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Comparison of low-complexity fall detection algorithms for body attached accelerometers

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Abstract

The elderly population is growing rapidly. Fall related injuries are a central problem for this population. Elderly people desire to live at home, and thus, new technologies, such as automated fall detectors, are needed to support their independence and security. The aim of this study was to evaluate different low-complexity fall detection algorithms, using triaxial accelerometers attached at the waist, wrist, and head. The fall data were obtained from standardized types of intentional falls (forward, backward, and lateral) in three middle-aged subjects. Data from activities of daily living were used as reference. Three different detection algorithms with increasing complexity were investigated using two or more of the following phases of a fall event: beginning of the fall, falling velocity, fall impact, and posture after the fall. The results indicated that fall detection using a triaxial accelerometer worn at the waist or head is efficient, even with quite simple threshold-based algorithms, with a sensitivity of 97–98% and specificity of 100%. The most sensitive acceleration parameters in these algorithms appeared to be the resultant signal with no high-pass filtering, and the calculated vertical acceleration. In this study, the wrist did not appear to be an applicable site for fall detection. Since a head worn device includes limitations concerning usability and acceptance, a waist worn accelerometer, using an algorithm that recognizes the impact and the posture after the fall, might be optimal for fall detection.

Keywords: Elderly; Independent living; Hip fracture; Movement analysis

1. Introduction

In developed countries the portion of the elderly population over 65 years of age is growing rapidly. Fall related injuries are a central problem with elderly people, both in a home environment [1,2] and in hospitals and residential homes [3], affecting the overall quality of life. Elderly people desire to live at home, and it appears that they are also willing to accept new technologies to support their independence and safety [4,5].

Most falls among home-dwellers happen when walking, when rising to stand, when trying to sit down, when turning, or when reaching for something [6,7]. After fainting or tripping, most people fall forwards or sideways, and in most cases the impact is located at the abdomen. Slipping is more likely to result in backwards or sideways falls, thus impacting the hip and buttocks equally [8].

Body attached accelerometers [9–12] and gyroscopes [13,14] have been used to detect human movement, including falls. The placement site at the waist is been thought to be optimal, when compared to wrist and knee [1]. Waist attached accelerometers are located near the body's center of gravity, providing reliable information on subject body movements, with the exception of specific movements of arms and legs [15].

The usability of a waist worn fall detector might be not optimal, e.g. when sleeping or changing clothes. Thus, there have been suggestions to integrate a fall detector into another device, such as a wrist watch [16] or a hearing-aid housing [17]. The usability of a wrist watch is excellent, highlighting the wrist as an attractive site for a fall detector.

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However, the acceleration signal measured from the wrist varies widely as a function of the fall type and orientation of the arm, indicating that this placement site would need the most complicated algorithm for fall detection [1].

Recently, we presented simple thresholds for accelerometry-based parameters for fall detection [18]. The aim of this study is to compare different low-complexity fall detection algorithms, applied for triaxial waist, wrist and head worn accelerometers, using intentional falls in middle aged subjects. Three different detection algorithms were investigated using two or more of the following phases of a fall event: beginning of the fall, falling velocity, fall impact, and posture after the fall. The protocol for the test falls was designed based on the typical fall causes and directions of elderly home-dwellers, obtained from the literature. Activities of daily living (ADL) were used as a reference.

2. Materials and methods

2.1. Subjects, falls and ADL

Intentional falls were performed with three healthy volunteers: one female (38 years) and two males (42 years and 48 years). Falls were performed towards a mattress (thickness 20 cm). Each subject performed three standardized type of falls in each of the three directions (forward, backward, and lateral) (Table 1) at least twice. A 15-cm high platform was used when stepping down to simulate missing a step, e.g. when stepping down from stairs. The falls were documented using digital video (Sony Handycam HDR-HC3).

ADL samples were collected from two subjects (female 38 years, male 22 years), representing dynamic activities (e.g. walking, walking on the stairs, picking up objects from the floor) and posture transitions [18].

2.2. Accelerometry

During the falls and ADL, accelerations were measured synchronously at the waist, wrist and head with triaxial accelerometers, each constructed using three uniaxial capacitive accelerometers (VTI Hamlin SCA CDCV1G, amplitude range $\pm 12g$) [19]. Each triaxial accelerometer was connected to a separate data logger (Tattletale, model 8v2, Onset Computer Corp.) with a sampling frequency of 400 Hz [19]. Each of the three axes was calibrated statically against the gravitation. The dynamic validation of the accelerometers has been described elsewhere [19,20].

Table 1
Different intentional test falls used in the study

Nr	Direction	Instructions	Accessories
1	Forward	Straight, no step is performed	–
2	Forward	Step down from platform	Platform
3	Forward	Sitting, getting up, short step, trip	Chair
4	Backward	Leg swing to front	–
5	Backward	Round back, knees pended	–
6	Backward	Sitting down on empty	–
7	Lateral	Step down from platform	Platform
8	Lateral	Straight, no step is performed	–
9	Lateral	Start falling back and turn to side	–

Accelerometers were attached to the non-dominant wrist, the corresponding side of the waist close to the iliac crest, and the front of the forehead. The sensitive axes of the devices were mediolateral, anteroposterior, and vertical.

2.3. Data processing

Data processing was similar to our previous study [18]. Accelerometer data (binary) were loaded from data loggers to a computer (software CrossCut 2.01, Borland International), and converted into gravitational units with a custom-made MATLAB (R2006a) program [20]. Data processing, analyses and fall detection simulation were done with a custom-made LabVIEW (8.0) program using a floating point data format.

The measured acceleration signal was processed by resampling at 50 Hz and median filtering with a window length of three samples to reduce the data amount and noise before any further analyses. The processed data were low-pass (LP) or high-pass (HP) filtered ($f_c = 0.25$ Hz) with a digital second order Butterworth filter for posture detection and dynamic analysis, respectively.

The use of accelerometer sensors with a limited acceleration amplitude range was simulated in a LabVIEW environment by restricting the amplitude of input acceleration data to $\pm 2g$ or $\pm 3g$ before any data processing.

2.4. Parameters

Parameters used in the analyses were similar to those in our previous study [18]. The total sum vector SV_{TOT}, containing both the dynamic and static acceleration components, was calculated from resampled data as indicated in Eq. (1).

$$SV = \sqrt{(A_x)^2 + (A_y)^2 + (A_z)^2}, \tag{1}$$

where A_x, A_y, A_z are the acceleration (g) in the x-, y-, and z-axes, respectively. While standing, SV_{TOT} has a value $\sim 1g$ (Fig. 1(A)). The start of the fall was determined as the pit before the impact, SV_{TOT} being equal or lower than $0.6g$.

The dynamic sum vector SV_D was calculated similarly (Eq. (1)) from the HP filtered data. SV_D has a value of $\sim 0g$ when standing (Fig. 1(A)). SV_D was used to detect fall-associated impacts.

Fast changes in the acceleration signal were investigated by constructing a sliding sum vector SV_{MaxMin}, which was calculated using the differences between the maximum and minimum values in a 0.1 s sliding window for each axis. When standing, SV_{MaxMin} has a value of $\sim 0g$ (Fig. 1(A)).

Vertical acceleration Z_2 was calculated as indicated in Eq. (2).

$$Z_2 = \frac{SV_{TOT}^2 - SV_D^2 - G^2}{2G}, \tag{2}$$

where SV_{TOT} is the total sum vector (g), SV_D is the dynamic sum vector (g), and G is the gravitational component (=1g). When the subject is standing, Z_2 has a value of $\sim 0g$ (Fig. 1(A)).

Velocity v_0 was calculated by integrating the area of SV_{TOT} from the pit, at the beginning of the fall, until the impact, where the signal value is lower than $1g$ [18]. The posture was detected 2 s after the impact from the LP filtered vertical signal, based on the average acceleration in a 0.4 s time interval, with a signal value of $0.5g$ or lower considered to be a lying posture [9,21].

For comparison with previous studies, the falling index (FI) was also calculated from waist measurements, as described earlier by

Yoshida et al. [22], using a time window of 0.4 s (Eq. (3)).

$$\mathrm{FI}_i = \sqrt{\sum_{i-19}^{i}((A_x)_i - (A_x)_{i-1})^2 + \sum_{i-19}^{i}((A_y)_i - (A_y)_{i-1})^2 + \sum_{i-19}^{i}((A_z)_i - (A_z)_{i-1})^2} \quad (3)$$

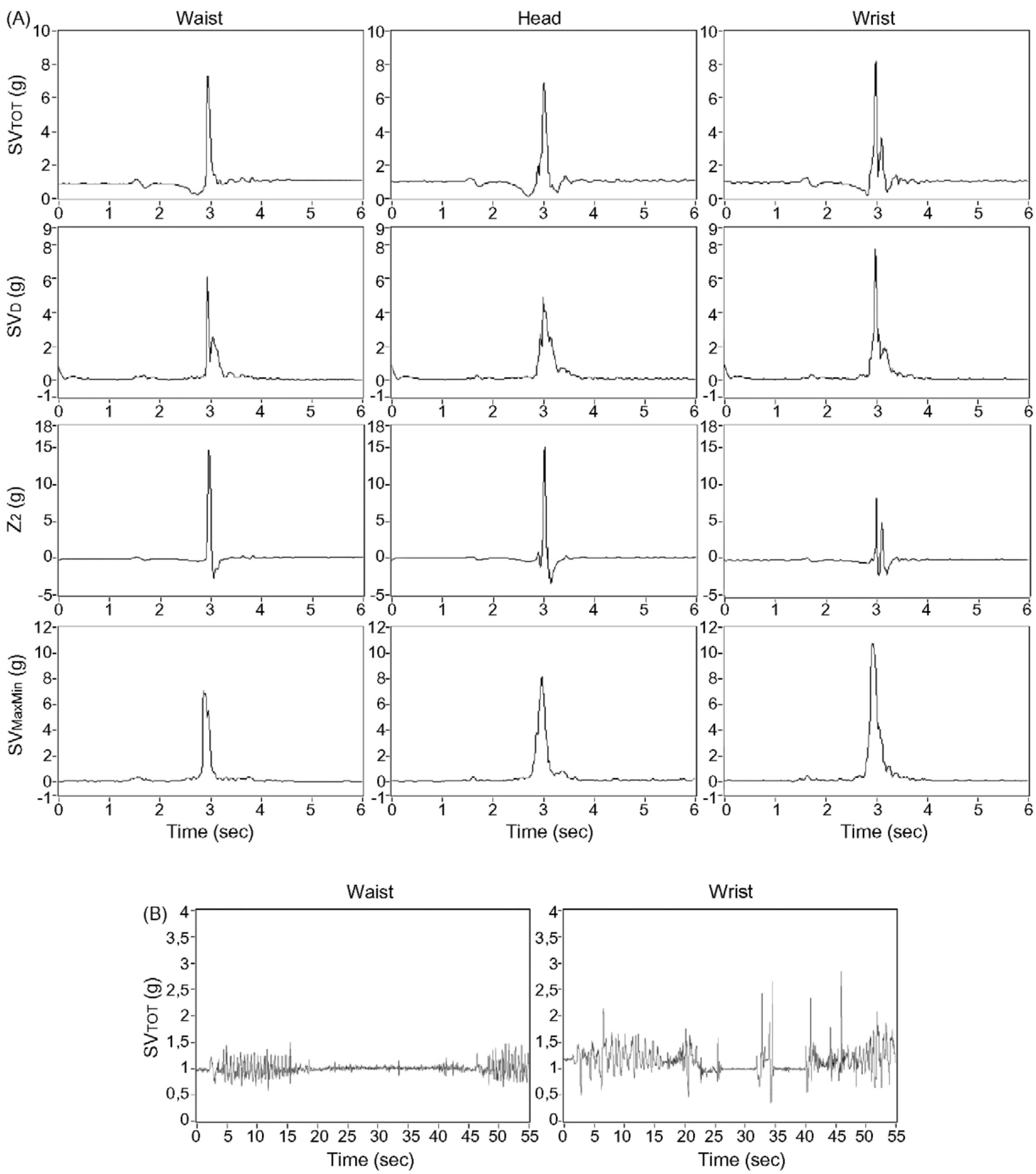

Fig. 1. (A) Examples of different accelerometric parameters (SV_{TOT}, SV_D, Z_2, and SV_{MaxMin}) from the waist, head and wrist worn accelerometers during a forward fall with an impact around the time point of 3 s. (B) An example of ADL activity measured from the waist and wrist, including sitting on a chair (∼0 s to 4 s), walking (∼4 s to 16 s), lying on a bed (∼23 s to 44 s) and walking (∼49 s).

Table 2
Threshold values of different parameters for fall detection algorithms

Parameter	Waist	Head	Wrist
SV_{TOT} (g)	2.0	2.0	5.2
SV_D (g)	1.7	1.2	5.1
Z_2 (g)	1.5	1.8	3.9
SV_{MaxMin} (g)	2.0	1.7	6.5
v_0 (m s^{-1})	0.7	1.0	0.9
SV_{DS} pit (g)	0.6	0.6	0.6

Adapted from [18].

where $(A_x)_i$, $(A_y)_i$, $(A_z)_i$ are the acceleration (g) of sample number i in x-, y-, and z-axes, respectively.

2.5. Algorithms for fall detection

Three different fall detection algorithms with increasing complexity were investigated, using two or more of the following phases of a fall event: beginning of the fall, falling velocity, fall impact, and posture after the fall. These algorithms were composed and tested with the data from the falls and ADL. In order to avoid ADL-related false fall alarms, the thresholds for different parameters used in the algorithms (Table 2) were adjusted for a specificity of 100%, as described earlier [18]. The posture detection was included in fall detection simulations with data measured from the waist and head, but not from the wrist.

The algorithm 1 (IMPACT + POSTURE) was based on the detection of the impact by a threshold value of SV_{TOT}, SV_D, SV_{MaxMin}, or Z_2, followed by monitoring of the posture of the person.

The algorithm 2 (START OF FALL + IMPACT + POSTURE) detected the start of the fall by monitoring SV_{TOT} lower than the threshold of 0.6g, followed by the detection of the impact within a time frame of 1 s by a threshold value of SV_{TOT} or Z_2, followed by monitoring of the posture.

The algorithm 3 (START OF FALL + VELOCITY + IMPACT + POSTURE) detected the start of the fall by monitoring SV_{TOT} lower than the threshold of 0.6g, followed by detection of the velocity v_0 exceeding the threshold, followed by detection of the impact within a time frame of 1 s by a threshold value of SV_{TOT} or Z_2, followed by monitoring of the posture.

2.6. Statistics

Sensitivity (percentage of true alarms; 100% = all falls detected) was calculated from the fall data, and specificity (percentage of false alarms; 100% = no false alarms) from the ADL data.

3. Results

Samples for different accelerometric parameters during a forward fall and ADL are shown in Fig. 1(A) and (B), respectively.

3.1. Sensitivity of fall detection algorithms

The sensitivity of the fall detection algorithms was tested in a LabVIEW environment using the fall samples. Results from the waist, head, and wrist are summarized in Table 3.

3.1.1. Waist

The fall detection sensitivity of the different algorithms at the waist varied from 76% to 97% (Table 3). Falls were best recognized

Table 3
Sensitivity (%) of fall detection algorithms using the data from waist, head and wrist

	n	Algorithm 1[a]				Algorithm 2[b]		Algorithm 3[c]	
		SV_{TOT}	SV_D	SV_{MaxMin}	Z_2	SV_{TOT}	Z_2	SV_{TOT}	Z_2
Waist									
F	21	100	95	100	100	100	100	71	71
B	21	90	62	76	90	86	86	71	71
L	17	100	82	94	100	100	100	88	88
All	59	97	80	90	97	95	95	76	76
Head									
F	15	100	100	100	100	93	93	47	47
B	21	100	100	100	95	81	81	43	43
L	20	95	95	95	95	85	85	50	50
All	56	98	98	98	97	86	86	47	47
Wrist[d]									
F	22	73	59	73	73	–	73	–	41
B	19	63	63	58	84	–	68	–	47
L	17	29	6	12	53	–	41	–	24
All	57	55	36	50	71	–	64	–	37

F = forward, B = backward, L = lateral.
[a] IMPACT + POSTURE.
[b] START OF FALL + IMPACT + POSTURE.
[c] START OF FALL + VELOCITY + IMPACT + POSTURE.
[d] Posture detection not included.

with algorithm 1 (IMPACT + POSTURE) using SV_{TOT} or Z_2 as markers of fall associated impacts. SV_{MaxMin} effectively detected falls to the front and side, whereas only 76% of backward falls were detected. The dynamic sum vector SV_D showed the lowest impact detection sensitivity.

The most sensitive parameters SV_{TOT} and Z_2 were used in the calculation of algorithms 2 and 3. The sensitivity of algorithm 2 (START OF FALL + IMPACT + POSTURE) was congruent with the sensitivity of algorithm 1 (Table 3). In general, algorithms 1 and 2 detected forward and lateral falls more efficiently when compared to backward falls. Algorithm 3 (START OF FALL + VELOCITY + IMPACT + POSTURE) had an average fall detection sensitivity of 76% (Table 3). Lateral falls were most efficiently detected.

The fall detection of forward falls using the FI parameter had 90% sensitivity with the detection threshold of 3.16g [22]. However, falls to the back and side were poorly detected with 56% and 71% sensitivity, respectively. When the threshold value of 2.6g was applied, an overall detection sensitivity of 74% was achieved.

3.1.2. Head

Algorithm 1 (IMPACT + POSTURE) detected 97–98% of the falls regardless of the parameters used for impact detection (Table 3).

The sensitivity of algorithm 2 (START OF FALL + IMPACT + POSTURE) was lower than the sensitivity of algorithm 1 (Table 3), detecting falls to the front more efficiently compared to falls to the back and side. Algorithm 3 (START OF FALL + VELOCITY + IMPACT + POSTURE) detected less than half of the falls (Table 3).

3.1.3. Wrist

Fall associated impacts were most efficiently detected using algorithm 1 (IMPACT + POSTURE) with parameter Z_2 (Table 3), the sensitivity being only moderate (53–84%). In general, impact detection was lowest in lateral falls.

The overall fall detection sensitivity of algorithm 2 (START OF FALL + IMPACT + POSTURE) using Z_2 was 64%, varying from 41% to 73% between fall directions (Table 3). When analyzed in more detail, most of the falls (79%) had a SV_{TOT} value lower than 0.6g at the pit just before the impact, but the impact detection was not fulfilled in all cases.

The overall fall detection sensitivity of algorithm 3 (START OF FALL + VELOCITY + IMPACT + POSTURE) using Z_2 was 37% (Table 3). The two stage criteria for the start of the fall ($SV_{TOT} < 0.6g$ and $v_0 > 0.9\,\mathrm{ms}^{-1}$ before the impact) was fulfilled in 56%, 69%, and 27% of the falls to the front, back, and side, respectively.

3.2. Simulation of accelerometer with restricted amplitude range

In order to test the possibility of using an accelerometric sensor with a lower amplitude range than $\pm 12g$, LabVIEW simulations with restricted acceleration values were performed. Simulated use of an accelerometer with $\pm 3g$ amplitude range had no effect on the sensitivity or specificity of the fall detection algorithms using the data measured from the waist level, whereas an amplitude range of $\pm 2g$ was not efficient for these algorithms (data not shown).

4. Discussion

Here we evaluated different fall detection algorithms using body attached accelerometers from intentional falls and activities of daily living (ADL). The results indicated that fall detection using a waist or head worn triaxial accelerometer is efficient, even with quite simple threshold-based algorithms. On the contrary, the wrist did not appear to be an applicable site for fall detection.

The fall detection sensitivity from the waist was maximally 97% when using an algorithm which detects the fall associated impact based on the total sum vector (SV_{TOT}) or acceleration towards the ground (Z_2), and the posture after the fall. The fall detection sensitivity of 97% and specificity of 100% from the waist is comparable to other reported results [7,9,11,22]. Even a sensitivity of 100% with young volunteers has been reported by Bourke et al. [13,24]. Their algorithm was very similar to our algorithm 1, indicating that even simple algorithms can be effective in fall detection.

Algorithm 2, also including the detection of the start of the fall, had almost identical fall detection sensitivity to the more basic algorithm 1, indicating that at waist level the start of the fall is characterized as a pit in the SV_{TOT} signal. The falls to the front and side in particular clearly showed these two fall phases, the start of the fall and impact. The velocity before the impact (included in algorithm 3) was often lower than the predetermined threshold, especially in forward and lateral falls. Video analyses showed that these falls were typically two-staged: falling first to the knees, followed by an impact at the waist or hands.

Backward falls, which are one of the risk factors for hip fractures, were most inefficiently detected. The evaluation of the falls from video recorded material suggested that these backward falls were not detected because of the subject's soft landing with a rounded back, resulting in minimal impact at the waist level.

Fall events were well characterized as an impact at the head level. This was the case especially in the backward and forward falls. Even the falls which were not detected from the waist because of soft landings were mostly detected as an impact to the head. The fall detection accuracy was 98%, which is slightly lower than the sensitivity reported by Lindemann et al. [17] in their study using sum vectors and velocity. However, they used a young test subject whereas we had middle-aged subjects, which supports our results on the head worn fall detector being highly reliable.

Posture detection with a head worn accelerometer is partly problematic since the posture of the head is not identical to the posture of the torso if the person lifts his/her head when lying. However, it is probably necessary to include posture detection as a part of a fall detection algorithm to eliminate false alarms. The placement of an accelerometer at the head requires more detailed planning of the hardware to ensure usability and acceptance of the application among the end users.

The use of a wrist worn accelerometer for fall detection proved to be more problematic than waist and head worn ones, as expected based on the earlier reports [1,7]. Here, many of the fall events were characterized by impact to the hands, indicating the active role of hands in these intentional falls. Also in the study of Degen et al. [16] the highest sensitivity was found in forward falls, indicating an impact to the hands. This is in contrast to the fact that for elderly people it is typical that they are unable to use their hands to protect the body during accidental falls [23]. Furthermore, hands are not necessarily part of the impact, since a person can try to grip something to prevent the fall.

The parameter Z_2, which was designed to monitor the acceleration towards the ground, was clearly the most effective parameter to distinguish between falls and ADL at the wrist. Most of the falls showed also the characteristic features for start of the fall (pit and high velocity toward the ground). In the future, algorithms 2 and 3 should be tested with lower threshold values for impact detection. This might improve the fall detection sensitivity but also maintain the good specificity.

This study is based on intentional falls in a laboratory environment, because no acceleration database of actual falls of elderly subjects was available. The falls were performed on a mattress since falls to the hard floor would neither be safe nor ethically acceptable. However, the loss of the actual maximum acceleration of the fall associated impact was not a problem, since our simulation suggests that acceleration information exceeding $3g$ does not have significant additional value in fall detection. Other reports of fall detection devices have successfully used accelerometers with an amplitude range as low as $\pm 2g$ [16,22], but here this range was insufficient for fall detection.

The fall and ADL samples used in this study are comparable to test material in earlier reports. For example, the values of maximum SV_{TOT} value during ADL varied between $1g$ and $3g$, as it was also reported by Bourke et al. [24]. The maximum SV_{TOT} value of fall-related impact varied between $2.0g$ and $6.1g$ in this study, while impact values for young persons between $3.5g$ and $12g$ [24] have been previously shown. This difference may be explained, in part, by the median filtering used here.

Testing our data with the earlier published falling index (FI) resulted in a fall detection sensitivity of 59%, which is somewhat lower than the 70% reported by Yoshida et al. [22]. The difference may be due to the diversity of fall detection sensitivity between individuals, reported to vary from 40% to 100% [22].

The number of individuals in our study was low but the number of fall samples was reasonable for sensitivity and specificity determinations. The test subjects performing the intentional falls in our study were middle aged instead of young persons used in the earlier studies [9,13,17,22,24–26]. However, we have to consider that even here, the mechanism of falls among elderly is different than suggested by the intentional falls of middle-aged people. Thus, tests with real end users (age 65+) in real home environment are required in the future for accurate evaluation of the implemented fall detection systems.

In this experimental study, we used the criterion of 100% for specificity. In reality, some compromise between specificity and sensitivity might be needed, depending on the acceptance of false alarms. In addition, this study concentrated on different low-complexity algorithms that can most easily be implemented for practical fall detection applications. The conclusions made here might be different if more complicated data processing methods were used.

We conclude that fall detection using waist or head worn triaxial accelerometers is efficient even with quite simple threshold-based algorithms. A head worn accelerometer provides excellent impact detection sensitivity, but it includes limitations concerning usability and acceptance. Thus, a triaxial waist worn accelerometer using an algorithm that recognizes the fall, impact and the posture after fall, might be optimal for fall detection.

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Conflict of interests

M.Sc. Kangas, M.Sc. Konttila, Ass. Prof. Lindgren, Prof. Jämsä, and Doc. Winblad have no conflict of interests.

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