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# ActimedARM – Design of a Wearable System to Monitor Daily Actimetry

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***Abstract*- We developed a low power kinematic sensor, ActimedARM, incorporating three-axis accelerometer and magnetometer, a microcontroller ARM3, a ZigBee wireless communication and µSD memory storage. With embedded algorithms it can detect in real time the postures of the subject. A preliminary assessment conducted on 12 subjects reached a 97% correct classification rate. The device exhibits 32 days of autonomy on a 3600 mAh capacity battery, which makes it convenient for field experiments in true daily life.**

***Index Terms*—Inertial sensors, actimetry monitoring, Embedded systems, autonomous systems.**

## I. Introduction

Daily activity of the subject is mainly imposed by vital needs (sleep, feeding, elimination, etc.) but are also influenced by interactions with environment (e.g. to move in and out home, etc.). It is therefore both a measure of the vitality of the subject and an image of its homeostasis. But to extract the long term features of this activity, it needs to monitor on the field, in unsupervised protocols and for long periods (several days to a few months).

The actimetry is the chronological record of postures (sitting, lying, standing, walking) successively adopted by a subject over a period of time to determine its intrinsic and personal characteristics [1]. This record occurs usually within a movement laboratory with heavy and expensive equipments, following a protocol lasting a few minutes to a few hours.

Recent advances in microelectronics and MEMS technologies, now made available integrated inertial sensors (accelerometers, gyroscopes, magnetometers), built-in high capacity memories (Flash Eprom) and powerful microcontrollers that enable to develop very integrated inertial systems, with connectivity and high autonomy [2] [3]. These devices can be easily embedded on the subject to follow without interfering in his life daily [4] [5]. There is a large availability of such devices, with a new problem arising with the management of large amount of data produced by these devices which requires large storage or transmission of data and therefore limits the duration of use to a few days, or even only a few hours, which is not exploitable in field situations.

We developed our inertial, namely ActimedARM, with the goal of mastering the operating time, by adjusting the energy budget. Some of the algorithms are embedded, to reduce the flow of data transmitted, or recorded, and it adapts the speed of calculations so to extend the lower energy sleep times.

## II. Material and Methods

### A. Material

The ActimedARM is based on a 32-bit ARM microcontroller, a three-axis accelerometer, a three-axis magnetometer, a wireless 802.15.4 module and a µSD Flash memory card. It is powered by a 3.6 Volts lithium battery followed by a 3.3 volt regulator (Fig.1).

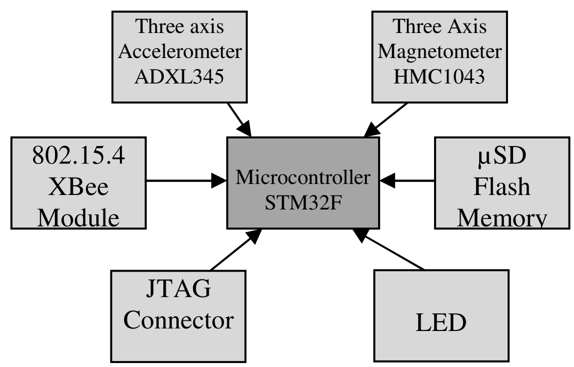


**Figure 1: Bloc diagram of the ActimedARM.**

The STM32F103RE microcontroller (STMicroelectronics) was selected for its computational power (core 32-bit cortex M3), its on-board memory (Flash 512 KB, 64 KB RAM), its low supply voltage (3.6 V), integrated peripherals (SPI, USART, ADC, RTC, µSD-card driver) and its low consumption in operation (28mA@48 MHz) and extremely low in standby mode (25µA) making it a component of choice when designing powerful embedded autonomous electronic systems.

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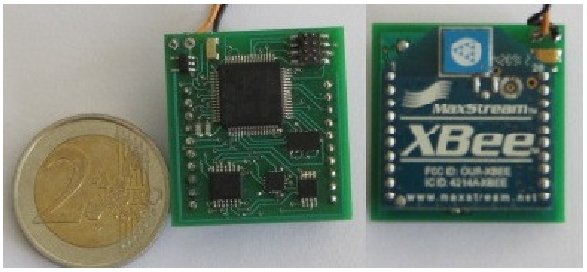


**Figure 2: The ActimedARM hardware (front side on the left and rear side on the right).**

The 802.15.4 wireless link (ZigBee), is supported by an additional module (XBee, MaxStream) communicating in serial asynchronous connection (Fig.2). It allows a flow rate of 250 Kbps and a range of 30 meters indoors. Its energy consumption is moderate (50 mA) but can be reduced in sleep mode (10µA) simply by switching the State of a PIN.

The µ-SD removable memory card (Fig.3) was chosen because it offers a large storage capacity in a reduced format. In addition, the STM32F103RE microcontroller has a hardware interface and Firmware dedicated to the management of the µ-SD.

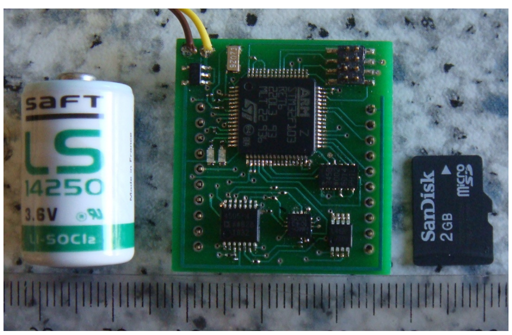


**Figure 3: The µ-SD Flash memory card**

The three-axis digital-output accelerometer (ADXL345, Analog Devices) is a stand-alone acquisition system, requiring no external component, which communicates on a simple SPI bus. It has a wide and adjustable measuring range (± 2 g to ±16g) for a fixed resolution of 10 bits. Above all, it works at very low voltage (2 - 3.6 V) and its consumption is reduced (65µA@25Hz). Thanks to the integrated internal buffer (32 samples) the microcontroller may access data only once per second (@ 25 Hz), thus remaining in standby mode most of the time.

The three-axis magnetometer (HMC1043, HoneyWell) integrates magneto-resistors, whose impedances vary linearly with the magnetic field (1 mV/V/Gauss). The HMC1043 requires the implementation of a Wheatstone Bridge type (Fig.4) circuit followed by a differential amplifier and analog-to-digital converter. The large initial bandwidth (5 MHz) is further reduced due to the high amplification factor (gain 60 dB). As a significant current supply is needed (30 mA) it requires adoption of a standby strategy.

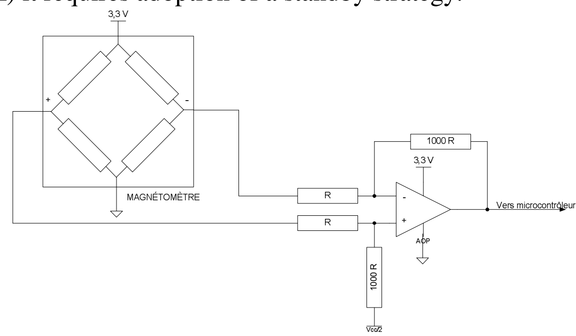


**Figure 4: Conditioning Circuit (per axis) of the magnetometer.**

The magneto resistors have a drift in time thus, to prevent their saturation, we implemented a reset circuit producing a pulse of current (Fig.5).

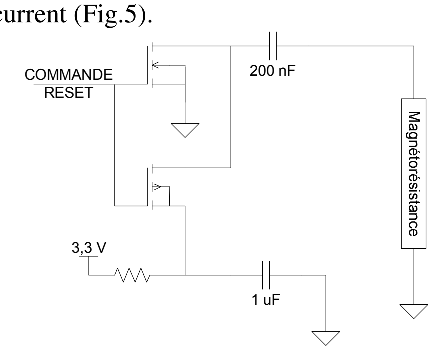


**Figure 5: The Reset circuit of the magnetometer.**

### *B. Practical Implementation*

The final device was made with surface components mounted on FR4 PCB double sided in class 5. It has a volume of 10 cm3 (28 x 30 x 12 mm) without the battery.

For the sake of acceptability (comfort and discretion), we opted for the placement of a single sensor. It is held in position in a Pocket sewn onto a T-shirt (Fig.6). The location on the bust was selected because this part of the body better represents the global postures of the body, unlike the distal segments which have free movements (i.e. bracelets placed on the wrist, thigh or head).The X-axis of the accelerometer corresponds to the anteroposterior (AP) rear axis, Y-axis is the vertical down axis and the Z-axis is mediolateral (ML) to the right. For the magnetometer, the X-axis corresponds to the AP axis forward, the Y-axis is the vertical upwards axis and the Z-axis is the ML axis to the right.

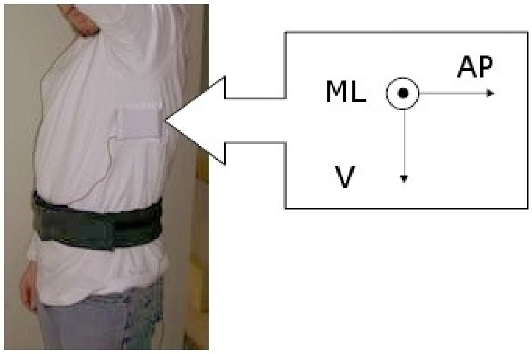


**Figure 6: Placement of the ActimedARM sensor on the body.**

### *C. Embedded Algorithms*

The main program loop is executed once per seconds to collect one magnetic field measure (1 Hz) and the last 25 samples from the buffer of accelerations (25 Hz).

It first switches on the magnetometer, collects the samples of data of both 3 axis magnetic and accelerations. It then switches off the magnetometer, low pass filters the data and performs all the processing on filtered signals to compute the posture (lying, sitting, standing, walking, transfer). Eventually, depending on the configurations parameters, it stores the raw data and/or send the new posture if it changed during the past second. After completion it returns to the standby low power mode.

#### *1) Detection of the body orientation*

The orientation of body is computed from the trigonometric functions applied on the magnitude of the vertical acceleration. When the subject is standing, the vertical acceleration is maximum, denoting a 90 degree angle above horizontal plane (90°=arcsinus(1)), whereas when lying it is minimum (0°=arcsinus(0)).

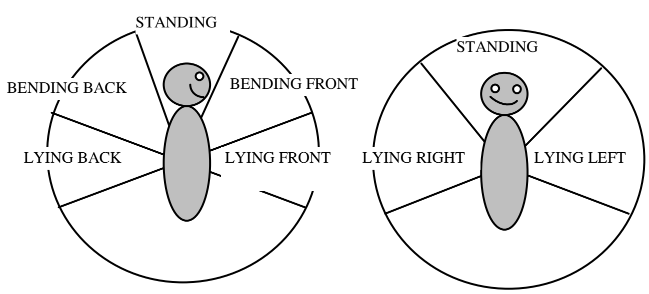


**Figure 7: The posture is classified on the value of arcsinus of vertical acceleration value: standing for interval [1-0.98], bending in [0.97-0.18] and lying in [0.17-0].**

#### *2) Detection of transfers*

The stand-to-lying and lying-to-stand transfers are simply detected when the posture changes from standing to lying and lying to standing.

As the orientation of the body are very similar in standing and sitting postures, we determine the sit-to-stand and stand-to-sit with our former algorithm [5] which uses the phase shift between vertical and horizontal accelerations signals which occurs during this transfer.

#### *3) Detection of the walking posture*

The detection of the walk is done via a spectral analysis of the vertical acceleration signal: walking is punctuated by the foot impacts and therefore looks like a pseudo periodic movement. We will therefore find a peak in the frequency spectrum of the vertical acceleration in the range 1.1 Hz - 5.4 Hz. This spectral analysis is performed with a fast Fourier transform on the last 64 samples (Fig.8), which provides a good compromise between computing time and frequency resolution. At a 25 Hz sampling rate, the frequency resolution is 0.39 Hz.

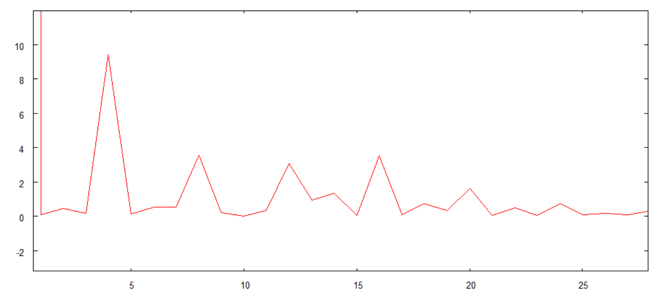


**Figure 8: The (64 samples) short time FFT on vertical acceleration signal during walking.**

We consider there is walking in a time window if the amplitude of the central frequency is higher than twice the maximum minus the following 2 subsequent maximums. This takes into account both the amplitude and slope of the maximum.

#### *4) Detection of change in direction*

The change in orientation mainly occurs while standing (walking) and thus it cannot be detected with the accelerometers which are projected on the vertical axis. We therefore implemented a three-axis magnetometer which brings additional information on the orientation relative to the North magnetic.

## III. RESULTS

### A. Measured autonomy

Instantaneous consumptions are visualized on a shunt precision resistor (1 Ω) placed in series on the ground circuit. This allows observing the consumption profile on the oscilloscope (Fig.9).

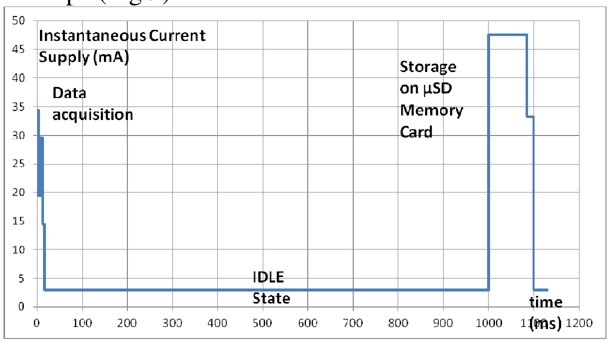


**Figure 10: The profile of current supplied during a data acquisition cycle (left) followed by a storage cycle (right).**

In a mode with periodic storage on the µSD, we measure an average consumption of 3.24 mA during data acquisition cycles and 7.11 mA during the writing. As 64% of the time is spent in first stage (3.24 mA) and 36% in second stage (7.11 mA), the average consumption is 4.64 mAh and the daily consumption is therefore estimated to 111.4 mAh. This anticipates autonomy larger than 32 days on a 3600 mAh battery (LS17500) or 10 days on a 1200 mAh (ER14250W). In a mode with periodic data transmission, we observe a 80mA peak consumption when data transmission and 6.25 mA mean consumption during normal cycle. The daily consumption thus reaches 150 mAh which reduces autonomy to 24 days (3600 mAh) or 8 days (1200 mAh).

### B. Performances

Our test Protocol involved 12 healthy subjects (25 ± 3.6 years), performing the following successive movements:

- 5 sit-to-stand, separated by 3 seconds
- 2 round trips on 10 meters at comfortable speed
- 1 return full speed
- 1 return slow speed
- 5 lying-to-standing, separated by 3 seconds

The sequences were performed under the control of a reference video for indexations of situations and for counting classified events (True Positives-TP, False Positives-FP, True Negatives-TN, and False Negatives-FN).

The performances were then evaluated considering the rate of situations correctly classified (sensitivity=TP/TP+FN) and misclassified situations (specificity=TN/TN+FP).

Most transfers were correctly detected with a rate of correct classification of 97%, thus the transfers were correctly identified. All the walking periods were detected, with a delay of 2 seconds due to our 1 second temporal window.

## IV. CONCLUSION

We developed our inertial sensor, ActimedARM, incorporating an accelerometer and a magnetometer, an ARM3 microcontroller, a ZigBee wireless communication and µSD memory storage. The device exhibits 32 days autonomy on a 3600 mAh capacity battery, which allows measures in environmental campaigns on the field.

Embedded algorithms allow us to detect in real time the postures of the subject, thus reducing the amount of data stored and/or transferred. A preliminary assessment conducted on 12 healthy subjects demonstrated a 97% rate of correct classification.

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