Proceedings of the 29th Annual International
Conference of the IEEE EMBS
Cité Internationale, Lyon, France
August 23-26, 2007.

Fall detection – Principles and Methods

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***Abstract*-- Fall detection of the elderly is a major public health problem. Thus it has generated a wide range of applied research and prompted the development of telemonitoring systems to enable the early diagnosis of fall conditions.**

This article is a survey of systems, algorithms and sensors, for the automatic early detection of the fall of elderly persons. It points out the difficulty to compare the performances of the different systems due to the lack of a common framework. It then proposes a procedure for this evaluation.

I. Introduction

The fall in the elderly is a major public health problem as it causes many disabling fractures [1] but also has dramatic psychological consequences which reduce the independence of the person [2,3,4]. It was established that the earlier the fall is reported, the lower is the rate of morbidity-mortality [5,6]. The detection of the fall is also an interesting scientific problem as it is a ill-defined process which one can approach using various methods.

Although the concept of a fall is in the common sense, it is difficult to describe it precisely, and thus to specify its means of detection. It can be described as the rapid change from the upright/sitting position to the reclining or almost lengthened position, but it is not a controlled movement, like lying down, for example. In 1987 the Kellogg international working group on the prevention of falls in the elderly defined a fall as “unintentionally coming to ground, or some lower level not as a consequence of sustaining a violent blow, loss of consciousness, sudden onset of paralysis as in stroke or an epileptic seizure” [7]. This definition has been used in many research studies, as it is general enough to be extended to include falls resulting of dizziness and syncope, consequences of an epileptic fit or cardiovascular collapses, such as postural hypotension and transient ischaemic attacks.

This paper presents a short review of the academic researches on the fall detection, the physics of a fall and the means for its detection are discussed, then the paper ends by presenting a proposal of a common evaluation framework for the fall detection systems.

II. State of the Art

In most of their academic works, the researchers have based their instrumentation on accelerometers, starting with Lord and Colvin [8] in 1991, followed by Williams [9] in 1998, with an autonomous belt device which detected the impact of the shock on the ground, and a mercury tilt switch to detect when the person was lying. Doughty [10] carried on this work with the evaluation on 20 volonteer, and could detect 180 different falling scenarios. Tamura [11] proposed an ambulatory monitor triggered by a photo-interrupter to record the falling sequences. Noury [12, 13], University of Grenoble-France, designed an autonomous sensor, attached under the armpit, which detects when the velocity exceeds a specific threshold, the sequence from a vertical posture to the lying posture, and the absence of movements after the fall. The device achieved a sensitivity and specificity close to 85% from 15 fall scenarios performed 5 times by 5 persons. Depeursinge [14] with 3 orthogonally arranged accelerometers and 3 successive integrations, could locate in real-time the spatial position of the device and, after training a neural network, could detect unusual events such as the fall of the wearer. Lindeman [15] placed a 3D accelerometer in an implant behind the wearer’s ear lobe and proposed 3 thresholds to trigger a fall: the sum-vector of acceleration in the xy-plane higher than 2 g; the sum-vector of velocity of all spatial components right before the impact higher than 0.7 m/s; and the sum-vector of acceleration of all spatial components higher than 6 g. Zhang [16] placed a tri-axial accelerometer in a mobile-phone, and monitored the following sequence of events: a daily activity, fall and then person remaining motionless. Mathie [17] with a triaxial accelerometer placed at the waist, used a range of parameters including tilt angle, the acceleration magnitude, duration of a posture, metabolic energy expenditure and previous and next activity. The system successfully distinguished between activity and rest, with sensitivities greater than 98% and specificities between 88% and 94% . Hwang [18], placed a tri-axial accelerometer and a gyroscope on the chest. Prado [19] developed an intelligent 4 axis accelerometer unit (IAU) worn like a patch, fixed to the back at the height of the sacrum. The IAU was evaluated by Diaz [20] in a laboratory study carried out over 8 volunteers, it showed that the device was able to distinguish true falling events from normal activities like fast walking or going up/downstairs. Recently, Bourke proposed fall algorithms separately based on thresholds on both signals from a tri-axial accelerometer [21] and a biaxial gyroscope [22] and reached a performance of 100%.

Other works have approached the fall with image processing techniques. Wu [23] from the University of Vermont-USA found that vertical and horizontal speeds are 3 times higher during a fall than for any other controlled movement, and that both speeds are of the same amplitude at the time of the fall whereas they are strongly dissimilar during "controlled"

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movements. This inspired Nait-Charif [24] and Rougier [25] to track the head movements and detect the fall with particles filters algorithms. Mihailidis [26], University of Toronto-Canada, placed a video camera on the ceiling and developed scene algorithms to detect a fall. The system was tested on 21 volunteers who carried out simulated falls, and was capable of detecting 77% of falls.

Some functional prototypes were successfully implemented, and several commercial products are available on the market. Nevertheless, there is no significant industrial deployment of the fall sensors and little use of these devices in daily geriatric practice. There are probably multiple reasons. Some devices demonstrated inadequate operation; some had inadequate ergonomics or were not accepted by the users due to the stigmatization of the fragility of the old person. But the major reason is "rejection" of the equipment by both the wearer and the remote monitoring systems due to the rate of "false alarms", which result in inappropriate alerts.

III. PRINCIPLES AND ALGORITHMS FOR THE FALL DETECTION

The methods for the fall detection are mainly based on analytical models, and some use the machine learning techniques.

A. *Analytical methods*

As many falls end lying on the ground, the simplest approach is to detect the lying position, from a horizontal inclination sensor. This method is very appropriate for monitoring an "isolated worker", but less suitable for the detection of falls of an older person in their home environment as the sleeping hours are not regular. Therefore this method is prone to many "false positives", i.e. detection as falls of situations which are not falls.

A complementary solution is to detect the person lying on the floor, using sensitive floor tiles installed in all the places. But the falls which do not end the ground, or which occur in locations which are not equipped with the specialized tiles, are obviously not detectable.

When falling, the person frequently hits the ground or an obstacle. The "impact shock" results in an intense inversion of the polarity of the acceleration vector in the direction of the trajectory, which one can detect with an accelerometer or a shock detector, which is actually an accelerometer with a previously determined fixed threshold. Even if most of the falls occur in the "frontal" plane (forwards or backwards), the direction of the fall trajectory is obviously variable from one fall to another. Also the location of the sensor on the body relatively to the point of impact modifies the "signature" of the signal recorded at the time of the shock.

Lack of movement can be used to detect the fall as, after a "serious" fall, where the person may be seriously injured, they frequently remain immobilized in a posture and/or a place. A movement/vibration sensor, placed on one of the mobile extremities of the body (e.g. wrist or ankle), can be used or, even simpler presence infra-red sensors disseminated in the home. The draw back with these approaches is the choice of latency time (the delay before decision) which should be long enough to reduce "false positives", which will result in a longer delay before an intervention.

As previously discussed, during a fall there is a temporary period of "free fall", during which the vertical speed increases linearly with time due to gravitational acceleration. If one measures the vertical speed of controlled movements of the person (to rise, to bend down, to sit down), one can then discriminate these speeds from those occurring during a fall, which would exceed an appropriate fixed threshold. The difficulty lies in the choice of this threshold, if it is too low the device will also detect negative events ("false positive"), but if the threshold is too high it will not detect positive events ("false negative"). This threshold is also dependent on the subject-to-subject variability. To overcome this difficulty, one can call upon a learning period of either "supervised" or "unsupervised" learning. During the first case one will ask the wearer to carry out a series of voluntary acts in order to "mark" the normal speeds of execution, in the second case it is sufficient to record the movements of the person, during a few hours or several days, and to then carry out a statistical analysis on measured speeds.

Image processing of video signals can also be used to detect a fall by either identifying the lying posture using scene analysis or by detecting abrupt movements using vector analysis. This last method typically consists in subtracting successive images to keep only the variations, which are then sorted according to their direction and/or their amplitude.

While these techniques are well established in controlled environments (laboratory, scene), they must be modified in uncontrolled environments where one controls neither the lighting nor the framing (it is obviously necessary that the subject be in the field of vision). Moreover, as the subject moves in a 3 dimensions space, it is also necessary to call upon more complex techniques, namely use of 2 cameras ("stereovision").

These techniques are becoming feasible, both technically and financially, thanks to the emergence of low cost cameras (web cams), the possibility to wirelessly transmit images over short distances and the availability of the required algorithms. Nevertheless the acceptance of this technology poses a major problem, as it requires the placement of video cameras in the person's living space, and in particular in the bedroom and the bathroom, with consequent concerns of privacy.

B. *Machine learning methods*

Without any analytical model, one can still carry out an "intuitive" approach to the development of machine learning based fall detection systems starting from observation (a training period) and then classification. Yet it is necessary to set criteria for classification that are sufficiently significant and independent (discriminating). If one proceeds through a supervised training period, one can train a neural network, which will then be used to automatically classify future situations. Only the situations met during training can be classified, the others being mixed in a class labeled "others" (to stumble, to slip, etc.). If the training is "unsupervised", a class "fall" is likely to be isolated if the training period is long enough, even infinite if the event of fall is rare. Moreover the first fall event is likely to be missed since its class is yet unknown before its first occurrence.

IV. Evaluation of the Fall Sensors

At present it is practically impossible to compare the performances of different fall sensors from the data in the literature ,as common criteria for their evaluation were not utilized nor were common procedures to carry out the tests adopted. We thus think that it is very important that objective criteria be adopted for the future evaluation of fall sensors with a framework for the evaluation of these devices.

A. *Criterion of quality*

Fall detection is either positive if the detector properly recognizes a fall, or negative if it does not. As the output is a binary one, the quality of the detector cannot be evaluated simply from a single test, instead it is necessary to carry out a statistical analysis on a series of tests.

There are 4 possible cases:

- True positive (TP): a fall occurs, the device detects it
- False positive (FP): the device announces a fall, but it did not occur
- True negative (TN): a normal (no fall) movement is performed, the device does not declare a fall
- False negative (FN): a fall occurs but the device does not detect it

To evaluate the response to these 4 situations 2 criteria are proposed:

- Sensitivity is the capacity to detect a fall,

$$Sensitivity = \frac{TP}{TP + FN} \quad (1)$$

- Specificity is the capacity to detect only a fall,

$$Specificity = \frac{TN}{TN + FP} \quad (2)$$

B. *Experimental set up*

The scenarios of falling are very various so one must test the devices with a limited number of situations of falls (positive situations) as well as of 'pseudo' falls situations (negative situations).

As most falls occur during intentional movements initiated by the person, they happen mainly in the antero-posterior plane, forward or backward: stumbling on an obstacle during walking, backwards slip on wet ground, transfer 'Stand-To-Sit". If the person becomes unbalanced in the forward direction, s/he will initially try to be recover by taking some steps forward, thus amplifying the movement of the fall, and he/she will perhaps finally fall while projecting his/her arms forwards for protection. S/he can also drop herself onto the knees. If imbalance occurs backwards, the person will try to sit down to possibly attenuate the intensity of the shock impact.

But in some cases, the fall occurs sideways, either during a badly controlled "Sit-To-Stand" transfer, or if the person, when becoming unbalanced, tries to grip the wall.

There are also daily life movements during which the amplitude or intensity of the movement can be similar to that encountered in accidental situations: the action of lying down, or of sitting down, if carried out "quickly". One can also encounter situations of fall initiation with recovery (stumbling).

From the discussion we propose the set of scenarios for the evaluation of fall sensors, based on those used to evaluate the Noury's fall sensor [27], completed by some scenarios used by Bourke to evaluate his fall algorithms [21,22]:

TABLE I
SCENARIOS FOR THE EVALUATION OF FALL DETECTORS

Category	Name	Outcome
Backward fall (both legs straight or with knee flexion)	Ending sitting	**Positive**
	Ending lying	**Positive**
	Ending in lateral position	**Positive**
	With recovery	**Negative**
Forward fall	On the knees	**Positive**
	With forward arm protection	**Positive**
	Ending lying flat	**Positive**
	With rotation, ending in the lateral right position	**Positive**
	With rotation, ending in the lateral to the left position	**Positive**
	With recovery	**Negative**
Lateral fall to the right	Ending lying flat	**Positive**
	With recovery	**Negative**
Lateral fall to the left	Ending lying flat	**Positive**
	With recovery	**Negative**
Syncope	Vertical slipping against a wall finishing in sitting position	**Negative**
Neutral	To sit down on a chair then to stand up (consider the height of the chair)	**Negative**
	To lie down on the bed then to rise up	**Negative**
	Walk a few meters	**Negative**
	To bend down, catch something on the floor, then to rise up	**Negative**
	To cough or sneeze	**Negative**

To perform only one realization of each scenario for each subject is insufficient. However, not to impose on the subjects unnecessarily, a maximum of 3 tests can be carried out by each subject in each condition. The subject should be allowed to rest as much as he wishes, when he wishes, during the tests, and be free to adapt his/her speed in carrying any of the predetermined scenarios.

As successive reproduction of the same scenario may result in habituation to the gesture, which becomes thus less natural, it would be beneficial to vary the order of the tests, or to leave it to the free choice of the subject, only annotating the order he selected.

Eventually, we obtain 20 scenarios (Table 1), with 50% "negative" and 50% "positive". If the subject performs 3 trials, this is 60 tests per subject.

Finally, with a reduced sample of 10 subjects one already gets 600 data points, which is statistically significant to compute the specificity and the sensitivity of the device.

The constitution of the sample should also respect gender (Man/Women). Although the goal of a fall sensor is to detect the fall of elderly people, it is actually impracticable to test the fall situations with them. Thus the fall situations may be simulated by younger persons, or even athletes, and the normal activities may be tested on elderly in the risk age group for falls.

V. CONCLUSIONS

The ideal fall detection system should exhibit both a sensitivity and a specificity of 100%. This was sometimes reached in experimental set up [21, 22], but when it comes to the design of an autonomous integrated fall sensors, there is a dramatic loss in performances [13, 27].

It could probably approach 99% from a multi-dimensional combination of both kinematic and physiological parameters. In the future, new promising techniques could also be investigated considering the fall as a chaotic event, with stable states and bifurcations, in the context of the theory of "complex systems".

The main technological improvements will be in the integration of the devices and on the level of maintenance required . The smaller the size of the sensor, the easier it will be fitted on the person, in garments or in accessories. Also the maintenance interval should ideally reach 1 or 2 years, to reduce interventions and associated costs.

Improvements may also be made on the functionality of these devices. First of all the activation must be fully automatic with no wearer intervention. Secondly, the device having a communication capability could bring enhanced services to the person, such as the provision of a "social link" which would augment the conventional alert system.

Daily use of such an intelligent device also introduces some ethical issues concerning the respect of intimacy and privacy (each movement of the person can be recorded) and also the risk of dependency of the subject on the technology.

But for the time being, the most urgent task facing the scientific community is to accept a common definition of a fall and of fall detection, and to agree a common protocol for the evaluation of the fall detection systems.

REFERENCES

[1] Sadigh S, A Reimers, R Andersson, L Laflamme "Falls and fall-related injuries among the elderly: a survey of residential-care facilities in a Swedish municipality". J. Community Health. 2004 Apr;29(2):129-40

[2] Gostynski M., "Prevalence, circumstances and consequences of falls in institutionalized elderly; a pilot study", Soz Praventivmed.;36(6):341-5, 1991.

[3] Ryynanen OP, SL Kivela, R Honkanen, P Laippala "Falls and lying helpless in the elderly". Z Gerontol.; 25(4):278-82, 1992.

[4] Kiel DP. "Falls". R I Med J.;74(2):75-9, Feb 1991.

[5] Gurley RJ, N Lum, M Sande, B Lo, MH Katz "Persons found in their homes helpless or dead". N Engl J Med.; 334(26):1710-6, 1996.

[6] Wild, D.U.S. Nayak and B. Isaacs "How dangerous are falls in old people at home?" Br Med J (Clin Res Ed). 282(6260) : 266-8, 1981.

[7] Gibson, M.J. et al. "The prevention of falls in later life. A report of the Kellogg International Work Group on the Prevention of Falls by the Elderly" Danish Medical Bulletin, 34 Supplement 4:1-24, 1987.

[8] Lord, C.J. and DP Colvin "Falls in the elderly: Detection and Assessment". in Ann. Int. Conf. IEEE Eng. Med. Biol. Society. 1991.

[9] Williams G. et al. "A smart fall and activity monitor for telecare applications", in 20th int. Conf. IEEE-EMBS 1998, Hong Kong, 29 Oct-1 Nov, pp 1151-4, 1998.

[10] Doughty, K.R. Lewis and A. McIntosh "The design of a practical and reliable fall detector for community and institutional telecare". J Telemed Telecare, 6 Sup 1 pp: S150-4, 2000.

[11] Tamura, T. et al. "An ambulatory fall monitor for the elderly", in Ann. Int. Conf. IEEE Eng. Med. Biol. Society 2000: Chicago, IL, pp: 2608-2610, 2000.

[12] Noury N. et al., "Monitoring behavior in home using a smart fall sensor and position sensors", in IEEE-EMBS « Microtechnologies in Medicine & Biology », Lyon-France, pp 607-610, Oct 2000.

[13] Noury N., A. Tarmizi, D. Savall, P.Boissy, P.Barralon, G. Virone, P.Rumeau, "A smart sensor for fall detection in daily routine", in SICICA2003, Aveiro-Portugal, 9-11 Jul 2003

[14] Y. Depeursinge, "Device for monitoring the activity of a person and/or detecting a fall", US patent 6,201,476 B1, 13 March 2001

[15] Lindemann U. "Evaluation of a fall detector based on accelerometers: a pilot study", Med Biol Eng Comput,;43(5):548-51, sep 2005.

[16] Zhang, T. et al. "Fall detection by embedding an accelerometer in cellphone and using KFD algorithm", International Journal of Computer Science and Network Security. 6(10) pp: 277-84, 2006.

[17] Mathie, M.J. Basilakis and BG Celler "A system for monitoring posture and physical activity using accelerometers" in 23rd Annual Int. Conf. IEEE Engineering in Medicine and Biology Society, Istanbul, 25-28 Oct. 2001.

[18] Hwang, J.Y. et al. "Development of Novel Algorithm and Real-time monitoring Ambulatory system using Bluetooth module for fall detection in the elderly" in Proceedings of the 26th Annual International Conference of the IEEE-EMBS. San Francisco, CA, USA. September 1-5, 2004.

[19] Prado, M.J. Reina-Tosina and L Roa, "Distributed intelligent architecture for falling detection and physical activity analysis in the elderly" in Proceedings of the second Joint EMBS/BMES conference. 2002. Houston, TX, USA. October 23-26, 2002.

[20] Díaz, A. et al. "Preliminary evaluation of a full-time falling monitor for the elderly" in Proceedings of the 26th Annual International Conference of the IEEE-EMBS, San Francisco, CA, USA. September 1-5, 2004.

[21] Bourke, A.K.V. J O'Brien J and GM Lyons , "Evaluation of a threshold-based tri-axial accelerometer fall detection algorithm" Gait Posture, 2006.

[22] Bourke AK, GM Lyons, "A threshold-based detection algorithm using a bi-axial gyroscope sensor", Med. Eng. Phys., 2006.

[23] Wu G., "Distinguishing fall activities from normal activities by velocity characteristics", Jour. of Biomechanics, 33, pp.1497-1500, 2000.

[24] Nait-Charif, H. and S Mckenna "Activity Summarisation and Fall Detection in a Supportive Home Environment". in 17th International Conference on Pattern Recognition, 2004.

[25] Rougier, C. and J Meunier, "Demo : Fall Detection Using 3D Head Trajectory Extracted From a Single Camera Video Sequence" in First International Workshop on Video Processing for Security (VP4S-06), June 7-9 . Quebec City, Canada, 2006.

[26] Mihailidis A. "An intelligent emergency response system: preliminary development and testing of automated fall detection" , J. Telemed. Telecare;11(4):194-8, 2005.

[27] Noury N, P Barralon, G Virone, P Boissy, M Hamel, P Rumeau, "A Smart Sensor Based on Rules and its Evaluation in Daily Routines", in IEEE-EMBC 2003, Cancun-Mexico, pp 3286-89, sept 2003.