Comparison of acceleration signals of simulated and real-world backward falls


1. Introduction

Over the past several decades, falls among older adults have gained increasing attention worldwide, with many studies focusing on fall prevention [1]. Facing the demographic shift and the observed high incidence rates of falls that often lead to injuries, fractures and even death, this common problem has become a very important public healthcare issue. Although much research has advanced the field, the understanding of falls is still limited.

Most of the knowledge on falls to date has been obtained from oral reports that might be biased in many ways. Fall simulations are widely used to gain insight into circumstances of falls, but the results, at least concerning fall detection, are not convincing. Variation of acceleration and maximum jerk of 5 real-world backward falls of 4 older persons (mean age 68.8 years) were compared to the corresponding signals of simulated backward falls by 18 healthy students. Students were instructed to “fall to the back as if you were a frail old person” during experiment 1. In experiment 2, students were instructed not to fall, if possible, when released from a backward lean. Data acquisition was performed using a triaxial acceleration sensor. In experiment 1, there was significantly more variation within the acceleration signals and maximum jerk was higher in the real-world falls, compared to the fall simulation. Conversely, all values of acceleration and jerk were higher for the fall simulations, compared to real-world falls in experiment 2.

The present findings demonstrate differences between real-world falls and fall simulations. If fall simulations are used, their limitations should be noted and the protocol should be adapted to better match real-world falls.

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sensor devices the events are relatively rare. The number of measurements needed strongly depend on the particular hypothesis. As an example, to capture 100 real-world falls it would be necessary to record approximately 100,000 days of physical activity (300 person years). Given a sensor observation period of 7 days this means about 15,600 observation intervals each with recharging and data download. In the absence of sufficient real-life fall recordings, researchers focus on data derived from fall simulation studies to develop biomechanical models of falls [4]. Most of the work is done in the field of fall detection, mainly using devices based on accelerometer technology [5–19]. There is a large consensus that sensor-based fall detection could prove to be very useful for patients. Primarily, it could automatically provide help and shorten rescue time if a faller is unable to send an alarm. Approximately 3% of all fallers lie for more than 20 min without external support [20]. In a cohort of people aged 90 years or older, 80% of the fallers were unable to get up by themselves and 30% remained on the floor for an hour or more [3]. Analysis of the pre-impact sensor signals could help to understand fall mechanisms, such as potential protective movements during the fall. Thus, specific exercise regiments could be developed. Furthermore, information on the impact intensity could lead to new preventive approaches like designing or choosing adequate absorbing floor surfaces. These approaches so far are derived from simulation models [21]. Unfortunately, most of the simulation approaches have failed so far to come up with satisfactory results when they are applied to real-world situations. For example, although fall detection algorithms achieved high sensitivity and high specificity in most simulation studies, the devices had a poor performance in real-life, resulting in high rates of either false positive or false negative alarms and therefore poor user compliance of the patients [22].

To our understanding, the observed gap between experimental and real-life performance of fall detection devices might be due to random and/or systematic differences between simulated and real-world falls for many reasons. For example, the experimental simulation implies consented information to the volunteer. Most experimental designs allow self-initiation of the fall leading to anticipation that may change postural control and response mechanisms, such as potential protective movements during the fall. Thus, specific exercise regimens could be developed. Furthermore, information on the impact intensity could lead to new preventive approaches like designing or choosing adequate absorbing floor surfaces. These approaches so far are derived from simulation models [21]. Unfortunately, most of the simulation approaches have failed so far to come up with satisfactory results when they are applied to real-world situations. For example, although fall detection algorithms achieved high sensitivity and high specificity in most simulation studies, the devices had a poor performance in real-life, resulting in high rates of either false positive or false negative alarms and therefore poor user compliance of the patients [22].

Table 1

<table>
<thead>
<tr>
<th>Qualitative description of real-world falls (n = 20).</th>
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<tbody>
<tr>
<td>Number of falls per condition</td>
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<tr>
<td>Location: Indoor (n = 19), outdoor (n = 1)</td>
</tr>
<tr>
<td>Activity before the fall: Standing (n = 8), sitting (n = 1), walking forward (n = 4), walking backwards (n = 1), sit-to-stand (n = 5), stand-to-sit (n = 1)</td>
</tr>
<tr>
<td>Reported direction of fall: Forward (n = 5), backward (n = 9), sideway (n = 6)</td>
</tr>
<tr>
<td>Impact spot: Floor (n = 12), against wall/locker before hitting the floor (n = 4), bed/sofa (n = 3), desk (n = 1)</td>
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</table>

recent European project (www.sensaction-aal.eu) within a high risk population. Based on these data, we tested two hypotheses in the corresponding experiments 1 and 2: (1) there are systematic differences in acceleration values between real-world and simulated, self-initiated backward falls; (2) a sudden release from a backwards lean during the simulation and the instruction to avoid falling will reduce the differences between real-world and simulated falls.

2. Methods

2.1. Subjects and design

Acceleration signals of 5 falls of 4 patients (mean age 68.8 years, SD 4.5, all women) suffering from progressive supranuclear palsy (PSP) were used to describe real-world backward falls. The data were taken from a cross-sectional study to describe clinical aspects of PSP patients [27] and from an intervention study to investigate the feasibility of audio-feedback to improve balance, which was offered to the participants after the cross-sectional study 3 times per week [28]. PSP is an atypical Parkinson’s syndrome with a prevalence of 5 per 100,000 [29]. Postural instability and falls are common and the most disabling features [30,31]. A 48-h activity measurement carried out using an ambulatory device based on accelerometers (DynaPort® MiniMod, McRoberts, The Hague, NL) was conducted as part of the assessment in the cross-sectional study and during days without intervention. The falls occurred during these measurements. Twenty-nine patients agreed to wear a motion monitor. During the observation periods with a total of 2100 h of recording, 20 falls were collected from 7 patients. The falls were different according to location, pre-fall phase, fall direction, and impact spot (Table 1). For the present analyses, 5 representative backward falls were used (4 persons). These falls were well described by the patients and/or their proxies, there was no contact to any obstacle before hitting the ground, and the analyses of the acceleration signals confirmed the fall direction. In addition, the variability of these movement patterns in general was hypothesized to be lower compared with falling to the anterior direction or falling to the side due to a restricted vision. A fall to the back seems to be quite relevant because this type of falling was shown to have the lowest rate of avoidance and the highest rate of full body impact [32]. Four backward falls were not included in the analyses, because the fall direction was not confirmed by the signals or the first impact spot was not the floor.

Physical performance of the patients was assessed to describe the cohort using maximum gait speed and balance in unsupported standing. Gait speed was calculated from a 10 m walk, measured by stop watch. Balance was measured as the sum of the time the patients were able to stand unsupported in open stance, closed stance (feet side by side), semi-tandem stance (feet side by side but heel of one foot touching the toe of the other foot), and tandem stance (one foot direct in front of the other foot) with a maximum of 10 s in each position.

Eighteen students (mean age 24.1 years, SD 1.91, 56% women) were recruited to perform the fall simulations for this study. They were active in sports (>8 h/week), healthy, and free of medications.
Anthropometric and functional description of the study population is provided in Table 2. All participants gave written informed consent. The studies were approved by the ethics committee of the local university.

2.2. Fall simulation protocol

“Experiment 1”: Fall simulation was conducted onto protective layers of mattresses (thickness = 15 cm; hardness = 3.6 kPa, pressure to compress a piece of foam by 40% of its original height) to reduce the impact. Participants stood at a distance of 1.5 times the lengths of their foot apart from the mattresses with the back to the mattress and were instructed to “fall to the back as if you were a frail old person”. No warm up trials to familiarize with the mattress, not even touching the mattress was allowed. From this “experiment 1” of fall simulation, the acceleration signals of the first trial were taken for data analysis to avoid learning effects.

“Experiment 2”: The participants now were instructed not to fall onto the mattresses, if possible, when released from a backward lean. The instruction was “when we release you, try as hard as you can not to fall”. The participants were held by a staff member in a backward lean of about 30–40°. They were asked to raise their toes and to stand without hip flexion just on their heels. The inclination of the body position was adjusted so a fall was unavoidable. This was not known by the participants and there was no possibility to anticipate the timing when they would be released. The protocol for experiment 2 is shown in Fig. 1. The acceleration signals of the first trial were taken for data analysis. Due to their failure to follow the instructions (no compensatory movements), the acceleration signals of 3 students were not included in the analysis.

2.3. Data acquisition and processing

Data acquisition was performed in PSP patients as well as in the fall simulation study using a DynaPort® MiniMod (McRoberts, The Hague, NL) data logger. The MiniMod® makes use of a tri-axial seismic acceleration sensor (LIS3LV02DQ, STMicroelectronics, Agrate Brianza, Italy). The orientation of the axes are x = medio-lateral (left/right), y = sagittal (forward/backward). The sensor has a range of ±20 m/s² with a resolution of 12 bit and a sampling frequency of 100 Hz. Data were stored for off-line analysis on an SD card. The sensor was fixed by a belt at the lower back. The analyses focused on the fall phase, which was defined as the interval 1.5 s before the impact. The beginning of the impact phase was approximated by video analysis and subsequently determined as the local minimum of the acceleration signal in the x-axis followed by a rapid increase of the acceleration value at impact. This turning point is caused by the braking-acceleration which is effective to the opposite direction of the fall direction. The definitions were based on the literature [4,33] as well as empirically derived from the data of real-world falls and from simulated falls, as shown in Fig. 2.

In the following acceleration is abbreviated using ‘a’ and the direction is subscripted if applicable. The maximum jerk and the variance during the fall phase in the x-, y- and z-directions served as outcome measures to describe the differences between real-world falls and simulated falls. The jerk (rate of change of acceleration, \( \Delta a/\Delta t \) [m/s³]) was calculated for all (150) data points according to the following formula (similar for y- and z-axis):

\[
\dot{j}_{x,i} = \frac{\Delta a_{x,i}}{\Delta t} \quad \text{(1)}
\]

where \( i \) and \( i - 1 \) refer to acceleration values separated by 0.01 s. The variance of the acceleration signals [m²/s⁴] along the medio-lateral and sagittal axes were calculated according to the following equation (similar for z-axis):

\[
\text{var}_y = \frac{\sum_{i=1}^{n}(a_{y,i} - \bar{a}_y)^2}{n - 1} \quad \text{(2)}
\]

where \( n \) is the number of data points. The variance of acceleration along the vertical axis was calculated in relation to the smoothed signal (moving median smoothing, window size: 21 data points). The rationale for this approach is the fact that the acceleration signals of the fall phase inescapably decrease from about 10 m/s² to around 0 m/s² during the fall phase (see Fig. 2). The variance in relation to the smoothed signal was calculated according to the following equation:

\[
\text{var}_x = \frac{\sum_{i=1}^{n}(a_{x,i} - a_{x,m,i})^2}{n - 1} \quad \text{(3)}
\]

where \( a_{x,m,i} \) refers to the smoothed data point at sample \( i \).

Finally, the resultant-trend-line for variance and maximum jerk was calculated as the root-mean-square of the x-, y- and z-measurements. Thus, 8 outcome variables were used to describe each fall, 4 jerk values and 4 variance values.

2.4. Statistics

The Wilcoxon–Mann–Whitney-U test was used to compare jerk and variance values between groups. The level of significance was set to \( \alpha = 5\% (p < 0.05) \). All analyses were conducted using SAS 9.2 (SAS Institute, Cary, USA).

3. Results

Fig. 2 shows the acceleration pattern of a real-world fall (a), a simulated fall of experiment 1 (b), and a simulated fall of exper-
Fig. 2. Examples of acceleration signals in vertical (x-axis), medio-lateral (y-axis) and sagittal (z-axis) direction during (a) a real fall, (b) a simulated fall of experiment 1 and (c) a simulated fall of experiment 2.

In experiment 1, when the participants tried to fall like an older person, there was significantly more variation within the acceleration signal during the fall phase in the real-world falls compared to the fall simulation. This observation is demonstrated by the fact that all median values of variance and maximum jerk along all axes were higher in real-world falls compared to the simulated falls of experiment 1. These differences were significant for both outcome variables along the x- and y-axes as well as for the resultant-trend-line.

All outcome variables were different between real-world falls and simulated falls in experiment 2, as well, but the general trend was reversed. All median values of variance of acceleration were higher for the fall simulation compared to the real-world falls (y- and z-axis significantly). Maximum jerk was higher for fall simulation in experiment 2 along the y- and z-axes as well as for the resultant-trend-line, compared to real-world falls, but only the comparison between the values measured along the y-axis reached statistical significance. All outcome results of the variables in experiments 1 and 2 are shown in detail in Table 3.

4. Discussion

This study, to the best of our knowledge, compared for the first time real-world falls of older persons with low level of functional performance with simulated falls of younger persons, while falls were measured with accelerometers. The real-world falls were well documented falls in the backwards direction; these falls were compared to simulated backwards falls. The acceleration signals of the fall phase (pre-impact) were used to describe the backwards fall. As shown in this study, the fall phase offers an appropriate source of acceleration signals at least to distinguish between real-world falling and fall simulation. Our choice to investigate the fall phase is corroborated by recent research that introduced fall detection algorithms derived from the fall phase [16,24–26]. Although a classification of fall phases was introduced almost 15 years ago [33], only a few studies focused on the pre-impact phase up to now.

Larger changes in acceleration (in terms of variance and maximum jerk) during the fall phase were observed in the real-world falls, compared to the fall simulation of experiment 1. These differences between outcome variables in real-world falls and experiment 1 might be explained by the fact that the PSP patients used compensation strategies to prevent an impact because their intention was not to fall, whereas the students in experiment 1 did not show this compensation, maybe because of their awareness of the mattress and/or because of their unprofessional knowledge of falls in older persons. It is likely that the instruction in experiment 1 as well as the mattress led to suppression of protective movements. In a similar study of fall simulations, the observed compensation strategies were governed by motor plans selected well before the fall in order to fall, but also to land safely [34].

Table 3
Variance of acceleration and maximum jerk of the fall phase for real falls and simulated falls.

<table>
<thead>
<tr>
<th>Outcome Measure</th>
<th>Real Falls</th>
<th>Simulated Falls</th>
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<tr>
<td></td>
<td>Median</td>
<td>Medians</td>
</tr>
<tr>
<td></td>
<td>(n=5)</td>
<td>Experiment 1 (n=18)</td>
</tr>
<tr>
<td>Var (x-trend-line) [m/s²]</td>
<td>5.98</td>
<td>0.80</td>
</tr>
<tr>
<td>Var (y-axis) [m/s²]</td>
<td>4.52</td>
<td>0.32</td>
</tr>
<tr>
<td>Var (z-axis) [m/s²]</td>
<td>5.55</td>
<td>2.16</td>
</tr>
<tr>
<td>Var (resultant-trend-line) [m/s²]</td>
<td>5.27</td>
<td>0.33</td>
</tr>
<tr>
<td>Max jerk (x-axis) [m/s³]</td>
<td>1253</td>
<td>253</td>
</tr>
<tr>
<td>Max jerk (y-axis) [m/s³]</td>
<td>653</td>
<td>175</td>
</tr>
<tr>
<td>Max jerk (z-axis) [m/s³]</td>
<td>1281</td>
<td>343</td>
</tr>
<tr>
<td>Max jerk (resultant) [m/s³]</td>
<td>1204</td>
<td>350</td>
</tr>
</tbody>
</table>

* Exact Wilcoxon–Mann–Whitney–U test, real falls compared with simulated falls (experiment 1 and experiment 2).
Conversely, when released from a backward leaning position, the students apparently showed more compensation movements than the PSP patients during a real-world fall. Here the situation for both the patient and students is similar: the aim is to prevent the fall. The results are not surprising. McVey et al. [35] showed that Parkinson’s disease patients have more problems than healthy subjects compensating from a backward push. Furthermore, The- len et al. [36] showed that younger subjects were more effective at preventing a fall when released from a leaning (to the front) position. Both studies show that younger persons are more effective at generating compensating movements, consistent with the present results.

This study has several limitations. The number of real-world falls collected was small and the recorded real-world falls were from a rare disease population that cannot be generalized to the older population at large. The simulation experiments had to be performed with constraints on the impact phase and anticipation. These restrictions were due to the safety of the participants. In experiment 2, the baseline acceleration signal in x-direction was lower than 10 m/s² due to the inclination of the subject at the beginning of the fall (Fig. 2c). However, this initial condition likely did not affect the results because the variance as well as the maximum jerk do not rely on an absolute zero but on differences. Still, the present findings demonstrate differences between real-world falls and fall simulation, confirming our primary hypothesis. The instructions and the type of experiment led to different results with an underestimation and overestimation of the variance and jerk signals if the simulation model would have been used to develop a model of falling. Therefore, for the development of this model, signals must be derived from data of real-world falls, at least when variance of the acceleration and maximum jerk during the fall phase are outcome parameters. When signals of the impact phase should be used, signals of real-world falls are necessary too, because signals derived from simulated impacts were shown to be not acceptable, at least when fall detection algo-

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Conflict of interest

RC van Lummel is the owner of McRoberts BV, the provider of the DynaPort® MiniMod.

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