Expert Systems with Applications 40 (2013) 7316–7330

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Design and evaluation of a device worn for fall detection and localization: Application for the continuous monitoring of risks incurred by dependents in an Alzheimer's care unit

Yoann Charlon [a,b,*], Nicolas Fourty [c], Walid Bourennane [a,b], Eric Campo [a,b]

[a] CNRS, LAAS, 7 avenue du Colonel Roche, F-31400 Toulouse, France
[b] Univ de Toulouse, UPS, UTM, LAAS, F-31400 Toulouse, France
[c] LCIS, Grenoble-INP, Université Pierre Mendès, 50, rue Barthélémy de Laffemas, BP54, F-26902 Valence, France

ARTICLE INFO

Keywords:
Elderly
Care unit
Smart monitoring system
Wireless sensor network
Fall detector
Indoor localization

ABSTRACT

The Homecare project, which is part of a research project funded by the French National Research Agency (ANR), aims to define a new multi-sensor monitoring system for the elderly with cognitive disabilities in a care unit. Two subjects were recruited to participate to experimental trials. The main objective of this project is to design and test a complete monitoring system at a real site. It is a new clinical and technical approach which is complex to implement: Homecare is intended to propose a possible technical solution, demonstrate its feasibility and illustrate its use working at a protected site. The system consists of a motion sensor network deployed on the ceiling to monitor motion and an electronic patch worn by the subjects to identify them and detect falls. In order to locate tagged subjects inside the care unit, a network of anchor points is used. From these positions and movement data, an analysis algorithm detects an abnormal situation and alerts the nursing staff in real time. A Web application allows the medical staff to access movements and alarms. The complete monitoring system has been functioning for several months and continuously monitors two patients around the clock. In this paper, we present the implementation of the system, the method of localization inside the care unit, and the characterization of the fall detector, and we show certain results relating to activity data.

1. Introduction

The aging population in developed countries has highlighted several economic and societal problems over the last decades. Indeed, the care of dependent people has emerged as a major economic and ethical issue. The situation in Europe is critical. For instance, France has more than 700,000 dependent people and this figure is predicted to increase by 2% a year until 2040. By 2050 (Duée & Rebillard, 2004), approximately 1.5 million dependent people will require the assistance of another person. Similar demographic changes are taking place in most European countries, the USA and Japan. Overall, approximately 20% of the world population will be at least 60 years old by 2050 (Chan, Estève, Escriba, & Campo, 2008). Health technologies represent an important market and develop products with high added value. The overall market is estimated at €185 billion and its annual growth is approximately 6–7% (Pammolli et al., 2005). The French market was estimated at €6.7 billion in 2005 (Pammolli et al., 2005). It includes medical devices, technical assistance, medical benefits and social/nursing facilities. Market studies suggest that autonomy and homecare has a potential value of €4 billion annually in France and will provide 50,000 new jobs, a figure which could be multiplied by three to four by 2050 (ALCIMED, 2007).

In a context of economic crisis, sensor networks and miniaturized devices are offering new technological solutions in the care of dependent persons. Research and development in smart monitoring systems, the purpose of which is to look after the elderly living at home or in institutions, has gathered considerable interest in academia and certain industries (Chan et al., 2008; Gentry, 2009). Such systems permit real time monitoring of movements and generate emergency alerts (abnormally rapid heartbeat, falls, etc.). They generally use sensor networks disseminated in the environment or worn by the person (e.g. on clothes or the skin). Some of these systems enable the monitoring of activities of daily living (ADLs) Fleury, Vacher, & Noury, 2010; Cerny, 2010; Helal et al., 2005; Kientz et al., 2008: life habits, movements, immobility, and restlessness. In order to monitor ADLs, some systems use sound or video (Kidd et al., 1999; Krumm et al., 2000; Riedel, Venkatesh, & Liu, 2012; Yamazaki, 2006). They have often been criticized and described as an intrusion into personal privacy. Some research

* Corresponding author. Tel.: +33 661451045.
E-mail addresses: ycharlon@laas.fr (Y. Charlon), nicolas.fourty@iut-valence.fr (N. Fourty), wbourenn@laas.fr (W. Bourennane), campo@laas.fr (E. Campo).

0957-4174/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.eswa.2013.07.031

teams use non-invasive sensors based on motion detection, such as infrared sensors (Barnes, Edwards, Rose, & Garner, 1998; Chan, Campo, & Esteve, 2003; Virone, Noury, & Demongeot, 2002), ultrasonic sensors (Helal et al., 2005; Kidd et al., 1999) or floors equipped with pressure sensors (Isoda, Kurakake, & Nakano, 2004; Kidd et al., 1999). The major problem with these sensors is the difficulty of distinguishing between the monitored subject and other people nearby (Chan, Campo, Estève, & Fourniols, 2009). Thus, monitoring is limited to time slots when the person is alone in the bedroom, for example during the night.

The Homecare project aims to address this technological limitation: an electronic patch worn by the patients was developed to identify them and monitor their health. The originality of the technology lies in the association between infrared (IR) motion sensors deployed inside the medical facility and the patches worn by the subjects. The identification function included in the patch allows patients to be followed around the clock in real time by linking the data related to their activity (measured by the motion sensors) directly to each one of them. Identification data are encrypted and can only be seen by the health staff on a web application via a login and a password. Thanks to an accelerometer chip, the electronic patch also implements a fall detection algorithm used in combination with radio Beacons (anchor points) distributed in the care unit. This infrastructure constitutes a smart system, able to monitor ADLs (the movements and activity levels of subjects), locate the patients and send an alert in the case of an emergency (a fall, nocturnal restlessness, immobility). ADL monitoring using a behavioral model based on supervised classification has already been undertaken by our research team (Bourennane et al., 2013; Campo, Chan, Bourennane, & Esteve, 2010; Chan, Hariton, Ringeard, & Campo, 1995). The results of this work are that:

- ADLs enrich criteria using histograms as a means of visualization via a web application;
- ADL monitoring allows medical staff to follow the development of the subject's dependence and provides an opportunity to adapt on-going treatments if necessary.

In this paper, we present the electronic design, implementation and characterization of the fall detector, the localization method inside the hospital, the deployment of the multi-sensor system in the care unit, and a number of results related to these activities. The paper is organized as follows: Section 2 presents the concept and method. Section 3 describes the hardware and software development. Section 4 focuses on the implementation of the fall detector. Section 5 presents the characterization of the Tag device. Section 6 concerns the deployment of the monitoring system in the care unit. Finally, Section 7 presents the results and work in progress.

2. Features, concept, methods and user interfaces

In this section, we present the features of the smart monitoring system, the concept and use cases, the general and communication architectures, the methods used for localization and detecting falls, and the user interfaces.

2.1. Homecare project features

The challenges of this project were to improve learning techniques previously developed (Bourennane et al., 2013; Campo et al., 2010; Chan et al., 1995), integrate functional and operational solutions, describe operational specifications, and evaluate the system in a real care unit. The following features are afforded at the end of the operational deployment of the platform:

- monitoring of the subject around the clock;
- identification and localization of the subjects anywhere in the care unit;
- ergonomic and optimized user interfaces;
- enriched criteria for ADLs;
- simplified data for health staff.

The main technological obstacle in this project was the design of the electronic patch to be worn by the subject. The major constraints governing the design of this patch were:

- the size and shape in order not to disturb or hurt the person wearing it;
- the location of the patch on the monitored person;
- the power consumption to guarantee sufficient lifespan (at least two weeks).

The deployment constraints at the real site strongly influenced our choices. Thus, we opted for technical solutions allowing fast and easy implementation, in particular at the level of communication architecture and localization method.

2.2. Concept and use cases

The system aims to help caregivers monitor patients, in this case those suffering from Alzheimer's disease at the Caussade hospital in France. Two residents (women, 84 and 88 years old) were recruited to participate in experimental trials. They were autonomous in their movements but needed help in their daily grooming routine. The medical staff obtained informed consent from the individuals or their families before participating in the trials.

In terms of method, first, a behavioral model derived from life habits is defined using learning techniques based on supervised classification (Campo et al., 2010). The development of learning techniques and the results of related research activities have been covered in previous papers (Bourennane et al., 2013; Campo et al., 2010). The remote unit recovers files containing movement and activity data in order to establish the behavioral model. From this model, danger detection thresholds are calculated based on the average of observed events over the previous 30 days. In a second step, real time events are compared with these thresholds and alerts are generated when thresholds are exceeded. When an alert occurs, the nurse in charge of monitoring receives a warning on his/her mobile phone and must check on a computer to validate (or not) the alert reported by the system. The thresholds can also be adjusted. This system generates three types of message (Table 1) according to the level of emergency:

- information: for the medical staff to monitor the subject's health;
- warning: for the nurse to respond quickly in the case of unusual behavior;
- alert: for the nurse to act immediately.

2.3. General and communication architectures

The general architecture of the system consists of two computers (local and remote), as shown in Fig. 1, and three devices:

- an infrared motion sensor network distributed in the subject's living room and in the common living areas of the care unit;
- a wireless electronic patch worn by each subject monitored;
- an RF Beacon network deployed in the care unit which receives information data from the electronic patch.

Table 1
Use cases.

Events	Area		Emergency level	Destination		Data sensor			Decision time	Platform
	Room	Care unit		Medical staff	Nurse	Patch	RF Beacon	IR		
Fall	x	x	ALERT		x	x	x	x	Real time	Real time application/ phone
Nocturnal restlessness (in bed)	x		ALERT		x			x	Real time	Real time application/ phone
Nocturnal immobility (in bathroom)	x		ALERT		x			x	Real time	Real time application/ phone
Group activity		x	INFORMATION	X				x	Deferred	Web application
Nocturnal restlessness (longitudinal follow-up)	x		INFORMATION	X				x	Deferred	Web application
Nocturnal immobility (longitudinal follow-up)	x		INFORMATION	X				x	Deferred	Web application
Decreased movement level	x	x	WARNING	X			x	x	Deferred	Web application
Increased movement level	x	x	WARNING	X			x	x	Deferred	Web application
Behavioural deviation		x	WARNING	X			x		Deferred	Web application

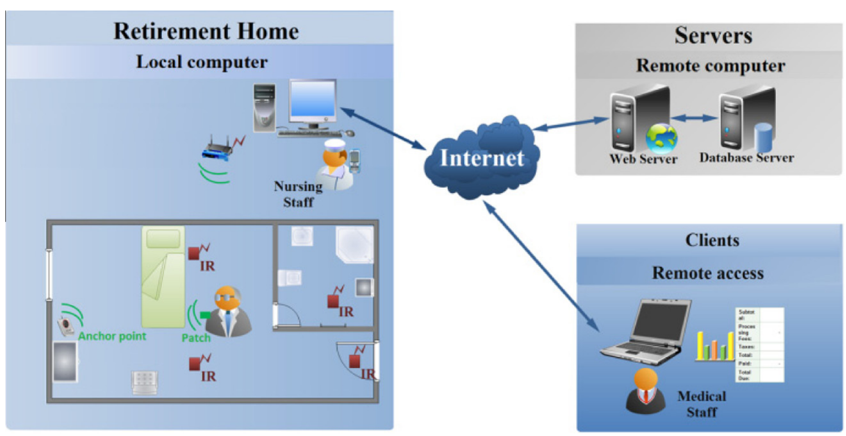


Fig. 1. General architecture of the Homecare system.

A real time application installed on the local computer gathers ADL and localization related data via the motion sensor network. The identification function of the electronic patch enables these data to be linked with the subject. It also generates emergency messages on both the local computer and the mobile phones of the careers if a dangerous situation occurs. A remote unit retrieves the ADL data files and stores them in a database. It also hosts the web application used by the medical staff to view ADL and alert data via remote access.

The infrared motion sensor network uses the 433 MHz ISM (industrial, scientific and medical) frequency band and can be configured remotely via a dedicated software interface. The communication between the electronic patch (called a Tag) and the anchor points (called Beacons) uses an IEEE 802.15.4 standard compliant transceiver (Man & Committee, 2006). In order to maximize compatibility with health facilities, which may be not equipped with an Ethernet network (as is the case at the experimentation site), we used power line communication (PLC) devices. These devices replace the Ethernet bus between the Beacons and the local computer. Each Beacon has a different static IP address (172.30.13.X) and is associated with a PLC device configured as a slave. A PLC device configured as a master allows transmission of the data packets to the local computer. PLC modules enable fast and easy implementation. These modules use the HomePlug-AV standard (Yousuf, Rizvi, & El-Shafei, 2008) and can carry up to 45 Mbits/s data on 300 m of electrical cable. In addition, QoS functionalities and 128-bit AES encryption enable reliable and secure data transport. All the data are sent by the sensors to the local computer and alarms are distributed to the medical staff via the GSM network as shown in Fig. 2.

2.4. Methods

2.4.1. Indoor localization method

Many indoor localization methods use the radio signal strength indicator (RSSI) received by anchor points and combine them to extract the position of the mobile node. These methods have several levels of complexity depending on the accuracy required. Three localization methods in increasing order of complexity are as follows:

- the cellular localization method (Huang & Chan, 2011; Kuo, Chen, Jen, & Lu, 2010; Noh, Lee, & Ye, 2008);
- the fingerprinting method that exploits the reference positions of the mobile node in its environment (RSSI mapping) Tsuji et al., 2010;
- mathematical models of wave propagation as a tool for localization (Navarro-Alvarez & Siller, 2009).

In the Homecare project, the accuracy of localization is not a determinant criterion. The goal of the localization function is to detect the patient's presence in specific areas of the hospital in order to measure ADLs using the IR motion sensors. Thus, the cellular localization method is used because it permits simple software development and fast deployment on site. This method consists of choosing the location of fixed nodes in the building to avoid

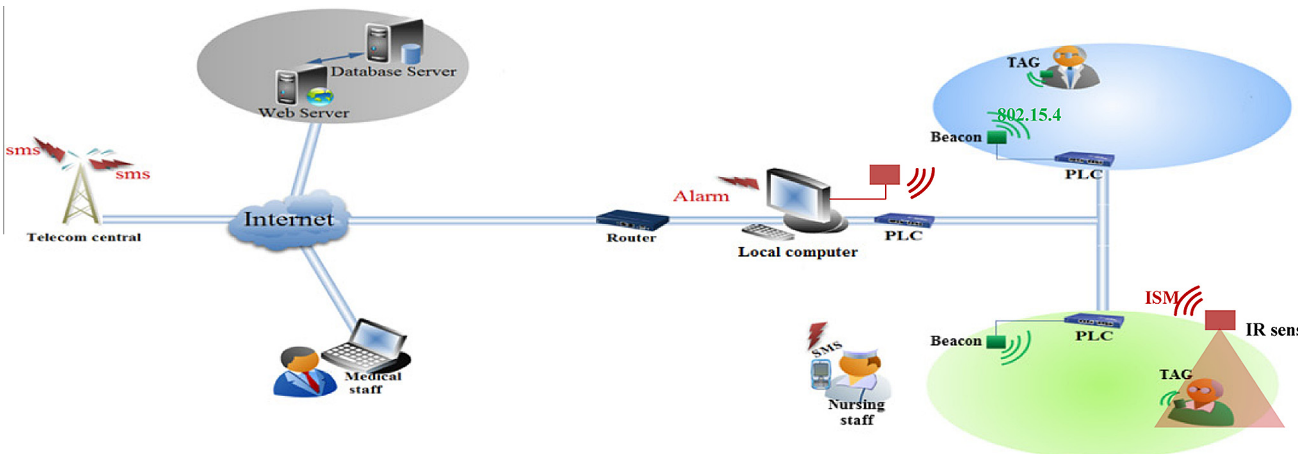


Fig. 2. Communication network architecture.

overlapping areas. The real-time application compares the RSSI levels received by the Beacons for each 802.15.4 frame transmission by the Tag and then selects the nearest Beacon.

2.4.2. Algorithms for the fall detection

Algorithms based on acceleration thresholds are a good compromise between performance and energy consumption (Lombardi, Ferri, Rescio, Grassi, & Malcovati, 2009; Yongli, Yin, & Han, 2012). As specified in the state of the art paper by Noury (Noury et al., 2007), two types of method are generally used for the implementation of thresholds:

- analytical methods: the warning thresholds are determined empirically in a laboratory;
- machine learning methods: the detection thresholds are determined during a learning phase in real situations of use.

With the analytical method, the calculations for the fall algorithm can be embedded in the microcontroller to save energy. This solution was chosen, in a first step, in order to guarantee sufficient lifespan.

2.5. User interfaces

2.5.1. Real time application

This application allows the nursing staff to locate the patient in real time indoors and in the hospital garden. Nursing staff receive alerts via their mobile phones and on the real time application. When an alert occurs, the nurse must confirm whether it is a true or a false alert. The detection thresholds are adjusted if it is a false alert. Fig. 3 shows the real time application interface.

2.5.2. Web application

The results of data processing can be visualized via an internet protocol with the remote PC in graphic formats (Fig. 4); this also allows the patient's medications to be viewed using forms completed by the nursing staff.

The results obtained during processing give a personalized profile for every subject observed. This profile is characterized by certain ADL parameters such as average motion speed, distance covered and level of activity. An example is shown in Fig. 5.

These ADL criteria allow the medical staff to follow the development of the subject's dependence and provide the opportunity to adapt on-going treatments if necessary (Bourennane et al., 2013; Campo et al., 2010).

3. Hardware and software development of the monitoring system

In this section, we present the hardware and software development of the network. The sensors in the network permit falls to be detected and located for the tagged subjects. In addition, the identification function allows data on activity measured by the motion sensors to be linked with the subject followed.

3.1. Activity monitoring system

The infrared motion sensor network enables the subject's activities to be monitored. Each sensor is placed on the ceiling and oriented towards the floor; the range area at floor level is adjustable from 1 to 2 m^2 using masks of various shapes and sizes. Depending on the sensitivity setting, it is able to detect the movements of a person or a limb. The power supply consists of two 1.5 V batteries (AA). The autonomy of these sensors varies from three months to one year depending on the number of sensor activations. For each activation, The ISM transceiver sends a radio frame containing the sensor identifier. The network has a transmission mode called "radio range extended" through which each sensor can relay the radio frame to the data receiver. Fig. 6 shows the infrared motion sensors.

However this activity monitoring system is difficult to implement in a multi-user environment due to the use of IR sensors that cannot recognize an individual among several people in the same area. Therefore, our principal contribution in this work consists of designing an electronic patch worn by the subjects associated with an 802.15.4 wireless communication network to identify and locate them. The patch integrates an accelerometer which is used to detect falls.

3.2. Fall identification and localization monitoring system

The system developed consists of two parts (Fig. 7):

- a radio transmitter worn by the subject – the Tag, and
- a radio receiver placed in the room to be monitored – the Beacon.
- Each device is made using the same hardware architecture.

3.2.1. The Tag device

The Tag sends an identifier associated with the tagged person every second. In the case of a fall it also transmits an alarm radio message. An internal control system in the battery allows it to send a warning message when the capacity is lower than 20%. The main

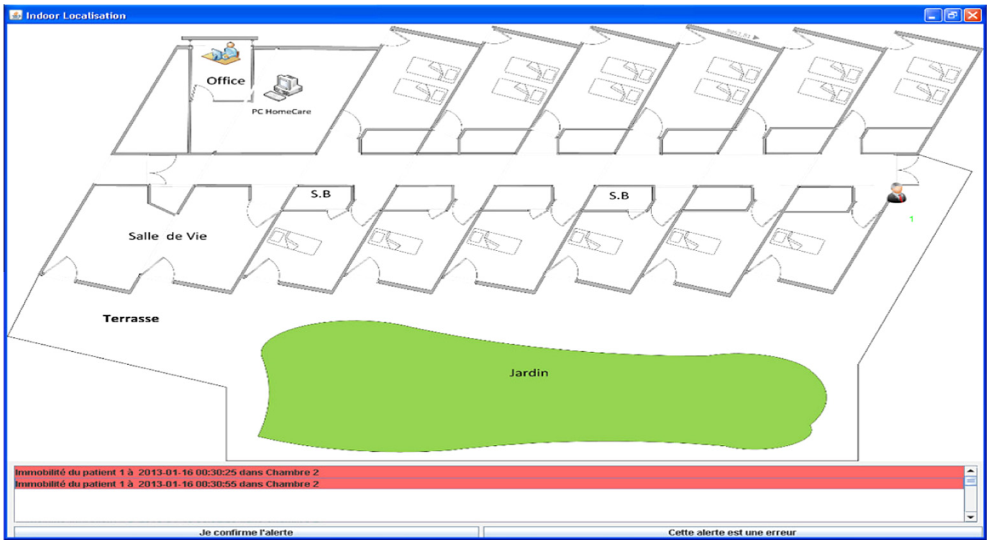


Fig. 3. Real time application interface.

Fig. 4. Web application.

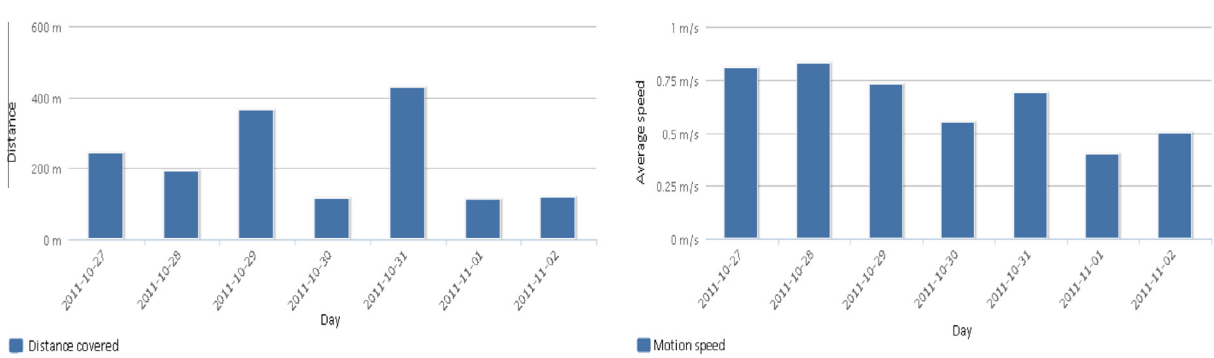


Fig. 5. ADL parameters.

component of the device is the MC13213 from Freescale Semiconductors (MC13213 Data Sheet, 0000). This component is a system in package (SIP) including a microprocessor unit (MCU) and an 802.15.4 compliant transceiver. Our design is inspired by the 13213-ICB reference design from Freescale and all necessary interfaces have been integrated in the board to configure and to debug our device. For fall detection, we also added a tri-axial accelerometer, the ADXL345 component from Analog Device (ADXL345 Data Sheet, 0000).

The size of the Tag device has been minimized in order not to disturb or hurt the tagged person. The dimensions are 3.2 cm × 2.2 cm × 3.5 mm and the total weight is 5 g (including the battery). The block diagram of the Tag is presented in Fig. 8.

The level of energy performance was an important factor in the choice of components and communication protocol. The purpose was to maximize the autonomy of the Tag by powering it using a lithium battery CR2016 with a capacity of 90 mA/h. The three main technical choices to reduce consumption are:

Fig. 6. Infrared motion sensors.

(1) Low power communication standard: the IEEE 802.15.4 standard (Man & Committee, 2006) defines the characteristics of the physical and MAC layers for low-rate wireless personal area networks (LR-WPAN). The physical layer supports three frequency bands: a 2450 MHz band (with 16 channels), a 915 MHz band (with 10 channels) and an 868 MHz band (one channel). This communication standard was adapted to the project specifications. Indeed, the advantages of this LR-WPAN are its ease of installation, the reliability of data transfer, the extremely low cost, and the reasonable battery life, while maintaining a simple and flexible protocol stack. The MC13213 component includes a low power 802.15.4 transceiver operating at 2450 MHz with a gross data rate of 250 kbps.

(2) Hybrid battery/capacitor power sources: In order to increase the lifespan of an embedded system, a common characteristic of battery power sources is that the battery is connected directly in parallel with the capacitor. In this configuration, the peak current generated by the transmissions (Fourty, van den Bossche, & Val, 2012; Fourty, van den Bossche, & Val. T., 2010) of the transceiver (30 mA @ nominal power) is limited. Limiting the peak current allows the maximum discharge current (10 mA) of the lithium battery not to be exceeded and avoids a rapid discharge (Fourty et al., 2010, 2012). A tantalum capacitor with a very low equivalent series resistance (ESR = 18 m Ohms) was chosen to minimize current losses in the capacitor.

(3) Low power accelerometer: The ADXL345 component has the characteristics required: small size (3 mm × 5 mm × 1 mm), low power consumption (23 µA @ 0.1 Hz to 140 µA @ 3200 Hz), a suitable measurement range (±16 g) and a high resolution (3.9 mg/LSB). It also has suitable functions for fall detection algorithms by using thresholds: free-fall and detection of activity and inactivity events with adjustable thresholds. When these thresholds are reached, they can generate interruptions on two dedicated outputs. The connection of these outputs on the keyboard interrupt inputs of MCU enables it to awaken on acceleration thresholds in order to launch an analysis of the acceleration spectrum. This is used to measure acceleration in real time without using the resources of MCU to save energy. An I2C interface between the MCU and accelerometer was chosen for the sake of scalability. The maximum operating frequency (400 kHz) of this interface is used to reduce the activity time of the system. Thus, the average consumption of the system decreases.

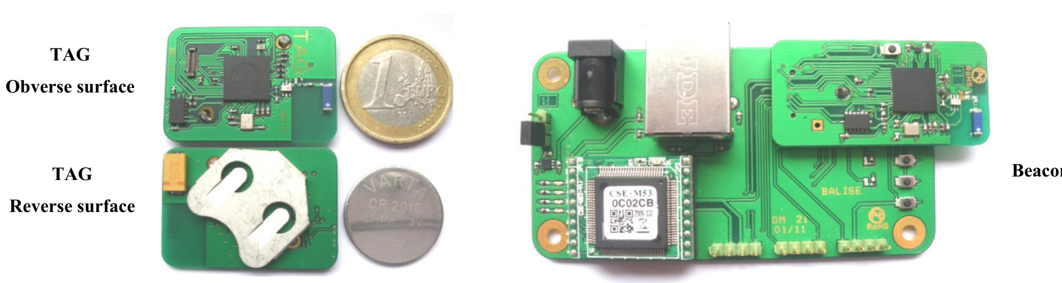


Fig. 7. The 802.15.4 Tag/Beacon devices.

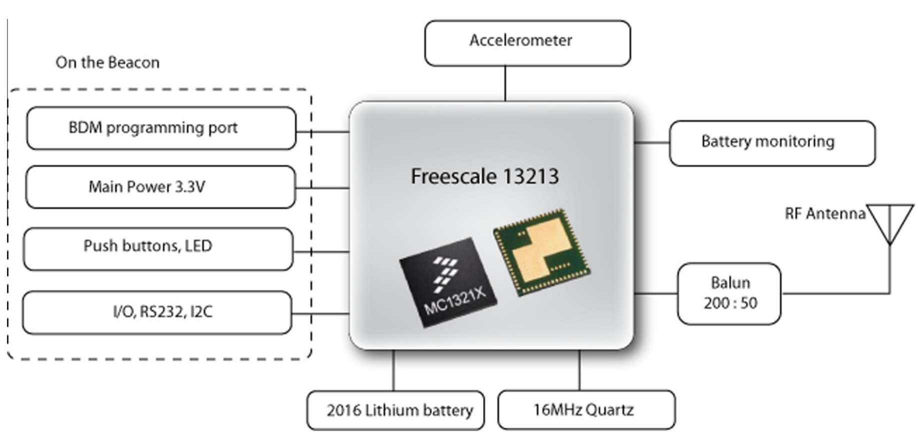


Fig. 8. Block diagram of the Tag device.

We characterize the performance of our Tag in terms of energy consumption and radio range in Section 5. The main features of the Tag are summarized as follows:

- radio range in the indoor environment: 15 m;
- radio range in the outdoor environment: 40 m;
- maximum current consumed for a radio transmission: 2.7 mA @ 3 V (reduced by capacitor);
- average current consumption: 160 μA;
- autonomy: 490 h (approximately three weeks).

These features are fully compliant with the project specifications including the Tag autonomy that exceeds two weeks.

3.2.2. Beacon device

The Beacon device is a radio receiver placed in the room of the subject to be monitored. It is designed around the Tag hardware architecture. We added a RS232/IP gateway (DataSheet, 0000); data received by the Beacon are sent via this gateway to the local computer. The Beacon device is powered by the electrical grid.

3.3. Software presentation

In order to program the application easily, Freescale offers several software solutions called Code Bases: a basic solution called SMAC (Simple Media Access Controller), a more complex 802.15.4 compliant stack and a ZigBee compliant stack. For our system we chose the basic SMAC for several reasons. The most important is that this code base is a completely open source program and gives access to very low power primitives (enabling maximal energy savings). Moreover, this code base is very small and easy to implement. The source code is in standard C language and the development environment is Code Warrior (Development Studio, 0000).

3.3.1. Tag application

In order to optimize the power consumption of the Tag application, we chose to use the lowest power consumption modes of the MC13213 (MC13213 Data Sheet, 0000; Garcia & Pape, 2004) in particular by connecting an external clock to the Tag board. The system spends most of its time in hibernation mode (Hib.). The system is woken every second by the Real Time Interrupt timer (RTI timer) and sends an identification and localization frame (Tx). This cycle is an infinite loop which corresponds to the sending of a radio frame every second. When an event on the accelerometer occurs (activity interrupt), the state machine enters in the algorithm of a fall detection (Fall). The Tag application is described by the state machine in Fig. 9.

3.3.2. Beacon application

The Beacon is always in reception mode (Rx). When it receives a radio data frame, it sends this frame to the local unit via the Ethernet protocol (Tip). It then goes back into reception mode (Rx). The Beacon application is described by the state machine in Fig. 10.

3.4. Frame format

3.4.1. Radio frames

The radio frame format uses the 802.15.4 standard header and adds some fields. Frames are between 12 and 14 bytes long. The 802.15.4 frame header enables the use of most network analysers, such as the Daintree Network SNA (Sensor Network Analyzer, 0000), to monitor the radio communications. The frame is composed of three parts:

- the header field which defines the data exchange format of the IEEE 802.15.4 standard;
- the data field which gives the level of emergency in the case of a fall, the battery voltage of the Tag device (once an hour) and the identifier of the tagged person;
- the footer field which enables frame error detection.

3.4.2. Serial frames

After the reception of a radio frame, the Beacon transmits the data to the local unit. When the Beacon receives a radio frame, a serial data frame is sent to the IP/RS232 gateway from the MCU. The format of frames exchanged between the MCU and the IP/RS232 gateway is shown in Fig. 11.

The frames are as follows:

- byte 1 is used as a start frame delimiter in order to limit erroneous frames;
- bytes 2 and 3 enable identification of the Beacon and Tag;
- byte 4 gives RSSI – this information is used to locate the subject;
- bytes 5 and 6 show the battery voltage;
- byte 7 gives the level of emergency in the case of a fall;
- byte 8 is used as a stop frame delimiter in order to limit erroneous frames.

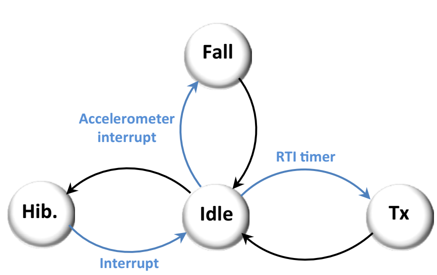
4. Implementation and characterization of the fall algorithm

In this section we show the steps in the implementation of the fall algorithm in the Tag device; we then characterize the performance of the fall detector in the laboratory.

4.1. Accelerometry

In order to guarantee good measurement acceleration with the ADXL345, we followed the following steps:

(1) Self-test of MEMS (the MicroElectroMechanical System) to check the proper functioning of the accelerometer (Tomoaki, 2010).
(2) Calibration of the tri-axial accelerometer signals. This stage was performed using the static method proposed by Tee, Awad, Dehghani, Moser, and Zahedi (2011).



Description of states
Hib.: MC13213 is inactive with:
- MCU in stop 3 mode
- Transceiver in hibernation mode

Idle: Transition stage
Tx: Sending the radio frame
Fall: Fall detection algorithm

Fig. 9. The state machine of the Tag.

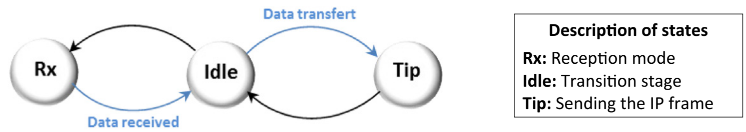


Fig. 10. The state machine of the Beacon.

1	2	3	4	5	6	7	8
Start	ID Balise	ID Tag	RSSI	Battery voltage		Em. level	Stop

Fig. 11. Serial frame format.

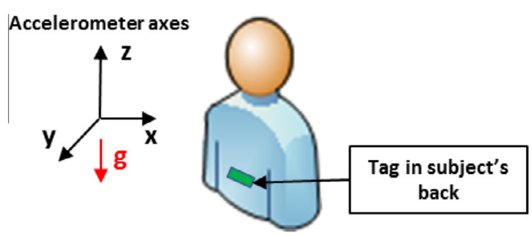


Fig. 12. Position of the Tag and axis of the accelerometer.

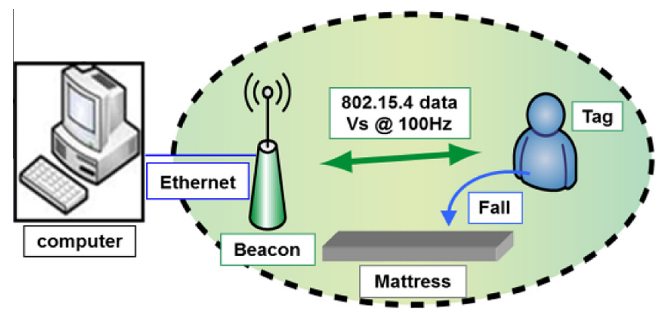


Fig. 13. Materials for the fall tests.

(3) Choice of the acquisition frequency. In most publications dealing with fall detection, the acquisition frequency is between 100 and 400 Hz (Anania et al., 2008; Bourke et al., 2010; Kangas, Konttila, Winblad, & Jamsa, 2007). As a first step, we fixed the acquisition frequency of the accelerometer at 100 Hz for the implementation of the fall detector. As a second step, the acquisition frequency was fixed at 400 Hz in order to increase the accuracy of the fall detector in the real situation of use.

(4) Filtering. The integrated electronics of the ADXL345 are composed of an analog–digital converter followed by a low-pass digital filter.

4.2. Parameters for the fall algorithm

The first parameter used to characterize the fall is the sum vector SV (Eq. (1)). It provides the acceleration amplitude cumulated on the three axes in g, it contains the static (gravity) and dynamic components of the acceleration. This parameter is the one most used and gives good results for fall detection (Bourke et al., 2010; Kangas et al., 2012; Shany, Redmond, Narayanan, & Lovell, 2012).

$$SV = \sqrt{(x_i^2 + y_i^2 + z_i^2)} \text{ with } x_i, y_i, z_i, \text{ samples acceleration } (g) \text{ of the axes } x, y, z \tag{1}$$

The second parameter used to characterize the fall is the posture measurement. For this it is necessary to measure the trunk inclination. In order to measure this inclination correctly, the z-axis must be oriented vertically. The position of the accelerometer on the subject's body is shown in Fig. 12.

First we measure the acceleration caused by the gravity for a specific orientation of the z-axis at time t ($g_{SEG,Zi}{}^{(t)}$). Then we calculate the average inclination angle relative to the vertical (Eq. (2)).

$$\phi_{z\text{-}axis} = \cos^{-1}\left(g_{SEG,Zi}^{(t)}\right)^{*} 180/\pi \tag{2}$$

The tilt measurement with an accelerometer implies a measure in a stable state (static acceleration) in order not to disturb the measurement. The tilt angle between the vertical z-axis and the floor enables the posture of the tagged person to be defined. Thus, according to the classification of Karantonis, Narayanan, Mathie, Lovell, and Celler (2006), we can define the posture as follows:

- standing posture (vertical posture): the vertical inclination is between 0° and 20°;
- sitting posture: the vertical inclination is between 20° and 60°;
- lying posture (horizontal posture): the vertical inclination is between 60° and 90°.

In our case, the inclination is measured between the back of the tagged subject and the floor following a fall (stable state).

4.3. Fall and ADL tests in the laboratory

Three volunteers, a woman (28 years old) and two men (26 and 29 years old), simulated falls on a mattress 25 cm thick when a combat sport. With the Tag/Beacon set, we had a tool to register the accelerometer data in real time and continuously on a computer via the 802.15.4 radio link. Thus, we were able to test the equipment in real conditions, that is to say, with the Tag worn on the volunteer's back. A specific program was implemented in the MCU of the Tag. This calculated the parameter SV sampled at 100 Hz. The Tag sends 100 radio frames per second, each containing the last computed value of SV. The fall tests were conducted with the receiver close to the mattress used in these tests. The use of the acknowledgment frame of the 802.15.4 protocol ensured the radio link. Data collected by the Beacon were then relayed to the PC Ethernet port. A data logger program written in C++ saved data in an Excel table. Then we plotted the acceleration measurements with Excel curves. The equipment used for the fall tests is shown in Fig. 13.

A protocol (Table 2) depicting several fall scenarios was established based on previous publications (Hsiao & Robinovitch, 1997; Smeesters, Hayes, & McMahon, 2001; Van den Kroonenberg,

Table 2
Fall scenarios.

Scenarios	Directions	Start of fall	Instructions	Accessories
1, 2, 3, 4	Front, back, left, right	Static	Straight legs during fall	Mattress
5, 6, 7, 8	Front, back, left, right	Static	Fall with flexed knees	Mattress
9, 10	Front, back	Moving	Tripping on the edge of the mattress by moving forward or backward	Mattress
11, 12, 13, 14	Front, back, left, right	Moving	Falling down while going down step	Mattress + step
15	Back	Static	Falling backwards from sitting	Mattress

Table 3
ADL scenarios.

Scenarios	Instructions	Accessories
1	Picking up an object on the floor	Pen
2, 3, 4, 5, 6	Sitting down and standing up	Armchair, kitchen chair, sofa, bed, stool
7	Lying down and standing up	Bed
8	Walking 20 m	None
9,10	Ascending and descending stairs	None

Hayes, & McMahon, 1996). Each scenario is associated with an instruction. Falls were conducted from the standing posture and in four directions (front, back, left and right). At the start of fall, the volunteer was either moving or was in a static position. We also used a step (35 cm) higher than the mattress to simulate a fall on stairs. The 15 fall scenarios are summarized in Table 2.

Volunteers were asked to perform four sets of the full protocol, 60 falls for each scenario. As in Hsiao and Robinovitch (1997), two series of our protocol allowed simulation of a swoon, with the instruction to relax the muscles during the fall. The two other series enabled simulation of an accidental fall, with tensed muscles and protection of the arms upon contact with the mattress (natural reflex) Hsiao & Robinovitch, 1997.

Our three volunteers also simulated the most commons ADLs for the elderly. A protocol staging several scenarios was established using two publications (Kangas et al., 2012; Karantonis et al., 2006). The 10 scenarios of ADLs are summarized in Table 3.

This protocol was carried out twice by each volunteer at three different speeds (slow, medium and fast) to cover a wider range of acceleration. Each volunteer performed six series of the full protocol, 60 activities each, providing a total of 180 activities.

4.4. Search for fall and ADL signatures

We aimed to identify the specific signatures of falls in order to fix appropriate acceleration thresholds and to distinguish between falls and ADLs (Fig. 14). Five steps were identified during our tests:

(1) The volunteer is standing opposite the mattress (static position); the amplitude of parameter SV is approximately 1 g (gravity).
(2) The volunteer is in free fall (foot raised off the floor); the amplitude of parameter SV decreases and tends towards 0 g (phenomenon of weightlessness).
(3) This step corresponds to the impact with the floor (mattress); the amplitude of parameter SV increases to a maximum value.
(4) The body bounces before reaching a stable state. It should be noted that the bounces are certainly amplified by the mattress.
(5) The volunteer is in a stable position, lying on the mattress.

Steps 2 and 3 are typical of falls and can be detected with thresholds on the SV parameter. During step 5 we were also able to estimate the posture of the person by measuring the inclination between the floor and the person's back with the parameter $\phi_{z\text{-axis}}$.

4.5. Threshold determination

Firstly, we search for fixed thresholds that would distinguish between falls and ADLs. To determine the threshold of free fall, we compared the values of SV_min_freefall with the values of SV_min_ADL. To determine the threshold of the impact, we also compared the values of SV_max_impact with the values of

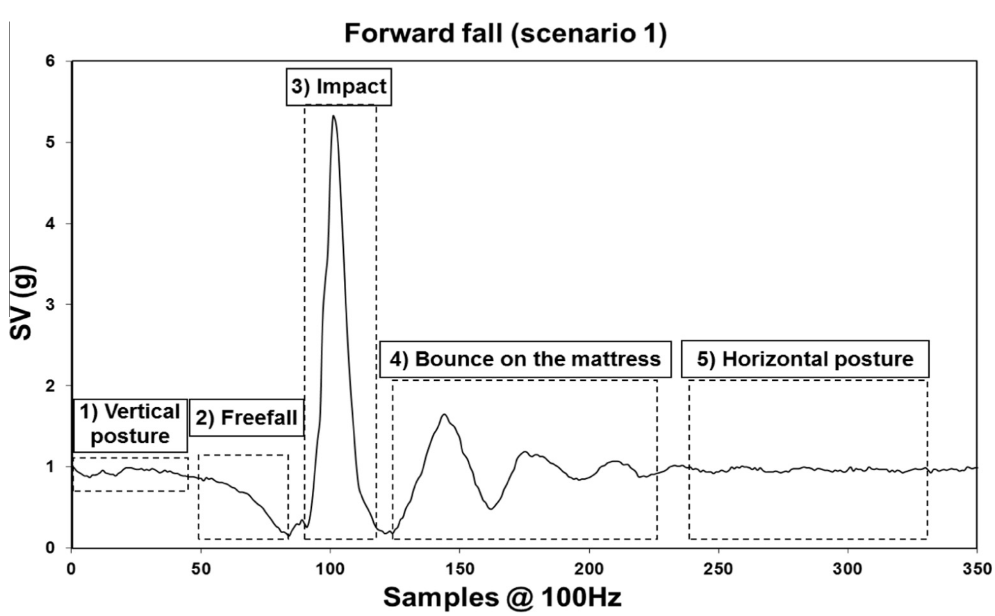


Fig. 14. Fall signatures.

SV_max_ADL. Fig. 15 shows SV parameter measurements for a forward fall and for normal walking.

4.5.1. Results

Following the implementation of the simulated scenarios, we had a database of 180 falls and 180 ADLs. Fig. 16 shows the statistical distribution of our tests in quartile box plots.

To determine the levels of acceleration, a simple algorithm based on acceleration thresholds on free fall and the impact is not sufficient to distinguish simulated falls from ADLs in every case. Thus, it seems necessary to measure the person's posture following free falls and impacts to increase the strength of the algorithm. In our ADL protocol, two scenarios can generate a lying posture: picking up an object from the floor and lying down on a bed. However, these ADLs do not generate acceleration higher than the acceleration of the fall impact event. Thus, the association between free falls, impacts and posture events enables distinction between falls and ADLs in 100% of our simulated cases. It also appears from the measurement of simulated falls that the transition period between different steps is stable. Then, by adding time limits between the different steps, we reduce the possibility of false alarms without decreasing the performance of the fall detection method using thresholds.

4.6. Fall algorithm

In order to choose transitional times, we used our database. Margins of safety were added. Fig. 17 shows the algorithm for falls implemented on the Tag.

The transition times and the acceleration thresholds chosen for our fall algorithm are summarized below:

- a free fall event is detected when SV < 0.75 g for a period of 30 ms;
- after detection of a free fall event, the maximum timeout of the impact event is Timeout_impact = 0.5 s;
- an impact event is detected when SV > 3.5 g;
- after detection of an impact event, the time before the calculation of the posture is T_wait_posture = 2 s;
- after the T_wait_posture time, the system calculates the average acceleration on the *z*-axis for a duration of 0.1 s (40 acquisitions) then it measures the vertical inclination. The inclination threshold that defines a horizontal posture is $60° < \phi_{z\text{-}axis} < 90°$.

We also added one more step that sets a critical fall if the person remains static on the floor for more than 10 s:

- an inactivity event is detected when ΔSV < 0.2 g for 10 s, corresponding to an absence of movement by the person (immobility).
- At this level, two cases are possible:
- case 1: the person moves before the end of 10 s and the Tag sends a fall alert (0xAA);
- case 2: the person does not move for 10 s and the Tag sends a critical fall alert (0xBB).

To ensure that the radio message alert (0xAA or 0xBB) is considered, we use the acknowledgement (ACK) frame of the 802.15.4 protocol. Following the transmission of the alert message by the Tag with the acknowledgement request (ACK_request), the Beacon must answer with an ACK message. If the Tag does not receive the ACK message, it continues to send the alert together with ACK_requests.

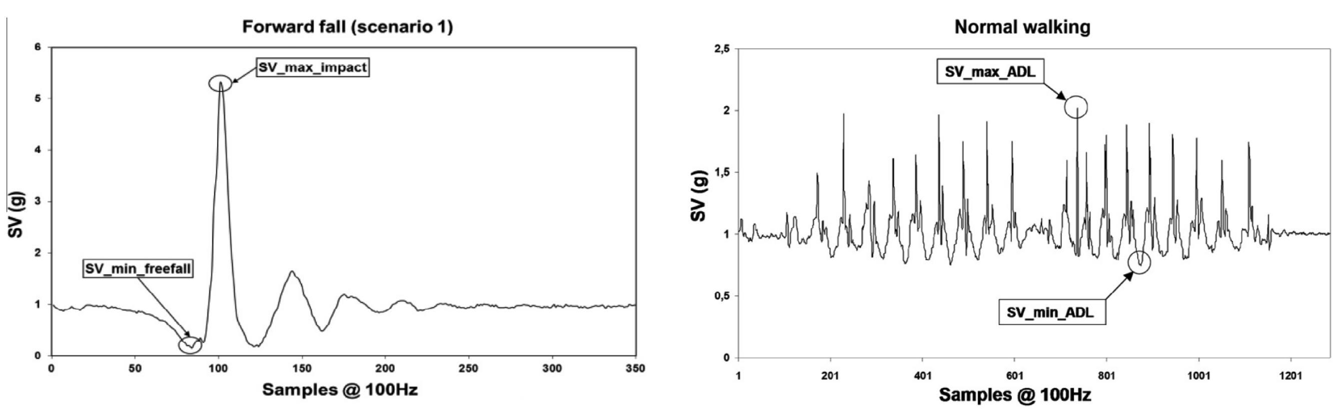


Fig. 15. Values measured to define thresholds of the fall detector.

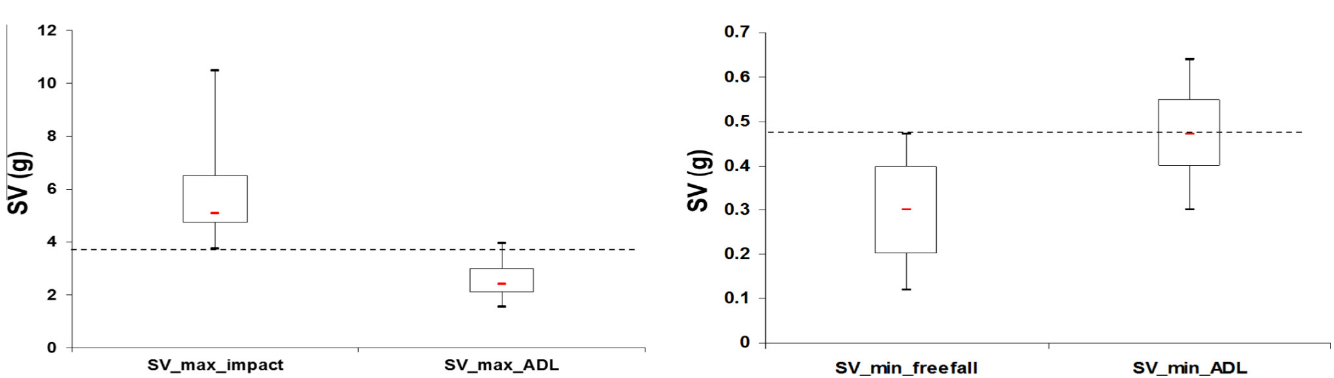


Fig. 16. Comparison between the statistical distribution of falls and ADLs.

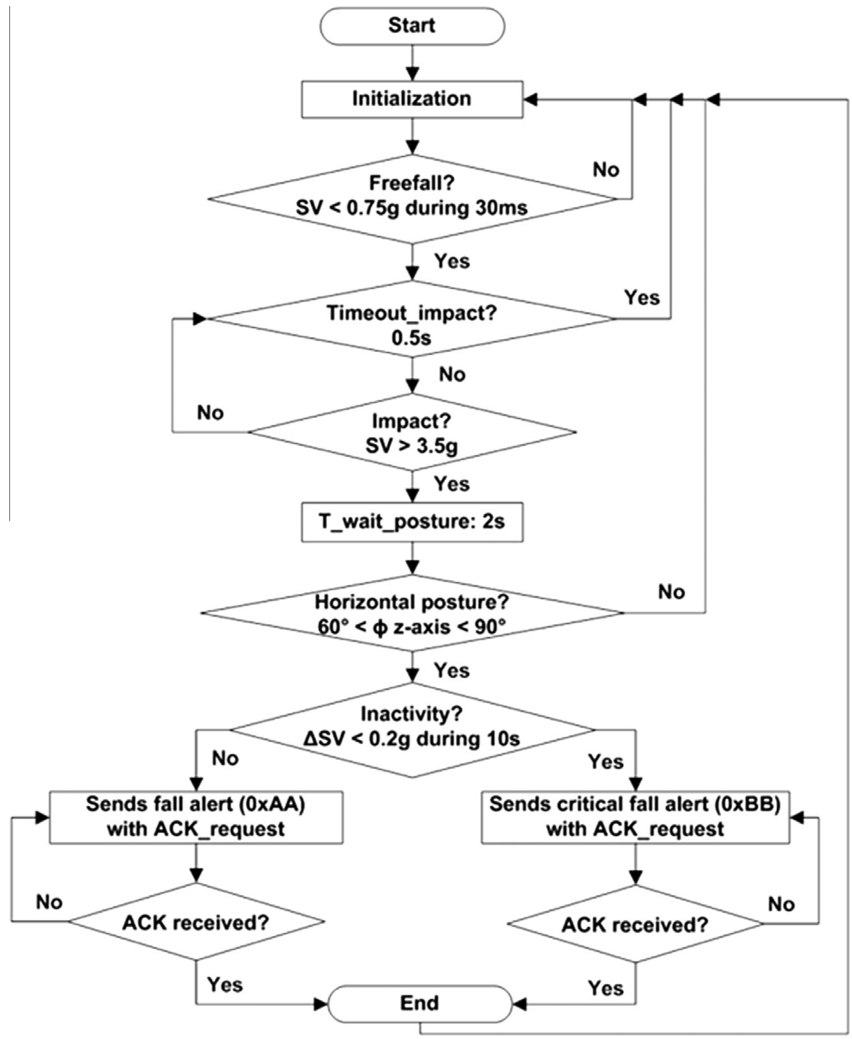


Fig. 17. Fall algorithm implemented on the Tag.

4.7. Characterization of the fall detector in the laboratory

To evaluate the quality of the fall detector, it was necessary to carry out a statistical analysis on a series of tests (Noury et al., 2007). There were four possible cases:

- true positive (TP): a fall occurs and the device detects it;
- false positive (FP): the device announces a fall that did not occur;
- true negative (TN): a normal movement is performed (not a fall) and the device does not declare a fall;
- false negative (FN): a fall occurs but the device does not detect it;
- To evaluate the responses to these four situations, we used two criteria:
- sensitivity is the capacity to detect a fall, thus

$$\text{Sensitivity} = \text{TP}/(\text{TP} + \text{FN})^{*}100 \quad (3)$$

- specificity is the capacity to detect only a fall, thus

$$\text{Specificity} = \text{TN}/(\text{TN} + \text{FP})^{*}100 \quad (4)$$

Our algorithm was tested with three new volunteers, two women (24 and 25 years old) and a man (31 years old), a combat sport. They performed the fall and ADL scenarios in the same way as that previously described in Section 4.3.

4.7.1. Results

The results of our tests are presented in Table 4.

The sensitivity is 98.33% and specificity is 97.77%. These results are encouraging because they are superior to the majority of results reported in the state of the art paper by Shany et al. (2012) on wearable fall detectors based on measurements with the tri-axial accelerometer without a learning method. We also note from our results and those set out in this state of the art paper that this method reaches these limits in terms of performance. Thus, to increase performance it seemed necessary to add a learning algorithm. The results published by Bourke et al. (2010) reach 100% sensitivity and specificity with the addition of supervised learning. This learning phase requires the sending of fall thresholds when the system detects a fall in order to adjust the thresholds. Thus, this method consumes more energy for the device worn. However, given that the Tag autonomy exceeds the requirements of the specifications (more than two weeks), we can now propose a compromise in terms of the system energy consumption with the addition of a learning method. The performance of the fall detector could

Table 4
Results of performance tests in the laboratory.

Protocol	Numbers of tests	TP	FN	TN	FP
ADL	180	–	–	176	4
Fall	180	177	3	–	–

Table 5
Software configuration of the Tag for the characterization of the electrical consumption.

V_{bat}	P_e (Tx)	RTI	Tx	F_{clk} transceiver	$F_{ADXL345}$
3 V	3,6 dBm (max)	1 s	1 s	16 MHz	400 Hz in low power mode (90 μA)

thus be increased. In this way, we are currently studying the implementation of supervised learning.

5. Characterization of the Tag features

This section addressed the characterization of the Tag in terms of current consumption and radio range.

5.1. Electrical consumption

These measurements were performed with prototypes to evaluate the consumption generated by the Tag device. In order to characterize the Tag electrically, we measured the current passing through a serial 100 Ω resistor at 3 V (battery voltage). Table 5 summarizes the software configuration of the Tag for the current consumption measurement.

Fig. 18 shows the measurement of the average voltage consumption of the Tag through a serial 100 Ω resistor.

The maximum current peak (Tx) is 2.63 mA, corresponding to the 802.15.4 frame sending. These current peaks are limited by a capacitor placed in parallel with the battery. The average consumption measure is 159 uA. The expected capacity is 566 h (23 days) with a CR2016 lithium battery of 90 mA/h.

5.2. Radio range

The measurements were performed outside in an empty parking lot and inside the corridors of the laboratory. We used a measuring tape to record the distance between the Tag and the Beacon. The Tag sends a data frame with an acknowledgment request every second. The acknowledgment is programmed without retransmission (a single round trip). It validates the arrival of the message on the receiver. We consider here that 99% of the messages arriving at the connection is a good result. We increased the distance between the devices by steps of 0.5 m and as long as the frame rate exchanged is higher than 99%, we take the maximum distance. With the maximum transmission power ($P = 3.6$ dBm), the radio range is 40 m outside and 15 m inside.

6. Deployment of the system

In this section, we present the deployment of sensors inside the hospital, the solution proposed by the medical staff for the Tag worn on the subjects, the first evaluation of the dressing tolerance, the performance of the fall detector in the real situation of use and the real autonomy of the Tag.

6.1. Deployment of sensors at the Caussade hospital

Fig. 19 shows the areas of surveillance deployed in the Alzheimer care unit. The coverage area of each sensor was recorded and plotted on a virtual map of the hospital and then stored in a system of coordinates.

The sensors are deployed in the rooms of two equipped subjects and in the main living areas (corridor, living room, terrace and garden). The local unit is in a room reserved for health staff. Subjects' rooms and the living room are also equipped with infrared motion sensors. These sensors are measuring the level of the group's activities in the living room and the activity level of the subjects in their own room (Bourennane et al., 2013; Campo et al., 2010).

The cellular localization method uses the RSSI values. Initial tests on site show localization errors, in particular in the overlapping areas of Beacons. To resolve this issue, the cover of each Beacon was reduced using software to avoid overlapping areas. The software only used those RSSI values which were sufficiently large to localize the Tag in the Beacon coverage area. Given that access to hospital areas is restricted for safety reasons related to the Alzheimer's patients, we used the passage areas authorized in order to choose the beacon locations in the hospital.

The localization method can be summarized by updating the localization when the person tagged passes close to a Beacon. The radio coverage of indoor Beacons and outdoor Beacons are approximately 10 and 30 m^2 respectively. When the localization is updated, two cases are possible:

(1) The person is in a living area: in this case, the system localizes the person in the middle of the Beacon coverage area.
(2) The person is in his/her bedroom: in this case, the system uses the detections of the IR sensors in order to localize the person precisely inside the bedroom.

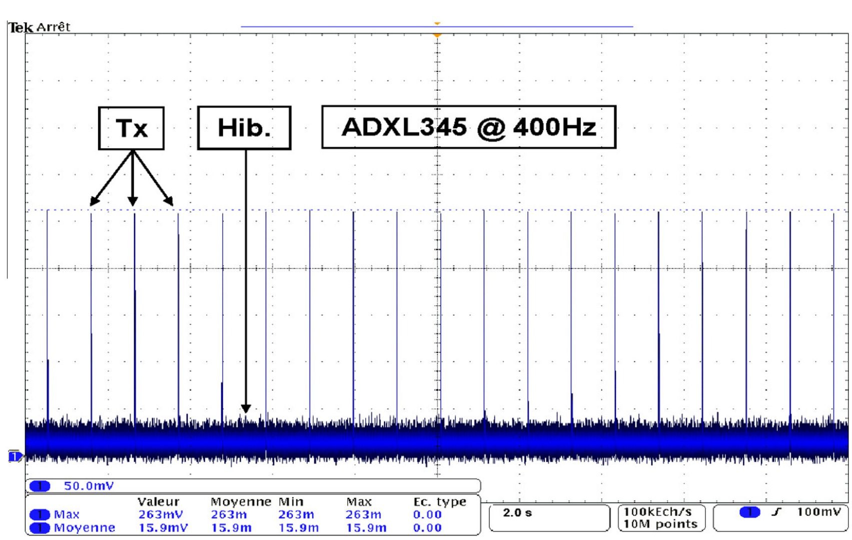


Fig. 18. Average voltage consumption of the Tag through a serial 100 Ω resistor.

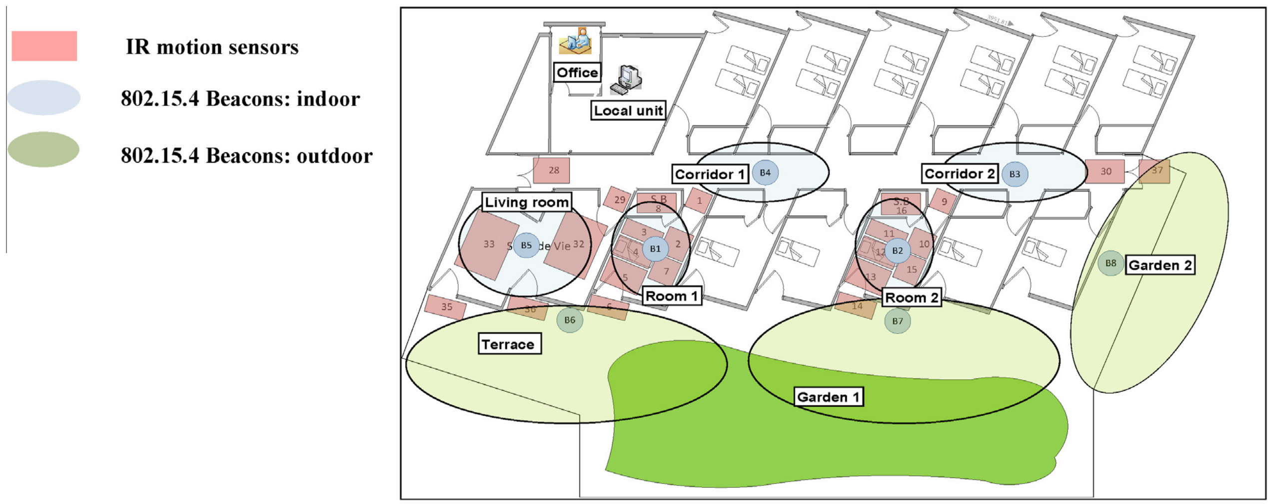


Fig. 19. Surveillance areas in an Alzheimer care unit in hospital.

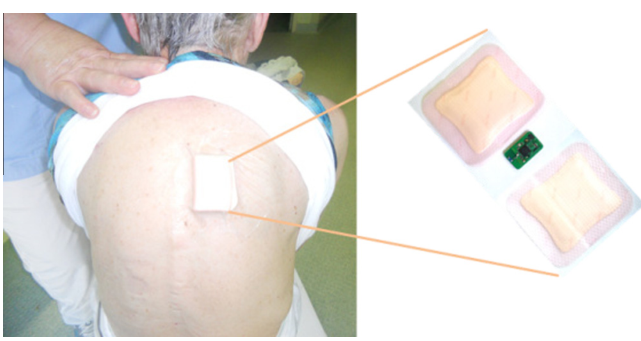


Fig. 20. Tag inserted between two dressings and attached to the backs of subjects.

Movements between the living areas allow computation of the distances covered. Movements inside the bedroom are more accurate and allow computation of the distances covered and also the gait speed (Bourennane et al., 2013).

6.2. Location of the Tag device

In order to monitor those suffering from severe cognitive impairments such as Alzheimer's disease, the solution proposed by the medical staff was to use a hydrocolloid dressing which avoids redness to secure the Tag to the subject's back (Fig. 20). This position prevents the subjects from removing the equipment and gives better results for fall detection because the sensor is attached to the body. Indeed, a loose attachment or insecure fit causes vibration and movement of the wearable system and it is liable to produce extraneous signal artefacts and to degrade sensing accuracy (Yang & Hsu, 2010).

6.2.1. Evaluation of the dressing tolerance

Evaluation of the dressing tolerance was performed using a questionnaire established by our research team and completed by medical staff with the contribution of the subjects' families:

- Is the subject trying to remove the patch? There was nothing to report on this item.
- Does the subject feel any discomfort or pain as a result of the patch? The subjects did not complain of discomfort. During the three months of experimentation the patch did not cause redness or marks on any of our two subjects.
- What is the opinion of the family about this experience? The families gave their written agreement following the presentation of the patch and the monitoring system. They asserted that they agreed as long as we respected the anonymity and the physical and mental integrity of their relative. The aspect they found the most interesting was the real-time monitoring with the possibility to intervene immediately in the case of danger.
- Do you check if the patch is in place during the day? The dressing was changed once a week, or when the battery had to be replaced. The subjects were able to have a shower wearing the patch without any problems. The patch was checked to see that it had not come off when getting dressed in the morning and before bedtime.

This first evaluation shows that wearing a hydrocolloid patch minimizes inconvenience and makes this experiment possible. This evaluation also shows that wearing a patch is accepted by patient and their families because it increases security.

6.3. Performance of the fall detector in real situations of use

Two subjects were equipped with the Tag around the clock for three months. The average number of movements made by the subjects that did not trigger falls (TN) over the period of three months is important but cannot be quantified with precision. According to the medical staff, the number of normal movements that could trigger a false alarm (sitting down, standing up, lying down, walking, picking up an object, etc.) is estimated at 20 per day at least. Thus the specificity was calculated on the basis of 20 movements per day for 90 days, totalling 1800 movements for each subject (TP + TN). Table 6 shows the results in the real conditions of use for our fall algorithm over a three-month monitoring period.

The sensitivity is 87.5% and the specificity is 98.72% in real situations of use. The cumulative number of false alarms for both subjects is 46 for a total of 180 days; in other words, there was one false alarm every four days for one subject on average. A similar study was conducted by Bloch et al. (2011) using the Vigi'Fall® system. This study took place in a geriatric ward with 10 subjects over 75 years old, all of whom presented a risk of falling. Eight "falling" events and 30 "alarm release" events were recorded over a period of 168 days for the group of subjects. The sensitivity and the specificity of the device came to 62.5% and 99.5% respectively, with one false alarm every 6 days for one subject on average. These

Table 6
Results of performance tests in real situations of use.

	TP	FN	TN	FP
Subject 1	7	1	1771	29
Subject 2	0	0	1783	17
Total	7	1	3554	46

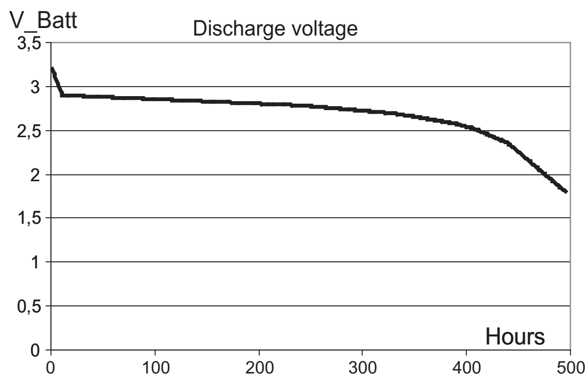


Fig. 21. Discharge voltage curve in real situations of use.

results can be compared to ours with an equivalent number of events. Our fall detector gives better results in terms of the number of detected falls with seven falls out of eight (against five falls out of eight with the Vigi'Fall® system). In terms of negative outcomes, our system generates more false alarms, one every four days (against one every six days for the Vigi'Fall® system). These preliminary results are encouraging but must be validated with more subjects and more events over a long monitoring period. The experiment in a real situation is maintained for an unlimited period because the system is functional and provides a safer environment for patients. This will also enable us to confirm our results.

6.4. Autonomy of the TAG system in real situation of use

Every hour the Tag sends the battery voltage in order to verify if the battery needs to be replaced. This measurement is done using the analog to digital converter (ADC) of the MCU. With these measurements we were able to plot the curve of battery discharge in real conditions of use. For this measure we asked the nurses to change the battery at the last moment. Fig. 21 shows the discharge curve of the battery.

The maximum life of the Tag is 490 h (three weeks). When the voltage delivered by the battery is less than 1.8 V, the TAG system stops because the voltage is insufficient for supply it.

7. Conclusion

A complete monitoring system was implemented in an institution for the elderly suffering from Alzheimer's disease. This system improved the daily surveillance of the medical staff by providing a more secure and safe environment. The main objectives of the Homecare project were achieved:

- the small size of the Tag worn via a hydrocolloid dressing minimizes the inconvenience caused and makes this experiment possible;
- the identification function enables monitoring of the subjects around the clock;
- the system provides greater autonomy and allows the subjects to be monitored continuously for three weeks.

The preliminary results for the fall detection function in real situations of use are encouraging: seven falls out of eight were detected. The number of false alarms is one every four days. The localization function allows the location of subjects in some areas of the hospital and in the garden. In case of alert messages, the medical staff can immediately locate the subject via their mobile phone. The ADL criteria enriched with histogram visualization via a web application make the system user friendly and accessible to medical staff.

The analytical method used to detect falls reached its limits. Thus, using a learning supervised machine could increase the performance of the fall detector. The solution being studied is the sending of acceleration thresholds during falls detected by the Tag device. Following a fall, the nurse in charge of monitoring is warned by mobile phone and validate (or not) the fall reported by the system. The thresholds can also be adjusted. Another option might be to combine the immobility time seen by the motion sensors (presumption of falling) with the fall detector attached to the person. These options are being studied.

Concerning localization, we plan to use the fingerprinting method to provide radio coverage of the entire hospital with a limited number of Beacons.

The current developments and tests should help validate the overall system and propose optimizations, particularly in terms of securing data on a remote unit, the miniaturization of the Tag device, and the improvement of the fall and localization algorithms.

The global Homecare solution is in the market research phase. In the case that the global solution is economically viable, our industrial partner is in charge of industrialization steps.

Acknowledgments

The authors would like to thank the nursing staff of the long-stay unit at the hospital of Caussade in France for their support in data reporting and the interfacing role with the participants. We also thank the French Research National Agency and CNSA for their grants (TECSAN program).

References

ALCIMED. (2007). Etude prospective sur les technologies pour la santé et l'autonomie. ALCIMED. <http://www.cnsa.fr/IMG/pdf/Rapport_final_ALCIMED_ANR_CNSA_VF2.pdf>.

Anania, G., Tognetti, A., Carbonaro, N., Tesconi, M., Cutolo, F., & Zupone, G., et al. (2008). Development of a novel algorithm for human fall detection using wearable sensors. In *Proceedings of IEEE sensors conference* (pp. 1336–1339).

Barnes, N. M., Edwards, N. H., Rose, D. A. D., & Garner, P. (1998). Lifestyle monitoring-technology for supported independence. *Computing Control Engineering Journal, 9*(4), 169–174.

Bloch, F., Gautier, V., Noury, N., Lundy, J. E., Poujaud, J., Claessens, Y. E., et al. (2011). Evaluation under real-life conditions of a stand-alone fall detector for the elderly subjects. *Annals of Physical and Rehabilitation Medicine, 54*(6), 391–398.

Bourennane, W., Charlon, Y., Bettahar, F., Chan, M., Esteve, D., & Campo, E. (2013). Ambient intelligence for monitoring Alzheimer patients. *International Journal of E-Health and Medical Communications (IJEHMC), 4*(1), 23–35.

Bourke, A. K., Van de Ven, P., Gamble, M., O'Connor, R., Murphy, K., Bogan, E., et al. (2010). Evaluation of waist-mounted tri-axial accelerometer based fall-detection algorithms during scripted and continuous unscripted activities. *Journal of Biomechanics, 43*(15), 3051–3057.

Campo, E., Chan, M., Bourennane, W., & Esteve, D. (2010). Behaviour monitoring of the elderly by trajectories analysis. In *Proceedings of the annual international conference of the IEEE engineering in medicine and biology society EMBS'10* (pp. 2230–2233).

Cerny, M. (2010). Movement activity monitoring of elderly people. In *Proceedings of the second international conference on computer engineering and applications ICCEA'10* (Vol. 2, pp. 454–455).

Chan, M., Campo, E., & Esteve, D. (2003). PROSAFE, a multisensory remote monitoring system for the elderly or the handicapped, In *Proceedings of the first International Conference On Smart homes and health Telematics ICOST'03* (Vol. 12, pp. 89–95).

Chan, M., Campo, E., Estève, D., & Fourniols, J. Y. (2009). Smart homes – Current features and future perspectives. *Maturitas, 64*(2), 90–97.

Chan, M., Estève, D., Escriba, C., & Campo, E. (2008). A review of smart homes – Present state and future challenges. *Computer Methods and Programs in Biomedicine, 91*(1), 55–81.

Chan, M., Hariton, C., Ringeard, P., & Campo, E. (1995). Smart house automation system for the elderly and the disabled. In *Proceedings of the IEEE international conference on systems, man and cybernetics, intelligent systems for the 21st century* (Vol. 2, pp. 1586–1589).

MC13213 Data Sheet [Online]. <http://www.freescale.com/webapp/sps/site/prod_summary.jsp?code=MC13213>. Access 05/2013.

ADXL345 Data Sheet Rev D [Online]. <http://www.analog.com/en/mems-sensors/mems-inertial-sensors/adxl345/products/product.html>. Access 05/2013.

CSE-M53 DataSheet [Online]. <http://www.eztcp.com/en/products/cse-m53.php>. Access 05/2013.

CodeWarrior Development Studio for HCS12(X) Microcontrollers (Classic IDE) [Online]. <http://www.freescale.com/webapp/sps/site/prod_summary.jsp?code=CW-HCS12X&tid=CWH>. Access 05/2013.

Duée, M., & Rebillard, C. (2004). La dépendance des personnes âgées: une projection à long terme. INSEE. <http://www.insee.fr/fr/publications-et-services/docs_doc_travail/g2004-02.pdf>.

Fleury, A., Vacher, M., & Noury, N. (2010). SVM-based multimodal classification of activities of daily living in health smart homes: sensors, algorithms, and first experimental results. *IEEE Transactions on Information Technology in Biomedicine, 14*(2), 274–283.

Fourty, N., van den Bossche, A., & Val. T. (2010). Etude de l'impact énergétique de l'algorithme d'accès au médium pour un réseau de capteurs sans fil industriel. In *Proceedings of the 6ème conférence internationale francophone d'automatique CIFA'10*.

Fourty, N., van den Bossche, A., & Val, T. (2012). An advanced study of energy consumption in an IEEE 802.15.4 based network: Everything but the truth on 802.15.4 node lifetime. *Computer Communications, 35*(14), 1759–1767.

Gentry, T. (2009). Smart homes for people with neurological disability: State of the art. *NeuroRehabilitation, 25*(3), 209–217.

Garcia D., & Pape, S. (2004). Freescale Semiconductor, Application Note, AN-2493 MC9S08GB/GT Low-Power Modes, Rev2 [Online]. <http://www.freescale.com/files/microcontrollers/doc/app_note/AN2493.pdf>. Access 05/2013.

Helal, S., Mann, W., El-Zabadani, H., King, J., Kaddoura, Y., & Jansen, E. (2005). The gator tech smart house: A programmable pervasive space. *Computer, 38*(3), 50–60.

Hsiao, E. T., & Robinovitch, S. N. (1997). Common protective movements govern unexpected falls from standing height. *Journal of Biomechanics, 31*(1), 1–9.

Huang, C. N., & Chan, C. T. (2011). ZigBee-based indoor location system by k-nearest neighbor algorithm with weighted RSSI. *Procedia Computer Science, 5*, 58–65.

Isoda, Y., Kurakake, S., & Nakano, H. (2004). Ubiquitous sensors based human behavior modeling and recognition using a spatio-temporal representation of user States. In *Proceedings of the international conference on advanced information networking and applications* (Vol. 1, pp. 512–517).

Kangas, M., Konttila, A., Winblad, I., & Jamsa, T. (2007). Determination of simple thresholds for accelerometry-based parameters for fall detection. In *Proceedings of the 29th annual international conference of the IEEE engineering in medicine and biology society EMBS'07* (pp. 1367–1370).

Kangas, M., Vikman, I., Nyberg, L., Korpelainen, R., Lindblom, J., & Jämsä, T. (2012). Comparison of real-life accidental falls in older people with experimental falls in middle-aged test subjects. *Gait & Posture, 35*(3), 500–505.

Karantonis, D. M., Narayanan, M. R., Mathie, M., Lovell, N. H., & Celler, B. G. (2006). Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring. *IEEE Transactions on Information Technology in Biomedicine, 10*(1), 156–167.

Kidd, C. D., Orr, R., Abowd, G. D., Atkeson, C. G., Essa, I. A., & MacIntyre, B., et al. (1999). The aware home: A living laboratory for ubiquitous computing research. In *Proceedings of the second international workshop on cooperative buildings, integrating information, organization, and architecture CoBuild '99* (pp. 191–198).

Kientz, J. A., Patel, S. N., Jones, B., Price, E. D., Mynatt, E. D., & Abowd, G. D. (2008). The Georgia tech aware home. In *Proceedings of the extended abstracts on Human factors in computing systems CHI'08* (pp. 3675–3680).

Krumm, J., Harris, S., Meyers, B., Brumitt, B., Hale, M., & Shafer, S. (2000). Multi-camera multi-person tracking for EasyLiving. In *Proceedings of the third IEEE international workshop on visual surveillance* (pp. 3–10).

Kuo, W. H., Chen, Y. S., Jen, G. T., & Lu, T. W. (2010). An intelligent positioning approach: RSSI-based indoor and outdoor localization scheme in Zigbee networks. In *Proceedings of international conference on the machine learning and cybernetics ICMLC'10* (Vol. 6, pp. 2754–2759).

Lombardi, A., Ferri, M., Rescio, G., Grassi, M., & Malcovati, P. (2009). Wearable wireless accelerometer with embedded fall-detection logic for multi-sensor ambient assisted living applications. In *Proceedings of IEEE sensors conference* (pp. 1967–1970).

Man, L. A. N., & Committee, S. (2006). IEEE Standard for Information technology – Telecommunications and information exchange between systems- Local and metropolitan area networks- specific requirements Part 15.4: Wireless medium access control (MAC) and physical layer (PHY) specifications for low-rate wireless personal area networks (WPANs). *IEEE Standard, 137*(2), 1–305.

Navarro-Alvarez, E., & Siller, M. (2009). A node localization scheme for Zigbee-based sensor networks. In *Proceedings of the IEEE international conference on systems, man and cybernetics* (pp. 728–733).

Noh, A. S. I., Lee, W. J., & Ye, J. Y. (2008). Comparison of the mechanisms of the Zigbee's indoor localization algorithm. In *Proceedings of ninth ACIS international conference on software engineering, artificial intelligence, networking, and parallel/distributed computing SNPD '08* (pp. 13–18).

Noury, N., Fleury, A., Rumeau, P., Bourke, A. K., Laighin, G. O., & Rialle, V., et al. (2007). Fall detection-principles and methods. In *Proceedings of the 29th annual international conference on IEEE engineering in medicine and biology society EMBS'07* (pp. 1663–1666).

Pammolli, F., Riccaboni, M., Oglialoro, C., Magazzini, L., Baio, G., & Salerno, N. (2005). Medical devices competitiveness and impact on public health expenditure. Enterprise Directorate-General, European Commission. <http://mpra.ub.uni-muenchen.de/16021/1/MPRA_paper_16021.pdf>.

Riedel, D. E., Venkatesh, S., & Liu, W. (2012). Spatial activity recognition in a smart home environment using a chemotactic model. In *Proceedings of the 2005 intelligent sensors, sensor networks and information processing conference* (pp. 301–306).

Sensor Network Analyzer (SNA) – Daintree Networks [Online]. <http://www.daintree.net/sna/sna.php>. Access 05/2013.

Shany, T., Redmond, S. J., Narayanan, M. R., & Lovell, N. H. (2012). Sensors-based wearable systems for monitoring of human movement and falls. *IEEE Sensors Journal, 12*(3), 658–670.

Smeesters, C., Hayes, W. C., & McMahon, T. A. (2001). Disturbance type and gait speed affect fall direction and impact location. *Journal of Biomechanics, 34*(3), 309–317.

Tee, K. S., Awad, M., Dehghani, A., Moser, D., & Zahedi, S. (2011). Triaxial Accelerometer Static Calibration. In *Proceedings of the world congress on engineering WCE'11* (Vol. 3, pp. 2164–2167).

Tomoaki, T. (2010). Analog Devices, Application Note, AN-1077, ADXL345 Quick Start Guide [Online]. <http://www.analog.com/static/imported-files/application_notes/AN-1077.pdf>. Access 05/2013.

Tsuji, J., Kawamura, H., Suzuki, K., Ikeda, T., Sashima, A., & Kurumatani, K. (2010). ZigBee based indoor localization with particle filter estimation. In *Proceedings of IEEE international conference on systems man and cybernetics SMC'10* (pp. 1115–1120).

Van den Kroonenberg, A. J., Hayes, W. C., & McMahon, T. A. (1996). Hip impact velocities and body configurations for voluntary falls from standing height. *Journal of Biomechanics, 29*(6), 807–811.

Virone, G., Noury, N., & Demongeot, J. (2002). A system for automatic measurement of circadian activity deviations in telemedicine. *IEEE Transactions on Biomedical Engineering, 49*(12), 1463–1469.

Yamazaki, T. (2006). Beyond the smart home. In *Proceedings of the international conference on hybrid information technology ICHIT'06* (Vol. 2, pp. 350–355).

Yang, C. C., & Hsu, Y. L. (2010). A review of accelerometry-based wearable motion detectors for physical activity monitoring. *Sensors, 10*(8), 7772–7788.

Yongli, G., Yin, O. S., & Han, P. Y. (2012). State of the art: A study on fall detection. In *Proceedings of world academy of science, engineering and technology* (Vol.62, Special Issue, pp. 294–298). <http://www.waset.org/journals/waset/v62.php>.

Yousuf, M. S., Rizvi, S. Z., & El-Shafei, M. (2008). Power line communications: An overview-Part II. In *Proceedings of the 3rd international conference on information and communication technologies: from theory to applications ICTT'08* (pp. 1–6).