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Maarit Kangas

DEVELOPMENT OF ACCELEROMETRY-BASED FALL DETECTION

FROM LABORATORY ENVIRONMENT TO REAL LIFE

UNIVERSITY OF OULU,
FACULTY OF MEDICINE,
INSTITUTE OF BIOMEDICINE,
DEPARTMENT OF MEDICAL TECHNOLOGY

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DEVELOPMENT OF ACCELEROMETRY-BASED FALL DETECTION

From laboratory environment to real life

Academic dissertation to be presented with the assent of the Faculty of Medicine of the University of Oulu for public defence in Auditorium A101 of the Department of Anatomy and Cell Biology (Aapistie 7 A), on 15 December 2011, at 12 noon

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Abstract

About one third of home-dwelling older people suffer a fall ech year. The most consuming falls occur when the person is alone and unable to get up, resulting in long lies which are associated with institutionalisation and high morbidity-mortality rate. Even though personal emergency response systems provide applications to call for help, older people are not always able or willing to activate them. Hence, an automatic fall detection system is an important setting. Even though pilot applications and commercial fall detection systems exist, the real-life validation of these systems is scant. The aim of this study was to develop a validated acceleration-based method for fall detection to be adapted for real-life applications among older people. Methods capable of discriminating between falls and activities of daily living (ADL) were determined based on laboratory tests. The threshold-based algorithms were validated with intentional falls in 20 middle-aged test persons and ADL in 20 middle-aged and 21 older people. The algorithm for the waist with impact and end posture detection was able to discriminate falls from ADL with 97% sensitivity and 100% specificity. In order to validate the fall detection system, a field test was performed with 16 residents in elderly care units wearing a wireless sensor. During the 6-month test period, acceleration data from five real-life falls were collected. One of the falls resulted in a hip fracture. These falls showed similar features as intentional falls. However, high pre impact velocity was detected in the case with a fracture, but not in all falls with preventative actions. The system had a fall detection sensitivity of 71.4% with a false alarm rate of 1.1 alarms over a 24-hour time period in this real-life pilot test. The data from real-life falls provide important material for further development of fall detection and studies on fall mechanism and fall prevention.

Keywords: acceleration, elderly, fall detection, fall detector, falling, older people, real-life

Kangas, Maarit, Kiihtyvyysanturiin perustuva kaatumisen tunnistaminen. Laboratoriokokeista käytäntöön
Oulun yliopisto, Lääketieteellinen tiedekunta, Biolääketieteen laitos, Lääketieteen tekniikka, PL 5000, 90014 Oulun yliopisto
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Tiivistelmä

Kotona asuvista yli 65-vuotiaista kaatuu vuosittain kolmannes. Mikäli kaatunut ei kykene nousemaan omin neuvoin, avun saaminen saattaa viivästyä. Tämä suurentaa sekä laitoshoitoon joutumisen todennäköisyyttä että kuoleman riskiä. Erilaisia hälytysjärjestelmiä on kyllä saatavilla, mutta ikääntyneet eivät aina kykene käyttämään niitä tai eivät jostain syystä halua tehdä hälytystä. Tämän vuoksi automaattiselle kaatumishälyttimelle on tarvetta.

Tässä tutkimuksessa kehitettiin ja testattiin ikääntyneiden tarpeisiin soveltuva kiihtyvyysanturiin perustuva kaatumisen tunnistumenetelmä. Aineisto koottiin laboratorio-olosuhteissa kokeilla, joihin osallistui sekä nuoria että keski-ikäisiä. Raja-arvoon perustuvia tunnistusalgoritmeja testattiin 20 keski-ikäisen ohjeistettujen testikaatumisten sekä 20 keski-ikäisen ja 21 ikääntyneen arkisten askareiden tuottamalla datalla. Kaatumistapahtuman impaktin ja loppuasennon tunnistaminen vyötäröltä mitatuista kiihtyvyysarvoista erotteli kaatumisen muusta liikkeestä 95 % sensitiivisyydellä ja 100 % spesifisyydellä. Tunnistusmenetelmää testattiin kenttäkokeessa, jossa 16 ikääntynyttä hoitokodin asukasta piti vyötäröllään mittauslaitetta. Kuuden kuukauden aikana kiihtyvyyssignaali saatiin viidestä kaatumisesta. Yksi niistä aiheutti lonkkamurtuman. Analyysin mukaan näiden todellisten kaatumisten kiihtyvyyssignaalit muistuttivat testikaatumisia. Lonkkamurtumatapauksessa ennen impaktia mitattu nopeus oli erittäin korkea. Vastaavaa ei havaittu tapauksissa, joissa oli merkkejä siitä, että kaatumista oli yritetty estää. Kenttäkokeessa kaatumishälytysjärjestelmän sensitiivisyys oli 71.4 % ja vääriä hälytyksiä oli 1.1 vuorokaudessa.

Tutkimuksessa saatua tietoa tosielämän kaatumistapahtumista voidaan käyttää hyväksi kehitettäessä kaatumisten ehkäisyä, niiden mekanismin tutkimista sekä kaatumisen tunnistusta kiihtyvyysanturien avulla.

Asiasanat: ikääntyneet, kaatuminen, kaatumisen tunnistaminen, kaatumistunnistin, kenttäkoe, kiihtyvyysanturi, vanhus

To my family and friends

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Abbreviations and symbols

ADL	Activities of daily living
g	Gravitation unit, 1 g = 9.81 ms^{-2}
HP	High-pass
LP	Low-pass
MA	Martial arts
MMSE	Mini-Mental State Examination
n	Number of subjects or samples
ND	Not determined
PERS	Personal emergency response systems
PI	Posture index
PY	Person years
SD	Standard deviation
SV	Sum vector
WHO	World Health Organisation

List of original publications

This thesis is based on the following publications, which are referred to in the text by their Roman numerals:

I Kangas M, Konttila A, Winblad I & Jämsä T (2007) Determination of simple thresholds for accelerometry-based parameters for fall detection. Conf Proc IEEE Eng Med Biol Soc 2007: 1367–1370.

II Kangas M, Konttila A, Lindgren P, Winblad I & Jämsä T (2008) Comparison of low-complexity fall detection algorithms for body attached accelerometers. Gait Posture 28: 285–291.

III Kangas M, Vikman I, Wiklander J, Lindgren P, Nyberg L & Jämsä T (2009) Sensitivity and specificity of fall detection in people aged 40 years and over. Gait Posture 29: 571–574.

IV Kangas M, Vikman I, Nyberg L, Korpelainen R, Lindblom J & Jämsä T (2011) Comparison of real-life accidental falls in older people with experimental falls in middle-aged test subjects. In press.

The thesis also contains previously unpublished data related to paper IV.

Contents

1 Introduction

The proportion of older population aged over 65 years is growing rapidly in most countries. In Finland alone, this would mean an estimated number of over 1,500,000 older people in the year 2030 (Official Statistics of Finland 2009). Studies have indicated that about one third of home-dwelling older people fall each year (Tinetti *et al.* 1988). Falls are the leading cause of deaths by injury for the older population. On average 20% of falls result in injury, including major soft tissue injuries and fractures (Bergland & Wyller 2004, Lehtola *et al.* 2006). Besides physical injuries, falls may have other negative outcomes through resulting in or increasing fear of falling that affects the quality of life among older people, threatening their independent living and restricting their mobility and social activities (Suzuki *et al.* 2002, Yardley & Smith 2002).

Older people are afraid of remain lying and being unable to get up after falling (Melander-Wikman *et al.* 2007), and in reality, around half of fallers were not able to get up themselves (Bueno-Cavanillas *et al.* 2000). On average, fallers lie helplessly for more than 10 minutes after a fall, and in 3% of non-injurious fall cases the faller had been waiting for more than one hour before getting help (Tinetti *et al.* 1993). These long lies are associated with hospitalisation, institutionalisation and a high morbidity-mortality rate (Gurley *et al.* 1996, Tinetti *et al.* 1993). Older people are interested in new technologies aimed to support their independence and safety (Brownsell & Hawley 2004, Melander-Wikman *et al.* 2007). To prevent long lies commercially available personal emergency response systems (PERS) provide applications to call for help. However, in the case of an emergency, the person may be unable or unwilling to activate the PERS alarm. According to some reports, 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 (Fleming *et al.* 2008a, Heinbüchner *et al.* 2010). In such cases an automatic fall detector could detect a fall and call for help automatically. Hence, a highly accurate fall detection system is an important setting.

Some commercially available automatic fall detection systems exist, typically applying accelerometry-based detection methods and attachment sites at the waist or wrist as summarised by Noury *et al.* (2008). However, most fall detection applications in the literature are prototypes or applications for research purposes (Bourke *et al.* 2007a, Diaz *et al.* 2004, Karantonis *et al.* 2006, Lindemann *et al.* 2005, Mathie *et al.* 2004a, Yoshida *et al.* 2005). They are usually designed and tested with data collected from intentional falls and activities of daily living from young test persons in a laboratory environment. Even though good fall detection sensitivity and specificity in laboratory settings has been reported, knowledge on the sensitivity and specificity as well as acceptability and usability of these systems in real life is still scant or missing.

Fall mechanism may differ between age groups (Bergstrom *et al.* 2008), and self-initiated intentional falls differ from sudden unexpected falls (Robinovitch *et al.* 2004). So far, only few reports exist on acceleration data from real-life falls. Tamura (2005) reported that they were able to collect acceleration data from 19 real-life falls from a Parkinson patient and that the falls were detected by the fall detection algorithm for impact and end posture. Boyle & Karunanithi (2008) recorded acceleration data from four falls during 309 days during stroke rehabilitation. However, they did not report detailed acceleration data from those falls. Thus, real-life data on falls among older people is important for studying fall mechanism among older people and for evaluation and validation of fall detection systems.

The present study examined fall detection methods using accelerometry-based data from intentional falls and activities of daily living in laboratory settings. Additionally, the data from intentional falls used for validation of the fall detection system were compared to data from real-life falls among older people. The fall detection sensitivity and false alarm rate were evaluated in a long-term real-life test.

2 Review of the literature

2.1 Ageing population and falls

In most countries people aged 65 years or more, here referred to as older people, are estimated to represent around 30% of the population in the next 20 years. In Finland the estimated proportion of older people by the year 2030 is around 26%, as opposed to 18% at the time. This would result in over 1,500,000 older people (Official Statistics of Finland 2009). A big proportion of older home-dwellers live alone. Based on data from the year 2009 in Finland, around 30% of home-dwelling men over 80 years and more than 50% of women in age groups around 80 years lived alone (Official Statistics of Finland 2010).

Falls are one of the major health risks that affect the quality of life among older people by producing injuries and fear, resulting in decreased mobility and a high risk of hospitalisation and institutionalisation (Tinetti & Williams 1997, Tinetti & Williams 1998). As a consequence, the health care costs associated with falls are high, between 0.85–1.50% of total health care expenditure, and up to 0.20% of the gross domestic product (Heinrich *et al.* 2010).

The exact definition of a fall event is vague and it varies between studies. Two commonly used definitions are from the World Health Organisation (WHO)[1]: "A fall is an event which results in a person coming to rest inadvertently on the ground or floor or other lower level" and from the Kellogg International Work Group: "Unintentionally coming to the ground or some lower level and other than as a consequence of sustaining a violent blow, loss of consciousness, sudden onset of paralysis as in stroke or an epileptic seizure" (Gibson *et al.* 1987). Some studies exclude specific events such as coming to rest against furniture, wall, or another structure (Bueno-Cavanillas *et al.* 2000), or categorise falls from stairs or otherwise from higher than 1-metre level (Bergstrom *et al.* 2008), while some studies include all of these (Luukinen *et al.* 1994). The WHO definition is favored in this study since various kinds of falls can result in emergencies targeted at fall detection applications.

[1] WHO, World Health Organisation,
http://www.who.int/violence_injury_prevention/other_injury/falls/en/index.html

2.1.1 Falls among older people

Falls occur through out the human life span, but the risk of falls increases greatly starting at the age of 50 years (Lord & Sturnieks 2005, Talbot *et al.* 2005). Among older population the incidence of falls varies depending on age and gender. In general, several studies have indicated that about 30% of community-dwelling people aged 65 years or more have a fall each year (Lach *et al.* 1991, Luukinen *et al.* 1994, Salva *et al.* 2004, Tinetti *et al.* 1988), and the percentage increases to 40% among those over the age of 80 (Fletcher & Hirdes 2002, Luukinen *et al.* 1994, Salva *et al.* 2004, Tinetti *et al.* 1988). The average fall incidence among older people is about 650/1,000 person years, PY (Rubenstein & Josephson 2002). It is higher among women compared to men (Luukinen *et al.* 1994), at least until the age of 90 years, after which the incidences are equal (Lehtola *et al.* 2006). Institutionalised older people have a two- or threefold higher rate of falls when compared to those living at home (Jensen *et al.* 2002, Luukinen *et al.* 1994). This is also the case for some special populations, such as patients with Parkinson's disease (Wood *et al.* 2002) or stroke (Forster & Young 1995).

In general, from 10% to 20% of older people fall recurrently, i.e., fall at least twice within the time period ranging from three to 12 months depending on the study (Fletcher & Hirdes 2002, Luukinen *et al.* 1994, Pluijm *et al.* 2006). The proportion of recurrent fallers increases with age, resulting in almost half of home-dwellers over 85 years being recurrent fallers (Fleming *et al.* 2008b, Lehtola *et al.* 2006). The number of falls for one individual is wide-ranging and not normally distributed. Ranges up to 11 falls within one year (Bergland & Wyller 2004) or even up to 76 falls within three months (Stevens *et al.* 2008) have been reported, although the median number of falls has been reported to be one within three months (Stevens *et al.* 2008) or two within two years (Talbot *et al.* 2005). Falls are not necessarily evenly time-distributed and independent of each other, but clustered episodes of falls occur (Fleming *et al.* 2008b).

The number of reported falls has been shown to be affected by the survey type (Ganz *et al.* 2005, Kunkel *et al.* 2011). Even though a similar proportion of fallers has been reported by retrospective and prospective methods, the recall methods may underestimate the number of repeated falls. It has also been shown that the longer the recall period, the higher the prevalence of falling and the lower the incidence of falls (Fleming *et al.* 2008b).

2.1.2 Circumstances of falls

Even though falls are a multicausal phenomenon with variable factors, they can be classified according to the precipitating cause to either intrinsic or extrinsic. Intrinsic causes for falls are non-accidental and more health- and physiology-related risk factors for falls, including medication status and age-related changes in sensory system and balance and in the musculoskeletal function and gait. Intrinsic causes result in collapse episodes such as vertigo or syncope, or balance and gait disturbance. Extrinsic causes for falls are accidental and related to environmental factors such as footwear, uneven or slippery surface, steps or objects on the surface, and lightning. These episodes typically result in slips and trips. (Bueno-Cavanillas *et al.* 2000, Luukinen *et al.* 1994).

The causes of falls differ with age groups. From young adulthood (20–45 years of age) to older age intrinsic causes of falls, especially balance and gait impairment, become dominant over extrinsic causes (Talbot *et al.* 2005), especially after the age of 80 years (Luukinen *et al.* 1994).

The majority of falls among home-dwelling older people occur during the active hours of the day (morning and afternoon) and around 55% of the falls take place indoors, and 45% while inside the home Falls happen most often when doing ambulatory activities such as walking (54%) and transferring, like rising to stand or sitting down (9–12%). Indoor falls are more common in women than in men, whereas men are more likely to fall outdoors. (Lehtola *et al.* 2006, Luukinen *et al.* 1994).

The incidence of falls among older people shows some seasonal variation since low outdoor temperature has been reported to result in higher fall incidence (Luukinen *et al.* 1996). This relationship was not found in a recent Swedish study (Vikman *et al.* 2011), but they showed the incidence to be inversely proportional to the amount of daylight photoperiod.

2.1.3 Consequences of falls

Falls are one of the most common reasons for death among older people. According to a Finnish survey (Kannus *et al.* 2005a), the mean incidence of fall-induced deaths was 36.0, 83.9, and 377.6 per 100,000 persons in age groups of 60 to 69, 70 to 79, and 80 or more, respectively. In the following other consequences of falls are presented.

Injuries

Among home-dwelling older population, more than half of the falls lead to fall-related injury (Bergland & Wyller 2004, Talbot *et al.* 2005). Depending on the population, 16–24% of falls result in severe injuries requiring medical treatment, including 9–13% of fractures, the rest being for example soft tissue injuries and dislocations (Bergland & Wyller 2004, Lehtola *et al.* 2006). Hospitalised falls are mainly the result of slipping, tripping, and stumbling on the same level (Ellis & Trent 2001). Time of day affects the occurrence of non-injury and injury-causing falls. Injurious falls are overrepresented specifically in the morning and in the evening when compared to non-injury falls, which comprise the majority in the daytime. An equal number of non-injury and injury-causing falls occur in the night time (Abolhassani *et al.* 2006, Bergstrom *et al.* 2008, Lehtola *et al.* 2006, Luukinen *et al.* 1994, Luukinen *et al.* 2000). Recurrently falling women have an almost 14-fold risk of fall-associated fracture when compared to those with one previous fall or less (Bergland & Wyller 2004).

The prevalence of head and lower limb injuries, such as knees and hip injuries, increases, while the prevalence of upper limb injuries decreases among older people when compared to younger population (Bergstrom *et al.* 2008). The distribution of fractures among older people differs between falls that occur indoors and outdoors: hip and wrist fractures are most common indoors, whereas rib and wrist fractures are most common outdoors (Abolhassani *et al.* 2006).

Among older people, hip fractures are typically a result of falling from standing height or less. About 90% of hip fractures are the result of a fall (Grisso *et al.* 1991, Parkkari *et al.* 1999), even though only 1% of falls result in hip fracture. Hip fractures are the major and most consuming result of falls, associated with long hospital stay, high reference to long-term care facilities and high mortality (Abrahamsen *et al.* 2009, Lönnroos *et al.* 2009, Tinetti & Williams 1997). From the late 1990s a decline in age-adjusted incidence of hip fracture has been reported in Finnish population (Kannus *et al.* 2006) as well as generally for Western populations (Cooper *et al.* 2011). The exact reason for this is unknown but it suggests a trend toward a healthier aging population and increased average body weight and improved functional ability among them (Kannus *et al.* 2006). On the other hand, based on the rising trend in age-adjusted incidences of severe head and cervical spine injuries, it has been suggested that a growing proportion of older people may fall more seriously than they predecessors (Kannus *et al.* 2007a, Kannus *et al.* 2007b).

Long lies and fear of falling

It has been established that the outcome for patients is generally the poorer the longer the time spent helpless after the accident. Long lies are associated with pneumonia, pressure sores, dehydration, and hypothermia and with hospitalisation, institutionalisation and high morbidity-mortality rate (Gurley *et al.* 1996, Tinetti *et al.* 1993).

It has been described that older people are afraid of remain lying on the floor, unable to get up after a fall (Melander-Wikman *et al.* 2007). According to studies around half of the older people were not able to get up themselves after the fall (Bueno-Cavanillas *et al.* 2000, Fleming *et al.* 2008b). The average time lying helpless after a fall among older people was more than 10 minutes, and almost 20 minutes in fall events not resulting in or resulting in injuries, respectively, and in approximately 3% of non-injurious falls the faller had been on the floor more than 1 hour before getting help (Tinetti *et al.* 1993). In a cohort study with 110 people over 90 years of age, 82% of falls occurred when the person was alone and around 30% of fallers had lain on the floor for an hour or more before getting help (Fleming *et al.* 2008a).

Fear of falling is common among older people. Around 40–60% of people who have fallen express fear of falling in surveys, but also among those who have not fallen 23–30% report fear of falling (Cumming *et al.* 2000). Fear of falling is a risk factor of falls, and it is associated with quality of life among older people (Ozcan *et al.* 2005, Suzuki *et al.* 2002). It contributes to insecurity and decline in ADL functions, restricting mobility and social activities (Curcio *et al.* 2009), especially among recurrent fallers and those fallers who have sustained serious injuries (Tinetti & Williams 1998).

2.1.4 Fall mechanism

Fall-associated injury severity is higher among older people when compared to younger population (Sterling *et al.* 2001). This has been suggested to be partly due to the increased incidence of falling and physiological factors related to fragility among older people (osteoporosis, loss of protective neuromuscular responses, and decreased energy absorption capacity of soft tissues). In addition, a role of differences in fall mechanism between young and older people has been suggested. (Järvinen *et al.* 2008).

Experimentally it has been shown that young adults use hands and stepping to avoid direct impacts or decrease the impact forces during sideway falls. Sudden unpredictable sideways falls resulted most frequently in impact cascade of the knee, hand, and hip (Feldman & Robinovitch 2007). During backward falls impact forces can be reduced by squatting response, *i.e.*, flexing the lower extremity joints during fall (Robinovitch *et al.* 2004, Sandler & Robinovitch 2001). The effect of active responses with the arm on decreasing impact forces on the shoulder and hip has also been shown in other reports (Lo & Ashton-Miller 2008, Sabick *et al.* 1999). The review by DeGoede *et al.* (2003) presents these fall-arrest strategies aimed to reduce upper body injuries.

It is known that older people have poorer balance performance when compared to younger persons (Aslan *et al.* 2008), which increases the likelihood of falling. Age-related decline in musculoskeletal function and longer reaction time affects older people's ability to recover from falls (Hsiao-Wecksler 2008) and exploit strategies to decrease fall-associated impact velocities and forces at the hip and wrist (Grisso *et al.* 1991, Sandler & Robinovitch 2001). Experimentally it has been tested that the tilt angle from the vertical axis where a person could recover balance with forward steps is around 20 degrees for older people and over 30 degree for young men (Thelen *et al.* 1997, Wojcik *et al.* 1999). Among people under 60 years of age, the dominant fracture sites after a fall are at the upper extremities, such as wrist or forearm, and the ankles. With increasing age most fractures are a result of slips or falls from standing height or less, and the frequency of hip and pelvis as fracture sites increases. The frequency of wrist fractures decreases, indicating that older people are not able to stretch their arm to brake the fall (Bergstrom *et al.* 2008).

In a prospective study by Parkkari *et al.* (1999), a typical fall event among older people resulting in hip fracture was a fall from standing height or lower directed sideways (76%) or obliquely backwards (12%), with the main impact at the greater trochanter (81%). In most (83%) of the cases the person was not able to brake the fall, e.g., with an outstretched arm. In fall cases not resulting in hip fracture the main fall directions were forwards (38%) or obliquely backwards (27%) with impacts directed on the buttocks, shoulder, and hands. In almost half (42%) of the cases, the faller was able to perform actions to brake the fall. (Parkkari *et al.* 1999).

The impact-associated parameters have been studied experimentally with fall and failure load studies. During lateral and backwards falls average impact forces of 2251–3247N have been measured (Nankaku *et al.* 2005). These are equal to the typical experimental failure loads of the hip for older people (Pulkkinen *et al.* 2006).

Based on the review by DeGoede *et al.* (2003) more than half of the falls among older people are directed forwards, the rest being equally divided between sideways and backwards falls. Most of the falls among the older people occur when walking; age-related decline in preferred speed of walking (Fitzpatrick *et al.* 2007) may thus influence the fall mechanisms. Experimentally it has been shown that in some fall types, fall directions and impact sites are related to the walking speed during the event (Smeesters *et al.* 2001). While fainting from a walking speed typical for young and middle-aged persons (at least 1.43 ms^{-1}) results almost entirely in forward falls, the distribution of fall directions after fainting from the slow gait speed more typical for older people (0.66 ms^{-1}) is equally to front and sideways, and in 71% of cases the impact is located to the abdomen, whereas the rest of the impacts are located to the hip. Slipping from walking is a heterogeneous fall type resulting in backward (43%), sideway (36%) or front (21%) falls, thus resulting in impacts equally between the hip and buttock. Tripping results almost entirely in front falls with abdomen impacts, and a few sideways falls with hip impacts. Stepping down on empty air shows a similar distribution of impact locations compared to fainting but most of the falls are directed to the front. (Smeesters *et al.* 2001).

2.2 Prevention of falls and consequent injuries

Falling has been a motivating target for preventative strategies. They aim to reduce the incidence of falls by reducing the risk factors for falls, or to decrease the severity of falls by improving bone characteristics (bone mass and density) or by modifying the type of falls that occur. These strategies include regular exercise, vitamin D and calcium supplementation, withdrawal of psychotropic medication, cataract surgery, environment hazard modification, and hip protectors. (Kannus *et al.* 2005b, Lord & Sturnieks 2005).

Evidence on the effectiveness of multifactorial fall prevention programmes is limited (Gates *et al.* 2008, Hendriks *et al.* 2008). However, the estimated effect of exercise was a 17% reduction in rate of falling among older people in community and residential facilities as reviewed by Sherrington *et al.* (2008). This survey highlighted that exercises including strength and balance training or the use of higher dose of exercise, but not including walking, can reduce the risk of falling. The advantageous effect of exercise on reduction of fall-related fractures among individuals with lowered bone mineral density has also been shown (de Kam *et al.* 2009, Korpelainen *et al.* 2010).

Experimentally it has been analysed that older people are capable of learning to recover better or adjust to slip perturbation through repeated exposure (Pavol *et al.* 2002). Martial arts (MA) fall techniques involve rolling on after impact. They may reduce hip fracture risk, as they are known to reduce fall-associated hip impact forces in laboratory experiments with experienced judokas (Groen *et al.* 2007) or after a short training session with young persons (Weerdesteyn *et al.* 2008). Martial arts training among older people was shown experimentally to be able to reduce hip impact forces by a mean of 8%, and the fear of falling was also reduced (Groen *et al.* 2010a). By using hip protectors, MA training has been considered to be safe also for persons with osteoporosis (Groen *et al.* 2010b). Other MA training techniques, such as TaeKwon-Do (Brudnak *et al.* 2002) or Tai Chi (Hackney & Earhart 2008), have been shown to have beneficial effects on balance performance. The effect on reducing falls has not been so evident (Lin *et al.* 2006, Logghe *et al.* 2011).

Hip protectors have been designed to absorb the hazardous fall-associated impact energy in order to prevent hip fractures. In a specific group of older women with fall history and low bone mineral density, the risk of hip fracture was reduced by hip protectors with incidence of 54.0/1,000 PY and 78.8/1,000 PY in intervention and control groups, respectively, while the risk of pelvis and other fractures was similar between groups (Koike *et al.* 2009). However, pooled data from several studies showed no significant reduction in hip fracture incidence among older people using hip protectors. The most common general problem with hip protectors is related to compromised user compliance and adherence as a result of discomfort, poor fit and skin irritation (Parker *et al.* 2003). A different strategy to protect the hip and head during falls is the use of wearable inflatable airbags, instead of foam pads or plastic shields, to protect the head and thighs from high fall-associated impacts, as suggested in the pilot system experimentally tested by Tamura *et al.* (2009).

2.3 Fall detection

Approaches for remote telemonitoring for older people have been seen as a way to meet the needs of an ageing population (Korhonen *et al.* 2003, Ni Scanaill *et al.* 2006, Rocha *et al.* 2011). Detection of falls is one of the areas of interest. General principles and methods of fall detection have been reviewed by Noury *et al.* (2007, 2008) and Yu (2008).

Applicable techniques for fall detection include a variety of methods and designs with body-worn or built-in devices. Worn devices include personal emergency response systems (PERS) that require the user to activate the alarm. Personal emergency response system is reported to have positive impact on user's life and high satisfaction (De San Miguel & Lewin 2008, Heinbüchner *et al.* 2010). Concern with falling is a major reason for activating PERS among older people. Mann *et al.* (2005) reported that 40% of alarms were generated because of fall-related reasons among people with disabilities and aged 60 years or more, and an even higher percentage (56%) was reported by De San Miguel & Lewin (2008). Among those who had not activated the alarm, 90% had never had an emergency situation where they needed to use it. Conversely, over 80% of fallen persons not able to get up did not activate the alarm (Fleming *et al.* 2008a, Heinbüchner *et al.* 2010). Reasons for not activating the alarm button were the desire for independence and for being able to manage by themselves, waiting for someone else to come, or not remembering the PERS (Fleming *et al.* 2008a). The general compliance is rather low, as well as the use in the shower, bath or in bed (De San Miguel & Lewin 2008). This reflects the reduced night-time security.

In automatic fall detector's favour, they are designed to generate alarm automatically. Some systems monitor changes in the user's activity level and generate alarms automatically if deviations from the normal long-term activity level occur (Särelä *et al.* 2003), whereas some systems are designed to detect specifically fall events (Noury *et al.* 2007, 2008). Studies on automatic fall detection methods based on ambient and body-attached sensors are presented in 2.3.1 and 2.3.2.

Evaluation of fall detection system is based on determining the number of falls detected (true positives TP) or not detected (false negatives FN) by the system, and the number of activity of daily living (ADL) detected (false positive FP) or not detected (true negative TN) as fall events. Based on those values sensitivity, specificity and accuracy of fall detection can be calculated as shown below. Sensitivity (Eq. 1) represents the percentage of true falls that were correctly detected, 100% indicating that all falls were detected.

$$Sensitivity = \frac{TP}{TP + FN} \times 100\% \qquad (1)$$

Specificity (Eq. 2) is related to the percentage of false fall alarms among ADL samples, 100% indicating that no false alarms were detected.

$$Specificity = \frac{TN}{TN + FP} \times 100\% \tag{2}$$

Accuracy (Eq. 3) represents the percentage of true discrimination between falls and ADL, 100% indicating 100% sensitivity and specificity.

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \times 100\% \tag{3}$$

In addition, some reports calculate a false alarm rate as the number of false fall alarms over a certain time period of ADL.

2.3.1 Ambient sensors

Ambient systems with video cameras and sensors embedded on the floors, walls or furniture are considered to be passive and unobtrusive to the resident because they do not require the user to wear any devices. Video-based algorithms designed to detect fall-associated changes in the height or shape of the person (Anderson *et al.* 2009, Perry *et al.* 2005) or in the angle between the person's main axis and floor level (Willems *et al.* 2009) have been reported. A pilot study with intentional falls showed fall detection sensitivity of 78–85% with 11–15% of ADL samples detected as falls (Willems *et al.* 2009). In addition to video, infrared technology has been used for developing algorithms for fall detection. Sixsmith & Johnson (2004) reported such a system with experimental fall detection sensitivity of 35.7% and specificity of 100%. In a field test over a two-month period the system generated one false fall alarm, but no real-life falls were reported. They also interviewed older people about the idea of using such a system. Some older participants expressed concerns about the intrusiveness and the replacement of human contact by technology (Sixsmith & Johnson 2004).

Electromechanical film, EMFi (Paajanen *et al.* 2000), has been used for bed monitoring system for falls and wandering prevention or presence detector in a chair etc. The study of Rimminen *et al.* (2010) presented the use of near field imaging technique embedded on the floor for spatial distribution of objects, such as persons, in an elderly care facility. In a pilot test with intentional falls and ADL they showed fall detection sensitivity and specificity of 91% and 91%, respectively (Rimminen *et al.* 2010). Other methods for ambient fall detection include for example acoustic- and vibration-based methods. An acoustic system was able to detect intentional falls with a specificity of 100% and false alarm rate of 5 alarms per hour (Popescu *et al.* 2008). A floor vibration-based fall detection method achieved 100% sensitivity and specificity in an experimental study with dummies for falls (Alwan *et al.* 2006). Litvak *et al.* (2008) combined these two techniques and tested the system experimentally with a human mimicking doll for forward falls, resulting in 95% sensitivity and specificity. No real-life evaluation of these ambient systems has been reported. In addition, these techniques are expensive and tied to fixed environment.

2.3.2 Body-attached fall detection applications

Body-worn systems are intrusive as they require the user to wear the detector device. One of the first fall detection applications was introduced by Williams *et al.* (1998). It was designed to detect fall-associated impacts, posture and recovery. Most of the body-attached fall detection applications include tilt sensors and/or inertial sensors, such as accelerometers and gyroscopes, to measure body posture and kinetic forces. The use of barometers has also been suggested as a method to detect height change related to a fall. Studies on fall detection applications using kinematic sensors and barometers are summarised in Table 1. In addition to these, the applicability of biosignals such as heart rate and skin resistance has been studied for fall detection (Nocua *et al.* 2009). Based on their results, monitoring of autonomic nervous system activation was able to detect experimental falls from standing-lying transition, but the system was not tested further.

Most of the studies on fall detection applications include off-line data processing and analysis for evaluation of fall detection sensitivity and specificity (Bourke *et al.* 2007a, Lindemann *et al.* 2005, Quagliarella *et al.* 2008). Some applications exhibit wider system functionality, including real-time data processing and analysis in order to detect falls and generate alarms to a call centre or relatives (Benocci *et al.* 2010, Estudillo-Valderrama *et al.* 2009, Kang *et al.* 2006). Today, many mobile phones include accelerometers; they can thus be applied for fall detection (Sposaro & Tyson 2009). In addition to these applications presented in scientific publications, commercial fall detection systems are available as shown in a review of Noury *et al.* (2008) with 7 examples of commercially available fall detection systems and over 40 patents on fall detectors. Commercial applications include devices typically attached either to the waist or the wrist. A bracelet-type solution has also been presented[2]. Even though commercial fall detection systems exist, knowledge on the sensitivity and specificity as well as acceptability and usability of these systems in real life is still scant or missing.

Detection of fall phases

Machine-learning methods applied for fall detection have been summarised by Noury *et al.* (2007). Dinh *et al.* (2009) evaluated five different machine-learning algorithms with data from an acceletometer and a gyroscope. They experimental results indicated that the Naïve Bayes algorithm performed most efficiently, showing fall detection accuracy of 97.3% and the shortest performance time. Lustrek & Kaluza (2009) used markers on the body and compared eight machine-learning algorithms for activity and fall detection. They tested the system experimentally and reported the highest classification accuracy of over 95% by Support Vector Machine. However, most of the fall detection systems use analytical methods, such as threshold-based methods, to detect fall phases in order to distinguish falls from ADL. These simple analytic methods seem to perform equally well to more advanced methods (Table 1).

Some characteristics of interrupted movement can indicate the incoming fall already some seconds before the actual fall event, as suggested by for example Tamura *et al.* (2000). However, most of the fall detection algorithms in the literature (Table 1) are designed to detect one or more of fall phases. Fall is a cascade of phases (Noury *et al.* 2008): 1) normal ADL, such as walking, sitting down; 2) critical phase or pre-impact phase, which can be further divided into sudden free fall-like movement of the body towards the ground and impact to the ground; 3) post-fall phase with the person lying on the ground; and 4) recovery phase if the person is able to get up and move after fall. Figure 1 shows an example of acceleration signal and fall phases in a fall starting from a standing posture and ending up in a horizontal end posture.

Pre-impact velocity before the impact (Figure 1) has been used to distinguish falls from ADL. Monitoring the velocity instead of acceleration is used to determine activities where high acceleration values but low velocities are generated, for example, when lying down, sitting down, or walking the stairs.

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[2] Philips Lifeline, http://www.lifelinesys.com/content/lifeline-products/auto-alert

Video-based movement analyses have suggested that upper body horizontal and vertical velocities from ADL are within a well-controlled range, and only in one direction at the time, but during intentional falls velocities are much higher when compared to ADL, and the increase in two directions is simultaneous (Wu 2000). Based on Bourke *et al.* (2007a) falls can be distinguished from ADL with a simple threshold for video-based vertical velocity.

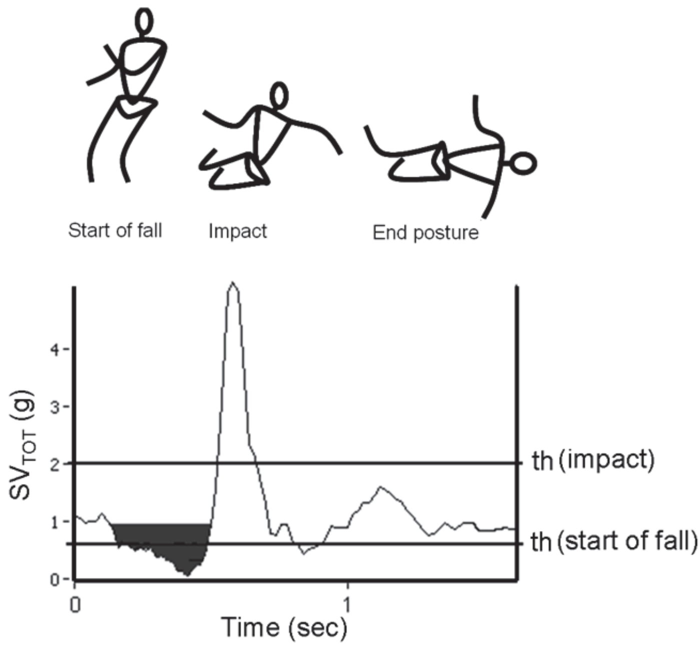

Fig. 1. Fall phases from 3D acceleration sum vector (SV) are detected with threshold (th) based methods. Start of the fall is detected at the pit before impact. By integrating the area in pit (dark) the pre-impact velocity from the free fall can be measured. The fall-associated impact is detected as a high peak in signal.

Also inertial sensors have been used to measure pre-impact vertical velocity for fall detection (Wu & Xue 2008). It has also been shown that the velocity integrated (Figure 1) from acceleration sum vector, SV (Eq. 4), is comparable to vertical velocity from video-movement analysis (Bourke *et al.* 2008a).

$$SV = \sqrt{(A_x)^2 + (A_y)^2 + (A_z)^2} \tag{4}$$

in which A_x, A_y, A_z = acceleration (g) in x-, y-, and z-axes, respectively.

Pre-impact velocity method has resulted in an average lead time of 300–400 ms (Bourke *et al.* 2008a), which is the time between specific detection of the coming fall from the pre impact and the impact to the ground. An even longer lead time has been achieved when using gyroscopes to measure the tilt angle of the body. This method has resulted in average lead time of 700 ms (Nyan *et al.* 2006, Nyan *et al.* 2008a, Nyan *et al.* 2008b). Pre-impact velocity has also been used for fall detection applications at the wrist (Degen *et al.* 2003) and head (Lindemann *et al.* 2005). In addition to velocity, the SV signal containing both dynamic and static acceleration components has been used to detect the start of the fall (Figure 1) from the pre-impact phase (Bourke *et al.* 2007a, Degen *et al.* 2003).

Fall-associated impacts have been detected with the threshold-based method for high acceleration (Karantonis *et al.* 2006, Bourke *et al.* 2010b) or a rapid change in acceleration (Yoshida *et al.* 2005). At its simplest, a single axis acceleration threshold value of 1.4g for waist has been used as a marker for a possible fall event (Diaz *et al.* 2004). However, the threshold for SV of triaxial accelerometer signal has been suggested to be more accurate in fall detection than single axis thresholds (Bourke *et al.* 2005). Chao *et al.* (2009) presented the use of cross product of current acceleration vector and reference acceleration vector from static standing to detect fall-associated impacts.

Most of the falls among older people begin when a person is in upright position and ends up in sitting or lying posture. Gyroscopes and tilt sensors (Hwang *et al.* 2004) as well as accelerometers (Fahrenberg *et al.* 1997, Karantonis *et al.* 2006) have been used for body posture detection. The study by Culhane *et al.* (2004) reported long-term accelerometry-based monitoring of static postures of older people with accuracy of 92%, 98%, and 95% for sitting, standing, and lying, respectively.

Body posture can be determined as an angle between the acceleration axis and gravity, by extracting the static gravitational component from the acceleration (Karantonis *et al.* 2006) or by taking the dot product of the reference gravity vector and the current gravity vector (Bourke *et al.* 2010b). Fall-associated posture is determined as a change in the posture before and after the impact (Boissy *et al.* 2007, Yoshida *et al.* 2005) or as the end posture a few seconds after the fall associated impact (Karantonis *et al.* 2006, Tamura 2005, Yoshida *et al.* 2005). The recovery from a fall is recognised as an upright posture or as a certain amount of activity after a possible fall event (Karantonis *et al.* 2006). The durations of posture changes from sitting to standing or from lying to standing were 3.5 and 6.0 s in a group of healthy 80- to 86-year-old people (Yoshida *et al.* 2005). The recovery after a fall probably takes even a lot longer than indicated above.

Evaluation of fall detection systems

Fall detection applications vary substantially from study to study, showing diversity in terms of attachment sites on the body, fall detection algorithms and study designs for sensitivity and specificity evaluations (Table 1).

The placement of an acceleration sensor for measuring body movements for fall detection has been studied to some extent. Doughty *et al.* (2000) showed that the acceleration patterns measured at the waist and chest are similar and evenly distributed between different fall types, while knee- or thigh-worn accelerometers result in lower fall-associated impact values when compared to signals from the waist (Doughty *et al.* 2000). Boissy *et al.* (2007) showed that the data from sensors on the chest or the underarm are similar.

Waist-attached accelerometers are located near the body's centre of gravity providing reliable information on subject's movements and posture, with the exception of movements of the arms and legs (Brownsell & Hawley 2004). Most fall detection applications are attached on the torso at the waist or chest (Table 1). They have fall detection sensitivity varying from 70 to 100% and specificity from 95 to 100% in laboratory settings with intentional falls. Fall detection sensitivity has shown variation between test subjects. For example, the study of Boissy *et al.* (2007) showed fall detection sensitivity of 80–100% and specificity of 50–80% in a test population of 10 young people.

Table 1. Overview of studies of body-attached fall detectors applying accelerometers, gyroscopes or barometers.

Study	Attachment[1]	Method[2]	Test subjects[3]	Algorithm[4]	Sensitivity[5]	Specificity[6]
Mathie *et al.* 2004a	W	A	2	I + ACT	80.5% (8)	100%
Diaz *et al.* 2004	W	A	8 (young)	I + energy of signal	89.6% (48)	40%
Chen *et al*. 2005	W	A	–	V + I + P	–	–
Tamura *et al.* 2005	W	A	1 (aged)	I + P	86% (22) RL	–
Yoshida *et al.* 2005	W	A	6 (young)	I + P	70% (30)	–
Karantonis *et al.* 2006	W	A	5 (young), 1 (aged)	I + ACT	96% (45)	–
Srinivasan *et al.* 2007	W	A	15 (young)		95% (96)	100% (1288)
Boyle & Karunanithi 2008	W	A	1	I	100% (201)	
Quagliarella *et al.* 2008	W	A	10 (aged), 10 (young)	I + P + ACT	100% (100)	100% (100)
Wu & Xue 2008	W	A, G	10 (young), 14 (aged)	V	100%	100%
Chao *et al.* 2009	W, C	A	7 (young)	I, I+P	98.2-100%	92.4–99.2%
Estudillo-Valderrama *et al.* 2009	W	A	31 (young)	I + P	100%	95.7%
Benocci *et al.* 2010	W	A	3 (young)	I+P	100% (67)	100%
Bianchi *et al.* 2010	W	A, B	5–20 (young)	I + ACT; I + P; I + pressure change + P + ACT	In: 1) 75.0–97.5% (160); Out 2) 83.3–86.7% (39)	1) 67.0-96.5% (160); 2) 100% (10)
Bourke *et al.* 2010b	W	A	10 (aged), 10 (young)	I, I+P, V+I+P, V+I, V	94.6–100% (240)	100%(360), FP 0.04–2.75/hour (RL 52.4h)
Nyan *et al.* 2008b	W, T	A, G	21 (young)	Lean angle	95.2% (42)	100% (216)
Noury 2003	UA	A	10 (young)	P	79% (450)	83% (300)
Hwang *et al.* 2004	C	A,T,G	3 (over 26y)	I + P + ACT	97% (90)	100% (3)
Bourke *et al.* 2005, Bourke *et al.* 2007	C, T	A, G	10 (aged), 10 (young)	Start of the fall, I	100% (240)	67.0-100%
Boissy *et al.* 2007	C and UA	A	10 (young)	I + P	93% (450)	71% (300)
Bourke & Lyons 2008	C	G	10 (young), 10 (aged)	P	100% (240)	100% (240)
Bourke *et al.* 2008a	C	A	5 (young)	V	100% (60)	100%

Study	Attachment[1]	Method[2]	Test subjects[3]	Algorithm[4]	Sensitivity[5]	Specificity[6]
Bourke et al. 2008b	C and UA	A	11 (young), 5 (aged, RL)	I + P + ACT	90.5-97.0%	99.4%, 42 false alarms/833 hours (RL)
Lindemann *et al.* 2005	H	A	1 young, 1 aged	I, V + I	100%	100%, (also RL)
Wang *et al.* 2008	H	A	5	I, V	(105) 100%	100%
Degen *et al.* 2003	WR	A	3	Start of the fall+V + I + ACT	65% (45)	100% (RL 48h)
Kang *et al.* 2006	WR	A	5	I+P	91.3% (150)	–

[1]W = waist, WR = wrist, C = chest, UA = under arm, T = thigh, H = Head; [2]A = accelerometer, T = tilt sensor, G = gyroscope, B = barometer; [3]n (age group)
[4]I = impact, P = posture, V = velocity, ACT = activity; RL = real-life; [5](n, fall samples); [6](n, ADL samples).

At the trunk pre-impact velocity (Bourke *et al.* 2008a, Lustrek & Kaluza 2009, Wu & Xue 2008) and pre-impact lean angle (Nyan *et al.* 2008a, Nyan *et al.* 2008b) have been suggested to be able to distinguish falls form ADL with 100% sensitivity and specificity. Also those studies were performed with data collected from intentional falls and ADL.

There have been suggestions to integrate a fall detector into another device, such as a wrist watch (Degen *et al.* 2003, Kang *et al.* 2006) or a hearing-aid housing (Lindemann *et al.* 2005). The usability of a wristband is considered to be excellent. However, the acceleration signal measured from the wrist varies widely as a function of fall type, and a person who has fallen and is incapable of getting up can still be able to move his/her arms (Doughty *et al.* 2000). The wrist-worn fall detector of Degen *et al.* (2003) showed experimentally good fall detection sensitivity as far as forward falls were concerned, but lower sensitivity for falls backwards (58%) and sideways (45%) resulted in moderate overall sensitivity of 65% (Table 1). There were no false alarms during a two-day test in real life. Their fall detection algorithm was based on pre-impact velocity and impact detection (Degen *et al.* 2003). In a study by Kang *et al.* (2006) intentional falls were detected with 91.3% sensitivity based on an algorithm identifying fall-associated impact and horizontal end posture. The specificity of the system was not reported.

The head as an attachment site is motivated by the argument that the people try to protect the head against high accelerations which are mostly associated with unpleasant movements, such as fall events. Head injuries are relevant injuries after falls among older people (Kannus *et al.* 2007a). Based on the pilot studies of Lindemann *et al.* (2005) and Wang *et al.* (2008), the detection of high pre-impact velocity and an impact resulted in fall detection sensitivity and specificity of 100% in experimental conditions. It is to be noted that not all older people use hearing aids, which may restrict the applicability of fall detection applications integrated on those.

Multisensorial applications have been tested for fall detection. Combining a gyroscope to an accelerometer does not necessarily improve the specificity of fall detection (Bourke *et al.* 2005). However, Bianchi *et al.* (2009, 2010) showed recently in their experimental study indoors and outdoors that adding fall-associated height change information from a barometer to acceleration data to detect fall phases, improves fall detection sensitivity, specificity and accuracy from 75.0% to 97.5%, from 91.5% to 96.5%, and from 85.3% to 96.9%, respectively. The system was not tested in real life with older people.

Because of the dangerous nature of fall events, fall detection studies are typically performed using intentional falls among young test persons (Table 1) to perform fall scenarios to mimicking falls among older people. Various fall scenarios have been summarised by Noury *et al.* (2007) including forwards, backwards and lateral falls with or without landing on knees, using protective movements such as arms or upper body rotation. There are some studies that have focused more on this issue, for example by using a stunt actor who was trained to fall like an older person (Popescu *et al.* 2008) or by showing young test persons videos of real-life falls among older people to mimic the characteristics of older people's falling mechanism (Boyle & Karunanithi 2008, Boyle *et al.* 2005).

Some attempts to collect real-life acceleration data from falls have been reported. Tamura (2005) reported that they were able to collect acceleration data from 19 real-life falls from a 82–year-old Parkinson patient. These falls were detected with algorithm monitoring characteristics for impact and end posture, but no acceleration signals or specificity evaluations were reported. Boyle & Karunanithi (2008) recorded acceleration data from four falls during 309 days in older stroke rehabilitation inpatients. However, they did not report detailed acceleration data on the falls. Recently, Klenk *et al.* (2011) reported acceleration data from five real-life backwards falls from four older Parkinson patients with progressive supranuclear palsy. However, they did not report any evaluation of fall detection algorithms.

Some attempts to evaluate fall detection applications in real life have been reported. Bourke *et al.* (2008b) incorporated their earlier developed accelerometry-based fall detection system into a custom design vest. The system was tested with older people in real life for two weeks during daytime. The sensor was designed to generate fall alarms and send them via a Bluetooth connection to a mobile phone, which sent the alarm message further to a care centre via a 3G network and Internet. During the monitored 833 hours the test population reported no falls, but the system generated 42 false fall alarms and technical problems in data communications were reported. The usability of vest-worn application was found to be limited because they were uncomfortable and intrusive (Bourke *et al.* 2008b). Another study involved testing of a waist-worn fall detection system for 52 hours among older people in their home environment (Bourke *et al.* 2010a). No falls occurred among the test population in that study, either.

Fall detection specificity is tested with ADL, mostly collected from instructed tasks, like walking, sitting down on a chair and standing up, and lying down on the bed and getting up. As seen in Table 1, fall detection specificity is often 100%

with instructed ADL, and in some reports also with short-term real-life tests. Bourke *et al.* (2010b) tested several fall detection algorithms with data collected from both instructed and real-life ADL among older people. Based on their study, algorithms resulting in 100% specificity with instructed ADL resulted in false alarm rate between 0.04 – 0.21 alarms per hour with data collected from real life.

In conclusion, despite the growing number of applications and surveys on fall detection in a laboratory environment, knowledge on the sensitivity and specificity as well as acceptability and usability of these systems in real life with older people is still scant or missing. In addition, real-life acceleration data on falls among older people is very limited.

3 Aims of the study

Falls are a serious health risk in the ageing population. Automatic fall detection has been suggested as a promising approach to decrease the consequences of falls. Even though some commercial fall detectors are available, knowledge on the sensitivity and specificity of fall detection in older people in real life setting is limited. This study examines accelerometric techniques to discriminate between falls and ADL for automatic fall detection applications. The general purpose of this study was to study methods for fall detection to be adapted for real-life applications in the older population.

The specific aims of the study were:

- to compare different attachment sites for measuring acceleration data for fall detection applications
- to define an algorithm for discriminating between falls and ADL
- to define the sensitivity and specificity of fall detection in a laboratory environment with the developed method
- to compare real-life data from falls among older people with data from intentional falls in younger subjects
- to define the sensitivity and false alarm rate of fall detection in real life with older people

4 Materials and Methods

This study is composed of three laboratory tests and one field test in Oulu, Finland and in Kalix and Luleå, Sweden. The subpublications of this thesis are referred to in the text by their Roman numerals I-IV. Table 2 summarises the subjects and study design in each study.

4.1 Subjects

All test subjects were voluntary participants who received oral information about the study and from whom a written informed consent was obtained. The study protocols in III and IV were approved by the local ethical board in Umeå, Sweden, (05–105M and 2443–2009, respectively), and in IV also in Oulu, Finland, (39/2009). In III and IV, the average walking speed of test persons was determined based on a 10-m walking test indoors and cognitive functions were assessed using the Mini-Mental State Examination, MMSE (Folstein *et al.* 1975).

In I and II, voluntary test persons were recruited by personal communication from among students and staff at the University of Oulu. In I two test persons (male and female, aged 22 and 38 years) performed intentional falls and ADL in a laboratory environment. In II three volunteers, one female (38 years) and two males (42 and 48 years), performed intentional falls. ADL samples collected in I were used (Table 2).

Study groups in III were collected from two populations (Table 2). The first population included 20 middle-aged persons (age range 40–65 years) recruited by personal communication from among staff at Luleå University of Technology. The inclusion criterion was the age of 40–65 years. They performed intentional falls and instructed ADL sequence in a laboratory environment. The second test group was 21 voluntary older people (age range 58–98 years) recruited from those living in or participating in activities in two residential care facilities. An inclusion criterion was the ability to walk alone. Older people performed an instructed ADL sequence at the care facility. The average indoor walking speed was 1.43 ± 0.20 ms^{-1} and 0.75 ± 0.30 ms^{-1} for middle-aged and older people, respectively.

In IV people living in elderly care units were recruited to wear the acceleration sensor system for real-life data collection. The inclusion criteria for the test subjects were age above 65 years and the ability to stand alone or with the help of one person. The test population of 16 subjects (age range 80–101 years) included 7 (all females) and 9 (6 females, 3 males) persons from Sweden and Finland, respectively. The average indoor walking speed of the test subjects was $0.56 \pm 0.31\ ms^{-1}$. The test period presented in this study was around six and two months in Sweden and Finland, respectively. The sensor system was used during waking hours or 24/7 if desired.

4.2 Accelerometry

Acceleration signals were collected during intentional falls and ADL (I, II, III) and during real-life falls (IV) with a body-attached sensor. Sensors were attached with elastic belts to the non-dominant wrist (I, II), to the waist in front of the anterior superior iliac spine (I, II, III), or in front of the forehead (I, II). The sensitive axes of accelerometers were mediolateral, anteroposterior, and vertical (I, II, III). In IV the sensor was attached with a clip into 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 accelerometers used in I and II were custom-made devices (Vihriälä *et al.* 2003) designed to collect acceleration data in short-term tests. The system included triaxial accelerometers, each constructed using three uniaxial capacitive accelerometers (VTI Hamlin SCA CDCV1G) with amplitude range of ±12g. Each triaxial accelerometer was connected to a separate data logger with a sampling frequency of 400Hz for each axis. The sensor dimensions were 20 mm x 15 mm x 20 mm.

A prototype device in III integrated a ±3g triaxial capacitive accelerometer (ADXL330, Analog Devices) with a sampling frequency of 50Hz for each axis. The hardware platform included a transceiver enabling RS232 communication. The sensor dimensions were 109 mm x 69 mm x 24 mm. Based on the protototype in III, a small-size wireless detector unit was developed (CareTech AB, Kalix, Sweden) containing a ±4g triaxial capacitive accelerometer (Analog Devices) and a transceiver (868.35 MHz). The dimensions of the device were 52 mm x 33 mm x 24 mm, and it weighed 26 g (Fig. 2).

Table 2. Summary of test subjects and number of acceleration samples for each study I-IV.

Study setup	Persons N	Sex (F/M), n	Age years	Activities	Samples, n Waist	Head	Wrist	Place and time
I: Laboratory test to compare different attachment sites for measuring acceleration data	2	1/1	30 ± 11	Falls	14	5	12	Oulu, 2006
	2	1/1	30 ± 11	ADL*	31	12	15	
II: Laboratory test to define algorithms for discriminating between falls and ADL	3	1/2	43 ± 5	Falls	59	56	57	Oulu, 2006
	2	1/1	30 ± 11	ADL*	31	12	15	
III: Laboratory test to define sensitivity and specificity in experimental conditions	20	14/6	48 ± 7	Falls	240	-	-	Luleå, 2007
	21	10/11	83 ± 9	ADL	164	-	-	
IV: Field test to compare real-life falls with intentional falls and to define sensitivity and false alarm rate	3/16**	13/3	88 ± 5	Falls	5	-	-	Oulu & Kalix, 2010–2011
	16	13/3	88 ± 5	ADL	9096***	-	-	

ND = not determined, F female, M male, *same data set, **3 fallers amongst study group of 16 subjects, with a total of 5 falls, ***hours of monitored data.

Fig. 2. Wireless sensor for acceleration measurements in real life worn on the waist with an elastic belt. The vertical axis of the system was marked as an arrow on the belt.

The sensor monitors acceleration continuously with a sampling frequency of 3200Hz. In order to minimise 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 0.75g as a marker for pre-impact phase. After activation, the implemented fall detection algorithm analyses the acceleration data at 3200Hz. To identify a fall, the algorithm detects impact from SV_{TOT} signal with a threshold of 2g and end posture from the vertical axis acceleration, with minor modifications (CareTech Ab, Sweden) from algorithm 1 used in this study.

Once the data collection is activated, the history of acceleration data before the activation is collected from a data buffer (30 samples, sampling frequency 6.25Hz), and 240 samples after the activation are collected with the sampling frequency of 50Hz, followed by data collection of 30 samples with sampling frequency of 6.25Hz. If a fall is detected, the collected acceleration data is labelled with a fall message. The collected data of around 14 seconds (Fig. 3) are transmitted to the base station located in each patient room. The data are transmitted further to the research database using IP-based technology.

Activity monitoring of the device (CareTech Ab) was used to evaluate the usage of the system. During the day, inactivity periods exceeding three hours were excluded. At night, if indication of any activities is seen, all hours were included.

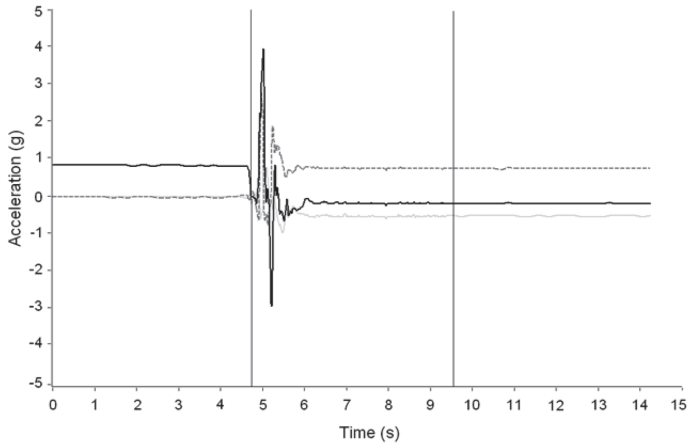

Fig. 3. Example of acceleration data collected from wireless detector in IV showing three data sets around 4.8 second each. Acceleration values form the database were converted into gravitation units (g). Axes: vertical (black), anterior-posterior (grey), lateral (dashed line).

4.3 Fall and ADL data collection

For this study, acceleration data from body movements were collected in a laboratory environment (I, II, and III) and in real life (IV).

4.3.1 Intentional falls and sequential ADL in a laboratory environment

The test protocol for intentional falls was selected to include typical fall type categories of older people (DeGoede *et al.* 2003, Lehtola *et al.* 2006, Luukinen *et al.* 1994). Test subjects performed falls (I, II, III) forwards, backwards and in lateral direction and falling out of bed towards a soft mattress as summarised in Table 3. Test subjects received short instructions for performing the test falls. They were asked neither to fall directly on their hand nor to make any recovery steps. The falls were documented using a digital video camera.

Table 3. Intentional fall types in studies I-III

Fall type	Instructions	Study
Forwards fall	Standing, no steps are performed	I, II
Forwards fall, missing a step	Step down from a platform	I, II
Forwards fall, tripping when getting up from a chair	Sitting on a chair, get up, take a short step to trip on a mattress	I, II
Forwards fall, tripping when walking	Walking, tripping on a mattress	III
Forwards fall, syncope	Standing, plain fall from standing	III
Backward fall, sitting on empty air, missing a chair	Standing, sitting down	I, II, III
Backward fall, slipping	Standing, leg swing to front	I, II
Backward fall, syncope	Standing, rounded back and knees bended	I, II, III
Sideway fall	Standing, no steps are performed	I, II, III
Sideway fall, missing a step	Sideways, step down from a platform	I, II
Sideway fall, lateral-posterior	Standing, starts falling back and turn to sideways	I, II
Falling out of bed	Lying on the bed, roll out of the bed	III

The number of collected acceleration samples is summarised in Table 2. The data in I were collected from the waist-, head- and wrist-attached accelerometer. These data were used for threshold determination. Thresholds as part of fall detection algorithms were validated with another set of samples in II (Table 2), during which acceleration samples from the waist, head, and wrist were collected synchronously. Because of malfunction of the sensors, all three synchronous data collections were not successful in some measurements. Acceleration samples from ADL represented dynamic activities (e.g. walking, walking on stairs, picking up an object from the floor, working on a computer) and posture transitions (e.g. sitting down, getting up, and lying down).

In III middle-aged test persons performed six different fall types, each fall type twice, resulting in 240 acceleration samples (Table 2) collected with a waist-worn accelerometer. In addition, middle-aged and older test subject performed an ADL protocol (sitting down on a chair and getting up, picking up an object from the floor, lying down on a bed and getting up, and both level walking and walking up and down the stairs) (Table 2).

4.3.2 Acceleration samples from real-life falls

In IV a wireless acceleration system worn on the waist was used to monitor and collect data from real-life falls among older persons living in residential care units.

Accidental falls among the test persons were documented by the care personnel according to their standard protocol and the acceleration data related to the event were obtained from the database. The documentation of falls included date and time of the accidental fall, place of accident, activity involved, the reason for the accident, general description of the accident, and injuries.

For the study in IV, accidental falls were classified according to the intentional falls presented in III (Table 3). Classification was performed based on care personnel's and older people's description of the events and estimated posture based on the collected vertical acceleration signal from the database. False fall alarms were calculated from the acceleration database based on the fall messages generated by the fall detection system.

4.4 Data processing

Acceleration data collected during tests were processed in a virtual environment in a computer using custom-made Matlab (R2006a, MathWorks Inc., Natic, U.S.A) or LabVIEW (8.0, 8.2 and 2009, National Instruments, USA) programs. The acceleration data in I and II were loaded from data loggers, in III the data were collected into a computer, and in IV data were obtained from the research database. Calibration against the gravity component was performed for each axis for converting the raw data into gravitational units ($1g = 9.81\ ms^{-2}$).

The measured acceleration signal in I and II was processed by resampling at 50 Hz for each axis to reduce the amount of data. The sampling frequency of 50Hz was chosen because it has been shown to be high enough for acceleration data analysis in fall-related motions (Karantonis *et al.* 2006, Mathie *et al.* 2004a). In I-III the data were median filtered with a window length of 3 samples to reduce noise and very fast acceleration peaks, such as knock, before any further analyses. The processed data were low-pass (LP) or high-pass (HP) filtered (cut-off frequency = 0.25Hz) (Mathie *et al.* 2004b) with a digital second-order Butterworth filter for posture detection and dynamic analysis, respectively. In IV the data from III were resampled to 50Hz without any further data processing for signal averaging. The use of accelerometer sensors with a limited acceleration amplitude range was simulated in LabVIEW environment restricting the amplitude of input acceleration data to ±2g or ±3g before data processing (III).

4.5 Data analysis

For choosing parameters and thresholds capable of discriminating falls and ADL, the ranges of maximum value of major impact for ADL and falls were determined as described in more detail in I. Parameters are summarised in Table 4. The threshold values were adjusted to optimal detection of falls with minimised false alarms from ADL samples, i.e., maximal sensitivity with 100% specificity when possible. The thresholds were used in fall detection algorithms composed of detection of different fall phases (II and III) and in evaluation of real-life falls (IV).

Different sum vectors, SV, were calculated from acceleration data as indicated in Eq. 1. Total sum vector SV_{TOT} (Degen *et al.* 2003) was used for pre-impact phase and impact detection (I, II, III, IV). The start of the fall (Degen *et al.* 2003) was determined as the pit before the impact, SV_{TOT} being equal or lower than the threshold chosen based on the data analysed in I. Velocity towards the ground v_0 was calculated by integrating the area of SV_{TOT} from the pit (Degen *et al.* 2003) between the beginning of the fall (SV_{TOT} <0.95g), until the beginning of the impact, where the signal value exceeds 1g. The time period between the start of a fall and the impact was determined from the measurements at the waist, by recognising the minimum value of SV_{TOT} in the pit and the impact-related maximum peak of SV_{TOT} or Z_2.

The dynamic sum vector SV_D was calculated as indicated in Eq. 4 from high-pass filtered data (Karantonis *et al.* 2006). Fast changes in the acceleration signal were investigated by constructing a sliding sum vector SV_{Maxmin}, a derivative which was calculated using the differences between the maximum and minimum values in a 0.1 s sliding window for each axis. The length of the window equals five samples at 50 Hz and was chosen to capture maximum acceleration change related to the fall-associated impact.

Table 4. Different parameters for fall phase detection using acceleration data. The detection of fall phases was used as different combinations in fall detection algorithms 1–3.

Fall phase	Parameter	Algorithm
Pre impact phase	Start of the fall, from SV_{TOT} [1]	2, 3
	Velocity towards to ground, v_0 (ms^{-1}), from SV_{TOT} [1]	3
Impact	SV_{TOT} (g) [1,2,3]	1, 2, 3
	SV_D (g) [4]	1, 2, 3
	SV_{Maxmin} (g)	1, 2, 3
	Z_2 (g)	1, 2, 3
End posture	Posture index, PI (g), from low-pass filtered vertical axis acceleration [4, 5]	1, 2, 3

Adapted from [1]Degen *et al.* 2003, [2] Bourke *et al.* 2005, [3] Lindemann *et al.* 2005, [4]Karantonis *et al.* 2006, [5]Yoshida *et al.* 2005

Calculated vertical acceleration Z_2 was used for impact detection and calculated as indicated in Eq. 5:

$$Z_2 = \frac{SV_{TOT}^{\ 2} - SV_D^{\ 2} - G^2}{2G} \tag{5}$$

in which SV_{TOT} = total sum vector (g), SV_D = dynamic sum vector (g), and G = gravitational component = 1g.

The detection of end posture was modified from earlier studies (Culhane *et al.* 2004, Culhane *et al.* 2005, Karantonis *et al.* 2006). It was determined two seconds after the main 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 (equal to tilt angle of 60 degrees) or lower considered to be a lying posture.

For the averaging of the SV_{TOT} signal from intentional falls (IV) the raw data from III with sampling frequency of 50Hz were used. The averaging of experimental falls was performed by aligning the SV_{TOT} signal at the impact data point where $SV_{TOT} \geq 2$g. This data point was chosen based on the threshold used for impact detection in fall algorithms.

4.6 Algorithms for fall detection

In II and III three fall detection algorithms with increasing complexity were investigated. The thresholds of fall phase detection determined in I were used without further optimatisation for each algorithm separately. For the analysis of data measured from the wrist the end posture detection was not used. The fall phases (Table 4) used in different algorithms are presented below:

- Algorithm 1 (IMPACT +POSTURE) was based on 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.
- Algorithm 2 (START OF FALL+IMPACT+POSTURE) detected the start of the fall by monitoring SV_{TOT} lower than the predetermined threshold, followed by the detection of the impact within the pre-impact time frame by a threshold value of SV_{TOT} or Z_2, followed by monitoring of the posture.
- Algorithm 3 (START OF FALL+VELOCITY+IMPACT+POSTURE) detected the start of the fall by monitoring SV_{TOT} lower than the predetermined threshold, followed by detection of the velocity v_0 exceeding the threshold, followed by detection of the impact within the pre-impact time frame by a threshold value of SV_{TOT} or Z_2, followed by monitoring of the posture.

4.7 Statistical methods

Test person characteristics, age (I-IV), MMSE score (III, IV), and walking speed (III, IV) were presented as mean ± standard deviation (S.D.). Value ranges in I were presented as quartile box plot with min, max, 25, 50 and 75 percentiles. Sensitivity (Sen) and Specificity (Spe) of fall detection (I, II, III) were calculated as indicated in Eq. 1 and 2. False alarm rate (IV) was determined by dividing the number of false alarms by the number of usage hours during the test period.

5 Results

This study has determined threshold-based acceleration methods for detection of fall phases in order to discriminate between falls and ADL (I).The sensitivity and specificity of fall detection algorithms using intentional falls and ADL in a laboratory environment (II, III) and in real life was evaluated. In addition, acceleration data collected from real-life falls were compared with intentional falls (IV).

5.1 Acceleration thresholds for discriminating between falls and ADL at various attachment sites on the body (I)

In general, fall-associated impacts measured from the wrist had higher acceleration values than those measured from the waist or head. Detailed value ranges for SV_{TOT}, SV_D, SV_{Maxmin}, and Z_2 are presented in I. Acceleration thresholds for discriminating between intentional falls and ADL are summarised in Table 5.

Table 5. Thresholds (Th) of different parameters and fall detection sensitivity (Sen, %) and specificity (Spe, %) based on impact detection and end posture for data collected from the waist or head. For the wrist, posture detection was not included.

Parameters	Waist		Head		Wrist*	
	Th	Sen//Spe	Th	Sen//Spe	Th	Sen//Spe
Start of the fall, SV_{TOT} (g)	≤0.6	ND	≤0.6	ND	≤0.6	ND
Velocity, v_0 (ms^{-1})	≥0.7	ND	≥1	ND	≥0.9	ND
Posture PI (g)	≤0.5	ND	≤0.5	ND		
Impact SV_{TOT} (g)	≥2.0	100/100	≥2.0	100/100	≥5.2	45/100
Impact SV_D (g)	≥1.7	100/100	≥1.2	100/100	≥5.1	32/100
Impact SV_{Maxmin} (g)	≥2.0	100/100	≥1.7	100/100	≥6.5	41/100
Impact Z_2 (g)	≥1.5	95/100	≥1.8	100/100	≥3.9	75/100

*Posture detection not applied in method, ND = not determined

At the waist and wrist the value ranges of the accelerometry-based parameters for impacts were overlapping between falls and ADL. However, when the impact detection was combined with monitoring horizontal end posture for the waist measurements, parameters SV_{TOT}, SV_D, and SV_{Maxmin} were able to discriminate between falls and ADL, with sensitivity of 100% and specificity of 100% (Table 5). At the waist, the velocity towards the ground, v_0, before the fall-associated impact ranged from 0.8 to 3.4 ms^{-1}.

At the wrist, the thresholds for impact alone were able to discriminate falls from ADL with sensitivity of 32–75% and specificity of 100% (Table 5). Posture detection was not included in the wrist measurement since posture determined from the wrist is not optimally related to the posture of the torso. The best fall detection at the wrist was achieved when a calculated acceleration towards the ground, Z_2, was used for impact detection.

In contrast to waist and wrist measurements, the value ranges of SV_{TOT}, SV_{Maxmin}, SV_D, and Z_2 measured from the head had specific value ranges for falls and ADL with no overlapping. Thus, thresholds for impact detection were able to discriminate between falls and ADL with specificity of 100% (Table 5). However, in II posture detection was included in fall detection algorithms for the head-worn application in order to certify high sensitivity and specificity of fall detection.

Based on the data in I, thresholds of velocity and start of the fall for waist-, head-, and wrist-worn application were chosen empirically for effective fall detection sensitivity and specificity (Table 5). On average, the main fall-associated impact was detected 0.3 s after the beginning of the fall, but the time range was up to 1 s; thus, the pre-impact phase in II, III and IV was determined in the time frame of 1 s before the impact.

5.2 Sensitivity and specificity of different fall detection algorithms in a laboratory environment (II, III)

Sensitivity and specificity of fall detection algorithms with different complexity is presented in detail in II and III and summarised in Table 6 showing the results from the parameter giving the highest fall detection sensitivity and specificity.

Based on the results in II, a head-worn accelerometer using fall detection algorithm 1, regardless of the parameter used for impact detection, would provide the best sensitivity (98%) and 100% specificity for fall detection (Table 6). However, the waist-worn application with algorithm 1 is almost as effective with sensitivity of 97% (Table 6). At the waist, falls were best recognised when using SV_{TOT} or Z_2 as markers for fall-associated impacts. At the wrist, the tested algorithms had only moderate fall detection sensitivity, varying from 71% with Z_2 in algorithm 1 to 37% in algorithm 3. Specificity was 100% for all algorithms (Table 6).

Table 6. Sensitivity (%, fall samples) and specificity (%, ADL samples) of different fall detection algorithms using the most effective parameter for impact detection, SV_{TOT} for head and waist, Z_2 for wrist.

Activity (study)	Algorithm 1[a]			Algorithm 2[b]			Algorithm 3[c]		
	waist	head	wrist[d]	waist	head	wrist[d]	waist	head	wrist[d]
Fall (II)	97.0	98.0	71.0	95.0	86.0	64.0	76.0	47.0	37.0
Fall (III)	97.5	ND	ND	92.5	ND	ND	78.3	ND	ND
ADL (II)	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
ADL (III)	100.0	ND	ND	100.0	ND	ND	100.0	ND	ND

[a]Algorithm 1 (impact+posture), [b]Algorithm 2 (start of the fall+impact+posture), [c]Algorithm 3 (start of the fall+velocity+impact+posture), [d]posture detection not included, ND = not determined

The results from II and III show no big differences between sensitivity of algorithm 1 and 2 at the waist (Table 6), indicating that impact and start of the fall phase were detected on average in 94% of the test falls. High velocity towards the ground was not detected in such a high proportion of falls, since algorithm 3 was able to detect 76.0% and 78.3% of falls in II and III, respectively. At the head the sensitivity of algorithm 2 was lower than the sensitivity of algorithm 1, and algorithm 3 detected less than half of the falls (Table 6).

In general, at the waist algorithms 1 and 2 detected forward and lateral falls more efficiently when compared to backward falls. More detailed analysis in III revealed that some backward falls were missed because the end posture was not detected as horizontal. In some cases fall-associated impacts were not detected, maybe due to the test persons bending their knees or rounding their backs when falling. Different fall detection algorithms showed the biggest difference in detection of fall from a bed (III). While algorithm 1 at the waist was able to detect 100% of those falls, algorithms 2 and 3 were able to detect 72% and 17.5% of the falls, respectively.

At the wrist the overall fall detection sensitivity of algorithm 2 using Z_2 was 64%, varying from 41% to 73% between fall types. When analysed in more detail, most of the falls (79%) had a pre-impact phase before the impact, but impact detection was not achieved in all cases. At the wrist, the overall fall detection sensitivity of algorithm 3 using Z_2 was 37%. The two-stage criteria for the start of the fall and high velocity before the impact were met in 56%, 69%, and 27% of the forwards, backwards, and sideways falls, respectively.

Based on the results presented I and II, acceleration measured from the head or waist would provide data for efficient fall detection. The waist was chosen as a measurement site in III and IV because of expected better real-life usability as an attachment site when compared to head-worn application. The effect of acceleration amplitude of the device was simulated with restricted acceleration values in II. Even though the maximum amplitude value of the impact acceleration exceeded ±10g in raw data in I (data not shown), the results suggested that the use of an accelerometer with at least ±3g amplitude range had no effect on the sensitivity or specificity of the fall detection algorithms tested here using the data measured from the waist level.

5.3 Comparison of real-life falls with intentional falls (IV)

The combined average signal of SV_{TOT} from all intentional falls (data from III) starting from a standing posture showed pre-impact and impact phases (Fig. 4). The averaged signal of falling out of bed did not show the typical SV_{TOT} pit (Fig. 4). Based on III, over 80% of intentional falls from a bed have low pre-impact velocity when calculated from the acceleration signal measured from the waist. Average signals for different fall types are presented in IV. Fall-associated impacts of all intentional fall types were averaged to one peak only. The highest average fall-associated impacts were measured from falls straight backwards and sideways.

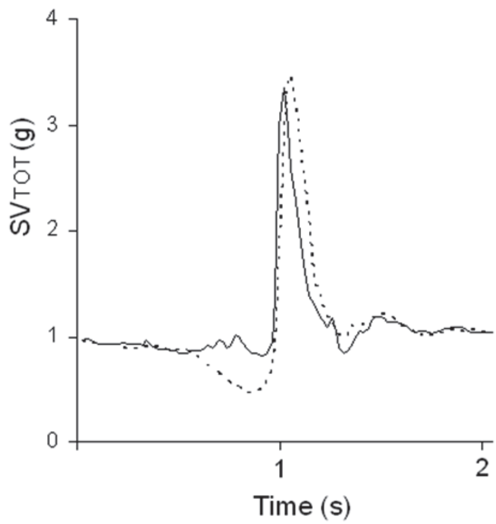

Fig. 4. Comparison of average acceleration signal (SV_{TOT}) from intentional falls starting from standing posture (dashed line) and falling out of bed (solid line).

During the field test in Finland and Sweden (IV), altogether 14 fall events were reported among eight older test persons. During five fall events, the fall detection system was known to be out of use because of battery or software update, server malfunction or loss of data connections. During two falls (Table 7, falls #8 and #9) the fall detection system was functional but the sensor was not worn at the time of the fall. Among the 7 falls during which the sensor was worn and the fall detection system was functional, data collection was activated in five cases (Table 7, falls #1 - #5). The details of these real-life falls are presented in Table 7 including the categorisation of falls corresponding to the intentional fall types used in III. Falls occured when the persons were alone in a bedroom or a toilet and they were unable to get up by themselves after the falls.

Falls #1 and #2 presented very similar fall events, during which the person had got entangled in a blanket and fallen forwards (Table 7). The falls had similarities also in acceleration SV_{TOT} signals showing multiple fall-associated impacts as shown for fall #2 in Fig. 5. The profile for fall #1 is presented in IV. Both of these real-life falls showed the start of the fall phase, but fall #1 had a velocity lower than expected for a fall event based on an intentional fall model (Table 8). Real-life falls #1 and #2 showed higher amplitude of fall-associated SV_{TOT} impacts than the average signal of intentional falls on a mattress (Fig. 5). In fall #2 the first peak after pre-impact phase was lower than 2g, but the main impact was more than 4.5g from the SV_{TOT} signal (Fig. 5).

The pre-imapact phase data from fall #3 was sampled at a frequency of 6.25Hz, which is too low for identifying movements in detail. The profile for fall #3 is presented in IV. However, the start of the fall and impact were detectable from the SV_{TOT} signal (Table 8). The fall-associated impact was higher than the average of intentional falls.

Table 7. Description and classification of real-life falls among older people

Fall	Person*	Description	Reported injuries	Acceleration data	Fall catecory
#1	A	The person was found fallen down in her room. She had gotten entangled in a blanket when moving from the bed.	Bruises on left side rib-cage	Collected	Forwards, tripping;
#2	A	The person was found fallen down in her room. The person got entangled in a blanket when moving from the bed.	No injuries	Collected	Forwards, tripping;
#3	B	The person found on the floor near the toilet seat.	Bruises, pain in her neck	Collected	Sitting on empty air;
#4	B	The person was found lying on the floor.	Hip fracture	Collected	Sideways or backwards;
#5	C	The person found lying on the floor next to the bed.	No injuries	Collected	Fallen out of bed.
#6	D	The person was found sitting on the floor next to the bed.	Radiographed, no fracture	Not collected, sensor worn	
#7	E	The person was found lying on the floor.	No injuries	Not collected, sensor worn	
#8	F	The person was found lying on the floor in her room.	No injuries	Sensor not worn	
#9	G	The person was found sitting on the floor next to a chair.	No injuries	Sensor not worn	

*A: female, 93 years, MMSE 28, walking speed 0.27 ms^{-1}; B: female, 91 years, MMSE 14, walking speed 0.49 ms^{-1}; C: male, 90 years, MMSE not determined, walking speed 0.20 ms^{-1}; D: female, 83 years, MMSE 5, walking speed 0.25 ms^{-1}; E: male, 88 years, MMSE 11, walking speed 0.66 ms^{-1}; F: female, 92 years, MMSE 11, walking speed 0.13 ms^{-1}; G: female, 85 years, MMSE 14, walking speed 0.98 ms^{-1}; H: female, 94 years, MMSE 8, walking speed 1.20 ms^{-1}.

Fall #4 resulted in a hip fracture (Table 7). The fall mechanism was not known for this event. The comparison of fall #4 to intentional falls from standing height is shown in Figure 6. The real-life fall had a profile similar to intentional falls since all fall phases were detected from this fall (Table 8). The first fall-associated impact after pre-imapct phase was the main one, and it was higher than the average impact from intentional falls (Fig. 6). The comparison of fall #4 with backwards and sideways intentional falls is presented in IV.

Fall #5 was categorised as falling out of bed based on the care personnel's description. The sum vector SV_{TOT} signal of this fall event did not have the pre-impact phase detectable from the SV_{TOT} (Table 8). This was a feature similar to the average of intentional falls of the same category (Fig. 4). The real-life fall out of bed had one fall-associated impact, and it was lower than the average impact of intentional falls from a bed. However, the impact was higher than the threshold for fall-associated impact (Table 8). All real-life falls in this study ended up with a lying posture (Table 8).

5.4 Fall detection sensitivity and false alarm rate in real-life (IV)

The acceleration data of real-life falls by older people were collected from five out of seven falls than occurred during the usage hours of the sensor. The data collection of the system was not activated in two cases. Our earlier validated fall detection algorithm 1 would detect all five real-life falls presented here (Table 8), resulting in a fall detection sensitivity of 71.4% with the triggering criteria used. Start of the fall was detected in all falls starting from a standing posture (#1-#4), while high pre-impact velocity was detectable in falls #2 and #4 (Table 8). The fall resulting in hip fracture showed all fall phases monitored in this study.

Table 8. Detection of fall phases based on parameters in I and II.

Fall	Pre-fall phase		Impact [3]	End posture[4]
	Start of fall[1]	High velocity [2]		
1	+	-	+	+
2	+	+	+	+
3	+	ND[5]	+	+
4	+	+	+	+
5	-	-	+	+

[1]SV_{TOT}<0.6g, [2] v_0>0.7 ms^{-1}, [3]SV_{TOT}>2g, [4]PI<0.5g, [5]Sample rate 6.25Hz. ND = not determined.

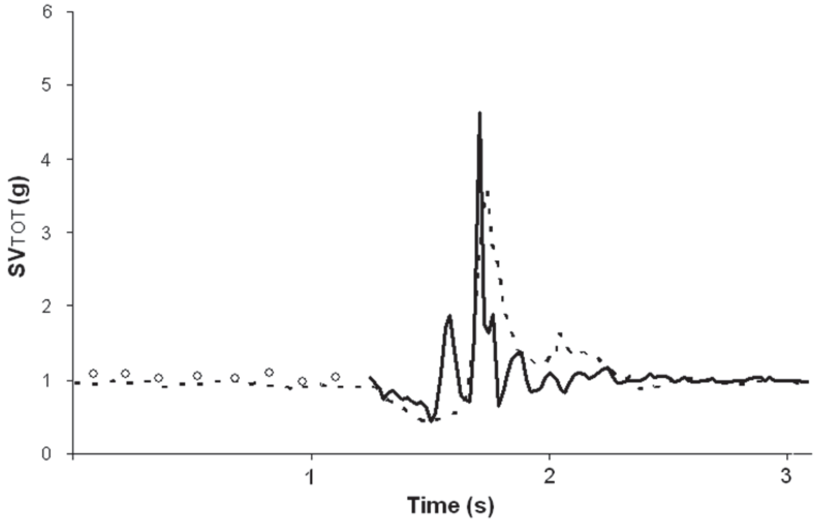

Fig. 5. Comparison of real-life fall #2 (solid line sampling frequency of 50Hz, open circles 6.25Hz) with intentional forward fall by middle-aged persons (dotted line).

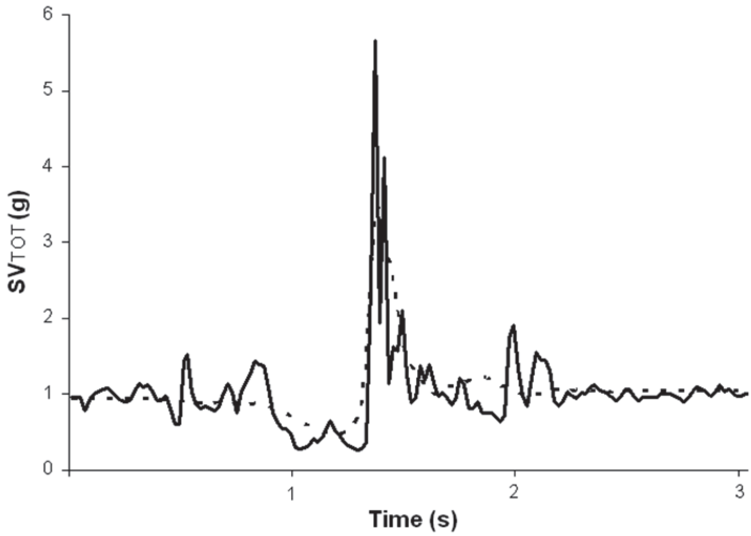

Fig. 6. Comparison of real-life fall #4 (solid line) with intentional falls from standing posture by middle-aged persons (dotted line).

During the field test altogether 9,096 hours of real life were monitored with the sensor system among older people living in care units (Table 9). Most of the test subjects wore the sensor during waking hours. The false alarm rate varied from 0.000 to 0.178 alarms per hour, with an average value of 0.045 alarms per hour, corresponding to 1.1 false alarms over a 24-hour time period.

Table 9. The usage of the sensor system among older people and the false alarm rate of the fall detection system.

Person*	Days (number)**		Usage	Average usage	False alarm rate
	Worn	Not worn	(hours)	(hours/day)***	(alarms/hour)
A[3]	149	14	1673	11.5 ± 2.6	0.014
B[1]	127	16	1232	9.8 ± 2.8	0.035
C[3]	33	19	359	10.9 ± 6.1	0.178
D[1]	37	46	265	7.8 ± 2.9	0.050
E[3]	5	0	25	5.0 ± 2.6	0.080
F[3]	24	18	198	8.6 ± 6.2	0.086
G[3]	28	1	590	21.1 ± 3.9	0.015
H[3]	134	32	2412	18.7 ± 6.2	0.054
I[1]	61	17	909	15.0 ± 6.1	0.050
J[2]	18	1	197	10.9 ± 4.2	0.020
K[3]	16	0	176	11.7 ± 1.3	0.085
L[2]	11	20	120	10.9 ± 3.8	0.025
M[3]	35	10	503	14.4 ± 5.2	0.068
N[3]	6	35	52	8.7 ± 1.6	0.058
O[3]	13	1	220	16.9 ± 3.4	0.000
P[2]	14	15	165	11.4 ± 6.2	0.000
TOT	711	245	9096	13.1±1.0	0.045 ± 0.004

*Status at the end of the test period: [1]dead or excluded because of decline in health status; [2]withdrawal from the study; [3]completed the test period; **Technical failure days excluded; ***Non-use days excluded.

6 Discussion

This study presents a validation of accelerometry-based fall detection method in a laboratory setting and an evaluation of the method in real life with older population. In addition, it is one of the first to present acceleration data from real-life falls of older people. The results showed similarities between real-life falls and intentional falls and they support our fall detection concept of waist-worn accelerometer for monitoring movement and simple threshold-based algorithm to detect fall-associated impact and horizontal end posture.

Our results showed that even if the different parameters measured from the waist showed typical characteristics for intentional falls and ADL, the value ranges had some overlapping. This indicates that using a simple threshold for impact alone is not optimal for practical fall detection. This is contrary to the report of Bourke *et al.* (2007a) where they were able to determine a simple SV threshold value for impacts capable of discriminating between intentional falls and ADL with 100% sensitivity and specificity. However, their experimental procedure used the chest as an attachment site for the sensor. Additionally, they used young test subjects for fall events and older people for ADL, whereas we used data collected from the waist from the same subjects for both falls and ADL.

In our study I, the acceleration data from the head showed specific value ranges for intentional falls and ADL with no overlapping. The reports from Lindemann *et al.* (2005) and Wang *et al.* (2008) with head-attached accelerometer and algorithm with pre-impact velocity and impact to detect experimental falls resulted in 100% sensitivity and specificity. Because a waist-worn sensor is expected to have better usability than a head-worn sensor, the waist was chosen as an attachment site in our further studies. Based on I and II, the wrist as an attachment site for an accelerometry-based fall detector showed lower fall detection sensitivity, but the parameter for calculated acceleration towards the ground (Z_2) showed some potential for further development. Other reports (Degen *et al.* 2003, Kang *et al.* 2006) have shown fall detection sensitivity between 65 and 91.3% with a wrist-worn detector in experimental studies.

Based on our studies in I, II and III, fall detection at the waist would be reliable with the algorithm detecting impact and end posture resulting in fall detection sensitivity of 97% and specificity of 100% in a laboratory environment with intentional falls. This has also been the strategy in other studies (Benocci *et al.* 2010, Chao *et al.* 2009, Tamura 2005), and the results have been supported by Bourke *et al.* (2010b), who tested sensitivity and specificity of various fall detection algorithms with intentional falls and samples from instructed and real-life ADL among older people. The data analysed in IV supports the use of accelerometry-based fall detection algorithm with impact and end posture detection in real life as well.

Fall detection specificity and false alarm rate affect the usability and acceptability of systems among end users. Bourke *et al.* (2008b) reported 42 false fall alarms during 833 hours of monitored real-life ADL among older people. This would result in a false alarm rate of 0.050 alarms per hour. The results of Bourke *et al.* (2010b) showed that even though impact detection alone resulted in a specificity of 97.8% with selected instructed ADL, the false alarm rate in real life was 1.37 alarms per hour with data collected during 52 usage hours by older people. Adding the end posture information based on a reference dot product method to the detection algorithm decreased the false alarm rate to 0.11 per hour. However, when combining pre-impact velocity with impact and end posture detection the false alarm rate decreased to 0.04 (Bourke *et al.* 2010b). Recently Bianchi *et al.* (2010) tested fall detection algorithms and reported that combining the detection of pressure change with accelerometric impact and posture change detection decreased the false alarm rate from 11 alarms to zero in a real-life 125-minute ADL test. Our results with real-life data from 9,096 hours showed an average false alarm rate of 0.045, which is in good agreement with the previous pilot studies.

The WHO definition of falls does not require horizontal end posture. Thus, using end posture as one determinant in fall detection may result in some unmissed fall cases. The attachment of the sensor may also affect the accuracy of posture recognition. During our experimental tests, some intentional backward falls were missed because the end posture was not detected as horizontal even though all intentional falls ended up with the subject in a lying position on the floor. The attachment configuration of the sensor was obviously not optimal in the missed cases.

Even though technical solutions, such as wireless sensor systems capable of collecting acceleration data from long-term real-life fall events have been proposed (Benocci *et al.* 2010, Nguyen *et al.* 2009), the use of real-life data from falls among older people has mostly been missing. Boyle & Karunanithi (2008) recorded acceleration data of four real-life falls from stroke patients and Tamura (2005) of 19 falls from a Parkinson patient, but they did not report the actual data from those falls. Thus, fall detection studies have mainly used younger test persons performing intentional falls designed to mimic typical fall scenarios among the elderly. However, this may result in data different from real-life falls.

Younger people may use preventative strategies to compensate high fall-associated impacts, and older people with longer reaction time and decreased neuromuscular function are considered to be less able to use these strategies efficiently. Preventative strategies include the use of arms or knees to brake the fall, bending the knees, ankles and pelvis to decrease impact velocity and impact force (Hsiao & Robinovitch 1998, Robinovitch *et al.* 2003, Robinovitch *et al.* 2004). In addition to differences of fall mechanisms between young and older population, intentional falls may differ based on the study design. As shown by Robinovitch *et al.* (2004), self-initiated falls result in lower pre-impact velocities and differences in impact sites when compared to falls that result from sudden release from lean angle or sudden disturbance of balance.

In our studies I, II and III, the test persons performing intentional falls were instructed not to try using their hands or knees to soften the major impact at the torso and not to take recovery steps to prevent the fall. Some falls did, however, show protective knee bending and a rounded back to soften the falls. The averaging of intentional fall signals resulted in one main fall-associated impact peak, implying that in most falls already the first impact was the major one with SV_{TOT} value of 2g or greater. In study IV, real-life falls showed multiple impact peaks. The two forward falls resulting in only minor injuries showed multiple peaks around the major impact and relatively low velocity at the pre-impact phase, suggesting protective motions. This is in agreement with a recent study by Klenk *et al.* (2011), who reported five real-life backwards falls in a specific disease population suffering from progressive supranuclear palsy, a disease with typical symptoms of loss of balance, lunging forward when mobilising, and falls. By calculating variance of acceleration from the pre-impact phase, they showed statistically significant differences between real-life falls and intentional falls with or without attempts to prevent the fall. According to their study, the pre-impact phase of real-life backwards falls showed some compensating strategies to prevent the fall. However, these compensating movements were less evident than in an intentional fall with an attempt to brake the fall (Klenk *et al.* 2011).

The pre-impact phase before the fall-associated impact has been suggested to be a usable marker for several fall associated applications. It has been used for fall detection algorithms (Bourke *et al.* 2010b, Chen & Bassett 2005, Degen *et al.* 2003, Wu 2000) and for launching the inflation of a wearable airbag to protect the head and thighs from high fall-associated impacts (Tamura *et al.* 2009). The pre-impact phase has been characterised in intentional falls by detecting the start of the fall from the acceleration sum vector SV (Degen *et al.* 2003), or by calculating velocity towards the ground (Bourke *et al.* 2007b, Wu & Xue 2008). The pre-impact velocity range in our laboratory falls (I) was 0.8 to 3.4 ms^{-1}, which is in good agreement with the average velocity of 3.0 ms^{-1} reported by Feldman & Robinovitch (2007). Here, we found that the pre-impact velocity not to be successful in either intentional falls in II and III or real-life falls in IV. 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.

Interestingly, in IV, the acceleration profile of the real-life fall resulting in a hip fracture had very high pre-impact phase velocity and one major impact peak followed by smaller impacts. The actual fall mechanism for that fall event is not known, but the hazardous outcome of this real-life fall may be partly due to lack of protective actions, resulting in a major impact at the hip. Most hip fractures occur when falling from standing level or during walks, and they are results of lateral falls without the person being able to slow the fall, for example with an outstretched arm or taking a grip of furniture (Parkkari *et al.* 1999).). In the hip fracture case in IV the inertial velocity at the pre-impact phase was 5.6 ms^{-1}, which is even higher than suggested by van den Kroonenberg *et al.* (1996) for intentional sideways falls from standing height.

Earlier surveys have suggested that older people are willing to accept security applications to improve their safety (Brownsell & Hawley 2004, Brownsell *et al.* 2000, Melander-Wikman *et al.* 2007). Our co-workers (Vikman 2011) collected acceptability feedback from older people receiving home-help services about using a waist-worn automatic fall detector capable of sending an alarm in a case of a fall event. Based on the results, 74% of the participants agreed that such a system would increase their feeling of security, 66% agreed that it would reduce the fear of falling, while 57% stated that it would increase their sense of freedom of movement. However, only 28% felt that the system could affect their privacy.

This study has some limitations. The number of individuals in I and II was very low, and we used young or middle-aged test persons to mimic real-life falls among older people. This has been typical in earlier studies as well (Mathie *et al.* 2004a, Yoshida *et al.* 2005, Karantonis *et al.* 2006). However, we validated the concept with a reasonable number of middle-aged test persons, and showed that these falls have similar features as real-life falls in older people. The thresholds of fall phase detection determined in I were used without further optimatisation for each algorithm separately. Improved sensitivity might have been obtained using more fine-tuned thresholds in triggering and fall phase detection. This study used an elastic belt as a method for sensor attachment. The attachment method and usability need to be further optimised for high compliance in large-scale use.

Even though the data from real life were collected during a long-term field test and from a reasonable number of test persons, the number of real-life falls recorded remained low and they present fall events from three individuals only. In addition, the mechanisms of the real-life falls were not known precisely, since they were not video-recorded and occurred when the faller was alone. The fallers in our study were people aged 90 years of age or more living in care units. It may be argued that they differ from home-dwelling older people; nevertheless, they do provide a heterogeneous source of knowledge on fall mechanism among older population. In the population aged 65 years or more, forward falls are the most common type of fall, and falls often happen when doing ambulatory activities such as walking or transferring (Luukinen *et al.* 1994, Talbot *et al.* 2005). This was also the case in our study.

In the future, more data on real-life falls among the elderly are needed to confirm the results and to obtain information on the sensitivity and specificity of fall detection. Usability issues should also be considered as an important field of future research and development. In addition to reliable fall detection, the effect of systems on older people's quality of life and sense of security has to be carefully studied. In this study a single sensor system was introduced, but in the future, multisensorial systems that alao detect general physical activity and health status with body-worn and embedded ambient sensors are the most probable visions.

7 Conclusions

The present study confirmed that body-worn accelerometers can be used for fall detection. The study suggests that the use of a waist-worn fall detector with a simple threshold-based algorithm provides a reliable system for discriminating falls from ADL. Moreover, this study presents acceleration data from real-life falls among older people. Based on the results, real-life falls show similar features as the intentional falls used for fall detection concept development. Based on the aims of this study, it can be concluded that:

- Acceleration signals measured from the head or waist are applicable for fall detection with simple fall detection algorithms. The wrist as an accelerometer attachment site did not provide good accuracy in detecting intentional falls with the algorithms used in this study.
- The acceleration signal from body-worn accelerometers shows differences between falls and ADL, and threshold-based methods for fall phases, such as pre-impact, impact and end posture are reasonable candidates for fall detection.
- The fall detection concept using a triaxial accelerometer worn on the waist with a fall detection algorithm recognising fall-associated impact and end posture resulted in a fall detection sensitivity of 97% and a specificity of 100% with intentional falls by middle-aged persons.
- The acceleration signals from real-life falls among older people present similar features as signals from intentional falls by middle-aged test persons. However, there is some difference in pre-impact velocity.
- The fall detection sensitivity was 71.4% and false alarm rate 0.045 per hour in a real-life pilot study among older people.

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II Kangas M, Konttila A, Lindgren P, Winblad I & Jämsä T (2008) Comparison of low-complexity fall detection algorithms for body attached accelerometers. Gait Posture 28: 285–291.

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