Z Gerontol Geriat 2012 · 45:707–715

DOI 10.1007/s00391-012-0403-6

Received: 27 July 2012

Revised: 3 September 2012

Accepted: 6 September 2012

Published online: 25 November 2012

© Springer-Verlag Berlin Heidelberg 2012

C. Becker¹ · L. Schwickert¹ · S. Mellone² · F. Bagalà² · L. Chiari² · J.L. Helbostad³,
⁴ · W. Zijlstra⁵ · K. Aminian⁶ · A. Bourke^{6,7} · C. Todd⁸ · S. Bandinelli⁹ · N. Kerse¹⁰ ·
 J. Klenk^{1,11} · For the FARSEEING Consortium and the FARSEEING Meta Database
 Consensus Group

¹ Department of Clinical Gerontology, Robert Bosch Hospital, Stuttgart

² Department of Electronics, Computer Science and Systems, University of Bologna

³ Department of Neuroscience, NTNU, Trondheim

⁴ Department of Geriatrics, St. Olav University Hospital, Trondheim

⁵ Institute of Movement and Sport Gerontology, German Sport University, Cologne

⁶ Laboratory of Movement Analysis and Measurement, Ecole Polytechnique Fédérale de Lausanne (EPFL)

⁷ Department of Electronic and Computer Engineering, Faculty of Science and Engineering,
 University of Limerick

⁸ School of Nursing, Midwifery and Social Work, The University of Manchester

⁹ ASF-Azienda Sanitaria di Firenze, Florence

¹⁰ School of Population Health, University of Auckland

¹¹ Institute of Epidemiology and Medical Biometry, Ulm University

Proposal for a multiphase fall model based on real-world fall recordings with body-fixed sensors

What is it with falls? An accurate and detailed understanding of unexpected falls and their mechanics is important for many reasons. From a clinical perspective, for example, it is interesting to know what kind of falls result in injury, what protective movements are performed during the fall, and how such movements change with aging [1]. From a technical perspective, kinetics and kinematics of falls are essential to develop fall protectors and fall detection devices or improve the ergonomic design of furniture and the home environment. In order to study unexpected falls it is important to reach consensus on a fall definition [2, 3], fall recording, and reporting including consistent collection of information about people who fall [4] and a description of the sensor technologies. One major step in this perspective is an agreement on a model describing the different phases of falls.

During the last two decades numerous observational and epidemiological studies have been conducted to examine unexpected falls in older people [5, 6]. Most of the fall reports rely only on patients' self-report [3, 7]. Fallers are sometimes able to

describe the circumstances and, to some degree, the events leading to the fall. Additionally, information on the recovery after a fall or the consequences of a fall such as injury or the inability to stand up without external support can usually be given [8]. Frequently, this information is inaccurate due to recall problems or a social report bias. Most fallers cannot accurately report what happened during the fall itself. Reliable information on fall direction, failed balance recovery strategies, landing responses, and possible multiple impacts is lacking or insufficient. Third-party information does not solve the problem. Less than 20% of all falls are observed by others [4]. In the interim, fall self-reports remain the most important source of information along with baseline assessment in epidemiological studies [9]. As a consequence, the development and testing of fall-prevention interventions [10, 11] may have relied on potentially inaccurate fall reports and not on reliable measurements of outcomes.

The development of new forms of gerontechnology along with video footage of fall events [12] has the potential to

improve our understanding of the interplay between intrinsic risk factors leading to falls and fall biomechanics. Body-fixed sensor (BFS) technology allows the measurement of people under real-life conditions in their natural environment. This includes indoor and outdoor activities as well as recordings in very private areas like the bathroom or the toilet. Other systems such as ambient sensors or sensor floors are limited to only some aspects of activities of daily living or certain locations.

Recording real-world fall events is difficult because of the short feasible recording periods of existing measurement devices. To capture 100 real-world falls in a representative sample of older persons aged 65 years and older, it would be necessary to record approximately 70,000–100,000 days of physical activity (300 person years) [13]. Given a sensor observation period of 7 days, this means about 15,600 observation intervals each with recharging and data download. In samples with a higher incidence of falls, the number of observation intervals can be decreased but they are still substantial. Therefore, because of the difficulties in recording re-

Fig. 1 ◀ Five-phase fall model

al-world falls, fall simulations have been used in the past to generate and record fall signals. However, simulated fall signals are not comparable with real-world falls [14]. This is partly due to the anticipation of the movement by the volunteers, called anticipated postural adjustments (APAs), and the impact protection during the experiments, which is necessary for ethical and safety reasons. The performance of existing fall-detection algorithms based on fall simulations is insufficient [13, 15]. This may also partly be due to the lack of a fall model. Most algorithms only consider the impact phase, some the posture after a fall, and fewer the velocity during a fall.

In the literature different approaches to a fall phase model have been presented [15, 16, 17, 18, 19, 20, 21, 22, 23]. The models either focus on the initial phases of a fall such as “dislocation of balance,” “descent,” and “impact” [17], or do not identify the recovery reaction as an important part of fall detection [16]. The newer four-phase model by Noury et al. [19] combined falling and impact. They emphasized the importance of the “post-fall” period including the recovery period.

There is potential for this model to be further improved to include all important aspects of a fall event. For instance, from a clinical perspective, the recovery after a fall might be as important as the impact itself. Furthermore, the pre-fall activity might highly influence the fall biomechanics. A multiphase model should at least be accepted by gerontechnological experts and it should have face validity to clinicians and other gerontological professions.

This paper presents results developed by the FARSEEING project. The FARSEEING consortium is funded by the European Commission to build up an open-access meta-database of real-world fall signals (<http://www.farseeingresearch.eu>).

We propose a five-phase fall model that is demonstrated with a case study of the first data of real-world falls stored in the FARSEEING meta-database.

Methods

The proposed fall phase model was developed during the FARSEEING consensus process about the recording and reporting of real-world fall signals. The results of the recommendations on the recording and reporting of falls will be published elsewhere. The participants included FARSEEING consortium members and invited experts with a wide range of professions including movement science, sport science, biomechanics, biomedical engineering, biostatistics, epidemiology, geriatric medicine, physiotherapy, computer science, and neurology (see Acknowledgements). The expert discussion was supported by a literature review on fall detection (manuscript submitted). For the phase model development, the ProFaNE definition of falls, slightly adapted by replacing the term “participant” with “person,” was used [2]: “A fall should be defined as an unexpected event in which the person comes to rest on the ground, floor or lower level.”

Fall signals

For each falling phase, one prototypical example of an acceleration signal of a real-world fall recording was selected from the FARSEEING database [13]. Data acquisition of these falls was performed using a DynaPort® Hybrid (McRoberts, The Hague, The Netherlands) device that included a tri-axial seismic acceleration sensor (LIS3LV02DQ, STMicroelectronics, Agrate Brianza, Italy). The orientation of the axes are x = vertical, y = mediolateral (left/right), and z = anterior–posterior (forward/backward).

The sensor had a range of ± 6 g with a resolution of 12 bit and a sampling frequency of 100 Hz. Data were stored on an SD card. The sensor was fixed using a belt at lower back level.

All fall examples are derived from one male subject, 72 years old, recorded during his stay in a rehabilitation clinic. His main diagnosis was progressive supranuclear palsy, a rare brain disorder causing serious problems in gait and balance control. For each of these falls a witness report was available allowing a verification of the signal and an iconographic description (■ Fig. 3, 4, 5).

The participant gave written informed consent. The recordings were approved by the ethical board of the University of Tübingen.

Results

The participants of the consensus process agreed that a fall model with five separate phases is needed (■ Fig. 1). It should include the activity before a fall (1), the falling phase (2), the impact on the ground, floor, or lower level (3), the resting phase (4), and finally, if present, the recovery phase such as the return to the previous activity (5).

Three representative examples of real-world fall recordings are reported in ■ Fig. 2.

The starting point of the analysis is the *pre-fall phase*. It is defined as the activity prior to the falling phase leading to the fall such as running, walking, turning, stair climbing, sitting, or lying. Extractable information might include gait variability, sit-to-stand characteristics, and balance recovery reactions. The expert group recommended recording at least 1 min before the impact to allow sufficient analyses.

■ Fig. 3 reports the activities performed by the subject up to 1 min prior to the fall. Depending on the approach, additional contextual information will be required such as the location of the fall and other environmental factors. This should be obtained by a structured interview or video footage if available. The end of the pre-fall phase is defined by the beginning of the falling phase. While clinically obvious, we cannot currently be sure how accurately this can be detected by sensor technology.

ogy or video footage. ■ **Fig. 4** shows the pre-fall phase, the falling phase, and the impact phase for the three fall examples in more detail.

The *falling phase* (synonym: descent phase) is defined by a lowering of the center of mass (COM) that can no longer be recovered by protective strategies such as ankle, hip, stepping strategies, or grasping strategies. From standing height, the duration of this phase of an unbroken fall is expected to be 0.4–0.8 s [14]. This will include an initial passive phase of about 120–200 ms with no compensation movements. The sensor signal during the falling phase might be influenced by falling responses such as unsuccessful stepping strategies and grabbing or hitting objects to reduce the impact. In some cases the initial falling direction (forward, backward, lateral) may change during falling due to rotational movements to reduce the impacts of the fall on vulnerable body parts like the face or the spine (■ **Fig. 4**). A lack of balance recovery and of falling or landing responses caused by syncope or due to disease-specific response failures can be equally important. The time of the falling phase will depend highly on the circumstances and can be considerably longer if a fall has multiple impacts (■ **Fig. 4a, c**) such as a fall on a staircase. As already mentioned, contextual information will be useful to improve the signal interpretation.

The *impact phase* is usually the most prominent part of the signal. The impact phase is identified by the person hitting the ground, floor, or lower level (■ **Fig. 4**). The beginning of the impact phase is, in principle, determined as the first abrupt change of direction in the acceleration signal. This turning point is caused by the braking–acceleration opposite to the initial fall direction. The number, amplitude, and sign of the acceleration peaks depend on the intensity and dynamics of the impacts. The acceleration signal will be heavily influenced by the ground surface such as tiles, carpets, or furniture and the presence of impact signals during the falling phase prior to the ground contact. In addition, the signal can give important information about the direction of the reaction force affecting the body. The duration of this phase is usually less than 1 s. Real-

Z Gerontol Geriat 2012 · 45:707–715 DOI 10.1007/s00391-012-0403-6
© Springer-Verlag Berlin Heidelberg 2012

C. Becker · L. Schwickert · S. Mellone · F. Bagalà · L. Chiari · J.L. Helbostad · W. Zijlstra · K. Aminian · A. Bourke · C. Todd · S. Bandinelli · N. Kerse · J. Klenk · For the FARSEEING Consortium and the FARSEEING Meta Database Consensus Group

Proposal for a multiphase fall model based on real-world fall recordings with body-fixed sensors

Abstract

Falls are by far the leading cause of fractures and accidents in the home environment. The current Cochrane reviews and other systematic reviews report on more than 200 intervention studies about fall prevention. A recent meta-analysis has summarized the most important risk factors of accidental falls. However, falls and fall-related injuries remain a major challenge. One novel approach to recognize, analyze, and work better toward preventing falls could be the differentiation of the fall event into separate phases. This might aid in reconsidering ways to design preventive efforts and diagnostic approaches. From a conceptual point of view, falls can be separated into a pre-fall phase, a falling phase, an

impact phase, a resting phase, and a recovery phase. Patient and external observers are often unable to give detailed comments concerning these phases. With new technological developments, it is now at least partly possible to examine the phases of falls separately and to generate new hypotheses.

The article describes the practicality and the limitations of this approach using body-fixed sensor technology. The features of the different phases are outlined with selected real-world fall signals.

Keywords

Accidental falls · Elderly · Fall phase model · Fall detection · Fall prediction

Vorschlag für ein Mehrphasensturzmodell auf der Basis von Sturzdokumentationen mit am Körper getragenen Sensoren

Zusammenfassung

Stürze sind die mit Abstand häufigsten Ursachen von Frakturen und häuslichen Verletzungen im Alter. In den Cochrane Reviews und anderen systematischen Analysen wurden mehr als 200 randomisierte Interventionsstudien zur Sturzprävention erfasst. Eine neue Metaanalyse liegt für die Risikofaktoren von Stürzen vor. Dennoch bleiben Stürze und sturzbedingte Verletzungen eine große Herausforderung. Ein neuer Ansatz zur Erkennung, Analyse und Prävention von Stürzen ist es, Stürze in Abschnitte aufzuteilen. Dies könnte bei der Erstellung diagnostischer und präventiver Ansätze helfen. Phänomenologisch ist offenkundig, dass es eine Vorphase, Fallphase, Aufprallphase, Ruhephase und mögliche Erholungsphase gibt. Patienten

und Fremdbeobachter sind allerdings nicht in der Lage, hierzu exakte Angaben zu machen. Durch technologische Neuentwicklungen ist es nunmehr möglich, diese Abschnitte zumindest teilweise zu beurteilen und daraus erste Hypothesen abzuleiten.

Der Artikel beschreibt dabei die Praktikabilität und Beschränkungen der Verwendung von am Körper getragenen Sensoren. Die Sturzphasen werden anhand von Fallbeispielen verdeutlicht.

Schlüsselwörter

Stürze · Ältere Menschen · Sturzphasenmodell · Sturzerkennung · Sturzprädition

world signals are needed to test the precision with which the end of the impact phase can be determined.

The *resting phase* is of varying duration (■ **Fig. 5**). In some cases nearly no resting phase is seen if the person directly recovers after the impact. The end of the resting phase can be detected with the start of the recovery phase, which usually includes COM movement, or as exceeding a predefined time interval. It is recom-

mended to record at least 5 min if there is no recovery. It is important to analyze the resting response, be it immediate or delayed. The signal may include indirect indications of causality such as clonic epileptic seizures and other severe medical events causing falls.

The *recovery phase* is the final phase of a fall. This can be independent recovery or assisted by a third party. It can be anything from full recovery in a relative-

Fig. 2 ▲ Real-world fall recordings; a time window of 2 min is centered on the fall event in agreement with the consensus process outcomes. Panels **a**, **b**, and **c** refer to three representative examples that are detailed in **Fig. 3, 4, und 5**. AP anterior–posterior axis, ML mediolateral axis, V vertical axis

ly timely manner to absence of recovery, such as long-lies or fatal falls (■ **Fig. 5a** no recovery after 1 min; ■ **Fig. 5b** no full recovery after 1 min but tentative recovery; ■ **Fig. 5c** full recovery in about 30 s). This phase is important as it may be useful to avoid under- and overreactions and false alarms. To date there are no published algorithms that detect this phase.

Discussion

In this paper we propose a five-phase fall model including: pre-fall phase, falling phase, impact phase, resting phase, and recovery phase. This model will be used within the FARSEEING database to develop and test fall-detection algorithms on real-world fall data. Currently, falls are a composite endpoint made up of undifferentiated aggregates of these phases, and we are primarily dependent on self-report

measures when investigating falls. However, different diagnostic or therapeutic approaches will probably work differently for different phases. Some implications for each of the described phases are discussed.

The given examples of acceleration signals from BFS demonstrate that they may provide information that cannot be achieved by other methods of fall recording and reporting. The aim is to provide a model that is applicable for body-fixed

Fig. 3 ▲ Detailed view of panels **a**, **b**, and **c** of **Fig. 2** [–60 s, –4 s]. Activities performed by the subject 60 s prior to the impact. AP anterior–posterior axis, ML mediolateral axis, V vertical axis

as well as ambient sensors and video recordings.

For the *pre-fall phase* several challenges are self-evident. It remains to be demonstrated how algorithms can accurately dif-

ferentiate between the phases of successful balance recovery and the beginning of the falling phase. This transition is likely to differ between frail subjects compared to physically trained persons with a high

capacity to perform, for instance, proactive stepping strategies. The addition of gyroscopes, altimeters, and magnetometers for the sensor measurement units is likely to improve the interpretation of the

Fig. 4 ▲ Detailed view of panels **a**, **b**, and **c** of **Fig. 2** [–4 s, 2 s]. The pre-fall phase (green bar) is identified as the last activity performed by the subject right before the falling phase. The falling phase (orange bar) is identified as the lowering of the center of mass. The impact phase (red bar) is identified as the part of the signal where a single impact (**b**) or multiple impacts (**a** and **c**) are recognizable. The figure also shows the beginning of the resting phase (yellow bar). AP anterior–posterior axis, ML mediolateral axis, V vertical axis

Fig. 5 ▲ Detailed view of panels **a**, **b**, and **c** of **Fig. 2** [2 s, 60 s]. Resting phase (yellow bar) and, when present, recovery phase (turquoise bar). The figure also shows the activities performed by the subject up to 1 min after the fall. AP anterior–posterior axis, ML mediolateral axis, V vertical axis

signals and make the detection and characterization of near falls easier by providing accurate information about body segment orientation. During the pre-fall phase it might also be possible to analyze activity patterns in real-time and detect a movement pattern with a high risk of falling and send an alarm to a person, family caregiver, or professional. A number of these parameters such as gait variability and transfer capacity during sit-to-stand maneuvers cannot be recognized by the persons themselves. Quantitative analysis during physical activity monitoring might also give new insight into dynamic changes of fall risk. Aside from the diagnostic value, a better understanding of these changes would possibly allow instant feedback to the person, including cueing or audio or tactile biofeedback called ecological momentary interventions (EMIs).

The *falling phase* allows insight into the presence or absence of balance recovery reactions and the velocity of fall. The inability to examine recordings of unsuccessful balance recovery reactions seems to be one major reason why simulation experiments of falls with young volunteers are inaccurate [14]. Another reason for the poor performance of fall-detection algorithms are the multiple impact signals during this phase that the person produces while trying to reduce the impact of the fall. Examples are falling on the knees, protective arm movements, hitting objects, or grasping strategies [13]. It can be expected that a considerable number of falls in real life are “broken” falls with multiple impacts, whereas most experiments have asked volunteers to simulate an “unbroken” fall. It is an open question whether these should be part of an adjusted total impact analysis or whether multiple impacts during the falling phase should be part of the fall pattern analysis. A better understanding of the signals and protection strategies during falling might also be helpful for developing new approaches to train high-risk populations, for example, by adapting martial art techniques to reduce impact magnitude [24]. So far, there is less consideration of the falling phase by fall-detection algorithms. High-resolution accelerometer signals will be necessary to allow advanced pattern analyses. It is likely that gyroscopes and altimeters (e.g., barometric pressure

sensors) will be helpful to improve the understanding of the falling patterns. Physiological signals such as heart rate could also improve the classification of falls and provide valuable information.

The *impact phase* signal is the most prominent feature of a fall signal. A number of impact-related questions of importance are currently not answered. The relationship between fall direction and likelihood of hip and pelvic fractures is poorly understood. Furthermore, the exact force needed to break the pelvis or hip in frail older persons is not known. Laboratory experiments can only give indirect answers. An improved understanding of the dynamics of fall events might result in the development of, for example, new shock-absorbing floor materials to be installed in high-risk environments such as toilets or bedrooms in long-term care. One long-term goal is to predict falls with a high likelihood of fracture [25] and to develop prevention strategies that target these multiple components of the fall. This might include strategies to reduce near falls or training of landing responses. Most published fall-detection algorithms consider the impact signal by applying a threshold. It has been shown that this simplistic approach is insufficient to detect falls with an acceptable number of false alarms [13]. The acceleration magnitude is not a reliable marker for falls, since some activities of daily living [26] show similar acceleration magnitudes as falls with low impacts (■ Fig. 4b). New features have to be developed to take into account, for example, jerk or the duration of the impact signal. Accurate identification of the end of the impact phase and the inclusion or exclusion of multiple impact signals during the falling phase are debated.

As mentioned above, the *resting phase* may last very short. On the other hand it is also possible to have very long lasting resting phases with hours or days or even some fatal falls leading to death [27]. The resting phase and the recovery phase are the time periods when signal analysis can detect possibly severe consequences versus a relatively benign fall event. The clinical challenge is to allow a person to recover as long as possible, to respect their autonomy but to be sufficiently sensitive so as to identify a critical and possibly life-threat-

ening condition requiring immediate medical attention such as seizures, stroke, or syncope. It seems therefore justified that algorithm development should include the detection of motionless behavior and body segment orientation, clonic movements, and possibly pain-related movement restrictions indicating a severe fall-related injury. The transition from resting to recovery might be hard to detect.

The *recovery phase* has not been extensively discussed in the literature on fall detection. This phase should improve the specificity of the medical response of fall alarm systems. A considerable number of false alarms will be generated even with a relatively high specificity of fall detection. The long-term uptake utility of technology is diminished if false alarms are too frequent and if they lead to overreactions of the medical or social environment [27].

Contextual information is complementary and will add to the understanding of all fall phases. Although the sensor data can provide reliable information on motor activities, they provide no or little information on environmental factors before, during, or after the fall. The patient and/or proxy report are needed to identify environmental cofactors. It is evident that other technological sources of information might have additional value such as video footage or optoelectronic sensors. The pros and cons of the different technologies are debated commonly between facility management and researchers, e.g., legal concerns, adherence, and privacy concerns. Video footage studies add to our understanding [12], but bedroom and bathroom areas will not be available. In these areas ambient sensors might be the method of choice. BFS will allow fall detection and description in the indoor and outdoor environment. They also allow the addition of other sensors to detect heart rate, blood pressure, or location, i.e., geographical positioning systems. However, BFS must be acceptable for the persons wearing them. Battery lifetime and data storage still limit utility. The use of smartphones as a sensor platform is an attractive alternative [28] but it opens up other questions. For example, a smartphone is normally not body-fixed, but body-worn with some movements relative to the body.

Finally, we would like to stress that this model is preliminary and will be validated. Less than 20 real-world fall signals have been published worldwide until June 2012. The FARSEEING meta-database currently has approximately 40 real-world fall signals. The aim is to collect several hundred fall signals in different cohorts over the next years. The five-phase fall model currently seems to be the most feasible approach to describing fall events. The proposed model should help to better understand the mechanics of falls and to improve fall prediction and detection. We encourage other expert groups to join the open source initiative of FARSEEING to share knowledge (<http://www.farseeingresearch.eu>).

Corresponding address

C. Becker

Department of Clinical Gerontology,
Robert Bosch Hospital
Stuttgart
Germany
clemens.becker@rbk.de

L. Schwickert

Department of Clinical Gerontology,
Robert Bosch Hospital
Stuttgart
Germany
lars.schwickert@rbk.de

Acknowledgments. The following experts are part of the FARSEEING consensus group and contributed to the discussion: Christophe Büla, Centre Hospitalier Universitaire Vaudois Lausanne, Switzerland; Michele Carenni, NoemaLife spa, Italy; Kim Delbaere, Neuroscience Research Australia, Australia; Matthias Gietzelt, University of Braunschweig and Hannover Medical School, Germany; Klaus Hauer, Agaplesion Bethanien Hospital Heidelberg, Germany; Jeffrey M. Hausdorff, Beth Israel Deaconess Medical Center and Harvard Medical School, USA and Israel; Helen Hawley, University of Manchester, United Kingdom; Anisoara Ionescu, EPFL Lausanne, Switzerland; Maarit Kangas, University of Oulu, Finland; Fabio La Porta, Azienda USL di Modena, Italy; Stephen Lord, Neuroscience Research Australia, Australia; Walter Mätzler, University of Tübingen, Germany; Michael Marschollek, University of Braunschweig and Hannover Medical School, Germany; Norbert Noury, University of Lyon, France; Rachel Potter, University of Warwick, United Kingdom; Kilian Rapp, Robert-Bosch Hospital Stuttgart and University of Ulm, Germany; Stephen Redmond, University of New South Wales, Australia; Stephen Robinovitch, Simon Fraser University, Canada; Stephane Rochat, Centre Hospitalier Universitaire Vaudois Lausanne, Switzerland; Johannes Salb, University of Erlangen, Germany; Michael Schwenk, Agaplesion Bethanien Hospital Heidelberg, Germany; Michael Setton, SENSARIS, France; Olav Sletvold, Norwegian University of Science and Technology, Norway; Stuart Smith, Neuroscience Research Australia, Australia; Mat-

this Synofzik, University of Tübingen, Germany; Enrico Valtolina, Bticino spa, Italy; Aleksandra Zecevic, Western University London Ontario, Canada; Tania Zieschang, Agaplesion Bethanien Hospital Heidelberg, Germany. The FARSEEING project is being funded by the European Commission. The companies participating in the FARSEEING project had no influence on the writing of the manuscript and the presented results.

Conflict of interest. On behalf of all authors, the corresponding authors state that there are no conflicts of interest.

References

- Cummings SR, Nevitt MC (1989) A hypothesis: the causes of hip fractures. *J Gerontol* 44:M107–M111
- Lamb SE, Jorstad-Stein EC, Hauer K, Becker C (2005) Development of a common outcome data set for fall injury prevention trials: the Prevention of Falls Network Europe consensus. *J Am Geriatr Soc* 53:1618–1622
- Hauer K, Lamb SE, Jorstad EC et al (2006) Systematic review of definitions and methods of measuring falls in randomised controlled fall prevention trials. *Age Ageing* 35:5–10
- Zieschang T, Schwenk M, Becker C et al (2011) Feasibility and accuracy of fall reports in persons with dementia: a prospective observational study. *Int Psychogeriatr* 1–12
- Lord SR, Sherrington C, Menz HB (2005) Falls in older people—risk factors and strategies for prevention. Cambridge University Press
- Campbell AJ (2008) Falls in older people. *BMJ* 337:a2320
- Zecevic AA, Salmoni AW, Lewko JH (2009) Utilization of the Seniors Falls Investigation Methodology to identify system-wide causes of falls in community-dwelling seniors. *Gerontologist* 49:685–696
- Parkkari J, Kannus P, Palvanen M et al (1999) Majority of hip fractures occur as a result of a fall and impact on the greater trochanter of the femur: a prospective controlled hip fracture study with 206 consecutive patients. *Calcif Tissue Int* 65:183–187
- Deandrea S, Lucenteforte E, Bravi F et al (2010) Risk factors for falls in community-dwelling older people: a systematic review and meta-analysis. *Epidemiology* 21:658–668
- Gillespie LD, Robertson MC, Gillespie WJ et al (2012) Interventions for preventing falls in older people living in the community. *Cochrane Database Syst Rev* CD007146
- Cameron ID, Murray GR, Gillespie LD et al (2010) Interventions for preventing falls in older people in nursing care facilities and hospitals. *Cochrane Database Syst Rev* CD005465
- Robinovitch SN, Feldman F, Yang Y et al (2012) Video capture of the circumstances of falls in older adults residing in long-term care. *Lancet* (in press). DOI 10.1016/S0140-6736(12)61263-X
- Bagala F, Becker C, Cappello A et al (2012) Evaluation of accelerometer-based fall detection algorithms on real-world falls. *PLoS One* 7:e37062
- Klenk J, Becker C, Lieken F et al (2011) Comparison of acceleration signals of simulated and real-world backward falls. *Med Eng Phys* 33:368–373
- Kangas M, Vikman I, Nyberg L et al (2012) Comparison of real-life accidental falls in older people with experimental falls in middle-aged test subjects. *Gait Posture* 35:500–505
- Hayes WC, Myers ER, Robinovitch SN et al (1996) Etiology and prevention of age-related hip fractures. *Bone* 18:775–86S
- Tideiksaar R (1998) Falls in older persons: prevention and management
- Srinivasan S, Han J, Lal D, Gacic A (2007) Towards automatic detection of falls using wireless sensors. *Conf Proc IEEE Eng Med Biol Soc* 2007:1379–1382
- Noury N, Rumeau P, Bourke AK et al (2008) A proposal for the classification and evaluation of fall detectors. *IRBM* 29:340–349
- Quagliarella L, Sasanelli N, Belgiovine G (2008) An interactive fall and loss of consciousness detector system. *Gait Posture* 28:699–702
- Nyan MN, Tay FE, Murugasu E (2008) A wearable system for pre-impact fall detection. *J Biomech* 41:3475–3481
- Lindemann U, Hock A, Stuber M et al (2005) Evaluation of a fall detector based on accelerometers: a pilot study. *Med Biol Eng Comput* 43:548–551
- Boissy P, Choquette S, Hamel M, Noury N (2007) User-based motion sensing and fuzzy logic for automated fall detection in older adults. *Telemed J E Health* 13:683–693
- Groen BE, Weerdesteyn V, Duysens J (2007) Martial arts fall techniques decrease the impact forces at the hip during sideways falling. *J Biomech* 40:458–462
- Rapp K, Becker C, Cameron ID et al (2012) Femoral fracture rates in people with and without disability. *Age Ageing* 41:653–658
- Bourke AK, O'Brien JV, Lyons GM (2007) Evaluation of a threshold-based tri-axial accelerometer fall detection algorithm. *Gait Posture* 26:194–199
- Fleming J, Brayne C (2008) Inability to get up after falling, subsequent time on floor, and summoning help: prospective cohort study in people over 90. *BMJ* 337:a2227
- Mellone S, Tacconi C, Schwickert L et al (2012) Smartphone-based solutions for fall detection and prevention: the FARSEEING approach. *Z Geriatr Gerontol* (in press)