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# Comparison of real-life accidental falls in older people with experimental falls in middle-aged test subjects

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ABSTRACT

Falling is a common accident among older people. Automatic fall detectors are one method of improving security. However, in most cases, fall detectors are designed and tested with data from experimental falls in younger people. This study is one of the first to provide fall-related acceleration data obtained from real-life falls. Wireless sensors were used to collect acceleration data during a six-month test period in older people. Data from five events representing forward falls, a sideways fall, a backwards fall, and a fall out of bed were collected and compared with experimental falls performed by middle-aged test subjects. The signals from real-life falls had similar features to those from intentional falls. Real-life forward, sideways and backward falls all showed a pre impact phase and an impact phase that were in keeping with the model that was based on experimental falls. In addition, the fall out of bed had a similar acceleration profile as the experimental falls of the same type. However, there were differences in the parameters that were used for the detection of the fall phases. The beginning of the fall was detected in all of the real-life falls starting from a standing posture, whereas the high pre impact velocity was not. In some real-life falls, multiple impacts suggested protective actions. In conclusion, this study demonstrated similarities between real-life falls of older people and experimental falls of middle-aged subjects. However, some fall characteristics detected from experimental falls were not detectable in acceleration signals from corresponding heterogeneous real-life falls.



## 1. Introduction

About one-third of home-dwelling elderly people fall each year [1]. Falling is the leading cause of injury-induced death in the elderly. In addition to physical injuries, falling and the associated fear of falling affect quality of life of older people, threaten their ability to live independently, and restrict mobility and social activities [2]. Roughly half of the fallers are not able to get up themselves [3]. To prevent these “long-lies” and to increase the feeling of security, commercially available personal emergency security systems (PERS) provide applications to call for help. However, around 80% of older people wearing PERS and being unable to get up after a fall did not use their alarm system to call for help [4]. In such cases, an automatic fall detector could detect a fall and call for help.

Many reported fall detectors are based on monitoring body movements by accelerometers. Fall detection algorithms are typically developed and tested based on acceleration data collected from a limited number of young subjects performing experimental intentional falls in a laboratory environment [5–8]. However, fall mechanism may differ between age groups [9], and self initiated intentional falls differ from sudden unexpected experimental falls [10].

Some attempts to test automatic fall detectors in real-life environments have been documented. Bourke et al. [11,12] tested a fall detection systems among older people in their home environment. However, no accidental falls occurred during the test periods. Acceleration data from real-life falls are scant. Technical solutions, such as wireless sensor systems capable of monitoring falls and generating fall alarms and collecting acceleration data, have been proposed [13] but not evaluated in real-life among older people. A further step toward collecting real-life data was taken recently by Klenk et al. [14], who reported one of the first acceleration data sets from a study of real-life falls. The data included five backward falls from four older Parkinson’s disease patients with progressive supranuclear palsy.

Thus, real-life acceleration data are needed to study fall mechanisms among older people and to develop reliable fall

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detection methods. In our earlier studies [15–17] we developed a fall detection concept that has been validated by collecting acceleration data during experimental falls from young and middle-aged test subjects. The aim of the present study was to collect acceleration signals from real-life falls among older people and compare them with the data from the experimental falls of middle-aged test subjects.

## 2. Methods

### 2.1. Acceleration data from experimental falls

Acceleration data during experimental falls were collected in our previous study [17]. Briefly, middle-aged volunteer subjects ($n = 20$, mean age = $48.4 \pm 6.8$ years) performed six different fall types: syncope ($n = 40$), tripping ($n = 40$), sitting on empty air, like when missing a chair while sitting down ($n = 40$), slipping ($n = 38$) (two of the original samples were discarded because no fall-associated impacts were detected), lateral fall ($n = 40$), and rolling out of bed ($n = 40$). Falls were completed on a soft mattress in a laboratory environment. Acceleration data were collected with a 3D accelerometer attached at the waist in front of the anterior superior iliac spine. The acceleration amplitude range of $\pm 3\,g$ and a sampling frequency of 50 Hz were used. Based on our earlier study [16] this amplitude range is sufficient for discriminating falls from ADL, even though the maximum acceleration values of fall associated impacts can be higher.

### 2.2. Acceleration data from real-life accidental falls

Older subjects living in elderly care units in Sweden and in Finland were recruited to wear a prototype fall detector. The study protocol was approved by the Regional Ethical Review Boards in Umeå, Sweden (2443-2009) and in Oulu, Finland (39/2009). Participants and their relatives received oral information about the

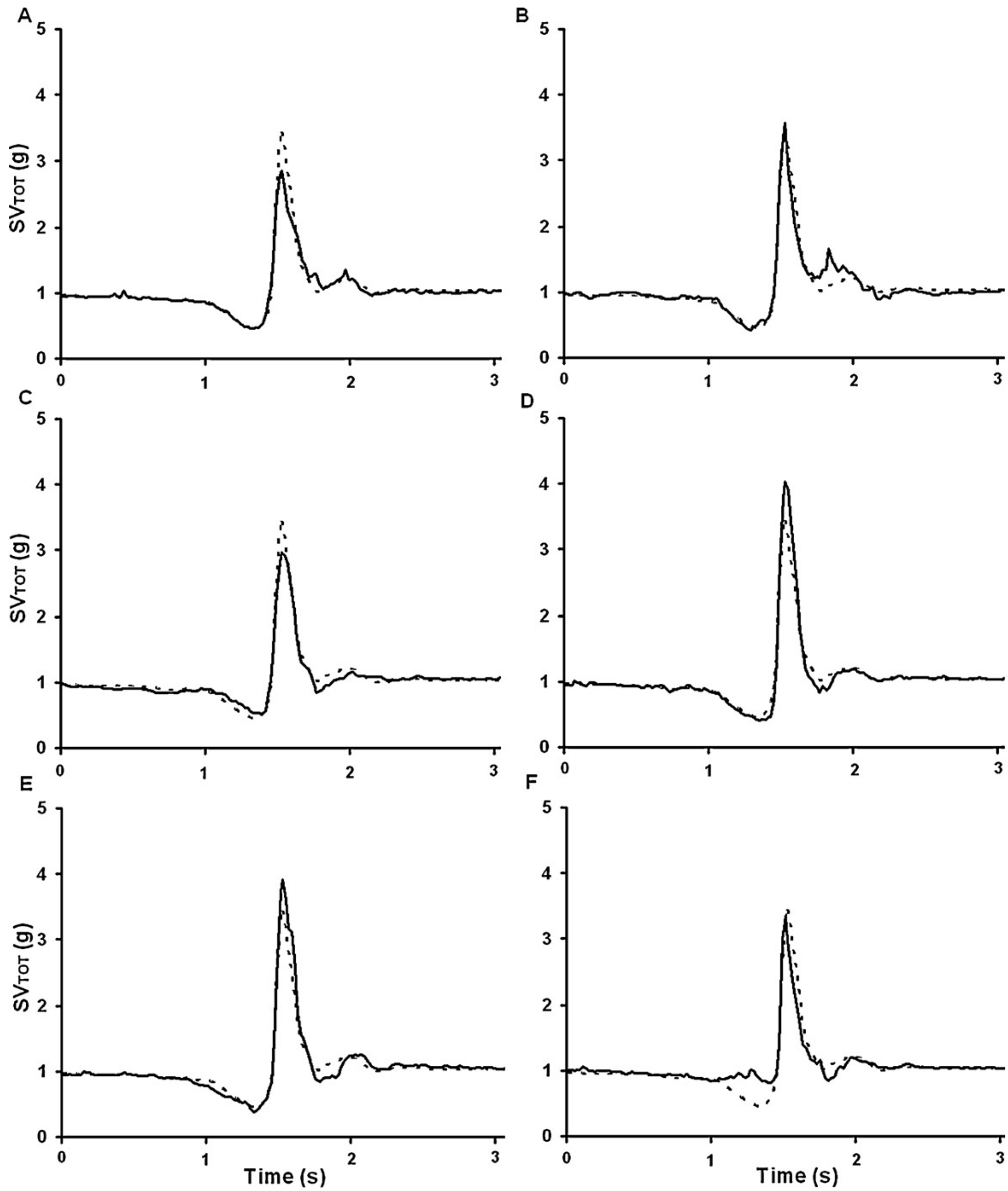


**Fig. 1.** An average $SV_{TOT}$ signal from different experimental fall types (solid line) compared to the average signal of all fall events starting from standing posture (dotted line). Fall types: (A) forwards, syncope; (B) forwards, tripping; (C) backwards, sitting on empty air; (D) backwards, slipping; (E) sideways; and (F) from a bed. Data from experimental falls of middle-aged volunteers ($n = 20$) in a laboratory environment [17].

**Table 1**
Real-life fall events.

| Fall # | Description | Local time and place | Injuries | Fall category |
|---|---|---|---|---|
| 1[a] | The subject got entangled in a blanket when moving from the bed to the arm chair. | 19:20 bedroom | Bruises on left side rib-cage | Forward |
| 2[a] | The subject got entangled in a blanket when moving from the bed. | 02:00 bedroom | No injuries reported | Forward |
| 3[b] | The subject was found on the floor near the toilet. | 12:35 toilet | Bruises, pain on her neck | Sitting on empty air |
| 4[b] | The subject was found lying on the floor. | 14:45 bedroom | Hip fracture | Backward or sideways |
| 5[c] | The subject likely fell out of bed. He was found lying on the floor next to the bed. | 01:10 bedroom | No injuries reported | Fallen out of bed |

[a] Female, 93 years old, MMSE score 28, walking speed 0.27 m/s.
[b] Female, 91 years old, MMSE score 14, walking speed 0.49 m/s.
[c] Male, 90 years old, MMSE not determined, walking speed 0.20 m/s.

study, and written informed consent was obtained. The inclusion criteria for the test subjects were age above 65 years and ability to stand independently or with the help of one person.

During the six-month study period (August 2010–January 2011) in Sweden and two-month study period (December 2010–January 2011) in Finland, seven (all females) and nine (six females, three males) subjects wore the sensor system, respectively. The average age, Mini-Mental State Examination (MMSE) score [18], and average walking speed based on 10-m indoor walking for the test population were $88.4 \pm 5.2$ years ($n = 16$), $13.13 \pm 8.22$ ($n = 15$), and $0.56 \pm 0.31$ m/s ($n = 13$) at baseline, respectively.

The prototype of the sensor unit (CareTech Ab, Sweden) contains a microcontroller, a battery, a tranceiver, and a 3D accelerometer (Analog Devices Inc.) with an amplitude range of $\pm 4$ *g*. The sensor size is 52 mm $\times$ 33 mm $\times$ 24 mm, and its weight is 26 *g*. The sensor was attached with a clip to a pocket on an elastic belt to fix the vertical axis of the device. The attachment site was at the waist, in front of the anterior superior iliac spine, but some variation was accepted because of the nature of the long-term field test.

The sensor monitors acceleration continuously with a sampling frequency of 3200 Hz. In order to minimize power consumption and data transmission, the device is designed to collect acceleration data using an event-based trigger. The trigger activates when the acceleration of all three axes is below a predetermined threshold of 0.75 *g* as a marker for pre impact phase. When activated, the history of acceleration data before the activation (30 samples with a sampling frequency of 6.25 Hz) is collected from a data buffer, and 240 samples after activation are collected with a sampling frequency of 50 Hz followed by further data collection of 30 samples with a sampling frequency of 6.25 Hz. The system transmits the collected data to the base station located at the care unit. The data are further transmitted using IP-based technology to the server computer.

### 2.3. Characterization of fall events

Accidental falls were reported at the care unit by care personnel. Real-life falls were classified according to the experimental fall models used in our earlier study [17]. Classification was performed based on care personnel's or test person's description of the events and estimated posture based on the collected vertical acceleration signal at the database.

### 2.4. Data processing

Acceleration data from experimental falls in the laboratory were collected and converted into gravitational units. Customized LabVIEW-software was used for data analysis.

Previously described parameters [15–17] for fall phases were used to evaluate the data from experimental and real-life falls. Briefly, a total sum vector ($SV_{TOT}$) was calculated from acceleration signals of each fall sample. The pre impact phase is typically exhibited in $SV_{TOT}$ as a lowering of the signal from the 1 *g* level. A threshold of 0.6 *g* for $SV_{TOT}$ was used to identify the start of the fall, and a velocity toward the ground of $v_0 \geq 0.7$ m/s was considered to be associated with the fall. The velocity was obtained by integrating the area of $SV_{TOT}$ from the pit before impact. The impact associated with the fall was defined as $SV_{TOT}$ being equal or higher than 2 *g*. End posture was detected from posture index (PI) 2 s after the main impact as a 0.5 s average from the low-pass, filtered (0.25 Hz) vertical signal. The fall phases of experimental falls presented here were evaluated in our earlier study [17]. Averaged $SV_{TOT}$ signals were determined by combining all experimental falls of the same fall type ($n = 38$–$40$) and for all experimental falls starting from a standing posture ($n = 198$). The averaging of experimental falls was performed by aligning the $SV_{TOT}$ signal at the impact data point where $SV_{TOT} \geq 2$ *g*.

## 3. Results

Average $SV_{TOT}$ profiles from various experimental falls were calculated and compared with an average signal of all combined fall types starting from a standing posture (Fig. 1A–F). The general $SV_{TOT}$ profiles of all experimental fall types starting from standing posture were similar and showed detectable pre impact and impact phases (Fig. 1A–E). The average signal obtained from the falls out of bed lacked a drop in $SV_{TOT}$ (Fig. 1F). Impacts associated with falls for all experimental fall types were averaged to one peak only. The highest average fall-associated impacts were measured from falls that occurred backwards without knee bending (Fig. 1D) and sideways (Fig. 1E).

During the six-month test period, acceleration data from five real-life falls from three test subjects were collected (Table 1). The falls typically occurred when the subjects were alone in either the bedroom or the bathroom, and, in all cases, the subject was unable to get up by him/herself after the fall.

Real-life falls were categorized into fall types based on the fall reports (Table 1). These categories corresponded to experimental falls from the laboratory studies. The comparison of $SV_{TOT}$ signal of real-life falls with the average signal of the corresponding experimental fall types is shown in Figs. 2 and 3.

Falls #1 and #2 presented similar events during which the subject became entangled in a blanket and fell in what was probably the forward direction (Table 1). These falls were also similar in acceleration $SV_{TOT}$ signals (Fig. 2) and showed multiple fall-associated impacts and a shorter pre impact phase in $SV_{TOT}$, as

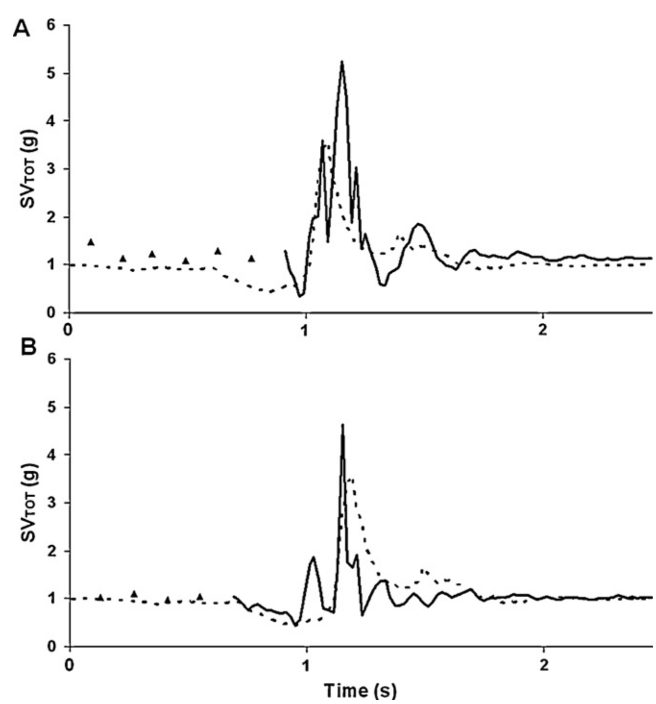


**Fig. 2.** $SV_{TOT}$ signal from real-life falls (solid line sampling frequency 50 Hz, triangles 6.25 Hz) compared with averaged signal from experimental forward falls (dotted line): (A) Fall #1 (tripping) and (B) Fall #2 (tripping).

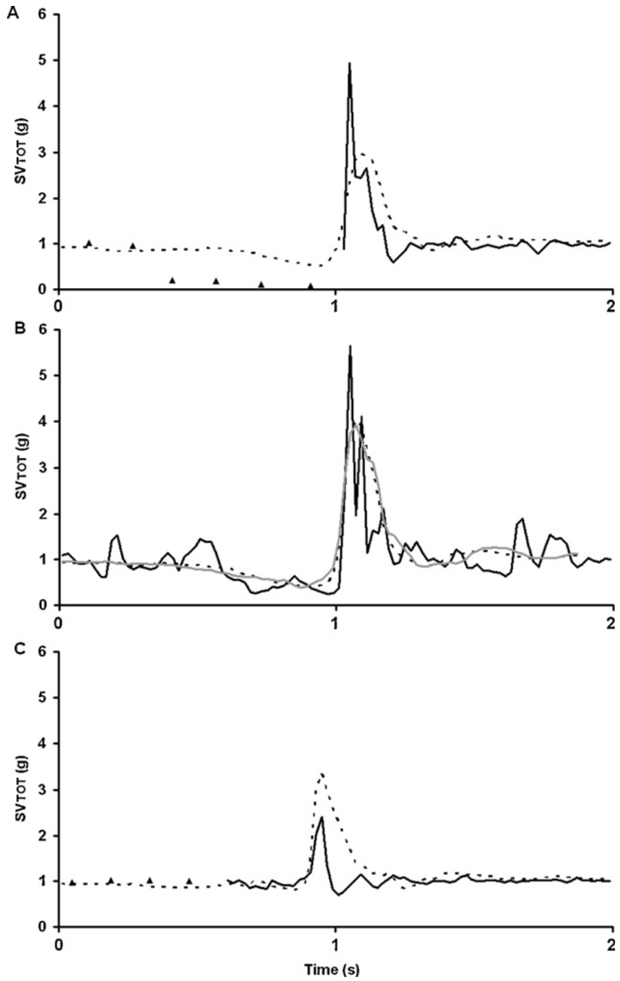


**Fig. 3.** $SV_{TOT}$ signal from real-life falls (black solid line sampling frequency 50 Hz, triangles 6.25 Hz) compared with averaged signal of experimental fall types. (A) Fall #3 and experimental fall induced by sitting on empty air (dotted line), (B) Fall #4 and experimental fall backward (dotted line) and sideways (gray solid line), (C) Fall #5 and experimental fall out of bed (dotted line).

predicted based on experimental falls. Both of these real-life falls show the start of fall phase, but fall #1 had a velocity lower than that expected for a fall (Table 2). In fall #2, the first peak after pre impact phase was lower than 2 *g*, but the main peak was above 4.5 *g* (Fig. 2).

The pre impact phase data from fall #3 were sampled at frequency of 6.25 Hz, which was too low to identify movements in detail. However, the pre impact phase and impact were detectable from the $SV_{TOT}$ signal (Table 2). The fall-associated impact was higher than the average of experimental falls on the soft mattress (Fig. 3A).

Fall #4 resulted in a hip fracture (Table 1). The $SV_{TOT}$ profile had similarities to the profile from experimental falls from a standing position (Fig. 3B) because the pre impact phase was as long as in the case of an experimental fall backward. All fall phases analyzed in this study were detected from this fall and it showed the highest pre impact velocity (5.6 m/s) among the real-life falls presented here (Table 2). The first fall-associated impact after the pre impact phase was the main one, and it was higher than the average impact from intentional falls (Fig. 3B).

Fall #5, a fall out of bed, did not have a pre impact phase detectable from the $SV_{TOT}$ (Fig. 3C, Table 2). This feature is similar to the average of the experimental falls of the same category (Fig. 3C). The real-life fall has one fall-associated impact, and it is lower than the average impact of the experimental falls from a bed. However, the impact is higher than the threshold of 2 *g* (Table 2).

**Table 2**
Fall phases based on previously published parameters [14,15].

| Fall # | Start of fall[a] | Velocity (m/s) | Impact[b] (g) | End posture[c] |
|---|---|---|---|---|
| 1 | + | 0.1 | >5.0 | + |
| 2 | + | 1.1 | >4.5 | + |
| 3 | + | ND[d] | >4.5 | + |
| 4 | + | 5.6 | >4.5 | + |
| 5 | – | <0.1 | >2.0 | + |

[a] $SV_{TOT} \leq 0.6\,g$.
[b] Acceleration range limit of the accelerometer was specified as $\pm 4\,g$; therefore, impact values may have been saturated.
[c] $PI \leq 0.5\,g$.
[d] ND, not determined, sample rate 6.25 Hz, not used for velocity calculations.

## 4. Discussion

This study is one of the first to present acceleration data from the real-life falls of older people. Furthermore, this is the first report to present acceleration data from a real-life fall resulting in a hip fracture. Data from five real-life falls were compared with the experimental falls of middle-aged subjects to evaluate how well these experimental falls, which were used to develop fall detection algorithms, mimic real-life fall mechanisms. The study showed similarities between real-life falls and experimental falls. However, some fall phases detected from experimental falls were not detectable in acceleration signals from heterogeneous real-life falls.

The pre impact phase has been suggested to be a usable marker for several fall-associated applications. The pre impact phase has been used for fall detection algorithms [11,16,17,19,20] and as an indicator for triggering the inflation of a wearable airbag to protect thighs from high fall-associated impacts [21]. The pre impact phase has been characterized from experimental falls by a body tilt angle [22], the start of the fall based on the acceleration sum vector ($SV_{TOT}$) signal [17,23], or velocity toward the ground. The velocity has been proposed to be accurate enough to distinguish falls from activities of daily living [24,25]. In this study, the start of the fall was detectable in all real-life falls starting from a standing posture. However, the high velocity toward the ground was not detected in all falls from a standing height. This oversight has also been observed when individual experimental falls have been assessed instead of an averaged signal of all falls [16,17]. The high pre impact velocity was not detected in a real-life fall out of bed. Based our earlier study [17] more than 70% of intentional falls from a bed do not show a high pre impact velocity.

Pre impact phase velocity and impact energy can be decreased by such strategies as squatting by flexing ankles, knees, and hip or using hands and knees to protect the torso from major impact [11,26,27]. This is in agreement with the data analyzed in this study showing higher average impact values in experimental falls involving a straight fall forward, backward or sideways than in falls involving previous events, such as knee flexion in syncope or sitting on empty air.

In this study, subjects performing experimental falls were instructed not to try to use their hands or knees to soften the major impact at the torso and not to take recovery steps to prevent the fall. This may partially explain why, in all experimental fall types, averaging resulted in one main fall-associated impact peak, implying that, in most cases, the first impact was already the major one with $SV_{TOT}$ value of 2 *g* or greater. In real-life falls, multiple impact peaks were present. The two forward falls resulting only in minor injuries showed multiple peaks around the major impact and relatively low velocity at the pre impact phase, suggesting protective motions. Recently, Klenk et al. [14] reported five real-life backward falls from a specific disease population suffering from progressive supranuclear palsy, a disease with typical symptoms of a loss of balance, lunging forward when mobilizing, and falls. By calculating the variance of acceleration from the pre impact phase, they showed differences between real-life falls and experimental falls with or without an attempt to prevent the fall. According to the authors, the pre impact phase of real-life backwards falls showed compensating strategies to prevent the fall [14]. In our study, this was also the case in forward falls with minor injuries showing multiple impacts and lower velocity as expected based on the experimental falls.

Interestingly, the acceleration profile of the real-life fall that resulted in a hip fracture had a high pre impact phase velocity followed by major impact peak followed by smaller impact peaks. The hazardous outcome of this real-life fall may be partially due to the lack of protective actions, which resulted in a major impact at the hip. Most hip fractures occur from the standing level or during walks, and they are the result of sideways falls when the subject is unable to slow the fall, i.e., with an outstretched arm or with the aid of furniture [28].

In real-life forward falls, the impacts were higher than the average of experimental fall types (Fig. 2). This may be due to the difference in landing surfaces; soft mattress in the case of the experimental falls and harder floor materials in real life. Additionally, averaging of the experimental fall signals and the different acceleration amplitude ranges, $\pm 3\,g$ in experimental falls and $\pm 4\,g$ real-life experiments, may partly explain the difference. All of the real-life falls were events in which the fallen subject was not able to recover by him/herself, suggesting that these were examples of hazardous falls. Contrary to forward falls, the real-life falling out of bed resulted in a softer impact than the experimental falls. In experimental falls, the upper and lower body rolled over the bed simultaneously, whereas in our real-life case, the subject may have slid over more softly, potentially with the upper or lower body first.

This study has some limitations. The number of real-life falls recorded remained low, and they represent fall events from three individuals only. In addition, the mechanisms of the falls were not known precisely because they were not video-recorded and the falls happened when the subject was alone. The subjects in our study were people aged 90 years or more living in care units. It may be argued that they differ from home-dwelling older people; however, they do provide a heterogeneous source of data of fall mechanisms among the older population. In the population aged 65 years or more, forward falls are the most common type of fall [29], and falls happen often during ambulatory activities, such as walking or transferring [30]. This was also the case in our study.

In conclusion, we were able to collect acceleration data from real-life falls among older people. The acceleration signals had features similar to those obtained from experimental falls by middle-aged subjects. However, there were some differences in parameters that could be used for monitoring fall phases. The use of experimental falls to mimic real-life falls has been a foundation for research in this field, but the data from real life provide important material for further applications, such as fall detection and studies on fall mechanisms and fall prevention.

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## Conflict of interest statement

The authors have no conflict of interest to declare.

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