ALMA MATER STUDIORUM
University of Bologna

DEIS - Department of Electronics, Computer Science and Systems

PhD in Bioengineering

From fall-risk assessment to fall detection: inertial sensors in the clinical routine and daily life

Thesis submitted for the degree of
PhD in Bioengineering(09/G2, ING-INF/06)
XXIV Cycle

Candidate:	**Fabio Bagalà**
PhD Coordinator:	Prof. **Angelo Cappello**
Supervisor:	Prof. **Angelo Cappello**
Co-Supervisor:	Prof. **Lorenzo Chiari**
Examiners:	Prof. **Ugo Della Croce**
	Dr. **Clemens Becker**

Thesis defense: April 2012

"Tutta una vita da arrampicare
come una scimmia sulla schiena di qualcuno,
come un uccello sul filo o un ubriaco per le scale
che quando cade sa cadere e non si fa male
o non lo fa vedere".

(F. De Gregori - Per brevità chiamato artista)

Prologue

Mobility problems, ranging from frequent accidental falls to difficulty standing up or walking, affect million of people both young and old. Falls are caused by complex interaction between multiple risk factors, including long-term or short-term predisposing factors, which may be modified by age, disease and environment. A variety of methods and tools for fall risk assessment have been proposed, most of which have discriminated poorly between fallers and non fallers, and none of which is universally accepted. Existing tools are generally not capable of providing a quantitative predictive assessment of fall risk, since they are based on visual observation and/or timing of physical performance.

The need for objective, cost-effective and clinically applicable methods, as well as methods that possess high sensitivity and specificity would enable quantitative assessment of fall risk on a subject-specific basis. Tracking objectively falls risk could provide timely feedback about the effectiveness of administered interventions enabling intervention strategies to be modified or changed if found to be ineffective.

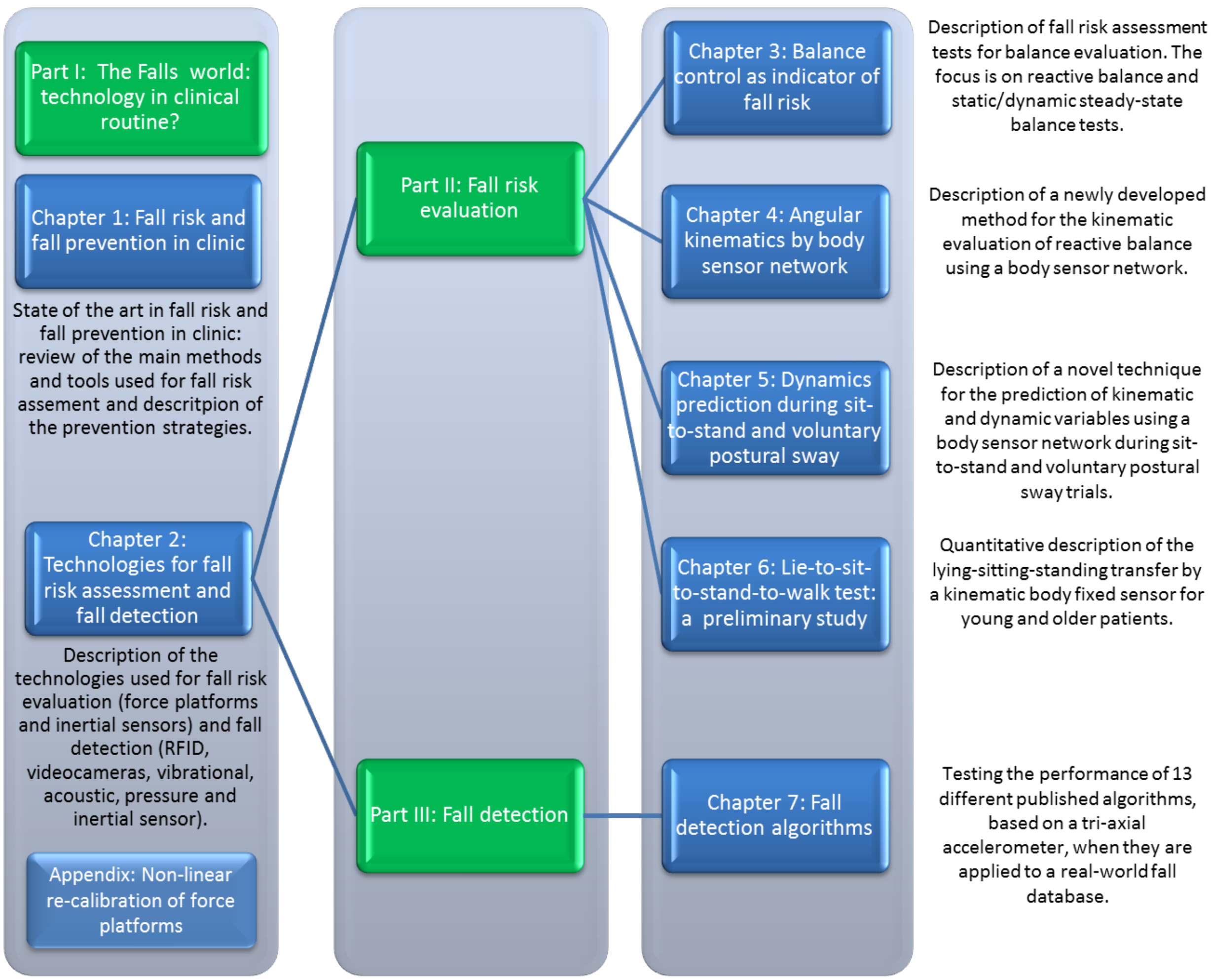
Moreover, even if extensive research has been conducted in the area of fall prevention, some of the fundamental factors leading to falls and what actually happens during a fall remain unclear. The low accuracy and reliability of oral reports about fall by the subject themselves, witnesses and by informal or formal caregivers make these reports biased in many ways. It is self-evident that objectively documented and measured falls are needed to improve knowledge of fall in order to develop more effective prevention strategies and prolong independent living.

The recent sensing hardware developments made available wearable inertial sensors for human movement analysis. In the last decade, several research groups have developed the idea to perform a sensor-based automatic or semi-automatic fall risk assessment using wearable inertial sensors, in order to overcome the often time-consuming nature of fall risk assessment test that frequently require experimental knowledge. Apart from offering continuous and objective data, this approach may also serve to detect falls events once they have happened, being aware of the fact that many falls go by undetected and a person may lie injured hours or even days in her or his flat.

At the moment, i) several fall-risk assessment studies based on inertial sensors, even if promising, lack of a biomechanical model-based approach which could provide accurate and more detailed measurements of interests (e.g., joint moments, forces) and ii) the number of published real-world fall data of older people in a real-world environment is minimal since most authors have used simulations with healthy volunteers as a surrogate for real-world falls.

With these limitations in mind, this thesis aims i) to suggest a novel method for the kinematics and dynamics evaluation of functional motor tasks, often used in clinics for the fall-risk evaluation, through a body sensor network and a biomechanical approach and ii) to define the guidelines for a fall detection algorithm based on a real-world fall database availability.

Thesis at a glance



Contents

List of Publications

Paper on International Journal

1. Bagalà F, Klenk J, Cappello A, Chiari L, Becker C, Lindemann U (2012) *Quantitative description of the Lie-to-Sit-to-Stand transfer by body-fixed sensors*, Submitted to Gait & Posture.

2. Bagalà F, Becker C, Cappello A, Chiari L, Aminian K, Hausdorff JM, Zijlstra W, Klenk J (2012) *Evaluation of accelerometer-based fall detection algorithms on real-world falls*, Under review on PlosOne.

3. Fuschillo VF, Bagalà F, Chiari L, Cappello A (2012) *Accelerometry-based dynamics prediction for balance monitoring*, Under review on Medical & Biological Engineering and Computing.

4. Bagalà F, Fuschillo VF, Chiari L, Cappello A (2012) *Calibrated 2D angular kinematics by single-axis accelerometers: from inverted pendulum to N-link chain*, IEEE Sensors Journal, 12(3): 479-486.

5. Cappello A, Bagalà F, Cedraro A, Chiari L (2011) *Non-linear re-calibration of force platforms*, Gait & Posture, 33(4): 724-726.

Abstract to National and International Conference

1. Bagalà F, Klenk J, Chiari L, Cappello A (2011) *Accelerometer-based algorithms on real falls database*, Proceedings of SIAMOC 2011, September 28 - October 1, Bosisio Parini, Italy, Gait & Posture (in press).

2. Bagalà F, Cedraro A, Chiari L, Cappello A (2010) *Non-linear re-calibration of force platforms*, Proceedings of GNB 2010, July 8-10, Torino - BOLOGNA, Patron, 2010, pp. 173-174.

3. Bagalà F, Fuschillo VF, Chiari L, Cappello A (2010) *Single-axis accelerometer kinematics estimation of an inverted pendulum balance model*, Proceedings of GNB 2010, July 8-10, Torino, Italy - BOLOGNA, Patron, 2010, pp. 175-176.

4. Fuschillo VF, Bagalà F, Chiari L, Cappello A (2010) *Single-axis accelerometer anthropometry estimation of an inverted pendulum balance model*, Proceedings of GNB 2010, July 8-10, Torino, Italy - BOLOGNA, Patron, 2010, pp. 219-220.

5. Fuschillo VF, Bagalà F, Chiari L, Cappello A (2010) *Single-axis accelerometer CoP, CoM and T prediction in an inverted pendulum model*, Proceedings of GNB 2010, July 8-10, Torino, Italy - BOLOGNA, Patron, 2010, pp. 221-22.

6. Bagalà F, Fuschillo VF, Chiari L, Cappello A (2009) *2D Kinematics estimation of postural sway using single-axis accelerometers*, Proceedings of SIAMOC 2009, September 28 - October 1, Alghero, Italy, Gait & Posture, 30(Suppl.1): S59.

7. Bagalà F, Fuschillo VF, Chiari L, Cappello A (2009) *Net joint moments prediction during balance using single-axis accelerometers*, Proceedings of SIAMOC 2009, September 28 - October 1, Alghero, Italy, Gait & Posture, 30(Suppl.1): S6-S7.

8. Fuschillo VF, Bagalà F, Chiari L, Cappello A (2009) *Anthropometric parameters and CoP and CoP prediction using single-axis accelerometers and force plate*, Proceedings of SIAMOC 2009, September 28 - October 1, Alghero, Italy, Gait & Posture, 30(Suppl.1): S14.

9. Chiari L, Cedraro A, Bagalà F, Cappello A (2009) *Portable system for the linear and non-linear re-calibration of force platforms*, Proceedings of ISPGR 2009, June 21-15, Bologna, Italy.

Part I

The Falls world: technology in clinical routine?

Chapter 1

Fall risk and fall prevention in clinic

Falls among elderly people are a widely documented public health problem predicting quality of life and disability [1, 2].

Several studies project that the number of persons aged 65 years and older will more than double by 2030, and the number of persons aged 85 years and older will increase by more than a factor of five by 2050 [3].

About a third of community-dwelling people over 65 years old fall each year [4, 5]. The 2006 Behavioural Risk Factor Surveillance System reported that 13% of adults aged 65-69 years, 14% of those aged 70-74 years, 16% of those aged 75-79 years, and 21% of those aged 80 years and older fell during 3 months preceding the survey [6].

The rate of fall-related injuries also increases with age. Fall-associated fractures in older people are a significant source of morbidity [7] and mortality [8]. Population-based studies of community-dwelling elderly persons have estimated annual total injurious fall rates from 84-229‰persons [9, 10] and fall injury hospitalization rates of 14‰[11]. Hip fractures are an especially severe complication of falls in older adults, resulting in more hospital admissions than any other injury; the age-adjusted hospitalization rate for hip fractures in USA was 775.7 per 100,000 population in 2003 [12]. More than 400,000 hip fractures occur caused by a fall in EU countries, and nine out of ten of them occur in people over 50 and 80% of them are women. There is a 10% to 20% reduction in expected survival during the first year following a hip fracture [13, 14], and roughly half of the survivors never recover normal function [15]. Twenty to 30% of those who fall suffer injuries that result in decreased mobility that limits subsequent independence [16].

Even falls that do not result in injury can lead to negative outcomes. In particular, experiencing a fall can increase an older person's fear of falling [17, 18], an important psychological outcome correlated with future falls [19]. Fear of falling leads older adults with

Figure 1.1: Physical, mental and social effects of falls

and without a history of falling to limit activities, which eventually increases fall risk through functional decline, deterioration in perceived health status, and increased risk for admission to institutional care [17, 18]. The loss of confidence can result in self-restricted activity levels resulting in reduction in physical function and social interactions [20].

Falling puts a strain on the family and is an independent predictor of admission to a nursing home [21]. This causes massive stress and burden for the individual and also enormous societal costs and indirect costs for the families. The financial burden of falls and fall-related injuries in Europe is enormous. Fall-related costs range between 0.85% and 1.5% of the total health care expenditures within the USA, Australia, EU15 and the United Kingdom. Including cost components beyond health care expenditures, future costs and considering ageing societies, the total burden is likely to be increasing [22]. Conservative estimates calculate the mean costs of all falls of €1,000. With an ageing population of approximately 100 million older persons in Europe and an incidence rate of 30%, more than 30 million falls occur each year and hence the societal burden exceeds €30 billion in the EC countries. Falls among older people thus remain a very important public healthcare issue.

1.1 Definition

Despite attempts to achieve a consensus definition of "a fall" [23, 24] many definitions still exist in the literature [25, 26, 27]. Investigators have adapted these consensus definitions in relationship with specific target populations or interventions [28, 29]. It is particular important to have a clear, simple definition for studies in which older people document their own falls; their concept of a fall may differ from that of researchers or health care professionals [29]. Even if everyone intuitively knows what a fall is, when asked to define it, people struggle for words. For clinical use, a standardised full definition may not be necessary for patients' undestanding of "what is a fall". However, for effective meta-analysis of data from different researchers, it is vital. The Kellog Report [24] recognized the need to define a fall in order to clearly identify which events could be included and which could not, and to classify different types of falls in order to allow comparability between research results. Since patients or their proxies can report the time, the place and the circumstances of the falls, other findings have been gathered during interviews with fallers. These rely on incomplete and sometimes controversial oral reports by the subjects themselves, witnesses and by informal or formal caregivers. These reports are biased in many ways [28] and have been critiqued for their accuracy and reliability [30]. Under-reporting or over-reporting of falls can be related to the cognitive status of the subjects, the shame of falling, fear of the social consequences, or simply by conceptually having a different definition of a fall. For example, falling to the ground without an injury are not reported spontaneously by older persons. The wording 'involuntary', 'unintentional', 'unexpected', 'inadvertent', 'unplanned', or 'sudden' describes an external perspective not always experienced or verbalised by fallers. People who fall may use different wording, e.g. stumbling, slipping or tripping. A recent consensus statement (ProFaNE, Prevention of Falls Network Europe) defines a fall as "an unexpected event in which the participant comes to rest on the ground, floor, or lower level" [31]. The wording recommended when asking participants is "In the past month, have you had any fall including a slip or trip in which you lost your balance and landed on the floor or ground or lower level?" [31]. The proposed operational definition of a fall should maximize the likelihood that elderly people reported all falling events.

1.2 Aetiology and Risk Factors

Falls are caused by complex interactions between multiple risk factors (Figure 1.2), including long-term or short-term predisposing factors, which may be modified by age, disease, and environment. Multi-factorial aetiology involves an interaction between two broad domains:

- **intrinsic factors** (patients related), e.g. chronic disorders and neurological deficits, increasing age, muscle weakness, gait and balance impairment, postural hypotension, medication use, low body mass index, history of recurrent falls, vision impairment, special toileting needs, urinary incontinence, comorbid illness, depression, and cognitive impairment [32, 33, 34, 35, 36, 37, 38, 39];

- **extrinsic factors** (external to the patient), classified as environmental factors, e.g. obstacles in a path of travel, poor lighting, slippery floors, uneven surface, footwear, clothing, and behavioural factors, e.g. activities and choices that can destabilize balance, such as running or wearing improper shoes, inappropriate walking aids or assistive devices [39, 40, 41].

At a population level, increasing age is the most important risk factor for falls. As people age, they may develop more than one risk factor for falls. Functional capacity may decrease with age due to physical and mental changes that lead to impairments in balance, gait and strength. People may develop impairment in vision and cognition with advancing age that may contribute to the risk for falls. Kron *et al.* [42] identified several risk indicators for fall in a prospective observational study with 1-year follow up in a sample of institutionalized frail elderly. The study population included 472 long-term-care residents whose mean age was 84 years (77% were female). Short-term memory loss, transfer assistance, urinary incontinence, positive fall history, use of trunk restraints were indicated as predictors of falls. Depressive symptoms, urinary incontinence and positive fall history were associated with frequent falls.

Recently, Rubenstein [43] summarized data from 12 of the large retrospective studies of falls among older persons living in a variety of settings.

Accident/Environmental-related "Accidental" or environment-related is the most frequently cited, accounting for 30-50% in most series. Connell *et al.* [40] analyzed 19 falls, of the 39 reported, associated with environmental and behavioural circumstances of fifteen subjects ranged in age from 70 to 81 years old. About one third of all incidents and half of those about which participants were interviewed occurred in bedrooms, about 10% in kitchens and bathrooms, 18% in living rooms and studies. The majority of falls occurred while individuals were engaged in routine behaviours, such as dressing, and during transfer (e.g. going from the bedroom to the bathroom). The patterns of environment-behaviour circumstances, associated with falls experienced by the sample, were collisions in the dark, failing to avoid temporary hazards, preoccupation with temporary conditions, frictional variations in foot contact, excessive environmental demands, habitual and inappropriate environmental use. Li *et al.* [39] analysed data on the most recent falls during the past year among participants

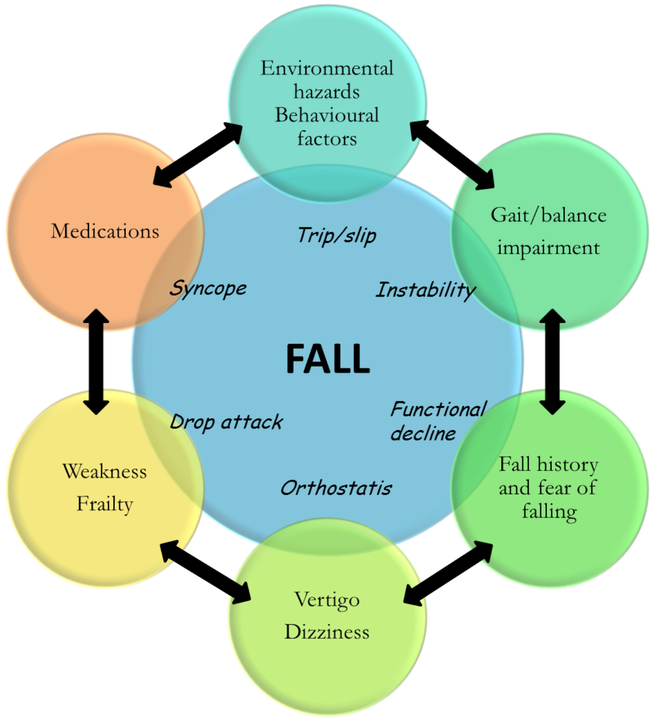


Figure 1.2: Risk factors for fall

aged 45 years and older in the control group (N=2193) of a case-control study of fractures. Falls occurred outdoors more often than indoors among most age groups. Most outdoor falls (73%) were caused by environmental factors, such as uneven surfaces and tripping or slipping on objects, and usually occurred on side-walks, curbs and street. Walking (47.3%) was the most common fall-related activity.

However, many falls attributed to accidents really stem from the interaction between identifiable environmental hazards and increased individual susceptibility to hazards from accumulated effects of age and disease. Age-associated impairments of vision, hearing and memory also tend to increase the number of trips and stumbles.

Gait and Balance The broad category of gait difficulties, muscular weakness and an impaired standing balance is the next commonest specific precipitating cause for falls (10-25% in most series) as also reported in a meta-regression analysis of the predisposing risk factors [44]. The ability to walk normally depends on several biomechanical components, including free mobility of joints, particularly in the legs, appropriate timing of muscle action, appropriate intensity of muscle action and normal sensory input, including vision, proprioception and vestibular system. Gait and balance problems have many aetiologies, and many therapeutic approaches can be effective. Gait problems can stem from simple age-related changes in gait and balance as well as from specific dysfunctions of the nervous, muscular, skeletal, circulatory and respiratory systems or from simple deconditioning following a period of inactivity. Quantitative measures of gait have been able to identify prospectively those older adults who are at greatest risk of falling. These quantitative studies of walking in elderly fallers have largely focused on properties of an average stride or gait cycle as measured over a few cycles [5, 45, 46, 47, 48, 49, 50]. Other studies [51, 52, 53] found controversial results about peak hip extension moment and reduction in knee power absorption in pre-swing in fallers.

Dizziness/vertigo The next major reported cause of falls is dizziness, which is an extremely common symptom among older persons. However, it is a less common cause of falls than its prevalence would indicate, probably reflecting the fact that most persons with the syndrome become accustomed to it and are able to find a seat or adjust before falling.

Drop attack Drop attacks are defined as sudden falls without loss of consciousness or dizziness and have in the past been implicated in between 1 and 10% of falls. Patients typically experience abrupt leg weakness, sometimes precipitated by sudden head movement. The weakness is usually transient but can persist for hours. Drop attacks are today reported much less often, probably reflecting better diagnostic precision.

Syncope Syncope, or sudden loss of consciousness, usually results from decreased cerebral blood flow or metabolic factors. It has been the attributable cause of between 2 and 10% of falls in several series but has been excluded from many other series either by definition (because syncope is not a typical type of fall) or because many elderly patients with syncope are acutely hospitalised and are treated differently.

Fall history and fear of falling Fall history represents another important non-modifiable marker to identify residents at high risk for several reasons. Friedman *et al.* [19] determined the temporal relationship between falls and fear of falling. In a population-based prospective study of 2212 older adults aged 65 to 84 at baseline, falls at baseline were an independent predictor for the onset of fear of falling after 20 months, and fear of falling at baseline independently predicted becoming a faller. Because each is predictor of the other, an individual who develops one of these outcomes is at greater risk for developing the other. These data provide evidence of a spiraling effect of increasing falls, fear and functional decline. Individuals who limit activities because of fear of falling are at particularly high risk of becoming fallers. It is certainly plausible that each syndrome may lead to the other. Namely, an individual who falls may subsequently develop fear of further falls. Moreover, it is possible that individuals who fall and have subsequent fear of falling had experienced fear before the fall as well. Conversely, fear of falling may in turn cause falls. Several studies have shown activity restriction secondary to fear of falling, which could in turn lead to de-conditioning and increased risk of falling, as also demonstrated in three prospective studies [18, 20, 54]. These studies indicated that about one-third of elderly people develop a fear of falling after an incident fall and this issue should be specifically addressed in any rehabilitation programme.

Medications Use of certain psychoactive and cardiac medications, and use of four or more medications, has been associated with an increased risk for falls [55, 56, 57]. The role of medications, as a contributing factor of falling among older persons, has received much attention, primarily because medication exposure may be an important modifiable risk factor in fall prevention. Mechanism suspected of contributing to the risk of falling include reduced metabolic capacity and renal activity as a result of the ageing process, therefore extending medication half-life, psycho-motor impairment resulting from some psychotropic medications, medications that lead to orthostatic hypothension and those that induce ambulation (associated with the use of diuretics) [58]. Kelly *et al.* [57] estimated the magnitude of association between medication use and risk of injurious falls in the community-dwelling older population, while controlling for the effects of co-morbidity, age, gender and income. The major findings were that taking medications from seven specific medication classes (narcotic, anti-convulsant, anti-depressant, anti-psychotic, sedative, anti-parkinsonian and anti-coagulant agents) were independent risk factors for predicting an injurious fall. However, when existing co-morbid conditions and being hospitalised within the previous year were also controlled for, only narcotic, anti-convulsant and anti-depressants were significant medication predictors of an injurious fall.

Other causes Other specific causes of falls include disorders of the central nervous system, cognitive deficits, poor vision, drug side-effects, alcohol intake, anaemia, hypothyroidism, unstable joints, foot problems, severe osteoporosis with spontaneous fracture and acute illness. Because most elderly individuals have multiple identifiable risk factors predisposing to falls, the exact cause can often be difficult to determine.

1.3 Clinical Practice for fall-risk assessment

Falls among older adults are prevalent and preventable. In the absence of evidence to support a population-based approach to prevention and the imperative to deliver cost-effective and efficient services, health care providers need risk assessment tools that reliably identify at-risk populations and guide intervention by highlighting remediable risk factors for falls and fall-related injuries. Such tools typically consist of a rating or scoring system designed to reflect the cumulative effect of known risk factors. However, risk profiles are not the same for all elderly people [59]. Among active seniors living in the community, fall risk tends to be mostly related to mobility status, exposure to hazardous environments and risk-taking behaviour. People who require support to live in the community tend to be more susceptible to falls owing to the direct effects of health problems such as arthritis, depression, use of psychotropics and the functional consequences of a chronic disease. Among older adults who are hospitalized, the risk of falling is greatly influenced by acute illness that often has a marked, sometimes temporary, impact on physical and cognitive function. Among residents of long-term care facilities, risk factors are influenced by impaired cognition, use of psychotropic medications, incontinence and urgency, lack of exercise. The time scale over which a prediction is needed varies from a few days or weeks in hospitalized patients to a year or more for community-living populations. Tools developed for one population may therefore be less accurate when used in a different settings since fall-risk profiles differ considerably among well, active seniors who live in the community, those who are frail and need support to live at home in the community, those who require long-term care, and those who are hospitalised for acute health problems.

A variety of methods and tools have been proposed for fall risk assessment, most of which have discriminated poorly between fallers and non fallers, and none of which is universally accepted. Wyatt and Altman [60] laid down "gold standard" criteria for the use of such tools. Essentially, they should be validated prospectively, using sensitivity/specificity analysis, in more than one population, with good face validity, inter-rater reliability and adherence from staff and transparent, simple calculation of the score.

Assessment of fall risk typically involves either the use of multi-factorial assessment tools that cover a wide range of fall-risk factors, or functional mobility assessments that typically focus on the physiological and functional domains of postural stability including strength, balance, gait and reaction times [59]. Some tools exist purely as a mechanism to screen for high-risk populations, while others allow for tailoring of intervention based on assessment.

Since 2000, seven reviews have been published that detail a cross-section of fall-risk assessment tools, focusing on institutional care [61, 62, 63], community dwelling [64, 65, 66] or both [59]. Other reviews including community-dwelling seniors in their testing sites have focused on tools limited to the assessment of balance with little consideration of other risk factors [67, 68, 69].

Multifaceted systems or instruments have been used in assessing frailer persons with multiple fall risk factors like the St. Thomas risk assessment tool (STRATIFY [70, 71, 72]) and the Morse Fall Scale (MFS [73, 74, 75]) for use in hospital, the Downton fall risk index [76, 77] and the Mobility Interaction Fall (MIF [78]) chart as well as staff judgement of fall risk and history of falls. Methods and tools for assessing fall risk in home-dwelling older persons with minor functional problems are several:

- functional balance and mobility assessment, by use of the Berg Balance Scale [79, 80, 81, 82], the Tinetti Mobility Scale [83, 84, 85, 86], the Functional Gait Assessment (FGA [87]), the Balance Evaluation Systems Test (BESTest [88]), the Timed Up-and-Go [89, 90, 91, 92, 93], 5-step test and floor transfer [85], functional reach [75, 85, 93, 94], getting up from lying on floor [95], one-leg balance [20], stop walking when talking [78], timed walk/distance walked [84, 85];

- physiological fall risk assessment, by use of the Physiological Profile Assessment (PPA [96]);

- posturography to measure quiet standing by use of force plates [65, 94] or active balance systems [92];

- assessment of psychological aspects of falls by the Falls Efficacy Scale International [97].

Other methods are based on assessment of gait characteristics like gait speed [98], step width [99], gait variability during simple and dual task conditions [48, 100].

The multi-factorial assessment tools typically check list comprising questions used to screen the level and nature of risk based on a combined score of multiple factors known to be associated with fall-related risk. In addition to questions that rely on self-report, the tools may or may not include physical assessments of health status (e.g. blood pressure) or mobility function. Most tools are administered in person and some are conducted by telephone or a postal survey. They are typically administered by a nurse or therapist on admission to hospital or a nursing home and are usually updated regularly or when there is a change in health status. Some take as little as 1 min to complete and others can take over 1 h.

Functional mobility assessments focus on functional limitations in gait, strength and balance and are often completed by physical therapists or physicians in outpatient or acute care settings. In most cases, the subject is required to perform a physical demonstration of ability while the assessor monitors limitations in function and time used to perform the test, compared to a pre-established standard.

Nevertheless, at present no tool exists that can be applied reliably across different settings to accurately predict risk of falling, and of the tools that do exist, few have actually been validated in more than one setting. Further research is needed to strengthen the evidence for the use of multi-factorial tools and functional mobility assessments within and across settings, and new tools may be required if no evidence exists to support the use of an existing tool in a specific setting. The use of fall-risk assessment as part of a multi-factorial approach for the prevention of falls is supported by evidence of strong associations between a multiple risk factors and falls, as well as from experimental studies demonstrating significant fall reductions where assessment is combined with tailored interventions [101].

Active partnerships between clinicians and researchers should be encouraged to ensure that any future tool developed is reliable and valid as well as feasible and acceptable in everyday practice in all health care settings. Future studies should use a sufficiently large sample size to estimate sensitivity and specificity with high precision, be conducted in a clinically relevant population, include a sufficient duration of follow-up, and have reliable methods of recording of falls. Moreover, selecting an appropriate tool is complicated by the lack of consistency in methods of reporting and interpreting the comparative properties of fall-risk assessment tools in the published literature.

The need for objective, cost-effective and clinically applicable methods, as well as methods that possess a high sensitivity and specificity, is hence clear. Instrumented tests would enable quantitative assessment of fall risk on a subject-specific basis, overcoming the limitations due to the lack of objectiveness related to individual judgement by a therapist or a nurse who report a score related to the physical performance. The use of assistive technologies could help to overcome this drawback. This issue will be discussed in the next chapters.

1.4 Clinical practice for fall prevention

Systematic reviews on fall prevention [35] or assessment [66] are underpinned by the attribution of falls to multiple interacting factors rather than one identifiable cause. Syncope, for instance, is often quoted as an isolated cause of falls in elderly but loss of consciousness may be the result of deteriorating function in several systems (e.g. cardiovascular, respiratory and hematological) in addition to defects in cerebral arterial circulation [102]. Therefore, it is reasonable to conclude that a substantial number of falls attributed to a single cause may in reality arise from the interplay of various causal factors [103]. This is consistent with the principle that complex system failure is usually due to the cumulative effect of several stressors. As discussed in the previous section, the lack of accuracy of fall risk assessment tools is problematic for clinicians and researchers implementing fall prevention interventions. Various falls-prevention interventions targeting a number of fall risk factors have been evaluated. Falls prevention approaches aim to increase older adults' strength and balance, identify and remove hazards in their environment, increase awareness of falls and associated risk factors, correct clinical conditions that may increase fall risk, or some combination of these approaches. Theoretically, a multi-factorial intervention for elderly people should be more effective than its single-intervention counterpart since causes and risk factors of falling are usually multiple with striking individual (fall to fall) and inter-individual variation (Figure 1.3). On the other hand, a single-factor intervention such as exercise could also reduce many impairments and disabilities and more distant risk factors for falling simultaneously. A major limitation with the interpretation of the findings of multi-disciplinary fall-prevention interventions is that they cannot distinguish between the independent role of individual modified risk factor, and thus which part of the intervention is effective and which is not cannot be established.

Since 2000, several published systematic reviews [35, 66, 101, 104, 105, 106, 107, 108, 109] for prevention of falls in older adults have concluded that fall prevention interventions are likely to be beneficial (Figure 1.4), except for a recent systematic review [110] who found limited evidence that multi-factorial fall prevention programs in primary care, community, or emergency care settings are effective in reducing the number of fallers or fall-related injuries. All of these reviews except two [106, 108] included institutionalized and hospitalized populations in addition to community-dwelling older adults.

In summary, fall-prevention programs including multi-factorial assessment and management, muscle strengthening and balance training, Tai Chi and group or home-based exercise with multiple components, withdrawal of psychotropic medication, vitamin D in people with lower vitamin D levels, home safety interventions for people with visual impairments and at higher risk of falling, reduce fall-risk.

According with a recent review [111], since 1996, two published evidence-based clinical guidelines for prevention of falls in older adults recommended routine assessment of falls history during the past year along with brief tests of gait and balance during primary care visits to identify older adults appropriate for further assessment and management to prevent

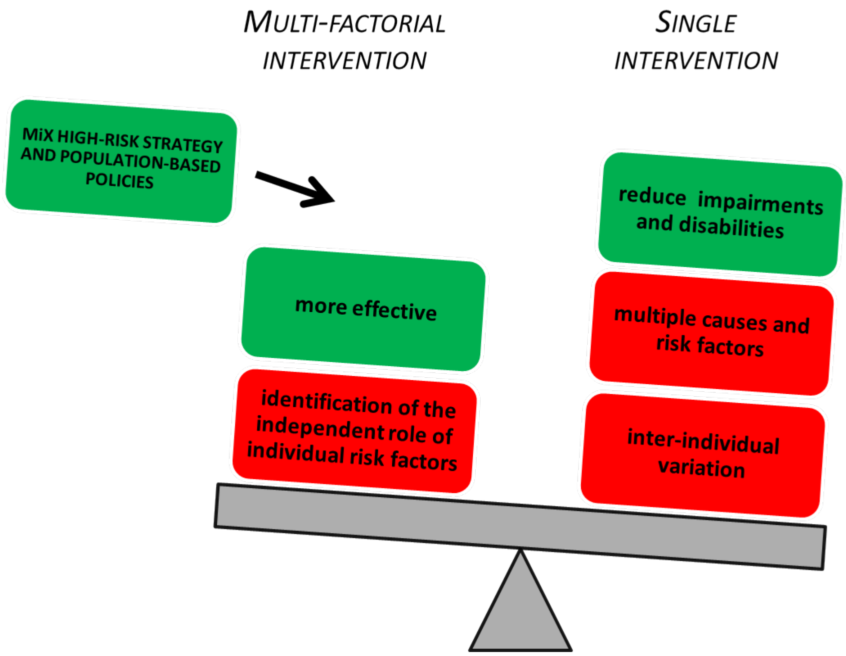


Figure 1.3: Multi-factorial vs Single-intervention for fall prevention

falls.Some of these recommendations are here reported:

- the National Institute for Clinical Excellence recommends that older people's health care providers routinely ask about recent falls; that those reporting falls be observed for balance and gait deficits and considered for interventions to improve strength and balance; and that older adults appearing to be at high risk for falls be offered an individualized, multi-factorial intervention including strength and balance training, home hazard assessment and intervention, vision assessment and referral, and/or medication review and modification [112];

- the America Geriatrics Society, the British Geriatrics Society, and the America Academy of Orthopaedic Surgeons jointly recommend asking all older persons about falls at least once per year and endorse several falls-prevention interventions, including gait and exercise training, home visits, and medical management [12];

- the Center for Disease Control and Prevention recommends that an annual check-up for chronic medical conditions includes a review of medications and a vision screening [113].

Despite these professional organization's recommendations for routine falls risk assessment and intervention in older persons, a comprehensive approach mixing high-risk strategies

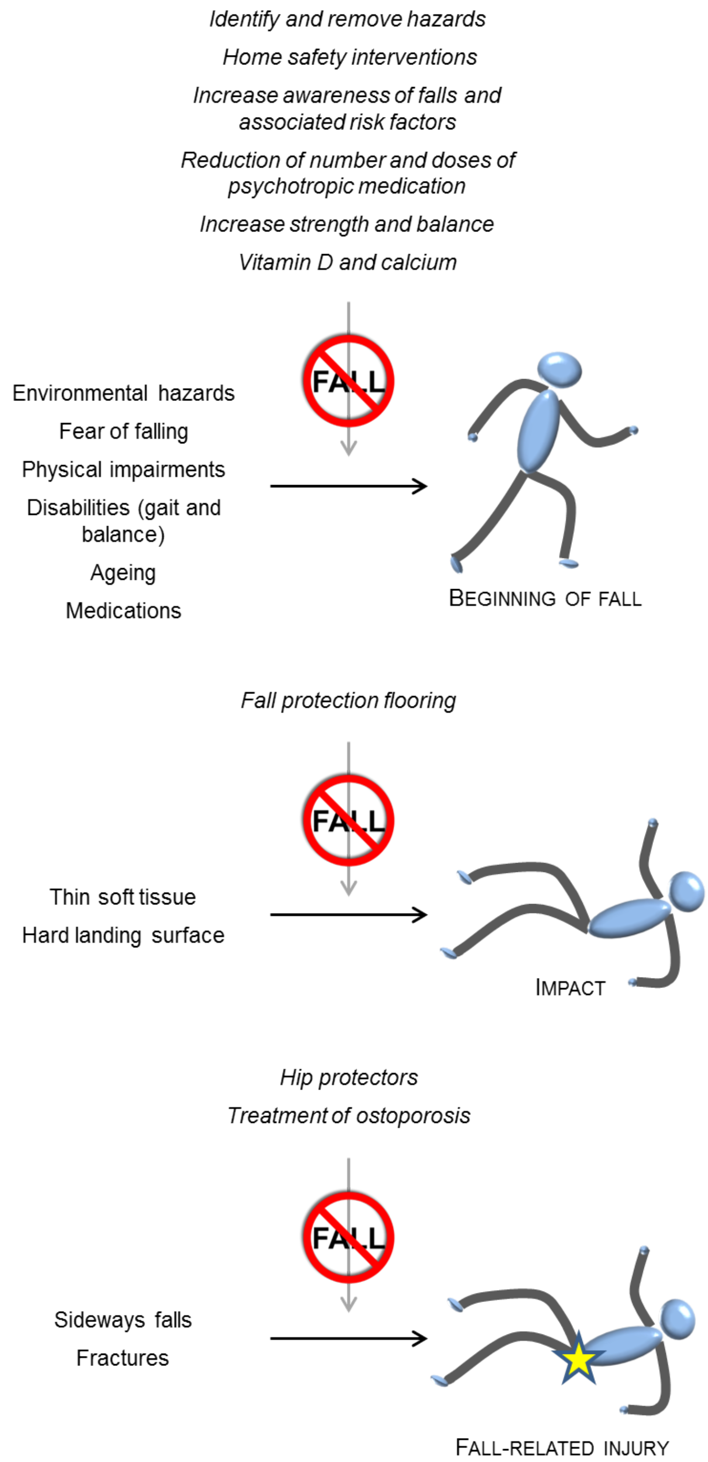


Figure 1.4: Phases of fall, causes/risk factors and possible prevention interventions

and population-based policies has been recently pointed out as desirable (but still missing) to tackle this population-wide problem [114, 115]. Even if extensive research has been conducted in the area of fall prevention, some of the fundamental factors leading to falls and what actually happens during a fall remain unclear.

Previous research, much of it by the ProFaNE group, [116, 117, 118, 119, 120, 121] into older people's attitudes and beliefs about interventions to prevent falls reveals that many older people do not believe that they themselves are at risk of falling (even when they are) and the sorts of interventions if they are to be successful must accord with older people's own beliefs, aspirations and lifestyles. Generic recommendations [122] stress

1. raising awareness in the general population that undertaking specific physical activities has the potential to improve balance and prevent falls,

2. promoting benefits which fit with a positive self-identity,

3. utilising a variety of forms of social encouragement,

4. ensuring the intervention is designed to meet the needs, preferences and capabilities of the individual,

5. encouraging self-management,

6. drawing on validated methods for promoting and assessing the processes, especially in the longer-term.

These principles are clearly generalisable to the use of assistive technologies [123], but technologies themselves present a series of challenges for older people and for those implementing technological solutions to older people's everyday living problems such as falls. In the next chapter, a review of the technologies used for fall-risk assessment and fall detection will be presented.

Chapter 2

From hospital to home: technologies for fall risk assessment and fall detection

Several fall risk assessment tools were developed to identify at-risk populations and guide intervention by highlighting remediable risk factors for falls and fall-related injuries, as discussed in the previous chapter. Despite the numerous clinical scores developed, these methods often depend on individual observation and subjective interpretation, which make the assessment results inconsistent [124] and have limited accuracy in recall [125]. Some standard tests also require subjective judgements. For example, the Timed Up-and-Go (TUG) Test is a simple test for evaluating one's ability to perform a sequence of basic activities, and the result of the TUG can be a predictor for risk of falling [126]. Distinguishing postural transitions in the TUG, however, depends on subjective judgement that counts the time taken for each posture transition. The Berg Balance Scale, a valid measure to evaluate balance control of the elderly individuals, also requires subjective observation and determination for scoring some test items [67]. Although their predictive value is undeniable, cut-off-values for clinical use merely correspond with clearly visible instability or reduced ambulation. Moreover, fall-risk assessments, from the most basic of screening tools to comprehensive environment, such as a hospital or dedicated falls clinic, are invariably administered by qualified care givers or experienced medical professionals.

The majority of these assessments are restricted to use in a clinical environment, as their correct execution often requires supervision, and so renders them unsuitable for long-term monitoring. Simple, unsupervised quantitative assessments of falls risk would enable continuous monitoring of falls risk in the elderly. The need for objective and clinically applicable methods is clear. Tracking objectively falls risk could provide timely feedback about the effectiveness of administered interventions enabling intervention strategies to be modified or changed if found to be ineffective.

Modern sensor technologies and healthcare can help to close this gap and allow for unobtrusive quantitative monitoring of patients at their environment [127, 128].

In the last decade, several approaches assessing automatically fall-risk during motor performance through quantitative measurements, provided by force platform or inertial sensors, have been suggested. The main reasons why these technologies are used for the evaluation of physical performance are that a history of falls and reported abnormalities of gait or balance are consistently found to be the best predictors of future falls [129], and little or no additional value may be gained by performing a complex screening test. A brief review is provided in the following chapter.

2.1 Force platforms for fall-risk assessment

One of the most relevant intrinsic factors for fall, described in the previous chapter, is the ability to maintain postural stability. A decrease in the quality of balance can also be related to additional fall-risk factors that are manifested by their effect on balance, such as visual, vestibular or proprioceptive problems. A commonly used method is to identify elderly with balance problems. The main method used to evaluate balance are clinical tests such as the Tinetti Balance Scale [5] or using a force plate (FP) to analyze the sway [337]. The FP technique is one of the tools most widely applied in assessing postural balance in a quantitative way. In most applications measurement is based on the registration of the ground reaction forces and the point of application (Center of Pressure, CoP) while the subject is standing on the platform. Some papers have shown that balance tests based on FP registrations are sensitive to differences in balance between young, middle-aged, and older subjects.

A recent systematic review by Piirotal and Era [65] evaluated the findings of follow-up prospective studies where FP measurements have been used as predictor of falls among elderly population. Only nine original studies [94, 81, 82, 131, 132, 133, 134, 135, 136] were included in the analysis according to the inclusion criteria assumed by the authors: i) the studies had to analyse the association between balance and risk of falling in elderly people and ii) the balance tests had to be done first and then the follow-up of the balance-tested subjects.

Falls and fall-related injuries were generally followed for a 12-month period but periods of 6 months and 3-year periods were also used. During the follow-up 21-59% of the subjects experienced one or more falls. Approximately half of the fallers fell two or more times. Different FP-based balance instruments were used to measure postural balance (OR6-5 [94], NeuroCoM Balance Master 6.1 [81], Chattecx Balance System [131, 134], Kistler 4060 [132], custom made platform [133], computerized dynamic posturography platform EquiTest [135], portable FP AccuSway System [136]). In five studies fall-related outcomes were associated with some parameters of sway [81, 94, 132, 133, 136] while in other four studies [82, 131, 134, 135] no association between sway and falls was found. The predictive sway parameters for falls were higher medio-lateral (ML) sway amplitude with eyes open and closed, higher anterior-posterior (AP) speed with eyes open [133], and higher root-mean-square values for ML CoP displacement with eyes closed.

Piirtola end Era [65] concluded that since there are some evidences that balance measurements using a FP and its parameters could be used in assessing the risk for falling among elderly populations, results of the studies are contradictory making difficult to draw definitive conclusions.

One possible reason for these inconclusive results concerns the testing situations used, which generally do not mimic real-life circumstances that cause falls. In many test situations, the participants have opportunity to compensate for their deficits by shifting toward other control strategies, e.g., single-task versus dual-task testing. Therefore, measurement protocols should challenge the participant in more complex conditions to avoid the use of these compensatory strategies.

Consequently, in their review, Zijlstra *et al.* [137] evaluated whether dual-task balance assessment have an "added value" over single-task balance assessment. The authors pointed out the importance to postural control as indicator of fall risk, due to the fact that attention resources are limited [138] and postural control is more attention demanding in older adults than in young adults [139, 140]. Also, older adults may prioritize tasks differently. In a study by Bloem *et al.* [141], older subjects seemed less inclined than younger subjects to use a 'posture first' strategy. This strategy consists of prioritizing balance maintenance (the 'primary' task) over the execution of a second task (e.g. manual or cognitive) [142], and thus can be considered as a 'safety first' strategy. Assessment methods incorporating dual-task paradigms appear to be helpful in revealing the effect of age or disease on the allocation of attention to postural tasks and may be sensitive in predicting fall risk and/or in evaluating outcomes of fall interventions in older people [140]. Out of 114 dual task studies in older people, 19 articles matched the inclusion criteria of the review [137]. In these studies the balance task consisted mainly of standing on FP in different conditions (eyes open vs eyes closed) and measuring postural sway, TUG test or walking. None of the 19 articles presented the same statistical measures for both tasks during dual-task performance as well for the single balance and cognitive task. Authors concluded that an added value of dual balance tasks for fall prediction or assessing fall intervention effects cannot be made due to incomplete comparisons of single and dual balance tasks. Nevertheless, two studies [84, 143] with prospective data collection of falls provided an indication that dual balance tasks may have added value for fall prediction.

Opposite to the findings of [137], Swanenburg *et al.* [144] claimed that dual task did not provide any extra value to the fall risk prediction model. Authors assess 270 elderly persons in a prospective study in order to determine whether FP (AMTI Accusway) variables in single and dual-task conditions were able to predict the risk of multiple falls in community-dwelling elderly population. The authors found that FP variable root means square amplitude in the ML direction in the single-task condition together with three co-variables (history of multiple falls, use of drugs and gender) were significant independent predictors of being a multiple faller. Moreover, multiple fallers had a narrower stance width compared to non-fallers.

Recently, several studies have been focused on FP-based assessment of fall risk [145, 146, 147, 148, 149, 150]. The studies in which fall-related outcomes were associated with parameters of sway and their main findings are reported in Table 2.1.

Considering the finding of [65] and the subsequent studies which investigated fall risk assessment through FPs, it seems that certain aspects of FP data may have predictive value for subsequent falls, especially various indicators of the lateral control posture. Some authors proposed statistical approach (discriminant function model [145], logistic regression model [147]) to found the best trade between sensitivity and specificity. Neverthless, many studies have some limitations related to the use of interviews for fall-risk factors [144] which could have resulted in recall bias when participants were asked to remember past events, smaller sample size [147, 149] or not random population (subject affected by mild cognitive impairment [148], or intermittent claudication [146]) and the retrospecitve nature of the studies [147, 148, 150] which limits the possibility to predict future episodes of falling from the data. One problems related to the use of instrumentation in clinical practice is the accuracy required by these device to provide reliable measurements. The ageing of the FP, its usage, and in-situ installation procedures may reduce the effectiveness of the calibration provided by the manufacturer and lead to a lack of accuracy which introduces errors in the FP data and may propagate to the calculated kinetic and energetic quantities. The FP accuracy can be increased by estimating the (6x6) recalibration matrix: this approach and its details are given in the Appendix of this thesis.

Table 2.1: Brief review of FP-based fall risk assessment studies. Abbreviations: EC (eyes closed), EO (eyes open), DT (dual-task), BW (body weigth), SOT (Sensory Organization Test). * are from Piirtola *et al.* [65]

Authors [ref]	**Force Platform**	**Predictive Parameters Test conditions**
Boulgarides *et al.* [81]*	NeuroCoM Balance Master 6.1	Higher mean CoP velocity EC
Thapa *et al.* [94]*	OR6-5	Higher sway ellipse
Bergland *et al.* [132]*	Kistler 4060	Higher ML CoP amplitude (indoor falls)
		Higher ML movement DT (injurious falls)
Maki *et al.* [133]*	Custom Platform	Higher mean CoP velocity EC
Stel *et al.* [136]*	AMTI AccuSway	Higher mean CoP velocity EC
Swanenburg *et al.* [144]*	AMTI AccuSway	Higher RMS ML CoP sway EO
Hewson *et al.* [145]*	Bertec 4060-08	Higher CoP velocity EO
Shin *et al.* [146]*	Good Balance	Higher ML CoP and velocity EO/EC
Bigelow *et al.**	Bertec 5050	ML CoP velocity and mean frequency
Schneider *et al.* [148]*	Soehnle Professional GmbH	Force and power knee during bends
Bhatt *et al.* [149]*	AMTI	Force > 30% BW
Mockford *et al.* [150]*	EquiTest	Not provided (combined use with SOT)

2.2 Inertial sensors for fall-risk assessment

In the last decade, several research groups have developed the idea to perform a sensor-based automatic or semi-automatic assessment using wearable inertial sensors, in order to overcome the often time-consuming nature of fall risk assessment test (e.g., POMA) that frequently require experimental knowledge. Apart from offering continuous and objective data, this approach may also serve to detect falls events once they have happened, being aware of the fact that many falls go by undetected and a person may lie injured hours or even days in her or his flat. Tables 2.2 and 2.3, similar to that provided in the previous section, show the type of sensors used and the main findings.

Authors [ref]	Study design, fall risk assessment Subjects	Sensor	Sensor position	Test	Predicitve parameters Classification Algorithms	Results
Najafi *et al.* [151]	Tinetti Balance score History of falls, visual, cognitive and depressive disorder score 11 community –dwelling elderly subject	Tri-axial gyroscope (Murata)	Chest	STS	Temporal postural transitions 	SP ≥0.95 SE ≥0.95
Giansanti *et al.* [152]	age - Tinetti Balance score age≤65, level 1 age≥65, level 1 age≥65, level 3 90 subjects 100 control subjects	Three mono-axial accelerometers (EuroSensor) Three mono-axial gyroscope (Murata) embedded	Back, L5	Standing sway EO(solid surface) EO/EC (foam surface)	Change trunk considering rotational kinematic energy Statistical clustering with Malanobis distance	SP ≥0.93 SE ≥0.94
Giansanti *et al.* [153]	See [154] See [154]	See [154]	See [154]	See [154]	See [154] Multi Layer Perceptron neural network	SP ≥0.88 SE ≥0.87
Gietzelt *et al.* [154]	STRATIFY 90 at risk of falling 151 healthy subjects	Tri-axial accelerometer	Waist	TUG	Energy expenditure and pelvic sway Machine Learning and decision tree	SP =0.91 SE =0.89
Marschollek *et al.* [155]	STRATIFY Barthel index 110 subjects	Tri-axial accelerometer (Freescale)	Waist	TUG	Temporal , energy and frequency related features Classification trees	SP =1.00 SE =0.58
O'Sullivan *et al.* [156]	History of falls 21 subjects	Tri-axial accelerometer (ActivPal)	L3	Standing unsupported EO/EC Standing on a math EO/EC	RMS of accelerometer outputs t-test	Standing on a math EC significantly correlated with BBS and TUG

Table 2.2: Brief review of inertial sensor-based fall risk assessment studies (1)

Based on the summary tables, some considerations can be drawn:

- **type of activity**: all the studies focused on four main tasks: balance with different test conditions (eyes open, eyes closed, solid or foam surface) [152, 153, 156, 158], sit-to-stand (STS) [151, 159], TUG [154, 155, 157, 162, 163] and walking [160, 161, 162]. Probably, the TUG test is the most commonly used because it appears to be more complete since it includes a transfer (standing-to-sit) and a walking phase, thus providing informations about balance (e.g., during STS) and gait. Sit-to-stand test was also used as functional test for discriminating subject at risk of falling. As discussed in the previous chapter, the majority of falls occurred while individuals were engaged in routine behaviours, mainly during transfer. A quantitative description of these complex tasks could provide additional information which are not clearly visible by a physical therapist or doctor who monitors the performance. Even if balance tests (static and/or dynamic) provide indications about the ability of the subject to stand still, functional tests could reveal wrong or non optimal strategies, which in turn could

Authors [ref]	Study design, fall risk assessment / Subjects	Sensor	Sensor position	Test	Predicitve parameters / Classification Algorithms	Results
Green *et al.* [157]	History of falls / 349 community-dwelling elderly subjects	Two Inertial Measurement unit (Shimmer)	Anterior part of shanks	TUG	Temporal gait parameters Angular velocity parameters / Logistic regression	SP =0.76 SE =0.77
Naranyan *et al.* [158]	Physiological Profile Assessment (PPA) / 68 clinic patients	Tri-axial accelerometer	Waist	TUG Alternate –step test Repeated STS	Temporal and energy related features / Linear least squares model	Correlation PPA p=0.73
Liu *et al.* [159]	See [159] / See [159]	See [159]	See [159]	See [159]	Features [160] and additional frequency-related features / Linear least squares model	Correlation PPA p=0.99
Bautmans *et al.* [160]	TUG test>15s Tinetti score≥24/28 History of falls / 40 elderly subjects at risk of falling 41 young controls 40 elderly controls	Tri-axial accelerometer (Dynaport MiniMod)	Pelvis	Two 18m-walk	Gait speed / t-test	SP =0.78 SE =0.78
Caby *et al.* [161]	History of falls / 15 elderly patients	10 accelerometers (Freescale)	Ankle, knee, wrist, elbow, shoulder	25m-walk	67 features (e.g., time walking, number of step, step frequency) / Features selection	SP =1 SE =0.93 (upper limb movement, step frequency)
Marschollek *et al.* [162]	STRATIFY Multidisciplinary geriatric care team score / 116 clinic patients (1 phase) 46 fallers (follow-up) (prospective study)	Tri-axial accelerometer (Freescale)	Waist	TUG 20m-walk	Temporal, energy and frequency related features / Logistic regression	SP =0.58 SE =0.78
Weiss et *et al.* [163]	History of falls / 23 community-dwelling elderly subjects 18 healthy controls	Tri-axial accelerometer (ADXL330)	Lower back	TUG	Temporal parameters / Binary logistic models	SP =0.82 SE =0.87

Table 2.3: Brief review of inertial sensor-based fall risk assessment studies (2)

lead to a fall.

In summary, the quantitative investigations about motor performance during the execution of functional tests have higher predictive value than observational studies and clinical tests in which the clinician simply assesses a score.

- **number and positioning of sensor**: except for two studies [157, 161], one single sensor (tri-axial accelerometer or tri-axial gyroscope, or both embedded in an inertial measurement unit) is often used for the evaluation of the movement. Greene *et al.* [157] placed two inertial measurement unit on the anterior part of the shanks in order to extract gait parameters during TUG test. Caby *et al.* [161] used a whole body accelerometer network composed of 10 tri-axial accelerometers placed on each limb on the left and right side of ankle, knee, and on the wrist and shoulder for the analysis of 25m-walk. Upper limb-attached sensor can significantly reflect gait-related features during locomotion or walking. Redundancy of sensors may provide more accurate information about some body segments which are not investigated when a single sensor is used, as confirmed by the findings of the study of Caby *et al.*, in which features related to the upper limb movement have the most significant discriminant power between fallers and non-fallers. The use of more than one sensor is therefore a commendable approach if in-depth analysis is required.

- **features extraction**: in all studies, the classification between fallers and non-fallers is based on features extraction from the accelerometer and/or gyroscope measurements. Temporal parameters (e.g., time used to perform the task, stride time, swing time, gait speed, number of steps), energy-related features (e.g., signal vector magnitude, rotational kinematic energy), frequency-domain features (e.g., the ratio of the magnitude under each harmonic of the accelerometry signal spectra) are the most commonly used. The identification of one of these features as markers for fall-risk and as indicator of any physiological impairment has been one of the main objectives of these studies. The detection of the discriminant feature should help to design an effective prevention strategies addressed to that specific impairment or cause of fall. Nevertheless, for example the time to perform the task or the signal vector magnitude, which could be the best discriminant features for the classification of fallers and non-fallers, do not provide no additional informations about the biomechanical of the movement. While we recognise the importance of identifying predicitve features of fall, the use of biomechanical measurements can be fundamental for the evaluation of subject-specific fall-risk related to balance and/or gait instability since it could help to identify a specific lack in muscle strength, balance impairment or physical functional reserve.

In summary, all these studies are lacking in biomechanical model-based approach which could provide accurate and more detailed measurements about the strategies adopted to perform the task or biomechanical measurements like joint moments and/or joint forces. One of the main aims of this thesis, discussed in Chapter 4 and 5, is to suggest a biomechanical approach for the evaluation of measurements of interests (e.g., Center of Mass and Center of Pressure displacements, net joint moments, sway angles) by using accelerometer body-network during the execution of functional motor tasks (e.g., repeated STS) often used in clinics for the fall-risk evaluation. Moreover, a more complex transfer (lying-to-sit-to-stand-to-walk test) was investigated in Chapter 6 by using a single inertial measurement unit and a sensor fusion algorithm for highlighting the different strategies adopted to perform the task.

2.3 Technologies for fall detection

At the moment no standardized tests for predicting fall risk have been developed based on inertial sensor-based assessment. Even if extensive research has been conducted in the area of fall prevention, some of the fundamental factors leading to falls and what actually happens during a fall remain unclear. As discussed in the previous chapter, the low accuracy and reliability of oral reports about fall by the subject themselves, witnesses and by informal or formal caregivers make these reports biased in many ways. It is self-evident that objectively documented and measured falls are needed to improve knowledge of fall in order to develop more effective prevention strategies and prolong independent living. In the literature, several approaches were proposed to automatically detect a fall. There have been a number of recent reviews of the use of technologies to support older and disabled people [164, 165, 166, 167]. These reviews cover a great range of assistive technologies and devices. The general failure in the literature to categorise the technologies and devices by some (e.g. functional) taxonomy makes it difficult to interpret what was actually done and thus what any results mean. However, generally the state of the science is that (a) there is a paucity of evidence on the appropriateness, acceptability and effectiveness of these technologies although there has been a general rush towards embracing technological solutions. (b) Results of research into telecare technologies aimed at assisting management of specific disease entities (e.g. diabetes, CVD, etc.) generally provide favourable results for technologies aimed at tele-monitoring and tele-follow up, although cost effectiveness is uncertain [168]. (c) There is generally insufficient evidence to support or refute the use of technologies in promoting independence or assisting older people in their everyday lives. (d) Little is known about psychological variables which are associated with use, or conversely non-use, of assistive technologies by older people.

Technologies in the home may be viewed as more intrusive and less acceptable than institutions [169]. In respect to monitoring solutions over longer durations, issues of user's acceptance becomes even more relevant in relation to effectiveness and social significance. Non-acceptance and non-usage can be regarded partly as a consequence of the failure of designs and operational procedures to respond to the wishes and feelings of a very heterogeneous group as the older people. In overview there is a paucity of evidence about older people's and other stakeholders views, beliefs and attitudes towards the use of technologies in the detection and prevention of falls, and more generally in the promotion of active and independent living. Older people are likely to embrace such technologies if they are congruent with their own beliefs, attitudes, lifestyle and aspirations and are designed in such a way as to be accessible to them. A number of candidate technologies and products or telemedicine services for managing falls (alarm and notification systems) and support-ing health monitoring is available on the market or in a prototypical stage. Some of these were specifically designed for elderly users some were not. A number of home automation tools is also available, but also marginally oriented to an older user. Successful application of technologies is strongly influenced by factors that relate to fit between demands of the technology and specific capabilities of the user [170, 171, 172], obtrusiveness of monitoring method [173, 174], and fit with users' expectations [175, 176]. Based on these considerations, the use of wearable, unobtrusive, low cost, low size, inertial sensors appears promising. In the following, some technologies for fall detection, their benefit and limitations, are briefly presented.

2.3.1 Environmental and Vision-based technologies

RFID Radio-Frequency IDentification (RFID) is a technology that allows exchanging data between a reader and an electronic tag by means of radio waves, for the purpose of identification and tracking. Some tags can be read from several meters away and beyond the line of sight of the reader. Companies are currently using RFID technology also in the healthcare industry as a way to enhance patient safety and improve inventory management capabilities, mostly in the hospital environment. Still, RFID technology can improve the care a patient receives in many ways, including patient tracking and identification. Initial attempts have been done for using RFID-based fall detection. A recent study of Miaou [177] proposed a fall detection system including an omni-directional camera, image processing and recognition algorithms, and an RFID set. The 91% successful fall detection rate was achieved on simulated falls. While this technique is attractive due to low-cost and simplicity, it has several drawbacks. Objects and people must be equipped with RFID readers and tags. In the elder care environment, this is a concern since many residents may forget to wear the devices. Additionally, object such as metallic objects, food, and very small items are not feasible to be tagged. Another concern in using this type of sensing method is the noise present in the environment. Noise is created by RF field strength, interference, and conflict between labels reading from two adjacent tagged objects.

Video-cameras Video-cameras have largely been used [178, 179, 180, 181, 182, 183, 184, 185, 186, 187, 188] for detecting falls but their poor adherence to real-life is particularly related to privacy concerns. While these techniques work well in controlled environments (laboratory, scene), they must be adapted in non-controlled environments in which neither the lighting nor the framing is controlled (it is obviously necessary that the subject be in the field of vision). Moreover, as the subject moves in a three dimensional space, it is also necessary to call upon more complex techniques, namely the use of two cameras ("stereovision"). Nevertheless, these techniques are becoming accessible, both technically and financially, thanks to the emergence of low cost cameras (web cams), the wireless transmission of images over short distances, and the possibility of embedding the required algorithms. But the video technology poses a major problem of acceptance as it requires the placement of video cameras in private living quarters, and especially in the bedroom and the bathroom, with consequent concerns about privacy.

Vibrational sensors Vibrational sensor can be useful in many ways for detecting fall events. A completely passive and unobtrusive system was introduced by Alwan *et al.* [189] that that developed the working principle and the design of a floor vibration-based fall detector. Detection of human falls is estimated by monitoring the floor vibration patterns. The principle is based on the vibration signature of the floor. The floor's vibration signature generated by the human fall is different from normal activities, such as walking. The concept of floor vibrations with sound sensing was investigated in [190], where pattern recognition is applied to differentiate between falls and other events. Shock response spectrum is one of the key special features used in classification. The system is unique in the detection of falls in critical cases, such as a subject being unconscious or in a stressful condition. Rimminen *et al.* in [191] proposed to use a floor sensor based on near-field imaging. The shape, size, and magnitude of the patterns are collected for classification. A set of features is computed from the cluster of observations. The system has problems with test subjects falling onto their knees as this produces a pattern very similar to a standing person. Toreyin *et al.* [192] fused the multitude of sound, vibration and passive infrared sensors inside an intelligent environment equipped with the above fusion elements. Wavelet based feature extraction is performed on data received from raw sensor outputs. Regular and unusual activities, such as falls, are used for training the Hidden Markov Models (HMM). The process of fusion is applied to all outputs from sensors to detect falls.

Vibrational sensor are hence another potential technology to use, but present several problems. It would require either the whole floor to be covered, a heavy expense and difficult to clean, or it would have edges which could cause falls.

Acoustic sensors Acoustic sensors have been also used for detect posture and falls. Hori and Nishida [193] developed an ultrasonic 3D tag system which locate ultrasonic tags in real time, and employed the system in a nursing home to monitor positions of the elderly people. If the system locates the elderly people continuously and robustly, and if it can notify caregivers about the occurrence of accident-prone activities promptly, caregivers will be revealed from their unnecessary workloads.

Pressure sensors Most ambient device based approaches use pressure sensors for subject detection and tracking. The pressure sensor is based on the principle of sensing high pressure of the subject due to the subject's weight for detection and tracking. It is a cost effective and less intrusive for the implementation of surveillance systems. However, it has a big disadvantage of sensing pressure of everything in and around the subject and generating false alarms in the case of fall detection, which leads to a low detection accuracy.

In summary, both visual-based and environmental device approach require a pre-built infrastructure, and this enables their use in hospital and houses, but it is hard to use them outdoor.

2.3.2 Wearable technologies

Wearable sensor systems for health monitoring are an emerging trend and are expected to enable proactive personal health management and better treatment of various medical conditions. These systems, comprising various type of small physiological sensors, transmission modules and processing capabilities, promise to change the future of personal care, by providing low-cost wearable unobtrusive solutions for continuous all-day and any-place health, mental and activity status monitoring. Personal wearable monitoring systems need to satisfy a great diversity of criteria and constraints. These include small weight and size, privacy of personal data, unobtrusiveness, ease of use, low cost, reliability and low power consumption. Designing such a system is a challenging task since a lot of highly constraining and often conflicting requirements have to be considered from the designers. In these thesis, the attention was focused on inertial sensors.

Inertial sensors Inertial tracking technologies are becoming widely accepted for the assessment of human movement in both clinical application and scientific research. Several of these studies focused on the monitoring of the activities of daily living (ADL) and fall detection using wearable sensors. Compared to commercial movement analysis systems, wearable sensors offer advantages in terms of cost, size, weight, power consumption, ease of use and, most importantly, portability. With wearable sensors, data collection is no longer confined to a laboratory environment, thus leading to their availability for health monitoring. In the last decade, a variety of different methods based on inertial sensors were developed to automatically detect falls . Many different approaches have been explored to solve the fall detection problem using only accelerometers or gyroscopes or both [194, 195, 196, 197, 198, 199, 200, 201, 202, 203, 204, 205, 206, 207, 208, 209, 210]. The first approach to fall detection using accelerometry was published by Williams *et al.* [211], and a fall detector was presented after a number of pilot studies [212]. In its design implementation, the fall detector consisted of two piezoelectric shock sensors to detect the impact and a mercury tilt switch to identify the orientation. A two-stage detection process which detects both impact (acceleration) and orientation was used to better eliminate false alarms. The two-stage detection process firstly screens if any impact greater than a certain threshold exists (the first stage). A fall emergency is registered after the first stage if the reclining posture remains unchanged (the wearer does not get up) for a specific period of time. This design implementation led to the product commercialization of the fall detector by Tunstall Group (http://www.tunstall.co.uk/).

The most common used method is using a tri-axial accelerometer with threshold algorithms. Such algorithms simply raise the alarm when the threshold value of acceleration is reached. There exist many problems about this kind of algorithms, including lacking of adaptability, deficiently in classification precision. For example, Hwang *et al.* [213] used tilt switch to trigger the detection program, when the tilt of the person's upper body over 70°, the program will start to process the acceleration signals to determine whether there is a fall occurred. However, if the person slides fall during going down-stairs, in general he will sit down on the stairs with only a small tilt degree on the upper body, and hence the detection program will not be triggered. A not exhaustive review of position, number of sensor and algorithms used is provided in Figure 2.1.

More details about fall detection algorithms and their poor reliability and pervasivity in the daily life will be provided in Chapter 7. The focus will be on threshold-based fall detection algorithms when they are applied to a real-world fall database, in order to provide the main drawbacks of these approaches which affect their acceptability among elderly people.

Smartphones Today's smartphone not only serves as the key computing and communication mobile device of choice, but it also comes with a rich set of embedded sensors, such as an accelerometer, digital compass, gyroscope, GPS, microphone and camera. Collectively, these sensors are enabling new applications across a wide variety of domains, such as healthcare [214], social networks, safety, environmental monitoring, and transportation, and give rise to the new area of research called mobile phone sensing [215]. Until recently mobile sensing research such as activity recognition, where people's activity (e.g. walking, driving, sitting, talking) is classified and monitored, required specialized mobile devices (e.g., the

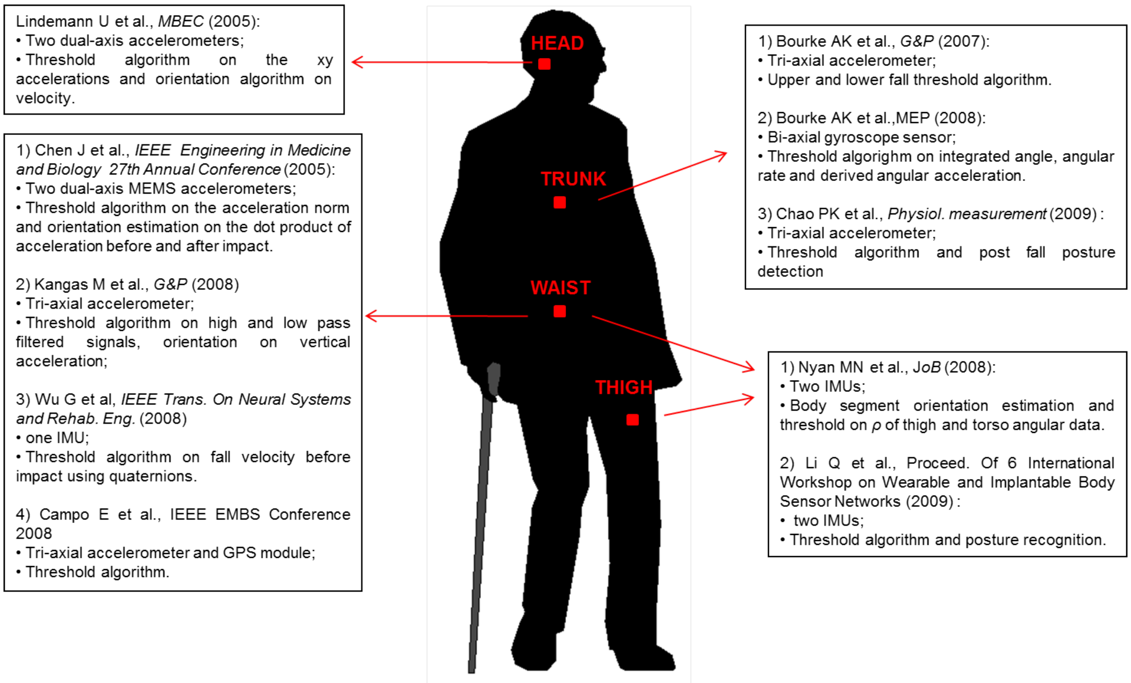


Figure 2.1: Example of sensor positions and algorithms for fall detection.

Mobile Sensing Platform MSP) [216] to be fabricated. Mobile sensing applications had to be manually downloaded, installed, and hand tuned for each device. User studies conducted to evaluate new mobile sensing applications and algorithms were small-scale because of the expense and complexity of doing experiments at scale. As a result the research, which was innovative, gained little momentum outside a small group of dedicated researchers. Although the potential of using mobile phones as a platform for sensing research has been discussed for a number of years now, in both industrial [217] and research communities [218], there has been little or no advancement in the field until recently.

In the fall-detection domain the iFall [219] application has been developed to detect fall events: data from the accelerometer is evaluated with several threshold-based algorithms and position data to determine a fall. If a fall is suspected a notification is raised requiring the user's response. If the user does not respond, the system sends alerts message via SMS. The fall-detection algorithm is based on simulated falls only: this may cause the need to perform a lot of threshold calibration without any assurance about its performance. The Mover [220] application has been developed to monitor human activity level and to detect falls. In order to measure activity levels, Mover reads data from the phone's accelerometer and sums it out throughout the day. People's average level of activity is then translated into a simplistic categorization of users: Sleeper, Sitter, Lagger, Walker, Mover or Hyper.

Mover can also detect user falls and send alerts to user's emergency contacts (through SMS or email). Before calling for help, Mover will play a sound to make sure you are unconscious. The feature is still experimental as the algorithm is still being tested (the algorithm is based on simulated falls only). Two preliminary studies [221, 222] has verified the suitability of consumer accelerometers, as those included in recent smartphone, to perform some clinical tests, such as the instrumented TUG test. In other two recent papers [223, 224] authors developed a computer algorithm for fall detection using mobile phone technology tested on simulated falls performed by healthy volunteers.

In summary, even if a myriad of ICT-based products or services are in place trying to satisfy the need of an early intervention in case of fall, existing solutions still do not have a remarkable social impact neither a significant market penetration: just 4.5% of Europe's potential end users have any of the existing social alarms. Three facts hinder their effectiveness of the existing systems, capping therefore the market demand: bad ergonomics (and hence poor acceptability from older users) and lack of reliability, due to a poor knowledge of real falls. This specific issue will be discussed in Chapter 7.

Part II

Fall-risk evaluation

Chapter 3

Balance control as indicator of fall risk

As discussed in Chapter 1 several studies are underpinned by the attribution of falls to multiple interacting factor. Fall prevention can therefore successfully addressed through adaptive and complex interventions focused on understanding of cumulative effect of several stressors and their inter-relationships [225]. Recently, it has been argued that exercise alone could prevent fall in older people, with the greatest relative effect size in programmes that challenge balance [107].

Normal ambulation and postural stability are complex processes that involve the rapid, automatic integration of information from the vestibular, somato-sensory, visual, and musculo-skeletal systems, in the presence of cognition, which includes attention and reaction time [227, 228]. The coordination of many different muscles acting on multiple joints is accomplished by the integration of activity in spinal neuronal circuitries with sensory feedback signals and with descending commands from the motor cortex.

Balance is therefore a higher order function that requires a significant degree of connectivity and coordination between several interdependent components (muscular, skeletal and nervous) of the complex system that is the human body. Consequently, individuals who may have lost the ability to integrate multiple inputs in the face of stress often present with falls [93]. The prediction of falls by abnormalities in gait and balance is consistent with the paradigm of complex system failure (see Figure 3.1).

As one gets older, the ability to maintain balance control deteriorates. This decline can be attributed to decline in the somato-sensory, visual, and vestibular systems to varying degrees [229]. Posture control, body-orienting reflexes, muscle strength and tone, and height of stepping all decline with ageing and impair ability to avoid a fall after an unexpected trip or slip. In old age, the "strategy" for maintaining balance after a slip shifts from the rapid correcting "hip strategy" (fall avoidance through weight shifts at the hip) to the "step

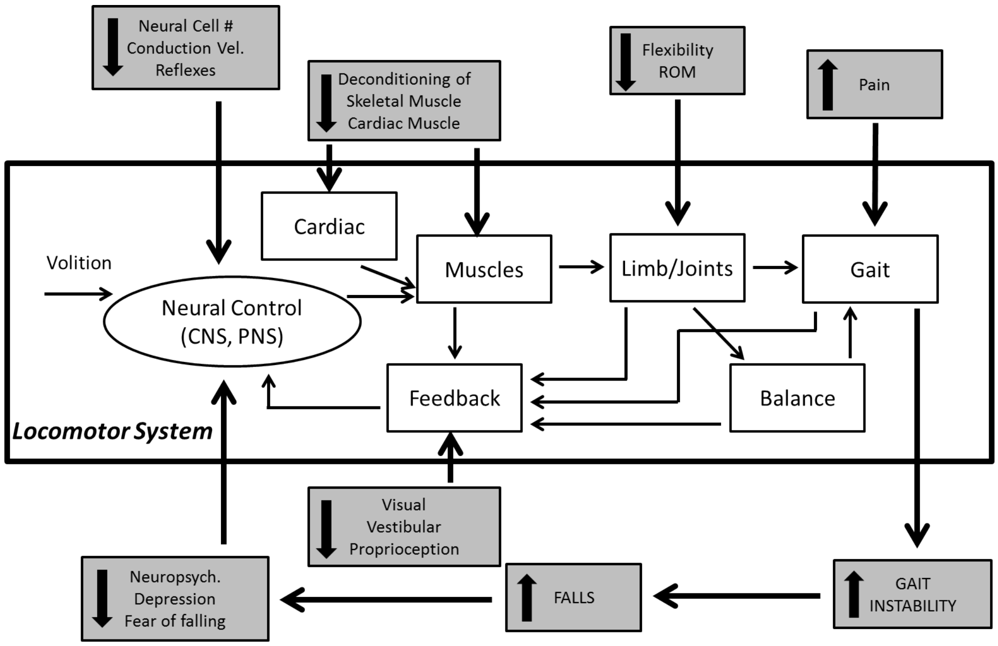


Figure 3.1: Simplified block diagram illustrating some of the physiological and neuropsychological factors that may be associated with gait and balance instability, adapted from [226]

strategy" (fall avoidance via a rapid step) to total loss of ability to correct in time to prevent a fall.

The measurement tools used to evaluate balance in the clinical setting are a means of quantifying the working capacity of the sum of the components that enable postural stability. Shumway-Cook and Woollacott [230] differ between the following strategies that help keeping balance:

1. **reactive balance**, used to recover from an unexpected external threat to stability during walking or standing;

2. **static/dynamic steady-state balance**, used during the maintenance of a steady position in sitting, standing, and walking;

3. **proactive balance**, used to stabilize balance in anticipation of a know threat to stability, such as when making a voluntary movement.

Falls primarily occur during ambulation (i.e., steady-state balance) or during slipping and tripping events (i.e., reactive balance) and not during quiet standing in the elderly. Since standing balance (i.e., static steady-state balance), walking balance (i.e., dynamic steady-state balance), and balance recovery (i.e., reactive balance) were reported to be unrelated [231, 232, 233], fall-risk assessment should particularly be carried out under dynamic steady-state balance (e.g., analysis of gait variability under single and particularly multi-task conditions) and reactive balance conditions (e.g., exposure to balance threats via the postural stress test) to identify older adults at risk of falling. It was frequently reported that deficits in reactive and steady-state balance performance put older adults at an increased risk of falling [234, 235]. For these reasons, tests for the analysis of reactive balance and steady-state should be incorporated into a standard fall- risk assessment protocol for older adults. In the following section these two different conditions are briefly described. In the next two chapters of this thesis the issue of the description of reactive and steady-state balance is addressed through a biomechanical approach based on a body sensor network.

Reactive balance From a biomechanical perspective, to maintain an upright posture during quiet stance the vertical projection of the whole-body centre-of-mass (CoM) must fall within the limits of the base of support (BoS) [236]. To accomplish this, models related to ankle stiffness [237, 238] and reactive muscle strategies [239, 240] predict that adjustments in the location of the underfoot centre-of-pressure (CoP) are used to guide the trajectory of the CoM towards an equilibrium position. In the event of a balance perturbation that causes the CoM to shift anteriorly (such as being nudged from behind), recovering balance without changing the BoS via stepping responses requires the CoP to be rapidly shifted anteriorly towards the toes to decelerate the CoM. If the CoM trajectory cannot be altered quickly enough by the anterior CoP displacement and consequently reaches the BoS boundaries, the individual must increase the BoS by taking a step in order to prevent a forward fall [236]. Thus, the proximity of the CoM to the BoS boundaries after perturbation (margin of safety (MoS)) provides an indication of the degree of instability following the perturbation. For elderly persons, a large MOS may be of increased importance in recovering balance due to age-related declines in strength, reaction time, and other sensor-motor capabilities.

Consequently, changes in support surface stiffness may influence CoP dynamics, which in turn could influence CoM trajectories [241, 242]. To more closely assess the interaction of musculo-skeletal and sensory components of postural stability, a number of investigations have been performed in which the subject is mechanically perturbed by applying a direct force to their body, or by tilting or translating the surface upon which they stand. These techniques are thought to provide useful information regarding how effectively the subject's sensory and motor systems respond to external stimuli.

The sternal shove test or nudge test is a simple test of balance recovery [340]. Subjects stand with feet close together. The examiner pushes with light even pressure over the

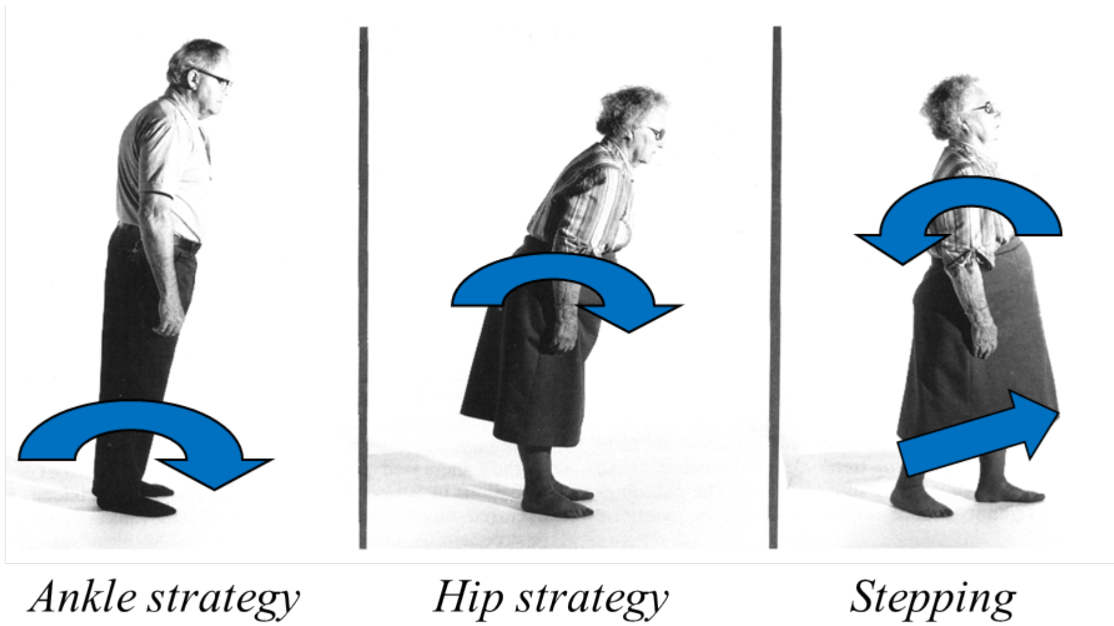


Figure 3.2: Strategy for balance recovery, adapted from [247]

sternum three times. The response is graded using a 0 to 2 scale with 0 meaning that the subjects start to fall and need assistance; 1 indicates that the subject maintains balance with feet movement; 2 means that the subject's stance remains stable. However, reliability and validity have not been established for this test [244]. This might be due to the fact that the intensity of the applied perturbation impulse as well as the rating of the balance recovery reaction is examiner dependent. A more sophisticated but still easy-to-administer test for the assessment of balance recovery reactions is the so-called postural stress test which was introduced by Wolfson *et al.* [245]. In this test, balance recovery reactions to postural perturbations of varying degrees are measured during normal standing using a simple pulley weight system that displaces the centre of gravity behind the base of support. More specifically, subjects have to withstand a series of posterior perturbation impulses that are applied at the level of the subject's waist using three different perturbation intensities (i.e., 1.51%, 3%, and 4% of the body mass). Scoring of the postural responses is based on a nine-point ordinal scale, where a score of 9 represents the most efficient postural response and a score of 0 represents a complete failure to remain upright. Chandler *et al.* [246] observed that elderly community-dwelling fallers score significantly lower on the postural stress test than either young adults or non falling elderly individuals.

Biomechanical tests are usually characterized by high criterion validity. In an earlier study, Maki *et al.* [133] compared the ability of different measures of postural balance to predict risk of falling prospectively in an ambulatory and independent elderly population aged between 62 and 96 years. Different balance tests including tests of spontaneous sway, induced sway, and one-legged tests were conducted. A force plate moving back and forth and side to side was used during the induced sway conditions. A number of measures showed evidence of significant differences between fallers and non-fallers. The differences were most pronounced for measures related to the control of both spontaneous and sway-induced stability. The authors suggested that this rather simple and safe force-plate measure of postural sway can be used in a clinical setting as a preliminary screening tool for risk of falling. In summary, as also discussed in the previous Chapter, the existing methods and clinical tests for the evaluation of reactive balance strategies, depend on subjective scores or, in studies which involved FPs, the strategies are investigated by focusing on CoP neglecting the biomechanics of the single body segments. In order tackle this issue, in Chapter 4, a method for the kinematic evaluation of sway angles (ankle, knee and hip) during perturbed stance by using a single-axis accelerometer per segment and a 3-link biomechanical model is presented. The method is suitable for the evaluation of the response strategy to unexpected perturbation even if it has been validate on a self induced sway only. The method is validated with a stereo-photogrammetric system. Results obtained suggest its possible use in clinical practice as tool for estimating how subject's motor system responds to external stimuli and for estimating quantitatively the balance recovery reaction.

Static/dynamic steady-state balance Steady-state balance can be assessed during standing and/or walking under single-task conditions and/or dual/multi-task conditions (i.e., standing/walking while concurrently performing a motor/cognitive interference task).

One-leg standing balance (i.e., ability to stand unassisted for 5 seconds on one leg) is an easy-to-administer and inexpensive clinical test for the assessment of the functional level and the frailty status of older community-living persons [20]. Notably, Vellas *et al.* [20] reported that this test can be used as a predictor of injurious falls. The Timed Up and Go Test (TUG) is a test of dynamic steady-state balance that is commonly used to assess functional mobility and risk of falling in community-dwelling, frail older adults (aged 70 to 84 years) [126].

The sit-to-stand (STS) is another simple test which is often used as measure of lower limb strength and is included in fall risk assessment scales. The STS transfer is a regular mobility related activity in daily life, it is performed multiple times a day, and studies have demonstrated that measures of STS performance are important indicators of overall functioning and balance performance in older persons [126, 248].

For the sit-to-stand test with five repetitions (rSTS), subjects were usually asked to

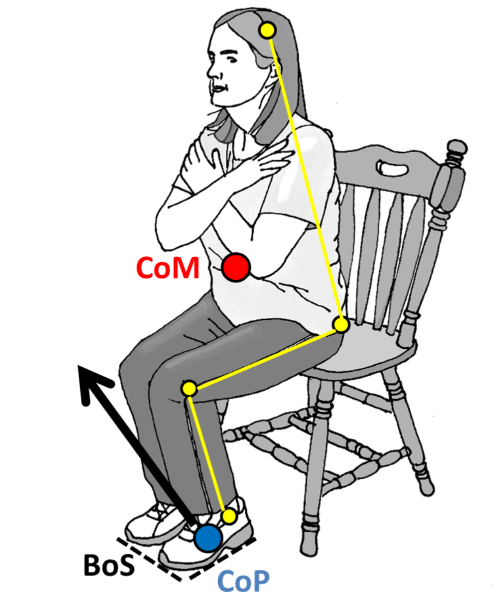


Figure 3.3: Sit to stand analysis

rise from a standard height (43 cm) chair without armrests, five times, as fast as possible with their arms folded. The single sit-to-stand task (time from sitting to standing) was also evaluated as it has been used in assessment scales as a measure of functional mobility, balance and lower limb strength. Previous studies have also reported that the STS test is significant predictor of falls in older community-living people [249, 250].

In particular Nevitt *et al.* [249] found that a patient's ability to stand up from a chair and to perform a tandem walk, were the most useful indicators of his or her risk of multiple falls, perhaps because these abilities require a combination of neuromuscular competencies: dynamic balance, strength, and an adequate range of motion in the lower extremities.

Buatois *et al.* [251, 252] found the the rSTS provided added value in the estimation of risk for recurrent falls, in community-dwelling individuals at moderate risk for falls, as those individuals in the "moderate risk" group with an rSTS score of greater than 15 seconds were found to have twice as many falls as those individuals who performed the rSTS in less than 15 seconds.

Traditional clinical evaluation of STS transition is based on visual observation of joint angle motion to describe alterations in coordination and movement pattern. However, the validity of such assessment essentially depends on clinicians' experience and training, as discussed in the previous Chapter. Results might not have the precision needed to objectively assess the effect of rehabilitative intervention or the decline over time in frail elderly persons [253]. One of the most straightforward parameter to characterize the subject's performance in STS postural transition is to measures its duration. Previous observations have shown that duration of STS transitions can distinguish between older people at low and high risk for falls [151]. Despite these encouraging observations suggesting the usefulness of duration of STS postural transition, other studies in patients suffering from Alzheimer's or Parkinson's disease also suggest that this parameter is not sufficient to fully describe the clinical performance in older persons [254, 255].

Overall, these observations confirm that the STS transition is a complex movement and suggest that more detailed characterization than merely a measure of duration are needed to fully capture the various aspects of motor control and performance. To achieve this aim, additional parameters are needed that more specifically assess kinematic phases within the STS transition, such as the maximum trunk flexion [255], key events as temporal locations of the major peaks of vertical and sagittal acceleration [256].

For instance, elderly frailty persons may use different compensatory strategies to achieve successful transitions such as deviation from normal motion. This deviation is due to several types of motion irregularities, among which sway is the most frequently encountered. Sway consists in repetitive, quick changes in motion orientation due to a temporary loss of balance or to insufficient strength in lower limbs. These results suggest that further investigation of postural transition with other additional parameters has the potential to provide important predictive information. Recently, Ganea *et al.* [257] extracted multi-parametric measures characterizing different features of STS transition in older persons, using a single inertial sensor attached to the chest, suggesting their use for fall risk estimation. Nevertheless, few studies focused on a biomechanical approach using inertial sensors.

In Chapter 5, the method for the kinematics evaluation presented in Chapter 4 is applied to young subjects during the execution of oscillatory trials ans repeated STS. Kinematic and dynamic variables were evaluated by the use of accelerometry only and a biomechanical approach. With the aim of balance control in mind, we provide a reliable algorithm to describe quantitatively the biomechanics of the STS through accelerometers body network. The set-up has the advantage to speed up the experimental sessions and to assess the motor task considering biomechanical measurements which are usually neglected during clinical assessments test.

Chapter 4

Angular kinematics by body sensor network

It has been recently demonstrated [258] a strong relations between voluntary postural sway measures and falls-history status in community-dwelling older adults considering Center of Pressure amplitudes and reaction time measures. An approach based on CoP excursions may be limited as they can only provide a global indication of body motion, neglecting the biomechanics of the single body segment. To obtain information about the inter-segmental dynamics of maintaining stability, it may be necessary to measure postural motion at additional locations such as lower and upper limb and trunk. The main aim of this chapter is to provide a quantitative assessment tool of body sway angles by using a body sensor network, consisted of one single-axis accelerometer (SAA) per segment. A preliminary calibration, using SAAs and a reference system (encoder or stereo-photogrammetry), allows the estimation of sensors position and orientation and segment lengths. These parameters are then used to predict the chain kinematics using the SAAs only. To evaluate the method, the algorithm is first tested on a mechanical arm equipped with a reference encoder. A general method for estimating the kinematics of an N-link chain is also provided. Finally, a three-link biomechanical model is applied to a human subject to estimate the joint angles during squat tasks; a stereo-photogrammetric system is used for validation. The results are very close to the reference values. Mean descriptive (predictive) root mean squared error (RMSE) is 0.15° (0.16°) for the inverted pendulum, and 0.39° (0.59°) for the shank, 0.82° (1.06°) for the thigh, 0.87° (1.09°) for the HAT (head-arm-trunk) in the three-link model. The mean value of RMSE without calibration is 1.02° for the inverted pendulum, and 11.01°

Bagalà F, Fuschillo VF, Chiari L, Cappello A (2012) *Calibrated 2D angular kinematics by single-axis accelerometers: from inverted pendulum to N-link chain*, IEEE Sensors Journal, 12(3): 479-486 (shank), 11.39° (thigh) and 12.21° (HAT) in the three-link model. These results suggest that, after the calibration procedure, one SAA per segment is enough to estimate 2D joint angles accurately in a kinematic chain of any number of links, providing the usability of this instrumented test in clinical practice.

4.1 Introduction

Several authors have used accelerometers and/or rate gyroscopes to study balance in unperturbed upright stance[259, 260, 261], to estimate the gait kinematic parameters[262, 263], and to evaluate joint angles during specific tasks[264, 265, 266, 267, 268, 269, 270]. In the balance studies, Kamen *et al.* [259] used two single-axis accelerometers (SAAs), taped to the back (at S2 level) and forehead, to quantify postural sway, evaluating the root mean square (RMS) and frequency spectrum of the accelerations in the anterior-posterior (AP) direction. Moe-Nilssen [260] used a tri-axial accelerometer placed on the trunk to investigate whether body sway during quiet standing could differentiate between young and elderly healthy subjects in different sensory conditions. In the study of Mayagoitia*et al.* [261], the authors compared the effectiveness of tri-axial accelerometer, placed at the back of the subject, and force plate measurements in distinguishing between different standing conditions. In the gait studies, Mayagoitia *et al.* [262] used four SAAs and one gyroscope per body segment to obtain the kinematics (shank, thigh and knee angle) in the sagittal plane. Their system was validated by an optoelectronic system, and the ratio of root mean squared errors (RMSEs) to average peak-to-peak values was 2-5%. Lyons *et al.* [263] used two SAAs to distinguish between static and dynamic activities and detect the basic postures of sitting, standing and lying. In the evaluation of the inclination angles of trunk and thigh in posture, the inertial term was neglected. The effect of this decision will be further discussed in the definition of our model. In joint angle evaluation studies, Liu *et al.* [264] used two tri-axial accelerometers to estimate the flexion/extension and abduction/adduction angles of the thigh segment; the RMSE of the thigh segment orientation was between 2.4° and 4.9° during normal gait, comparing accelerometric and stereo-photogrammetric (SP) data. Cooper *et al.* [265] estimated knee flexion/extension angles with RMSEs from 0.7° up to 3.4° using two inertial measurement units (i.e., a combination of gyroscopes and accelerometers). Similar results for the 3D knee joint angle measurements were obtained by Favre *et al.* [266] with the same instrumentation. O'Donovan *et al.* [267] found RMSE between 0.5^o and 4^o degrees for 3D lower limb joint angles estimation during static and dynamic tasks by using tri-axial accelerometers, gyroscopes and magnetometers. Dejnabadi *et al.* [268] showed RMSEs of 1°

and 1.6° for shank and thigh segments, respectively, in the sagittal plane using a combination of accelerometers and gyroscopes. Most of these methods usually require at least two inertial sensors per segment. In contrast, the aim of this study is to develop an alternative method using (only) one SAA per segment aligned with the AP axis of the anatomical reference frame. Off-line evaluation of sagittal plane kinematics is performed through a model-based approach. To validate the method, three models are used.

- *Inverted pendulum model*: experimental tests using a mechanical arm equipped with an absolute encoder and an SAA.
- *N-link model*: a simulation shows the possible extension of the algorithm to a kinematic chain with N links.
- *Three-link biomechanical model*: an experimental session is conducted with a subject during squat tasks.

A calibration for the inverted pendulum and the three-link model is provided to give the position and the orientation of the sensors and the anthropometric parameters of the subject (lengths of the shank and the thigh). These parameters are used, together with accelerometric data, to predict the joint angles which are then compared to the encoder outputs (for the inverted pendulum model) or to the SP outputs (for the three-link biomechanical model).

4.2 Methods and Materials

4.2.1 Inverted Pendulum Kinematics

An inverted pendulum model (1 degree of freedom) is initially analyzed. First, the kinematic equation of the model is shown and the estimation algorithm of the angular sway is provided. Next, to validate the method in a simple set-up, a mechanical arm equipped with an absolute encoder and an SAA are used and the sway angle is estimated after a calibration.

Inverted Pendulum Model: the Angle Estimation Method

The SAA is placed at height h from the pivot point P, with the sensitive axis orthogonal to the longitudinal axis of the inverted pendulum (see Figure 4.1a).

The accelerometer output $a(t)$ can be expressed, in the continuous-time domain, as the sum of two terms:

inertial contribution depending on the angular acceleration $\ddot{\theta}(t)$

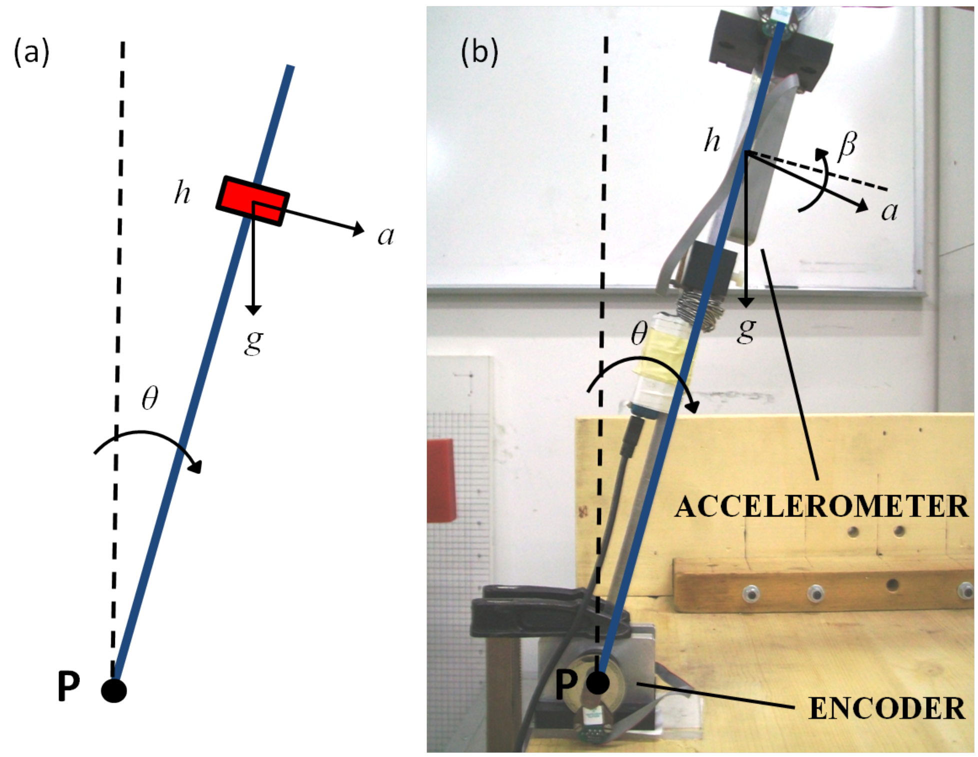


Figure 4.1: (a) Inverted pendulum model. (b) Mechanical Inverted pendulum

gravitational term depending on the sway angle $\theta(t)$

$$a(t) = h\ddot{\theta}(t) - g\sin\theta(t) \tag{4.1}$$

where g is the gravitational acceleration. Several authors [260, 261, 262, 263, 271, 272] used an inverted pendulum and a quasi-static (QS) model in which the inertial term in (4.1) is neglected, so the accelerometer output can be approximated as $a(t) \approx -g\sin\theta(t)$. This approximation is overcome by the angular sway estimation algorithm presented in this chapter, which is based on the dynamic model shown in Eq.(4.1). First, Eq.(4.1) can be rewritten, in the discrete-time domain, as the sum of a linear (L) and nonlinear (NL) term:

$$a(k) = \underbrace{h\ddot{\theta}(k) - g\theta(k)}_{\text{Linear Term}} + \underbrace{g(\theta(k) - \sin\theta(k))}_{\text{Corrective nonlinear term}} = a_L(k) + a_{NL}(k)$$

$$k = 1, \ldots, n \tag{4.2}$$

where n is the number of samples. Under the approximation of small angles, $(sin\theta(k) \approx \theta(k))$, the nonlinear term is negligible, Eq. (4.1) is linearizable and the linear model transfer function is

$$H(s) = \frac{\theta(s)}{a(s)} = \frac{1}{hs^s - g} \tag{4.3}$$

Equation (4.3) clearly shows that the system is unstable, because one of the roots of the denominator is positive. We refrain in this thesis from discussing the inverted pendulum model stabilization and focus instead on the angular sway estimation. This can be solved in the frequency-domain rewriting (4.3) as the product of two first-order low-pass filters (F_F, forward filter; B_F, backward filter):

$$H(j\omega) = \frac{\theta(j\omega)}{a(j\omega)} = -\frac{1}{g} \underbrace{\frac{1}{1 - \frac{j\omega}{\omega_c}}}_{B_F} \underbrace{\frac{1}{1 + \frac{j\omega}{\omega_c}}}_{F_F} \tag{4.4}$$

$$\omega_c = \sqrt{\frac{g}{h}}$$

The cutoff frequency of the two filters equal the corresponding natural frequency of the system

$$f_c = \frac{1}{2\pi}\sqrt{\frac{g}{h}} \tag{4.5}$$

which is related to the distance h between the pivot point and the origin of the reference system of the inertial sensor. Equation (4.5) represents the frequency response of a second-order low-pass filter with zero-phase. Therefore, the angular sway can be computed through the *bidirectional* filtering of the accelerometric signal as follows (using the *filtfilt* function in Matlab):

$$\theta(j\omega) = -\frac{1}{g} B_F(j\omega) F_F(j\omega) a(j\omega) \tag{4.6}$$

The corrective nonlinear term takes into account the nonlinearities due to large angular excursions. The problem of evaluating the nontrivial, large angular displacements in Eq.(4.2) is solved using an iterative methods with the following steps.

1. the angle vector $\boldsymbol{\theta} = [\theta(1) \ldots \theta(n)]$ is initialized, neglecting the nonlinear and the inertial terms, as $-\mathbf{a}/g$, where $\mathbf{a} = [a(1) \ldots a(n)]$ is the accelerometer output.

2. the corrective nonlinear term $\mathbf{a}_{NL}$ is evaluated form Eq.(4.2) by substituting the angle vector $\boldsymbol{\theta}$.

3. the linear acceleration vector is estimated as $\mathbf{a}_L = \mathbf{a} - \mathbf{a}_{NL}$ and new samples are added at the beginning and at the end of the vector using the Symmetric Padding technique [273] in order to neglect the transient effect after filtering. The length of the two extensions has been chosen equal to six times the time constant, $\sqrt{h/g}$, of the filter.

4. the angle vector $\boldsymbol{\theta}$ is estimated by filtering the acceleration $\mathbf{a}_L$ through the bidirectional low-pass filter, and the added extensions are removed.

5. the residual error at step j is estimated as $\mathbf{e}^{(j)} = \boldsymbol{\theta}^{(j)} - \boldsymbol{\theta}^{(j-1)}$.

6. the cost function is evaluated as $f^{(j)} = \mathbf{e}^{(j)} \left(\mathbf{e}^{(j)}\right)^T$

Iterations 2-6 stopped when $f^{(j)} < \epsilon_0$, where $\epsilon_0 = 10^{-25}$ is the chosen threshold. Usually, the method converges in 10-15 steps.

Mechanical Inverted Pendulum

To test the method, an aluminum rectangular link is used as an inverted pendulum driven by hand to sway with a fixed pivot point. The frequency content of the angular sway is about 2Hz. Five trials are performed. The mechanical arm is equipped with an absolute encoder (Gurley, mod. 7700, resolution 19 bit) and a tri-axial accelerometer (Dynaport® Minimod, McRoberts, range ±2g, resolution ±1mg) placed at height $h = 0.31$m from the pivot point, P (Figure 4.1b). For the present study only the accelerometer output related to the axis orthogonal to the mechanical arm is acquired at 100Hz sampling rate. Unlike the ideal condition of the mathematical model, the placement of the sensor on the mechanical link potentially introduces some errors due to the non-orthogonality of the sensitive axis of the SAA to the segment. This effect is even more evident in the human body segment, where the soft tissue between the bone and the skin affects the ideal orthogonality of the SAA sensitive axis. Equation (4.1) is modified by taking into account the projections of the tangential, centripetal and gravity accelerations on the sensitive axis, in order to quantify this undesired effect, as follows:

$$a(k) = h\ddot{\theta}(k)\cos\beta - h\dot{\theta}^2\sin\beta - g\sin(\theta(k) - \beta)$$
$$k = 1, \ldots, n \tag{4.7}$$

where the angle β describes the SAA non-orthogonality (see Figure 4.1b). Preliminary calibration is required to evaluate the two geometric parameters h and β. In the calibration trial the encoder output, $\boldsymbol{\theta}_{enc}$, is used as reference. This algorithm estimates the parameter vector $\mathbf{p} = [h, \beta]$ through a least-squares approach by minimizing the cost function $f^{(j)} = \mathbf{e}^{(j)} \left(\mathbf{e}^{(j)}\right)^T$, where $\mathbf{e}^{(j)} = \boldsymbol{\theta}_{enc}^{(j)} - \boldsymbol{\theta}^{(j-1)}$ is the residual error at step j. The angle vector $\boldsymbol{\theta}$ is estimated through the iterative algorithm described previously.

In order to test the robustness of the calibration, the two parameters are estimated for each trial and then their mean values are used to predict the angular sway of the inverted pendulum using the SAA; this prediction is compared to the encoder output. Angular RMSE is evaluated both in the calibration and prediction trials. In order to demonstrate the advantage of the angle estimation method with respect to the QS model, the encoder output is compared with the angular sway approximated as $\theta \approx \beta + g \arcsin(a/g)$, neglecting the inertial terms $\dot{\theta}$ and $\ddot{\theta}$. RMSEs between QS and reference angles are evaluated and the percentage of time in which the QS model is valid is provided. In fact, according to Eq.(4.4), if the frequency content of the accelerometer output is below the frequency $f_{max} = f_c\sqrt{e_{\%}/100}$, which implies an angle percentage error less than $e_{\%}$ (e.g., $h = 1$m, $e_{\%} = 5\%$, $f_{max} = 0.11$Hz), the QS model approximation is valid; if the frequency content exceeds f_{max} significantly, the accelerometer output, in absolute value, can reach the gravitational acceleration and the QS model provides imaginary angular values.

4.2.2 Multilink Kinematics

A kinematic chain model (N degrees of freedom) is analyzed. First, the kinematic equations of the model are described and the outputs of the N accelerometers are simulated. The angular sway of each link is evaluated with the iterative method presented in the Section 4.2.1. The experimental validation of the model is then performed, after a calibration trial in a movement analysis laboratory, on a subject during squat tasks; the human body is assumed to be a three-link model.

N-link Model

A continuous curve, with a fixed point in the joint ankle, is modelled. The curve can be discretized with any finite number of links, as shown in Figure 4.2. In this first simulation phase, a linear array of N=40 SAAs, equally spaced with $l_i = 2cm (i = 1, \ldots, n)$ (Figure 4.2), is assumed. The N angular trends are then simulated by a superposition of sinusoidal functions.

The output of the i-th accelerometer is obtained from Eq.(4.2), adding the projection on the measurement axis of the accelerations, a_i^x and a_i^y, at the lower joint. These two contributions can be evaluated considering the second derivative of the lower joint position with respect to the pivot point (e.g., $[l_1 \sin\theta_1, l_1 \cos\theta_1]$ for the first segment, and for

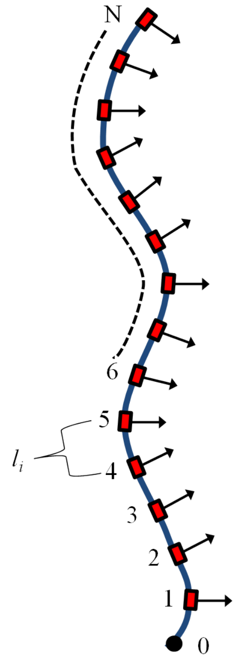


Figure 4.2: Snake-like profile for a 40-link kinematic chain

the second segment $[l_1 \sin\theta_1 + l_2 \sin\theta_2, l_1 \cos\theta_1 + l_2 \cos\theta_2]$). Therefore, by simple geometric considerations, the acceleration of the i-th joint will be given by the recursive expressions:

$$\begin{aligned} a_i^x(k) &= a_{i-1}^x(k) + l_{i-1} \left. \frac{d^2[\sin\theta_{i-1}(t)]}{dt^2} \right|_{t=kT} \\ &\approx a_{i-1}^x(k) + l_{i-1} \frac{[\sin\theta_{i-1}(k+1) - 2\sin\theta_{i-1}(k) + \sin\theta_{i-1}(k-1)]}{T^2} \end{aligned}$$

and

$$\begin{aligned} a_i^y(k) &= a_{i-1}^y(k) + l_{i-1} \left. \frac{d^2[\cos\theta_{i-1}(t)]}{dt^2} \right|_{t=kT} \\ &\approx a_{i-1}^y(k) + l_{i-1} \frac{[\cos\theta_{i-1}(k+1) - 2\cos\theta_{i-1}(k) + \cos\theta_{i-1}(k-1)]}{T^2} \end{aligned}$$

for $k = 1, \ldots, n$, $i = 1, \ldots, N$, where T is the sample time and l_{i-1} is the length of the (i-1)-th segment (it is assumed that $a_0^{x,y} = 0$, $l_0 = 0$). Therefore, the simulated i-th accelerometer output is expressed as:

$$\begin{aligned} a_i(k) = h_i\ddot{\theta}_i(k) - g\sin\theta_i(k) + a_i^x(k)\cos\theta_i(k) - a_i^y(k)\sin\theta_i(k)& \\ k = 1, \ldots, n& \\ i = 1, \ldots, N& \end{aligned} \tag{4.8}$$

In order to simulate the accelerometers output, a random Gaussian noise (zero-mean, std=0.01) is added to each of the simulated signals expressed in Eq.(5.2). The same iterative method described in Section 4.2.1 allows the evaluation of the time-dependent snake-like profile, by summing and subtracting the linear gravitational contribution $g\theta_i(k)$ in Eq.(5.2). In this case, the non-linear term of the acceleration, used in step-2 of the estimation method, is defined as:

$$
\begin{aligned}
a_{NL,i}(k) = g\theta_i(k) - g\sin\theta_i(k) + a_i^x(k)\cos\theta_i(k) - a_i^y(k)\sin\theta_i(k) \\
k = 1, \ldots, n \\
i = 1, \ldots, N
\end{aligned}
\tag{4.9}
$$

The estimated profile of the kinematic chain is compared to the simulated profile.

Three-Link Biomechanical Model

In the second experiment, the method is tested on one subject (female, 27 years-old, weight 59kg, height 167cm), who participated after giving her informed consent. In order to estimate the body sway in the sagittal plane during squat tasks [274], a three-link biomechanical model is introduced. The feet are supposed to be rigidly connected to the ground; the ankle, knee and hip joints are represented as three hinge joints and the shank (segment 1, length $l_1 = 0.40$m), thigh (segment 2, length $l_2 = 0.49$m) and HAT (segment 3) are modelled as three rigid segments. The subject is asked to perform a repetition of squat exercises for 30 seconds with her arms folded, keeping her movement in the AP direction. Four trials are perfomed. In order to estimate the shank, thigh and HAT angles with respect to the vertical line, three tri-axial accelerometers (Dynaport® Minimod, McRoberts, range ±2g, resolution ±1mg) are placed at measured heights $h_1 = 0.30$m, $h_2 = 0.29$m, $h_3 = 0.29$m, with respect to the ankle, knee and hip joint, respectively, in order to minimize the skin artifact effect. Each of the three sensors is placed on a rhomboid rigid plate and mounted on the skin at the lateral side of the thigh, shank and HAT by using three hook-and-loop fastener belts, as shown in Figure 4.3. For the present study only the AP accelerometer outputs are acquired at a 100Hz sampling rate.

Four reflective markers are placed on the vertices of each plates, and a SP system (SMART eMOTION, BTS) is used for calibration and validation. SP and accelerometer data are low-pass filtered (zero-phase) at a cut-off frequency of 3Hz. The 12 markers are projected onto the plane which best approximates the point cloud in the observation interval, and the three reference angles are evaluated through the 2D Singular Value Decomposition (SVD) method

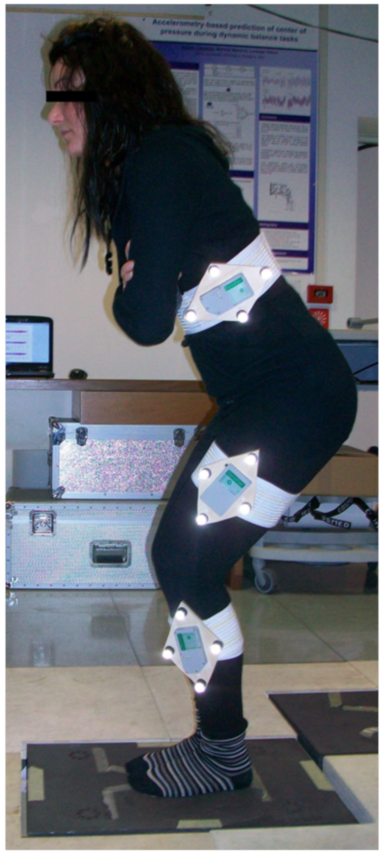


Figure 4.3: Experimental testing setup

[275, 276]. The SP angles are related to the first acquisition frame which defines the cluster model. As explained in Section 4.2.1, the sensors on the skin surface introduce potential errors, due to non-orthogonality of the measurement axis of the SAAs to the body segment anatomical axis. In order to model this undesired effect, Eq.(5.2) is modified by taking into account the projections of the tangential, centripetal, gravity and lower joints acceleration on the measurement axis. The method proposed in this paper provides angles from accelerometric measures with respect to the vertical, rather than from the first acquisition frame as for SP data. In order to take this fact into account, Eq.(5.2) is modified as follows:

$$\begin{aligned} a_i(k) = h_i\ddot{\theta}_i(k)\cos\beta_i - h_i\dot{\theta}_i^2(k)\sin\beta_i - g\sin\left(\theta_i(k) - \beta_i + \theta_{i0}\right) \\ +a_i^x(k)\cos\left(\theta_i(k) - \beta_i + \theta_{i0}\right) - a_i^y(k)\sin\left(\theta_i(k) - \beta_i + \theta_{i0}\right) \\ k = 1, \ldots, n \\ i = 1, \ldots, 3 \end{aligned} \tag{4.10}$$

where the angles β_i describe the SAAs non-orthogonality (see Figure 4.1) for each segment, and the angle $\theta_{i0} = -a_{i0}/g$ is related to the first acquisition frame, in which the inertial and non-linear terms are negligible.

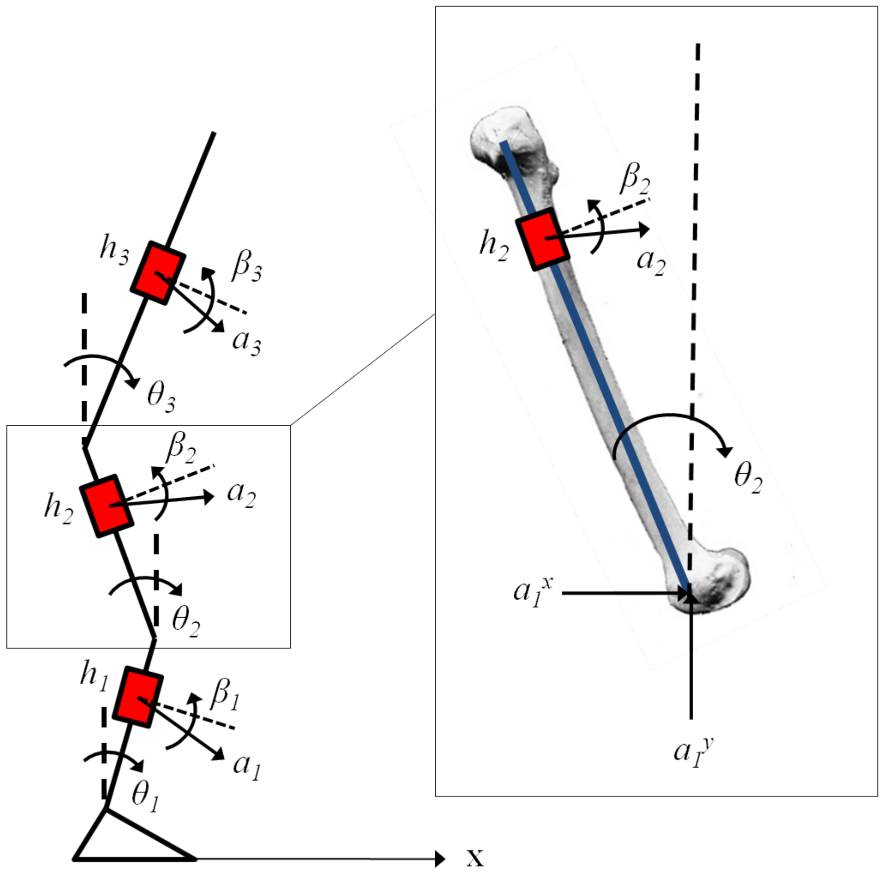


Figure 4.4: Three-link biomechanical model

The parameters h_i, β_i and l_m $(m = 1, 2)$ are estimated by the calibration algorithm using the least-squares minimization, as in Section 4.2.1; the SP angles are used as reference values. The angle vectors $\boldsymbol{\theta_i} = [\theta_i(1) \ldots \theta_i(n)]$ are estimated through the iterative algorithm described in Section 4.2.1. In order to test the robustness of the calibration, the 8 parameters are estimated for each trial; the mean values of the parameters are then used to predict the subject's angular sways using the three SAAs. The estimated angles are compared to the SP outputs by evaluating the RMSE.

4.3 Results

4.3.1 Mechanical Inverted Pendulum

The calibration algorithm, presented in Section 4.2.1, provides two parameters (mean±std): the distance $h = 0.31 \pm 0.00$m, of the origin of the sensor reference system to the pivot point P (the measured distance equals 0.30m), and an angle $\beta = -1.17 \pm 0.15°$, related to the non-orthogonality of the measurement axis of the SAA to the link. These two parameters are used along with the SAA data to predict the angles which are compared with the encoder angles. Calibration and prediction RMSEs and Peak-to-Peak (P-P) ranges are reported in Table 4.1, along with the results obtained with the QS model and the percentage of time in which it is valid.

Table 4.1: RMSEs and P-P range for the mechanical inverted pendulum

	Trial 1	**Trial 2**	**Trial 3**	**Trial 4**	**Trial 5**	mean±std
RMSE[°] calibration	0.16	0.18	0.14	0.15	0.12	0.15 ± 0.02
RMSE[°] prediction	0.17	0.18	0.16	0.15	0.12	0.16 ± 0.02
RMSE[°] QS model	30.02 (95.2%)	30.08 (91.2%)	25.28 (85.3%)	21.89 (83.5%)	21.15 (85.4%)	25.68 ± 4.28
P-P range[°]	126.5	117.9	125.4	108.3	151.4	125.9 ± 16.0

The mean ratio between the RMSEs and the P-P ranges in description and prediction is approximately 0.12%. The mean ratio between the RMSEs and the P-P range obtained without calibration, by neglecting the parameter β and using the measured parameter h, is about 0.82% and the mean value of RMSEs is 1.02°. The use of the calibration parameters therefore allows a less biased estimation. Table I also shows that the mean angular error of the QS model is very high, about 25°, due to the high frequency sways.

4.3.2 Multilink Kinematics

N-link model

The linear array of N=40 SAAs, equally spaced with $l_i = 2cm(i = 1, \dots, N)$, is simulated. The snake-like profile for 3 different frames is shown in Figure 4.5, comparing the simulated and estimated profiles: the continuous curve represents the simulated N-link chain, the points of the silhouette are the estimated joint positions, with respect to the pivot point, between two consecutive links. The positions of the joints are evaluated using the estimated angles and segment lengths.

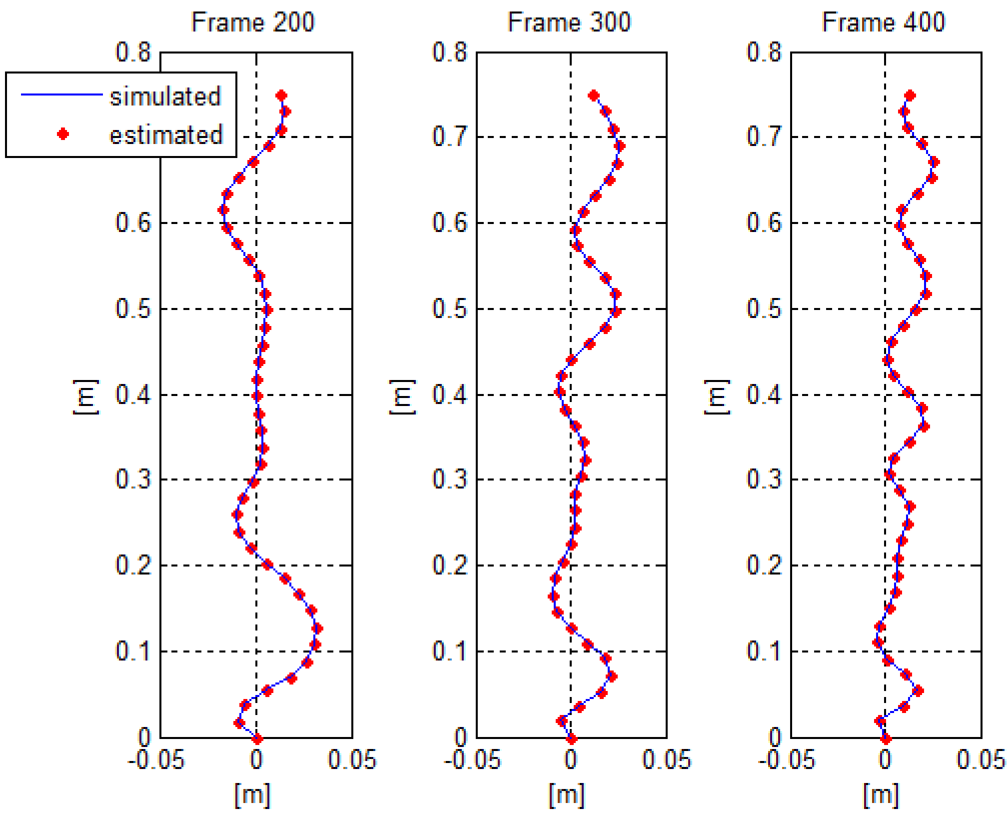


Figure 4.5: Snake-like profile for a 40-link kinematic chain

The angular RMSE between the sway angle of each link and the reference angle is evaluated. The values of the RMSE and P-P range, averaged out the N-link, are (mean±std) $0.37 \pm 0.16°$ and $70.42 \pm 10.19°$, respectively. The Euclidean distance between the joint positions of the estimated and simulated N-link is (mean±std) 0.3 ± 0.1mm.

Three-link biomechanical model

The mean values and standard deviations of the calibration parameters for the 4 trials, estimated by using the accelerometer output and the SP data as reference, are (mean±std) $h_1 = 0.31 \pm 0.01$m, $h_2 = 0.32 \pm 0.00$m, $h_3 = 0.30 \pm 0.07$m, $l_1 = 0.51 \pm 0.06$, $l_2 = 0.52 \pm 0.06$ and $\beta_1 = -10.96 \pm 0.21°$, $\beta_2 = -11.83 \pm 0.64°$ and $\beta_3 = -13.17 \pm 0.4^o$. These parameters are used to predict angular sway by using the three SAA outputs. The angles obtained are

Table 4.2: RMSEs and P-P range for the subject during squat tests

	Trial 1	**Trial 2**	**Trial 3**	**Trial 4**	mean±std
RMSE shank [°] calibration	0.34	0.40	0.50	0.85	0.39 ± 0.08
RMSE shank [°] prediction	0.38	0.47	0.56	0.93	0.59 ± 0.24
P-P shank[°] range	26.54	24.64	28.11	23.79	25.77 ± 1.94
RMSE thigh [°] calibration	0.73	0.98	0.86	0.72	0.82 ± 0.12
RMSE thigh [°] prediction	0.81	1.32	1.16	0.95	1.06 ± 0.23
P-P thigh [°] range	42.74	59.74	48.30	47.45	49.55 ± 7.21
RMSE HAT [°] calibration	0.85	0.99	0.81	0.84	0.87 ± 0.08
RMSE HAT [°] prediction	0.93	1.06	0.97	1.42	1.09 ± 0.22
P-P HAT [°] range	39.73	56.14	37.30	47.74	42.23 ± 8.53

then compared with the SP data. Calibration and prediction RMSEs and P-P ranges are reported in Table 4.2 for shank, thigh and HAT angles, respectively.

The ratios between the mean values of RMSEs and the P-P ranges are 1.5%, 1.7%, 1.9% for shank, thigh and HAT angles, respectively, for the calibration trials, and 2.3%, 2.1%, 2.4% for the prediction trials. The three angular patterns for stereo-photogrammetry and accelerometry data are reported in Figure 4.6 for one prediction trial. The mean RMSEs obtained without calibration, thus neglecting the parameters β_i and using the measured parameters h_i and l_i, are 11.01°, 11.39° and 12.21° for shank, thigh and HAT, respectively.

4.4 Discussion

This chapter suggests a novel method based on the use of one SAA per segment, which provides the accurate estimation of 2D joint angles, taking into account the inertial term of the accelerometer output is suggested. Several authors used the QS model to evaluate the angular sway: the procedure of separating the gravitational and inertial components of the accelerometer output has usually been considered very difficult unless multiple accelerometers are used [264, 276, 277, 278, 279]. Our method improves the QS model approximation: the use of the iterative method based on the bidirectional low-pass filter, with a cut-off frequency related to the sensor position with respect to the pivot point, provides RMSEs of approximately 0.1% of the angular range as shown in Table 4.1. The experimental sessions on the mechanical arm provided a simplified situation in which the method was successfully tested, as demonstrated by the mean RMSE values of 0.15° with a mean P-P range of

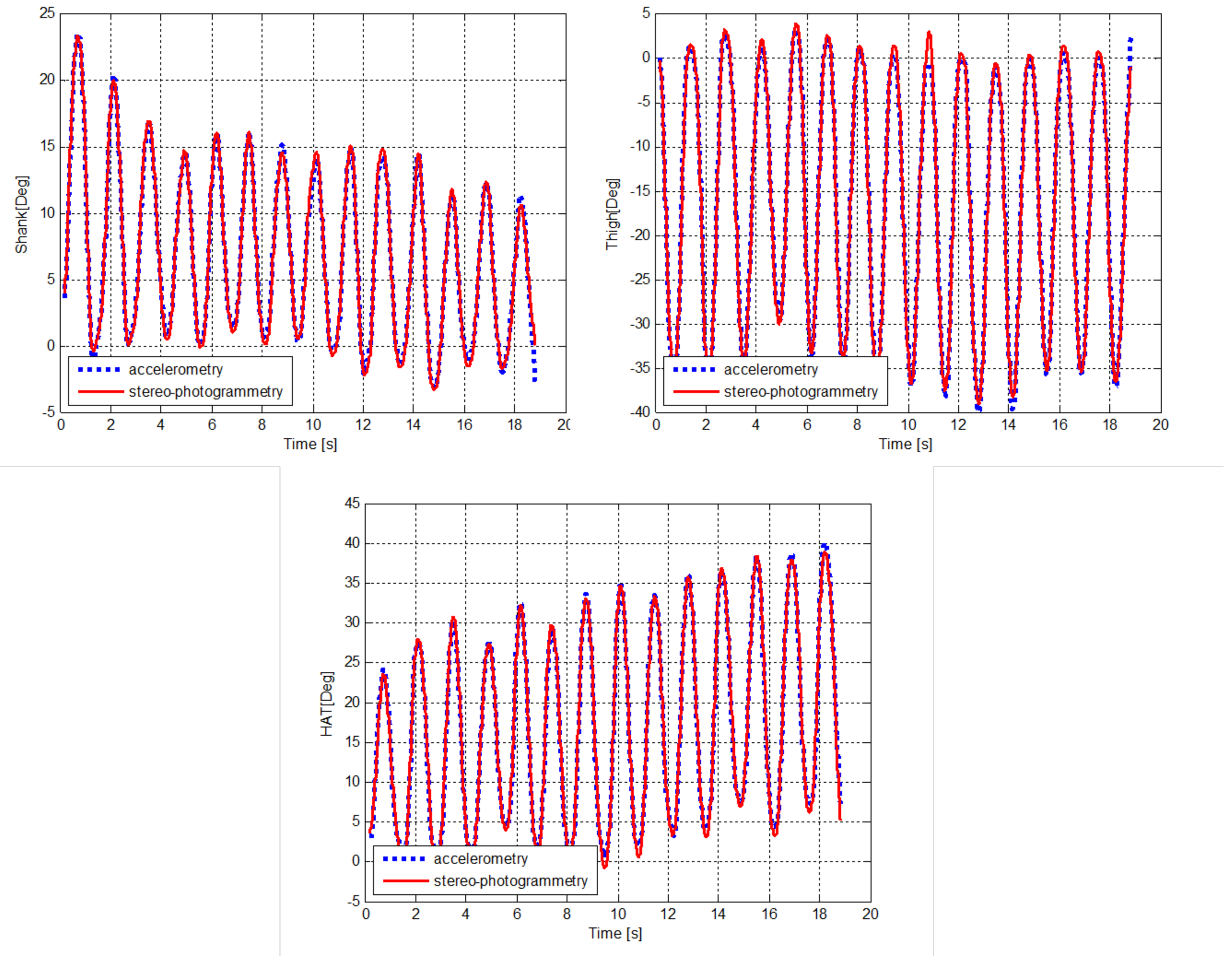


Figure 4.6: Shank, thigh, HAT angular patterns in prediction

126.1°. This error term partly reflects the encoder resolution (0.036°) and the accelerometer performance limits. As shown in the Methods, the angle evaluation can be extended to an N-link model, providing the possibility of estimating the silhouette of a kinematic chain with any number of links. The results obtained in simulation suggest possible applications in various fields like trunk posture evaluation and swimming, and most importantly to evaluated different strategies response to external stimuli in terms of sway angles. Additional discussion is required about the subject tests. Description and prediction RMSEs are smaller than those previously reported in the literature. For example, reported shank and thigh angle RMSEs range from 0.7° to 4.1° [264, 265, 267], although these studies analyse 3D joint angle estimation during gait instead of 2D squat tasks. RMSEs of the calculated angular displacements of the three segments (thigh, shank and HAT), as shown in Table 4.2, are larger than those in the inverted pendulum tests, due to several factors:

- *2D errors*: motion is inherently 3D and 2D analysis is an approximation. 2D projection of the markers' coordinates on the best fit plane produces a distortion affecting the SP angles estimation and therefore the validation measures. Consequently, there is not the certainty that SP provides a gold standard kinematics. Therefore both calibrated and predicted RMSE values in Table 4.2 should be considered as measures of the distance between estimates provided by two differently approximated methods;

- *sensor mounting*: it is difficult to firmly affix the accelerometers and the rhomboid rigid plates onto the segments without any relative motion. Unlike the mechanical arm, the soft tissue artefacts and the muscle activation add noise to the accelerometric measures. In particular, respiration represents an undesired effect for the sensor placed on the lateral side of the trunk, upon the rib;

- *propagation errors*: RMSEs are lower in the distal segment and increase in the thigh and HAT. As shown in Eq.(5.2), the accelerations are related to the estimated angles of the lower links, therefore the errors in the angle estimation of the (i-1)-th link propagate to the angle estimation of the i-th link.

Despite these considerations, the results are very encouraging for several reasons. First, it is important to note the effectiveness of the calibration procedure, both for the mechanical arm and the three-link biomechanical model, which allows the evaluation of the sensor position and misalignment and thus provides a better kinematic estimation. The parameter estimation provides unbiased results, both for description and prediction. Significantly, calibration allows us to reduce the errors from 11.0°-12.2° to 0.6°-1.1°. Second, our estimation method provides a simple, accurate and portable joint angle evaluation for postural tasks. The movement analysis laboratory is required only in the calibration phase, after which the clusters of markers are removed and only the three SAAs are used. Squatting exercises are often performed to characterize the bilateral lower-extremity kinematics after anterior cruciate ligament reconstruction. The main outcome measures are the sagittal plane ankle, knee and hip angles and their maximum excursion [274], in addition to the net joint moments. The procedure presented in this chapter speeds up the experimental sessions, reducing the computational and economic costs, especially when several subject are involved. The novel method presented in this chapter overcomes the limitation of the QS model, often used in literature [260, 261, 262, 263, 271, 272], in which the accelerometers are used as inclinometers. Since some authors used more than one sensors per segment [262, 264, 265], we demonstrated one SAA per segment is enough to estimate 2D joint angles accurately in a kinematic chain of any number of link providing errors smaller than those reported in literature. The methods presented in this Chapter is therefore suitable to be also included in fall risk assessments tests which includes perturbed postures by applying a direct force to the subject or by tilting or translating the surface upon which he stands. The presented approach could be able to discriminate among different strategies adopted for recovery balance after external stimuli by the evaluation of sway angles, highlighting how the subject's motor system responds in terms of hip, ankle or combined ankle-hip strategies. These quantitative measurements could help to monitor the effect of fall prevention approach aiming to increase muscular strength and/or balance.

Chapter 5

Dynamics prediction during sit-to-stand and voluntary postural sway

In the previous chapter a novel method was proposed for estimating the kinematics of a multi-link model by using a body sensor network during squat tasks. The same method is extended in this Chapter for the kinematic description of sit-to-stand and oscillatory voluntary trials. In addition, this chapter proposes a functional subject-specific 2D evaluation tool for estimating body-segment and dynamic parameters which makes use of a simple motor task (repeated sit-to-stand, rSTS), recorded with one single-axis accelerometer (SAA) per segment and a force plate (FP). After this preliminary estimation, the quasi-real-time prediction of Ground Reaction Force (anterior/posterior, Fx, and vertical, Fz, components), Center of Pressure (CoP) and Mass (CoM), during rSTS and postural oscillation in the sagittal plane, is performed by the use of accelerometry only. Predicted dynamic variables and those obtained using anthropometric parameters derived from De Leva were compared to FP outputs, in terms of Root Mean Squared Errors (RMSEs). RMSEs increase, using De Leva's parameters in place of those estimated, from 12N to 21N (Fx), from 21N to 24N (Fz), and from 21.1mm to 55.6mm (CoP) in rSTS, and from 3.1N to 3.3N (Fx), and from 5.5mm to 6.6mm (CoP) in oscillatory trials. A telescopic inverted pendulum was adopted to analyse the balance control in rSTS using only predicted CoP and CoM. Results suggest that one SAA per segment may be used to predict the dynamics of a biomechanical-model of any degrees of freedom.

Fuschillo VF, Bagalà F, Chiari L, Cappello A (2012) *Accelerometry-based dynamics prediction for balance monitoring*, Under review on Medical & Biological Engineering and Computing

5.1 Introduction

The trajectories of the body Center of Pressure (CoP) and the body Center of Mass (CoM) are commonly investigated in studies on human posture and balance control [280, 281, 282, 283] and in many functional tests [284, 285, 286]. In balance-related studies [287], it is often interesting to quantify the motion of CoM and CoP in order to investigate kinetic quantities such as the moment of the ground reaction force (GRF) with respect to the CoM or the whole body stiffness around the ankles [237]. However, while the CoP can be measured by means of a force plate (FP), the whole body CoM location is not directly observed and it should be estimated. Kinematics-based [237, 288] and FP-based methods [289, 290, 291] have been proposed to estimate CoM position, involving the definition of an adequate biomechanical model of the body and the identification of anthropometric properties of body-segments.

Body-segment parameters are typically derived from geometric models [292, 293, 294, 295, 296] and/or regression models scaled to the height and the weight of the subject (e.g. cadaver segmentation [297, 298] and imaging methods [299, 300, 301, 302, 303, 304]). The intrinsic limits of the geometric models are the assumption of a common model which neglects individual differences in segment shape and density, and the requirement of a large number of measurements (between 90 [296] and 248 [293]). About regression models, if equations are obtained from cadaver's data, they assume that embalmed and frozen tissue properties are similar to their in vivo state. Regression equations derived from imaging methods provide more accurate anthropometric parameter estimates, but they are invasive and expensive. Recently, optimization methods combining model-based and experimental approaches were proposed to estimate anthropometric parameters [305, 306]. Riemer *et al.* [306] used a 2D two-step optimization approach to solve a constrained non-linear optimization problem. Three calibration motions were considered: i) a long motion that involved a single cycle of a flexion and hyperextension of the hips, followed by flexion and extension of the knees, ii) a squat motion, and iii) a sway motion. The authors used a stereo-photogrammetric (SP) system and a FP, minimizing the residuals between measured GRF and the one calculated via a top-down inverse dynamics approach. Chen *et al.* [305] developed a 3D non-invasive, radiation-free optimization method, using a SP system and two FPs. The authors evaluated the performance by comparing the predicted GRF and CoP to those directly measured for static postures, squatting and walking. They obtained mean CoP errors less than 5 mm during stationary standing postures, 9.4 mm for squatting and 12.8 mm for walking. These methods need costly laboratory instrumentations and complex experimental protocols. Their implementation requires a fully equipped movement analysis laboratory, with a SP system and skilled personnel (e.g. in [305] each subject wore 54 retro-reflective markers placed by a well-trained physical therapist).

In conclusion, while the current state of the art offers several alternatives for anthropometric parameters estimation, to the best of our knowledge, there are no published methods based on inertial measurements related to this relevant topic. Even if inertial tracking technologies are becoming widely accepted for the assessment of human movement both in clinical applications and scientific research, there is still a lack of applications of inertial wearable technology for dynamics evaluation of human movement.

Aims of this chapter are:

1. to present a novel, functional, model-based approach to estimate subject-specific body-segment parameters using a single-axis accelerometer (SAA) per segment and a FP;
2. to predict GRF, CoP and CoM using only the SAAs and the estimated anthropometric parameters, during sit-to-stand and postural oscillation tasks.

The predicted dynamic variables are compared to those measured by the FP and those obtained using anthropometric parameters derived from De Leva's tables [307]. Moreover, an inertial-based quasi-real-time balance monitoring during sit-to-stand and posture is suggested.

5.2 Methods

5.2.1 Experimental set-up

Three young healthy subjects - two males, Body Mass Index (BMI) = [25.5, 22.3]kg/m^2; one female, BMI = 23.6kg/m^2- with no previous orthopaedic ailment, participated in this study after giving their informed consent. The subjects, standing on a FP (Bertec 4060-08) with the feet supposed rigidly connected to the ground, were asked to perform two different motor tasks:

- five trials of ten repeated sit-to-stand (rSTS) on a chair with height;
- five trials of voluntary postural oscillations, using as much as possible a pure ankle strategy,

with their arms folded and keeping their movement in the anterior/posterior (AP) direction. The first five repetitions of each rSTS trial were performed at the subjects' maximum speed, and the second five at the subjects' self-selected speed. Each oscillatory trial was also performed at the subjects' maximum speed in the first part and at the subjects' self-selected

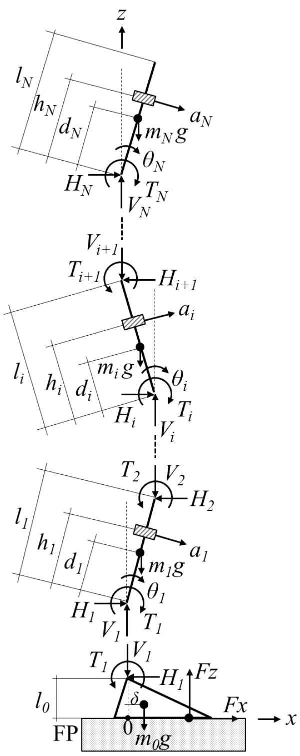


Figure 5.1: N-link free-body diagram in the sagittal plane

speed in the second part. In both tasks, three SAA (Analog Device, ADXL 103) were placed at measured heights h_1, h_2, h_3, with respect to the ankle, knee, and hip joint, respectively. Each of the three sensors was mounted directly on the skin, in a central position on the lateral side of the thigh and the shank, and on the posterior side of the Head-Arms-Trunk (HAT), in order to minimize skin artefact effects and model errors. In order to measure the sensor position, $h_i (i = 1, \ldots, 3)$, and the segment length, $l_i (i = 1, \ldots, 3)$, anatomical landmarks of body-segments (lateral malleolus, lateral epicondyle and L5 vertebra) were identified by palpation. FP and accelerometer signals were acquired at a 100Hz sampling rate and low-pass filtered (2nd order zero-phase Butterworth filter) at a cut-off frequency of 3Hz.

5.2.2 N-link Biomechanical model

In order to describe the new method in the most general way, a N-link biomechanical model (N degrees of freedom) in the sagittal plane is initially analyzed.

The free-body diagram (Figure 5.1) was used to define the dynamic equilibrium equations of the N-link model and the relationships between kinematic and kinetic variables. Feet and other body segments were considered separated from each other and the interaction between adjacent segments was described by horizontal and vertical forces, H_i and V_i , and net joints moments, T_i. The AP and the vertical components of the GRF, F_X and F_Z, and the moment component about the medium/lateral (ML) axis, M_Y, can be expressed, in the discrete-time domain, as follows:

$$
\begin{aligned}
&F_X(k) = \tilde{\mathbf{D}}^T \ddot{\mathbf{S}}_\theta(k) \\
&F_Z(k) = Mg + \tilde{\mathbf{D}}^T \ddot{\mathbf{C}}_\theta(k) \\
&M_Y(k) = \tilde{\mathbf{D}}^T [g\mathbf{S}_\theta(k) - l_0 \ddot{\mathbf{S}}_\theta(k) - \mathbf{A_{IS}}(k)] - \tilde{\mathbf{J}}^T \ddot{\theta}(k) \\
&k = 1, \ldots, n
\end{aligned}
\tag{5.1}
$$

where $\ddot{\theta}(k)$, $\mathbf{S}_\theta(k)$, $\ddot{\mathbf{S}}_\theta(k)$, $\ddot{\mathbf{C}}_\theta(k)$, $\mathbf{A_{IS}}(k)$, $\tilde{\mathbf{D}}$, $\tilde{\mathbf{J}}$ are $[N \times 1]$-column vectors and n is the number of samples. The vectors' elements are defined as follows:

$$
\begin{aligned}
S_{\theta,i}(k) &= \sin\theta_i(k) \\
C_{\theta,i}(k) &= \cos\theta_i(k) \\
A_{IS,i}(k) &= \textstyle\sum_{j=1}^{i-1} l_j \{[\ddot{\theta}_j(k) + \ddot{\theta}_i(k)]\cos[\theta_i(k) - \theta_j(k)] + \\
&\quad [\dot{\theta}(k)_j^2 - \dot{\theta}(k)_i^2] sin[\theta_i(k) - \theta_j(k)]\} \\
\tilde{D}_i &= m_i d_i + l_i \textstyle\sum_{j=i+1}^{N} m_j \\
\tilde{J}_i &= J_i + m_i d_i^2 + l_i^2 \textstyle\sum_{j=i+1}^{N} m_j \\
k &= 1, \ldots, n \\
i &= 1, \ldots, N
\end{aligned}
$$

The vector $\boldsymbol{\theta_i} = [\theta_i(1) \ldots \theta_i(n)]$ represents the i-th angular deviation from the vertical line, $\dot{\boldsymbol{\theta}}_{\boldsymbol{i}}$, the i-th angular velocity vector, and $\ddot{\boldsymbol{\theta}}_{\boldsymbol{i}}$ the i-th angular acceleration vector. The two sensitivity vectors $\tilde{\mathbf{D}}$ and $\tilde{\mathbf{J}}$ are defined as linear combinations of the anthropometric parameters, as segment length, l_i, mass, m_i, distance of CoM from distal joint axis, d_i, and moment of inertia, J_i.

The i-th SAA output vector, $\mathbf{a_i} = [a_i(1) \ldots a_i(n)]$, along the sensitive axis directed normally to the segment and oriented anteriorly, can be expressed as the sum of an inertial and a gravitational term plus two contributions, related to the horizontal and vertical accelerations at the lower joint, $\mathbf{a_i^x}$ and $\mathbf{a_i^y}$, due to the underlying chain kinematics (see Chapter 4):

$$
\begin{aligned}
a_i(k) = h_i\ddot{\theta}_i(k) - g\sin\theta_i(k) + a_i^x(k)\cos\theta_i(k) - a_i^y(k)\sin\theta_i(k) \\
k = 1,\dots,n \\
i = 1,\dots,N
\end{aligned}
\tag{5.2}
$$

According to the iterative technique presented in Chapter 4, the i-th sway angle of the N-link model, $\boldsymbol{\theta_i}$, can be evaluated from the accelerometer outputs, using a low-pass bi-directional filter with cut-off frequencies depending on sensor positions. After computing $\boldsymbol{\theta_i}$ and its first numerical derivative $\dot{\boldsymbol{\theta}}_{\boldsymbol{i}}$, its second derivative, $\ddot{\boldsymbol{\theta}}_{\boldsymbol{i}}$, can be computed by Equation (5.2). Therefore, the dynamic equilibrium equations can be expressed as linear combinations of the i-th angular position, $\boldsymbol{\theta_i}$, the i-th angular velocity, $\dot{\boldsymbol{\theta}}_{\boldsymbol{i}}$, and the i-th SAA output, $\dot{\mathbf{a}}_{\mathbf{i}}$, through the 2N unknown anthropometric parameters, $\tilde{\mathbf{D}}$ and $\tilde{\mathbf{J}}$.

5.2.3 Subject-specific anthropometric parameters estimation

Adequate to the trials carried out, a 3-link model is then used for anthropometric parameters estimation. The rSTS trials were used to estimate the anthropometric parameters $\tilde{\mathbf{D}}$ and $\tilde{\mathbf{J}}$, for each subject. After computing $\boldsymbol{\theta_i}(i = 1,\dots,N)$, $\tilde{\mathbf{D}}$ and $\tilde{\mathbf{J}}$ can be calculated by a linear regression using the FP outputs, $\mathbf{F}_{X,FP}$, $\mathbf{F}_{Z,FP}$ and $\mathbf{M}_{Y,FP}$, as the dependent variables, and the angular position vector, $\boldsymbol{\theta_i}$, the angular velocity vector, $\dot{\boldsymbol{\theta}}_{\boldsymbol{i}}$, and the SAA outputs, $\mathbf{a_i}(i = 1,\dots,N)$, as the regressors. Three offset parameters must be also taken into account: two instrumental offsets are related to the forces and the third, M_Y^0, is related to the distance between the origin of the FP's reference system and the equilibrium position. Parameters reliability was assessed by calculating the Intra-Class Correlation coefficient (ICC3,1) from the five measurements of the three subjects. The significance level for all tests was set to an uncorrected $\alpha = 5\%$ (two-sided). Additionally, the mean value of each estimated parameter was compared with the one provided by De Leva's anthropometric tables [307].

5.2.4 Dynamics Prediction

The predictive ability of the 3-link model is finally tested on each subject in both rSTS and oscillatory trials. The estimated parameters, $\tilde{\mathbf{D}}$ and $\tilde{\mathbf{J}}$, were used to predict $\mathbf{F}_X$, $\mathbf{F}_Z$, the displacement of the CoP in the AP direction, $\boldsymbol{\Delta}\mathbf{CoP}_X$, and the displacements of the CoM in the AP and in the vertical direction, $\boldsymbol{\Delta}\mathbf{CoM}_X$ and $\boldsymbol{\Delta}\mathbf{CoM}_Z$, the net joint moments at the ankle, the knee and the hip, $\mathbf{T}_i(i = 1, 2, 3)$, using the three SAAs only and a top-down approach, as follows:

$$
\begin{aligned}
&F_X(k) = \tilde{\mathbf{D}}^T\ddot{\mathbf{S}}_\theta(k)\\
&F_Z(k) = Mg + \tilde{\mathbf{D}}^T\ddot{\mathbf{C}}_\theta(k)\\
&\Delta CoP_X(k) = \frac{\Delta M_Y(k) + m_0 g\delta}{F_Z(k)} - CoP_X^0\\
&\Delta CoM_X(k) = \frac{1}{M}[\tilde{\mathbf{D}}^T\mathbf{S}_\theta(k)]\\
&\Delta CoM_X(k) = \frac{1}{M}[\tilde{\mathbf{D}}^T\mathbf{C}_\theta(k)]\\
&T_i(k) = T_{i+1}(k) + \tilde{J}_i\ddot{\theta}_i - g\tilde{D}_i\sin\theta_i +\\
&+\tilde{D}_i\sum_{k=1}^{i-1} l_k[\ddot{\theta}_k\cos(\theta_k-\theta_i) - \dot{\theta}_k^2\sin(\theta_k-\theta_i)]+\\
&+l_i\sum_{k=i+1}^{3}\tilde{D}_k[\ddot{\theta}_k\cos(\theta_k-\theta_i) - \dot{\theta}_k^2\sin(\theta_k-\theta_i)]\\
&k = 1,\ldots,n
\end{aligned}
\tag{5.3}
$$

where m_0 is the estimated feet mass, δ is the AP location of the feet CoM with respect to the malleolus (see Figure 5.1), $\Delta M_Y(k) = M_Y(k) - M_Y^0$, and $CoP_X^0 = \frac{M_Y^0}{F_Z^0} = m_0 g\delta$ is the CoP value at the equilibrium position. For comparison, the moment at the ankle can be obtained form the FP outputs as follows:

$$
T_{1,FP}(k) = F_{Z,FP}(k)CoP_{X,FP}(k) + F_{Z,FP}(k)l_0 - m_0 g\delta \tag{5.4}
$$

The effectiveness of the method was evaluated for each subject in terms of Root Mean Squared Error (RMSE) between the measured and estimated FP outputs, as follows:

- the mean description error was computed by averaging the RMSEs obtained by using the estimated parameters of the p-th rSTS trial for the evaluation of the dynamic variables of the same p-th trial;
- the mean prediction error was computed by averaging the RMSEs obtained by using the estimated parameters of the p-th rSTS trial ($p = 1,\ldots,5$) for the evaluation of the dynamic variables of the q-th rSTS trial ($q = 1,\ldots,5, q \neq p$), and the r-th oscillatory trial;
- the mean De Leva's prediction error was evaluated considering the De Leva's parameters [307] in place of the estimated parameters $\tilde{\mathbf{D}}$ and $\tilde{\mathbf{J}}$;

- the predicted ankle moment $\mathbf{T_1}$ and that obtained using De Leva's parameters, $\mathbf{T_{1,DeLeva}}$, was compared to that provided by FP outputs, $\mathbf{T_{1,FP}}$, in terms of RMSEs.

For an effective description of the rSTS task by using the accelerometry-based predicted CoP and CoM in the AP direction, the telescopic inverted pendulum (TIP) model, presented by Papa and Cappozzo [285], was analysed. In this study, a minimum measured-input model, which used only information obtained from a six-component FP, a seat uniaxial load-cell and anthropometric data derived from [308], was adopted. In the present paper, only the information derived from accelerometers were assumed as measured input. According to [285], two TIP models were used in temporal sequence: the first one (TIP_1) is related to the time preceding seat-off, in which only the HAT system moves, and the second one (TIP_2) to the whole body movement during the interval of time following seat-off. For the TIP_1 model, the vertical projection of the first sample of the predicted ΔCoP_X on the seat surface, $P_1 = (\Delta CoP_X(1); h_c)$, was considered in place of the midpoint between the hips. For the TIP_2 model, the last sample of the predicted ΔCoP_X under the feet, $P_2 = (\Delta CoP_X(n); 0)$, was considered in place of the midpoint between the ankles. The linear actuator (LA) and the sagittal plane rotational actuator (SA) were taken into account to describe the elongation and the forward and backward rotations of the link. The telescopic link joined P_1 to the position of the predicted CoM of the HAT (phase TIP_1), and P_2 to the whole-body predicted CoM position (phase TIP_2). The linear and angular velocity of the SA and LA actuators were evaluated and compared with those presented in [285].

5.2.5 Quasi-real-time prediction

Prediction of dynamic variables could be extended to real-time applications for balance monitoring during rSTS and oscillatory tasks. The ΔCoP_X and ΔCoM prediction is based on quasi-real-time estimation of the sway angles $\boldsymbol{\theta_i} (i = 1, \ldots, N)$ from the accelerometer outputs. The quasi-real-time technique is derived from the procedure described in Chapter 4 by applying the low-pass bi-directional filter to a sliding time window of the i-th accelerometer outputs $\mathbf{a_i} (i = 1, \ldots, N)$. The length of the time window is set to $N_W = 160$ samples ($T_W = 1.6s$). For the sake of clarity, the procedure is reported here for a single segment and the index i is neglected (e.g. $a_i(k)$ becomes $a(k)$). At the k-th instant of time ($k = \frac{N_W}{2}, \ldots, \frac{N_W}{2}$) the angle $\theta(k)$ is evaluated as follows:

1. the $1.6s$ time-window $\mathbf{a}_W = [a(k - \frac{N_W}{2}), \ldots, a(k + \frac{N_W}{2})]$ is filtered using the low-pass bidirectional filter-based technique and the vector angle $\boldsymbol{\theta}_W = [\theta_W(1), \ldots, \theta_W(N_W)]$ evaluated;

2. the central value $\theta_W(\frac{N_W}{2})$ is considered as $\theta(k)$ estimate.

These two steps are repeated by shifting, sample by sample, the $1.6s$ time-windows.

The method was evaluated on-line using Matlab R2011a 7.12.0. The time required for the execution of the described two-steps procedure is 2ms only. The kinematic and dynamic variables can be estimated with a delay of 0.8s since $\frac{N_W}{2}$ accelerometer future samples have to be taken into account. The technique provides results consistent with Chapter 4.

5.3 Results

Test-retest reliability was good for the estimated parameters $\tilde{D}_i$ and $\tilde{J}_i (i = 1, \ldots, 3)$, with $ICC_{3,1}$ equal to 0.98, 0.99, 0.99 and 0.91, 0.89, 0.92, respectively. Subjects' characteristics (sex, age and BMI), the mean value (standard deviation) of subject-specific estimated anthropometric parameters and the De Leva's parameters [307] are reported in Table 5.1.

Table 5.1: Characteristics of participants, estimated and De Leva's inertial parameters. The three rows for each subject represent the i-th element ($i = 1, \ldots, 3$) of the sensitivity vectors $\tilde{\mathbf{D}}$ and $\tilde{\mathbf{J}}$.

Subject	**Sex**	**Age**	**BMI** $[Kg/m^2]$	$\tilde{\mathbf{D}}$ mean(std) $[Kgm]$	$\tilde{\mathbf{J}}$ mean(std) $[Kgm^2]$	$\tilde{\mathbf{D}}_{\mathbf{DeLeva}}$ $[Kgm]$	$\tilde{\mathbf{J}}_{\mathbf{DeLeva}}$ $[Kgm^2]$
				32.2 (0.6)	10.1 (0.8)	32.4	25.9
1	M	29	25.5	30.8 (0.4)	10.2 (0.9)	16.1	13.9
				15.2 (0.2)	6.5 (0.8)	10.5	7.9
				24.4 (0.5)	9.7 (0.5)	25.1	17.9
2	M	28	22.3	22.9 (0.3)	10.9 (0.3)	12.3	10.2
				12.7 (0.3)	9.3 (0.6)	6.1	5.8
				23.8 (0.8)	10.0 (0.8)	26.4	21.3
3	F	31	23.6	20.8 (0.1)	8.7 (1.0)	13.0	11.1
				9.3 (0.4)	5.9 (1.1)	8.4	6.2

Mean description and prediction RMSEs are shown in Figure 5.2 for the rSTS trials and in Figure 5.3 for the oscillatory trials. The vertical force is not reported for the oscillatory trial since the CoM vertical acceleration is negligible and $\mathbf{F_Z}$ is approximately Mg.

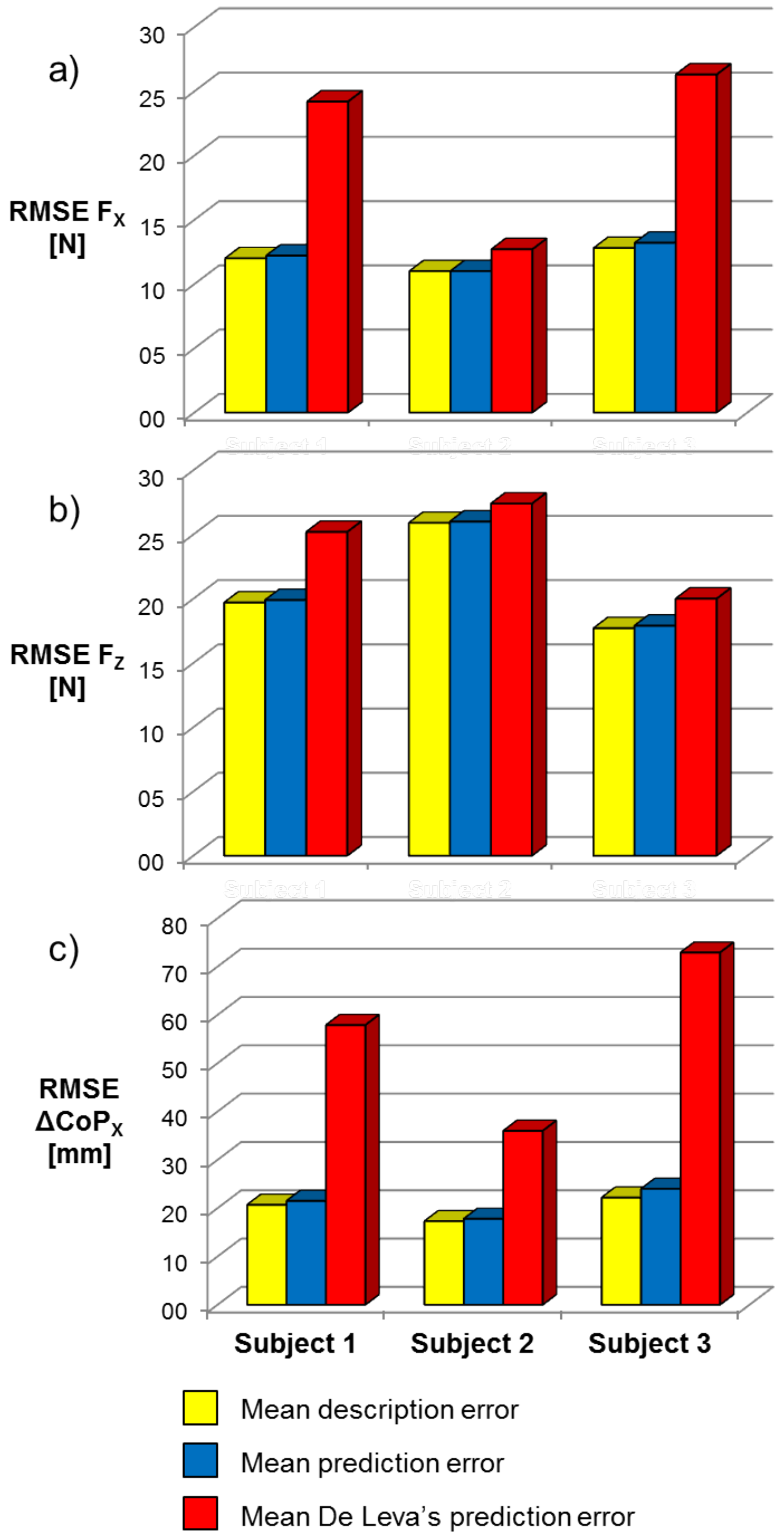


Figure 5.2: RMSEs of: a)$\mathbf{F}_X$, b)$\mathbf{F}_Z$, c)$\mathbf{\Delta CoP}_X$, for rSTS trials

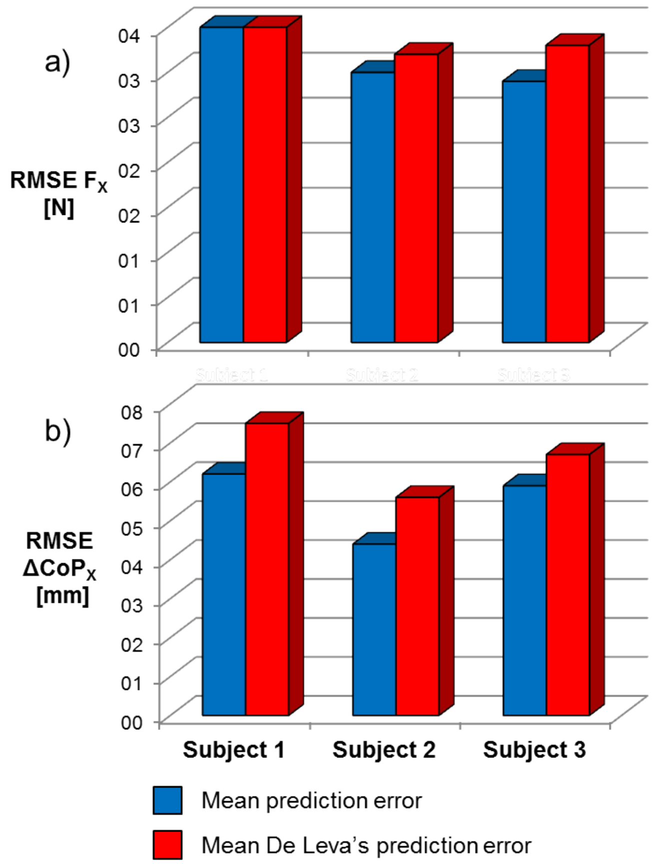


Figure 5.3: RMSEs of: a)$\mathbf{F}_X$, b)$\mathbf{\Delta CoP}_X$, for oscillatory trials

As shown in Figure 5.2, for each subject the mean prediction error is close to the mean description error: the difference ranges from 0.1N to 0.4N for the forces and from 0.1mm to 1.8mm for $\mathbf{\Delta CoP_X}$. De Leva's parameters provide prediction errors higher than those obtained with the estimated parameters. RMSEs of $\mathbf{F_Z}$, $\mathbf{F_Z}$ and $\mathbf{\Delta CoP_X}$, get worse in all cases. For the three subjects, the mean prediction error of $\mathbf{\Delta CoP_X}$ increases, using De Leva's parameters in place of those estimated, from 21.5mm to 57.9mm, from 17.8mm to 36.0mm, and from 24.0mm to 72.9mm, respectively.

Results for oscillatory trials are shown in Figure 5.3. The mean prediction error of dynamic variables obtained using the rSTS estimated parameters is lower than the one obtained by using De Leva's parameters. For the three subjects, the mean prediction error of $\mathbf{\Delta CoP_X}$ increases, using De Leva's parameters in place of those estimated, from 6.2mm to 7.5mm, from 4.4mm to 5.6mm, and from 5.9mm to 6.7mm, respectively.

FP outputs and residuals between measured signals and signals predicted by SAAs are reported in Figure 5.4 for one rSTS trial and in Figure 5.5 for one oscillatory trial of Subject 2.

In Figures 5.6- 5.7 two examples of patterns related to the predicted $\mathbf{\Delta CoP_X}$, $\mathbf{\Delta CoM_X}$ and $\mathbf{\Delta CoM_X}$, during a rSTS and an oscillatory trial respectively, are shown for Subject 2. Figure 5.6 helps to identify the functional phases of the rSTS by monitoring the CoM position with respect to the CoP, in terms of linear and angular velocities. These variables were obtained by accelerometer-based prediction. The figure in the box is from Papa and Cappozzo [285].

In Figure 5.7, the predicted $\mathbf{\Delta CoP_X}$ and the predicted difference $\mathbf{\Delta CoM_X} - \mathbf{\Delta CoM_X}$ are in counter-phase as one would expect in an optimal balance control strategy.

RMSEs of $\mathbf{T_1}$ and $\mathbf{T_{1,DeLeva}}$, averaged on the three subjects, are 10.3Nm and 17.0Nm, respectively. In Figure 5.8 the predicted net joint moments are reported for Subject 2. In Figure 5.9 the ankle moment provided from FP outputs is shown at the top of the picture. The residual errors between: i) measured signal and signal predicted using the SAAs, and ii) measured signal and signal evaluated using the De Leva's parameters are shown at bottom of the picture.

5.4 Discussion

This chapter suggests a novel method aimed at estimating subject-specific anthropometric parameters using one SAA per segment and a FP, using a functional motor task (rSTS) and taking advantage of a model-based approach. Several authors estimated these parameters in different ways, but no study, at our knowledge, evaluates the body-segment properties using inertial tracking technologies. FP and portable and cost-effective inertial sensors represent an easy and non-invasive alternative for anthropometric measurements, compared to previous invasive [297, 298, 299, 300, 301, 302, 303, 304] or expensive [305, 306] setups. The use of a traditional instrument for movement analysis, as the FP, is exclusively required for the subject-specific anthropometric parameters estimation, after which only the SAA outputs and the estimated parameters allow the GRF, CoP and CoM prediction in rSTS and postural oscillation tasks. During these trials, the above mentioned kinetic variables are often used for balance monitoring [286, 309, 310], and to extract temporal and power-related features [311, 312].

The effectiveness of the suggested method was evaluated by comparing the predictive ability of the estimated parameters and those derived from the De Leva's tables [307]. As shown in Table 5.1, the mean values of $\tilde{\mathbf{D}}$ and $\tilde{\mathbf{J}}$ are significantly different from $\tilde{\mathbf{D}}_{DeLeva}$ and

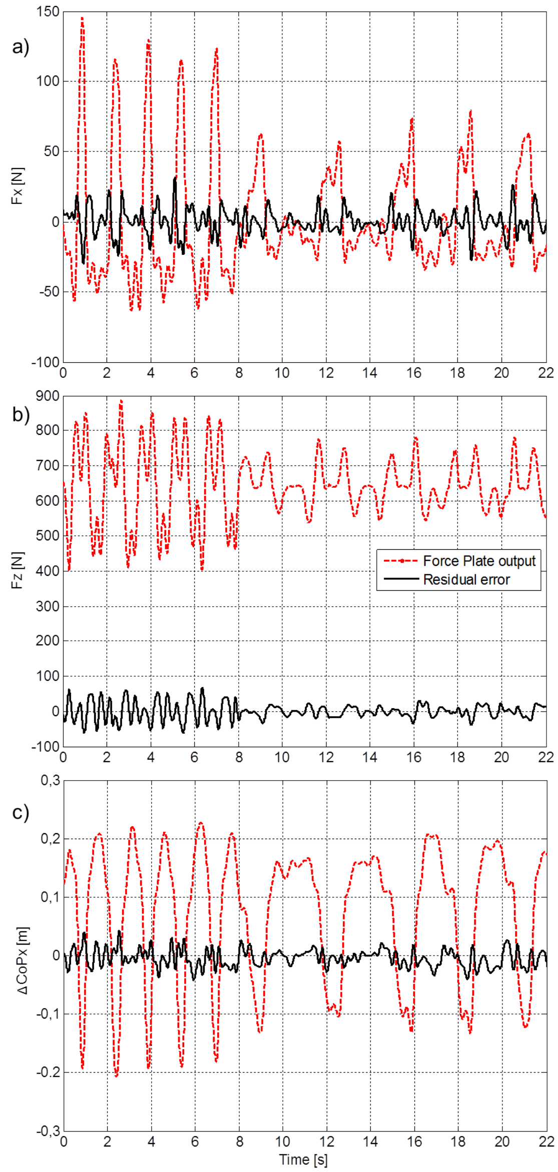


Figure 5.4: Pattern of: a)$\mathbf{F}_X$, b)$\mathbf{F}_Z$, c)$\mathbf{\Delta CoP}_X$ and residual errors during a rSTS trial (Subject 2)

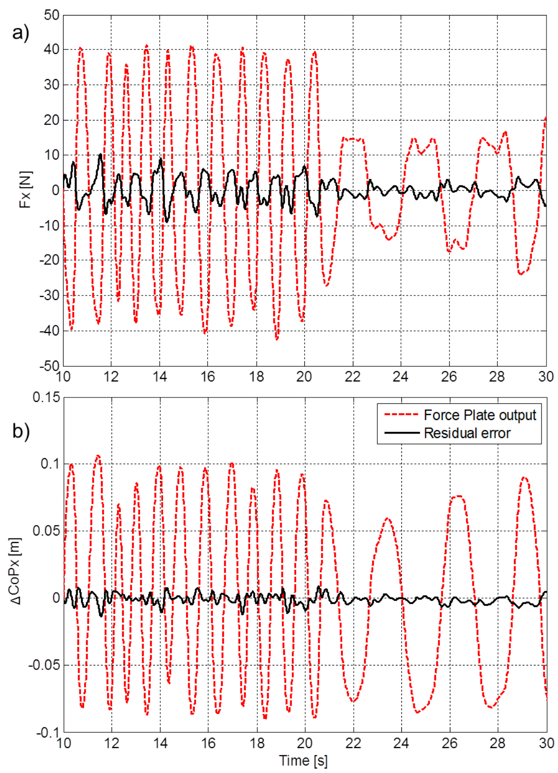


Figure 5.5: Pattern of: a)$\mathbf{F}_X$, b)$\mathbf{\Delta CoP}_X$ and residual prediction errors during an oscillatory trial (Subject 2)

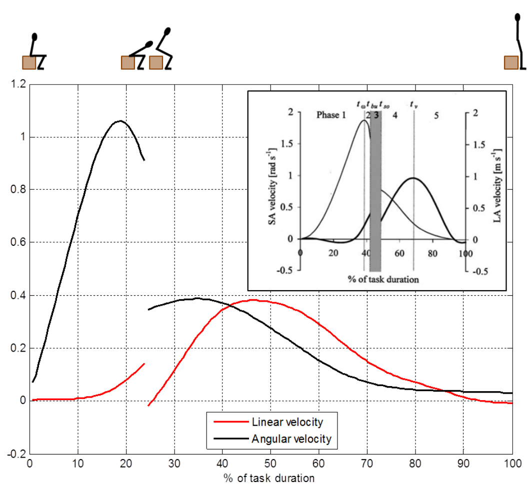


Figure 5.6: Linear and angular velocity of the rotation (SA) and linear (LA) actuator during a rSTS trial (Subject 2). Image in the box is from [285]

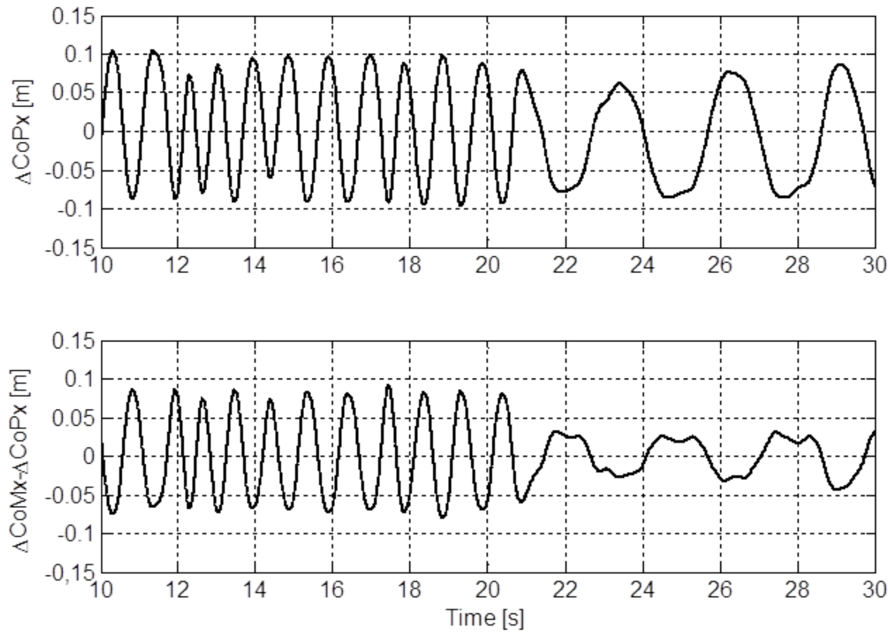


Figure 5.7: Pattern of: a)$\mathbf{\Delta CoP}_X$ and b)$\mathbf{\Delta CoM}_X - \mathbf{\Delta CoP}_X$ during an oscillatory trial (Subject 2)

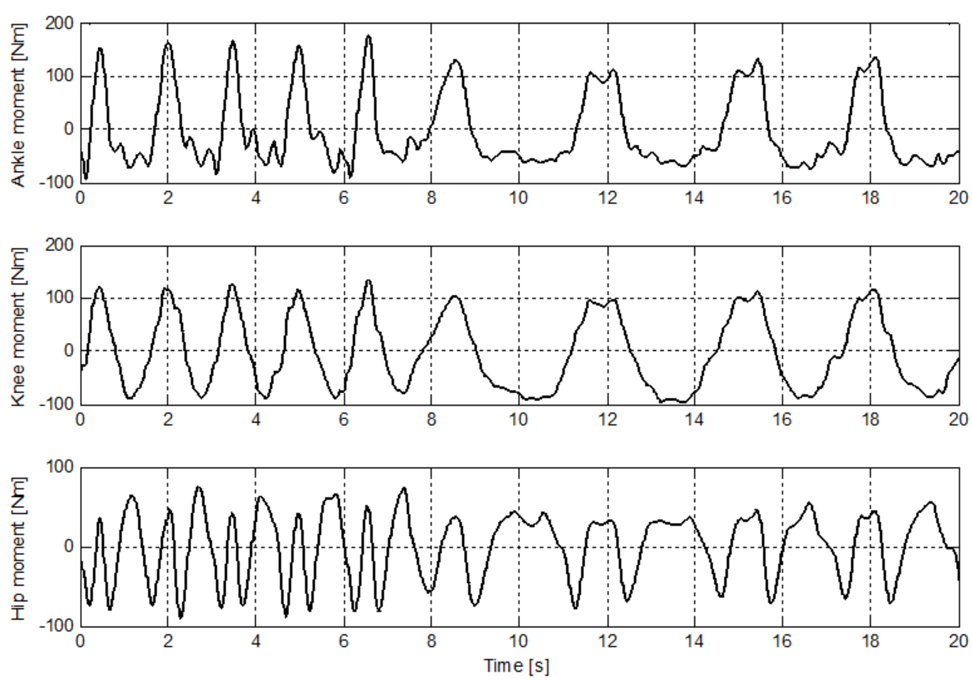


Figure 5.8: Patterns of ankle, knee and hip joint moments during a rSTS trial (Subject 2)

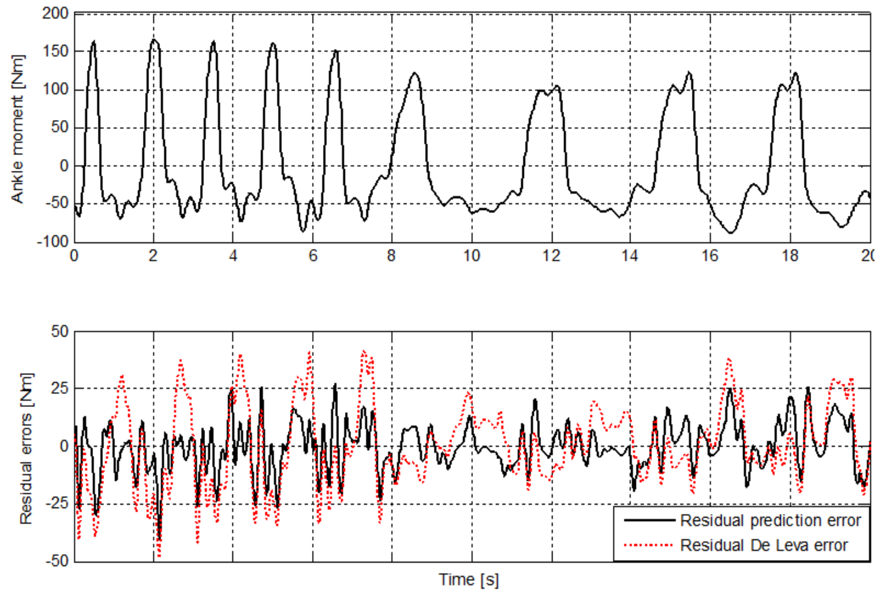


Figure 5.9: Patterns of ankle joint moment provided from FP and residual errors during a rSTS trial (Subject 2)

$\tilde{\mathbf{J}}_{DeLeva}$. These differences can be related to the specific morphology of the subjects' segments, not taken into account by the De Leva's parameters, which depend only on mass and height of the subjects. The good reliability of each estimate ($ICC_3, 1$ always higher than 0.89) and the negligible difference between the mean description and prediction errors for the dynamic variables of the three subjects (see Figure 5.2) suggest that a single rSTS trial is enough to estimate the subject-specific anthropometric parameters. The model-based approach and the integration of FP and SAAs data allow "one-shot" regression estimation. As computational cost is concerned, previously published studies [306, 313], combining model-based and experimental approaches, showed higher complexity and computational requirements.

One of the main aims of the presented study was to predict the GRF, and the displacement of the CoP and CoM in the AP direction, using only the SAAs and the estimated parameters during rSTS and postural oscillation tasks.

In the rSTS trials (Figure 5.2), mean prediction RMSEs, averaged on the three subjects, are about 12N, 21N and 21.10mm for $\mathbf{F_Z}$, $\mathbf{F_Z}$ and $\mathbf{\Delta CoP_X}$, with mean peak-to-peak ranges of 203N, 520N and 0.401m, respectively. These values are lower than those obtained with the De Leva's parameters, which are about 21N, 24N and 55.60mm for $\mathbf{F_Z}$, $\mathbf{F_Z}$ and $\mathbf{\Delta CoP_X}$. These considerations are confirmed by the results obtained in the oscillatory trials, as shown in Figure 5.3. Since the differences between mean prediction errors and mean De Leva's prediction errors are less significant than in the rSTS trials, the presented experimental protocol provides the best anthropometric parameter estimates.

By comparing $\mathbf{\Delta CoP_X}$ prediction errors with those presented in a previous study [305], the results are very encouraging. Chen *et al.* [305] obtained mean errors (standard deviations) of about 2.72(1.23)mm, 4.68(1.52)mm and 3.30(1.44)mm during static postures with 30° trunk flexion, 45° hip flexion and 90° shoulder abduction, respectively. As shown in [282], during quiet standing, the range of the CoP displacement is around 14.30 mm, as confirmed by experimental evidences. The percentage ratio between the mean CoP error provided by [305] and the CoP range is around 25%. In the oscillatory trials presented in this paper, subjects performed voluntary oscillations, with a mean CoP range, averaged on the three subjects, of 190mm in the AP direction and with a mean error of about 5.50mm. The related percentage ratio between $\mathbf{\Delta CoP_X}$ error and the range is hence about 3%, significantly lower than that obtained by [305]. Similar results are obtained from the dynamic trials evaluation: even if Chen *et al.* [305] obtained a mean CoP error (standard deviation) of 9.40(2.95)mm for arm-swing squatting, lower than the proposed prediction method in rSTS (about 21.10mm), the CoP range should be taken into account with relation to the performed task. During squatting, the CoP displacement is confined to few centimetres, whereas during rSTS movement the $\mathbf{\Delta CoP_X}$ range is about 40cm. Therefore, the percentage ratio is about 5%, significantly lower than that reported in [6]. Moreover, Chen *et al.* [305] assumed 3D geometric shapes for the body segments instead of a rigorous biomechanical model. Despite of these encouraging results, one limitation of the presented study is the 2D model-based approach, which neglects the ML movement during the performed trials.

The CoP prediction by using only SAAs and the estimated parameters during sit-to-stand tasks could have several positive feedbacks from clinical applications. Sit-to-stand is an important task in daily life, and it has been identified as one of the most mechanically demanding activities, confirming the general acceptance of its use as an indicator of the mobility level. In several studies, rSTS performance has been associated with age-related changes in muscular strength in leg extensor [314] and vestibular disorders as well as changes in movement strategies [315]. Consequently, standardized assessment of rSTS postural transitions has been used for multiple purposes, including evaluation of postural control [316, 317], risk of fall [251, 311], lower-extremity strength [308, 318], and impairment after stroke [319, 320]. The proposed method allows the kinematics and dynamics prediction by using a simple, accurate and portable setup. Since rSTS and postural tasks are frequently used in clinical routine, the procedure presented in this paper can speed up the experimental sessions, reducing the computational and the economic costs, especially when several subjects are involved.

Sit-to-stand task requires coordination, balance, adequate mobility and strength. The transfer from sitting to standing and back to sitting requires voluntary movement of the different segments that contribute to the change of posture and balance control during the CoM forward and backward displacement. Several authors investigated the CoM control during sit-to-stand movement [284, 286, 310] using SP systems and FPs. The traditional movement analysis systems, usually considered as a goal standard for the kinematics and dynamics evaluation, show several drawbacks, as lack in portability and usability, costs, and high computing demanding for real-time applications. These drawbacks could be overcome by using inertial sensors. In this study the quasi-real-time CoP and CoM prediction is accomplished by using only SAAs and a set of subject-specific anthropometric parameters. As shown in Figure 5.7, the dynamics accelerometer-based prediction provides results consistent with the relevant study of Papa and Cappozzo [285], related to the TIP model applied to rSTS movements. Linear and angular velocity of LA and SA were evaluated by using only CoP and CoM positions, predicted through SAAs, the inputs of the minimum measured-input model, in place of FP and seat uniaxial load-cell data as suggested by [285]. Therefore, applications of the balance control techniques during rSTS tasks could take advantage of accelerometry, in terms of portability, availability of the setup in either clinical/laboratory settings or free-living environments, both for off-line and real-time monitoring. These benefits are not task-related, since the subject-specific anthropometric parameters, estimated in a single rSTS trial, can be well-applied to different motor tasks sharing the same biomechanical model. As shown in Figure 5.7, the accelerometry-based predicted CoP and CoM in the AP direction are suitable to quantifying standing balance during postural oscillations. In a simple inverted pendulum the difference $\mathbf{\Delta CoM_X} - \mathbf{\Delta CoM_X}$ is directly proportional to the CoM acceleration. The ankle moment, and consequently the CoP, is then in counter-phase in order to keep balance.

In summary, this chapter provides a subject-specific evaluation tool for estimating inertial parameters through a simple motor task (rSTS), involving only few SAAs and a FP. After this preliminary estimation, the quasi-real-time prediction of GRF, CoP and CoM during rSTS, postural sway, squatting, etc., could be performed by the use of accelerometry only, and this is one of the most relevant findings of this thesis. Future developments will be addressed to test older patients in order to describe through biomechanical measurements their motor performance during rSTS.

Chapter 6

Lie-to-sit-to-stand-to-walk test: a preliminary study

In the two previous chapters a biomechanical approach and a body sensor network were used to describe quantitatively some motor tasks, like squat and sit-to-stand, often used in clinics for the fall risk assessment. In the following chapter a more complex transfer, the lying-to-sit-to-stand-to-walk (LSSW) test, is described through a single inertial measurement unit. Up to now, the transfer from LSSW was investigated only by functional testing or subjective rating. The aim of this study was to describe the complex movement of the LSSW transfer in young and older subjects by kinematic body-fixed sensors. Fifteen older patients of a geriatric rehabilitation clinic (median age 81 years) and 10 young healthy persons (median age 37 years) were instructed to stand up from bed in a continuous movement and to start walking. Data acquisition was performed using a single sensor device including tri-axial accelerometers and gyroscopes. Parameters, such as the beginning and the end of the movement, jerk, fluency, and velocity were extracted from the accelerometer and gyroscope outputs and were able to classify $\geq$92% of the subjects into correct group with a sensitivity of $\geq$93% and a specificity of $\geq$90%. $ICCs_{3,1}$ of the descriptive parameters ranged between 0.848 and 0.947 in the cohort of older patients. Moreover, a sensor fusion algorithm was suggested for the estimation of the different strategies adopted to transfer from lying to sitting at bedside. Instrumented LSSW test allowed evaluating objectively the performance of younger and older subjects in terms of movement duration and fluency. The results obtained in this study suggest the usability of this instrumented test in clinical practice.

Bagalà F, Klenk J, Cappello A, Chiari L, Becker C, Lindemann U (2012) *Quantitative description of the Lie-to-Sit-to-Stand transfer by body-fixed sensors*, Submitted to Gait & Posture

6.1 Introduction

Complex movement patterns, such as standing up from a bed or from a chair are basic movements of daily activity and are strongly associated with falls in older persons [321]. Sufficient capacity and quality of performance of such complex movements is a prerequisite for independent living. The chair rise movement can be described by functional testing [322, 323, 324] as well as by kinetic and kinematic assessment [151, 312, 325]. Here, any lateral movement assessed by accelerometry has been shown to indicate undesirable movement [326]. Higher complexity, including walking following the chair rise, can be assessed functionally by stop watch [126] or qualitatively by kinematic body-fixed sensors [327]. In contrast, to date the transfer from lying to standing is investigated only by functional testing [328] or by subjective rating [329], but not by kinematic measures. Moreover, as discussed in Chapter 1, several falls are associated with behavioural circumstances. The majority of falls occurred while individuals were engaged in routine behaviours, such as dressing, and during transfer (e.g., going from bedroom to the bathroom) [40]. This confirms the importance to assess motor tasks which generally mimic real-life circumstances that cause falls. The aims of this preliminary study were to describe the complex movement of the LSSW transfer by kinematic body-fixed sensors, to investigate the test-retest reliability of the outcome measures, and to compare the outcome measures between younger and older subjects. An Extended Kalman Filter (EKF) was implemented for the description of the strategies from lying to standing up.

6.2 Methods and Materials

Subjects and design Fifteen older patients of a geriatric rehabilitation clinic (median age 81 years, 63-89 years, 80% women) and 10 young healthy employees of the same hospital (median age 37 years, 25-45 years, 60% women) were recruited for this experimental study. For reliability testing the LSSW transfer was performed twice in the cohort of older patients.

Inclusion criteria for the group of patients were age of 60 years and older, disease patterns which affect the body symmetry (e.g. after hip surgery, stroke) or disease patterns which make transfers difficult in general (e.g. Morbus Parkinson). Exclusion criteria were the inability to walk with at least a walking aid, cognitive impairment indicating a possible dementia, assessed by the Short Orientation Memory Concentration test ($>$ 10 [330]), the presence of uncontrolled cardiac illness, orthostatic dizziness, and impaired arm function. Inclusion criteria for the group of young subjects was age between 25 and 45 years.

Exclusion criteria were identical with the other group and self-reported functional relevant disease (e.g. neurological and/or orthopedic), which significantly influences transfer performance. In order to describe the cohort of older patients, habitual gait speed was measured by stop watch over a distance of 10 metres. Basic information of all persons included is listed in Table 6.1. The study was conducted in concordance with the declaration of Helsinki. All participants had to give written informed consent. The study was approved by the ethical committee of the local university.

Table 6.1: Characteristics of all included participants (n=25). Short Orientation Memory Concentration (SOMC) test with values higher than 10 indicating cognitive impairment

	Young subjects (n=10, 6 woman)			Older patients (n=15, 12 woman)		
	Median	1.-3.Q	Min-Max	Median	1.-3.Q	Min-Max
Age[years]	37	32.5-41.25	25-45	81	75-85	63-89
Height[cm]	1.67	1.62-1.81	1.60-1.81	1.55	1.50-1.64	1.44-1.75
Weight[kg]	67.0	60.25-86.75	56.0-96.0	58.0	54-68	35.0-85.0
Gait Speed [m/s]				0.52	0.44-0.62	0.27-0.77
SOMC(0-28)				4	0-8	0-10

Procedure Participants were instructed to stand up in a continuous movement from a lying position on a conventional nursing bed to upright standing and to start walking. Starting point was the supine position on bed, arms parallel to the body. Bed height was adjusted individually, with a knee angle of 110° when sitting at the bedside with feet on the ground. The head position during lying was also adjusted individually, with the upper side of the bed raised to a maximum of 20° and the head of the patient resting on a small pillow. The assessment was repeated on the consecutive day for evaluation of test-retest reliability in the cohort of older patients.

Data acquisition and processing Data acquisition was performed in all subjects using a DynaPort® Hybrid (McRoberts, The Hague, NL) data logger. The DynaPort® Hybrid makes use of a tri-axial seismic acceleration sensor (LIS3LV02DQ, STMicroelectronics, Agrate Brianza, Italy) and three orthogonally placed gyroscopic sensors (XV-3500CB, Epson, San Jose, USA). The orientation of the axes are x=vertical (V), y=medio-lateral (ML), and z=anterior-posterior (AP). The accelerometer sensors have a range of ±20m/s^2 with a resolution of 2mm/s^2. The gyroscopic sensors have a range of ±100deg/s and a resolution of 7mdeg/s. Both sensors are sampled at frequency f_s=100Hz. Data were stored for off-line analysis on a micro SD card.

The sensor was fixed in a belt at the lower back, so that the technical frame (TF) axes were aligned with the anatomical axis of the lower trunk. The analyses focused on the lying-to-walking (first heel strike) transfer. The movement is performed mainly in the sagittal plane. Therefore only the V and AP accelerometer's outputs were considered, according to the small values of the accelerometer's output in ML direction. The accelerometer outputs have patterns that are used to automatically detect the different phases of the LSSW test, both for young subjects and older patients (see Figure 6.1). Three postures/transitions were considered:

- *lying posture*: the subject lies on the bed. In this condition the AP accelerometer axis is approximately aligned with the gravity acceleration, measuring about 1g. This static condition can be assumed as zero-position. The beginning of the movement (T_{start}) is detected when the variation of the V ($\mathbf{A_X}$) or the AP ($\mathbf{A_Z}$) acceleration is $\pm 3\%$ of the acceleration related to the zero-position;

- *lying-to-sit-to-stand transition*: the subject rotates to the bedside to standing up. A first upright position, T_g, with vertical trunk is detected when $\mathbf{A_X}$ overcomes the 95% of the gravity acceleration. This posture is obtained through a rotation around the ML axis. The gyroscope outputs in ML directions, $\mathbf{G_Y}$, will measure the angular velocity associated with this rotation. Then, the subject rotates around the V axis to the bedside. The related angular rate is measured by the gyroscope outputs $\mathbf{G_X}$. When the subject reaches this position, he starts to prepare the standing up phase by tilting his trunk forward. This movement produces a decrease of $\mathbf{A_Z}$ from 1g to negative values. Then the signal exhibits a trough due to the rising phase from the bed (yellow marker in Figure 6.1).

- *standing-to-walking transition*: the first heel strike (when the foot first touches the floor) is assumed as the end of the movement (T_{end}). According to [331] the AP acceleration data show a basic pattern of acceleration and deceleration during a gait cycle. At foot contact, forward acceleration reaches peak values and after foot contact a sharp decline is followed by a period of deceleration. This gait event is detected as the first peak on $\mathbf{A_Z}$ after the trough.

Based on these considerations four parameters were defined:

1. *Total time TT*: the total time $TT = T_{end} - T_{start}$ is defined as the time between the beginning of the movement (T_{start}) and the first step (T_{end});

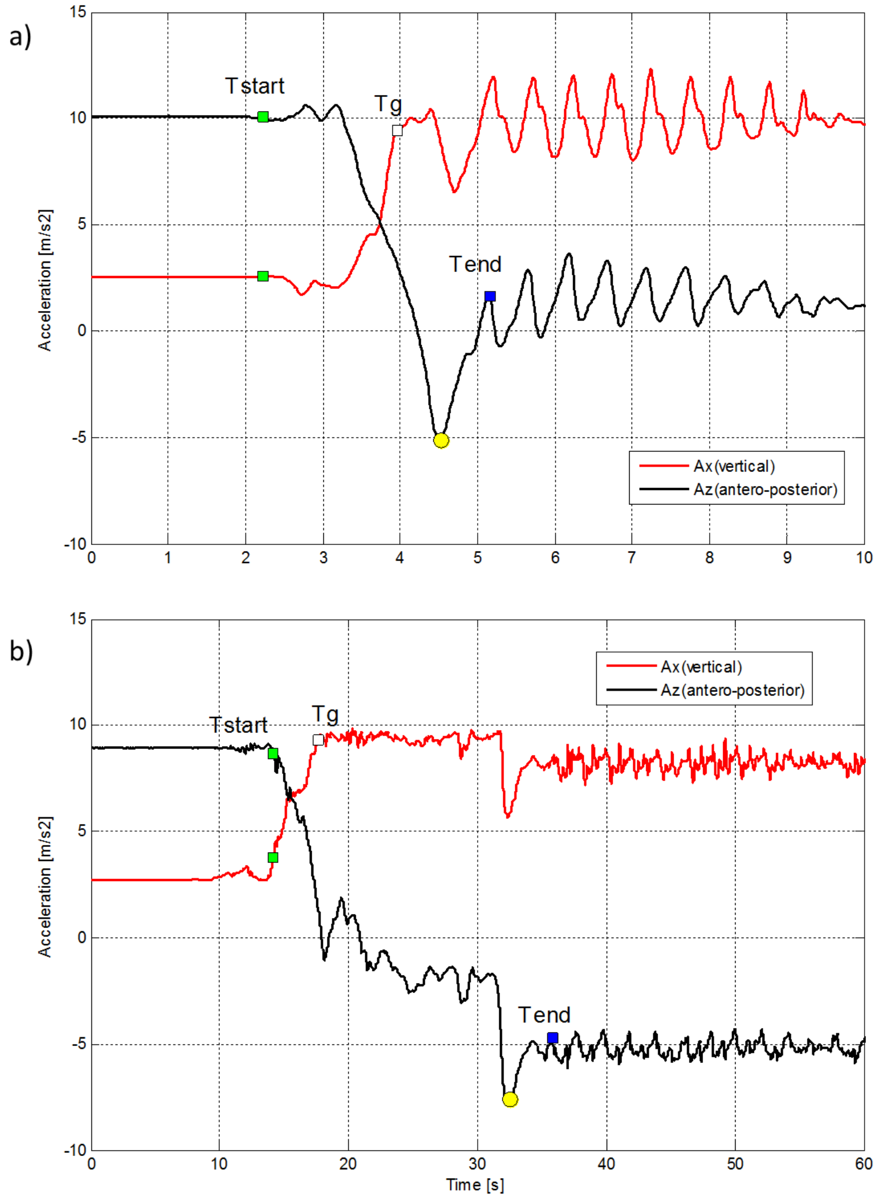


Figure 6.1: Patterns of $\mathbf{A_X}$ and $\mathbf{A_Z}$ and related temporal markers for a young subject (a) and a patient (b).

2. *Jerk J*: since the smoothness is widely regarded as features of skilled, coordinated movement, a measurement of this quality extracted from accelerometric data is the jerk (i.e., the time derivative of acceleration). This parameter varies with movement duration, thus according with [332] it is normalized by the duration to have a time-independent measurement. The jerk values for the AP and V directions are defined as:

$$J_{V,i} = f_s \frac{A_{X,i+1} - A_{X,i-1}}{2} \qquad J_{AP,i} = f_s \frac{A_{Z,i+1} - A_{Z,i-1}}{2}$$
$$i = 2, \ldots, n-1 \tag{6.1}$$

   where n is the number of samples considered. By summing the jerk values between T_{start} and T_{end}, normalizing by the third power of time, two time-independent measurements of smoothness were calculated:

$$\begin{aligned} J_V &= (T_{end} - T_{start})^3 \sum_{i=f_s \cdot T_{start}}^{f_s \cdot T_{end}} |J_{X,i}| \\ J_{AP} &= (T_{end} - T_{start})^3 \sum_{i=f_s \cdot T_{start}}^{f_s \cdot T_{end}} |J_{Z,i}| \end{aligned} \tag{6.2}$$

   The mean value $J = \frac{J_V + J_{AP}}{2}$ between the two directions (V and AP) is considered as index of smoothness.

3. *Fluency F*: fluency is defined as the sum of the residuals with respect to the trend line of the accelerometry outputs. It is considered as measurement of smoothness. According with [199], a low pass filter with cut-off frequency at 0.25Hz is employed to separate the acceleration components due to gravity and bodily motion. The V and AP accelerometer's outputs were hence filtered with a second order zero-phase digital low-pass filter (cut-off frequency 0.25Hz). By summing-up the differences between the filtered (trend line) and unfiltered signals and normalizing by the second power of time, the two indices of fluency are obtained:

$$
\begin{aligned}
Fl_V &= (T_{end} - T_{start})^2 \sum_{i=f_s \cdot T_{start}}^{f_s \cdot T_{end}} |A_{X,i} - A_{X,i,filtered}| \\
Fl_{AP} &= (T_{end} - T_{start})^2 \sum_{i=f_s \cdot T_{start}}^{f_s \cdot T_{end}} |A_{Z,i} - A_{Z,i,filtered}|
\end{aligned} \tag{6.3}
$$

The mean value $Fl = \frac{Fl_V + Fl_{AP}}{2}$ between the two directions is considered as second index of smoothness. Values of jerk and fluency will be expressed in logarithmic scale.

4. *Root mean square (RMS) of the gyroscope outputs RMS_G*: gyroscope outputs are considered to define two additional parameters. RMS of the angular rate in V and AP directions, which are related to the two main rotations during the execution of the LSSW test, as described previously, are calculated as follow:

$$
\begin{aligned}
RMS_{G_X} &= \sqrt{\sum_{i=f_s \cdot T_{start}}^{f_s \cdot T_{end}} \frac{G_X(i)^2}{f_s\,(T_{end} - T_{start})}} \\
RMS_{G_Y} &= \sqrt{\sum_{i=f_s \cdot T_{start}}^{f_s \cdot T_{end}} \frac{G_Y(i)^2}{f_s\,(T_{end} - T_{start})}}
\end{aligned} \tag{6.4}
$$

The mean value $RMS_G = \frac{RMS_{G_X} + RMS_{G_Y}}{2}$ between the two directions is considered as index of movement speed.

These parameters were evaluated for both young and older patients.

In order to describe the strategies adopted by the subject for rotates to the bedside from the lying postures, a sensor fusion approach was carried out. In particular, the EKF [333, 334] was implemented to accurately estimate the relative orientation of the sensor by fusing the accelerometer and gyroscope outputs. The block diagram of the EKF is shown in Figure 6.2.

All the rotations estimated through the EKF were referred to rotations of the TF frame of the sensor with respect to the TF at time T_{start} which was assumed as global frame (GF). The translation vector from the TF to GF was defined as ${}^{GF}\mathbf{t}_{TF} = \begin{bmatrix} t_V & t_{ML} & t_{AP} \end{bmatrix}^T$ (Figure 6.3). The three rotation angles are: θ_V, which corresponds to the rotation around the V axis of the sensor, θ_{ML}, related to the rotation around the ML of the sensor and θ_{AP}, corresponding

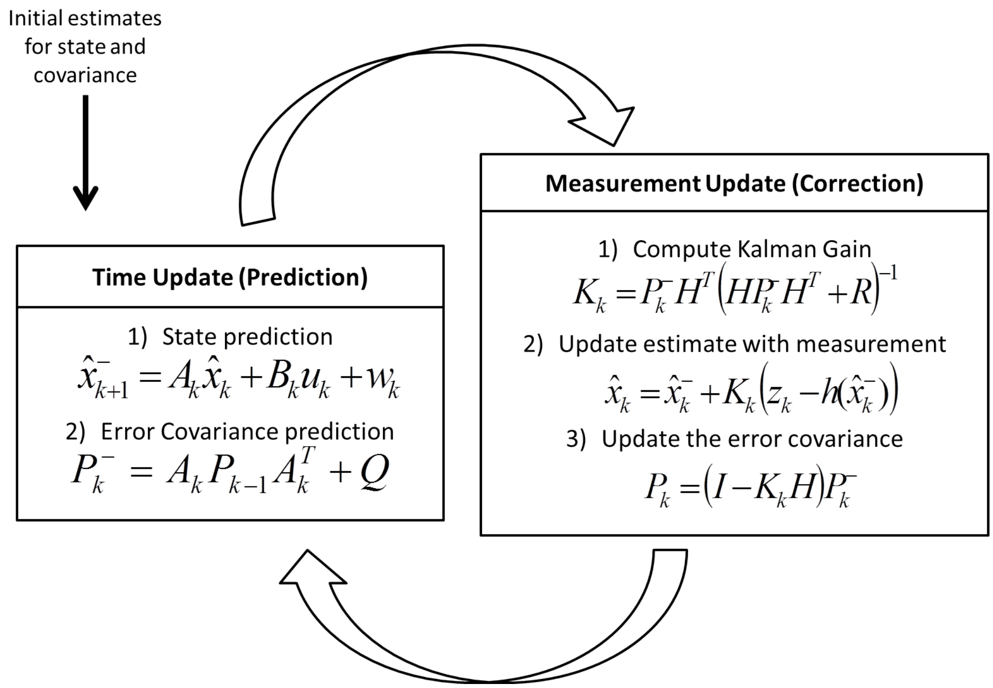


Figure 6.2: Summary scheme of the operation implemented in the Kalman Filter

to the rotation around the AP axis of the sensor. The rotation matrix from the TF to the GF, ${}^{GF}\mathbf{R}_{TF}$, was defined as ${}^{GF}\mathbf{R}_{TF} = \mathbf{R}_Z(\theta_{AP})\mathbf{R}_Y(\theta_{ML})\mathbf{R}_X(\theta_V)$. The state vector of the EKF, $\mathbf{X}_{[18x1]}$, at every sampled instant of time k, was defined considering the angles $\theta_{V,ML,AP}$, their first and second time derivatives, $\omega_{V,ML,AP}$ and $\alpha_{V,ML,AP}$ respectively, and the translations $t_{V,ML,AP}$, with their first and second time derivatives, $v_{V,ML,AP}$ and $a_{V,ML,AP}$ respectively, as $\mathbf{X}(k) = \begin{bmatrix}\mathbf{\Theta_V}(k) & \mathbf{\Theta_{ML}}(k) & \mathbf{\Theta_{AP}}(k) & \mathbf{T_V}(k) & \mathbf{T}_{ML}(k) & \mathbf{T}_{AP}(k)\end{bmatrix}^T$.

The vectors $\mathbf{\Theta}$ and $\mathbf{T}$, for each direction V, ML and AP, were defined as follows:

$$\mathbf{\Theta}(k) = \begin{bmatrix} \theta(k) \\ \omega(k) \\ \alpha(k) \end{bmatrix} \qquad \mathbf{T}(k) = \begin{bmatrix} t(k) \\ v(k) \\ a(k) \end{bmatrix} \tag{6.5}$$

In the time-discrete domain the prediction of the state at the instant *k+1* was obtained from the last update one (instant k) as:

$$\begin{bmatrix} \theta(k+1) \\ \omega(k+1) \\ \alpha(k+1) \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & T & \frac{T^2}{2} \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix}}_{\mathbf{A}_{\theta,[3x3]}} \begin{bmatrix} \theta(k) \\ \omega(k) \\ \alpha(k) \end{bmatrix} \qquad \begin{bmatrix} t(k+1) \\ v(k+1) \\ a(k+1) \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & T & \frac{T^2}{2} \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix}}_{\mathbf{A}_{t,[3x3]}} \begin{bmatrix} t(k) \\ v(k) \\ a(k) \end{bmatrix} \tag{6.6}$$

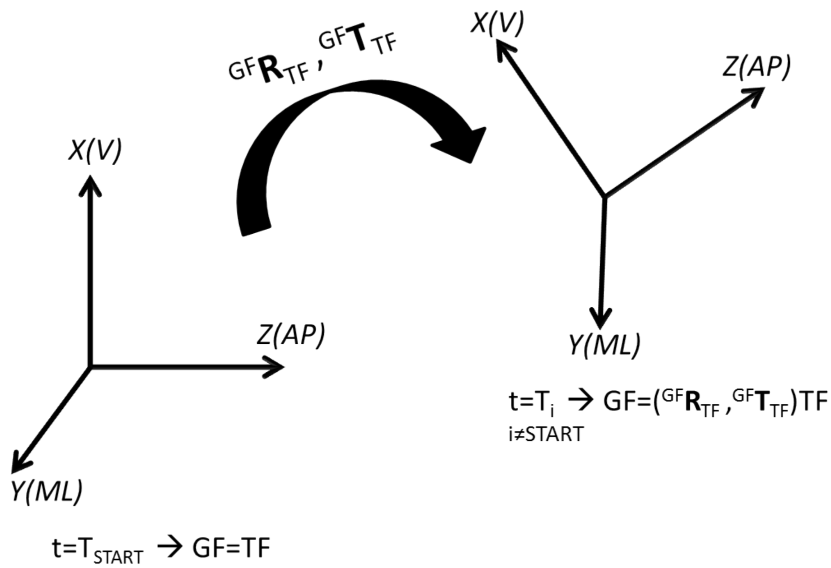


Figure 6.3: Relative rotations and translation between technical and global frames

The state matrix $\mathbf{A}_{[18x18]}$, indicated in the scheme of Figure 6.2, was obtained considering the extension of $\mathbf{A}_{\theta,[3x3]}$ and $\mathbf{A}_{t,[3x3]}$ to the [18x1]-state vector as follow:

$$\mathbf{A} = \begin{bmatrix} \mathbf{A}_{\theta,[3x3]} & \mathbf{0}_{[3x3]} & \mathbf{0}_{[3x3]} & \mathbf{0}_{[3x3]} & \mathbf{0}_{[3x3]} & \mathbf{0}_{[3x3]} \\ \mathbf{0}_{[3x3]} & \mathbf{A}_{[\theta,3x3]} & \mathbf{0}_{[3x3]} & \mathbf{0}_{[3x3]} & \mathbf{0}_{[3x3]} & \mathbf{0}_{[3x3]} \\ \mathbf{0}_{[3x3]} & \mathbf{0}_{[3x3]} & \mathbf{A}_{\theta,[3x3]} & \mathbf{0}_{[3x3]} & \mathbf{0}_{[3x3]} & \mathbf{0}_{[3x3]} \\ \mathbf{0}_{[3x3]} & \mathbf{0}_{[3x3]} & \mathbf{0}_{[3x3]} & \mathbf{A}_{t,[3x3]} & \mathbf{0}_{[3x3]} & \mathbf{0}_{[3x3]} \\ \mathbf{0}_{[3x3]} & \mathbf{0}_{[3x3]} & \mathbf{0}_{[3x3]} & \mathbf{0}_{[3x3]} & \mathbf{A}_{t,[3x3]} & \mathbf{0}_{[3x3]} \\ \mathbf{0}_{[3x3]} & \mathbf{0}_{[3x3]} & \mathbf{0}_{[3x3]} & \mathbf{0}_{[3x3]} & \mathbf{0}_{[3x3]} & \mathbf{A}_{t,[3x3]} \end{bmatrix} \tag{6.7}$$

The vector of the measurements $\mathbf{z}(k)_{[6x1]}$ was defined considering the outputs of the sensor:

$$\mathbf{z}(k) = \begin{bmatrix} \mathbf{G}_X(k) \\ \mathbf{G}_Y(k) \\ \mathbf{G}_Z(k) \\ \mathbf{A}_X(k) \\ \mathbf{A}_Y(k) \\ \mathbf{A}_Z(k) \end{bmatrix} \tag{6.8}$$

The accelerometer and gyroscope outputs measured at the instant i and defined in the TF were expressed according to [335] as follows:

$$\begin{bmatrix} 0 & -G_Z & G_Y \\ G_Z & 0 & -G_X \\ -G_Y & G_X & 0 \end{bmatrix} = {}^{GF}\mathbf{R}_{TF}^{T} \frac{d^{GF}\mathbf{R}_{TF}}{dt}$$

$$\begin{bmatrix} A_X \\ A_Y \\ A_Z \end{bmatrix} = {}^{GF}\mathbf{R}_{TF}^{T}({}^{GF}\mathbf{g} + {}^{GF}\ddot{\mathbf{T}}_{TF}) \tag{6.9}$$

The state of the measurements is related to the state vector through a non-linear relationship $z(k) = h(x_k)$, according to the Equation (6.9). The output matrix $\mathbf{H}(k)_{[6x18]}$ which relates the state the measurements $\mathbf{z}(k)$ to the state $\mathbf{x}(k)$ was thus obtained evaluating the jacobian matrix of partial derivatives of $h(x_k)$ with respect to the state vector as follows:

$$H_{[i,j]} = \frac{\delta h_{[}i]}{\delta x[j]}(x_k) \tag{6.10}$$

$$i = 1, \ldots, 6$$

$$j = 1, \ldots, 18 \tag{6.11}$$

The process noise covariance matrix $\mathbf{Q}_{[18x18]}$ was defined under the assumption that state noise affects the jerk only and there are not correlations between the state noises. $\mathbf{Q}_{[18x18]}$ has therefore only nine non-zero elements $(Q(i,i), i = (3, 6, 9, 12, 15, 18))$. The values $Q(i,i)$ are set to 0.01. The measurement noise covariance matrix $\mathbf{R}_{[6x6]}$ is defined considering the noise which affects the gyroscope and accelerometer outputs. Since correlations between noise of the sensors are assumed to be zero, the matrix is diagonal, which values are set to 10^{-7} for the first three elements related to the gyroscopes noise, and to 10^{-8} for the last three elements related to the accelerometer noises. All these tuning parameters weasre defined after an optimization procedure in which a stereo-photogrammetric system was assumed as gold standard. In order to run the filtering procedure, initial estimate of the state vector was zeroed whereas the initial estimate of the error covariance matrix $\mathbf{P}_{[18x18]}$ was set equal to the identity matrix.

Statistics Due to the small sample size and a non-parametric distribution in some parameters, median values, 1^{st} and 3^{rd} quartile, minimum and maximum were used for descriptive statistics. Differences between groups were calculated by Mann-Whitney-U tests. Discriminative ability was assessed by receiver operating characteristic (ROC) curve analysis with

Table 6.2: Descriptive parameters of the complex movement of the lying-sitting-standing transfer for young subjects and older patients. Jerk and Fluency are expressed in logarithmic scale. All differences between groups are p<0.0001.

	Young subjects (n=10, 6 woman)			Older patients (n=15, 12 woman)		
	Median	1.-3.Q	Min-Max	Median	1.-3.Q	Min-Max
Total Time[s]	3.00	2.38-3.55	1.70-4.50	12.10	6.60-17.30	4.70-22.90
J [m]	11.20	10.50-11.75	9.60-12.50	15.40	13.80-16.60	12.10-17.80
F[m]	7.70	7.25-8.18	6.80-8.90	10.60	9.50-11.20	8.30-12.20
$RMS_G[/s]$	48.5	44.73-56.15	38.40-81.70	17.20	13.30-26.00	9.30-31.30

sensitivity and specificity indicating correct classification of older patients and young persons. The association between the parameters was described by Spearman's coefficients of correlation. Reliability was assessed by calculating the intra-class correlation coefficient ($ICC_{3,1}$) from 2 measurements with 1 day interval in the cohort of older women. The significance level for all tests was set to an uncorrected $\alpha = 5\%$ (two-sided). All analyses were conducted using SPSS version 16 software (SPSS Inc., Chicago, IL, USA).

6.3 Results

There were no negative side effects during the measurements. The group of older patients consisted of 7 patients after hip fracture, 3 patients after other fractures, and 5 other patients de-compensated after an acute internal illness. Fixation and taking off the sensor as well as starting and stopping the measurement took about 1 minute in total for each person. All results derived from acceleration and gyroscopic outputs, such as total time of the movement TT, J, F, RMS_G, were significantly different between younger and older participants (all p<0.0001). The results in detail are presented in Table 6.2.

The different parameters derived from acceleration and gyroscope outputs classified 92% or more of the subjects into correct group with a sensitivity of 93% or higher and a specificity of 90% or higher and an area under the curve of 0.97 or more (all p<0.0001) identified from ROC analysis and shown in Table 6.3.

There was a significant association (all p-values <0.0001) of TT with J (r=0.993), F (r=0.985), and RMS_G (r=0.957). All correlations between these parameters were $r > 0.9$. In the cohort of older patients $ICC_{3,1}$ of total time, J, F and RMS_G were 0.848, 0.883, 0.876, 0.929, and 0.947 respectively. Angle V versus angle ML plots visually demonstrated

Table 6.3: Results of ROC analysis of TT, J, F and RMS_G

	Cut-off	Sensitivity[%]	Specificity[%]	Area under the curve
Total Time	4.6[s]	100	100	1.00
J	12.7[m]	93	100	0.98
F	8.75[m]	93	90	0.98
RMS_G	48.5[/s]	100	100	1.00

different strategies to transfer from lying to sitting at bedside as shown in Figure 6.4. In particular, the young subject turns the trunk around the V and ML axis in the same time in a continuos movement. The patient first moves the trunk forward with a rotation around the ML axis and then turns to the bedside rotating around the V axis.

6.4 Discussion

Clear differences could be observed between young subjects and older patients using the descriptive parameters TT, J, F, RMS_G,. The reliability of these parameters also can be regarded as good. With regard to TT, J, F the results of discriminative validity are in concordance with a study of Klenk *et al.* [336] where the same parameters derived from accelerometers were used to describe the complex movements of falls and were able to show differences between real-world falls and simulated falls. In general, the discriminative ability of all parameters derived from acceleration and gyroscope outputs were excellent. Although stop watch timing alone has been shown to be a valid measure to describe the lying-to-sit-to-stand-to-walk transfer [328], biomechanical measures provide a higher objectivity than functional assessment or subjective rating [329]. Furthermore, the association between total time and all other parameters is high, but additional objective information is provided in terms of fluency and velocity of the movement. Here, the quality of the movement is not only described in total, but every phase of the movement can be described in detail. Even individual movement patterns are described appropriately, especially by parameters describing the smoothness of the movement. Thus, a movement pattern which may be regarded in-economic and slow may show good results, if the movement is continuous and has a clear direction. For this purpose the ML-rotation versus V-rotation plots might help to visualize the patient's strategy to transfer from lying to sitting at bedside, obvious for the clinician as well as for the patient. Since transfer movements are strongly associated with falls in older persons [321], this test may help better investigating the lying-to-sit-to-stand transfer and

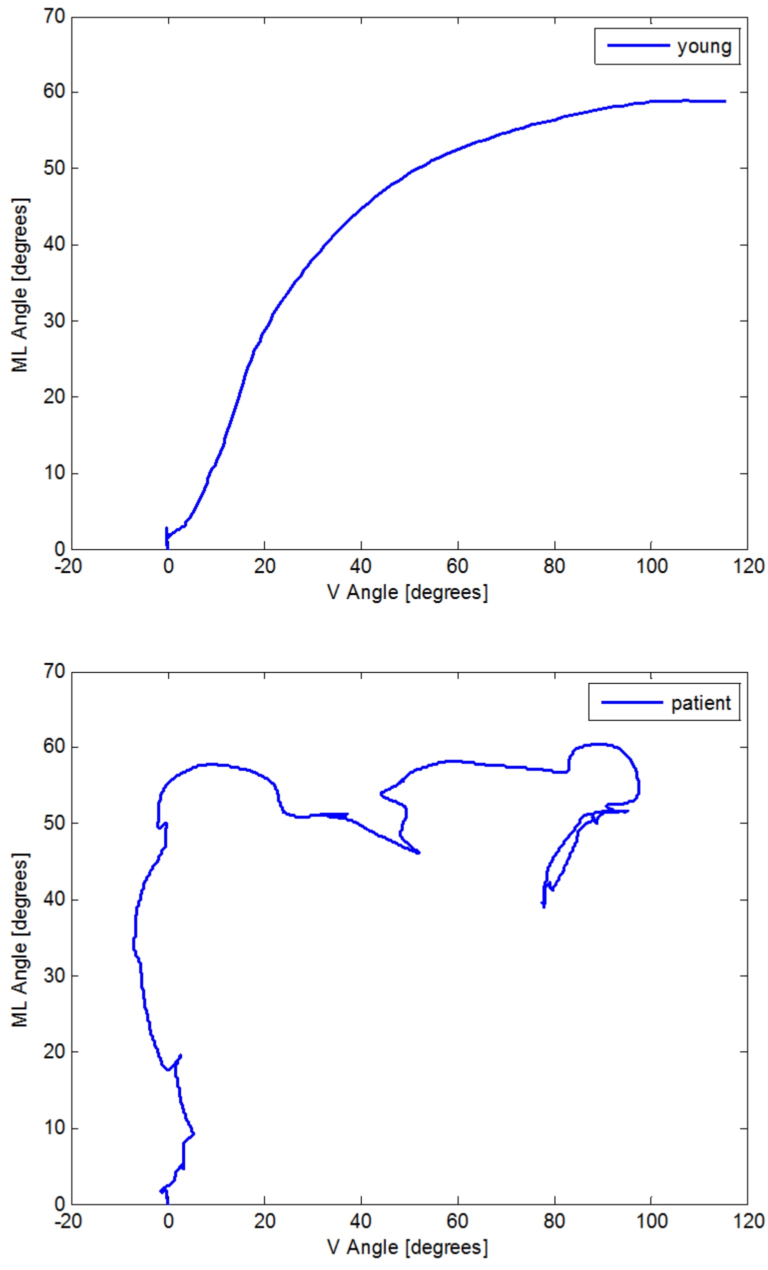


Figure 6.4: ML-rotation vs V-rotation of a young participant and a patient

to understand the association between transfers and falls in older persons. In this context the clinical relevance of the position of the hospital bed near the wall, meaning to stand up to the left side or to the right side of the bed, is obvious and should be investigated in future studies.

Although the small number of included persons is a limitation of this study, the clear results underline the general findings. Since this study was not designed to show intra-individual changes over time or for different test conditions, future research has to focus on this issue.

In conclusion, this test is able to show qualitative and quantitative differences of the lying-to-sit-to-stand transfer between young healthy subjects and older patients. Other studies should investigate special cohorts of interest and the sensitivity to change in pre-post assessments.

Part III

Fall detection

Chapter 7

Fall detection algorithms

As discussed in Chapter 2, even if extensive research has been conducted in the area of fall prevention, some of the fundamental factors leading to falls and what happens during a fall remain unclear. Objectively documented and measured falls are needed to improve knowledge of fall in order to develop a more effective prevention strategies and prolong independent living. Real-time detection of falls and their urgent communication to a telecare center may enable rapid medical assistance, thus increasing the sense of security of the elderly and reducing some of the negative consequences of falls. Many different approaches have been explored to automatically detect a fall using inertial sensors. Although previously published algorithms report high sensitivity (SE) and high specificity (SP), they have usually been tested on simulated falls performed by healthy volunteers. We recently collected acceleration data during a number of real-world falls among a patient population with a high-fall-risk as part of the SensAction-AAL European project. The aim of the present study is to benchmark the performance of thirteen published fall-detection algorithms when they are applied to the database of 29 real-world falls. To the best of our knowledge, this is the first systematic comparison of fall detection algorithms tested on real-world falls. We found that the SP average of the thirteen algorithms, was (mean±std) 83.0%±30.3% (maximum value = 98%). The SE was considerably lower (SE=57.0%±27.3%, maximum value = 82.8%), much lower than the values obtained on simulated falls. The number of false alarms generated by the algorithms during 1-day monitoring of three representative fallers ranged from 3 to 85. The factors that affect the performance of the published algorithms, when they are applied to the real-world falls, are also discussed. These findings indicate the importance of testing

Bagalà F, Becker C, Cappello A, Chiari L, Aminian K, Hausdorff JM, Zijlstra W, Klenk J (2012) *Evaluation of accelerometer-based fall detection algorithms on real-world falls*, Under review on PlosOne fall-detection algorithms in real-life conditions in order to produce more effective automated alarm systems with higher acceptance. Further, the present results support the idea that a large, shared real-world fall database could, potentially, provide an enhanced understanding of the fall process and the information needed to design and evaluate a high-performance fall detector.

7.1 Introduction

Real-time detection of falls allows for the immediate communication of these adverse events to a telecare center so that medical assistance can be supplied quickly. Such assistance is needed to promote the sense of security of older adults, especially among those who are living alone, and to reduce fear of falling and the subsequent negative impact of falls. Indeed, one of the serious consequences of falling is the "long-lie" condition, where a faller is unable to get up and remains on the ground for several hours. "Long-lies", and falls, in general, are associated with social isolation, fear of falling, muscle damage, pneumonia, pressure sores, dehydration and hypothermia [249, 337, 338, 339]. Half of the elderly people who experience a 'long-lie' die within 6 months [340], even if no direct injury from the fall has occurred. The 'long-lie' occurs in more than 20% of elderly people admitted to hospital as a result of a fall [341] and up to 47% of non-injured fallers are unable to get up off the floor without assistance [342]. Detection of a fall, either through automatic fall detection or through a personal emergency response system, might reduce the consequences of the 'long-lie' by reducing the time between the fall and the arrival of medical attention [343]. If an older person living alone experiences a fall at home, he or she may not be able to get to the phone or press an alarm button due to sustained injuries or loss of consciousness [343]. Moreover, some elderly people do not activate their personal emergency response systems, even when they have the ability to do so [344].

As discussed in Chapter 2, in the last decade, a variety of different methods were developed over the last decade to automatically detect falls. These have been based on video-cameras, acoustic or inertial sensors, and mobile phone technology. Several of these studies focused on the monitoring of the activities of daily living (ADL) and fall detection using wearable sensors.

Many different approaches have been explored to solve the fall detection problem using only accelerometers or an inertial measurement unit (both gyroscopes and accelerometers). The analysis of accelerometer and/or gyroscope outputs allows for detecting specific events, such as voluntary (e.g., walking, sitting, lying) or involuntary (e.g., fall) activities of daily living, based on statistical or threshold-based algorithms. The inertial sensor-based fall detection algorithms usually provide: i) a definition of a set of parameters related to the accelerometer and gyroscopes outputs, used for the characterization of the movement, ii) impact detection, using a threshold-based method, iii) orientation detection, e.g., using the vertical accelerometer output or angular rate measurements, and iv) fall alarm, which occurs when all the test conditions are true.

Published algorithms have usually been tested only on simulated falls. Most authors have used simulations with healthy volunteers [195, 196, 198, 199, 202, 206, 208, 223] or martial arts students [194] as a surrogate for real-world falls to develop biomechanical models of falls [345]. To the best of our knowledge, there are no published inertial measurement-based real-world fall data of older people measured in a real-world environment.Although the rate of falls is quite high (approximately 30% of persons over 65 years fall at least once per year), it is very difficult to capture real-world fall data. This largely is a result of the relatively short measurement intervals allowed by commercially available sensors. As an example, to capture 100 real-world falls, it would be necessary to record approximately 100,000 days of physical activity (300 person years). If the battery lifetime is limited to 10 days, 10,000 measurement cycles would be needed. Additionally, compliance problems may arise with long measurement periods. As far as we know, most international studies have failed to gather sufficient numbers of fall events. Recently, Kangas *et al.* [346] collected acceleration data of 5 real-world falls during a six-month test period in older people.

To address the challenges of capturing real-world falls, we began to collect acceleration data during a number of real-world falls as part of a European project (SensAction-AAL) that studied a population with a high-risk of falling. Based on these data, a recent study [336] compared acceleration signals, measured using a tri-axial accelerometer placed on the waist of the subjects, from simulated falls and these real-world falls and found large differences between them, even though a relatively simple example of falling backward to the ground was selected. Several problems are associated with the simulation approach including the anticipation of the volunteer that a fall will occur and the choice of the floor material to reduce the impact of the falls for safety reasons. These findings underline the importance of gathering real-world fall data for designing accurate algorithms.

With the limitations of simulated falls in mind, the aim of the present chapter is to benchmark, for the first time, the performance of 13 different published algorithms as applied to the database of 29 real-world falls collected during the SensAction-AAL project. In order to compare the performance in the same test conditions as our real-world fall data, only algorithms based on waist or trunk accelerometer measurements were investigated.

Algorithms based on gyroscopes measurements or on more than one sensor are not considered in this study.

7.2 Methods and Materials

7.2.1 The real-world fall database

Acceleration signals of 32 falls of 15 subjects were collected during a recent European project (SensAction-AAL) and clinical routine assessments. 30 falls from 9 subjects (7 women, 2 men, age: 66.4 ± 6.2 years, height: 1.63 ± 8.68m, weight: 77.2 ± 11.5kg) were recorded within a cross-sectional study of patients suffering from progressive supra-nuclear palsy (PSP) [347] and from an intervention study to investigate the feasibility of audio-biofeedback to improve balance [348]. PSP is an atypical Parkinson's syndrome with a prevalence of 5 per 100,000 [349]. Postural instability and falls are common and are the most disabling features of the disease [350, 351]. A 48-h activity measurement was conducted on 29 subjects as part of the assessment in the cross-sectional study and during days without intervention. A fall was defined as *"an unexpected event in which the participant comes to rest on the ground, floor, or lower level"* [28]. Patients or their proxies reported the time, the place and the circumstances of the falls.

Two additional falls were recorded from one subject within a cross-sectional study in community-dwelling older people. All of these falls were recorded during daily physical activity measurement using an ambulatory device based on accelerometers (Dynaport® MiniMod, McRoberts, The Hague, NL). For the sake of the present study, for each fall, we extracted, from the 24 hour recording, a 60 second time-window centered around the fall event. The falls were characterized with respect to location, pre-fall phase, fall direction, and impact spot (Table 7.1). The MiniMod®, composed of a tri-axial seismic acceleration sensor (LIS3LV02DQ STMicroelectronics, Agrate Brianza, Italy), was fixed by a belt at the lower back. The orientation of the axes are x=vertical, y=medio-lateral (left/right), and z=anterior-posterior (forward/backward). The sensor has a resolution of 12 bit and a sampling frequency of 100Hz. The published fall detection algorithms were usually based on measurements carried out by accelerometers with a sampling frequency varying from 50Hz to 250Hz and a range of $\pm$10g or $\pm$12g. We recorded 14 falls with a sensor's range of $\pm$6g, the remaining 18 falls with a sensor's range of $\pm$2g. When the acceleration exceeds the threshold $\pm$2g, the so-called "clipping effect" (or saturation) produces a cut-off of the signal. Since this could affect the results of the analysis, three falls that show saturation effects are not included in the analysis. Therefore, the total number of falls considered in this study was 29. Raw data were stored for off-line analysis on a SD card.

Table 7.1: Description of real-world falls (n=32)

	Number of falls per condition
Location	Indoor (n=30), outdoor (n=2)
Activity before the fall	Standing (n=16), walking forward (n=8), walking backward (n=1), sit-to-stand (n=5), stand-to-sit (n=2)
Reported direction of fall	Forward (n=8), backward (n=18), sideward (n=6)
Impact spot	Floor (n=23), bed/sofa (n=4), desk (n=1), against wall/locker before hitting the floor (n=4)

7.2.2 The algorithms

The algorithms used are summarized here; additional details can be found in the literature [194, 195, 196, 197, 352]. Table 7.2 summarizes the parameters, thresholds and the phases of a fall event that are considered: beginning of the fall, falling velocity, fall impact and orientation after the fall. The outputs of the tri-axial accelerometer are $A_x(k)$,$A_y(k)$,$A_z(k)$ with $k = 1, \ldots, n$ and n as number of samples.

Chen *et al.* [194] used a tri-axial accelerometer worn on the waist of two martial arts students, who performed some common fall motions over 10 trials. If the root sum vector (SV) of the three squared accelerometer outputs exceeds a threshold, it is possible that a fall has occurred (IMPACT DETECTION). Additionally, the orientation is calculated over 1 second before the first impact and 2 second after the last impact using the dot product of the acceleration vectors (CHANGE IN ORIENTATION). The angle change that constitutes a change in orientation can be set arbitrarily based on empirical data, as suggested by the authors. We set this threshold to 20° in order to have the best sensitivity and specificity. No results are reported in the paper, but the authors point out the benefits due to the evaluation of change in orientation.

Kangas *et al.* [195] attached a tri-axial accelerometer to the waist, wrist and head of three healthy middle-aged volunteers, who performed three standardized types of falls (forward, backward, and lateral) towards a mattress. Examples of activities of daily living (ADL) were collected from two healthy subjects, representing dynamic activities (e.g., walking, walking on the stairs, picking up objects from the floor). Four different detection algorithms, Kangas1a to Kangas1d, with increasing complexity were investigated. The thresholds are related to the waist measurement. These four algorithms had in common IMPACT DETECTION + POSTURE MONITORING. They were based on the detection of the impact by threshold on the sum vector (SV), the dynamic sum vector (SV_D) related to the high-pass filtered (HPF) accelerometer outputs, the sliding sum vector (SV_{MaxMin}) and the vertical acceleration (X_2), followed by monitoring of the subject's posture. The posture was detected 2 seconds after the impact from the low-pass filtered (LPF) vertical signal, based on the average acceleration in a 0.4 seconds time interval, with a signal value of 0.5g or lower considered to be a lying posture.

Two further algorithms, Kangas2a and Kangas2b, were considered from Kangas *et al.* [195] based on START OF FALL + IMPACT DETECTION + POSTURE MONITORING. These algorithms detected the start of the fall by monitoring lower than a threshold of 0.6g, followed by the detection of the impact within a time frame of 1s by a threshold value of SV or X_2, followed by monitoring of the posture.

Three further algorithms, Kangas3a to Kangas3c, based on START OF FALL + VELOCITY + IMPACT DETECTION + POSTURE MONITORING were considered from [195]. These algorithms detected the start of the fall, followed by detection of the velocity v_0 (calculated by integrating the area of SV from the trough (see Figure 7.1), at the beginning of the fall, until the impact, where the signal value is lower than 1 g) exceeding the threshold, followed by the detection of the impact within a time frame of 1s by a threshold value of SV or X_2, followed by monitoring of the posture. The fall detection sensitivity, declared by the authors [195], of the different eight algorithms at the waist varied from 76% to 97% and the specificity was 100%.

Bourke *et al.* [196] mounted two tri-axial accelerometers to the trunk (at the sternum) and the thigh. Ten young subjects were involved in simulated falls onto large crash mats. Ten community-dwelling elderly subjects performed ADL in their own homes (e.g., sit to stand, lying, walking). In these algorithms (Bourke1a and Bourke1b), the SV of the three signals was evaluated from the sternum and thigh accelerometer outputs and a fall was detected when the SV is over the upper (UFT) threshold (3.52g) or lower than the lower (LFT) thresholds (0.41g). Declared specificity is 100% for the upper threshold and 91.25% for the lower threshold, related to the trunk sensor. In this paper, as suggested by the authors [196], the thresholds were set according with the falls database. The UFT and LFT were set at the level of the smallest magnitude upper fall peak (Bourke1a) and at the level of the biggest magnitude lower fall peak (Bourke1b), respectively. Based on the accelerometric data of the 29 falls, we set the two thresholds to 1.79g (UFT) and 0.73g (LFT). Exceeding any individual limit would indicate a fall.

Bourke *et al.* [197] developed a second fall detection system using a tri-axial accelerometer to detect impacts. The algorithm (Bourke 2), considered the SV of the accelerometer outputs, and monitor posture, assuming a lying posture if the vertical accelerometer signal value is between -0.5g and 0.5 g. The sensor was attached to a custom designed vest. Two teams of 5 elderly subjects tested the algorithm. Over 833 hours of monitoring, no actual falls were recorded, although the system registered a total of 42 false alarms (i.e., false positives).

Recently, Bourke *et al.* [352] evaluated 21 fall-detection algorithms of varying degrees of complexity for a waist-mounted accelerometer based system. The algorithms were tested against a comprehensive data-set recorded from 10 young healthy volunteers performing 240 simulated falls and 120 ADL and 10 elderly healthy volunteers performing 240 scripted ADL and 52.4 waking hours of continuous unscripted normal ADL. Here, we evaluated the algorithm (Bourke3) VELOCITY+IMPACT+POSTURE that achieved 100% sensitivity and specificity and with the lowest false-positive rate (0.6 false positive per day) when applied to simulated falls and tested it on the real-world falls database. The algorithm is based on the detection of the four distinct phases of a fall [345] (pre-fall, critical phase, post-fall phase and recovery) when the SV exceeds the LFT (0.65g) and the UFT (2.8g) thresholds. Two temporal features and their related thresholds are considered: the falling-edge time, t_{FE}, is from the SV signal last going below the LFT until it exceeds the UFT (threshold set to 600ms), and the rising-edge time, t_{RE}, is the last time when the LFT is exceeded until the UFT is exceeded (threshold set to 350ms). The vertical velocity is further considered as an indicator of a fall when it overcomes the threshold (-0.7m/s). It is evaluated through the numerical integration of the SV signal with the gravity component subtracted. The post-fall posture is determined taking the dot product of the gravity vector g_{REF} and the current gravity vector estimated relative to the body segment g_{SEG}. Lying is detected if the waist posture, $\theta(t)$, from t+1 s to t+3 s exceeds 60° for more than 75% of the duration.

As summarized in Table 7.2, the SV is a common feature among all the algorithms. An example of prototypical signal of the SV is shown Figure 7.1. The signal reflects a forward real-world fall in which the subject fell directly on the floor while bending to pick up an object. The typical trough before the impact, the impact and the maximum magnitude due to the impact are also indicated.

The 29 accelerometer fall recordings were used to test the performance of the algorithms in terms of sensitivity (SE, percentage of falls correctly detected as such). Further signals analysis was performed in order to evaluate the specificity (SP, percentage of ADL correctly identified as non-falls).

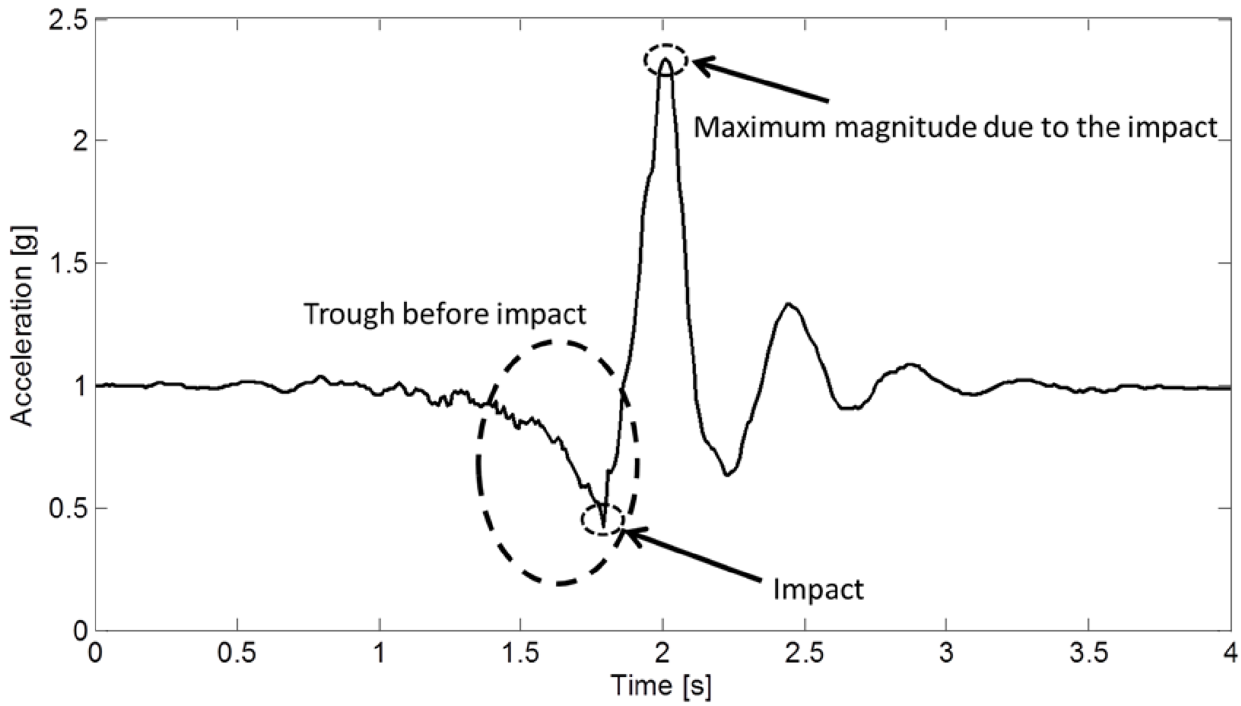


Figure 7.1: Prototypical acceleration sum vector of a fall. This real-world example illustrates components that are common to many falls.

Previous studies tested the specificity of ADL performed in the laboratory environment by the same subjects who simulated falls (generally healthy young subjects) or community-dwelling elderly subjects. These data could be biased, since subjects are forced to perform activities, which are typically spontaneous. To avoid biased results for specificity, we extracted ADL based on the individual physical activity recordings from each subject excluding the 60 second fall-time-windows. The remaining observation time was also separated into 60 second time-windows.

The recordings of 8 of the 15 fallers were carried out using the sensor with range ± 2g and therefore were excluded from the specificity evaluation. We collected, for the remaining 7 subjects, 168h of accelerometer recordings, i.e., 10,050 time-windows of 60 seconds (the 29 time-windows related to falls were excluded). These time windows could be related to resting periods. In all these cases, the fall detection algorithms correctly identify 100% of ADL as not-falls. Thus, the SP will show high values because of the high number of time windows with inactivity included in the analysis. According to these considerations, the time windows related to resting periods were excluded and those related to activity periods were considered in the study according with a simple procedure.

Authors	Parameters	Thresholds	Algorithm's rationale
Chen et al.	$\mathbf{SV}=\sqrt{\mathbf{A}_x^2+\mathbf{A}_y^2+\mathbf{A}_z^2}$ $\text{orientation}=\overline{\mathbf{A}}[t_0-1]\cdot\overline{\mathbf{A}}[t_0+2]$ (1)	>3 g Set arbitrarily based on empirical data (>20°)	IMPACT DETECTION + CHANGE IN ORIENTATION
Kangas et al. (1a)	$\mathbf{SV}=\sqrt{\mathbf{A}_x^2+\mathbf{A}_y^2+\mathbf{A}_z^2}$ $\text{Posture}=\overline{\mathbf{A}}_{x,LPF}$ (2)	>2 g <0.5 g	IMPACT DETECTION + POSTURE MONITORING
Kangas et al. (1b)	$\mathbf{SV}_D=\sqrt{\mathbf{A}_{x,HPF}^2+\mathbf{A}_{y,HPF}^2+\mathbf{A}_{z,HPF}^2}$ (3) $\text{Posture}=\overline{\mathbf{A}}_{x,LPF}$	>1.7 g <0.5 g	IMPACT DETECTION + POSTURE MONITORING
Kangas et al. (1c)	$SV_{MaxMin}(k)=\max(SV(k:k+0.1*fs))-\min(SV(k:k+0.1*fs))$ $k=1,..n-0.1*fs$ $\text{Posture}=\overline{\mathbf{A}}_{x,LPF}$	>2 g <0.5 g	IMPACT DETECTION + POSTURE MONITORING
Kangas et al. (1d)	$\mathbf{X}_2=\frac{\mathbf{SV}^2-\mathbf{SV}_D^2-G}{2G}\quad(G=1g)$ $\text{Posture}=\overline{\mathbf{A}}_{x,LPF}$	>1.5 g <0.5g	IMPACT DETECTION + POSTURE MONITORING
Kangas et al. (2a)	$\mathbf{SV}=\sqrt{\mathbf{A}_x^2+\mathbf{A}_y^2+\mathbf{A}_z^2}$ (start of fall) $\mathbf{SV}$ $\text{Posture}=\overline{\mathbf{A}}_{x,LPF}$	<0.6 g >2 g <0.5g	START OF FALL + IMPACT DETECTION + POSTURE MONITORING
Kangas et al. (2b)	$\mathbf{SV}$ (start of fall) $\mathbf{X}_2$ $\text{Posture}=\overline{\mathbf{A}}_{x,LPF}$	<0.6 g >1.5 g <0.5g	START OF FALL + IMPACT DETECTION + POSTURE MONITORING
Kangas et al. (3a)	$\mathbf{SV}$ (start of fall) $v_0=\int_{t_{startfall}}^{t_{impact}} SV(\tau)d\tau$ $\mathbf{SV}$ $\text{Posture}=\overline{\mathbf{A}}_{x,LPF}$	<0.6 g >0.7 m/s >2 g <0.5g	START OF FALL + VELOCITY + IMPACT DETECTION + POSTURE MONITORING
Kangas et al. (3b)	$\mathbf{SV}$ (start of fall) $v_0=\int_{t_{startfall}}^{t_{impact}} SV(\tau)d\tau$ $\mathbf{X}_2$ $\text{Posture}=\overline{\mathbf{A}}_{x,LPF}$	<0.6 g >0.7 m/s >1.5 g <0.5g	START OF FALL + VELOCITY + IMPACT DETECTION + POSTURE MONITORING
Bourke et al. (1(a))	$\mathbf{SV}=\sqrt{\mathbf{A}_x^2+\mathbf{A}_y^2+\mathbf{A}_z^2}$	>UFT 1.79 g	IMPACT DETECTION
Bourke et al. (1(b))	$\mathbf{SV}=\sqrt{\mathbf{A}_x^2+\mathbf{A}_y^2+\mathbf{A}_z^2}$	<LFT 0.73 g	IMPACT DETECTION
Bourke et al. (2)	$\mathbf{SV}=\sqrt{\mathbf{A}_x^2+\mathbf{A}_y^2+\mathbf{A}_z^2}$ $\text{orientation}=\mathbf{A}_x$	>1.79 g $-0.5g < A_x < 0.5g$	IMPACT DETECTION + POSTURE DETECTION
Bourke et al. (3)	$v_0=\int_{t_{startfall}}^{t_{impact}} SV(\tau)d\tau$ $\mathbf{SV}=\sqrt{\mathbf{A}_x^2+\mathbf{A}_y^2+\mathbf{A}_z^2}$ $\vartheta(t)=\cos^{-1}\left(\frac{\mathbf{g}_{SEG}(t)\bullet\mathbf{g}_{REF}}{\lvert\mathbf{g}_{SEG}(t)\rvert\bullet\lvert\mathbf{g}_{REF}\rvert}\right)\frac{180}{\pi}$	<-0.7 m/s >UFT 2.8 g <LFT 0.65 g 60°	VELOCITY + IMPACT DETECTION + POSTURE

Table 7.2: Brief review of the main fall detection algorithms; [1] An angle of change can be estimated using the dot product of the acceleration vectors before a fall and after, where the vectors are from averaging over 1-second windows. [2-3] Accelerometric data were low-pass (LPF) or high-pass (HPF) filtered ($fc = 0.25Hz$) with a digital second order Butterworth filter.

We assumed that an activity is performed if the dynamics of the signal (the difference between the maximum and the minimum value) in a 60 second time window overcomes a fixed threshold TH. This was selected from the following steps:

- the difference $M_i = max\,(SV_i) - min\,(SV_i)\,(i = 1, \ldots, 10,050)$ was evaluated from the accelerometer outputs for each of the 10,050 time-windows;
- the 10,050 time-windows were tested by the 13 algorithms;
- if the kth time window was wrongly identified as fall, the value M_k was allocated in a vector $\mathbf{M}$;
- after testing the 13 algorithms, the minimum element of $\mathbf{M}$ was considered as the threshold TH for discriminating resting from activity periods.

All the time-windows with $M_i > TH$ were considered as ADL and thus selected for the analysis. The threshold evaluated by the procedure was TH=1.01 g. The total number of time-windows considered was 1170. The accuracy (ACC, the ratio between the number of correct assessments, falls and ADL, and the number of all assessments), the positive predictive value (PPV, the probability that a time window with a positive test result, fall detected, really does have the condition for which the test was conducted) and the negative predictive value (NPV, the probability that a time window with a negative result, fall undetected, really does have the condition for which the test was conducted) were evaluated for each algorithm. Moreover, the performance of the tested algorithms were evaluated on 24 hour accelerometer recordings for three of the PSP fallers, in order to evaluate the number of false alarms (ADL detected as falls) generated by the different algorithms. Data analysis was performed using MATLAB 7.9.0 (R2009B).

7.3 Results

In order to show an example of real-world fall signals, the sum vector of a backward fall and its detail is reported in Figure 7.2A. The sum vector related to one of the randomly extracted ADL is shown in Figure 7.2B. The SE and SP of the tested algorithms for fallers are shown in Figure 7.3.

The SP is over 94% for all the algorithms, except for the algorithm Bourke2 and Bourke1(a, b), which have the best performance in terms of SE (the thresholds are set to hit this mark) and the worst in terms of SP, as one would expect. The SE is low (SE=57.0%±27.3%, maximum value = 82.8%). Although a trade-off is achieved with the Chen and Bourke3

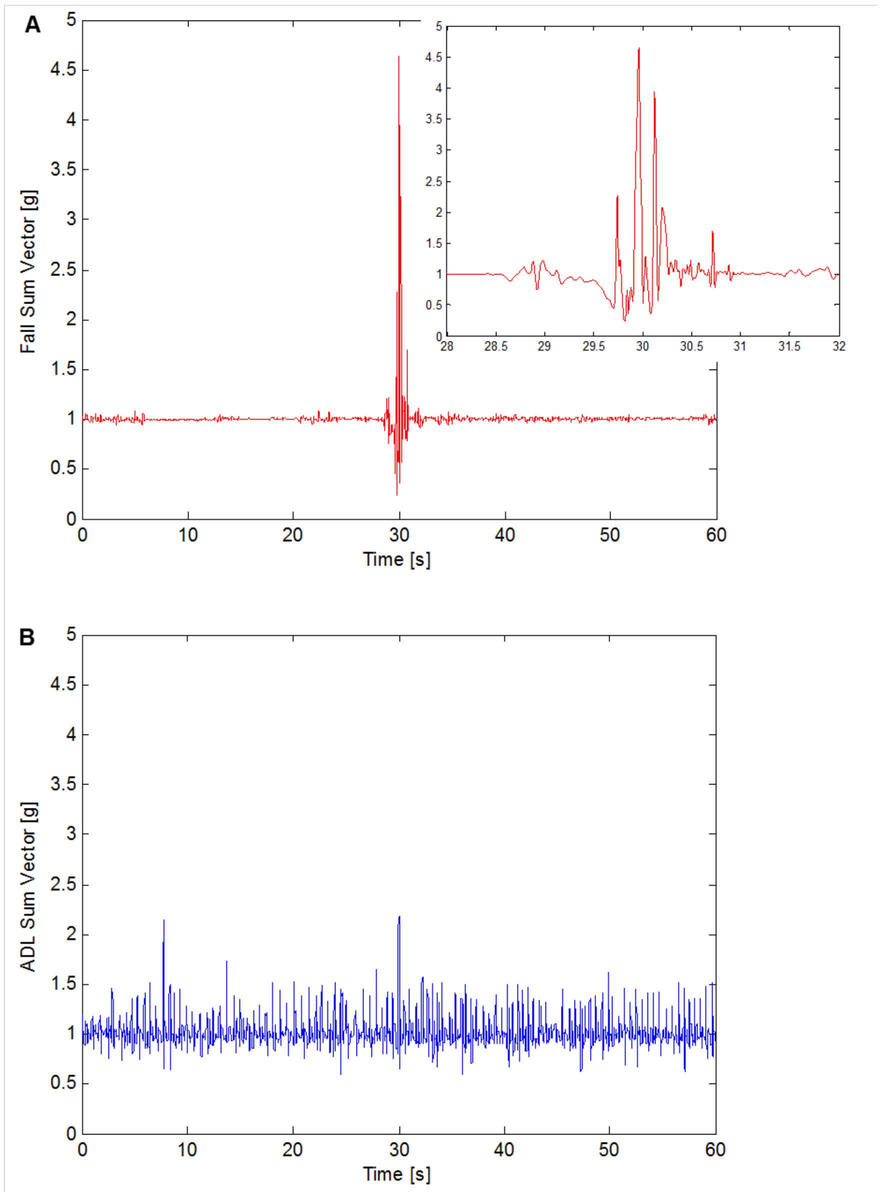


Figure 7.2: Sum vector of (a) backward fall and detail and (b) example of selected ADL (walking)

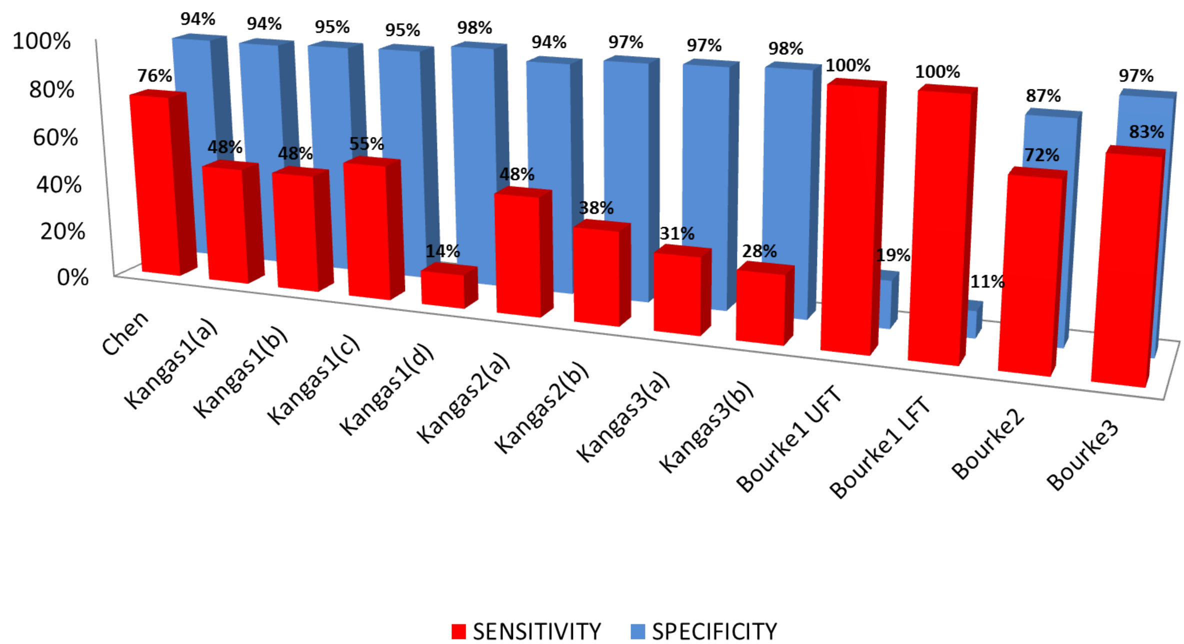


Figure 7.3: Sensitivity and Specificity for the tested algorithms

algorithms (SE=75.9%±82.8%, SP=94.2%-96.7%, respectively), the results are considerably worse than those previously reported in laboratory environments. The ACC, the PPV and the NPV are reported in Table 7.3A for each algorithm. The number of false alarms generated in 24 hours is shown in Figure 7.4 for three fallers. Bourke1(a, b) shows the highest number of false alarms, although it has the maximum value of sensitivity. Kangas' algorithms generated less than 9 false alarms, but sensitivity was lower than 55% (Figure 7.3).

7.4 Discussion

The aim of this chapter was to compare different accelerometer-based fall detection algorithms on a database of real-world falls. Consistent with a previous work which demonstrated marked differences between real-world and simulated falls [336], we find that algorithms that were successful at detecting simulated falls did not perform well when attempting to detect real-world falls.

To our knowledge, no other studies in the literature have evaluated fall detection algorithms based on a relatively large dataset of real-world falls. Fifteen older patients (age 67±18 years) assessed as having a high risk of falling were involved in an 18-day study [197].

Table 7.3: Accuracy (ACC), positive (PPV) and negative (NPV) predictive values of the tested algorithms

Algorithm	**ACC[%]**	**PPV[%]**	**NPV[%]**
Chen	93.7	24.4	99.4
Kangas1a	92.9	16.7	98.7
Kangas1b	93.7	18.9	98.7
Kangas1c	94.5	23.2	98.8
Kangas1d	96.4	18.2	97.9
Kangas2a	93.3	17.7	98.7
Kangas2b	95.3	22.4	98.4
Kangas3a	95.8	23.1	98.3
Kangas3b	96.7	29.6	98.2
Bourke1a	21.3	3.0	100.0
Bourke1b	13.0	2.7	100.0
Bourke2	86.8	12.3	99.2
Bourke3	96.3	38.1	99.6

Unfortunately only four falls were recorded and the data were not analyzed. Recently, Kangas *et al.* [346] collected accelerometer data for 5 real-world falls during a 6 month test period in older adults and compared some features (SV, pre-fall velocity) of real-world falls with simulated falls. They suggested that there are important differences between real and simulated falls.

Based on a data-set with recorded real-world falls, our study evaluated thirteen accelerometer-based algorithms for fall detection which have been previously evaluated on simulated falls only. SE and SP of these algorithms (Figure 7.3) shows how the sensitivity and specificity obtained by the authors (often declared to be 100%) are different when the algorithms are tested on real-world falls.

By analyzing the main drawbacks of the presented algorithms, we noted that several factors affect the difference between simulated and real-world falls. Thresholds are usually calibrated on simulated fall signals and are not suitable for real-world fall signals. For instance, the SV is considered to be a feature for impact detection in all the presented algorithms, but each author used a different threshold to detect the impact. Our results are consistent with the considerations of Kangas [346] who found that some fall phases detected in experimentally simulated falls were not detectable in acceleration signals from

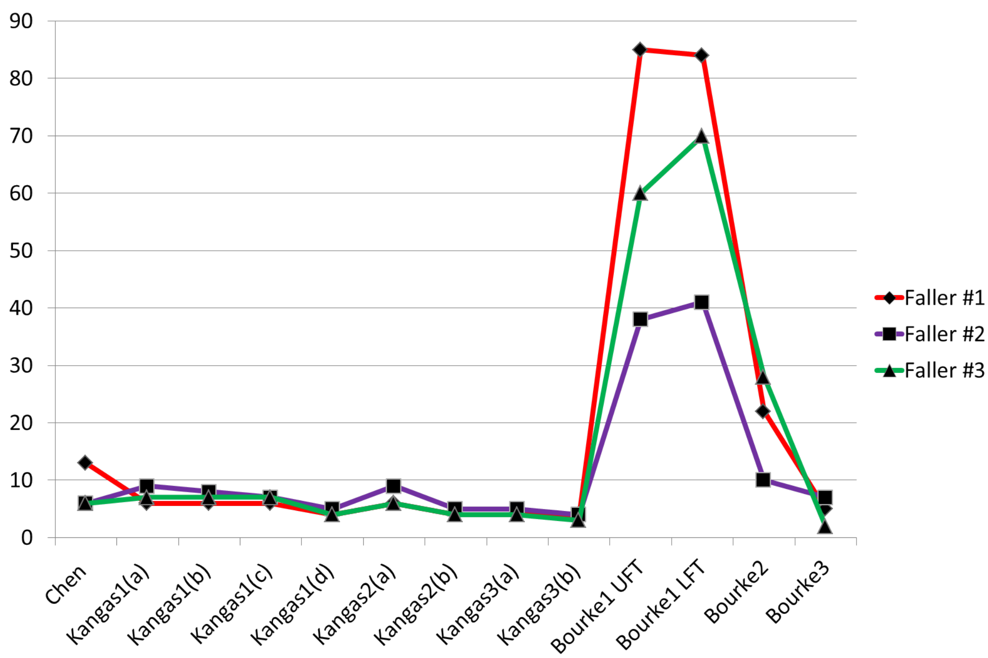


Figure 7.4: False alarms generated in 24 h recordings for three fallers

heterogeneous real-world falls.

Nevertheless, all the algorithms have low computational cost and low-complexity, allowing them to be easily implemented in a microcontroller for real-time applications. This approach is commendable because it helps to increase the security of the subject, hopefully reducing the number and severity of falls. The use of the sum vector of the three accelerometer outputs as the main parameter provides robustness against the incorrect position of the sensor.

Chen's algorithm [194] provides a good trade-off in terms of SE (76%) and SP (94%). Since the high threshold for impact detection allows for reduction of false positives, some "low-magnitude" falls are not detected due to their maximum peak values. Despite the efforts of the authors to pay attention to orientation change, this parameter does not provide an optimal discrimination between real-world falls and ADL. Since we set a low angle orientation threshold, in many conditions the subject's orientation does not show a significant change before and after the fall (e.g., falling on the knees).

Kangas *et al.* [195] investigated three different algorithms with increasing complexity. Since the threshold values allow detection of most impacts, the posture monitoring test fails against several types of falls. The LPF vertical signal rarely reaches values under 0.5g, which is considered to be a lying posture [199, 200]. In our falls database, subjects who fell on their buttocks, knees, or against a table or the walker, did not lie on the floor. However, the lying posture detection is very important to detect falls in which the subject lies on the floor for a long time. Moreover, according to the SE values shown in Figure 7.3, the more complex the algorithm is the more difficult it is to detect a fall, since the signal has to pass several tests. The algorithms related to the vertical acceleration X_2 (Kangas1d, Kangas2b, Kangas3b) provide the lowest sensitivity values due to the high threshold set for this parameter. Kangas3(a, b) show the worst results: the velocity before the impact is often lower than the predetermined thresholds.

Results of Bourke's algorithm [196] require additional discussion. The authors suggest setting the two thresholds according to the falls database in order to have 100% of SE. Nevertheless, the Bourke1(a, b) algorithms provide the worst results in terms of SP (19.3% and 11.9%, respectively). This offline method is not recommended for several reasons. First, the two thresholds, UFT (1.79g) and LFT (0.73g), are set according to the real-world fall database and therefore have to be tuned every time a new fall occurs. Consequently, the predictive ability of the fall detection algorithm is impaired: if the fall detector is used in real-life conditions, falls with a maximum peak lower than UFT or the minimum peak greater than LFT are not detected. The Bourke1b algorithm, based on the LFT algorithm, provides the lowest SP. The majority of real-world falls we collected provide a trough before the impact related to the free-fall phase. However some ADL (e.g., sitting on a chair or on a bed) show values of the sum vector lower than the LFT=0.73g, due to the phenomenon of weightlessness. This explains why the lowest specificity was found for Bourke's algorithm. Moreover, as shown in Figure 7.4, the high number of false alarms during 24h recordings, from 22 to 85 for the three fallers for Bourke1a, and from 27 to 84 for Bourke1b, is unacceptable (more than 2 false alarms per hour). The major reason for failure is rejection by monitoring services due to a high number of false alarms [353, 354]. This weak point is more evident in the Bourke LFT algorithm as compared to the other algorithms, since these have fewer than ten false alarms.

The second algorithm suggested by Bourke *et al.* [197] provides results similar to Chen's algorithm. Since the threshold, which is the same as Bourke1b, ensures detection of several impacts, the SP is higher than Bourke1(a,b) because the algorithm provides posture monitoring after fall. The subject's "long-lie" condition (vertical accelerometer signal value between -0.5g and 0.5g) allows increasing the SP but this did not occur in all falls. The Bourke2 algorithm emphasizes the drawbacks of the Bourke1 algorithms, which are based on thresholds lacking considerations of posture monitoring after a fall. Adding information about posture after the impact can improve the results in terms of SP. As shown in Figure 7.4, the number of false alarms is reduced threefold from Bourke1 (mean of 61-65 false alarms) to Bourke2 (20 false alarms).

Bourke's recently proposed algorithm (Bourke3) [352] provides the best trade-off in terms of SE (83%) and SP (97%) but the results are still different from those obtained by the authors on their simulated-falls database (100% sensitivity and specificity). The algorithm fails to detect falls with low impact magnitude (mainly forward falls, falling on bed/sofa, against the wall) which are common, since more than half of all in-patient falls in elderly people in acute care settings occurred at bedside, during transfer or while getting up [321, 355]. Moreover, Kangas *et al.* [346] also found differences between simulated and real-world falls on beds in terms of low impact magnitude. Despite of this, the number of false alarms is considerably lower than with other Bourke's algorithms (about 5 false alarms per day).

Table 7.3 provides results related to PPV and NPV, which are usually stable characteristics of diagnostic tests when the prevalence of disease is high among the population of interest (in this study prevalence of disease is equivalent to fall risk). The same diagnostic test will have varying predictive values in different populations. As mentioned in the Methods section, the recorded ADL, used for testing the algorithms, are related to the PSP and geriatric rehabilitation unit patients, both with a high risk of falling.

Since the results for NPVs (98.9%±0.7%) indicate that with these algorithms there is a high probability that when an event is not detected as a fall it is not really a fall, the PPVs (19.3%±9.7%) are low, i.e., there is a low probability that when a fall is detected it is really a fall. This means that some events incorrectly detected as falls are activities of daily living.

Furthermore, since the number of real-world falls (29) is small compared with the total number of time-windows tested (1170), the SP is affected by these differences and does not provide useful information for the evaluation of the algorithms (e.g., Bourke3 has 97% specificity i.e. 39 false positives). From a more practical point of view, if the fall detector is connected to a tele-alarm system, the robustness of the fall detection algorithm should be evaluated in terms of high sensitivity and small number of false alarms generated. For example, consider a recording of 48h, i.e. 2880 time windows of 60s. If the algorithm incorrectly detects 100 ADL as falls, the SP will be 96%. This is an acceptable value for a test but if we imagine that the fall detector could trigger an alarm when a fall is detected, 100 false positive results within 48h means that about 2 false alarms per hour are generated.

The weaknesses of the tested algorithms enable us to understand certain complex aspects of a fall but could also be a starting point for future development of an accurate fall detector. The tested algorithms set a fixed threshold for features extracted by accelerometer signals but are tested on individuals with different mass, age, clinical history and diseases. These factors could affect the accelerometer data and the algorithms could fail; a fixed threshold may not be the optimal strategy compared to a subject-specific threshold. Inertial sensors-based fall detection algorithms could be designed not only to automatically detect a fall but also to provide additional information regarding direction of falls in order to better understand injuries and to offer a prevention intervention. Since results are related to the thresholds provided by the authors, the performance of the tested algorithms could be optimized by using the Receiving Operating Characteristic (ROC) in order to identify the threshold with the best trade-off between sensitivity and specificity. By the way of example, four out of the 13 algorithms were optimized in order to maximize the product $\frac{SExSP}{100}$. Results are shown in Figure 7.5 for SE and SP and in Figure 7.6 for false alarms. A good trade-off between SE and SP was obtained for all algorithms, except for Bourke1(b).

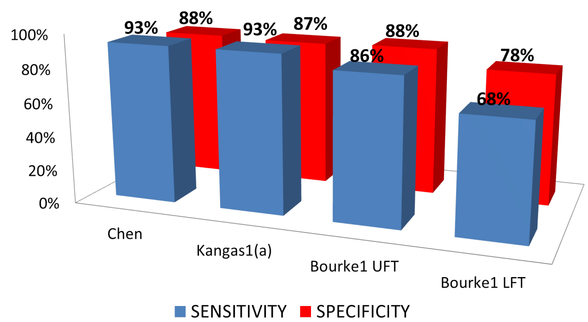


Figure 7.5: Sensitivity and specificity after thresholds optimization for four out of the 13 algorithms

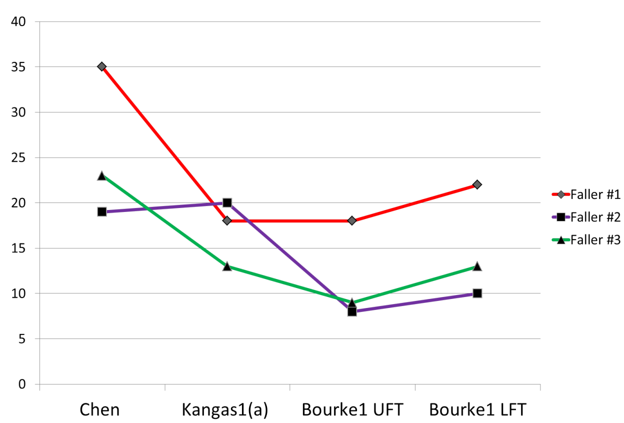


Figure 7.6: False alarms generated in 24 h recordings for three fallers after thresholds optimization for four out of the 13 algorithms

Nevertheless, the number of false alarms significantly increases for the algorithms by

Chen and Kangas1a, which had low SE before threshold optimization, and decreases for the two Bourke's algorithms which had 100% SE and low SP before optimization. The number of false alarms still remains too high. These results suggest that statistical algorithms (e.g., based on Gaussian Mixture Model, Hidden Markov Model) should be preferred to threshold algorithms.

Despite this, the results presented in this chapter showed the importance of testing algorithms in real-world situations. The main limitation of the study is that the recorded real-falls were from a rare disease population, but conclusions may be generalized to the older population at large. Moreover, the tested algorithms are based only on waist or trunk accelerometer measurements and therefore did not represent an exhaustive set of all published fall detection algorithms.

The development of a larger shared real-world fall database should provide additional data and deepen our knowledge of the fall process in general. The FARSEEING European project, which started in January 2012, aims to build the world's largest fall repository of long-term analysis of the behavioural and physiological data collected using smartphones, wearable and environmental sensors. This project could provide the necessary data to design an accurate, portable and high-performance fall detector and a more valid model of falling. The present study represents a preliminary study in this direction.

Appendix A

Non-linear re-calibration of force platforms

let Force platforms (FPs) are used in human movement analysis to measure the ground reaction force and the center of pressure (COP), and calculate derived kinetic and energetic quantities. We propose a re-calibration method that compensates for the FP non-linearity induced by top plate bending under loading. The method develops a previous solution that was proposed for a linear re-calibration and proved suitable for both local and global error compensation (Cedraro *et al.*, 2008). The new method was experimentally tested on 4 commercial FPs by estimating the non-linear re-calibration matrix in a first training trial and by using it to assess the three force components and the COP in a validation trial, comparing the new method to the previously proposed solution for global, linear re-calibration. The average COP accuracy (mm) in the training trial was (mean$\pm$std): 2.3$\pm$1.4, 2.6$\pm$1.5, 11.8$\pm$4.3, 14.0$\pm$2.5 for the 4 FPs before re-calibration, and 0.7$\pm$0.4, 0.6$\pm$0.2, 0.5$\pm$0.2, 2.3$\pm$1.3 after non-linear re-calibration. In the validation trial, for one of the 4 tested FPs, mean errors for the three force components (N) and COP (mm) were: 3.6$\pm$2.3 (Fx), 3.0$\pm$0.7 (Fy), 5.0$\pm$2.5 (Fz), 1.2$\pm$0.68 (COP) after linear re-calibration, and 2.5$\pm$0.7 (Fx), 2.6$\pm$0.5 (Fy), 3.9$\pm$1.2 (Fz), 0.6$\pm$0.3 (COP) after non-linear re-calibration. The proposed global, non-linear method performed equally well as the local, linear re-calibration method, proving well-suited to compensate for the mild non-linear behavior of FP with the advantage of estimating a single re-calibration matrix.

Cappello A, Bagalà F, Cedraro A, Chiari L (2011) *Non-linear re-calibration of force platforms*, Gait & Posture, 33(4): 724-726

A.1 Introduction

Force platforms (FPs) are precision instruments used in human movement analysis to measure the ground reaction force and the center of pressure (CoP). The ageing of the FP, its usage, and in-situ installation procedures may reduce the effectiveness of the calibration provided by the manufacturer and lead to a lack of accuracy [356] which introduces errors in the FP data and may propagate to the calculated kinetic and energetic quantities [357, 358]. The FP accuracy can be increased by estimating the (6x6) re-calibration matrix, C [359, 360, 361], which describes the linear functioning of the FP. Matrix C can be used to model the behavior of either the entire platform (global re-calibration), or part of it (local re-calibration) [359]. However, possible non-linearities largely attributable to the bending of the top plate are not dealt with, and hence compensated, when a global linear model is used [362, 363, 364]. In a previous study it has been shown that local re-calibration is more effective than global re-calibration [359] because it allows increasing FP accuracy mainly in a specific area of the FP, but this may be unacceptable when the loaded area is wide, as in gait analysis. Aim of this appendix is to propose and validate a non-linear, global re-calibration method that compensates for the FP non-linearity and is valid for the whole FP surface.

A.2 Materials and Methods

The output vector ($\mathbf{L}$) of a six-component FP can always be described by its force and moment components [359]:

$$\mathbf{L} = \begin{bmatrix} F_X \\ F_Y \\ F_Z \\ M_X \\ M_Y \\ M_Z \end{bmatrix} \tag{A.1}$$

where axis Z is orthogonal to the FP surface, assuming the origin of the reference system on the top surface of the FP. $\mathbf{L}$ can be calibrated,$\mathbf{L}_C$, by a linear re-calibration [359, 360]:

$$\mathbf{L}_C = \begin{bmatrix} C_{11} & \cdots & C_{16} \\ \vdots & \cdots & \vdots \\ C_{61} & \cdots & C_{66} \end{bmatrix} \mathbf{L} = \mathbf{C}_L \mathbf{L} \tag{A.2}$$

A main cause of the FP non-linearity is the bending of its top plate [362, 363, 364, 365], caused by the load applied. As shown in [364], bending in turn introduces systematic errors on the CoP which depend on the point of force application. As a consequence, the non-linearity can be modeled and compensated with a re-calibration equation which takes into account the CoP coordinates measured by the FP, $X_{CoP} = M_Y/F_Z$ and $Y_{CoP} = M_X/F_Z$:

$$\mathbf{L}_C = \mathbf{C}_0\mathbf{L} + \begin{bmatrix} C_{X_{11}} & C_{X_{12}} & 0 & C_{X_{14}} & C_{X_{15}} & C_{X_{16}} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ C_{X_{61}} & C_{X_{62}} & 0 & C_{X_{64}} & C_{X_{65}} & C_{X_{66}} \end{bmatrix} \begin{bmatrix} F_X \\ F_Y \\ F_Z \\ M_X \\ M_Y \\ M_Z \end{bmatrix} X_{CoP} +$$

$$+ \begin{bmatrix} C_{Y_{11}} & C_{Y_{12}} & 0 & 0 & C_{Y_{15}} & C_{Y_{16}} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ C_{Y_{61}} & C_{Y_{62}} & 0 & 0 & C_{Y_{65}} & C_{Y_{66}} \end{bmatrix} \begin{bmatrix} F_X \\ F_Y \\ F_Z \\ M_X \\ M_Y \\ M_Z \end{bmatrix} Y_{CoP} =$$

$$= \left(\mathbf{C}_0 + \mathbf{C}_X X_{CoP} + \mathbf{C}_Y Y_{CoP}\right)\mathbf{L} = \mathbf{C}_{NL}\mathbf{L} \tag{A.3}$$

where $\mathbf{C}_X$, $\mathbf{C}_Y$ and $\mathbf{C}_{NL}$ are (6x6) matrices. Matrix $\mathbf{C}_0$ and vector $\mathbf{L}$ represent the linear re-calibration terms. Vectors $X_{CoP}\mathbf{L}$ and $Y_{CoP}\mathbf{L}$ introduce in the re-calibration method a second-order non-linearity, due to cross-products between output vector components. Matrices $\mathbf{C}_X$ and $\mathbf{C}_Y$ represent the weights of the different non-linear terms included in the model. The elements of the third column of $\mathbf{C}_X$ and $\mathbf{C}_Y$ are zeroed because the cross-products $X_{CoP}F_Z$ and $Y_{CoP}F_Z$ are already taken into account in the linear term $\mathbf{C}_Y\mathbf{L}$; the elements of the fourth column of $\mathbf{C}_Y$ are zeroed because the cross-product $M_X M_Y/F_Z$ is already taken into account in the product $X_{CoP}\mathbf{L}$. The elements of the non-linear re-calibration matrix $\mathbf{C}_{NL}$ are hence linearly related to the CoP measured by the FP; this is in agreement with the results of Schmiedmayer and Kastner [366], who found an error on CoP estimation which was a function of the point of force application. This new method was experimentally tested using the system for the FP re-calibration presented in [357, 359] which includes a high-accuracy, tri-axial load cell, to be placed in 13 known positions on the FP surface and then loaded by a subject that generates the same 3D time-varying force on the FP and the load cell. Briefly, the re-calibration matrix $\mathbf{C}$, linear or non-linear can be estimated by solving the following equations in a least-squares sense:

$$\mathbf{L}_0^k(t) = \mathbf{L}_C^k(t) + \mathbf{E}^k(t) = \mathbf{C}\mathbf{L}^k(t) + \mathbf{E}^k(t)$$
$$k = 1, \dots, n$$
$$n \geq 5 \tag{A.4}$$

where $\mathbf{L}^k(t)$ is the FP output, $\mathbf{L}_0^k(t)$ is calculated from the force measured by the load cell and the knowledge of the kth point of force application, and $\mathbf{E}^k(t)$ represents the residual error. A cost function $\sum_{k,t} \mathbf{E}^k(t)^T \mathbf{E}^k(t)$ is minimized [367] by updating the elements of $\mathbf{C}$ [358]. As also described in [357], 4 commercial FPs were tested and their local and global C's were estimated: AMTI OR6, Bertec 4060-08, Bertec 4080-10, and Kistler 9286A. The same data set was used to estimate the global, non-linear re-calibration matrix $\mathbf{C}_{NL}$. The effectiveness of the non-linear re-calibration was verified:

1. quantifying the FP accuracy in the measurement of the CoP before and after re-calibration;

2. evaluating the ability of the non-linear re-calibration to estimate force components and CoP better than linear re-calibration in a second validation trial, by ensuring the same measurement sites.

A.3 Results

Table A.1 shows the CoP accuracy before and after the re-calibration process, for the 4 tested FPs.

Table A.1: The CoP accuracy before and after the re-calibration process, for the 4 tested FPs

CoP accuracy mean±std [mm]	FP#1	FP#2	FP#3	FP#4
1 - Initial accuracy	2.3±1.4	2.6±1.5	11.8±4.3	14.0±2.5
2 - Linear global	1.1±1.4	1.8±1.1	1.0±0.6	3.2±1.1
3 - Linear local	0.7±1.4	0.8±0.5	0.5±0.3	2.0±1.2
4 - Non-linear global	0.7±1.4	0.6±0.2	0.5±0.2	2.3±1.3

Row(1) shows the FP accuracy using the manufacturers' $\mathbf{C}$. Each FP will be addressed by a unique identifier such as FP#1,#2, #3 and #4.

Table A.2: Mean values of the RMS errors in the validation trial for FP#3

Mean±std	F_X[N]	F_Y[N]	F_Z[N]	CoP accuracy [mm]
Linear re-calibration	3.6±2.3	3.0±0.7	5.0±2.5	1.2±0.7
Non-linear re-calibration	2.5±0.7	2.6±0.5	3.9±1.2	0.6±0.3

Figure A.1 reports the results of the validation trial where, by the way of example, FP#3 was considered.

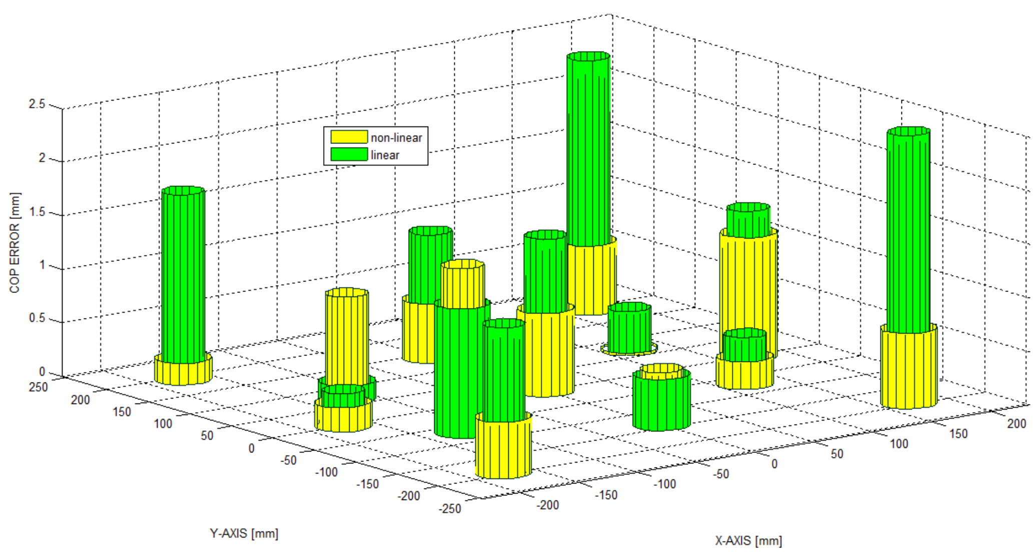


Figure A.1: Error on CoP measurement (in mm), after global linear and non-linear calibration for FP#3, in the 13 different measurement sites

Table A.2 shows the mean values of the root mean squared (RMS) validation errors for the three force components and the CoP for FP#3.

A.4 Discussions

Results displayed in rows 1, 2 and 3 of Table A.1 recapitulate those reported in [357]. The non-linear, global re-calibration method (row 4) ensured similar results as the local, linear re-calibration (row 3) proving its suitability to well re-calibrate the FPs, but with the clear advantage of compensating the non-linearity, due to the bending of the top plate, with no additional computational costs. In fact, the non-linear, global re-calibration method estimates a single matrix, instead of several local matrices that could be unpractical to manage in the routine FP usage. As shown in Figure A.1, the use of the non-linear re-calibration allows reducing CoP errors below 0.8mm in all measurement sites, both in the training and validation trial. The mean values of RMS errors for force components and CoP estimation in the validation trial (see Table A.2) prove the effectiveness of the non-linear re-calibration compared to the linear re-calibration. Indeed, the mean CoP error plus 2 standard deviations keeps around 1mm, which is comparable to the expected placement error of the load cell tip on the FP.

Epilogue

The aims of the work presented in this thesis were to suggest a novel methods for the quantitative description of some motor tasks often used in clinical settings for the fall risk assessment and to define the guidelines for a fall detection algorithm based on a real-world fall database availability. First, a biomechanical approach and a body sensor network allowed evaluating kinematic and dynamic variables of human movement, which are usually neglected in widespread clinical tests for the assessment of fall risk, through a portable, cost-effective set-up. Second, the guidelines for the design of an optimal fall detector were defined, based on experimental evidence that several published fall detection algorithms, based on accelerometers, fail when they are applied to a real-world database. In this epilogue, after a brief summary of previous chapters will be given, some directions for future research, as well as some possible clinical applications of the work presented in this thesis will be outlined.

Overview of chapters

In **chapter one** several tools for fall risk assessment and fall prevention in clinic were discussed. It appeared that the existing clinical tests for fall risk assessment lack of objectiveness related to individual judgement by a therapist or a nurse who report a score related to the physical performance. The use of assistive technology could help to overcome this drawback further providing timely feedback about the effectiveness of administered interventions enabling intervention strategies to be modified or changed if found to be ineffective.

In **chapter two** the specific issue addressed to of the use of technology for fall risk assessment and fall detection was treated by reviewing the main studies based on force platforms and inertial sensors. With regard to the fall risk assessment, it was concluded that several studies identified discriminant feature for predicting the risk of fall without focusing on the biomechanics of the motor tasks performed. The use of biomechanical measurements can be fundamental for the evaluation of subject-specific fall risk since it could help to identify quantitatively a specific lack in muscle strength, balance impairments or physical functional reserve. With regard to the fall detection, even if a myriad of ICT-based product are proposed, existing solutions still do not have a remarkable social impact neither a significant market penetration due the the low reliability and poor knowledge of real falls.

In **chapter three** two different balance strategies (reactive balance and static/dynamic steady state balance) were introduced and analyzed in depth in **chapter four and five**, where a novel method based on a biomechanical model and a body sensor network was tested to describe quantitatively the repeated sit-to-stand and voluntary postural oscillations. In particular, the usability of these inertial sensors to predict dynamic variables like the Center of Pressure and the net joint moments was demonstrated.

A single inertial measurement unit was used in the pilot study presented in **chapter six** to describe the lying-to-sit-to-stand-to walk test. In particular, two populations, young subjects and old patients, performed the test and a quantitative analysis based on accelerometric and gyroscope measurements allowed detecting different features related to the task executed. A sensor fusion algorithm (Extended Kalman Filter) was implemented to describe the strategies adopted to complete the test. These chapters suggested the possibility to use inertial tracking technologies to perform in-depth analysis of the motor performance according to an adequate model-based approach. Since the use of these sensors appear promising, several limitations still exist in the field of fall detection, as underlined in **chapter seven**, where some published accelerometer-based algorithms were tested on a 29 real-world falls database. The sensitivity and specificity obtained was considerably lower than those declared by the authors in their papers and the high number of false alarms generated on 24h accelerometric recordings demonstrated the reasons of the low pervasivity of these sensors in real-life.

Future works

One of the most vital reasons for preventing falls is to avoid fractures and other serious injuries, which have the greatest consequences for people's health and resource use. As often underlined in this thesis, currently, falls are managed through a reactive care model. Fall risk is assessed in a clinical setting by expert physiotherapists, geriatricians, or occupational therapists following the occurrence of an injurious fall. Falls are sometimes managed using body worn sensors and alarm pendants to notify others when a fall event occurs and to trigger an urgent communication to a telecare center to assure a fast medical assistance. However this model does not prevent a fall from occurring. There is now a growing focus on multifactorial assessment and personalized targeted intervention for preventing falls and injuries among older people in community and emergency care settings. Still, as the population ages, this reactive model of care will become increasingly unsatisfactory, and a proactive community-based prevention strategy will be required.

In agreement with the line of reasoning presented in this thesis, it seems that a logical next step would be to start a prospective study involving elderly subjects whose biomechanical measurements will be evaluated through the algorithms presented in this thesis. Simple, unsupervised quantitative assessments of such measurements could help "to track" objectively the fall risk, providing feedback about the effectiveness of administered prevention interventions. These quantitative measurements could help to monitor the effect of fall prevention approach aiming to increase muscular strength and/or balance. Moreover, the procedure could speed up the experimental sessions, reducing the computational and economic costs, especially when several subject are involved.

In summary, the work presented in this thesis suggests that a biomechanical approach based on wearable inertial sensors may provide reliable measurements to accurately and quantitatively describe performance of subject-specific reactive balance strategies (**chapter four**) and functional motor tasks (**chapter five, six**). Moreover, the quantitative description of fall event through reliable algorithms which satisfy defined criteria (**chapter seven**) could substantially increase our knowledge of falls.

Acknowledgements

I am deeply grateful to prof. Angelo Cappello, for his teachings and guidance, to prof. Lorenzo Chiari, for his smart and inspiring suggestions, to my partner Valeria Lucia Fuschillo, for sharing with me hours and hours of exprimental sessions and signal processing, and, of course, to my family.

List of Figures

List of Tables

Bibliography

[1] Fuller GF (2000) *Falls in the elderly*, American Family Physician, **61**: 2159-2168.

[2] Ferrucci L, Guralnik JM, Studenski S, Fried LP, Cutler GB Jr, Walston JD (2004) *Designing randomized, controlled trials aimed at preventing or delaying functional decline and disability in frail, older persons: a consensus report*, Journal of the American Geriatrics Society, **52**: 625-634.

[3] Rubestein LZ, Josephson KR (2002) *The epidemiology of falls and syncope*, Clinics in Geriatric Medicine, **18**: 141-158.

[4] Campbell AJ, Borrie MJ, Spears GF, Jacskon SL, Brown JS, Fitzgerald JL (1990) *Circumstances and consequences of falls experienced by a community population 70 years and over during a prospective study*, Age and Ageing, **19**): 136-141.

[5] Tinetti ME, Speechley M, Ginter SF (1988) *Risk factors for falls among elderly persons living in the community*, New England Journal of Medicine, **319**: 1701-1707.

[6] Centers for Disease Control and Prevention (2008) *Self-reported falls and fall-related injuries among person aged* ≥ 65 *years-United States, 2006*, Morbidity and Mortality Weekly Report, **57**: 225-229.

[7] Sattin RW (1992) *Falls among older persons: a public health perspective*, Annual Review of Public Health, **13**: 489-508.

[8] Keene GS, Parker MJ, Pryor GA (1993) *Mortality and morbidity after hip fractures*, BMJ, **307**(6914): 1248-1250.

[9] O'Loughin JL, Robitaille Y, Boivin JF, Suissa S (1993) *Incidence and risk factors for fall-related injurious falls among the community-dwelling elderly*, American Journal of Epidemiology, **137**: 342-354.

[10] Sattin RW, Lambert Huber DA, DeVito CA, Rodriguez JG, Ros A, Bacchelli S, Stevens JA, Waxweiler RJ (1990) *The incidence of fall injury events among the elderly in a defined population*, American Journal of Epidemiology, **131**: 1028-1037.

[11] Alexander BH, Rivara FP, Wolf ME (1992) *The cost and frequency of hospitalization for fall-related injuries in older adults*, American Journal of Public Health, **82**: 1020-1023.

[12] Centers for Disease Control and Prevention (2006) *Fatalities and injuries from falls among older adults-United States, 1993-2003 and 2001-2005*, Morbidity and Mortality Weekly Report, **55**: 1221-1224.

[13] Jensen GF, Christiansen C, Boesen J, Hegedus V, Transbol I (1982) *Epidemiology of postmenopausal spinal and long bone fractures: a unifying approach to postmenopausal osteoporosis*, Clinical Orthopaedics and Related Research, **166**: 75-81.

[14] Lu-Yao GL, Baron JA, Barrett JA, Fisher ES (1994) *Treatment and survival among elderly Americans with hip fractures: a population-based study*, American Journal of Public Health, **84**: 1287-1291.

[15] Cummings SR, Kelsey JL, Nevitt MC, O'Dowd KJ (1985) *Epidemiology of osteoporosis and osteoporotic fractures*, Epidemiologic reviews, **7**: 178-208.

[16] Sterling DA, O'Connor JA, Bonadies J (2001) *Geriatric falls: injury severity is high and disproportionate to mechanism*, The Journal of Trauma, **50**: 116-119.

[17] Lachman ME, Howland J, Tennstedt S, Jette A, Assmann S, Peterson EW (1998) *Fear of falling and activity restriction: the Survey of Activities and Fear of Falling in the Elderly (SAFE)*,The Journal of Gerontology, Series B, Psychological sciences and social sciences, **53**: 43-50.

[18] Cumming RG, Salkled G, Thomas M, Szonyi G (2000) *Prospective study of the impact of fear of falling on activities of daily living, SF-36 scores, and nursing home admission*, The Journal of Gerontology, Series A, Biological sciences and medical sciences, **55**: M299-M305.

[19] Friedman SM, Munoz B, West SK, Rubing GS, Fried LP (2002) *Falls and fear of falling: which comes first? A longitudinal prediction model suggests strategies for primary and secondary prevention*, Journal of the America Geriatrics Society, **50**: 1329-1335.

[20] Vellas BJ, Wayne SJ, Romero LJ, Baumgartner RN, Garry PJ (1997) *Fear of falling and restiction of mobility in elderly fallers*, Age and Ageing, **26**(3): 189-193.

[21] Tinetti ME, Williams CS (1997) *Falls, injuries due to falls, and the risk of admission to a nursing home*, The New England Journal of Medicine, **337**(18): 1279-1284.

[22] Heinrich S, Rapp K, Rissmann U, Becker C, König HH (2010) *Cost of falls in old age: a systematic review*, Osteoporosis International, **21**(6): 892-902.

[23] Buchner DM, Cress ME, de Lateur BJ, Esselman PC, Margherita AJ, Price R, Wagner EH (1997) *The effect of strength and endurance training on gait, balance, fall risk, and health services use in community-living older adults*, The Journal of Gerontology, Series A, Biological sciences and medical sciences, **52**(4): M218-M224.

[24] No authors listed (1987) *The prevention of falls in later life. A report of the Kellogg International Work Group on the Prevention of Falls by the Elderly*, Danish Medical Bullettin, **34**(4): 1-24.

[25] Means KM, Rodell DE, O'Sullivan PS, Cranford LA (1996) *Rehabilitation of elderly fallers: Pilot study of a low to moderate intensity exercise program*, Archives of Physical Medicine and Rehabilitation, **77**: 1030-1036.

[26] Carter ND, Khan KM, McKay HA, Petit MA, Waterman C, Heinonen A, Janssen PA, Donaldson MG, Mallinson A, Riddell L, Kruse K, Prior JC, Flicker L (2002) *Community-based exercise program reduces risk factors for falls in 65- to 75-years-old women with osteoporosis: Randomized controlled trial*, Canadian Medical Association Journal, **167**: 997-1004.

[27] Tideiksaar R (2002) *Falls in older people: prevention and management*, Baltimore, MD: Health Professions Press.

[28] Hauer K, Lamb SE, Jorstad EC, Todd C, Becker C (2006) *Systematic review of definitions and methods of measuring falls in randomized controlled fall prevention trials*, Age and Ageing **35**: 5-10.

[29] Zecevic AA, Salmoni AW, Speechley M, Vandervoort AA (2006) *Defining a fall and reasons for falling: comparisons among the views of seniors, health care providers, and the research literature*, The Gerontologist, **46**(3): 367-376.

[30] Skelton DA, Hauer K, Lamb S (2007) *Re: 'Falls Definition Validation'*, Age & Ageing, **36**(1): 111-112.

[31] Lamb SE, Jørstad-Stein EC, Hauer K, Becker C (2005) *Development of a common outcome data set for fall injury prevention trials: the prevention of falls network Europe consensus*, Journal of the American Geriatrics Society, **53**(9): 1618-1622.

[32] Tinetti ME, Doucette JT, Claus EB (1995) *The contribution of predisposing and situational risk factors to serious fall injuries*, Journal of the American Geriatrics Society, **43**: 1207-1213.

[33] Sattin RW, Rodriguez JG, DeVito CA, Wingo PA (1998) *Study to assess falls among the elderly (SAFE) group. Home environmental hazards and the risk of fall injury events among community-dwelling older persons*, Journal of American Geriatrics Society, **46**: 669-676.

[34] Stalenhoef PA, Diederiks JP, Knottnerus JA, Kester AD, Crebolder HF (2002) *A risk model for the prediction of recurrent falls in community-dwelling elderly: a prospective study*, Journal of Clinical Epidemiology, **55**: 1088-1094.

[35] Kannus P, Sievanen H, Palvanen M, Jarvinen T, Parkkari J (2005) *Prevention of falls and consequent injuries in elderly people*, Lancet, **366**: 1885-1893.

[36] Gill T, Taylor AW, Pengelly A (2005) *A population-based survey of factors relating to the prevalence of falls in older people*, Gerontology, **51**: 340-345.

[37] French DD, Campbell R, Spehar R, Cunningham F, Foulis P (2005) *Outpatient medications and hip fractures in the US: a national veterans study*, Drugs Ageing, **22**: 877-885.

[38] Stevens JA (2005) *Falls among older adults-risk factors and prevention strategies*, Journal of Safety Research, **36**: 409-411.

[39] Li W, Keegan TH, Sternfeld B, Sidney S, Quesenberry CP Jr, Kelsey JL (2006) *Outdoor falls among middle-aged and older adults: a neglected public health problem*, America Journal of Public Health, **96**: 1192-1200.

[40] Connell BR, Wolf SL (1997) *Atlanta FICSIT Group. Environmental and behavioural circumstances associated with falls at home among healthy elderly individuals*, Archives of Physical Medicine and Rehabilitation, **78**: 179-186.

[41] Tinetti ME (2005) *Preventing falls in elderly persons*, The New England Journal of Medicine, **348**: 42-49.

[42] Kron M, Loy S, Sturm E, Nikolaus T, Becker C (2003) *Risk indicators for falls in institutionalized frail elderly*, American Journal of Epidemiology, **158**(7): 645-653.

[43] Rubenstein LZ (2006) *Falls in older people: epidemiology, risk factors and strategies for prevention*, Age and Ageing, **35-S2**: ii37-ii41.

[44] American Geriatrics Society, British Geriatrics Society, and American Academy of Orthopaedic Surgeons Panel on Falls Prevention (2001) *Guideline for the prevention of falls in older persons* **49**(5): 664-672.

[45] Wolfson L, Whipple R, Amerman P, Tobin JN (1990) *Gait assessment in the elderly: a gait abnormality rating scale and its relation to falls*, Journal of Gerontology, **45**: M12-M19.

[46] Maki BE (1997) *Gait changes in older adults: Predictors of falls or indicators of fear?*, Journal of American Geriatrics Society, **45**:313–320.

[47] Hausdorff JM, Edelberg HE, Mitchell SL, Goldberger AL, Wei JY (1997) *Increased gait unsteadiness in community-dwelling elderly fallers*, Archives of Physical Medicine and Rehabilitation, **78**: 278-283.

[48] Hausdorff JM, Rios DA, Edelberg HK (2001) *Gait variability and fall risk in community-living older adults: a 1-year prospective study*, Archives of Physical Medicine and Rehabilitation, **82**(8): 1050-1056.

[49] Auvinet B, Berrut G, Touzard C, Moutel L, Collet N, Chaleil D, Barrey E (2003) *Gait abnormalities in elderly fallers*, Journal of Aging and Physical Activity, **11**: 40-52.

[50] Barak Y, Wagenaar R, Holt K (2006) *Gait characteristics of elderly people with a history of falls: a dynamic approach*, Physical Therapy, **86**(11): 1501-1510.

[51] Kerrigan DC, Lee LW, Nieto TJ, Markman JD, Collins JJ, O'Riley PO (2000) *Kinetic alterations independent of walking speed in elderly fallers*, Archives of Physical Medicine and Rehabilitation, **81**(6): 730-735.

[52] Gehlsen GM, Whaley MH (1990) *Falls in the elderly: part I, gait*, Archives of Physical Medicine and Rehabilitation, **71**: 735-738.

[53] Feltner ME, MacRae PG, McNitt-Gray KL (1995) *Quantitative gait assessment as a predictor of prospective and retrospective falls in community-dwelling older woman*, Archives of Physical Medicine and Rehabilitation, **75**: 447-453.

[54] Luukinen H, Koski K, Kivela SL, Laippala P (1996) *Social status, life changes, housing conditions, health, functional abilities and life-style as risk factors for re- current falls among the home-dwelling elderly*, Public Health, **110**: 115–118.

[55] Leipzig RM, Cumming RG, Tinetti ME (1999) *Drugs and falls in older people: a systematic review and meta-analysis, I: psychotropic drugs*, Journal of the American Geriatrics Society, **47**: 30-39.

[56] Leipzig RM, Cumming RG, Tinetti ME (1999) *Drugs and falls in older people: a systematic review and meta-analysis, II: cardiac and analgesic drugs*, Journal of the American Geriatrics Society, **47**: 40-50.

[57] Kelly KD, Pickett W, Yiannakoulias N, Rowe BH, Schopflocher DP, Svenson L, Voaklander DC (2003) *Medication use and falls in community-dwelling older persons*, Age and Ageing, **32**: 503-509.

[58] Mustard CA, Mayer T (1997) *Case-control study of exposure to medication and the risk of injurious falls requiring hospitalization among nursing home residents*, American Journal of Epidemiology, **145**:738-745.

[59] Scott V, Votova K, Scanlan A, Close J (2007) *Mutlifactorial and functional mobility assessment tools for fall risk among older adults in community, home-support, long-term and acute care settings*, Age and Ageing, **36**: 130-139.

[60] Wyatt JC, Altman DG (1995) *Prognostic models: clinically useful or quickly forgotten?*, British Medical Journal, **311**: 539-541.

[61] Myers H (2003) *Hospital fall risk assessment tools: a critique of the literature*, International Journal of Nursing Practice, **9**(4): 223-235.

[62] Oliver D, Daly F, Martin FC, McMurdo ME (2004) *Risk factors and risk assessment tool for falls in hospital in-patients: a systematic review*, Age Ageing, **33**(2): 122-130.

[63] Perell KL, Nelson A, Goldman RL, Luther SL, Prieto-Lewis N, Rubenstein LZ (2001) *Fall risk assessment measures: an analytic review*, Journal of Gerontology, Series A, Biological Sciences and Medical Sciences, **56**(12): M761-M766.

[64] Jarnlo GB (2003) *Functional balance tests related to falls among elderly people living in the community*, European Journal of Geriatrics, **5**(1): 7-14.

[65] Piirtola M, Era P *Force platform measurements as predictors of falls among older people: a review*, Gerontology, **52**(1): 1-16.

[66] Gates S, Smith LA, Fisher JD, Lamb SE (2008) *Systematic review of accuracy of screening instruments for predicting fall risk among independently living older adults*, Journal of Rehabilitation Research & Development, **45**(8): 1105-1116.

[67] Berg K (1989) *Balance and its measure in the elderly: a review*, Physiotherapy Canada, **41**(5): 240-246.

[68] Nakamura DM,Holm MB,Wilson A (1998) *Measures of balance and fear of falling in the elderly: a review*, Physical & occupational therapy in geriatrics, **15**(4): 17-32.

[69] Whitney SL, Poole JL, Cass SP (1998) *A review of balance instruments for older adults*, The American Journal of Occupational Therapy, **52**(8): 666-671.

[70] Oliver D, Britton M, Seed P, Martin FC, Hopper AH (1997) *Development and evaluation of evidence based risk assessment tool (STRATIFY) to predict which elderly inpatients will fall: case-control and cohort studies*, BMJ, **315**(7115): 1049-1053.

[71] Coker E, Oliver D (2003) *Evaluation of the STRATIFY falls prediction tool on a geriatric unit*, Outcomes Management, **7**(1): 8-16.

[72] Papaioannou A, Parkinson W, Cook R, Ferko N, Coker E, Adachi JD (2004) *Prediction of falls using a risk assessment tool in the acute care setting*, BMC Medicine, **2**(1): 1-7.

[73] Schwendimann R, De GS, Milisen K (2006) *Evaluation of the Morse Fall Scale in hospitalised patients*, Age & Ageing, **35**(3): 311-313.

[74] McCollam ME (1995) *Evaluation and implementation of a research- based falls assessment innovation*, The Nursing Clinics of North America, **30**(1): 507-514.

[75] Eagle DJ, Salama S, Whitman D, Evans LA, Ho E, Olde J (1999) *Comparison of three instruments in prediction accidental falls in selected inpatients in a general teaching hospital*, The Journal of Gerontological Nursing, **25**(7): 40-45.

[76] Rosendahl E, Lundin-Olsson L, Kallin K, Jensen J, Gustafson Y, Nyberg L (2003) *Prediction of falls among older people in residential care facilities by the Downton index*, Ageing Clinical and Experimental research, **15**(2): 142-147.

[77] Nyberg L, Gustafson Y (1996) *Using the Downton Index to predict those prone to falls in stroke rehabilitation*, Stroke, **27**(10): 1821-1824.

[78] Lundin-Olsson L, Jensen J, Nyberg L, Gustafson Y (2003) *Predicting falls in residential care by a risk assessment tool, staff judgement, and history of falls*, Aging Clinical and Experimental research, **15**(1): 51-59.

[79] Muir SW, Berg K, Chesworth B, Speechley M (2008) *Use of the Berg Balance Scale for predicting multiple falls in community-dwelling elderly people: a prospective study*, Physical Therapy, **88**(4): 449-459.

[80] Thorbahn LB, Newton RA (1996) *Use of the Berg balance test to predict falls in elderly persons*, Physical Therapy, **76**(6): 576-583.

[81] Boulgarides LK, McGinty SM, Willett JA, Barnes CW (2003) *Use of clinical and impairment-based tests to predict falls by community-dwelling older adults*, Physical Therapy, **83**(4): 328-339.

[82] Brauer SG, Burns YR, Galley P (2000) *A prospective study of laboratory and clinical measures of postural stability to predict community-dwelling fallers*, The Journals of Gerontology Series A: Biological Sciences and Medical Sciences, **55**(8): M469-M476.

[83] Tinetti ME (1986) *Performance-oriented assessment of mobility problems in elderly patients*, Journal of the American Geriatrics Society, **34**:119-126.

[84] Verghese J, Buschke H, Viola L, Katz M, Hall C, Kuslansky G, Lipton R (2002) *Validity of divided attention tasks in predicting falls in older individuals: A preliminary study*, The Journal of the American Geriatrics Society, **50**(9): 1572-1576.

[85] Murphy MA, Olson SL, Protas EJ, Overby AR (2003) *Screening for falls in community-dwelling elderly*, Journal of Aging and Physical Activity, **11**: 66-80.

[86] Faber M, Bosscher RJ, Van Wieringen PC (2006) *Clinimetric properties of the performance-oriented mobility assessment*, Physical Therapy, **86**(7): 944-954.

[87] Leddy AL, Crowner BE, Earhart GM (2010) *Functional Gait Assessment and Balance Evaluation System Test: Reliability, Validity, Sensitivity, and Specificity for Identifying Individuals With Parkinson Disease Who Fall*, Physical Therapy, **91**(1): 102-113.

[88] Horak FB, Wrisley DM, Frank J (2009) *The Balance Evaluation Systems Test (BESTest) to differentiate balance deficits*, Physical Therapy, **89**(5): 484-498.

[89] Nordin E, Lindelof N, Rosendahl E, Jensen J, Lundin-Olsson L (2008) *Prognostic validity of the Timed Up-and-Go test, a modified Get-Up-and-Go test, staff's global judgement and fall history in evaluating fall risk in residential care facilities*, Age & Ageing, **37**(4): 442-448.

[90] Whitney SL, Marchetti GF, Schade A, Wrisley DM (2004) *The sensitivity and specificity of the Timed "Up & Go" and the Dynamic Gait Index for self-reported falls in persons with vestibular disorders*, Journal of Vestibular Research, **14**(5): 397-409.

[91] Morris R, Harwood RH, Baker R, Sahota O, Armstrong S, Masud T (2007) *A comparison of different balance tests in the prediction of falls in older women with vertebral fractures: A cohort study*, Age Ageing, **36**(1): 78-83.

[92] Trueblood PR, Hodson-Chennault N, McCubbin A, Youngclarke D (2003) *Performance and impairment-based assessments among community dwelling elderly:Sensitivity and specificity*, Issues Aging, **24**(1): 2-6.

[93] Rockwood K, Awalt E, Carver D,Macknight C (2000) *Feasibility and measurement properties of the functional reach and the timed up and go tests in the Canadian Study of Health and Aging*, The Journals of Gerontology Series A: Biological Sciences and Medical Sciences, **55**(2): M70-M73.

[94] Thapa PB, Gideon P, Brockman KG, Fought RL, Ray WA (1996) *Clinical and biomechanical measures of balance as fall predictors in ambulatory nursing home residents*, JThe Journals of Gerontology Series A: Biological Sciences and Medical Sciences, **51**(5): M239-M246.

[95] Bergland A, Laake K (2005) *Concurrent and predictive validity of "getting up from lying on the floor"*, Aging Clinical and Experimental Research, **17**(3): 181-185.

[96] Lord SR, Menz HB, Tiedemann A (2003) *A physiological profile approach to falls risk assessment and prevention*, Physical Therapy, **83**(3): 237-252.

[97] Yardley L, Beyer N, Hauer K, Kempen G, Piot-Ziegler C, Todd C (2005) *Development and initial validation of the Falls Efficacy Scale-International (FES-I)*, Age & Ageing, **34**(6): 614-619.

[98] Espy DD, Yang F, Bhatt T, Pai YC (2010) *Independent influence of gait speed and step length on stability and fall risk*, Gait&Posture, **32**(3): 378-382.

[99] Nordin E, Moe-Nilssen R, Ramnemark A, Lundin-Olsson L (2010) *Changes in step-width during dual-task walking predicts falls*, Gait&Posture, **32**(1): 92-97.

[100] Kressig RW, Herrmann FR, Grandjean R, Michel JP, Beauchet O *Gait variability while dual-tasking: fall predictor in older inpatients?*, Aging Clinical and Experimental Research, **20**(2): 123-130.

[101] Gillespie LD, Gillespie WJ, Robertson MC, Lamb SE, Cumming RG, Rowe BH (2003) *Interventions for preventing falls in elderly people*, Cochrane Database of Systematic Reviews: CD000340.

[102] Fairweather DS, Campbell AJ (1991) *Diagnosis accuracy: the effects of multiple aetiology and the degradation of information in old age*, Journal of the Royal College of Physicians of London, **25**(2): 105-110.

[103] Nowak A, Hubbard RE (2009) *Falls and frailty: lessons from complex systems*, Journal of the Royal Society of Medicine, **102**(3): 98-102.

[104] Chang JT, Morton SC, Rubenstein LZ, Mojica WA, Maglione M, Suttorp MJ, Roth EA, Shekelle PG (2004) *Interventions for prevention of falls in older adults: systematic review and meta-analysis of randomised clinical trials*, BMJ **328**(7441): 680.

[105] Gillespie LD, Gillespie WJ, Robertson MC, Lamb SE, Cumming RG, Rowe BH (2007) *Interventions for preventing falls in elderly people*, Cochrane Database of Systematic Reviews: CD000340.

[106] Beswick AD, Rees K, Dieppe P, Ayis S, Gooberman-Hill R, Horwood J, Ebrahim S (2008) *Complex interventions to improve physical function and maintain independent living in elderly people: a systematic review and meta-analysis*, Lancet **371**: 725-735.

[107] Sherrington C, Whitney JC, Lord SR, Herbert RD, Cumming RG, Close JC (2008) *Effective exercise for the prevention of falls: a systematic review and meta-analysis*, Journal of the American Geriatrics Society **56**: 2234-2243.

[108] Gillespie LD, Robertson MC, Gillespie WJ, Lamb SE, Gates S, Cumming RG, Rowe BH (2009) *Interventions for preventing falls in older people living in the community*, Cochrane Database of Systematic Reviews: CD007146.

[109] Cameron ID, Murray GR, Gillespie LD, Robertson MC, Hill KD, Cumming RG, Kerse N (2010) *Interventions for preventing falls in older people in nursing care facilities and hospitals*, Cochrane Database of Systematic Reviews: CD005465.

[110] Gates S, Fisher JD, Cooke MW, Carter YH, Lamb SE (2008) *Multifactorial assessment and targeted intervention for preventing falls and injuries among older people in community and emergency care settings: systematic review and meta-analysis*, BMJ **336**: 130-133.

[111] Michael YL, Lin JS, Whitlock E, Gold R, Fu R, O'Connor E, Zuber SP, Beil TL, Lutz KW (2010) *Interventions to prevent falls in older adults: an updated systematic review*, Evidence Synthesis No.80. AHRQ Publication No. 11-05150-EF-1. Rockville, MD: Agency for Healthcare Research and Quality; December 2010.

[112] National Institute for Clinical Excellence (2004) *Falls: the assessment and prevention of falls in older people. Clinical Guideline No.21*, London: National Institute for Clinical Excellence, accessed at `http://www.nice.org.uk/nicemedia/live/10956/29583/29583.pdf` on 8 December 2010.

[113] National Center for Injury Prevention and Control (2009) *What you can do to prevent falls*, Atlanta, GA: Centers for Disease Control and Prevention, accessed at `http://www.cdc.gov/HomehandRecreationalSafety/Falls/WhatYouCanDoToPreventFalls.html` on 8 December 2010.

[114] Campbell AJ, Robertson MC (2010) *Comprehensive Approach to Fall Prevention on a National Level: New Zealand*, Clinics in Geriatrics Medicine, **26**(4): 719-731.

[115] Scott V, Wagar B, Sum A, Metcalfe S, Wagar L (2010) *A Public Health Approach to Fall Prevention Among Older Persons in Canada*, Clinics in Geriatrics Medicine, **26**(4): 705-718.

[116] Yardley L, Bishop FL, Beyer N, Hauer K, Kempen GIJM, Piot-Ziegler C, Todd C, Cuttelod T, Horne M, Rosell A (2006) *Older people's views of falls prevention interventions in Six European countries*, Gerontologist **46**(5): 650-660.

[117] Yardley L, Donovan-Hall M, Francis K, Todd CJ (2006) *Older people's views of advice about falls prevention: A qualitative study*, Health Education Research, **21**(4): 508-517.

[118] Yardley L, Donovan-Hall M, Francis K, Todd CJ (2007) *Attitudes and beliefs that predict older people's intention to undertake strength and balance training*, Journal of Gerontology: Psychological Sciences, **62**:119-125.

[119] Horne M, Speed S, Skelton DA, Todd C (2009) *What do community dwelling Caucasian and South Asian 60-70 year old think about exercise for fall prevention?*, Age % Ageing, **38**: 68-73.

[120] Yardley L, Kirby S, Ben-Shlomo Y, Gilbert R, Whitehead S, Todd CJ (2008) *How likely are older people to take up different falls prevention activities?*, Preventive Medicine, **47**: 554-558.

[121] Horne M, Speed S, Skelton DA, Todd CJ (2010) *he influence of primary health care professionals in encouraging exercise and physical activity uptake among White and South Asian older adults: experiences of young older adults*, Patient Education and Counseling, **78**(1): 97-103.

[122] Yardley L, Beyer N, Hauer K, McKee K, Ballinger C, Todd CJ (2007) *Recommendations for promoting the engagement of older people in activities to prevent falls*, Quality and Safety in Health Care, **16**: 230-234.

[123] McCreadie C, Tinker A (2005) *The acceptability of assistive technology to older people*, Ageing & Society, **25**: 91-110.

[124] Meijer GAL, Westerterp KR, Verhoeven FMH, Koper HBM, Hoor F (1991) *Methods to assess physical activity with special reference to motion sensors and accelerometers*, IEEE Transactions on Biomedical Engineering, **38**(3): 221-229.

[125] Cummings SR, Nevitt MC, Kidd S (1991) *Forgetting falls: the limited accuracy of recall of falls in the elderly*, Journal of the American Geriatrics Society, **36**: 613-619.

[126] Podsiadlo D, Richardson S (1991) *The timed Úp & Go:́ a test of basic functional mobility for frail elderly persons*, Journal of the American Geriatrics Society, **39**: 142-148.

[127] Saranummi N (2008) *IT applications for pervasive, personal, and personalized health*, IEEE Transactions of Information Technology in Biomedicine, **12**: 1-4.

[128] Marschollek M, Mix S, Wolf KH, Effertz B, Haux R, Steinhagen-Thiessen E (2007) *ICT-based health information services for elderly people: past experiences, current trends, and future strategies*, Medical Informatics and the Internet in Medicine, **32**: 251-261.

[129] Ganz D, Bao Y, Shekelle PG, Rubenstein LZ (2007) *Will my patient fall?*, The Journal of the American Medical Association, **297**(1): 77-86.

[130] Lord SR, Dayhew J (2001) *Visual risk factors for falls in older people*, Journal of the American Geriatrics Society, **49**: 508-515.

[131] Hill K, Schwarz J, Flicker L, Carroll S (1999) *Falls among healthy, community-dwelling older women: a prospective study of frequency, circumstances, consequences and prediction accuracy*, Australian New Zealand Journal of Public Health, **23**: 41-48.

[132] Bergland A, Wyller TB (2004) *Risk factors for serious fall related injury in elderly women living at home*, Injury Prevention, **10**(5): 308-313.

[133] Maki BE, Holliday PJ, Topper AK (1994) *A prospective study of postural balance and risk of falling in an ambulatory and independent elderly population*, Journal of Gerontology, **49**: M72-M84.

[134] Baloh RW, Corona S, Jacobson KM, Enrietto JA, Bell T (1998) *A prospective study of posturography in normal older people*, Journal of the American Geriatrics Society, **46**: 438-443.

[135] Kario K, Tobin JN, Wolfson LI, Whipple R, Derby CA, Singh D, Marantz PR, Wassertheil- Smoller S (2001) *Lower standing systolic blood pres- sure as a predictor of falls in the elderly: a community-based prospective study*, Journal of the American College of Cardiology, **38**: 246-252.

[136] Stel VS, Smit JH, Pluijm SM, Lips P (2003) *Balance and mobility performance as treatable risk factors for recurrent falling in older persons*, Journal of Clinical Epidemiology, **56**: 659-668.

[137] Zijlstra A, Ufkes T, Skelton DA, Lundin-Olsson L, Zijlstra W (2008) *Do Dual Tasks Have an Added Value Over Single Tasks for Balance Assessment in Fall Prevention Programs? A Mini-Review*, Gerontology, **54**(1): 40-49.

[138] Shumway-Cook A, Woollacott M (2000) *Attentional demands and postural control: the effect of sensory context*, Journal of Gerontology, Series A, Biological Sciences and Medical Sciences, **55**: M10-M16.

[139] Lajoie Y, Teasdale N, Bard C, Fleury M (1993) *Attentional demands for static and dynamic equilibrium*, Experimental Brain Research, **97**: 139-144.

[140] Woollacott M, Shumway-Cook A (2002) *Attention and the control of posture and gait: a review of an emerging area of research*, Gait&Posture, **16**: 1-14.

[141] Bloem BR, Valkenburg VV, Slabbekoorn M, Willemsen MD (2001) *The Multiple Tasks Test: development and normal strategies*, Gait&Posture, **14**: 191-202.

[142] Shumway-Cook A, Woollacott M, Kerns KA, Baldwin M (2001) *The effects of two types of cognitive tasks on postural stability in older adults with and without a history of falls*, Journal of Gerontology, Series A, Biological Sciences and Medical Sciences, **52**: M232-M240.

[143] Ashburn A, Stack E, Pickering RM, Ward CD (2001) *Predicting fallers in a community-based sample of people with Parkinson's disease*, Gerontology, **47**: 277-281.

[144] Swanenburg J, de Bruin ED, Uebelhart D, Mulder T (2010) *Falls prediction in elderly people: a 1-year prospective study*, Gait&Posture, **31**: 317-321.

[145] Hewson DJ, Singh NK, Snoussi H, Duchene J (2010) *Classification of elderly as fallers and non-fallers using centre of pressure velocity*, Proceedings 32th Annual International Conference of IEEE EMBS, August 31-September 4, Buenos Aires, Argentina, pp. 3678-3681. **31**: 317-321.

[146] Shin BM, Han SJ, Jung JH, Kim JE, Fregni F (2011) *Effect of mild cognitive impairment on balance*, Journal of the Neurological Sciences, **305**: 121-125.

[147] Bigelow KE, Berne N (2011) *Development of a protocol for improving the clinical utility of posturography as a fall-risk screening tool*, Journal of Gerontology, Series A, Biological Sciences and Medical Sciences, **66A**(2): 228-233.

[148] Schneider P, Schwab M, Hanscheid H (2011) *Identification of factors associated with risk of fall using a force platform and power spectrum analysis technique*, Journal of Biomechanics, **44**: 2008-2012.

[149] Bhatt T, Espy D, Yang F, Pay YC (2011) *Dynamic gait stability, clinical correlates, and prognosis of falls among community-dwelling older adults*, Archives of Physical Medicine and Rehabilitation, **92**(5): 799-805.

[150] Mockford KA, Mazari FAK, Jordan AR, Vanicek N, Chetter IC, Coughlin PA (2011) *Computerized Dynamic Posturography in the Objective Assessment of Balance in Patients With Intermittent Claudication*, Annals of Vascular Surgery, **25**(2): 182-190.

[151] Najafi B, Aminian K, Loew F, Blanc Y, Robert PA (2002) *Measurement of stand-sit and sit-stand transitions using a miniature gyroscope and its application in fall risk evaluation in the elderly*, IEEE Transactions on Biomedical Engineering, **49**: 843-851.

[152] Giansanti D (2006) *Investigation of fall-risk using a wearable device with accelerometers and rate gyroscopes*, Physiological Measurement, **27**: 1081-1090.

[153] Giansanti D, Maccioni G, Cesinaro S, Benvenuti F, Macellari V (2008) *Assessment of fall-risk by means of a neural network based on parameters assessed by a wearable device during posturography*, Medical Engineering & Physics, **30**: 367-372.

[154] Gietzelt M, Nemitz G, Wolf KH, Shchwabedissen HMZ, Haux R, Marschollek M (2009) *A clinical study to assess fall risk using a single waist accelerometer*, Informatics for Health & Social Care, **34**(4): 181-188.

[155] Marschollek M, Nemitz G, Gietzelt M, Wolf KH, Shchwabedissen HMZ, Haux R (2009) *Predicting in-patient falls in a geriatric clinic*, Zeitschrift fur Gerontologie und Geriatrie, **42**: 317-321.

[156] O'Sullivan M, Blake C, Cunningham C, Boyle G, Finucane C (2009) *Correlation of accelerometry with clinical balance tests in older fallers and non-fallers*, Age Ageing, **38**: 308-313.

[157] Greene BR, O'Donovan A, Romero-Ortuno R, Cogan L, Scanaill CN, Kenny R (2010) *Quantitative falls risk assessment using the Timed Up and Go test*, IEEE Transactions on Biomedical Engineering, **57**(12): 2918-2926.

[158] Narayanan MR, Redmond SJ, Scalzi ME, Lord SR, Celler BG, Lovell NH (2010) *Longitudinal fall-risk estimation using tri-axial accelerometry*, IEEE Transactions on Biomedical Engineering, **57**(3): 534-541.

[159] Liu Y, Redmond SJ, Wang N, Blumenkron F, Narayanan MR, Lovell NH (2010) *Spectral analysis of accelerometry signals from a direct-routine for falls-risk estimation*, IEEE Transactions on Biomedical Engineering, **58**(8): 2308-2315.

[160] Bautmans I, Jansen B, Van Keymolen B, Mets T (2011) *Reliability and clinical correlates of 3D-accelerometry based gait analysis outcomes according to age and fall-risk*, Gait & Posture, **33**: 366-372.

[161] Caby B, Kieffer S, de Saint Hubert M, Cremer G, Macq B (2011) *Feature extraction and selection for objective gait analysis and fall risk assessment by accelerometry*, BioMedical Engineering OnLine, **10**: doi: 10.1186/1475-925X-10-1.

[162] Marschollek M, Rehwald A, Wolf KH, Gietzelt M, Nemitz G, Shchwabedissen HMZ, Schulze M (2011) *Sensor vs. experts - A performance comparison sensor-based fall risk assessment vs. conventional assessment in a sample of geriatric patients*, BMC Medical Informatics and Decision Making, **11**: 48.

[163] Weiss A, Herman T, Plotnik M, Brogzol M, Giladi N, Hausdorff JM (2011) *An instrumented timed up and go: the added value of an accelerometer for identifying fall risk in idiopathic fallers*, Physiological Measurement, **32**: 2003-2018.

[164] Miskelly FG (2001) *Assistive technology in elderly care*, Age & Ageing, **30**(6): 455-458.

[165] Martin S, Kelly G, Kernohan WG, McCreight B, Nugent C (2008) *Smart home technologies for health and social care support*, Cochrane Database of Systematic Reviews: CD006412.

[166] Currell R, Urquhart C, Wainwright P, Lewis R (2000) *Telemedicine versus face to face patient care: effects on professional practice and health care outcomes*, Cochrane Database of Systematic Reviews: CD002098.

[167] Zijlstra W, Becker C, Pfeiffer K (2011) *Wearable systems for monitoring mobility related activities: from technology to application for healthcare services*, Chapter 11 in: E-Health, Assistive Technologies and Applications for Assisted Living: Challenges and Solutions, edited by Ziefle and Rocker.

[168] Barlow J, Singh D, Bayer S, Curry R (2007) *A systematic review of the benefits of home telecare for frail elderly people and those with long-term conditions*, Journal of Telemedicine and Telecare, **13**(4): 172-179.

[169] Fisk MJ (1998) *Telecare at home: factors influencing technology choices and user acceptance*, Journal of Telemedicine and Telecare, **4**: 80-83.

[170] Salvendy G (1997) *Handbook of human factors and ergonomics*, Wiley, New York.

[171] Rogers WA, Fisk AD (2003) *Technology Design, Usability, and Aging: Human Factors Techniques and considerations*, in: Impact of technology on successful ageing, edited by Charness and Schaie, Springer, New York.

[172] Czaja SJ, Sharit J, Charness N, Fisk AD, Rogers WA (2001) *The Center for Research and Educationon Aging and Technology Enhancement (CREATE): A program to enhance technology for older adults*, Gerontechnology, **1**: 50-59.

[173] Hensel BK, Demiris G, Courtney KL (2006) *Defining obtrusiveness in home telehealth technologies: a conceptual framework*, Journal of the American Medical Informatics Association, **13**: 428-431.

[174] Courtney KL, Demiris G, Hensel BK (2007) *Obtrusiveness of information-based assistive technologies as perceived by older adults in residential care facilities: a secondary analysis*, Medical Informatics and the Internet in Medicine. **32**(3): 241-249.

[175] Oliver R (1980) *A cognitive model of the antecedents and consequences of satisfaction decisions*, Journal of Marketing Research, **17**: 460-469.

[176] Spreng RA, Mackenzie SB, Olshavsky RW (1996) *A re-examination of the determinants of consumer satisfaction*, Journal of Marketing, **60**: 15-32.

[177] Miaou SG, Sung PH, Huang CY (2006) *A customized human fall detection system using omni-camera images and personal information*, Proceedings of 1st Transdisciplinary Conference on Distributed Diagnosis and Home Healthcare, April 2-4, Arlington, VA, USA, pp.39-42.

[178] Huang B, Tian G, Li X (2008) *A method for fast fall detection*, Proceedings of 7th of World Congress Intelligent Control Automation, June 25-27, Chongqing, China, pp. 3619-3623.

[179] Anderson D, Keller JM, Skubic M, Chen X, He Z (2006) *Recognizing falls from silhouttes*, Proceedings of 28th Annual International Conference of IEEE EMBS, August 30- September 3, New York City, USA, pp. 6388-6391.

[180] Lee YS, Lee HJ (2006) *Multiple object tracking for fall detection in real-time surveillance system*, Proceedings of 11th International Conference on Advanced Communication Technology, February 15-18, Gangwon-Do, Korea, pp. 2308-2312.

[181] Fu Z, Culurciello E, Lichtsteiner P, Delbruck T (2008) *Fall detection using an address-event temporal contrast vision sensor*, Proceedengs of the IEEE International Symposium on Circuits and Systems, May 18-21, Seattle, WA, USA, pp. 424-427.

[182] Qian G, Guo F, Ingalls T, Olson L, James J, Rikakis T (2004) *A Gesture-Driven Multimodal Interactive Dance System*, Proceedings of the International Conference on Multimedia and Expo, June 30, Taipei, Taiwan, vol. 3, pp. 1579-1582.

[183] Sukthankar G, Sycara K (2005) *A Cost Minimization Approach to Human Behavior Recognition*, Proceedings of the 4th International Joint Conference on Autonomous Agents and Multiagent Systems, July 25-29, Utrecht, Netherlands, pp. 1067–1074.

[184] Vishwakarma V, Mandal C, Sura S (2005) *Automatic Detection of Human Fall in Video*, Proceedings of the 2nd International Conference on Pattern Recognition and Machine Intelligence, December 18-22, Kolkata, India, pp. 616–623.

[185] Wu G (2000) *Distinguishing fall activities from normal activities by velocity characteristics*, Journal of Biomechanics, **33**(11): 1497–1500.

[186] Nait-Charif H, McKenna SJ (2004) *Activity summarisation and fall detection in a supportive home environment*, Proceedings of the 17th International Conference on Pattern Recognition, August 23-26, Cambridge, UK, pp. 323-326.

[187] Sixsmith A, Johnson N (2004) *A smart sensor to detect the falls of the elderly*, IEEE Pervasive Computing, **32**(2): 42-47.

[188] Lin CW, Ling ZH (2007) *Automatic fall incident detection in compressed video for intelligent home-care*, Proceedings of 16th International Conference on Computer Communications and Networks, August 13-16, Honolulu, HI, pp. 1172-1177.

[189] Alwan M, Rajendram PJ, Kell S, Mack D, Dalal S, Wolfe M, Felder R (2006) *A smart and passive floor-vibration based fall detector for elderly*, IEEE International Conference on Information & Communication Technologies, November 28-30, Guilin, China, pp.1003-1007.

[190] Zigel T, Litvak D, Gannot I (2009) *A method for automatic fall of elderly people using floor vibrations and sound proof of concept on human mimicking doll falls*, IEEE Transactions on Biomedical Engineering **56**: 2858-2867.

[191] Rimminem H, Lidstrom J, Linnavuo M, Sepponen R (2010) *Detection of falls among the elderly by a floor sensor using the electric near field*, IEEE Transaction on Information Technology in Biomedicine, **14**: 1475-1476.

[192] Toreyin BU, Soyer EB, Onaran I, Cetin AE (2007) *Falling person detection using multi-sensor signal processing*, Proceedings of 15th Signal Processing and Communication Applications Conference, June 11-13, Eskisehir, Turkey, pp 1-4.

[193] Hori T, Nishida Y (2005) *Ultrasonic sensors for elderly and caregivers in a nursing home*, Intelligent Conference Enterprise Information System, May 24-28, Miami, USA, pp.110-115.

[194] Chen J, Kwong K, Chang D, Luk J, Bajcsy (2005) *Wearable sensors for reliable fall detection*, Proceedings of 27th Annual International Conference of IEEE EMBS, September 1-4, Shangai, China, pp. 3551-3554.

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

[196] Bourke AK, O'Brian JV, Lyons GM (2007) *Evaluation of a threshold-based tri-axial accelerometer fall detection algorithm*, Gait&Posture **26**: 194-199.

[197] Bourke AK, Van de Ven PWJ, Chaya AE, Olaighin GM, Nelson J (2008) *Testing of a long-term fall detection system incorporated into a custom vest for the elderly*, Proceedings of 30th Annual International Conference of IEEE EMBS, August 20-24, Vancouver, Canada, pp. 2844-2847.

[198] Boyle J, Karnanithi M (2008) *Simulated fall detection via accelerometers*, Proceedings 30th Annual International Conference of IEEE EMBS, August 20-24, Vancouver, Canada, pp. 1274-1277.

[199] Karantonis DM, Narayanan MR, Mathie M, Lovell NH, Celler BG (2006) *Implementation of a real-time human movement classifier using a tri-axial accelerometer for ambulatory monitoring*, IEEE Transactions on Information Technology in Biomedicine **10**: 156-167.

[200] Culhane KM, Lyons Gm, Hilton D, Grace PA, Lyons D (2004) *Long-term mobility monitoring of older adults using accelerometers in a clinical environment*, Clinical Rehabilitation **18**: 335-343.

[201] Jia N *Fall detection application by using 3-axis accelerometer ADXL345*, Available `http://www.analog.com/static/imported-files/application_notes/AN-1023.pdf`.

[202] Benocci M, Tacconi C, Farella E, Benini L, Chiari L, Vanzago L (2010) *Accelerometer-based fall detection using optimized ZigBee data streaming*, Microelectronics Journal **41**: 703-710.

[203] Lee Y, Kim J, Son M, Lee M (2007) *Implementation of accelerometer sensor module and fall detection monitoring system based on wireless sensor network*, Proceedings 29th Annual International Conference of IEEE EMBS, August 23-26, Lyon, France, pp. 2315-2318.

[204] Li Q, Stankovic JA, Hanson M, Barth A, Lach J, Zhou G (2009) *Accurate, fast fall detection using gyroscopes and accelerometer-derived posture information*, 6th International Workshop on wearable and implantable body sensor networks, June 3-5, Berkeley, USA, pp. 138-143.

[205] Nyan MN, Tay FEH, Tan AWY, Seah KHW (2008) *Distinguishing fall activities from normal activities by angular rate characteristics and high-speed camera characterization*, Medical Engineering & Physics **28**: 842-849.

[206] Nyan MN, Tay FEH, Murugasu E (2008) *A wearable system for pre-impact detection*, Journal of Biomechanics **41**: 3475-3481.

[207] Tamura T, Yoshimura T, Sekine M, Uchida M, Tanaka O (2009) *A wearable airbag to prevent fall injuries*, IEEE Transactions on Information Technology in Biomedicine **13**(6): 910-914.

[208] Lindemann U, Hock A, Stuber M, Keck W, Becker C (2005) *Evaluation of a fall detector based on accelerometers: a pilot study*, Medical & Biological Engineering & Computing **43**: 548-551.

[209] Díaz A, Prado M, Roa LM, Reina-Tosina J, Sánchez G (2004) *Preliminary evaluation of a full-time falling monitor for the elderly*, Proceedings of the 26th Annual International Conference of IEEE Engineering in Medicine & Biology Society, September 1-5, San Francisco, CA, USA, pp. 2180–2183.

[210] Noury N, Barralon P, Virone, G, Boissy P, Hamel M, Rumeau P (2003) *A smart sensor based on rules and its evaluation in daily routines*, Proceedings of the 25th Annual International Conference of IEEE Engineering in Medicine & Biology Society, September 17-21, Cancun, Mexico, pp. 3286-3289.

[211] Williams G, Doughty K, Cameron K, Bradley DA (1998) *A smart fall and activity monitor for telecare applications*, Proceedings of 20th Annual International Conference of the IEEE EMBS, 29 October–1 November, Hong Kong, pp. 1151-1154.

[212] Doughty K, Lewis R, McIntosh A (2000) *The design of a practical and reliable fall detector for community and institutional telecare*, Journal of Telemedicine and Telecare, **6**(1): 150-154.

[213] Hwang JY, Kang JM, Jang YW, Kim HC (2004) *Development of novel algorithm and real-time monitoring ambulatory system using bluetooth module for fall detection in the elderly*, PProceedings of 26th Annual International Conference of IEEE EMBS, September 1-5, San Francisco, CA, USA, pp. 2204-2207.

[214] Consolvo S, McDonald DW, Toscos T, Chen MY, Froehlich J, Harrison B, Klasnja P, LaMarca A, LeGrand L, Libby R, Smith I, Landay JA (2008) *Activity sensing in the wild: a field trial of UbiFit garden*, Proccedings of 26th Annual SIGCHI Conference on Human factors in computing systems, Aprile 5-10, Florence, Italy, pp. 1797-1806. **48**(9): 140-150.

[215] Lane ND, Miluzzo E, Lu H, Peebles D, Choudhury T, Campbell AT (2010) *A Survey of Mobile Phone Sensing*, IEEE Communications Magazine, **48**(9): 140-150.

[216] Choudhury T, Consolvo S, Harrison B, Hightower J, LaMarca A, LeGrand L, Rahimi A, Rea A, Bordello G, Hemingway B, Klasnja P, Koscher K, Landay JA, Lester J, Wyatt D, Haehnel D(2008) *The Mobile Sensing Platform: An Embedded System for Activity Recognition*, IEEE Pervasive Computing, **7**(2): 32-41.

[217] Nokia *Workshop on Large-Scale Sensor Networks and Applications*, Kuusamo, Finland, February 3–6, 2005.

[218] Eagle N, Pentland A (2006) *Reality Mining: Sensing Complex Social Systems*, Personal Ubiquitous Computing, **10**(4): 255-268.

[219] Sposaro F, Tyson G (2009) *iFall: an Android application for fall monitoring and response*, Proceedings 30th Annual International Conference of IEEE EMBS, September 2-6, Minneapolis, USA, pp. 6119-6122.

[220] `http://mover.projects.fraunhofer.pt/index.html`

[221] Palmerini L, Mellone S, Rocchi L, Chiari L (2011) *Dimensionality reduction for the quantitative evaluation of a smartphone-based Timed Up and Go test*, Proceedings 33th Annual International Conference of IEEE EMBS, August 30 - September 3, Boston, USA, pp. 7179-7182.

[222] Mellone S, Tacconi C, Chiari L (2011) *Validity of a Smartphone accelerometer to instrument the Timed Up and Go test: a preliminary study*, Gait&Posture, doi:10.1016/j.gaitpost.2012.02.006.

[223] Lee RYW, Carlisle AJ (2011) Detection of falls using accelerometers and mobile phone technology, Age and Ageing, **40**(6): 690-696.

[224] Dai J, Bai X, Yang Z, Shen Z, Xuan D (2010) *PerFallD: a pervasive fall detection system using mobile phones*, Proceedings of 8th IEEE PERCOM Workshops, March 29-April 2, Mannheim, Germany, pp. 292-297.

[225] Brown CA (2006) *The application of complex adaptive systems theory to clinical practice in rehabilitation*, Disability and Rehabilitation, **28**(9): 587-593.

[226] Hausdorff JM, Nelson ME, Kaliton D, Layne JE, Bernstein MJ, Nuernberger A, Sing MAF (2001) *Etiology and modification of gait instability in older adults: a randomized controlled trial of exercise*, Journal of Applied Physiology, **90**: 2117-2129.

[227] Horak FB (2006) *Postural orientation and equilibrium: what do we need to know about neural control of balance to prevent falls*, Age and Ageing, **35**(2): 7-11.

[228] Lord S, Sherrington C, Menz H, Close J (2007) *Falls in older people: risk factors and strategies for prevention*, Cambridge, United Kingdom: Cambridge University Press.

[229] Enrietto JA, Jacobson KM, Baloh RW (1999) *Aging effects on auditory and vestibular responses: a longitudinal study*, American Journal of Otolaryngology, **20**(6): 371-378.

[230] Shumway-Cook A, Woollacott MH (2007) *Motor Control: Translating Research into Clinical Practice*, Lippincott Williams & Wilkins, Philadelphia, Pa, USA.

[231] U. Granacher, S. A. Bridenbaugh, T.Muehlbauer, A.Wehrle, andR.W.Kressig (2011) *Age-related effects on postural control under multi-task conditions*, Gerontology, **57**(3): 247-255.

[232] Shimada H, Obuchi S, Kamide N, Shiba Y, Okamoto M, Kakurai S (2003) *Relationship with dynamic balance function during standing and walking*, American Journal of Physical Medicine and Rehabilitation, **82**(7): 511-516.

[233] Kang HG, Dingwell JB (2003) *A direct comparison of local dynamic stability during unperturbed standing and walking*, Experimental Brain Research, **172**(1): 35-38.

[234] Pijnappels M, Bobbert MF, Van Dieeen JH (2003) *Push- off reactions in recovery after tripping discriminate young subjects, older non-fallers and older fallers*, Gait&Posture, **21**(4): 338-394.

[235] Beauchet O, Annweiler C, Dubost V, Allali G, Kressig RW, Bridenbaugh S, Berrut G, Assal F, Herrmann FR (2003) *Stops walking when talking: a predictor of falls in older adults?*, European Journal of Neurology, **16**(7): 786-795.

[236] Winter DA (2009) *Biomechanics and Motor Control of HumanMovement*, 4th edition, John Wiley & Sons Canada Ltd., Mississauga, Ontario, Canada.

[237] Winter DA, Patla AE, Prince F, Ishac M, Gielo-Perczak K (1998) *Stiffness control of balance in quiet standing*, Journal of Neurophysiology, **80**: 1211-1221.

[238] Winter DA, Patla AE, Rietdyk S, Ishac MG (2001) *Ankle muscle stiffness in the control of balance during quiet standing*, Journal of Neurophysiology, **85**: 2630-2633.

[239] Morasso PG, Schieppati M (1999) *Can muscle stiffness alone cannot stabilize upright standing?*, Journal of Neurophysiology, **83**: 1622-1626.

[240] Morasso PG, Sanguineti V (2002) *Ankle muscle stiffness alone cannot stabilize balance during quiet stance*, Journal of Neurophysiology, **88**: 2157-2162.

[241] Marigold DS, Patla AE (2005) *Adapting locomotion to different surface compliances: neuromuscular responses and changes in movement dynamics*, Journal of Neurophysiology, **94**: 1733-1750.

[242] Maclellan MJ, Patla AE (2006) *Adaptations of walking pattern on a compliant surface to regulate dynamic stability*, Experimental Brain Research, **173**: 521-530.

[243] Wild D, Nayak USL, Isaacs B (1981) *Prognosis of falls in old people at home*, Journal of Epidemiology and Community Health, **35**(3): 200-204.

[244] Duncan PW, Studenski S (1994) *Balance and gait measures*, Annual Review of Gerontology and Geriatrics, Lawton and Teresi, Springer, New York, NY, USA, pp. 76–92.

[245] Wolfson LI, Whipple R, Amerman P, Kleinberg A (1986) *Stressing the postural response. A quantitative method for testing balance*, Journal of the American Geriatrics Society, **34**(12): 845-850.

[246] Chandler JM, Duncan PW, Studenski SA (1990) *Balance performance on the postural stress test: comparison of young adults, healthy elderly and fallers*, Physical Therapy, **70**(7): 410-415.

[247] Horak FB, Nashner LM, Diener HC (1989) *Postural strategies associated with somatosensory and vestibular loss*, Experimental Brain Research, **82**(1): 167-177.

[248] Whitney SL, Wrisley DM, Marchetti GF, Gee MA, Redfern MS, Furman JM (2005) *Clinical measurement of sit-to-stand performance in people with balance disorders: validity of data for the five-times-sit-to-stand test*, Physical Therapy, **85**: 1034-1035.

[249] Nevitt MC, Cummings SR, Kidd S, Black D (1989) *Risk factors for recurrent nonsyncopal falls*, JAMA, **261**: 2663-2668.

[250] Tiedemann A, Shimada H, Sherrington C, Murray S, Lord S (2005) *The comparative ability of eight functional mobility tests for predicting falls in community-dwelling older people*, Age & Ageing, **37**: 430-435.

[251] Buatois S, Miljkovic D, Manckoundia P, Gueguen R, Miget P, Vancon G, Perrin P, Benetos A (2008) *Five times sit-to-stand test is a predictor of recurrent falls in healthy community-living subjects aged 65 and older*, Journal of American Geriatrics Society **56**(8): 1575-1577.

[252] Buatois S, Perret-Guillaume C, Gueguen R, Miget P, Vancon G, Perrin P, Benetos A (2010) *A simple clinical scale to stratify risk of recurrent falls in community-dwelling adults aged 65 years and older*, Physical Therapy, **90**: 550-560.

[253] Jeng SF, Schenkman M, Riley PO, Lin SJ (1990) *Reliability of a clinical kinematic assessment of the sit-to-stand movement*, Physical Therapy, **70**(8): 511-520.

[254] Inkster LM, Eng JJ (2004) *A simple clinical scale to stratify risk of recurrent falls in community-dwelling adults aged 65 years and older*, Experimental Brain Research, **154**(1): 33-38.

[255] Kralj A, Jaeger R, Munih M (1990) *Analysis of standing up and sitting down in humans: definitions and normative data presentation*, Journal of Biomechanics, **23**: 1123-1238.

[256] Kerr KM, White JA, Barr DA, Mollan RA (1997) *Analysis of the sit-stand-sit movement cycle in normal subjects*, Clinical Biomechanics, **12**(4): 236-245.

[257] Ganea R, Paraschiv-Ionescu A, Bula C, Rochat S, Aminian K (2011) *Multi-parametric evaluation of sit-to-stand and stand-to-sit transitions in elderly people*, Medical Engineering & Physics, **33**: 1086-1093.

[258] Tucker MG, Kavanagh JJ, Morrison S, Barrett RS (2010) *What are the relations between voluntary postural sway measures and falls-history status in community-dwelling older adults?*, Archives of Physical Medicine and Rehabilitation, **91**(5): 750-758.

[259] Kamen G, Patten C, Duke D, Sison S (1998) *An accelerometry-based system for the assessment of balance and postural sway*, Gerontology, **44**(1): 40-45.

[260] Moe-Nilssen R (1998) *A new method for evaluating motor control in gait under real-life environmental conditions. Part 1: The Instrument*, Clinical Biomechanics, **13**(4-5): 320-327.

[261] Mayagoitia RE, Lötters JC, Veltink PH, Hermens H (2002) *Standing balance evaluation using a tri-axial accelerometer*, Gait&Posture, **6**(1): 55-59.

[262] Mayagoitia RE, Nene AV, Veltink PH (2002) *Accelerometer and rate gyroscope measurement of kinematics: an inexpensive alternative to optical motion analysis systems*, Journal of Biomechanics, **35**: 537-542.

[263] Lyons GM, Culhane KM, Hilton D, Grace PA, Lyons D (2005) *A description of an accelerometer-based mobility technique*, Medical Engineering and Physics, **27**: 497-504.

[264] Liu K, Liu T, Shibata K, Inoue Y, Zheng R (2009) *Novel approach to ambulatory assessment of human segmental orientation on a wearable sensor system*, Journal of Biomechanics, **42**: 2747-2752.

[265] Cooper G, Sheret I, McMillian L, Siliverdis K, Sha N, Hodgins D, Kenney L, Howard D (2009) *Inertial sensor-based knee felxion/extension angle estimation*, Journal of Biomechanics, **42**: 2678-2685.

[266] Favre J, Jolles M, Aissaoui R, Aminian K (2008) *Ambulatory measurement of 3D knee joint angle*, Journal of Biomechanics, **41**: 1029-1035.

[267] O'Donovan KJ, Kamnik R, O'Keeffe DT, Lyons GM (2007) *An inertial and magnetic sensor based technique for joint angle measurement*, Journal of Biomechanics, **40**: 2604-2611.

[268] Dejnabadi H, Jolle BM, Casanova E, Fua P, Aminian K (2006) *Estimation and visualization of sagittal kinematics of lower limbs orientation using body-fixed sensors*, IEEE Transactions on Biomedical Engineering, **53**: 1385-1393.

[269] Roetenberg D, Slycke PJ, Veltink PH (2007) *Ambulatory position and orientation tracking fusing magnetic and inertial sensing*, IEEE Transactions on Biomedical Engineering, **54**: 883-890.

[270] Tanaka S, Motoi K, Nogawa M, Yamakoshi K (2004) *A new portable device for ambulatory monitoring of human posture and walking velocity using miniature accelerometers and gyroscopes*, Proceedings of 26th Annual International Conference of IEEE EMBS, September 1-5, San Francisco, CA, USA, pp. 2283-2286.

[271] Williamson R, Andrews BJ (2001) *Detecting absolute human knee angle and angular velocity using accelerometers and rate gyroscopes*, Medical & Biological Engineering & Computing, **39**: 1-9.

[272] Kemp B, Janssen JMW, Van der Kamp B (1998) *Body position can be monitored in 3D using miniature accelerometers and earth-magnetic field sensors*, Electroencephalography and Clinical Neurophysiology, **109**: 484-488.

[273] Smith G (1989) *Padding point extrapolation techniques for the digital Butterworth filter*, Journal of Biomechanics, **22**(8-9): 967-971.

[274] Salem GJ, Salinas R, Harding FV (2003) *Bilateral kinematic and kinetic analysis of the squat excercise after anterior cruciate ligament reconstruction*, Archives of Physical Medicine and Rehabilitation, **84**: 1211-1216.

[275] Arun K, Huang T, Blostein S (1987) *Least-squares fitting of two 3-D point sets*, IEEE Transactions on Pattern Analysis and Machine Intelligence, **9**: 698-700.

[276] Hanson R, Norris M (1981) *Analysis of measurements based on the singular value decomposition*, SIAM Journal on Scientific Computing, **2**: 363-373.

[277] Elble RJ (2005) *Gravitational artifact in accelerometric measurements of tremor*, Clinical of Neurophysiology, **116**: 1638-1643.

[278] Hayes WC, Gran JD, Nagurka ML, Fieldman JM, Oatis C (1983) *Leg motion analysis during gait by multi-axial accelerometry: Theoretical foundations and preliminary validations*, Journal of Biomechanics, **105**: 283-289.

[279] Padgaonkar AJ, Krieger KW, King AI (1975) *Measurement of angular acceleration of a rigif body using linear accelerometers*, Journal of Applied Mechanics (Transactions ASME), **42**: 552-556.

[280] Horak FB (1997) *Clinical assessment of balance disorders*, Gait & Posture, **6**(1): 76-84.

[281] Iqbal K (2011) *Mechanisms and models of postural stability and control*, Proceedings of the 33rd Annual International Conference of IEEE Engineering in Medicine & Biology Society, August 30 - September 3, Boston, USA, pp 7837-7840.

[282] Prieto TE, Myklebust JB, Hoffman RG, Lovett EG, Myklebust BM (1996) *Measures of postural steadiness: differences between healthy young and elderly adults*, IEEE Transaction on Biomedical Engineering, **43**: 956-966.

[283] Winter DA (1995) *Human balance and posture control during standing and walking*, Gait & Posture, **3**: 193-214.

[284] FUJIMOTO M, CHOU LS (2012) *Dynamic balance control during sit-to-stand movement: an examination with the center of mass acceleration*, Journal of Biomechanics, **45**: 543-548.

[285] PAPA E, CAPPOZZO A (1999) *A telescopic inverted-pendulum model of the musculo-skeletal system and its use for the analysis of the sit-to-stand motor task*, Journal of Biomechanics, **32**: 1205-1212.

[286] PAI YC, NAUGHTON BJ, CHANG RW, ROGERS MW (1994) *Control of body center of mass momentum during sit-to-stand among young and elderly adults*, Gait & Posture, **2**: 109-116.

[287] LENZI D, CAPPELLO A, CHIARI L (2003) *Influence of body segment parameters and modeling assumptions on the estimate of center of mass trajectory*, Journal of Biomechanics, **36**: 1335-1341.

[288] HASAN SS, ROBIN DW, SZURKUS DC, ASHMEAD DH, PETERSON SW, SHIAVI RG (1996) *Simultaneous measurement of body center of pressure and center of gravity during upright stance. Part I: methods*, Gait & Posture, **4**: 1-10.

[289] ZATSIORSKY VM, KING DL (1998) *An algorithm for determining gravity line location from posturographic recordings*, Journal of Biomechanics, **31**: 161-164.

[290] SHIMBA T (1984) *An estimation of center of gravity from force platform data*, Journal of Biomechanics, **7**: 53-60.

[291] CARON O, FAURE B, BRENIÉRE Y (1997) *Estimating the center of gravity of the body on the basis of the center of pressure in standing posture*, Journal of Biomechanics, **30**: 1169-1171.

[292] HANAVAN EP (1964) *A mathematical model of the human body*, AMRL Technical Report: 64-102, Wright-Patterson Air Force Base, OH.

[293] HATZE H (1980) *A mathematical model for the computational determination of parameter values of anthropomorphic segments*, Journal of Biomechanics, **13**: 833-843.

[294] JENSEN RK (1978) *Estimation of biomechanical properties of three body types using a photogrammetry method*, Journal of Biomechanics, **11**: 349-358.

[295] WICKE J, DUMAS GA (2008) *Estimating segment inertial parameters using fan-beam DEXA*, Journal of Applied Biomechanics, **24**: 180-184.

[296] YEADON MR (1990) *The simulation of aerial movement-II. A mathematical inertia model of the human body*, Journal of Biomechanics, **23**(1): 67-74.

[297] CHANDLER RF, CLAUSER CE, MCCONVILLE JT, REYNOLDS HM, YOUNG JW (1975) *Investigation of inertia properties of the human body*, AMRL Technical Report: 74-137, Wright-Patterson Air Force Base, OH

[298] DEMPSTER WT (1955) *Space requirements for the seated operator*, WADC Technical Report: 55-219, Wright-Patterson Air Force Base, OH.

[299] Cheng CK, Chen HH, Chen CS, Chen CL, Chen CY (2000) *Segment inertial properties of Chinese adults determined from magnetic resonance imaging*, Clinical Biomechanics, **15**: 559-566.

[300] Durkin JL, Dowling JJ (2003) *Analysis of body segment parameter differences between four human populations and the estimation errors of four popular mathematical models*, Journal of Biomechanical Engineering, **125**: 515-522.

[301] Sandoz B, Laporte S, Skalli W, Mitton D (2010) *Subject-specific body segment parameters' estimation using biplanar X-rays: a feasibility study*, Computer Methods in Biomechanics and Biomedical Engineering, **13**(6): 649-654.

[302] Sheets AL, Corazza S, Andriacchi TP (2010) *An automated image-based method of 3D subject-specific body segment parameter estimation for kinetic analysis of rapid movements*, Journal of Biomechanical Engineering, **132**(1), Article (011004).

[303] Vette AH, Yoshida T, Thrasher TA, Masani K, Popovic MR (2011) *A complete, non-lumped, and verifiable set of upper body segment parameters for three-dimensional dynamic modeling*, Medical Engineering & Physics, **33**: 70-79.

[304] Zatsiorsky VM, Seluyanov VN, Chugunova LG (1990) *Methods of determining mass-inertial characteristics of human body segments*, Chernyi GG, Regirer SA (eds), Contemporary Problems of Biomechanics, CRC Press, Boston, pp 272-291.

[305] Chen SC, Hsieh HJ, Lu TW, Tseng CH (2011) *A method for estimating subject-specific body segment inertial parameters in human movement analysis*, Gait & Posture, **33**(4): 695-700.

[306] Riemer R, Hsiao-Wecksler ET (2009) *Improving net joint torque calculations through a two-step optimization method for estimating body segment parameters*, ASME Journal of Biomechanical Engineering, **131**(1): 011007.

[307] De Leva P (1996) *Adjustments to Zatsiorsky-Seluyanov's segment inertial parameters*, Journal of Biomechanics, **29**(9): 1223-1230.

[308] Chandler J, Duncan P, Kochersberger G, Studenski S (1998) *Is lower extremity strength gain associated with improvement in physical performance and disability in frail, community-dwelling elders?*, Archives of Physical Medicine and Rehabilitation, **79**: 24-30.

[309] Chiari L (2011) *Wearable systems with minimal set-up for monitoring and training of balance and mobility*, Proceedings of the 33rd Annual International Conference of IEEE Engineering in Medicine & Biology Society, August 30 - September 3, Boston, pp 5828-5832.

[310] Pai YC, Patton J (1997) *Center of mass velocity-position predictions for balance control*, Journal of Biomechanics, **30**(4): 347-354.

[311] Donhey EP, Fan CW, Foran T, Green BR, Cunningham C, Kenny A (2011) *An instrumented sit-to-stand test used to examine differences between older fallers and non-fallers*, Proceedings of the 33rd Annual International Conference of IEEE Engineering in Medicine & Biology Society, August 30 - September 3, Boston, USA, pp 3063-3066.

[312] Zijlstra W, Bisseling RW, Schlumbohm S, Baldus H (2010) *A body-fixed-sensor-based analysis of power during sit-to-stand movements*, Gait & Posture, **31**: 272:278.

[313] Vaughan CL, Andrews JG, Hay JG (1982) *Selection of body segment parameters by optimization methods*, ASME Journal of Biomechanical Engineering, **104**(1): 38-44.

[314] Roebroeck M, Doorenbosch C, Harlaar J, Jacobs R, Lankhorst G (1994) *Biomechanics and muscular activity during sit-to-stand transfer*, Clinical Biomechanics, **9**: 235-244.

[315] Kaya BK. Krebs De, Riley PO (1998) *Dynamic stability in elders: momentum control in locomotor ADL*, Journal of Gerontology Series A: Biological Science and Medical Science, **53**A(2): M126-M134.

[316] Duncan RP, Leddy AL, Earhart GM (2011) *Five Times Sit-to-Stand Test performance in Parkinson's disease*, Archives of Physical Medicine and Rehabilitation, **92**: 1431-1436.

[317] Lord SR, Murray SM, Chapman K, Munro B, Tiedemann A (2002) *Sit-to-stand performance depends on sensation, speed, balance and psychological status in addition to strength in older people*, Journal of Gerontology Series A: Biological Science and Medical Science, **57**: M539-M543.

[318] Csuka M, McCarty D (1985) *Simple method for measurement of lower-extremity muscle strength*, American Journal of Medicine, **78**: 77-81.

[319] Lecours J, Nadeau S, Gravel D, Teixera-Salmela L (2008) *Interactions between foot placement, trunk frontal position, weight-bearing and knee moment asymmetry at seat-off during rising from a chair in healthy controls and persons with hemiparesis*, Journal of Rehabilitation Medicine, **40**: 200-207.

[320] Mazzà C, Stanhope SJ, Taviani A, Cappozzo A (2006) *Biomechanical modeling of sit-to-stand to upright posture for mobility assessment of persons witch chronic stroke*, Archives of Physical Medicine and Rehabilitation, **91**(2): 288-297.

[321] Rapp K, Becker C, Cameron ID, König HH, Büchele G (2011) *Epidemiology of falls in residential aged care: analysis of more than 70,000 falls from residents of bavarian nursing homes*, Journal of the American Medical Directors Association, **13**(2): 187.e1-187.e6.

[322] Csuka M, McCarty DJ (1985) *Simple method for measurement of lower extremity muscle strength*, The America Journal of Medicine, **78**: 77-81.

[323] Guralnik JM, Simonsick EM, Ferrucci L, Glynn RJ, Berkman LF, Blazer DG (1994) *A short physical performance battery assessing lower extremity function: association with self-reported disability and prediction of mortality and nursing home admission*, Journal of Gerontology, **49**(2): M85-M94.

[324] Jones CJ, Rikli RE, Beam WC (1999) *A 30-s chair-stand test as a measure of lower body strength in community-residing older adults*, Research Quarterly for Exercise and Sport, **70**: 113-119.

[325] Lindemann U, Claus H, Stuber M, Augat P, Muche R, Nikolaus T, Becker C (2003) *Measuring Power during the sit-to-stand transfer*, Europeab Journal of Applied Physiology, **89**: 466-470.

[326] Janssen WG, Kulcu DG, Horemans HL, Stam HJ, Bussmann JB (2003) *Sensitivity of accelerometry to assess balance control during sit-to-stand movement*, IEEE Transactions on Neural Systems and Rehabilitation Engineering, **16**: 479-484.

[327] Salarian A, Horak FB, Zampieri C, Carlson-Kuhta P, Nutt JG, Aminian K (2010) *iTUG, a sensitive and reliable measure of mobility*, IEEE Transactions on Neural Systems and Rehabilitation Engineering, **18**: 303-310.

[328] Reicherz A, Brach M, Cerny J, Nicolai S, Becker C, Lindemann U (2011) *Development of the Lie-to-Sit-to-Stand-to-Walk Transfer (LSSWT) test for early mobilization in older patients in geriatric rehabiliation*, Zeitschrift für Gerontologie und Geriatrie, **44**: 262-267.

[329] Shields RK, Enloe RE, Smith KB, Steckel SD (1995) *Reliability, validity, and responsiveness of functional tests in patient with total joint replacement*, Physical Therapy, **75**: 169-176.

[330] Katzman R, Brown T, Fuld P, Peck A, Schechter R, Schimmel H (1983) *Validation of a short Orientatio-Memory-Concentration Test of cognitive impairment*, The American Journal of Psychiatry, **140**: 734-739.

[331] Zijlstra W, Hof AL (2003) *Assessment of spatio-temporal gait parameters from trunk accelerations during human walking*, Gait & Posture, **18**: 1-10.

[332] Hogan N, Sternad D (2009) *Sensitivity of smoothness measures to movement duration, amplitude and arrests*, Journal of Motor Behavior, **41**(6): 529-534.

[333] Kalman RE (1960) *A new approach to linear filtering and prediction problems*, Journal of Basic Engineering, **82**(1): 35-45.

[334] Welch G, Bishop G (2001) *An introduction to the Kalman Filter*, Design, **7**(1): 1-16.

[335] Giansanti D, Maccioni G, Macellari V (2005) *The development and test of a device for the reconstruction of 3D position and orientation by means of a kinematic sensor assembly with rate gyroscopes and accelerometers*, IEEE Transactions on Biomedical Engineering, **52**(7): 1271-1277.

[336] Klenk J, Becker C, Lieken F, Nicolai S, Maetzler W, Alt W, Zijlstra W, Hausdorff JM, Van Lummel RC, Chiari L, Lindemann U (2011) *Comparison of acceleration signals of simulated and real-world backward falls*, Medical Engineering & Physics **33**: 368-373.

[337] Lord R, Sherrington C, Menz HB (2001) *Falls in older people: risk factors and strategies for prevention*, Cambridge: Cambridge University Press.

[338] Mallinson W, Green M (1985) *Covert muscle injury in aged persons admitted to hospital following falls*, Age Ageing, **14**(1): 174-178.

[339] King MB, Tinetti ME (1995) *Falls in community-dwelling older persons*, Journal of the American Geriatrics Society, **43**: 1146-1154.

[340] Wild D, Nayak US, Isaacs B (1981) *How dangerous are falls in old people at home?*, British Medical Journal, **282**(6260): 266-268.

[341] Vellas B, Cayla F, Bocquet H, De Pemille F, Albarede JL (1987) *Prospective study of restriction of activity in old people after falls*, Age Ageing, **16**(3): 189-193.

[342] Tinetti ME, Liu WI, Claus EB (1993) *Predictors and prognosis of inability to get up after falls among elderly persons*, Journal of the American Medical Association, **269**: 65-70.

[343] Roush RE, Teasdale TA, Murphy JN, Kirk MS (1995) *Impact of a personal emergency response system on hospital utilization by community-residing elders*, Southern Medical Journal, **88**(9): 917-922.

[344] Gurley RJ, Lum N, Sande M, Lo B, Katz MH (1996) *Persons found in their homes helpless or dead*, The New England Journal of Medicine, **334**(26): 1710-1716.

[345] Noury N, Rumeau P, Bourke AK, Olaighin G, Lundy JE (2008) *A proposal for the classification and evaluation of fall detectors*, IRBM **29**(6): 340-349.

[346] Kangas M, Vikman I, Nyberg L, Korpelainen R, Lindblom J, Jamsa T (2012) *omparison of real-life accidental falls in older people with experimental falls in middle-aged test subjects*, Gait & Posture, **35**(3): 500-505.

[347] Lindemann U, Nicolai S, Beische D, Becker C, Srulijies K (2010) *Clinical and dual tasking aspects in frequent and infrequent fallers with progressive supranuclear palsy*, Movement Disorders **25**: 1040-1046.

[348] Nicolai S, Mirelmann A, Herman T, Zijlstra A, Mancini M, Becker C, Lindemann U, Berg D, Maetzler W (2010) *Improvement of balance after audio-biofeedback. A 6-week intervention study in patients with progressive supranuclear palsy*, Movement Disorders **25**: 1040-1046.

[349] Schrag A, Ben-Schlomo Y, Quinn NP (1999) *Prevalence of progressive supranuclear palsy and multiple system atrophy: a cross-sectional study*, Lancet **354**: 1771-1775.

[350] Golbe L (2005) *Progressive supranuclear palsy*, In: Beal MF, Lang A, Ludolph AC, editors. Neurodegenerative disease: neurobiology, pathogenesis, and therapeutics. Cambridge: Cambridge University Press, pp. 663-681.

[351] Litvan I, Bhatia KP, Burn DJ (2003) *Movement disorders society scientific issues committee report: SIC task force appraisal of clinical diagnostic criteria for Parkinsonian disorders*, Movement Disorder **18**: 467-486.

[352] Bourke AK, Van de Ven P, Gamble M, O'Connor R, Murphy K, Bogan E, McQuade E, Finucane P, Olaighin G, Nelson J (2006) *Evaluation of waist-mounted tri-axial accelerometer based fall-detection algorithms during scripted and continuous unscripted activities*, Journal of Biomechanics, **43**: 3051-3057.

[353] Noury N, Fleury A, Rumeau P, Bourke AK, OLaighin G, Rialle V, Lundy JE (2007) *Fall detection-principles and methods*, Proceedings 29th of Annual International Conference of IEEE EMBS, August 23-26, Lyon, France, pp. 1663-1666. **35**: 5-10.

[354] Perolle G, Fraisse P, Mavros M, Extebberia I (2006) *Automatic fall detection and activity monitoring for elderly*, Proceedings of Med-e-tel, April 5-7, Luxembourg, Luxembourg, pp. 65-70.

[355] Vass DC, Sahota O, Drummond A, Kendrick D, Gladman J, Sach T, Avis M, Grainge M (2010) *REFINE (Reducing Falls in In-patient Elderly - a randomized controlled trial*, Trials, **10:83**.

[356] Chockalingam N, Giakas G, Iossifidou A (2002) *Do strain gauge force platfroms need in situ correction?*, Gait&Posture, **16**: 233-237.

[357] Cedraro A, Cappello A, Chiari L (2009) *A portable system for in-situ re-calibration of force platforms: experimental validation*, Gait&Posture, **29**: 449-453.

[358] Mc Caw ST, De Vita P (1995) *Errors in alignment of center of pressure and foot coordinates affect predicted lower extremity torques*, Journal of Biomechanics, **28**: 985-988.

[359] Cedraro A, Cappello A, Chiari L (2008) *A portable system for in-situ re-calibration of force platforms: theoretical validation*, Gait&Posture, **28**: 488-494.

[360] Cappello A, Lenzi D, Chiari L (2004) *Periodical in-situ re-calibration of force platforms: a new method for the robust estimation of the calibration matrix*, Medical & Biological Engineering & Computing, **42**: 350-355.

[361] Hall MG, Fleming HE, Dolan MJ, Millbank SF, Paul JP (1996) *Static in-situ calibration of force plates*, Journal of Biomechanics, **29**(5): 659-665.

[362] Bobbert MF, Schamhardt HC (1999) *Accuracy of determining the point of force application with piezoelectric force plates*, Journal of Biomechanics, **23**: 701-705.

[363] Middleton J, Sinclair P, Patton R (1994) *Accuracy of centre of pressure measurement using a piezoelectric force platform*, Clinical Biomechanics, **14**(5): 357-360.

[364] Schmiedmayer HB, Kastner J (2000) *Enhancements in the accuracy of the center of pressure (COP) determined with piezoelectric force plates are dependent on the load distribution*, Journal of Biomechanical Engineering, **122**: 523-537.

[365] Mita K, Akataki K, Itoh K, Nogami H, Katoh R, Watakabe SNM, Suzuki N (1993) *An investigation of the accuracy in measuring the body centre of pressure in a standing posture with a force plate*, Frontiers of Medical and Biological Engineering, **5-3**: 201-213.

[366] Schmiedmayer HB, Kastner J (1999) *Parameters influencing the accuracy of the point of force application determined with piezoelectric force plates*, Journal of Biomechanics, **32**:1237-1242.

[367] Draper N, Smith H (2000) *Applied regression analysis*, John Wiley & Sons,Inc, 1996.