



Fall Detection on Ambient Assisted Living using a Wireless Sensor Network

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KEYWORD

*Ambient assisted living
Elderly
Fall Detection
Logistic Regression
Wireless Sensor Networks*

ABSTRACT

In this work, a distributed system for fall detection is presented. The proposed system was designed to monitor activities of the daily living of elderly people and to inform the caregivers when a falls event occurs. This system uses a scalable wireless sensor networks to collect the data and transmit it to a control center. Also, an intelligent algorithm is used to process the data collected by the sensor networks and calculate if an event is, or not, a fall. A statistical method is used to improve this algorithm and to reduce false positives. The system presented has the capability to learn with past events and to adapt its behavior with new information collected from the monitored elders. The results obtained show that the system has an accuracy above 98%.

1 Introduction

At a socioeconomic level, one of the major challenges of the century is that the world's population is aging. This is most visible in the developed countries, where the increase in life expectancy associated with the drastic decrease in birth rates has led to a rapidly aging population. In developing countries, while the birth rate still is not a problem, the elderly population has been increasing since the 1990s. The declining birth rates in developed countries, associated with increased life expectancy in developing countries, has led to a point where for the first time in history, the percentage of the world population with over 65 years is larger than the population under the age of 5 years [KINSELLA, K. et al. 2009].

Economically, the aging of the population brings major problems. These problems include a spending increase on pensions, health care and continuing care, but also a decrease in the number of active people. In Europe, this decrease is expected to be from a ratio of

close to 3 workers for each pensioner in 2005, to 1.5 workers for each pensioner in 2050 [CARONE, G. 2005].

Thus, with the population's aging, it is necessary to look for new ways of providing increased quality of life for this population. Ambient Assisted Living (AAL) aims to prolong the time people can live in a decent way in their own home by increasing their autonomy and self-confidence, the discharge of monotonously everyday activities, to monitor and care for the elderly or ill person, to enhance the security and to save resources [STEG, H. et al 2006].

In the context of AAL, the detection of falls is a major concern, since falls are one of the main problems affecting the elderly population living alone.

Even taking into account that there are solutions that have a perfect accuracy, these solutions are still not ideal for application in the intended environment. Solutions based on the use of video image processing [WU, G. 2000] require data provided by devices placed outside the system being monitored. Therefore, the resulting system is restricted to a particular



location, since it does not move with the user. Taking into account this problem, we opted to use a solution based on wirelessly connected sensors. This allows an unrestricted monitoring of the elders and also allows that the resulting platform have a wider range of applications (for example, monitoring vital signs like heart rate, blood pressure or oxygen levels).

For this part, the existing solutions based on accelerometers placed on the user [BOURKE, A. & LYONS, G. 2007], also have their own limitations, because they need to calculate the speed of the person to be able to detect a fall. As to calculate the acceleration resulting from the user is only necessary to use data from the acceleration of each axis at a given moment, using the formula

$$accel = \sqrt{x^2 + y^2 + z^2} - 1 \quad (1)$$

(the subtraction by one is relative to the gravity to which all the bodies are constantly subject and which has an intensity of $1g$) for calculating speed is necessary not only to obtain the acceleration in each instant, but also to have in account any variation of the acceleration. Thus, this process requires a higher sampling rate and the application of multiple filters. Another way to calculate the speed without depending of a sampling rate so large is to compensate for the inaccuracy of the accelerometers attached to the change in motion, using a gyroscope and a magnetometer. It is not enough to use a gyroscope in conjunction with a tri-axial accelerometer because, as the accelerometer, the gyroscope is also subject to error when there are abrupt changes in direction [PFLIMLIN, J. et al. 2007]. Then, the precise calculus of the speed requires a high sampling rate and the use of filters or the fusion of the data from three different sensors.

So, the challenge presented to us was to get a fall detection system with high precision, both in the detection of falls (sensitivity) and in the level of distinction between falls and daily activities (specificity). The work allowed us to develop a system that, taking advantage of a network of wireless sensors placed on the elderly, is able to detect falls and send alerts, so that older people can be rescued in time.

The rest of the paper is structured as follows. In Section 2 we introduce our own test platform and explain how we collected the testing data. Section 3 contains

a summarized introduction to logistic regression and odds ratio. In Section 4 we present our main results, including the multiple iterations necessary. The discussion of these results and how the knowledge gathered should be applied is presented in Section 5.

2 Material and methods

One of this project's directives was relative to the cost of deploying resulting system, especially considering that its target is one of the most impoverished part of our population. With this in mind and taking into account the high price of all the existing commercial solution, we opted for developing our own low cost wireless sensor node. This implied not only having to develop the hardware, but also a complete testing platform for making sure that it worked as expected.

2.1 Fall Detection Architecture

The fall detection algorithm should work using the data provided by a wireless sensor network (WSN). The first proposed fall detection architecture raises from the initial analysis carried out to this problem and already takes into account all the limitations and advantages of a WSN. In this architecture, the detection of falls is left to the peripheral WSN nodes which are equipped with accelerometers. Therefore, the algorithm being developed will also be implemented in the peripheral nodes.

During normal operation, the accelerometer data are processed by the algorithm. In the case of abnormal values being detected, an alert message is sent to the network's main node (Coordinator), which will forward this message to the system's control center. It was decided that, although the detection of falls was conducted by WSN, the decision about what kind of measures should be taken based on the received warning data would be in charge of the control center. A diagram of this architecture can be studied in figure 1.

The decision on the location of the nodes sensory accelerometer was made taking into account technical factors, such as the location from which originates the lowest possible noise in the collected data. In relation to the minimization of noise, it was clear that the sen-

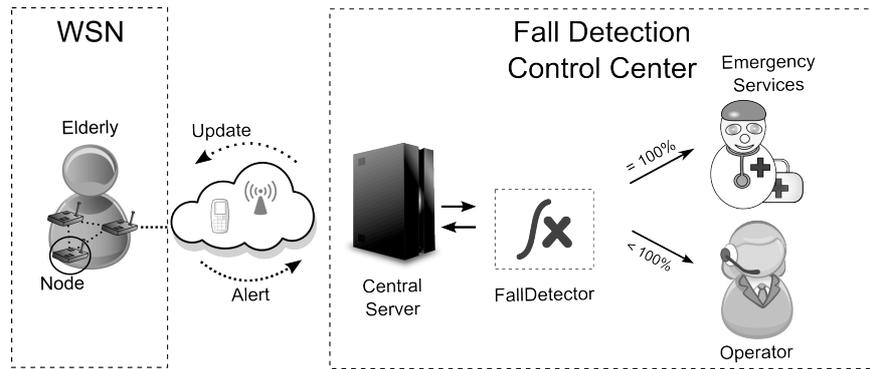


Fig. 1. Fall Detection Architecture

sors could not be placed in the limbs or head of the elderly; it would be necessary to filter all values of normal movement. At usability's level, it was also important to choose a location where network nodes did not affect the elderly's movement and could be easily placed by himself, with the objective of maximizing the acceptance of the system. In addition, it would be necessary to develop an algorithm capable of filtering the more abrupt movements which could easily exceed the acceleration of a fall.

Having restricted the location of the sensory nodes to the area of the trunk, were then taken into account the usability issues. One of the areas under consideration for placing the node was the upper chest area near the shoulders, but the one that was selected as the best placement area for the node was the waist region. This is an excellent area in terms of usability, because not only does not interfere with the user's movement but it is also an area which is already commonly used to carry accessories, by fixing them to the belt. Moreover, the pelvis area is one the most affected by falls, pelvic fracture is the leading cause of death and disability related to falls [FREEMAN, C. et al. 2002].

2.2 Wireless Sensor Node

Wireless sensor networks can sometimes be very complex and require that the sensors presents in it to be very energy efficient and to have some degree of processing. Therefore, the equipment has to have some kind of tradeoff between processing power and energy efficiency, because the two cannot coexist even with all the sleep technologies and clock changing features in the most recent microcontrollers. It

was essential to develop our own wireless sensor to fulfill our needs, and the most valuable features was making them as most generic as possible, adaptable to almost every situation and independent external equipment.

To ensure that our test platform was not confined to a specific group of sensors, a scalable architecture was adopted. This allows the development of interchangeable sensor boards that can then be attached to the sensor node.

The wireless sensor features a high end 8 bits microcontroller with the latest sleep technology (at time of developing); those allow for some processing power (around 16 million instructions per second) and, at the same time, have sleep consumption down to 20nA when the microcontroller is idle). The wireless connectivity falls on the IEEE 802.15.4 standard, witch fully fulfill the needs of the sensor. The standard allows a data transfer rate of 250 kbps with a maximum transmit power of 10 dBm. The standard also allows the transceiver to be in sleep mode and when needed a beacon is used to awake it. That feature is used for energy efficiency since most of the energy consumption is due to the radio link. The link between two nodes at approximately 300 meters outdoor and 50 meters indoor was successfully tested with this system.

In terms of power management, the system has information about the remaining battery capacity and can warn the central system when the remaining charge is low. The system also has a USB port that serves two purposes, the first is charge the internal battery and the other one is to communicate directly to the microcontroller.

In the specific case of the fall detection, an additional sensor board was created and attached to the

main board. That allows the system to detect gravity acceleration, essential for fall detection.

2.2 Tests

Our tests are separated in four phases. At the first phase, we have chosen the hardware, calibrated and implemented the detection model. The second phase consisted in copulate the sensor to a box and simulate a vertical fall, and after that to copulate the sensor to a wood board mechanism in order to simulate more accurately the fall, creating an arc trajectory instead of a vertical linear movement. The third phase consisted in studying the usual human movements and gathering sensor information to further comparison with the values obtained in phase two, and therefore to understand the differences between falls and, for instance, sitting down. The fourth phase consisted in gather information on falls on real and voluntarily humans, having more accurate values. All of these four phases are going to be summarily described below.

To be able to correctly test the prototype, it was first necessary to correctly calibrate the sensors and prepare the system for the acceleration data being returned. This is very important because the accelerometer sensors do not only return acceleration when there actually occurs movement; they are always returning the acceleration applied to them by the gravity field. It was also important to gather data of a fall when there was only the force of gravity in action.

To accomplish this, it was necessary to design a second testing phase with as few as possible external interferences, so it was decided not to use any human subjects in this phase. In order to study a vertical fall it was used a 5kg box with the sensor coupled to it, and then this box was dropped from a height of one meter. To test a fall where there were more axis involved that just the vertical axis, was design a system that would create falls with a consistent arc trajectory. This system consists of two wood boards, one of them with the size of 1,7m to simulate the height of a human being, the size of the other board is irrelevant as it only serves to fixate the system to the ground; the one representing the human is placed upright and are both connected on the extremities by a hinge. This test system is illustrated in figure 2.

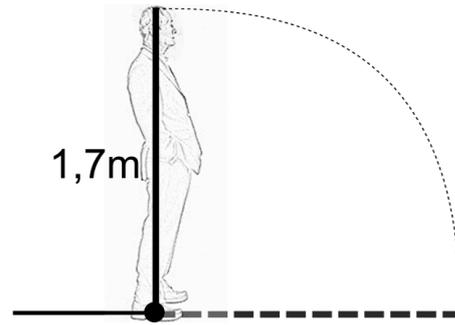


Fig. 2 – Fall simulation system

During the actual test the sensor was placed in one of two positions, at a high of 0,85m to simulate the height of the hip and at 1,45m to simulate the height of the shoulder. In order to obtain this distances it was used the ideal proportions defined by Leonard da Vinci in its work the Vitruvian Man.

Following the calibration of sensors and the creation of a reference table with the values from the previous tests, comes the third testing phase that consists on the study of the ADL of a voluntary. As it is not practical to record the complete day of a person and then evaluate the results, due to the immense data that would be obtained, some simple and direct tasks were performed instead. The tasks performed by the voluntary were:

- Walk in both directions on an L-shaped route;
- Sit and raise from a chair;
- Pick an object from the ground, in the correct way (by bending the knees) and the wrong way (by bending the back);
- Go up and down a flight of stairs, both in a slow pace and in a quick one.

The fourth and last phase consisted on testing actual falls using young voluntaries in a controlled environment. This final test was used to validate the gathered information and to confirm that if with even more noise it was still possible to correctly detect a fall.

4 Theory

In this section we estimate a fall detection model, using a standard logistic regression model. Beginning with an acceleration based model, we introduce further information (the observed acceleration in each angle) and increased the classification accuracy from 16% to 98%.

4.1 The Logistic Model

The logistic model is a Generalized Linear Model (see [MCCULLAGH, P. & NELDER, J. 1989]) that presents a linear predictor (logit) defined as

$$\ln\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \beta_1 x_1 + \dots + \beta_p x_p \quad (2)$$

where

$$\pi = P(Y=1). \quad (3)$$

For the Elder Care context, the Y variable only takes values 0 or 1, because we are interesting in detecting whenever the elderly has a problem. Therefore, $Y=1$ represents the situation when an alarm signal should be sent to the control center and $Y=0$ the situation when such alarm is unnecessary.

Each variable X_i , $i=1, \dots, p$, represent a parameter monitored by the body sensor. When some combination of (X_1, \dots, X_n) suggests that the user is having problem, the estimated value of π should be greater than 0.5 (or greater then other predefined value) and therefore the alarm is triggered. In the corrent state of the work development, we are dealing with fall detection, and so we can track the variables $(X, Y, Z, Acel)$ that represent the acceleration in each angle plus the final acceleration, obtained using formula 1.

The β_i parameters are connected with the importance of the respective X_i variables, and represent the logit change produced by an unitary increase in X_i , assuming for simplicity purposes that X_i has a linear effect and that no interactions

between the X_i variables are relevant. Under these conditions,

$$\begin{aligned} & \left[\begin{array}{c} \beta_0 + \beta_1 x_1 + \dots + \beta_i (x_i + 1) + \\ + \dots + \beta_p x_p \end{array} \right] - \\ & - \left[\begin{array}{c} \beta_0 + \beta_1 x_1 + \dots + \beta_i x_i + \\ + \dots + \beta_p x_p \end{array} \right] = \beta_i \end{aligned} \quad (4)$$

as stated.

4.2 Odds and Odds Ratio

4.2.1 Odds

Let

$$\pi_i = P(Y=1 | x_i) \quad (5)$$

where

$$x_i^T = (x_{i1}, \dots, x_{ip}). \quad (6)$$

An odd is described as

$$O_i = \frac{\pi_i}{1-\pi_i}. \quad (7)$$

So, for each elderly, the possibility of a problem to occur is simply the quotient between the probabilities of success and insuccess. Under this circumstances, it is straightforward to note that if $\pi_i > 0.5$ then $O > 1$ and if $\pi_i < 0.5$ then $0 < O < 1$. For instance, if $\pi_i = 0.2$ then $O_i = 0.2/0.8 = 1/4$, and we might say the odds of an elderly problem occur are 1 to 4.

4.2.2 Odds Ratio

Probably the more important feature of the logistic model is the simplicity of the odds ratio calculation and interpretation that is achieved under this model. An odds ratio is defined as the quotient between to possibilities, that is

$$OR = \frac{O_1}{O_2} = \frac{\frac{\pi_1}{1-\pi_1}}{\frac{\pi_2}{1-\pi_2}}. \quad (8)$$

Clearly, if $OR > 1$ than the first data set as higher odds than the second, and if $OR < 1$ we have the reverse situation.

For interpretation purposes, let us consider a simple model

$$\ln\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \beta_1 x_1 \quad (9)$$

where $x_1 = 0, 1$. Then

$$OR = \frac{e^{\beta_0 + \beta_1 \times 1}}{e^{\beta_0 + \beta_1 \times 0}} = e^{\beta_1} \quad (10)$$

and

$$\beta_1 = \ln(OR), \quad (11)$$

providing a very simple relation among the coefficient and the odds ratio. Therefore, the odds ratio is an association measure that indicates how much more likely (or unlikely) it is for the success ($Y=1$) to be present among those with $X_1=1$ than among those with $X_1=0$ [HOSMER, D. & LEMESHOW, S. 2000].

For example, if $X_1=1$ when the body sensor user heart rate is above some level, $OR=5$ indicates that a problem is five times more likely to happen when the elderly has that high heart rate.

When we are considering more complex models, the interpretation still is similar for a binary X_i variable. Considering

$$\ln\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \beta_1 x_1 + \dots + \beta_p x_p, \quad (12)$$

then

$$OR = \frac{e^{\beta_0 + \beta_1 x_1 + \dots + \beta_1 \times 1 + \dots + \beta_p x_p}}{e^{\beta_0 + \beta_1 x_1 + \dots + \beta_1 \times 0 + \dots + \beta_p x_p}} = e^{\beta_i}. \quad (13)$$

For a continuous and linear X_i variable, an increase of C unites implies that

$$OR = \frac{e^{\beta_0 + \beta_1 x_1 + \dots + \beta_i (x_i + C) + \dots + \beta_p x_p}}{e^{\beta_0 + \beta_1 x_1 + \dots + \beta_i x_i + \dots + \beta_p x_p}} = e^{\beta_i C}. \quad (14)$$

For instance, if X_i is the user heart rate, an increase of C units on this heart rate originate an increase on the OR of $e^{\beta_i C}$.

For categorical X_i variables, the procedure is similar to the one performed for binary variables. For further details, see [TURKMAN, A. & SILVA, G. 2000].

5 Results

In this section we estimate a fall detection model, using a standard logistic regression model. Beginning with an acceleration based model, we introduce further information (the observed acceleration in each angle) and increase the classification accuracy from 16% to 98%.

5.1 Initial Results

The first conclusion that could be made from the data collected is that the only ADLs that can be confused with actual falls are the sit actions. All other tests show only minor variations in acceleration, none of them comparable with the values present before and during the impact of a fall.

In the case of the sit tests, the data that can be confused with falls stems from the actions of sitting where the elder lets go of his body on to the chair without any kind of support. This acceleration has higher than normal values because the upper body is without any support. Without support, the body is only subject to the force of gravity and accelerates as if in free fall.

With this in mind and resorting to the aforementioned simulation system, a set of one hundred and fifty simulations of falls (thirty each direction plus the vertical) and one hundred and ten simulations of the act of sitting down abruptly were conducted. These tests were first analyzed using a tool developed for this purpose. Of these two hundred and sixty, four tests were removed due to recording errors.

The resulting accelerations (without the gravitational component) from two hundred and fifty six of simulations were then calculated using formula 1. From this new set of results were selected a maximum and a minimum values for both the fall tests and for the sitting tests, thus obtaining table 1.

Type	Number of tests	Max. acceleration	Min. Acceleration
Fall	146	2.190	0.938
Sit	110	2.024	0.154

Table 1. Maximum and minimum observed acceleration

As it can be seen in Table 1, the minimum value of the acceleration obtained during fall tests is smaller than the maximum value obtained during the sitting testing. If we just used the resultant acceleration to distinguish between falls and the ADLs, 92 of these sitting tests would be considered as real falls. This is easily observed in the chart present in figure 3 where all values above the line would be incorrectly detected. Using only acceleration would result in a precision of only 16%.

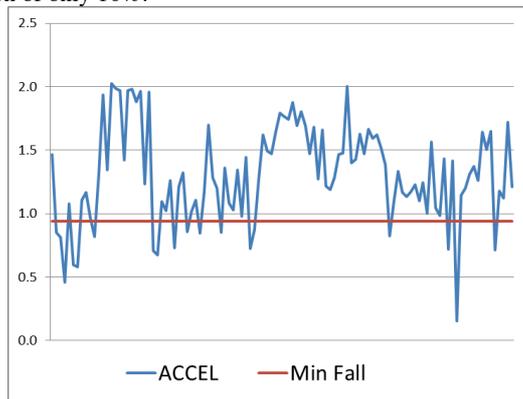


Fig. 3 Minimum fall acceleration relative to all the sit actions.

5.2 Logistic Regression Results

After analysis, all covariates were considered statistically significant at a significance level of 5%. A summary table showing the classification of the fall / no fall simulations can be found in table 2.

Type	Correct	Wrong	Percentage correct
Fall	138	8	94.5
Sit	105	5	95.5
Total	243	13	94.9

Table 2. Logistic Regression using the resultant acceleration and the acceleration from all three axis

With an error of only 5%, the percentage of correct classifications was very high. But there was still room for improvement, because during the preliminary data analysis were found small errors in recording. It was then decided that it would be better to check if more errors were present in the data set.

So, to better identify the data incongruities we opted to use the difference in beta values (DfBeta) [BELSLEY, D. et al. 2004] obtained as a sub product of the logistic regression analyzes. A box plot graph (figure 4) was then created using the DfBetas, and two influential observations were identified.

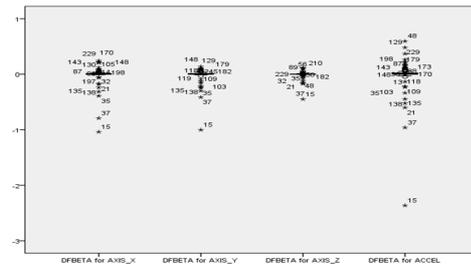


Fig. 4. First DFBetas box plot.

The analyses process was repeated, this time without the newly identified influential observations and the results in table 3 were obtained.

Type	Correct	Wrong	Percentage correct
Fall	142	4	97.3
Sit	103	5	95.4
Total	245	9	96.5

Table 3. Logistic Regression without the first detected influential observations

The DfBetas were again studied and another four tests were considered mistakes. The resulting box plot can be seen in figure 5.



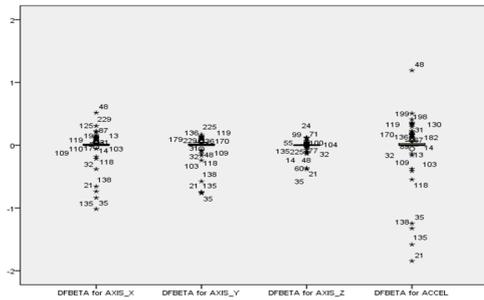


Fig. 5. Second DFBetas box plot.

Table 4 contains the final results since the study of the following DfBetas did not reveal any new influential observations.

Type	Correct	Wrong	Percentage correct
Fall	143	2	98.6
Sit	102	3	97.1
Total	245	5	98.0

Table 4. Final results of the logistic regression study

Having considered this to be the final variable set, it was now necessary to extract each variable value to be used on the logistic regression equation. Table 5 contains each variable and its corresponding coefficient.

Type	β_i
Axis X	11.905
Axis Y	12.622
Axis Z	4.081
Resultant Ace	21.556
Constant	5.479

Table 5. Variable coefficients to be used on the logistic regression equation

So, for the matrix containing the acceleration for each axial and the resulting acceleration ($X;Y;Z;Acel$), we got the following *logit*, where $\hat{\pi}$ represents the fall probability estimator

$$\ln\left(\frac{\hat{\pi}}{1-\hat{\pi}}\right) = 5.479 + 11.905X + 12.622Y + 4.018Z + 21.556Acel \quad (15)$$

Thus, a fall probability will be originated by

$$\hat{\pi} = \frac{e^{11.905X+12.622Y+4.018Z+21.556Acel}}{0.0041375 + e^{11.905X+12.622Y+4.018Z+21.556Acel}} \quad (16)$$

According with the above equation, we can configure several alert levels. If a serious alert (red) is transmitted when, for instance, $\hat{\pi} > 0.5$, this will correspond to solve the inequality

$$\frac{e^{11.905X+12.622Y+4.018Z+21.556Acel}}{0.0041375 + e^{11.905X+12.622Y+4.018Z+21.556Acel}} > 0.5.$$

As for the odds ratio interpretation, remember that (see 4.2. – odds ratio.) an increase of c units in one of the selected variables will lead to an estimated odds ratio increase of $e^{\beta c}$. For example, if the acceleration ($Acel$) increases from 0.9 to 1, an elderly fall will be $e^{21.556 \times 0.1} = 8.63$ more likely.

6 Discussion

After the logistic regression results were studied and the possible impact of implementing the algorithm in the wireless module itself analyzed, we concluded that it would be advantageous for the system, both in terms of logistic and energy consumption, if the logistic regression calculation were made in the central system instead of the WSN.

In this new proposed architecture, the WSN detects possible falls using the simplest method, namely by applying the threshold to the resulting acceleration. In the central system, the data is then processed, and depending on the resulting probability of the alert being an actual fall a different type of response is given:

- If the returned probability is close to 1 (eg. greater than 0.9), the central system immediately contacts the medical emergency services, so that the elderly can receive medical support as soon as possible.
- In case of a high probability being returned but less than 0.9 (eg 0.5 to 0.9), the action taken is more restrained, the operator first attempts to establish contact with the elderly, followed by his closest relatives. If both contacts fail, then the medical emergency services are notified.



- Finally, if the system reports a moderate probability of an accident (for example between 0.1 and 0.5) the system attempts to establish contact with the elderly, his closest relatives and with any relative who is referenced in the system, to be carried out personal check before sending any notification to the medical services.

Even when the system indicates a probability close to 0, it is always done some kind of verification. What is meant by taking such action is to allow the system to learn from each alert, and not rely solely on tests. The system would then be able to re-check the variables of equation (3) and (4), improving its own accuracy.

7 Conclusions

This paper presents a distributed system for fall detection. The system takes advantage of a network of wireless sensors placed on the elderly, to detect falls and send alerts. The principal characteristics of the developed wireless sensorial nodes are: scalability, low cost and battery durability. In the falls architecture presented, the wireless sensors nodes analysis the acceleration and, based on a specific threshold, determines if the event occurred is, or not, a fall. These thresholds are obtained at the initial tests phase of the system, because it is necessary to distinguish a real fall from an ADL, using the least energy possible.

When the wireless sensor node detects a fall communicates it to the control center. This control

center uses an algorithm based on logistic regression to confirm the fall alert and to act accordingly. The system presented is intelligent since it learns with the sequence of the alerts and with the decisions made by it.

Also, in this paper the logistic regression model is presented and applied to the collected data set. The results obtained show that with the provided final model, only two real falls weren't detected. Although false negatives are an important problem, in this study they probably occurred due to sensor errors or very intense sit actions. Even though, 98% of the actions (falls and sits) were correctly identified, and so the developed architecture is much more efficient than the usual ones. Besides, it contributes to a smaller battery consumption.

As a future work, we intend to explore and apply genetic algorithms to the logistic regression model. This procedure might contribute to optimize the obtained logistic model, and so to eradicate the false negatives without increasing the false positives.

8. Acknowledgment

This work has been partially supported by the RICE (Rede de Inovação da Região Centro, Portugal) Project co-funded by Portuguese program Mais-Centro (call SAICT).

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