35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Artificial Neural Networks as an Alternative to Traditional Fall Detection Methods

Marcela Vallejo, Claudia V. Isaza, José D. López *

Abstract—**Falls are common events among older adults and may have serious consequences. Automatic fall detection systems are becoming a popular tool to rapidly detect such events, helping family or health personal to rapidly help the person that falls. This paper presents the results obtained in the process of testing a new fall detection method, based on Artificial Neural Networks (ANN). This method intends to improve fall detection accuracy, by avoiding the traditional threshold – based fall detection methods, and introducing ANN as a suitable option on this application.Also ANN have low computational cost, this characteristic makes them easy to implement on a portable device, comfortable to be wear by the patient.**

I. INTRODUCTION

The development and miniaturization of computing devices has enabled the appearance of new applications in many fields.

In medicine, this context has allowed the emergence of monitoring systems, including fall detection systems. These systems are usually used in the context of elderly people and are designed to generate an alarm in case of a fall event. The importance of fall detection systems lies in the high prevalence of falls among older adults. In U.S., an estimated one third of people over 65fall each year[1], and other countries, such as Spain [2]and Colombia[3], have similar reports.

In this paper, a new fall detection system based on ANN is proposed and implemented on a device (designed for such purpose) and tested with volunteers.

The rest of this paper is divided in 5 sections. Section II presents a summary of fall detection methods, showing some of the main problems with traditional approaches; section III describes the device designed for the implementation of the fall detection method and describes the way in which data was obtained; section IV presents the fall detection method based on Artificial Neural Networks; section V present results obtained with this method and, finally, conclusions are presented in section VI.

II. FALL DETECTION SYSTEMS

There are different approaches that have been used in fall detection systems.

* M. Vallejo is with GEPAR research group. Dep. of Electronic Engineering, Universidad de Antioquia, Medellin-Colombia (mvallejov@udea.edu.co).

C. V. Isaza and J.D. López are with SISTEMIC research group. Dep. of Electronic Engineering, Universidad de Antioquia, Medellin-Colombia (cisaza@udea.edu.co, josedavid@udea.edu.co).

Most of the systems are based on a wearable device [4] [5] [6][7][8][9], that the patient uses attached to either the clothing or accessories (such as belts and necklaces) as an element to detect the fall.

The wearable devicesuse sensors that measure movement characteristics of the person. The sensors are usually attached to the waist [10]or chest [5].

The most common variables measured are acceleration and speed[5] [4][8], with the accelerometer being the most popular sensor in fall detection devices. Using the sensor data, each system detects falls using a different method for analyzing the information.

Many of the analysis employed are based on the use of a threshold in the signals. If the threshold is exceeded, a fall is detected. However, finding an appropriate value for the threshold that allows detecting all kinds of falls has proved to be a complicated problem.

Each systempresents different results about the election of the threshold[8], some use a threshold for the accelerations, other for the velocity (integrated from acceleration data), the angle of inclination or a combination of several thresholds.

Although some of these threshold-based systems have shown high fall detection accuracy, there is no evidence that these methods work well with different subjects and most of them have not been tested under real-life conditions[9]. The main problem is that, although falls produce, in general, higher accelerations than other activities, there are some normal movements (such as sitting down quickly, going down stairs, etc.) that might be associated with high accelerations. Also, some falls (such as falls beginning with the person sitting on a chair or when the person reaches to hold on from something before falling) may have lower values of acceleration.

A good way to analyze whether a threshold is adequate for fall detection systems or not, is analyzing box plots containing information from several falls and normal activities.

Fig. 1 shows a box plot for the acceleration data from falls and normal activities from 10 subjects, measured as described in [11].

The acceleration was measured with a 3-axis accelerometer and the sum vector was calculated with (1).

$$a = \sqrt{a_x^2 + a_y^2 + a_z^2} \quad (1)$$

Where a is the sum-vector of axial accelerations, a_x is the acceleration on the x axis, a_y is the acceleration on the y axis and a_z is the acceleration on the z axis.

In Fig. 1, the first column shows accelerations during normal activities and the second shows acceleration from falls.

This type of graphic shows the distribution of data,its median, minimum and maximum values, and lower and upper quartiles.

The interest on this graphic lies in the fact that it illustrates the way in which accelerationduring falls overlaps whit acceleration during normal activities. This make it difficult to separate falls from other activities using a threshold.For instance, if a threshold of 5g is selected to separate falls from normal activities, some falls that have lower acceleration would not be detected, and some normal activities would generate a false alarm.

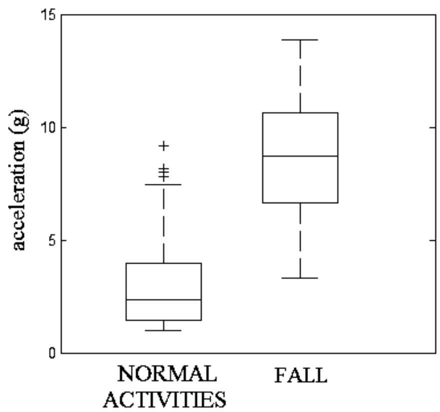

Figure 1.Boxplot for the sum-vector of axial instant accelerations.

The reason to calculate the sum vector is that it is one of the most common parameters used onfall detection systems [12][6][13] and it provides information about the general acceleration of the person, considering the three axes at the same time.

By analyzingthis graphic, it is possible to say that it is important to consider strategies for fall detection that do not require setting a threshold for signal values in order to detect falls.

In order to overcome the problems related to the use of a threshold, the use oflearning algorithms has been proposed in some systems. Some examples of this are the work by Strucket al.[14], that uses a fuzzy inference system whose output is classified by an ANN and the work by Ojetola et al. [9]that uses decision trees to distinguish between falls and normal activities.

These approaches reached an accuracy of 90.3%and 81% respectively. Although the performance of these approaches is lower than the one obtained with traditional methods, they have proven that machine learning techniques are an option for fall detection without the use of thresholds.

III. MATERIALS AND EXPERIMENTAL SET-UP

Acceleration data was obtainedusing a triaxial accelerometer ADXL345 integrated into a portable prototype designed to use in fall detection systems. The device was placed at the waist and is shown in Fig. 2.

The fall detection device includes a MCF51JM128 Freescale microcontroller, a ZigBee module for wireless communication, leds for status indication (on/off and low battery), a 950mA/H lithium battery and a push button for operation mode selection.

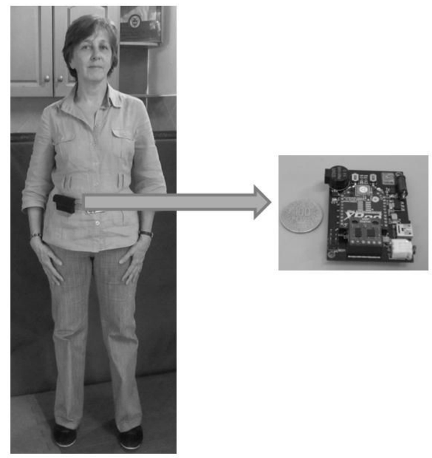

Figure 2. Fall detection device.

This device has two operation modes:

A. *Data recording mode*

In this mode, the device sends acceleration data to a computer, where it is stored. This mode was used to record acceleration data that was later used to train an Artificial Neural Network, as explained in section IV.

To obtain data, 10 volunteers (2 women, 8 men, aged between 18 and 56 years, weighing between 56 and 84kg) performed 11 different types of falls and 13 kinds of normal activities.These activities were carried out according to the experimental setup described in [11].

B. *Fall detection mode*

In this mode, a fall detection algorithm is implementedon the device, so that it measures acceleration, processes data and determines the moment when a fall occurs. If a fall is detected, an alarm is wirelessly sent to a computer. This operation mode was used to test the fall detection method after training, as explained in section V.

To obtain data in this mode, 11 volunteers (2 women, 9 men, aged between 19 and 56 years, weighing between 55 and 90kg) performed the same 11 different types of falls and 13 kinds of normal activities performed before, using the same protocol used on data recording mode.

In this case acceleration data was not recorded. Instead, in each one of the activities performed by the volunteers, the occurrence (or not) of an alarm was registered.

IV. FALL DETECTION METHOD BASED ON ARTIFICIAL NEURAL NETWORKS

The fall detection method has the general structure shown in Fig. 3.

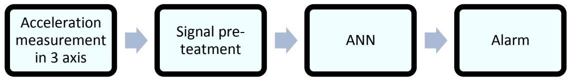

Figure 3. Fall detection method structure.

A. *Signal pre-treatment*

The signal pretreatment consist of two stages.

- Absolute values

In the original data, the sign indicates the direction of the movement. By calculating the absolute value of the signal, it is possible to analyze the magnitude of the acceleration, regardless the direction.

- Integration

The integral of the signals is calculated with (2)

$$I_x = \frac{1}{t}\int_0^t a_x\,dx$$
$$I_y = \frac{1}{t}\int_0^t a_y\,dy \qquad (2)$$
$$I_z = \frac{1}{t}\int_0^t a_z\,dz$$

Where I_x is the integral of the acceleration in the *x*-axis, a_x is the acceleration in the *x* axis, I_y is the integral of the acceleration in the *y* axis, a_y is the acceleration in the *y* axis, I_z is the integral of the acceleration in the *z*-axis,a_z is the acceleration in the *z* axis, and t = 10 (sampling points, sampling window).

B. *Artificial Neural Network*

An Artificial Neural Network was chosen to take the data after the pre-treatment and classify it in one of two possible categories: normal activity or fall.

The ANN It is a feed forward network with three hidden layers with 5 neurons in each layer, as shown in Fig. 4 (to simplify the graphic, figure does not include activation functions).

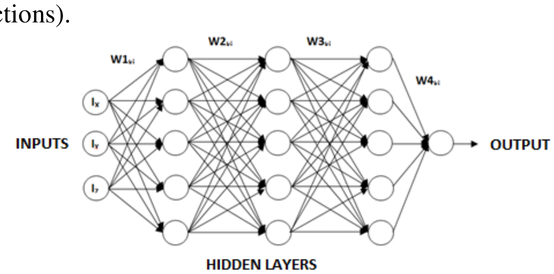

Figure 4. ANN structure

Where *W1kj* is the matrix containing the weightsof the connections between input neurons and neurons on layer 1, including the polarizations (*W1k0*),*W2kj* is the matrix containing the weightsof the connections between neurons on layer 1 and neurons on layer 2, including the polarizations (*W2k0*), *W3kj* is the matrix containing the weightsof the connections between neurons on layer 2 and neurons on layer 3, including the polarizations (*W3k0*), and *W4kj*is the matrix containing the weightsof the connections between neurons on layer 3 and neurons the output layer, including the polarizations (*W4k0*).

- Network training

Acceleration data, stored as explained in section III-A, was used to train the ANN.

First step was separating data set in two subsets, as follows:

First subset contains data from 329 falls and 392 normal activities. This data was used to train the network using a back-propagation algorithm.

Second subset contains 216 falls and 250 normal activities. This data was used to test the Neural Network after training. The objective is to present the network a data set different from the one used for training, and analyze the network`s capability for generalizing the good performance with new data.

Table I shows the error percentages obtained during the network training process and during the test process (after training). The percentage of not detected falls is also presented in each case. The reason to present the not detected fall percentage is that, although it is ideal to reduce all types of errors in the system, it is considered as a much more serious error the failure to detect a fall than the occurrence of a false alarm.

TABLE I. TRAINING AND TEST ERROR

Training error percentage	1.25%
Test error percentage	1.07%
Training not detected falls percentage	1.52%
Test not detected falls percentage	1.86%

Having trained the ANN, additional tests were performed to validate the generality of the results obtained.

In this case 10-fold cross-validation [16]was used to evaluate whether the results were independent of the manner in which data was partitioned into training and test groups. The results from cross-validation are shown in table II.

TABLE II.10 FOLD CROSS VALIDATION RESULTS.

Average training error %	**Average test error %**
1.09	1.43

Average training error was 1.09% and average test error was 1.43%. These values are in the range of the results obtained during the first stage of training this network (1.25% and 1.07%).

V. TEST AND RESULTS

The fall detection method described, with the Artificial Neural Network trained as explained before, was implemented in the fall detection device presented in section III.

To validate the performance of the method, using different data from the one used during training and test of the ANN, a new set of tests was made, as explained in section III-B. These tests, used for validation of the algorithm, were made with volunteers using the portable device with the method already implemented on the microcontroller. During validation test, data processing (pre-treatment and ANN) was performed by the microcontroller and an alarm was generated and sent to a computer when a fall was detected.

Table IIIshows the results of validation test.

TABLE III.VALIDATION RESULTS.

Total falls	381	Total normal activities	429
Detected falls	375	Correctly identified normal activities	423
Not detected falls	6	False alarms	6
Not detected falls %	1.57	False alarm %	1.4
Total error %			1.47
Sensitivity	**0.984**	**Specificity**	**0.986**

Where specificity and sensitivity are calculated as shown in (3).These performance indicators have been extensively used in fall detection systems [15][5][7].

$$Specificity = \frac{TN}{TN+FP} \qquad (3)$$

$$Sensitivity = \frac{TP}{TP+FN}$$

Where *TN* are the normal activities correctly classified, *FP* are the normal activities that caused a false alarm, *TP* are the falls correctly classified and *FN* are the falls that were not detected by the algorithm.

Table IV shows the results of this work compared whit previous works. The results are in the range of other studies, improving some of them.

TABLE IV. PREVIOUS WORKS RESULTS.

	Sensitivity	**Specificity**
Li et al. [5]	0.91	0.92
Perry et al. [8]	0.8	0.89
Bourke et al. [7](test with different algorithms)	0.94 – 1	0.96 - 1
This work	0.984	0.986

Additionally, an all-day use test was made, intended to prove the system's capability to not generate false alarms. A volunteer (Age 30 years, weight 60 kg) used the device during 12 hours. During this period of time the person performed her daily activities (go to work, ride a bus, go up and down stairs, etc.). During this test there were no false alarms.

VI. CONCLUSIONS

A fall detection prototype was designed and used to test an Artificial Neural Network – based fall detection method. This method is able to correctly identify several types of falls, and it doesn't use a threshold-based strategy.

Such values are comparable with those obtained with traditional threshold based systems, even though the tests made in this work include some activities difficult to identify correctly, such as falls from sitting and strong movements such as jumping and jogging.

These results also show that Artificial Neural Networks are a suitable option to use in fall detection systems.

Future works include the possibility of developing a localization system based on the wireless technology used to send the alarm. This system would localize the person that falls, helping the medical staff to attend the emergency quickly.

REFERENCES

[1] United Nations. Population Division, Departament of Economic and Social Affairs. *Population Ageing.*

[2] M. Sáinz *Estudio de investigación sobre Seguridad en el domicilio de personas mayores*. MAPFRE. 2008. Disponible en http://www.mapfre.com/documentacion/publico/i18n/consulta/registro.cmd?id=128697.

[3] G.M. Henao, C.L. Curcio , J. F.Gómez.Consecuencias de las caídas en ancianos institucionalizados. *Revista de la asociación colombiana de gerontología y geriatría* Vol. 23. No. 1. 2009.

[4] X.Yu Approaches and Principles of Fall Detection for Elderly and Patient. *10th International Conference on e-health Networking, Applications and Services*. HealthCom. 2008.

[5] Q. Li, J.A. Stankovic ,M. A .Hanson , A. T. Barth, J. Lach ,G. Zhou. Acurate, Fast Fall Detection Using Gyroscopes and Accelerometer-Derived Posutre Information.*Body Sensor Networks*.2009.

[6] C. Wang , C. Chiang , P. Lin, Y. Chou,I. Kuo, C. Hung, C. Chan.Development of a Fall Detecting System for the Elderly Residents.*The 2nd International Conference on Bioinformatics and Biomedical Engineering*. ICBBE. 2008.

[7] A. K. Bourke,P. Van de Ven, M. Gamble, R. O'Connor, K. Murphy, E. Bogan, E. McQuade, P. Finucane, G. ÓLaighin, J. Nelson.Evaluation of Waist-mounted Tri-axial Accelerometer Based Fall-detection Algorithms During Scripted and Unscripted Activities. *Journal of Biomechanics*. Vol. 43. No 15. 2010.

[8] J. T. Perry, S. Kellog, S. M. Vaidva, Y. Jong-Hoon , A. Hesham,H. Sharif. Survey and evaluation of real-time fall detection approaches. *6th International Symposium on High-Capacity Optical Networks and Enabling Technologies* (HONET), 2009.

[9] O. Ojetola, E.I. Gaura & J. Brusey. Fall detection with weareable sensors -- Safe (Smart Fall Detection).*7th International Conf. on Intelligent Enviroments (IE)*, 2011

[10] J. Boyle, M. Karunanithi.Simulated fall detection via accelerometers. *30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. EMBS. 2008.

[11] M. Vallejo, C. V. Isaza, A. Osorio. Fall detection system based on artificial Neural Networks. *Imaging and Signal Processing in Health Care and Technology.* Baltimore. USA. 2012.

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

[13] R. Narayanan, S. R. Lord, M.M. Budge, B. G. Celler & N. H. Lovell.Falls management: detection and prevention using a waist-mounted triaxial accelerometer.*International Conf. of the IEEE-EMBS*, Lyon, France, 2007, 4037-4040

[14] M. Struck, C. Dinh.A new real-time fall detection approach using fuzz logic and a neural network.*6th International Workshop on Wearable Micro and Nano Technologies for Personalized Health (pHealth),* 2009, 57-60.

[15] N. Noury , P. Rumeau, A. K. Bourke, G. Ólaighin, J. E. Lundy. A proposal for the classification and evaluation of fall detectors. *IRBM* .Vol. 29. No6. 2008

[16] S. Haykin. *Neural Networks: A comprhehensive Foundation.*Editorial Prentice Hall.1999.