Application of Statistical Methods to Improve an Acceleration Based Algorithm

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Abstract. Falls are the leading reason for death related accidents in people over 65 years old. Concerning this situation, it is necessary to develop a viable way of detecting these falls as fast as possible, so that medical assistance can be provided within useful time.

In order for a system of this kind to work correctly, it must have a low percentage of false positives and a good autonomy. In this paper we present the research done in order to improve an existing acceleration based algorithm, which despite being inaccurate is however highly energy efficient. The study of its improvement was done resorting to the use of cluster analysis and logistic regression.

The resulting algorithm distinguishes itself by being, at the same time, very accurate and having low energy consumption.

Keywords: health monitoring, logistic regression, fall detection, cluster analysis, wireless sensor network, aging.

1 Introduction

Today's society faces many challenges, being one of the most worrying the increase in the percentage of the elderly population. In a 2008 study from Eurostat [1], it is presented data which indicates that, in Europe, the percentage of population over 65 years will rise from 17.1% to 30.0%, in the period between 2008 and 2060.

Problems related to an aging population are both at a social and economic level. Knowing the duality of this problem, the Elder Care project [2] was started in 2009 with the objective of applying the new technologies of the Information Age to help improve the quality of life for elderly. These objectives spread from more social levels, like reducing the social exclusion that affects a big part of the elderly population [3], to some more economic and health care related problems,

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like enabling the elderly to continue living in their own homes, while still having the same health monitorization they would have if they were living in a nursing home.

In order to accomplish these distinct objectives, the Elder Care project was divided in various workgroups. The one responsible by the work being presented in this paper is the Body Monitor workgroup. This workgroup is doing research in the area of Wireless Sensor Networks (WSN) applied to health care, with the objective of developing a network of sensors, capable of monitoring many aspects of the daily living of its user.

A big problem that has been faced, is how to precisely detect and, at the same time, distinguish a fall from an activity of the daily living (ADL). As we will be later show in this paper, if the sensory data from the network is not correctly processed, false alerts can be triggered by some types of ADL. A system with this kind of problem would end up being almost as ineffective as no system at all. Like in the children's tale, where the young shepherd yelled wolf where there was none, then when the wolf did actually attack, the shepherd ended up losing all his sheep. This system would also perish from this same problem, because when a fall did actually occur it would be treated with disbelief and might even be completely ignored. So, to be able to avoid this type of situation without compromising the actual usability of our WSN, it was decided to study the effects of using statistical methods like cluster analysis [4] and logistic regression [5].

This paper will start by introducing the concept of fall detection and describing some previous work done in this area. It will continue by explaining the testing system used to acquire the necessary data. Afterwards, both the cluster analysis and the logistic regression approaches will be described, followed by the conclusions taken from this study and ending with the description of the steps being taken next by this workgroup.

2 Fall Detection

One of the first big steps, towards an actual autonomous fall detection system was taken on the early '90s by Lord and Calvin [6]. In this study, it was shown, that through the study of movement of the human body during a fall, it would be possible to develop a sensor network capable of detecting those same types of falls.

Over the years and with the development of new technology areas, newer and different ideas on how to more precisely detect fall have emerged. In 2000, using video image processing, Ge Wu [7] studied multiple ADLs and compared them to falls. This study has shown that the only ADLs that could be mistaken for falls were sit down actions. Ge Wu was also able to not only correctly detect falls, but also to distinguish them from ADLs. This work was later improved in a 2008 study by Alan K. Bourke [8]. In this study, video image processing was used to train a tri-axial accelerometer system and was proven that by resorting to vertical velocity alone, it was possible to detect and distinguish a fall with 100% certainty.

Even though there might already exist solutions with perfect precision, these solutions are still far from ideal. The video image processing solution relies on data being acquired, using a device placed outside the system being monitored. The accelerometer solution requires a big sampling rate and the use of multiple filters in order to correctly calculate velocity. While using video image processing, it is relatively easy to measure the body's velocity during the fall, by measuring the movement during each frame. In a system that relies on data being acquired by sensors placed on the user's body, what is commonly obtained is the acceleration. Also, this acceleration is acquired through sampling so it is prone to errors. These errors must be mitigated through the use of big sampling rates or the use additional sensors, like gyroscopes and magnetometers [9]. Finally, to precisely obtain velocity it is necessary to constantly integrate the corrected acceleration data. Using this process with the existing equipment, would create a very energy constrained solution, like we observed in a previous study we conducted [10].

3 Tests and Control Results

In order to develop a system with accuracy close to that obtained by using a high sampling rate, it was first necessary to study the data acquired from an accelerometer during both falls and different ADLs. The sampling rate we decided to use was 20Hz, less than half that used both in [8] and [11].

The WSN module chosen for this research was the Intel Mote2 platform [12]. This network module has a scalar processor that can achieve processing speeds from 14 MHz up to 520MHz. The accelerometer used was the one present on the Crossbow iMote2 sensor board, the ST Micro LIS3L02DQ[13].

To be able to record multiple tests without having too many external variables and random results, it was decided not to use any human subjects during the initial fall data acquisition. For the vertical fall study, it was used a 5kg box with the sensor coupled to it, this box was then dropped from a height of one meter. To test a fall where there were more axis involved than 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. 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.

As it was aforementioned, Ge Wu work shown that the type of ADL more prone to values similar to a fall are the sit down actions. During the testing of the equipment itself, this was proven to be even more evident when relying solely on accelerometers. ADLs like normal walking, running, going up and down stairs did not manifest big changes in acceleration. Sit down actions, especially rougher ones, on the other hand, presented big spikes in acceleration. Due to this fact, it was decided to center the attention on recording different types of sit actions. As there is no other way to recreate the human action of siting down, human volunteers were used. The sit action tests were conducted by both male and female volunteers and the tests were conducted in both a chair and a couch.

During the testing phase 150 fall tests (30 for each direction plus vertical) and 110 sit action tests were conducted. After a preliminary analyze of the data had been done, four fall tests were removed due to recoding errors.

To test the precision and improvement brought by the use of statistical models, the resultant acceleration without the gravitational component was first calculated for each instant, using the formula

$$a = \sqrt{x^2 + y^2 + z^2} - 1. \tag{1}$$

From this new data set, was extracted the highest value of each test run and table 1was obtained.

Table 1. Table containing the summary of the recorded data

Type	Number of Tests	Max Acceleration	Min Acceleration
Fall	146	2.190	0.938
Sit	110	2.024	0.154

As can be seen on table 1, the minimum acceleration value obtained from the fall tests is smaller than the maximum value obtained on the sit actions. So if only the raw acceleration was to be used in order to distinguish a fall from an ADL, 92 of this fall actions would be considered actual falls. Using only acceleration would than give a 16% precision.

4 Cluster Analysis for Fall Detection

Since we are interested in developing a fall detection system, we need to separate our data into two classes of objects; one meaning that a fall occurred and another stating that a fall did not occur. After that, knowing ours groups, we are interested in assigning a new item to one of the two classes. Thereby, a nonhierarchical clustering method, such as K-means method, could be applied. Cluster analysis is a technique in that no assumptions are made concerning the group structure.

We could start with a "learning" sample, which will be divided into two regions, R1 and R2 such that if a new observation falls in R1 it will be allocated to group "a fall occur" and if it falls in R2, we allocate it to "a fall did not occur".

k-means algorithm [4] is composed of three steps:

1. partition the items into 2 initial clusters ($k = 2$);
2. assigning an item to the cluster whose centroid (mean) is nearest. Recalculate the centroid for the cluster receiving the new item and for the cluster losing the item;
3. repeat step 2 until no more assignments take place.

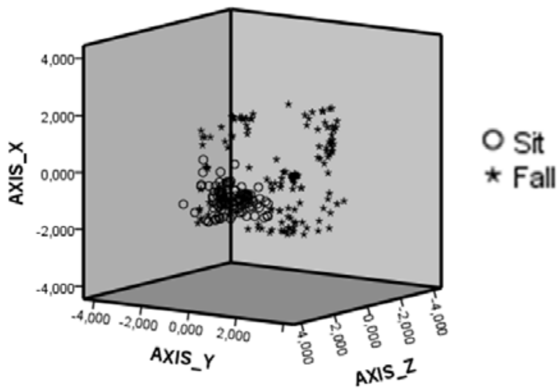

Fig. 1. Data over X, Y and Z

The test data was exported to be used by the statistical analysis software PASW Statistics (previous SPSS) [14].

Exploring our data, we can see the data in a 3D plot, Fig. 1, along X, Y and Z axes.

We can also notice that it will be difficult to group the observations into two clusters, since the observations "sit" and "fall" are strongly mixed. Running a k-means method with two clusters we obtain the final centers, see table 2:

Table 2. Final cluster centers

	Cluster	
	1	2
AXIS_X	-1,282	680
AXIS_Y	-1,206	1,506
AXIS_Z	-0,632	0,132
ACCEL	1,331	1,698

From the ANOVA table 3, we can see that the most significant variables to clusters definition are Y and X, following by Acceleration and Z, at last, because greater values of F statistics shows the most significant variables in analysis.

Comparing the cluster analysis results with our data, table 4, we can see that there are many misclassifications, and they all report to falls that were considered as sits.

As cluster analysis provides that X, Y and Accel are the most significant variables in clustering, we can see in Fig.2, based on them, the results and misclassifications.

Table 3. ANOVA table

ANOVA						
	Cluster		Error			
	Mean Square	df	Mean Square	df	F	Sig
AXIS_X	211,866	1	0,908	254	233,317	0,000
AXIS_Y	404,597	1	0,791	254	511,647	0,000
AXIS_Z	32,096	1	1,176	254	27,298	0,000
ACCEL	7,400	1	0,108	254	68,296	0,000

Table 4. Results with k-means cluster analysis

Type	Data	Correct	Wrong	Percentage correct
Fall	146	80	66	54,8%
Sit	110	110	0	100%
Total	256	190	66	74,2

5 Logistic Regression

The logistic regression model is part of a class of statistical models known as generalized linear models (GLM)[5]. The logistic regression model is very similar to the more common linear regression model. The main difference is that while the response variable of linear regression is typically continuous, the one from logistic regression is binary or at least categorical [15].

Like in several others situations (experiment planning, clinical trials, epidemiology studies, observational studies), the Elder Care's response variables [16] are dichotomous. Under these circumstances, is more appropriate to use a linear predictor (logit) defined as

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

where

$$\pi = P\left(Y = 1\right). \tag{3}$$

In the fall detection context, the response variable Y should be 1 if a fall occurs and 0 otherwise. Each x_i represents a movement variable collected by the sensors placed on the elder.

So the test data was again imported into PASW Statistics, like before the first test was only run using the individual acceleration values. The first logistic regression results are shown in table 5.

These were already better results than those obtained using cluster regression, the next step consisted on adding the resultant acceleration to the study and the results are on table 6.

These results were clearly better than both the control and the cluster analysis ones. But there was still room for improvement, one thing that was already

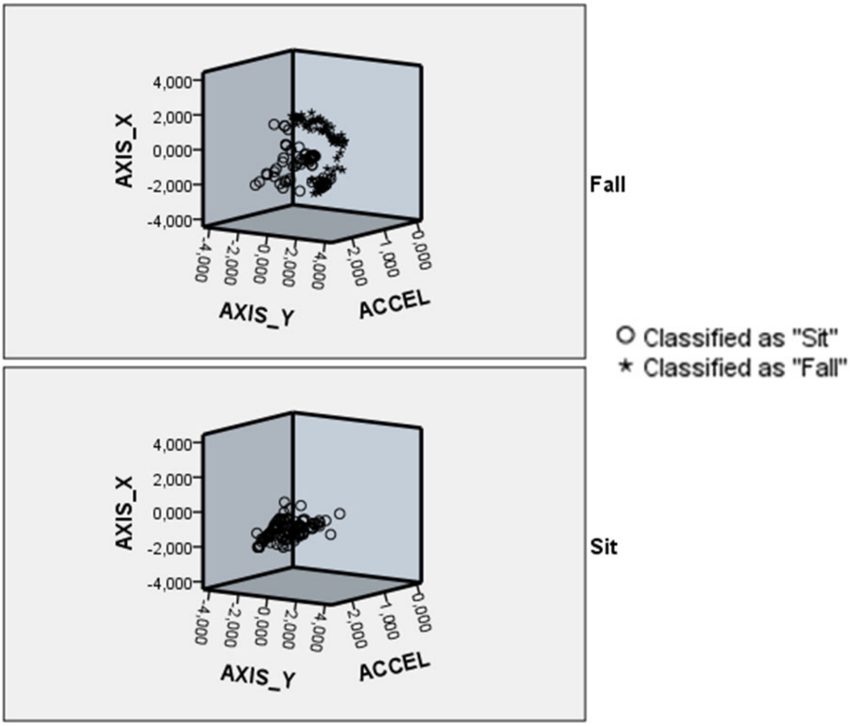

Fig. 2. Misclassifications with cluster analysis

noticed during the preliminary study was that many of the tests had small recording mistakes. These mistakes were expectable as the equipment used is just a prototype so the sensors and batteries were not strongly secure to the processor board, leading to small data losses.

So to better identify the data incongruities we decided to use the difference in beta values (DfBeta) [17] obtained as a sub product of the logistic regression analyzes. A box plot graph was then created using the DfBetas and two influential observations were identified. The analyses' process was repeated, this time without the newly identified influential observations and the results in table 7 were obtained.

Table 5. Logistic Regression using only the acceleration from the three axis

Type	Correct	Wrong	Percentage correct
Fall	127	19	87.0
Sit	104	6	94.5
Total	243	13	90.2

Table 6. Logistic Regression using the resultant acceleration and the acceleration from all three axis

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

Table 7. Logistic Regression without the first detected influential observations

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

Table 8. Final results of the logistic regression study

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

Table 9. Coefficients to be used on the logistic regression equation

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

The DfBetas were again studied and another four tests were considered mistakes. Table 8 contains the final results since the study of the following DfBetas did not reveal any new influential observations.

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 9 contains each variable and its corresponding value.

The estimated logit is then

$$\ln\left(\frac{\hat{\pi}}{1-\hat{\pi}}\right) = 5.479 + 11.905X + 12.622Y + 4.081Z + 21.556Ace \tag{4}$$

and the fall can be estimated by

$$\hat{\pi} = \frac{e^{11.905X+12.622Y+4.081Z+21.556Ace}}{0.0041735 + e^{11.905X+12.622Y+4.081Z+21.556Ace}}. \tag{5}$$

6 Conclusions

In this article we showed how hard it can be to distinguish an actual fall from an ADL. While there are already proven solutions, all still have their inherent problems, like being constrained to a specific location or having energy limitations.

Our study of cluster analysis proved to be a bad choice for fall detection. While it was able to correctly distinguish ADLs, it failed to detect several falls. However, its results are still important, as they helped understand how entangled the different results are and the problems that this brings to the problem being studied.

On the other hand, the use of logistic regression proved to be a good bet. Its inclusion in the Elder Care project brought different advantages, the most obvious one being the high precision in distinguishing falls from ADLs. This enables us to send alerts with different degrees of urgency, in this way reducing the risk of discrediting the system by sending urgent alerts where there was no accident. Another improvement logistic regression brings to the system, is in terms of battery saving. The logit can be processed in the central system; only requiring the data from the actual instant the alert was produced. Also, to be able to create the alert the system only needs a small sampling frequency from a single data source, where the other solutions needed a big sampling rate or multiple data sources.

7 Future Work

Having concluded that using logistic regression is a viable solution to minimize the processing stress applied to the WSN module, the next step will be to perfect this system in order to obtain 100% precision on fall detection. In parallel, we will also start testing this system with our own in house developed WSN module. Finished this step, we will start expanding our research to more areas of health care than just fall detection.

References

1. Giannakouris, K.: Ageing characterises the demographic perspectives of the European societies. Eurostat: Statistics in Focus. Retrieved 9, 08–072 (2009)
2. Marcelino, I., Barroso, J., Bulas Cruz, J., Pereira, A.: Elder care architecture. In: Proceedings of the 2008 Third International Conference on Systems and Networks Communications, pp. 349–354 (2008)
3. Jehoel-Gijsbers, G., Vrooman, C.: Social exclusion of the elderly: A comparative study of EU Member States. Ceps (2008)
4. Johnson, R., Wichern, D.: Applied Multivariate Statistical Analysis, 3rd edn. Prentice Hall, New Jersey (1992)
5. McCullagh, P., Nelder, J.: Generalized linear models. Chapman & Hall/CRC, Boca Raton (1989)

6. Lord, C., Colvin, D.: Falls in the elderly: Detection and assessment. In: Proceedings of the Annual International Conference of the IEEE, pp. 1938–1939 (October 1991)
7. Wu, G.: Distinguishing fall activities from normal activities by velocity characteristics. Journal of Biomechanics 33, 1497–1500 (2000)
8. Bourke, A.K., O'Donovan, K.J., Nelson, J., OLaighin, G.M.: Fall-detection through vertical velocity thresholding using a tri-axial accelerometer characterized using an optical motion-capture system. In: Engineering in Medicine and Biology Society, EMBS 2008, pp. 2832 –2835 (August 2008)
9. Pflimlin, J., Hamel, T., Soueres, P., Metni, N.: Nonlinear attitude and gyroscope's bias estimation for a VTOL UAV. International Journal of Systems Science 38(3), 197–210 (2007)
10. Felisberto, F., Moreira, N., Marcelino, I., Fdez-Riverola, F., Pereira, A.: Elder care's fall detection system. Ambient Intelligence-Software and Applications, 85–92 (April 2011)
11. Mathie, M., Lovell, N., Coster, A., Celler, B.: Determining activity using a triaxial accelerometer. In: Proceedings of the Second Joint 24th Annual Conference and the Annual Fall Meeting of the Biomedical Engineering Society, EMBS/BMES Conference, Engineering in Medicine and Biology 2002, vol. 3, pp. 2481–2482. IEEE, Los Alamitos (2002)
12. Imote2 datasheet. PDF, `http://tinyurl.com/6bt9zqb`
13. Its400 data sheet. PDF, `http://tinyurl.com/5rqjqdq`
14. Corporation, I.: Ibm spss statistics (April 2011), `http://www.spss.com/`
15. Hosmer, D., Lemeshow, S.: Applied logistic regression. Wiley-Interscience, Hoboken (2000)
16. Seco, A., Felgueiras, M., Fdez-Riverola, F., Pereira, A.: Elder Care Alert Management-Decision Support by a Logistic Regression Model. In: Corchado, J.M., Pérez, J.B., Hallenborg, K., Golinska, P., Corchuelo, R. (eds.) Trends in Practical Applications of Agents and Multiagent Systems. AISC, vol. 90, pp. 9–16. Springer, Heidelberg (2011)
17. Belsley, D., Kuh, E., Welsch, R.: Regression diagnostics: Identifying influential data and sources of collinearity. Wiley-Interscience, Hoboken (2004)