# Ambulatory mobility characterization using body inertial systems: an application to fall detection

Marc Torrent[1], Alan Bourke[2], Xavier Parra[1] and Andreu Català[1]

[1] Technical Research Centre for Dependency Care and Autonomous Living – CETpD
Technical University of Catalonia - UPC
Edifici Neàpolis – Rambla de l'Exposició, 59-69
08800 Vilanova i la Geltrú – Catalonia – Spain
{marc.torrent-ponch, xavier.parra, andreu.catala}@upc.edu

[2] Wireless Access Research Centre – Biomedical Electronics Lab
Department of Electronic & Computer Engineering – University of Limerick
Limerick – Ireland
alan.bourke@ul.ie

**Abstract.** The aim of this paper is to study the use of a prototype of wearable device for long term monitoring of gait and balance using inertial sensors. First, it is focused on the design of the device that can be used all day during the patient daily life activities, because it is small, usable and non invasive. Secondly, we present the system calibration to ensure the quality of the sensors data. Afterwodrs, we focus in the experimental methodology for data harvest from extensive types of falls. Finally a statistical analysis allows us to determine the discriminant information to detect falls.

## 1 Introduction

In recent years, the progressive aging in our society has produced an increase in the number of dependents or disabled people and at least a growing number of persons that need special attention. In Spain, for example, there are 7.7 million of people older than 65 years. The 32.2 % of them presents some sort of disability, and this percentage is greater as the age range grows [1], [2]. The new requirements arising from this situation require social efforts, but also efforts in science and technology to design together new services and systems in order to improve people's wellbeing and quality of life.

It is a fact that the third part of the population older than 65 years suffers falls each year doing their daily life activities. This falls are one of the major causes of disability and dependency as they can cause major injuries. For instance, the 90% of hip fractures in the elderly are caused by a fall [3]. This is a dramatic factor in disability and mortality as the 33 % of the old people that suffers from a hip fracture dies in the next 12 months, and a 60 % develops some sort of disability that difficult their daily activities and makes their quality of life worse [4].

The early detection of fall risk persons is the most efficient way to not only prevent hip fractures, but also in dependency, institutionalization, and mortality in the elderly. The existent methods for the falling risk estimation are based in interviews with the patient about his fall historical [5], or in an exploration of gait and equilibrium at the laboratory [6]. These methods have numerous disadvantages as they take into account only punctual determinations of the state of the patient and include subjectivity. Thus monitoring the body movements for long periods of time during the patients daily life activities could be a good source of information for a fall risk diagnosis. Moreover, the reliable detection of falls could be crucial in emergency situations.

Inertial sensors such as accelerometers and gyroscopes have proven to be useful in the analysis of human motion [7] with the advantage that they can be integrated in some sort of wearable device. Although many works and research groups related to the area have reached good results, as for example, in the classification of activities [8] , detection of falls [9], [10] and fall risk prediction [11], this is still is an open research subject which needs more robust algorithms, technological improvement with user experience and adaptation and integration in complete ambient intelligent systems.[12]

The aim of this paper is to study the use of a prototype of wearable device for long term monitoring of gait and balance using inertial sensors. First, it is focused on the design of the device that can be used all day during the patient daily life activities, because it is small usable and non invasive. Secondly, we present the system calibration to ensure the quality of the sensors data. Third, we focus in the experimental methodology for data harvest from a extensive types of falls. Finally an statistical analysis allows us to determine the discriminant information to detect falls.

## 2 Inertial Sensor System

The wearable device, as seen in fig.1) is composed by a central Intelligent Hardware Unit (IHU) and three different inertial sensor technologies. The IHU is the central part of the system, and its function is handling the sensor data. It features a microcontroller based process unit, a communications module, external memory, and interfacing circuitry. The core of the IHU is a dsPIC (Microchip Technology Inc.), a hybrid microcontroller with basic digital signal processor (DSP) features that enables the system with mathematic capabilities. The microcontroller operates at 20 MIPS (Mega Iterations Per Second) and have an internal program memory of 24Kbytes which allows a wide range of programming possibilities. The dsPIC uses different digital interfaces to communicate with the sensors in order to provide robustness to the readings. Another interesting feature of the dsPIC is his low power consumption along with its low power operation modes which enhances battery life.

The device integrates three different MEMS inertial sensors which can measure 3D linear acceleration, angular rate and compass orientation. The accelerometer is a three-axis sensor model LIS3LV02 (ST Microelectronics Inc.) with a measuring range of ±6 g and a sensitivity of 323 bit/g. The sensors have a built-in digital circuitry that uses to apply a first low pass filter to the data captured and to transmit it using a digital $I^2C$ interface. The three-axis gyroscope is constructed by assembling two different MEMS gyroscopes, the one-axis ADIS16100 (Analog Devices Inc.), and the two-axis IDG300 (Invensense Inc.). The two sensors have similar characteristics and work well in conjunction, with a typical range of ±300 deg./s. and a typical sensitivity of 4 bit/deg/s. The analog output signals from the IDG300, are redirected to the auxiliary inputs of the ADIS16100 which has a digital interface used to send the three-axis signals digitally to the IHU. The magnetometer or electronic compass is a three-axis sensor which can determine the absolute orientation of the device using the earth magnetic field as reference. The sensor has a resolution of 0.2 degrees of deviation and is very sensible to tiny variations in the magnetic field in its surroundings. For this reason its application is reduced to controlled scenarios.

The device can operate in two different modes: online or offline. In online mode the sensors readings are transmitted in near real time via Bluetooth radio. It integrates a Bluetooth transceiver Parani- ESD200 (Sena Technologies Inc.) capable to establish a wireless communication with another device using the RFCOMM protocol (virtual serial RS232 connection). This is a much extended protocol, so it enables the system to communicate with a large range of devices including laptops, handheld devices and mobile phones. The alternative is the offline mode where the sensors readings together with a time stamp are stored in an external memory. The memory used is a micro SD flash card of 1 or 2 Gbytes capacity. The main features of this memory are its reduced size, high capacity, low power consumption and the possibility to use a standard SPI interface to communicate with de microcontroller.

**Fig. 1.** Inertial system

The device, including the sensors, is powered by a single Lithium Polymer rechargeable battery with a capacity of 610 mAh. With this battery the system can run for about 5 hours without interruption. All the electrical interface circuits including the battery charger, battery monitor, battery protection and voltage regulation are integrated in the device. The size of the sensor system with the battery and the casing included is 78x40x22 mm. and has an approximate weight of 30 gr.

## 3 Inertial system calibration

In order to extract useful information from the designed system it is necessary to calibrate the inertial sensors, to translate the output electrical signals to understandable physical measurements. This calibration process has to be done with each single sensor, correcting its main sources of error such as drift, sensitivity error, misalignment of the axes and other errors due to environmental factors like temperature. This calibration process in inertial sensors is complex and normally requires the use of expensive precision instruments. An alternative is the simple but systematic procedure designed by Ferrari et al. [13], for accelerometers and gyroscopes and the one designed by O'Donovan [14] for the calibration of the magnetometer.

These procedures provide correction for the major sources of error in inertial sensors: these are the drift, the sensitivity and the axis misalignment. They also have the advantage of not needing any special equipment to carry them out, as they use physical phenomenon’s (i.e. gravity, earth magnetic field) as references for the calibration.

### 3.1 Combined Sensor Calibration

The calibration processes for the three sensors can be joined in a single process that involves putting the sensor in 12 predefined static positions and 3 full revolution rotations, reducing the calibration time. This calibration process, once developed, is also suitable for its integration in the on board device controller, as it only involves sum and matrix multiplication for each sensor.

### 3.2 Temperature Compensation

The calibration of the sensors is hampered by one main issue; it only takes into account the internal sensor factors but not the external ones. The main external factor that affects inertial sensors is the temperature. Only a few degrees of temperature variation can modify the sensor parameters introducing errors in the readings that cannot be neglected.

In applications such as subject movement monitoring, great temperature gradients are not to be expected, and as the sensor would be directly attached to the patient’s body, one can expect constant temperatures between 20°C and 40°C. For this reason, a linear approximation can be a good solution for this kind of systems. The effectiveness of this approximation has been proved experimentally with all the sensors and with a large number of trials, as can be seen in figure 2.

This method provides a long term calibration valid for a range of temperatures, so it is not longer necessary to carry out a calibration each time the sensor has to be used. This procedure can be also embedded in the on-board controller in devices that have a temperature sensor.

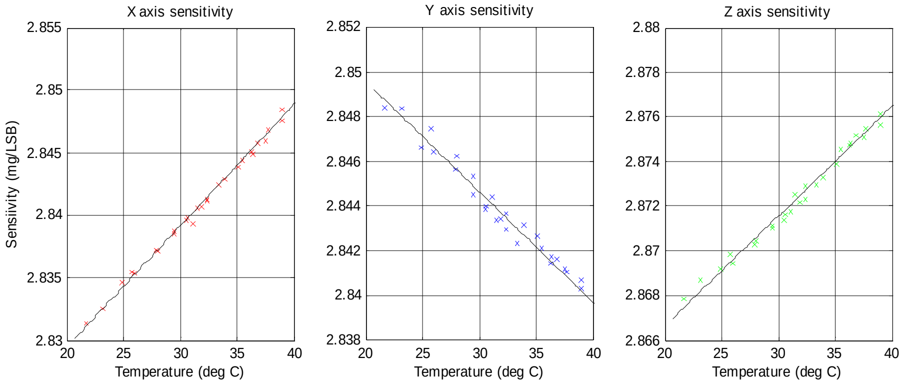


**Fig. 2.** Accelerometer sensitivity variation over temperature.

## 4 The simulated fall study

The fall study involved 16 healthy volunteers performing falls over large crash mats for two different scenarios and performing three repetitions each exercise. Signals from the three sensors in the device were recorded during each fall-event with the device located at the chest. These subjects ranged in age from 24-35 years old, with a body mass from 68 to 111 kg, and a height from 1.65 to 1.96m. The University of Limerick Research Ethics Committee (ULREC) approved the falls protocol.

The fall types used during testing for the current study were selected to simulate common fall types in elderly people The falls performed were similar to those performed in the study of Bourke et al. [15]. The different types of falls are the following:

*Forward falls*

1. Faint with flexed knees.
2. Step down from a platform and fall forward. Thick (>15cm) soft mat on floor.
3. Walking and trip yourself up. Thick (>15cm) soft mat on floor.

*Backward falls*

4. Faint with Round back and flexed knees.
5. Backward Sitting down on empty (on the floor without using your arms or taking a step back). Thick (>15cm) soft mat on floor.
6. Backward to the base of a padded wall. Thick (>15cm) soft mat on wall and floor.

*Side falls left*

7. Faint with flexed knees.
8. Fall backward and turn to the side.
9. Side fall to the base of a padded wall. Thick (>15cm) soft mat on wall.

*Side falls right*

10. Faint with flexed knees.
11. Fall backward and turn to the side .
12. Side fall to the base of a padded wall. Thick (>15cm) soft mat on wall.

*Free falls*

13. Falling off a chair.
14. Unrestricted activities (fall-over as you like).

In order to compare the falls data with other movements we inquire to the same group of young healthy subjects performing Activities of Daily Living while fitted with the same sensor as the simulated-fall study, performing three repetitions. Each subject started and finished each ADL in a standing position. The ADL chosen were those that may have produced impacts or abrupt changes in a person's movement (and thus possibly results in false triggering of a threshold-based fall-detection algorithm) resembling activities carried out during the normal course of an elderly person's daily life.

*Activity tests*

15. Walking 10 meters.
16. Standing position to a sitting position in a normal chair. (height 43cm).
17. Standing position to a sitting position in a bank. (height 44.5cm).
18. Standing position to a lying on a mat or bed. (height 40cm).

In one month we achieved to compile a signal database of 636 data sets, 468 of which are falls in a large diversity of scenarios. This rich database is used now to train different algorithms for the movement/fall identification problem. Also using two different sensor technologies during the same experiments can give us the opportunity to compare the differences between sensors on different body locations.

## 5 Fall detection algorithm

The data recorded from the three-axis accelerometer was derived by taking the equation norm to calculate the module. With this signals and looking at the exact moment of the fall, an extraction of characteristics was done. The characteristics analyzed were the following:

a) *Upper fall threshold*. This threshold is related to the peak of acceleration produced during the impact with the floor in a fall. This acceleration peak can be very high in direct falls to the floor, but it is lower in faints or falls to a wall. So it is not possible to distinguish completely a fall with only this characteristic because of the acceleration peaks produced in some ADLs.
b) *Lower fall threshold*. There is always a minimum peak related to the bounce occurred after the fall
c) *Time between upper and lower fall threshold*.
d) *Difference between upper and lower threshold*.
e) *Maximum angular velocity peak*.

The analysis of these characteristics with a Box Plot with Median, 25 and 75

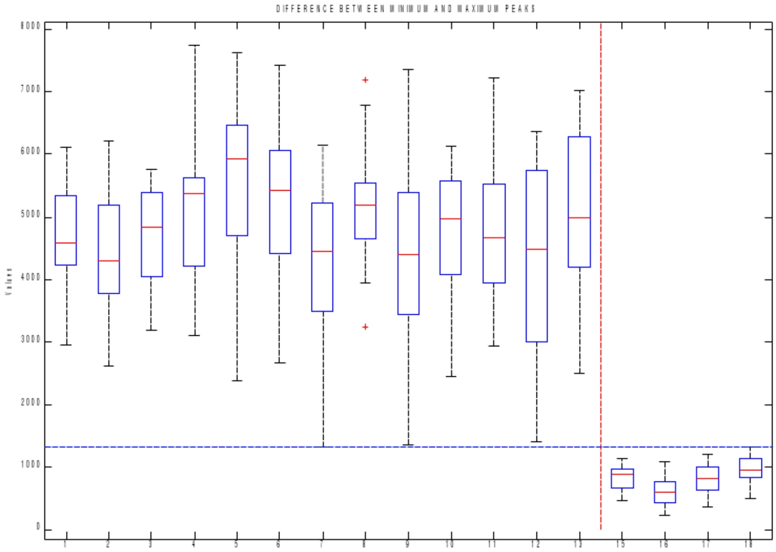

Fig. 3. Box Plot of the difference between max. and min. acceleration peaks

Percentile and outlayers is ploted in Fig 3 for the difference between upper and lower threshold. This characteristic is the most discriminant and allows us to define a threshold between falls (1-13) and DAL (15-18)

# 6 Conclusions and future work

An ambulatory inertial system for mobility analysis is presented. The first results show that the system could be useful for fall detection. Further work is needed to develop algorithms for activity identification and to embed it into the on-board controller of the device.

# 7 Acknowledgment

This work is partially supported by the Spanish MEC project ADA (DPI2006-15630-C02-01) and the European Community project CAALYX (IST-STREP-045215)

# References

1. Las personas mayores en España. Informe 2004. Madrid: IMSERSO, 2004.

2. Libro blanco de la dependencia. Madrid: Ministerio de trabajo y asuntos sociales, 2005, Ref Type: Catalog.
3. M.E. Tinetti, Clinical Practice, Preventing falls in elderly persons. Waltham, MA: New England Journal of Medicine, January 2003, 348(1):42-9.
4. E.L. Hannan, J. Magaziner, J.J. Wang, E.A. Eastwood, S.B. silberzweig, M. Gilbert et al., Mortality and locomotion 6 months after hospitalization for hip fracture: risk factors and risk-adjusted hospital outcomes. Chicago, IL: J. of the American Medical Association, June 2001, 285(21): 2736-42.
5. D.A. Ganz, T. Higashi and L.Z. Rubenstein. Monitoring falls in cohort studies of community-dwelling older people: effect of the recall interval. New York: J. of the American Geriatrics Society, December 2005, 53(12): 2190-4.
6. S.G. Brauer, Y.R. Burns and P. Galley, A prospective study of laboratory and clinical measures of postural stability to predict community-dwelling fallers. Baltimore, MD: J. of Gerontology: Medical Sciences, August 2000, 55(8): 469-476.
7. M. Mathie, A.C.F. Coster, N.H. Lovell and B.G. Celler, Accelerometry: providing an integrated, practical method for longterm, ambulatory monitoring of human movement. Physiol. Measure., Vol. 25, No. 2, R1-R20, April 2004.
8. J. Pärkkä, M. Ermes, P. Korpipää, J. Mäntyjärvi, J. Peltola and I. Korhonen, Activity classification using realistic data from wearable sensors. IEEE Trans. on Information Technology in Biomedicine, vol. 10, No. 1, January 2006.
9. U. Lindemann, A. Hock, M. Stuber, W. Keck and C. Becker, Evaluation of a fall detector based on accelerometers: a pilot study. Med. Biol. Eng. Comput., 2005, 43, 548-551.
10. N. Noury, A. Fleury, P. Rumeau, A.K. Bourke, G.Ó. Laighin, V. Rialle and J.E. Lundy, Fall detection – Principles and Methods. Proceedings of the 29th Ann. Int. Conf. of the IEEE EMBS, August 2007, pp. 1663-1666.
11. D. Giansanti, Investigation of fall-risk using a wearable device with accelerometers and rate gyroscopes. Physiol. Meas., 2006, Vol. 27, No. 11, pp. 1081-1090.
12. A.R. Molinero, A. Catala, M Díaz, Caalyx: Evidence-based selection of helth sensors for eldery telemonitoring. International Society of Gerontechnology, 2008.
13. F. Ferraris, U. Grimaldi, and M. Parvis. Procedure for effortless in-field calibration of three-axis rate gyros and accelerometers, Sens. Mater., 7 (1995) 311-30.
14. Karol J. O'Donovan , Derek T. O'Keeffe, and Gerard M. Lyons. A Technique for the Calibration of a Miniature Tri-Axial Magnetometer for Kinematic Analysis Applications, Ph.D. Thesis, Cap. 5.
15. A.K. Bourke, J.V. O'brien and G.M. Lyons. Evaluation of a threshold-based tri-axial accelerometer fall detection algorithm. Gait and Posture. 2006