more power than the ASIC-based single-axis implementations in [1][2], they may allow a drastic reduction in development time and cost, thus being an attractive option for IMDs. But even when using state-of-the-art hardware, an accurate physical activity estimation in the µW power consumption order will require intelligent and adaptive signal processing and plenty of tests with many individuals while doing different physical activities. This work is a first step towards this objective.

II. System Description

A simple prototype was developed to test two different off-the-shelf accelerometers and signal processing techniques. Fig. 1 shows a block diagram of the system, while Fig. 2 shows a photograph of the working prototype. The microSD card is for simple data acquisition but would not be part of the finished product.

A. Hardware

The prototype was implemented in a 4x6 cm^2 dual-layer PCB. The selected microcontroller is a 16-bit

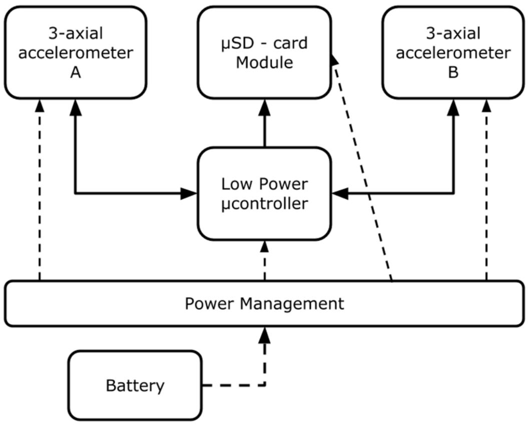

Fig. 1. Block diagram of the physical activity estimation prototype.

Fig. 2. Photograph of the implemented prototype.

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PIC24F16KL402 [5], which is a low-power microcontroller running up to 20MHz clock, programmed via ICSP. The two accelerometers under test are the ADXL362 [4] and the LIS3DH [5]. Both accelerometers provide 3 axis data at variable frequency and precision that can be selected by the microcontroller. There is a trade-off between precision and data rate with power consumption. The microSD interface is a regular off-the-shelf module with an SPI interface, as this is only to get the crude data during tests.

When designing the circuit, care was taken to align both accelerometers' measurement axes to ensure a proper comparison.

A single 3.7V LiPo battery was selected as the power source. Equivalent batteries are utilized in rechargeable IMDs, but pacemaker normally use primary batteries of Lithium iodine type with a $2.8V_{nom}$ supply voltage (beginning of life [6]), so a LDO [7] regulator was used to set a more realistic V_{dd} = 2,7V supply for the microcontroller and accelerometers. A L6920DC step-up [8] was used to boost the voltage to 5V to power the microSD module [9].

B. Firmware

A simple firmware was implemented to collect data from both accelerometers; its flowchart diagram is shown in Fig. 4. The frequency selected for data sampling was firstly 12.5Hz and 10Hz for each accelerometer (as close as possible) to preserve a low power consumption. For this sampling rate, the power consumption of each accelerometer is approximately 1.8µA and 3.7µA respectively.

The microcontroller handles the configuration of the accelerometers and uses rising-edge external interrupts to read the 16-bit data output of the accelerometers, storing the formatted data on a text file on the microSD card with a FAT32 filesystem for easy access.

A sampling run is started with a push button, and with each subsequent interrupt a LED provides visual feedback to the user. Pressing the push button again stops the sampling process and saves the data onto the microSD card for later analysis.

C. Activity estimation setup

Because the objective is to measure the overall patient's physical activity, a location close to the center of mass is usually desirable.

For the tests in this work the module was installed on the right side of the hip [10] as shown in Fig. 3, in a healthy individual. With this configuration, the accelerometers' X axes point upwards, the Y axes point backwards, and the Z axes point to the right. The prototype's reduced size and weight allows for a comfortable wear while taking measurements.

III. EXPERIMENTAL MEASUREMENTS

Experimental data was obtained from one subject, recording five common activities that are interesting to discriminate: sitting down, lying down, walking, and climbing up and downstairs. More than 50 samples, each of a 6-second sampling window, were obtained for each activity. The exact conditions of the measurements will be described in this section.

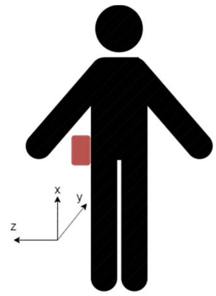

Fig. 3. Prototype placement for the tests.

A. Sitting down

The subject sat down on an office chair while carrying out office work on a computer. The amount of activity is limited to a minimal, with sporadic movements of the body (arms, hips), which keeps the acceleration measurements almost restricted to measuring the Earth's gravity, serving as a baseline for the rest of the experiments.

B. Lying down

Similar to the sitting down experiment, the subject lay down facing upwards on a bed and had a minimal activity. The subject remained lying down on a bed while using a cellphone, which requires minor movement and effort.

C. Walking

While walking can sometimes require considerable effort, for this experiment the subject walked at a normal pace on flat ground, with no obstacles on the way.

D. Climbing up and downstairs

For this experiment the subject took turns at climbing up and down a single 12-step stair. The measurements were taken continuously climbing up and down, starting on the way up, and each subsequent run was separated with a 2-3 second wait

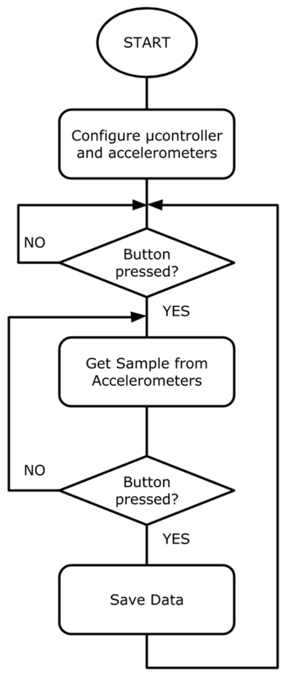

Fig. 4. Simplified diagram of the implemented firmware for data collection.

that made it easy to then identify each climb during the signal processing stage.

IV. Activity Determination

The measured physical activity was processed using 6 second intervals, which correspond to 60 samples for the LIS3DH and 75 samples for the ADXL362. Each of these packets was analyzed to extract the parameters to use for the classification algorithm. The main processing was performed off-line using Scilab [11]. When comparing the data from the different accelerometers, no significant difference was obtained, concluding that any of the chosen accelerometers can be used in this application. Even though the LIS3DH is cheaper, its larger power consumption makes the ADXL362 the better candidate for this application.

To determine the activity, we will develop a series of machine learning algorithms that can infer the activity from a group of parameters that can be extracted from the acceleration data.

A. Parameter extraction

Several different parameters were extracted for each data packet trying to minimize computational effort, as the final application should be performed by a low power microcontroller. The following characteristics were extracted following a procedure similar to [10]:

$$SMA_X = \frac{\sum_{i=1}^{n}|x_i|}{n}\ ; SMA_Y = \frac{\sum_{i=1}^{n}|y_i|}{n}\ ; SMA_Z = \frac{\sum_{i=1}^{n}|z_i|}{n} \qquad (1)$$

$$E_x = \frac{\sum_{i=1}^{n} {x_i}^2}{n}\ ;\ E_y = \frac{\sum_{i=1}^{n} {y_i}^2}{n}\ ;\ E_z = \frac{\sum_{i=1}^{n} {z_i}^2}{n} \qquad (2)$$

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}\ ;\ \bar{y} = \frac{\sum_{i=1}^{n} y_i}{n}\ ;\ \bar{z} = \frac{\sum_{i=1}^{n} z_i}{n} \qquad (3)$$

$${\sigma^2}_x = \frac{\sum_{i=1}^{n}(x_i-\bar{x})^2}{n-1}\ ;\ {\sigma^2}_y = \frac{\sum_{i=1}^{n}(y_i-\bar{y})^2}{n-1}\ ;\ {\sigma^2}_z = \frac{\sum_{i=1}^{n}(z_i-\bar{z})^2}{n-1} \qquad (4)$$

In equations 1-4, the symbols *x*, *y*, and *z* represent the samples of each axis of the accelerometer. *SMA* in (1) is the signal magnitude area, *E* in (2) is the energy of the signal, and finally (3) is the average and (4) is the variance of each signal.

The 12 parameters were calculated, four parameters per axis. From these characteristics, we would like to select which are the most important to implement in the microcontroller.

B. Visualization and Classification

To visualize and apply different classification methods, the Orange Data Mining Python software [12] was used.

Fig. 5 shows a dispersion diagram using just two variables, (SMA_Y and σ^2_X) which already shows a good discrimination between the different activities and which information is stored in each parameter. Fig. 6 shows a linear projection using 4 parameters, which further separates the different activities into different clusters.

Three different simple classification methods were tested: Logistic Regression [13], Support Vector Machine (SVM) [13], and nearest neighbors (kNN) [13]. Using the experimental data, the models were trained using 10-fold cross validation, and their performances analyzed via their confusion matrices [14]. In tables I-III, the confusion matrices are presented for each of the algorithms.

TABLE I. LOGISTIC REGRESSION

Actual	Predicted				
	Down	*Lying down*	*Sitting*	*Up*	*Walking*
Down	**54**	0	0	*3*	0
Lying down	0	**64**	0	0	0
Sitting	0	0	**68**	0	0
Up	*3*	0	0	**53**	0
Walking	0	0	0	0	**141**

TABLE II. SVM

Actual	Predicted				
	Down	*Lying down*	*Sitting*	*Up*	*Walking*
Down	**53**	0	0	*4*	0
Lying down	0	**64**	0	0	0
Sitting	0	0	**68**	0	0
Up	*2*	0	0	**54**	0
Walking	0	0	0	0	**141**

TABLE III. KNN

Actual	Predicted				
	Down	*Lying down*	*Sitting*	*Up*	*Walking*
Down	**52**	0	0	*5*	0
Lying down	0	**64**	0	0	0
Sitting	0	0	**68**	0	0
Up	7	0	0	**49**	0
Walking	0	0	0	0	**141**

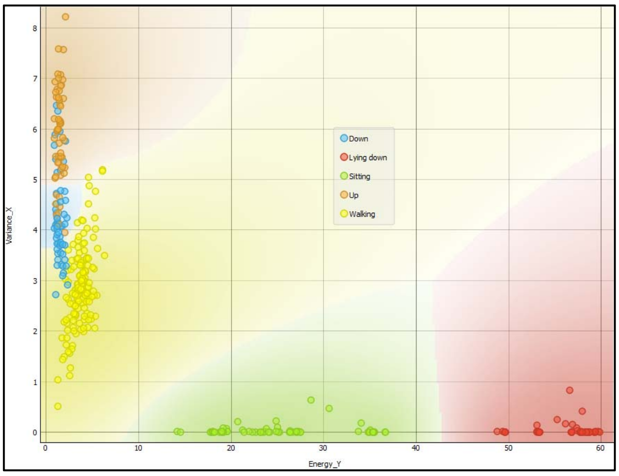

Fig. 5. Dispersion diagram using two variables (E_Y horizontal, σ^2_X vertical). Blue = down, red = lying down, green = sitting, brown = up, yellow = walking.

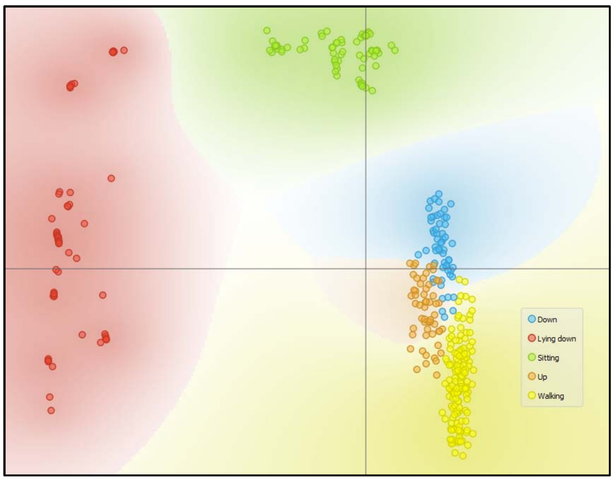

Fig. 6. Linear projection using four parameters (SMA_X, SMA_Z, E_Z, σ^2_X). Blue = down, red = lying down, green = sitting,brown = up, yellow = walking.

C. *Results*

The results from the three algorithms are virtually similar. All of them detect the difference between lying down, sitting, walking and going up and down the stairs. There are a few identification errors (6/386 for Logistic regression and SVM while 12/386 for kNN) but they always occur between going up and downstairs. The kNN methods is slightly worse at predicting whether the person is climbing up or down a stair but all methods are excellent in determining if the person is walking, sitting, lying down or climbing a stair.

V. CONCLUSIONS

A first prototype for activity recognition using a commercial triaxial accelerometer was developed. Two different accelerometers were tested, yielding almost identical results. The data collected was analyzed and using some simple parameters that can be easily extracted, three different classification method were tested, which show excellent results.

The next step in this project is implementing the classification method in the microcontroller. To this end, the calculations for each of the algorithms from tables I through III have to be coded into the microcontroller as done in the Orange Data Mining software. We will pay special attention to Logistic Regression, as it requires the least amount of computational effort, therefore requiring less power.

Further consumption reduction can be achieved in a number of ways, such as adjusting the clock speed and microcontroller sleep cycles during samples, as well as putting the accelerometer asleep for longer periods under certain conditions, for example, if the subject has been lying down for a reasonably long period (which would equate to assuming the subject is asleep and will remain so for an extended period, and therefore requiring no frequent measurements).

The ADXL362 accelerometer has the capability of generating interrupts when the acceleration detected is above a certain threshold, which can be used to detect when each activity exceeds a certain level of intensity (the threshold will likely depend on each activity and each individual), allowing the microcontroller to remain asleep for longer and further reduce power consumption until the intensity of the activities carried out is of interest.

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