ECAI 2012
Luc De Raedt et al. (Eds.)

doi:10.3233/978-1-61499-098-7-1013

Confidence: Ubiquitous Care System to Support Independent Living

Mitja Luštrek[1] and **Boštjan Kaluža**[1] and **Božidara Cvetković**[1] and **Erik Dovgan**[1] and **Hristijan Gjoreski**[1] and **Violeta Mirchevska**[2] and **Matjaž Gams**[1]

Abstract. The Confidence system aims at helping the elderly stay independent longer by detecting falls and unusual movement which may indicate a health problem. The system uses location sensors and wearable tags to determine the coordinates of the user's body parts, and an accelerometer to detect fall impact and movement. Machine learning is combined with domain knowledge in the form of rules to recognize the user's activity. The fall detection employs a similar combination of machine learning and domain knowledge. It was tested on five atypical falls and events that can be easily mistaken for a fall. We show in the paper and demo that neither sensor type can correctly recognize all of these events on its own, but the combination of both sensor types yields highly accurate fall detection. In addition, the detection of unusual movement can observe both the user's micro-movement and macro-movement. This makes it possible for the Confidence system to detect most types of threats to the user's health and well-being manifesting in his/her movement.

1 INTRODUCTION

The European population is aging rapidly, threatening to overwhelm the society's capacity for taking care of its elderly members. The percentage of persons aged 65+ in the European Union is projected to rise from 17.4% in 2010 to 28.8% in 2050 [2]. As a consequence, there will be less than two persons of working age (20–64) for every person aged 65+. Such projections drive the urgent development of ambient assisted living solutions to help the elderly live longer independently with minimal support of the working-age population.

We developed such a solution in the European FP7 project Confidence [1]. The Confidence system detects falls and unusual movement which may indicate a health problem. Timely detection of falls is important to avoid the so-called "long lie" – being injured and unable to call for help for a long time. Research showed that half of the elderly who experience the long lie die within six months [11]. The detection of unusual movement can alert the caregivers to issues such as pain in the leg or stroke (unusual gait) and cognitive problems (unusual traffic patterns).

A Confidence user wears an accelerometer and a location tag at the neck. The coordinates of the location tag are detected with radio sensors installed in the apartment. The combination of these two sensor types and some background knowledge about the apartment results in highly accurate fall detection.

The detection of falls was tested on five events: three falls of different types, and two events that may easily be mistaken for falls. The detection using both sensor types outperformed the detection using either sensor type alone. These five events are included in the demo.

2 THE CONFIDENCE SYSTEM

The architecture of the Confidence system is shown in Figure 1. The data from the location sensors is first preprocessed, and then the user's activity is recognized. The activity together with the location is used for the detection of unusual micro- and macro-movement. The activity and the location combined with the data from the accelerometer are used for fall detection. If a fall is detected, an alarm is raised, and if an unusual movement is detected, a warning is raised. An initialization procedure can be used to adapt the activity recognition to the end-user. The fall detection is also adapted if the user cancels false alarms or raises alarms manually.

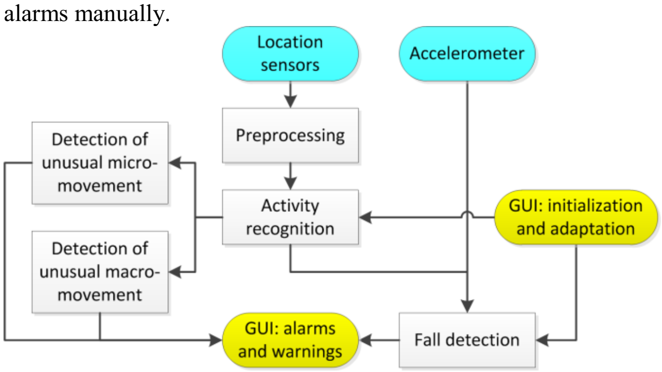

Figure 1. Architecture of the Confidence system

The Confidence system can use an arbitrary inertial and location hardware system. By default, the sensors are placed at the neck. Optionally, the sensors can be also placed to the waist and both feet, which increases the detection capabilities. Sensor data are preprocessed with three filters to reduce the considerable noise in the tag locations [5].

Activity recognition is performed by a machine-learning module and a rules module. Eight basic activities are recognized: walking/standing, sitting, lying, sitting on the ground, on all fours, the process of sitting/lying down, the process of standing up and falling. The machine-learning module [7] first computes attributes such as the tag velocities and the distances between tags. These are fed into a Random Forest classifier. The classifier outputs the user's activity act_{ML}, for example, lying, walking or falling. The

[1] Department of Intelligent Systems, Jožef Stefan Institute, Slovenia, email: {mitja.lustrek, bostjan.kaluza, boza.cvetkovic, erik.dovgan, hristijan.gjoreski, matjaz.gams}@ijs.si
[2] Result d. o. o., Slovenia, email: violeta.mircevska@ijs.si

rules module [9] employs similar attributes, except that domain knowledge in the form of rules is used to determine the user's activity act_R. Bayesian inference is used to determine the final activity from the outputs of the machine-learning and rules modules. It is finally smoothed with a Hidden Markov Model, which eliminates infeasible activity transitions, e.g., from lying to standing without standing up in between [4].

Fall detection is performed using the location sensors and the accelerometer separately, and finally a joint decision is made. First, using the location sensors we consider an event a fall if the user does not get up for 5 seconds. The fall detection – like the activity recognition – is performed by a machine-learning and a rules module [10]. We use the ratio of the user's activities and amount of movement in the last t seconds, whether the user's location is intended for lying, and how long ago the last falling activity was detected. Second, to detect falls with inertial sensors [3], we use the length of the acceleration vector, more precisely, a threshold over the minimum and the maximum acceleration within a one-second window. Finally, both detection approaches are merged and the Confidence system declares that a fall has occurred if: (1) the location sensors detected a fall AND the user was not moving afterwards; OR (2) the accelerometer detected a fall AND the location was not intended for lying.

To detect unusual micro-movement, a number of attributes characterizing the user's movement compiled into a movement signature. The signatures are measured for various time periods and stored for an initial training period, during which the movement is considered normal. Afterwards, an outlier detection algorithm is used to detect signatures that deviate from the training data [8]. Similarly, to detect unusual macro-movement, the user's traffic patterns for a day are represented as daily signatures that consist of spatial-activity distributions [6].

3 DEMO

This demo shows the usability of the fall detection in the Confidence system, which was tested on five events selected in consultation with medical experts. First, tripping is a typical fall which occurs quickly and ends with a strong impact. Second, falling slowly may occur when a person grows weak and collapses slowly, without a strong impact. Third, tripping followed by standing up occurs if the user falls, but is not injured enough to be unable to stand up by him/herself; however, it is still treated as a fall, because it is not uncommon for an elderly to suffer an injury and either not realize it, or not realize its seriousness. Fourth, lying down quickly is not a fall, but may appear like one to sensors. Finally, searching for an object on the ground, either on all fours or lying, is also not a fall, but may appear like one.

The performance was evaluated with the recordings of 10 volunteers. Each event was repeated five times by each volunteer. The volunteers were young, but a physician provided advice on the movement of the elderly. The results of the evaluation are shown in Table 1. The first two columns show the accuracy of the fall detection using the location sensors only, either with four tags or with one tag. The next column shows the accuracy of the fall detection using the accelerometer only. The last column shows the final decision using one location tag and the accelerometer.

Looking at the individual fall types, one can see that tripping is indeed a typical fall, which was recognized accurately by both the location sensors and the accelerometer. Falling slowly was easy to recognize for the location sensors, since they rely on the recognition of lying. However, from the accelerometer's viewpoint it appeared like lying down voluntarily. Tripping + standing up was impossible to recognize for the location sensors, because the period of lying was too short, but it was recognized perfectly by the accelerometer, since there was a strong impact and some lying afterwards. Of the non-fall events, lying down quickly was recognized perfectly by the location sensors, because they could use the information about the bed and considered lying there safe. From the accelerometer's viewpoint, however, lying down quickly was almost indistinguishable from a fall. Searching on the ground was somewhat difficult to recognize for the location sensors, since it involved lying at a location not intended for lying – just like a fall. The accelerometer, though, performed perfectly, since no strong impact was involved. The combination, however, does not always perform perfectly, since it depends on the amount of lying on the floor and moving while searching.

In conclusion, Table 1 shows that because of the limited view of an event possessed by each sensor type, each fails to recognize some of the events correctly as falls or non-falls. However, since the sensors complement each other, using both types yielded almost perfect fall detection.

Table 1. Accuracy of the fall detection

Event	**Location sensors**		**Accel.**	**Both sensors**
	4 tags	**1 tag**		
Falls				
1. Tripping	100.0%	93.9%	100.0%	100.0%
2. Falling slowly	95.9%	100.0%	10.6%	100.0%
3. Tripping + standing up	0.0%	0.0%	100.0%	100.0%
Non-falls				
4. Lying down quickly	100.0%	100.0%	34.0%	100.0%
5. Searching on the ground	83.7%	61.2%	100.0%	61.2%
Average	77.5%	70.9%	68.9%	92.2%

REFERENCES

[1] Confidence project, http://www.confidence-eu.org.

[2] European Comission, *Demography report 2010*, Publications Office of the European Union, Luxembourg, 2011.

[3] H. Gjoreski, M. Luštrek and M. Gams, 'Accelerometer placement for posture recognition and fall detection', in *Proc. IE*, pp. 47–54 (2011).

[4] B. Kaluža, 'Reducing spurious activity transitions in a sequence of movement', in *Proc. ERK 2009, vol. B*, pp. 163–166 (2009).

[5] B. Kaluža and E. Dovgan, 'Denoising human-motion trajectories captured with radio technology', in *Proc. IS 2009, vol. A*, pp. 97–100 (2009). In Slovene.

[6] B. Kaluža and M. Gams, 'Analysis of daily-living dynamics', to appear in *Journal of Ambient Intelligence and Smart Environments*.

[7] M. Luštrek and B. Kaluža, 'Fall detection and activity recognition with machine learning', *Informatica* **33**(2), 197–204 (2009).

[8] M. Luštrek, B. Kaluža, E. Dovgan, B. Pogorelc and M. Gams, 'Behavior analysis based on coordinates of body tags', in *Lecture Notes in Computer Science 5859*, pp. 14–23 (2009).

[9] V. Mirchevska, M. Luštrek and M. Gams. 'Combining machine learning and expert knowledge for classifying human posture', in *Proc. ERK 2009*, pp. 183–186 (2009).

[10] V. Mirchevska, B. Kaluža, M. Luštrek and M. Gams, 'Real-time alarm model adaptation based on user feedback', in *Proc. Workshop on Ubiquitous Data Mining*, ECAI, pp. 39–43 (2010).

[11] D. Wild, U.S. Nayak and B. Isaacs, 'How dangerous are falls in old people at home?', *British Medical Journal* **282**(6260), 266–268 (1982).