SPEEDY: A Fall Detector in a Wrist Watch

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Abstract

We present a wrist worn fall detector for elderly people. The detector is easy to wear and offers the full functionality of a small transportable wireless alarm system. It implements a fall detection algorithm which will alert a call center after a heavy fall. This occurs even if the wearer is unconscious or too agitated to press the alarm button himself. The algorithm is designed to work with the fall detector attached to the wrist. This is probably the most difficult place for detecting a fall. The algorithm can therefore be expected to function at other locations on the body. The system combines complex data analysis and wireless communication capabilities in a truly wearable watch-like form. This paper summarizes the functionality, architecture and implementation of the system.

1. Introduction

Health monitoring is among the most attractive application fields for wearable electronics and has been studied by many research groups [1, 2]. A variety of wearable devices for monitoring physiological parameters are commercially available today, with many others in the research and development stage. Most monitoring devices target people needing special care (e.g., VITAPHONE) or young and active people (e.g., POLAR www.polar-usa.com).

We developed Speedy, a first prototype of a fall detector built into a wrist watch. Small, ubiquitous and very easy to handle, it is aimed at elderly people living alone at home or in social housing. If they press the incorporated alarm button, or if they are unconscious after a fall, Speedy will alert relatives or a call center via a wireless link to a local telephone central. The function is the same as the commercially available device telealarm (www.teletronic.com) plus an autonomous fall detector. There are other commercially available fall detectors, but they are all attached to a belt around the hip (e.g Tunstall www.tunstall.co.uk). This makes them less comfortable and inadequate to be worn during sleep. The critical phase of getting up can not be covered by such devices.

A fall detector in the form of a wrist watch will not feel alien to the wearer. The major disadvantage of this solution is the complexity of the fall detection algorithm. The arm can move and rotate, thus has six degrees of freedom in its movement. There are two possibilities: either use six sensors (three for acceleration and three for rotation) or adapt the algorithm to function with only incomplete information. To comply with the small space available and the low-power requirement, we use only three axes of acceleration sensed and an algorithm using only very low computing power. Our goal was to develop a much smaller device than the systems found in most case studies like [3] and [4].

2. Concept of Speedy

Speedy is integrated in the case of a wrist watch.

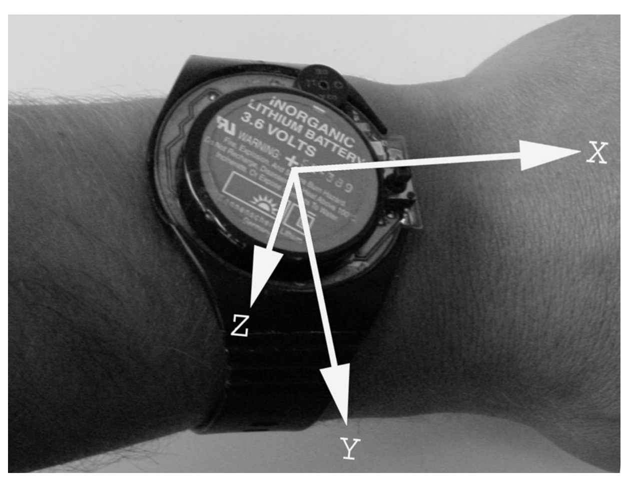

Figure 1. Speedy and its axes

Two sensors (Analog Device ADXL202) measure the acceleration on all three axes. There are no sensors for rotation. The detection is based on the norm of the acceleration; there is no information about how the device is orientated. An obvious approach to detect a fall would be to measure the speed of the person relative to the ground. This could be done by integrating the downward directed fraction of the acceleration. Yet, the orientation of Speedy is not known. At rest, there is a static acceleration sensed by Speedy of $9.81ms^{-2}$ due to gravity. This static acceleration could be used to determine the orientation of Speedy as follows: If Speedy measures a steady acceleration of $9.81ms^{-2}$ over a certain time period, the algorithm assumes that this acceleration is perpendicular to the ground. But during a fall this information about orientation would be lost due to possible rotations which can not be detected based on only the three axes of acceleration

3. Principle of Detection

Our approach is to integrate the norm of the three axes acceleration vector. Due to the static acceleration the norm can only be smaller than $9.81ms^{-2}$ during a fall as shown in fig. 2.

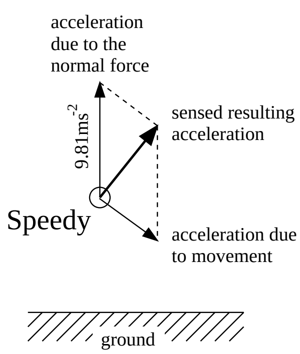

Figure 2. Resulting acceleration vector during a fall

To detect a fall Speedy uses three different parameters. One parameter is the norm of the three axes acceleration vector.

$$|n| = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{1}$$

This norm is independent of Speedy's orientation. To obtain information about the velocity of Speedy we need to integrate this norm. To obtain the correct velocity relative to the ground we need to compensate the static acceleration of $9.81ms^{-2}$. A correct compensation is not possible because we do not know the orientation of Speedy. We approximate the current velocity by integrating the norm after subtracting a fixed value of $9.81ms^{-2}$:

$$v_1 = \int \left(\sqrt{a_x^2 + a_y^2 + a_z^2} - 9.81 \right) \mathrm{d}t \tag{2}$$

This approximation is only correct for vertical movements. The error between our approximation and the correct vertical component of acceleration is shown in figure 3:

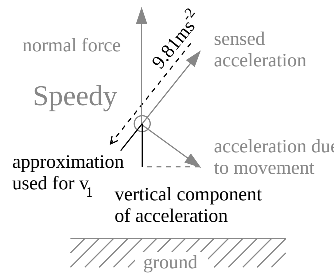

Figure 3. Rough approximation of vertical component

The approximation is best for vertical movements and worst for nearly horizontal movements. More problematic is that fast accelerated movements towards the ground (acceleration $\geq 9.81ms^{-2}$) result in an incorrectly estimated velocity. Nevertheless, this approximation has some beneficial properties. It is independent of the orientation and even rotation of Speedy. During a vertical movement, the approximation results in an underestimated velocity. This point helps reduce the sensitivity to horizontal movements. Only during a fall are negative values integrated. Because we are not interested in other movements, the implemented algorithm integrates negative values and damps the integral during positive values following the formula:

$$v_1 = \begin{cases} \int (|n| - 9.81)\, dt & \text{if } |n| - 9.79 < 0 \\ v_1 \cdot 0.95 & \text{else} \end{cases} \tag{3}$$

Instead of the full value of $9.81ms^{-2}$ we subtract only a value of 9.79 to prohibit the integration of possible offsets and the noise of the acceleration sensors. The value of 0.95 is the damping factor which slowly resets the integral during rest and positive accelerations.

To handle the above mentioned fast accelerated movements towards the ground, we use a second integral which also approximates the speed of the device. Instead of integrating the norm, we first integrate each axis separately and then calculate the norm. To limit the effect of possible offset errors, we reduce the length of the computed integral to 120 samples (800ms).

$$v_2 = \sqrt{\left(\int a_x dt\right)^2 + \left(\int a_y dt\right)^2 + \left(\int a_z dt\right)^2} - \int 9.81 dt \tag{4}$$

This integral is again an estimation and yields a second speed approximation of Speedy. This approximation is very good, as long as the device is not rotated during the fall. If the device is rotated while falling, the integral results in a large error. The effect of the error is over after 120 samples. Yet we did not find a real-world example where both approximations went wrong at the same time.

All three parameters, the norm $|n|$ and the two integrals v_1 and v_2, are continuously calculated and used as input in the fall detection algorithm. The algorithm uses three different thresholds to distinguish between a common movement and a potentially harmful velocity towards the ground.

The speed estimation is only the first step in the process of detecting a potentially harmful fall. First, a high velocity towards the ground has to be detected. Then, within 3 seconds an impact has to be detected, or the event will be discarded. The impact is detected based on the differentiation of the norm $|n|$. After the impact the general activity will be observed for 60 seconds. If during this interval at least 40 seconds of inactivity are recorded, Speedy will generate an audible alarm. The wearer can then deactivate the alarm by pushing on the button for 1 second. If the wearer does not respond to the alarm tone by pressing the button, the alarm will be transmitted wireless to the basestation, which will then alert a call center.

Speedy targets elderly people and has a minimal user interface. Only one button is provided to either generate an alarm by pressing for more than 10 seconds, or to cancel an alarm triggered by the fall detection algorithm. All other settings, like threshold values or telephone numbers, are programmed by the call center.

4. Results

The main components of Speedy are two accelerometers (Analog Devices ADXL202E), a Microcontroller (Texas Instruments MSP430F149) and a wireless RF-Link to the base station (RFM DR3001). The range of the accelerometers is $\pm 2ms^{-2}$. We use the pulse-width signal of the ADXL202E. The sampling rate is 150Hz. The noise level measured is 5mg rms on each of the three axes. The power consumption is 2.6mA in monitoring mode and 11 mA during the wireless transmission of an alarm. The workload of the processor is only about 25%. With the employed batteries (1000mAh/ 3.6V) the device works constantly for approximately 2 weeks in the monitoring mode.

The next figure depicts the values of the three axes measured by Speedy during a typical fall. The three phases detected by the algorithm are also put in evidence.

The following two figures represent two similar patterns. Figure 5 shows the signals during a fall with a fast acceleration towards the ground.

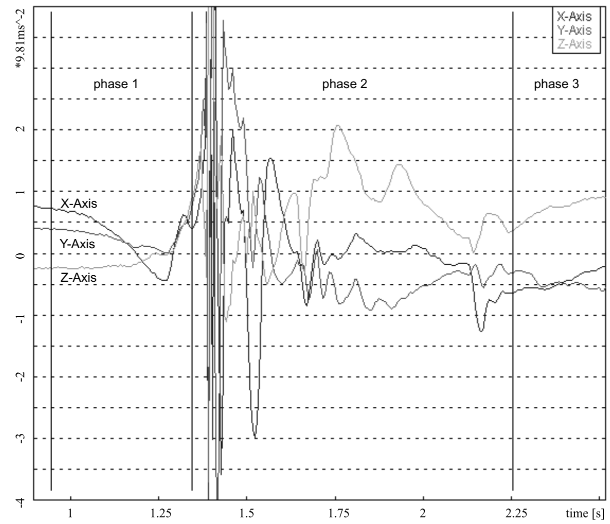

Figure 4. A typical fall as measured by Speedy. The three phases detected by the algorithm are 1) high velocity towards the ground 2) impact 3) inactivity

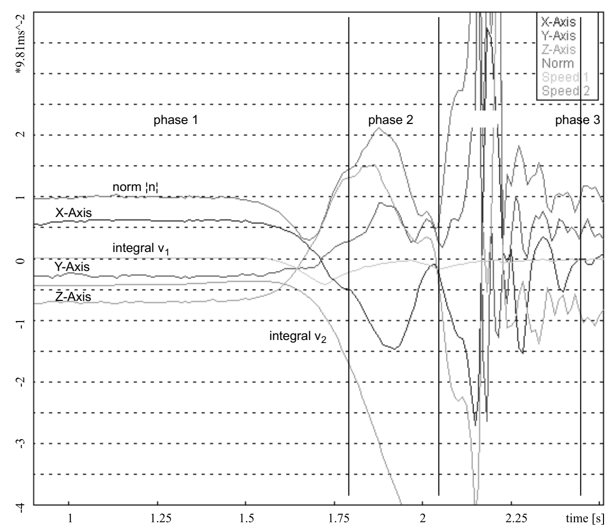

Figure 5. Recording during a fast fall showing the three axes, the norm ($|n|$) and the integral 1 and 2 (v_1 and v_2).

Notice that the norm $|n|$ drops below 1 only for a short moment. This is due to the fast movement towards the ground. The integral v_1 fails to detect the dangerous situation. Yet the fall was successfully detected based on the second integral v_2. The second example in figure 6 shows a strong handshake. Notice that the norm $|n|$ and the first integral v_1 look very similar to the fast accelerated fall in figure 5.

However, this time no fall is detected because the second integral v_2 has no notable value.

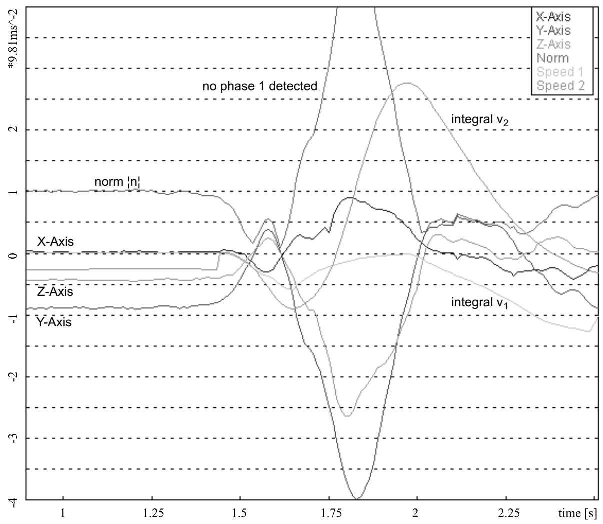

Figure 6. Recording during a fast fall. No fall is detected because of integral 2 (v_2)

To evaluate the reliability of the fall detection we did a series of tests. A test subject was wearing the device while falling on a mattress. The results are summarized in table 4:

Table 1. Three subjects did falls in different directions. The algorithm detects a fall only if all three phases are recorded consecutively: a) high velocity towards the ground b) impact c) inactivity

fall	#	a)	b)	c)	succes
forwards	10	10	10	10	100%
backwards	24	15	14	14	58%
sideways	11	7	5	5	45%
total	45	32	29	29	65%

We can see that not all fall situations are detected with the same certitude. One problem was sideways falls on the side the device is worn because the distance to ground can be very short. The second difficult fall to detect was the fall backwards because the arms are often first moving in the opposite direction of the fall. In some cases phase 2 was not detected. This is mainly because of the soft mattress.

After these test series the device was worn for 48 hours. The wearer was walking, cycling, washing dishes and doing all kinds of day-to-day activities. No false alarm was given. Yet the device worked fine in a subsequent falltest.

The following table resumes the thresholds used to detect high velocity towards the ground:

Table 2. For detecting the first phase three thresholds are used. If all three values are exceeded the algorithm assumes high velocity towards the ground

	norm $\|n\|$	integral v_1	integral v_2
threshold	0.46	-1.72	-2.62

5. Conclusions

We are able to detect a potentially harmful fall with a small and light fall detector which is easily integrated into a wrist watch. This is a new approach where the fall detector is integrated into a truly ubiquitous device. There was no false alarm during a two-day trial. All this is important for the acceptance of such a device especially for elderly people. In our tests not all fall situations were detected. But we believe the algorithm can be improved by optimizing the thresholds based on long-term tests. This could be done in social housing with medical staff and an in-house telephone central. For a commercial device the battery life is too short. Thus the power consumption has to be reduced by a factor of at least 20. Again we believe this is possible by using low-power accelerometers ($60\mu W$). Additionally the microcontroller will be put to sleep during periods of low activity. A low-power barometer ($60\mu W$) may be added to further improve the performance of the algorithm.

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