Detecting Falls with Location Sensors and Accelerometers

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Abstract

Due to the rapid aging of the population, many technical solutions for the care of the elderly are being developed, often involving fall detection with accelerometers. We present a novel approach to fall detection with location sensors. In our application, a user wears up to four tags on the body whose locations are detected with radio sensors. This makes it possible to recognize the user's activity, including falling any lying afterwards, and the context in terms of the location in the apartment. We compared fall detection using location sensors, accelerometers and accelerometers combined with the context. A scenario consisting of events difficult to recognize as falls or non-falls was used for the comparison. The accuracy of the methods that utilized the context was almost 40 percentage points higher compared to the methods without the context. The accuracy of pure location-based methods was around 10 percentage points higher than the accuracy of accelerometers combined with the context.

Introduction

The world 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 developed countries is projected to rise from 7.5 % in 2009 to 16 % in 2050 (United Nations 2009). Even more alarmingly, the ratio of the working-age population (15–64) to those aged 65+ is projected to decline from 4.3 to 2.3. This urgently drives the development of technical solutions to help the elderly live longer independently with minimal support of the working-age population.

There are at least two reasons why fall detection is one of the most active topics in elderly care. First, falls and the fear of falling are important causes for nursing home admission (Tinetti and Williams 1997). And second, fall detection can be tackled fairly effectively with the currently available technology. The usual approach is with accelerometers, which detect the high acceleration upon the impact with the ground. Accelerometers are accurate, lightweight and inexpensive. Their limitations are that some safe activities result in high acceleration, and more importantly, not all falls result in high acceleration.

We developed an alternative approach to fall detection in the European Union project Confidence (2011). A Confidence user wears up to four tags on the body. The locations of these tags are detected with radio sensors, and from the tag locations the user's activity and location in the apartment are inferred. Such rich information enables reliable detection even of atypical falls. However, the equipment is expensive and somewhat cumbersome, so it probably needs a few years to mature.

In this paper we compare fall detection with location sensors and with several accelerometer-based methods. We show that a typical fall and the lying after a fall can indeed be reliably detected with accelerometers. However, to recognize atypical falls, some contextual information is needed. In our case it consists of the location in the apartment, which is provided by location sensors.

Related Work

Most research on fall detection uses accelerometers (which measure linear acceleration) and gyroscopes (which measure angular velocity). They typically detect falls by applying thresholds to accelerations, velocities and angles. Jantaraprim et al. (2009) used a triaxial accelerometer worn on the chest; by applying a simple threshold to the acceleration, they detected falls with 98.9 % accuracy. Nguyen, Cho and Lee (2009) used a triaxial accelerometer worn on the waist; by applying thresholds to the acceleration, they detected a potential fall and the activity after the fall, resulting in 100 % accurate fall detection. Bourke and Lyons (2008) used a biaxial gyroscope worn on the chest; by applying thresholds to the peaks in the angular velocity, angular acceleration and torso angle change, they also detected falls with 100 % accuracy.

Some researchers used machine learning instead of threshold-based algorithms. Zhang et al. (2006) and Shan and Yuan (2010) both used a triaxial accelerometer worn on the waist. Using SVM machine learning algorithm on various features derived from accelerations, they detected falls with 96.7 % and 100 % accuracy, respectively.

Of particular interest to us is the work of Li et al. (2009). They used two triaxial accelerometers and gyroscopes worn on the chest and thigh; by applying thresholds to accelerations, angular velocities and angles, they detected a potential fall and the activity after the fall, resulting in 90.1 % accurate fall detection. The lower accuracy compared to the previous work is likely due to the more difficult test data: their method sometimes failed on lying down quickly and on two atypical fall types. Exactly such situations are tackled by locations sensors in this paper.

It is also possible to detect falls from video (for example Anderson et al. 2009), floor vibration (Alwan et al. 2006), sound (Zhuang et al. 2009) etc. These approaches perform well in laboratory tests and can be considered more comfortable than body-worn sensors. However, body-worn sensors are still the most mature approach to fall detection and will likely be used for many years to come, so the paper is focused on them. We are aware of no attempts to detect falls with location sensors outside of our work.

Fall Detection Methods

We detected falls with the Confidence system, which uses location sensors. The Confidence system was compared to several accelerometer-based methods. This section describes all the methods, whereas the results of their experimental comparison are presented in the next section.

Location Sensors and the Confidence system

The Confidence system uses Ubisense (2011) real-time location system for sensing. It employs ultra-wideband radio technology to determine the locations of up to four tags worn on the user's chest, waist and both ankles. The number of tags can be reduced, but the chest tag is mandatory. If not all four tags are used, the locations or the missing tags are estimated. The locations are sampled with 10 Hz. The Confidence system performs three main steps: filtering of sensor noise, activity recognition on filtered data, and fall detection based on the recognized activities.

Filtering is needed because the tag locations are noisy – the specified accuracy is 15 cm, but much larger deviations are observed in practice. First, a median filter is applied, which eliminates large short-term changes in tag locations due to noise. Second, a filter that enforces anatomic constraints is used. It corrects errors such as an apparent lengthening of a limb. Third, the Kalman filter is applied, which smoothes sharp changes in both locations and speed.

Filtered tag locations are used for **activity recognition**, which is performed by a machine-learning module and a rules module. Basic activities are recognized: walking/standing, sitting, lying, the process of sitting/lying down, the process of standing up and falling. The machine-learning module (Luštrek and Kaluža 2009) 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. Weka (Hall et al. 2009) implementation of all the machine learning algorithms mentioned in the paper was used. The classifier was trained on a training scenario which contains all the activities of interest and three types of fall. The scenario was recorded by five persons, five times by each. The recordings are available from the UCI Machine Learning Repository (Luštrek et al. 2010). The rules module (Mirchevska, Luštrek and Gams 2009) employs similar attributes, except that expert-crafted rules are used to determine the user's activity act_{R}. Bayesian inference is used to determine the final activity as the most probable activity given the outputs of the two modules act_{ML} and act_{R}, as computed from the true activities and the modules' outputs on the training recordings. It is smoothed with a Hidden Markov Model, which eliminates infeasible activity transitions, for example from lying to standing without standing up in between.

The user's activity and the context are finally combined to **detect falls**. The context at the moment consists of the user's location in the apartment (on the bed, on the chair), which is provided by location sensors. We consider an event fall if the user falls and does not get up for 10 seconds. Like activity recognition, fall detection is performed by a machine-learning and a rules module (Mirchevska et al. 2010), which were both designed to detect such events.

The machine-learning module uses as attributes the percentages of the user's activities in the last 5, 7.5 and 10 seconds, whether the user is on the bed or chair, and how long ago the last falling activity (moving rapidly towards the ground) was detected. These attributes are fed into an SVM and a C4.5 classifier to classify the current situation as a fall or non-fall. Since both classifiers are prone to false alarms, the module declares that a fall has occurred only if both classifiers output fall. The classifiers were trained on the training recordings used in activity recognition.

The rules module detects the following types of events:

- Falling activity was recognized AND the user was lying/sitting outside the bed/chair afterwards AND the user was not moving; OR
- Falling activity was recognized AND the user was lying/sitting outside the bed/chair afterwards; OR
- The user was lying/sitting outside the bed/chair for some time AND the user was not moving; OR
- The user was lying/sitting outside of the bed/chair for a longer time.

The exact rules are more complicated, since they allow for errors in activity recognition and thus require only certain percentages of lying/sitting and immobility; they also distinguish between lying and sitting on the ground. They were tuned to maximize the accuracy of fall detection on the training recordings used in activity recognition and the machine-learning module. We are not relying on the detection of the falling activity only because it always lasts a very short time and is thus difficult to recognize.

We declare that a fall has occurred if either both the machine-learning and the rules module output fall, or if one of them outputs fall continuously for 3 seconds.

The Confidence system is also capable of detecting various changes in movement patterns of the user, which may indicate a health problem (Luštrek et al. 2009; Kaluža et al. 2010). It reports its findings as alarms and warnings to the user and his/her caregivers. However, this is not discussed in this paper.

Accelerometers

To detect falls with accelerometers, we used one triaxial accelerometer worn on the chest. The accelerations were sampled with 10 Hz. We employed multiple fall detection methods.

Methods Using Threshold and Orientation

A typical acceleration pattern during a fall is a decrease in acceleration followed by an increase, as shown in Figure 1. This is because an accelerometer at rest registers 1 g (the Earth's gravity) and during free fall 0 g. When a person starts falling, the acceleration decreases from 1 g to around 0.5 g (perfect free fall is never achieved). Upon the impact with the ground, a short strong increase in the acceleration is measured.

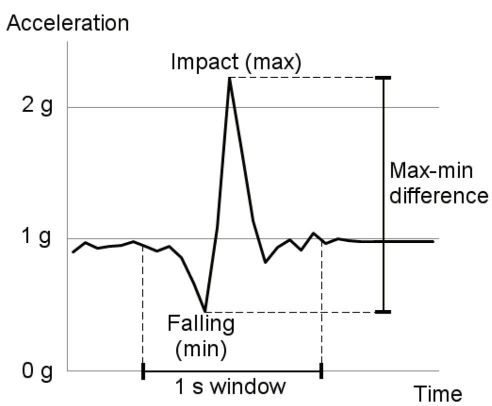

Figure 1: Acceleration pattern during a fall.

To detect falls with a threshold, we used the length of the acceleration vector, which means that we ignored the direction of the acceleration. The minimum and the maximum acceleration within a one-second window were measured. If the difference between the maximum and the minimum exceeded 1 g and the maximum came after the minimum, we declared that a fall had occurred.

We augmented fall detection with the measurement of the person's orientation after a potential fall. We assumed that the acceleration vector $a = [a_x, a_y, a_z]$, which consists of the accelerations along the three axes of the accelerometer, generally points downwards (in the direction of the Earth's gravity). Let z be the axis pointing downwards when the person is standing upright. The angle φ between the acceleration vector and the z axis thus indicates the person's orientation, and was computed as follows:

$$\cos\varphi = \frac{a_z}{\sqrt{a_x^2 + a_y^2 + a_z^2}}$$

Since each person has his/her characteristic posture and the accelerometer may not always be worn in exactly the same way, the average orientation of each person during 15 seconds of walking was measured as φ_0. Subsequently when a new orientation φ was measured, it was normalized as follows: $\varphi_{norm} = \varphi - \varphi_0$. A person was considered to be oriented upright if $-30° < \varphi_{norm} < 30°$. This was used for fall detection: if an acceleration was detected that exceeded the threshold as described previously, and the orientation for 10 seconds afterwards was not upright, we declared that a fall had occurred.

Finally, we took advantage of the context in terms of the location in the apartment. This was measured by a single location sensor, since locations sensors were used anyway. In principle, however, some other solution could be used – for example pressure sensors on the bed and chair. Using the context, we declared that a fall had occurred if:

- An acceleration was detected that exceeded the threshold as described previously AND the person was not on the bed/chair for the following 10 s; OR
- The orientation was not upright AND the person was not on the bed/chair for 10 s.

Methods Using Machine Learning

To detect falls with machine learning, we used a sliding window to transform the stream of acceleration data into instances for machine learning. The following attributes were derived from the data within each 0.8-second window:

- The average length of the acceleration vector within the window
- The variance of the length of the acceleration vector
- The average acceleration along the x, y and z axes
- The maximum and the minimum acceleration along the x, y and z axes
- The difference between the maximum and the minimum acceleration along the x, y and z axes
- The speed of change in acceleration between the maximum and the minimum along the x, y and z axes
- The orientation as defined for the use in combination with the threshold

Before training a classifier, greedy attribute selection as implemented in Weka (Hall et al. 2009) was applied to the attribute list. The variance of the length of the acceleration vector, the average, maximum and minimum acceleration along the y axis, the speed of change along the z axis and the orientation were selected. The variance within a window was defined as follows:

$$\delta^2 = \frac{\sum_{i=1}^{N} (a_i - \overline{a})^2}{N}$$

N is the number of acceleration data within the window, a_i is the length of the i-th acceleration vector and $\overline{a}$ is the average length of the acceleration vector of the person. The speed of change in acceleration along the z axis within a window was defined as follows:

$$spd_z = \tan \frac{\max(a_z) - \min(a_z)}{t(\max(a_z)) - t(\min(a_z))}$$

Max(a_z) and min(a_z) are the maximum and minimum acceleration along the z axis within the window, and t(max(a_z)) and t(min(a_z)) are the times they were measured.

The selected attributes were used to train a Random Forest classifier. The classifier was trained on the training scenario used by the Confidence system. The scenario was again recorded by five persons, five times by each.

Fall detection by machine learning was also augmented by the context in terms of the location in the apartment, which was again measured by a single location sensor. We declared that a fall had occurred when the classifier detected a fall and the person was not on the bed/chair.

Experiments

We compared the performance of the fall detection methods on a scenario recorded by 10 healthy volunteers (6 male and 4 female), 5 times by each. None of the recordings were used to train or tune any of the methods, and none of the volunteers participated in any of the training recordings.

Test Scenario

The scenario was designed specifically to investigate events that may be difficult to recognize as falls or non-falls. It contains nine different events listed in Table 1. They were recorded in single recordings interspersed with short periods of walking, each recording lasting around 20 minutes. Example videos of the events can be viewed here: http://dis.ijs.si/confidence/iaai.html.

No.	Description	Fall
1	Sitting down normally on the chair	No
2	Tripping, landing flat on the ground	Yes
3	Lying down normally on the bed	No
4	Falling slowly (trying to hold onto furniture), landing flat on the ground	Yes
5	Sitting down quickly on the chair	No
6	Falling when trying to stand up, landing sitting of the ground	Yes
7	Lying down quickly on the bed	No
8	Falling slowly when trying to stand up (trying to hold onto furniture), landing sitting of the ground	Yes
9	Searching for something on the ground on all fours any lying	No

Table 1: Fall and non-fall events in the test scenario.

Representative falls types were selected from a list of 18 fall types compiled in consultation with medical personnel. As shown in the section on related work, accelerometers can accurately detect typical falls, so we included only one such fall (event number 2) to demonstrate that the Confidence system can recognize it as well. We included three atypical falls (4, 6 and 8) to test the use of contextual information, namely that a person is not expected to lie or sit on the ground (as opposed to the bed or the chair). They are atypical in speed (4 and 8) and starting/ending posture (6 and 8). The falls were demonstrated by a physician, who also provided guidance during initial recordings.

We included two events (5 and 7) that involve high acceleration and could thus be misclassified as falls by accelerometers. We also included an event (9) that involves voluntary lying on the ground, which could mislead the methods that use information other than acceleration. The last two events (1 and 3) are perfectly normal and were included to verify that all the methods work correctly and do not recognize them as falls.

Results

We compared the performance of the Confidence system using the full complement of four tags and the chest tag only, and of all the accelerometer-based methods described in the previous section using one accelerometer on the chest. The accelerometer-based methods utilizing the context were provided with the location in the apartment as determined by the location sensors using the chest tag. This was possible because the volunteers performing the test scenario were wearing all the equipment simultaneously.

Table 2 shows the accuracies of correctly recognizing events as falls or non-falls for the four falls and the four potentially misleading events described in the previous subsection. Both events consisting of sitting down quickly are merged into one line. The average accuracy was averaged over the eight events. The accuracies of the two normal events (1 and 3 in Table 1) are not included explicitly; instead, the total number of other false alarms (activities incorrectly recognized as falls) during these two events and during the walking between the events is given.

The first event in Table 2, tripping, is a typical fall that was recognized fairly accurately by all the methods, as expected based on related work. The Confidence system with one tag failed to recognize a few instances because the Confidence system was not truly designed to operate with a single tag. The machine-learning-based detection with an accelerometer made the most mistakes, probably because it was trained on a variety of falls, many of them atypical, and it tried to build a classifier capable of recognizing all of them.

Falling slowly was in one case misclassified by the Confidence system with four tags because of the person's unusual posture after the fall. In this case a single tag was actually an advantage, since the detection was based on its height above the ground only. Threshold and orientation were not adequate to detect this fall with an accelerometer because the falling was too slow; only the context helped, because it made it possible to recognize that the person is lying outside the bed. The machine-learning-based detection with an accelerometer was able to recognize

Event	Confidence		Accelerometers				
	Four tags	One tag	Thr.	Thr., or.	Thr., or., con.	ML	ML, con.
Falls							
Tripping (2)	100.0 %	93.9 %	100.0 %	100.0 %	100.0 %	89.2 %	82.2 %
Falling slowly (4)	95.9 %	100.0 %	10.6 %	10.6 %	100.0 %	90.8 %	90.8 %
Falling sitting (6)	91.8 %	85.7 %	48.9 %	12.8 %	55.3 %	86.2 %	86.2 %
Falling sitting slowly (8)	91.8 %	89.8 %	17.2 %	6.4 %	38.3 %	90.8 %	90.8 %
Non-falls							
Lying quickly (7)	100.0 %	100.0 %	34.0 %	34.0 %	100.0 %	7.7 %	100.0 %
Sitting quickly (5)	100.0 %	100.0 %	36.2 %	96.8 %	100.0 %	1.5 %	100.0 %
Searching on the ground (9)	83.7 %	61.2 %	100.0 %	100.0 %	78.7 %	12.3 %	12.3 %
Average	94.7 %	90.1 %	49.6 %	51.5 %	81.8 %	54.1 %	80.3 %
Other false alarms	2	1	0	0	0	10	10

Table 2: Fall detection accuracy of the Confidence system and of the accelerometer-based methods: threshold (thr.), orientation (or.), context (con.) and machine learning (ML) for fall and non-fall events (event numbers from Table 1 are in parentheses).

falling quite well. It was likely able to learn the pattern of acceleration during falling, instead of relying on the magnitude of the acceleration and orientation only. We could not take advantage of the context, though, because the classifier was designed to detect falling, not lying, so it could not detect that the person is lying outside the bed.

Both instances of falling sitting were somewhat difficult to recognize for all the methods, because neither clear falling nor lying was involved. The Confidence system did best because – unlike the other methods – it could recognize sitting, and it had the information about the location, which was not the chair. In the case of accelerometers, machine learning again had an advantage over the other methods, because it was apparently able to learn the pattern of acceleration during falling. The worst was the combination of threshold and orientation, since the method assumed that upright orientation meant that no fall had occurred, which was not true for these two events. This fall was similar to one of the atypical falls by Li et al., for which they achieved 60 % accuracy. Their result is somewhat surprising, since their method most resembles our threshold and orientation (albeit they used more sensors).

Lying and sitting quickly were easy to recognize for all the methods using the context, since they were taking place on the bed and chair. Threshold and orientation with an accelerometer recognized sitting quickly quite accurately, because unlike in the case of falling sitting, upright orientation correctly indicated that no fall had occurred. The other methods did poorly, since these two events were very similar to falls. Li et al. reported accuracies of 40 % and 100 % for lying and sitting quickly, respectively, which is slightly better than our results with threshold and orientation (probably due to their additional sensors).

In the case of searching on the ground, the context was a disadvantage, because the activity was similar to lying and the location was not the bed. Of the methods using the context, the Confidence system with four tags slightly outperformed the rest. However, an accelerometer using threshold (and orientation) only was still better.

Looking at the average accuracies and other false alarms, one can make three conclusions:

- The context helps a lot (Coutaz et al. 2005). Admittedly the test scenario was designed to show this, but the events in the scenario are not unrealistic.
- The Confidence system achieved higher accuracy than the accelerometer-based methods, even using only one tag. The advantage over the second-best method (an accelerometer with threshold, orientation and context) was due to the falling sitting events, where the Confidence system could recognize sitting (from the height of the tag above the ground when using a single tag). The Confidence system did raise a few false alarms outside the eight events we studied in depth, though.
- When using an accelerometer, the threshold-based methods somewhat outperformed machine learning. Considering the simplicity of these methods, this may seem surprising, but the related work shows that threshold-based methods are just as good at fall detection as machine learning.

Conclusion

Fall detection is an important application in elderly care which has been studied and implemented many times, most often with accelerometers. The experimental results reported in the literature are very good, so at the first glance the problem of fall detection may appear to be solved, particularly since accelerometers are lightweight and inexpensive. However, we suspect that most of the experiments on fall detection involved typical falls with a high acceleration upon the impact with the ground. Slow falls are more difficult to detect, but they also occur in practice. Furthermore, fall-like events which trigger false alarms can limit the acceptance of fall-detection applications. Therefore we investigated events difficult to recognize as falls or non-falls, which are common in real life. We used not only accelerometers but also location sensors. Location sensors can be used both to detect falling and to supply contextual information, such as the location in the apartment.

We presented the Confidence system, which utilizes location sensors to monitor elderly users and detect falls and other health problems. The system is at the stage of a mature prototype and is currently undergoing long-term tests with end-users. We compared the Confidence system to a number of accelerometer-based fall detection methods on a scenario consisting of atypical falls and fall-like events. The Confidence system significantly outperformed the accelerometer-based methods, but the key advantage proved to be the information about the location in the apartment where a potential fall took place. When this information was supplied to the accelerometer-based methods, their performance increased substantially. The location sensors used in the Confidence system are expensive, somewhat cumbersome and not particularly accurate, so at the moment they are admittedly not a very practical solution. However, we are confident this problem will be solved before long. Considering the potential these sensors showed in our experiments, they certainly deserve further investigation.

We believe the promising direction of research is exploiting additional contextual information. The user's high-level activity would be useful because fall-like events are much more common, for example, during exercising than during watching TV. A small but easy-to-make step in this direction would be exploiting the time of the day. The location could be extended outside the apartment via the GPS to identify places where falls and fall-like events are likely. Also valuable and computationally easy to obtain would be the user's vital signs, but measuring them would require additional sensors.

Another interesting research direction is combining location sensors with accelerometers. The former are ideally suited for detecting the user's location and height above the ground, whereas the latter are better at detecting the orientation and quick movement because they measure acceleration much more accurately than location sensors measure location.

Acknowledgements

The research leading to these results has received funding from the European Community's Framework Programme FP7/2007–2013 under grant agreement nº 214986. Operation part was also financed by the European Union, European Social Fund.

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