Fall Detection Using Wearable Accelerometers and Smartphone

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Abstract The governments are investing in research on solutions for independent living, active ageing, at home health monitoring, with the objective of a significant prolongation of personal autonomy of older people. Fall avoidance and fall detection are important aspects of health care of ageing people. The proposed fall detection system consists in a wireless network with a smartphone and a board with another 3-axis accelerometer. The algorithm for fall detection is a part of a user friendly application developed for the smartphone. A comparison with existing fall detection systems and algorithms is reported.

1 Introduction

The risk of degradation of quality of life and the exclusion to the active participation in the society is high for ageing people. The increment of the number of ageing people in industrialized countries makes this risk a social problem. Furthermore the cost for maintaining services for the health of ageing people that the government or the single person must pay is increasing.

Therefore the governments are investing in research on solutions for independent living, active ageing, at home health monitoring, leading to a significant prolongation of personal autonomy.

The falls, in particular, are among the most damaging events for the health of an ageing people [1]. The risk of falling increases with age and in many cases fall happens at home, for a person living alone. The ultimate goal of the fall caring is instantly detect the fall, estimate the degree of gravity and help quickly and efficiently the person.

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Many research works have been developed for the design of devices and/or algorithm for fall detection [1–20].

In [2] the authors investigated the feasibility of a portable preimpact fall detector in detecting falls. It was hypothesized that a single sensor with the appropriate kinematics measurements and detection algorithms, located near the body center of gravity, would be able to distinguish an in-progress and unrecoverable fall from nonfalling activities.

In [3] a complex system consisting of several battery powered wireless sensor boards with a 3-axial accelerometer and a biaxial gyroscope. The data are elaborated offline with a complex signal processing developed in MATLAB to identify the movements of the monitored person.

In [4] an 802.15.4 wireless network with six nodes posed in different places of the body of an elderly has been developed. The data are collected by a node connected via USB to a PC that elaborates the signals of the six triaxial accelerometers to identify a possible fall. In [5] an application for fall detection on a smartphone using only the triaxial accelerometer of the smartphone is presented. In [6] system for fall detection consists in a single board with accelerometer wireless connected to a PC with the algorithm for fall detection.

2 Description of the System

2.1 Hardware Components

The proposed system is composed of battery supplied wearable board, a smartphone, and a smartphone application. The wearable board consists of a 3-axis accelerometer, a microcontroller and a Bluetooth transceiver. The board, shown in Fig. 1 and described in detail in [7], is based on the Freescale Freedom KL25Z demoboard with a low-power 3-axis accelerometer (MMA8451Q). A Bluetooth shield has been connected to the board via the UART port. At start up the

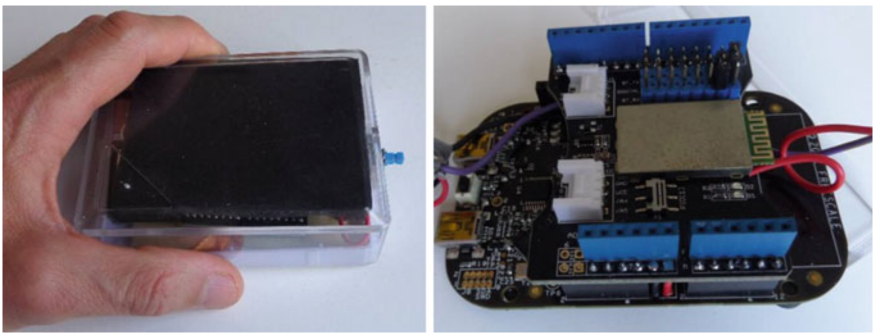

Fig. 1 Wearable board with freescale freedom KL25Z demoboard and the Bluetooth shield

microcontroller creates the connection with the Bluetooth module and the 3-axis accelerometer. Then the Bluetooth module establishes a Bluetooth connection with the smartphone (the board is slave and the smartphone is master). Finally the microcontroller continuously collects data from the accelerometer and sends data through the Bluetooth module to the smartphone.

The power consumption of the module has been measured, with the current probe of a high performance oscilloscope. On the basis of the analysis reported in [7], the average current during continuous transmission is about 36.9 mA. As a consequence the life of the device that is continuously monitors the person can be estimated as 3 days using a 2500 mAh battery.

2.2 Fall Detection Algorithm

In order to test the device and to acquire preliminary data useful for the definition of the fall detection algorithm some measurements have been carried out.

The smartphone and the device have been placed in different positions of the body to identify the best solution for the fall detection. The smartphone has been placed in the waist and in the shirt pocket and the device has been placed in the foot, ankle and arm as shown in Fig. 2.

The accelerometers measure the 3 components of the acceleration A_x, A_y, A_z. If the person does not move the acceleration magnitude is the gravity acceleration. Therefore, measuring the 3 components of the acceleration of the smartphone and of the device, and knowing the position of smartphone and device in the body, it is possible to estimate the orientation of the smartphone and of the device with respect to the vertical position. This information can be used to estimate the position of the person (sitting, standing or lying). The idea is summarized in Fig. 3, in the case in which the smartphone in a pocket in the waist and the device is in the ankle.

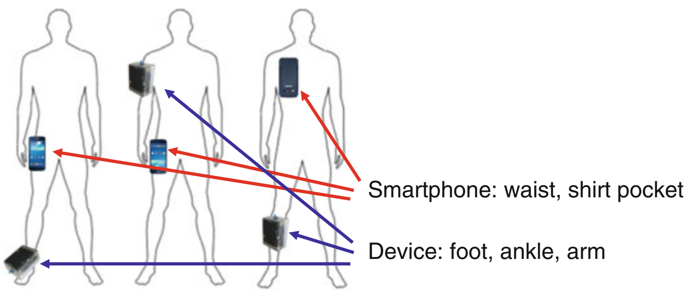

Fig. 2 Different test with smartphone and device placed in different positions

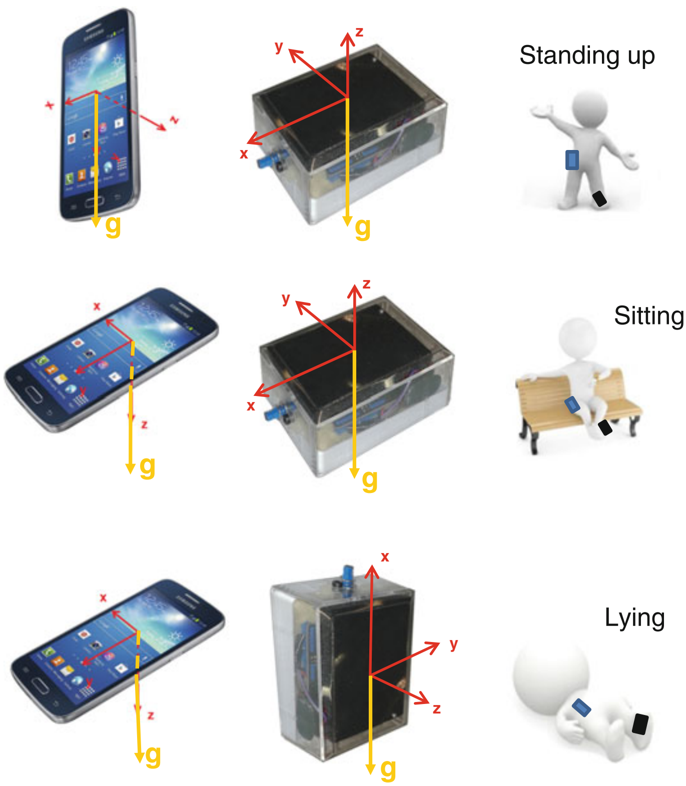

Fig. 3 Estimation of the position of the person using the 3-dimensional accelerations of the smartphone and of the device

Preliminary test measurements evidenced that the acceleration measured on the ankle and foot is high when the person is moving (walking, going upstairs or down stairs) and comparable to the acceleration when he is falling. On the other hand the acceleration of the waist or shirt pocket is low while the person is moving and high while sitting, rising or falling. Let us define S_x, S_y, S_z, D_x, D_y, D_z the acceleration components measured by the smartphone and the device, respectively, and S and D the acceleration magnitude by the smartphone and the device

$$S = \sqrt{S_x^2 + S_y^2 + S_x^2} \quad D = \sqrt{D_x^2 + D_y^2 + D_x^2} \tag{1}$$

As an example of the test cases, Fig. 4 shows the acceleration magnitude S and D measured on the waist by the smartphone and on the ankle by the device while the user is going upstairs for the first 28 seconds and falling at about the 30-th second. In the ankle the positive and negative variation of the acceleration with respect to the gravity acceleration is high going and falling. Conversely, the variation is high only during a fall for the acceleration measured by the smartphone in the waist.

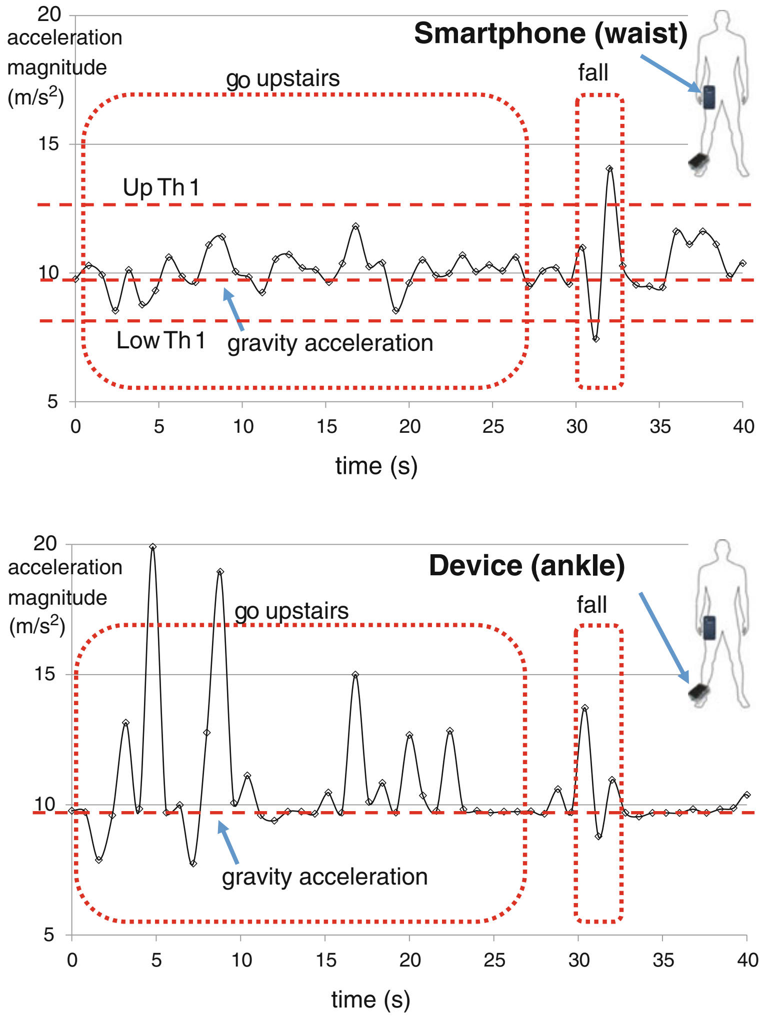

Fig. 4 Acceleration magnitude of waist and ankle going upstairs and falling

Figure 5 reports for the same test the acceleration components defined as in Fig. 4 measured on the waist by the smartphone and on the ankle by the device. Before the fall, the position of the smartphone in the waist is vertical (see Fig. 4), that is the S_y component is approximately the gravity acceleration. Few seconds after a fall the position of the person is lying and the S_y component is lower.

On the other hand, before the fall the position of the device is horizontal, that is the D_z component is approximately negative and equal to the gravity acceleration. After a fall the position is lying and the D_z component is approximately zero.

Previous considerations allowed us to define the algorithm for fall detection has been defined as follows, for the smartphone placed in the waist and the device placed in the ankle.

The accelerations are monitored and displayed on the smartphone.

(1) When the acceleration magnitude S of the smartphone (on the waist) is higher than a threshold value (Low_Th_1 in Fig. 4) or lower than another threshold value (Up_Th_1 in Fig. 4), a possible fall is considered.
(2) After a defined number (n) of seconds the position of the person is estimated.
(3) If the position is "lying" the fall detection event is asserted. The person is considered lying if the acceleration component S_y of the smartphone (in the waist) is higher than a threshold value (Low_Th_2 in Fig. 5) or lower than another threshold value (Up_Th_2 in Fig. 5) and the acceleration component D_z of the device (in the ankle) than a threshold value (Low_Th_3 in Fig. 5).

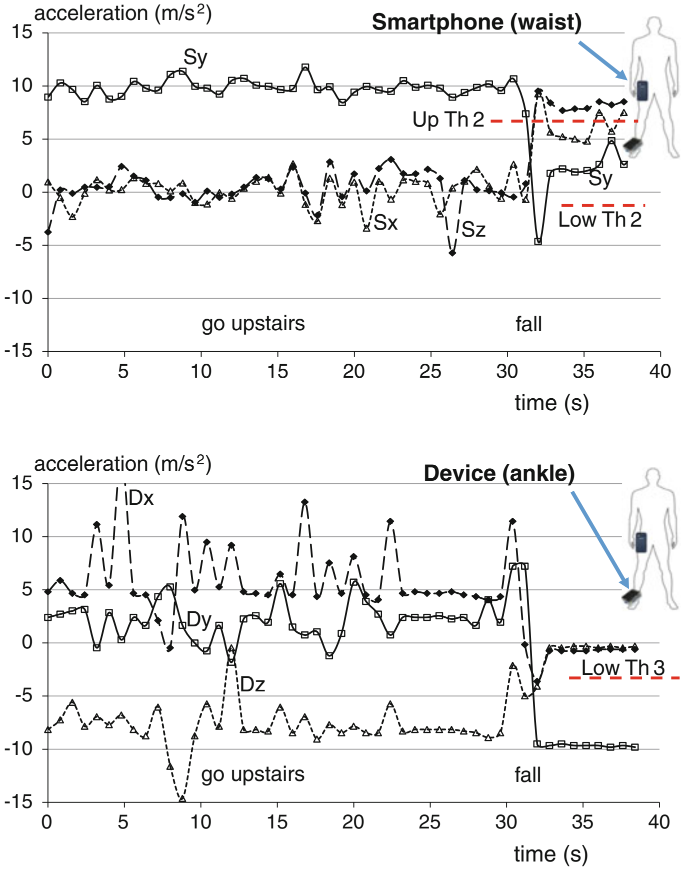

Fig. 5 Acceleration components of waist and ankle going upstairs and falling

3 Smartphone Application

An application for Android smartphone has been developed for the fall detection applying the algorithm described above. The application can be started by the user or approaching the smartphone to the device using the NFC feature. The user selects the emergency phone numbers that will be called in event of fall and he must activate the GPS in order to send the actual position of the user to the emergency assistance.

Pressing the start button the Bluetooth connection with the device is activated and the fall monitoring starts. When monitoring is active, the menu (4) in Fig. 6 is displayed, with the actual data of the accelerometers, the GPS coordinates, date and time. If requested, the data are continuously stored in the smartphone memory. The user can pause monitoring or send an alarm request manually.

When the fall event is detected, the menu (5) in Fig. 6 is displayed, an alarm is activated and sms messages or phone calls are scheduled to be sent after few seconds. The user can deactivate the alarm and avoid the automatic calls pressing a button in (5) of Fig. 6.

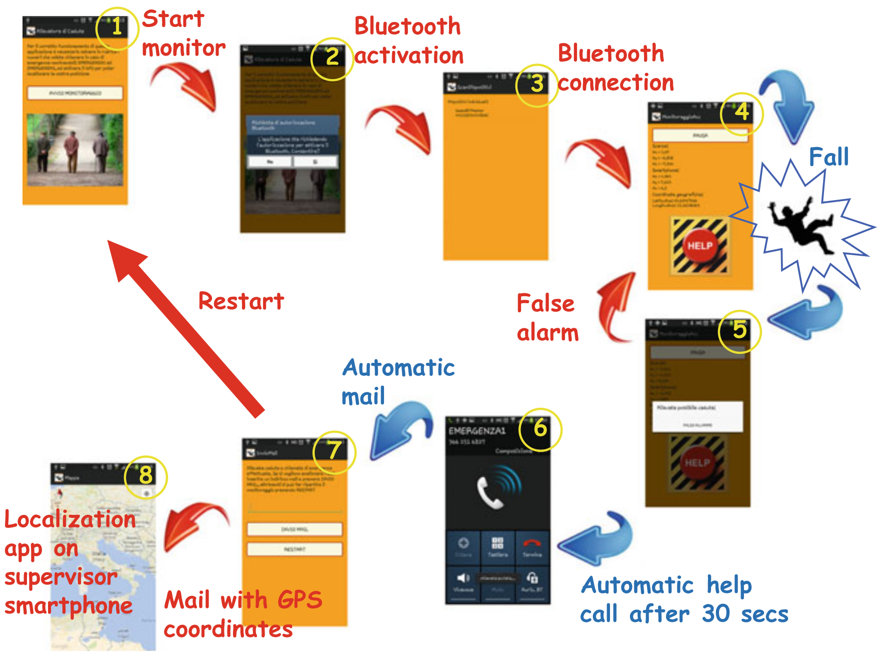

Fig. 6 Flow diagram and screenshots of the application developed

4 Test of the System

The complete system (hardware, algorithm and application) has been primarily tested on a reduced number of persons. Different test situations have been carried out: placing the board in different positions (foot, arm and ankle) and the smartphone placed in the pocket (waist), while the person was sitting (20 cases), lying (20 cases), standing up (20 cases), going upstairs and downstairs (20 cases) and falling (41 cases), for a total of 111 tests. The test conditions are summarized in Fig. 7. We used the data stored in the smartphone and applied the proposed algorithm using different parameter settings and we applied the algorithms reported in [4–6] for comparison.

To verify and compare the goodness of the algorithms, we used the standard formulae commonly accepted in the literature for Sensitivity, Specificity, Accuracy and False Negative Rate (FNR). The parameter FNR indicates the percentage of not detected falls with respect to the total number of falls. In a fall detection system it can be more important to detect all the falls accepting possible false alarms, that the user can correct using the smartphone application developed.

Fig. 7 Test of the complete system and fall detection algorithm

	Fall	Not fall
Fall detected	TP (true positive)	FP (false positive)
Fall not detected	FN (false negative)	TN (true negative)

$$\text{Sensitivity} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} = \frac{\text{fall correctly identified}}{\text{fall}}$$

$$\text{Specificity} = \frac{\text{True Negative}}{\text{True Negative} + \text{False Positive}} = \frac{\text{not fall correctly identified}}{\text{not fall}}$$

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{all cases}} = \frac{\text{correct responses}}{\text{all cases}}$$

$$\text{FNR} = \frac{\text{False Negative}}{\text{True Positive} + \text{False Negative}} * 100 = \frac{\text{fall not detected}}{\text{fall}} * 100$$

The values of the five parameters (Up_Th_1, Low_Th_1, Up_Th_2, Low_Th_2, Low_Th_3) of the algorithms affect the performance of the system. The performance of three setting have been reported in this works. The values of the settings are reported in Table 1. Setting A has been used as a reference example, setting B has been chosen to optimize the specificity, white setting C allows the best value of the sum of sensitivity, specificity and accuracy, this setting allows the best value of FNR too.

Table 2 reports the results for different algorithms, different settings and different test data. The test data column indicates the results obtained applying the algorithm to the complete data set of 111 cases (total), the 61 cases in which the device is placed in the foot (foot), 25 cases in the arm (arm) and 25 cases in the ankle (ankle).

The row “reference results” indicates the results reported in the reference. The algorithm reported in [4] has been developed for a smartphone and up to six additional devices, for our test case it has been applied to the data of the accelerometer and of the device. The algorithms reported in [5, 6] use only the acceleration of the smartphone, therefore the data of device are not used. The parameters of the algorithm of the papers [4–6] have been chosen to optimize the sum of sensitivity, specificity and accuracy.

In general the results obtained, with a parameter optimization, are better with our algorithm with respect to the algorithms [4–6].

Better results are obtained if the device is placed in the foot or in the ankle with respect to the placement in the arm. Changing the parameters settings of our algorithms we can improve sensitivity at the cost of reducing specificity or vice versa. Figure 8 reports the performances as a function of the values of the parameters, in particular the parameter Low_Th_1.

Table 1 Values of the 5 parameters of the proposed algorithm for three settings

Setting	Up_Th_1 (m/s^2)	Low_Th_1 (m/s^2)	Up_Th_2 (m/s^2)	Low_Th_2 (m/s^2)	Low_Th_3 (m/s^2)
A	10.5	9.0	6.0	−6.0	−8.0
B	11.3	7.0	6.0	−3.0	−6.4
C	10.7	9.3	6.1	−4.4	−6.4

Table 2 Test results of the detection accuracy for different values of the parameters of the algorithm and for different algorithms in the literature

Algorithm	Setting	Test data	TP	FP	TN	FN	Sensitivity (%)	Specificity (%)	Accuracy (%)	FNR (%)
Proposed algorithm	A	Total	30	37	43	1	96.8	53.8	65.8	3.2
	B	Total	23	0	80	8	74.2	100	92.8	25.8
	C	Total	31	15	65	0	100	81.3	86.5	0
	C	Foot	21	4	36	0	100	90	93.4	0
	C	Arm	5	7	13	0	100	65	72	0
	C	Ankle	5	4	16	0	100	80	84	0
[4]	Reference results		–	–	–	–	–	–	99.55	–
	D	Total	19	3	77	12	61.3	96.3	86.5	38.7
	D	Foot	15	0	40	6	71.4	100	90.2	28.6
	D	Arm	1	1	19	4	20	95	80	80
	D	Ankle	3	2	18	2	60	90	84	40
[5]	E	Total	19	36	44	12	61.3	55	56.8	38.7
[6]	Reference results		–	–	–	–	97.7	94.8	–	–
	F	Total	20	28	52	11	64.5	65	64.9	35.5

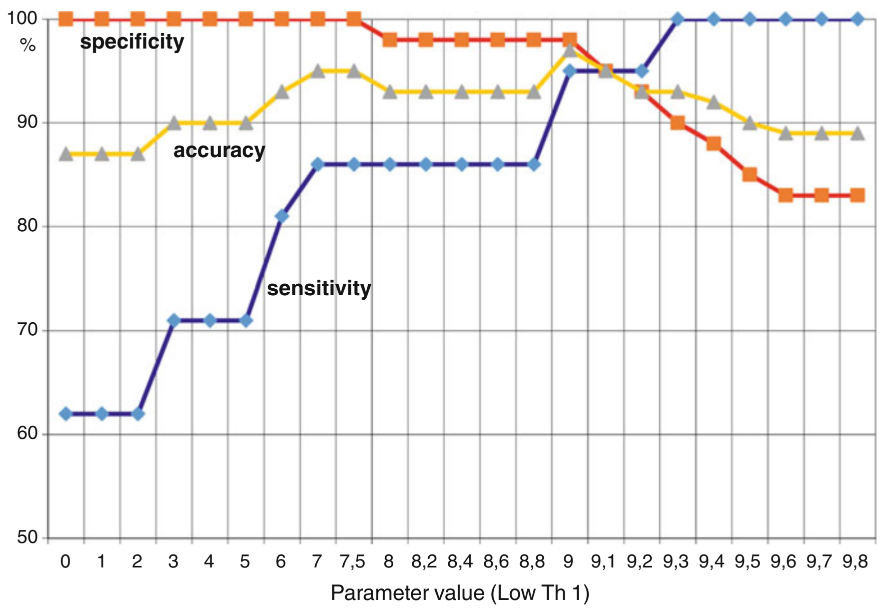

Fig. 8 Performances as a function of the values of the parameter Low_Th_1

Figures 9, 10 and 11 report the number of detected and not detected falls for the different test cases: sitting (20 cases), lying (20 cases), standing up (20 cases), going upstairs and downstairs (20 cases) and falling (41 cases). Setting A, B and C has been used in Figs. 9, 10 and 11 respectively. Figure 8 shows that setting B allows no erroneous falls have been detected but 8 real falls have not detected. Conversely, setting C detects all the real falls at the cost of some False positive, in particular laying is sometimes confused with a fall.

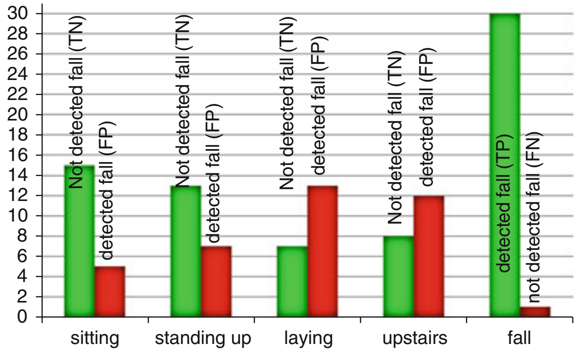

Fig. 9 Number of detected and not detected falls for the different test cases for setting A

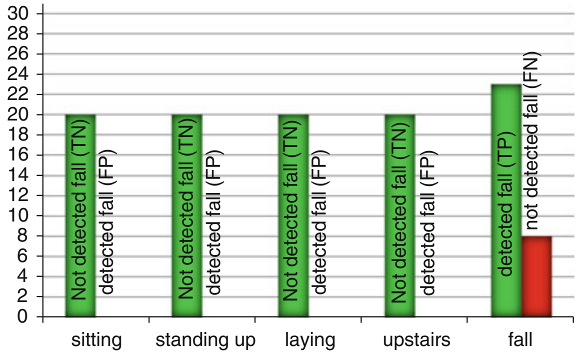

Fig. 10 Number of detected and not detected falls for the different test cases for setting B

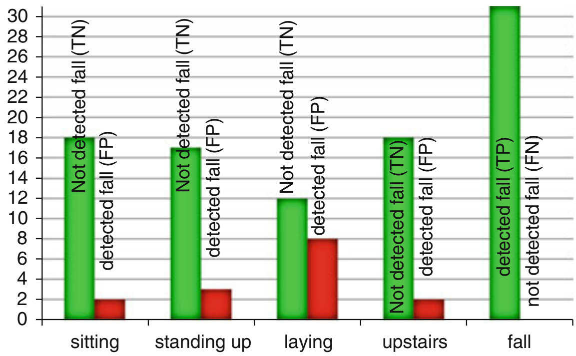

Fig. 11 Number of detected and not detected falls for the different test cases for setting C

5 Conclusions

The algorithm for fall detection presented in this work uses the measures of the 3-axis accelerometers of a smartphone and of a Bluetooth device designed specifically for this purpose. A user friendly application has been developed for the smartphone. The system has been tested in many different situations and the results compared with other algorithm reported in literature.

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