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Assessing fall risk of older adults using accelerometry-based methods

Heidi Similä

VTT

VTT SCIENCE 163

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Thesis for the degree of Doctor of Technology to be presented with due permission for public examination and criticism in auditorium L2, at University of Oulu, on the 17th of November 2017 at 12 noon.

ISBN 978-951-38-8573-1 (Soft back ed.)
ISBN 978-951-38-8572-4 (URL: http://www.vttresearch.com/impact/publications)

VTT Science 163

ISSN-L 2242-119X
ISSN 2242-119X (Print)
ISSN 2242-1203 (Online)
http://urn.fi/URN:ISBN:978-951-38-8572-4

JULKAISIJA – UTGIVARE – PUBLISHER

Teknologian tutkimuskeskus VTT Oy
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Juvenes Print, Tampere 2017

Abstract

Falls pose a serious threat to older people, since they may lead to severe injuries, reduced quality of life and increased health care costs. Every third person over 65 years old falls at least once each year, and the number of falls increases with age and frailty level. Falls are multifactorial by nature and a person can have several risk factors contributing to a fall. A variety of assessment scales have been developed for assessing fall risk factors and estimating the probability of future falls. These are typically administrated by a health care professional. However, selection of an assessment scale with high enough sensitivity and specificity and reasonable administration time can be difficult.

The goal of this thesis was to develop new methods for fall risk assessment utilizing accelerometry-based movement sensing, which enables objective detection and assessment of a person's balance deficits. The first objective was to investigate the perceptions of prospective end-users of new technologies via focus group interviews. The analysis showed that familiarity, prior experience and self-efficacy presumably affect the acceptance of new solutions. The second objective was to investigate how an individual's fall risk is manifested through different assessment scales. The Disease State Fingerprint visualization method was examined for its potential in comparing different fall risk assessment scales. It was found useful in discovering the most relevant assessment scales for separating fallers from non-fallers in the study population, and for presenting how the overall fall risk of an individual is constituted. The third objective was to study how body-worn accelerometry could be utilized in the assessment of individual fall risk. For the third objective, three data sets were collected from a total of 111 subjects. The results showed that features derived from the body-worn accelerometer signals could be used for assessment of a person's balance. Furthermore, they seem to be able detect balance deficits even earlier than the traditionally used clinical assessment scales. The results provide a basis for studies validating these methods and further transferring them into practice.

Tiivistelmä

Kaatumiset ovat uhka ikääntyneille, koska ne voivat aiheuttaa vakavia vammoja, heikentää elämänlaatua ja lisätä terveydenhuollon kustannuksia. Joka kolmas yli 65-vuotias kaatuu vähintään kerran vuodessa, ja kaatumisten lukumäärä kasvaa iän ja heikentyneen kunnon myötä. Kaatumiset voivat johtua lukuisista eri tekijöistä, ja yhden kaatumisen taustalla voi vaikuttaa useita riskitekijöitä. Kaatumisriskitekijöiden ja kaatumisten todennäköisyyden arviointiin on kehitetty useita erilaisia mittareita, joita käyttävät tyypillisesti terveydenhuollon ammattilaiset. Käytettävän mittarin valinta ei ole helppoa, sillä mittarin tulisi olla sensitiivinen ja spesifinen ja arviointi tulisi voida suorittaa kohtuullisessa ajassa.

Tämän väitöstyön päätavoitteena oli kehittää uusia menetelmiä kaatumisriskin arvioimiseksi hyödyntämällä kiihtyvyysanturipohjaista liikkeenmittausta, joka mahdollistaa henkilön tasapaino-ongelmien tunnistamisen objektiivisesti. Ensimmäinen tavoite oli selvittää fokusryhmähaastattelujen avulla, miten loppukäyttäjät kokevat nykyiset ja tulevaisuuden kaatumisriskin arviointiin ja kaatumisten ennaltaehkäisyyn suunnatut teknologiat. Aineiston analyysi osoitti, että aiheeseen liittyvä tuttuus, aiempi kokemus sekä minäpystyvyys oletettavasti vaikuttavat uusien ratkaisujen hyväksyttävyyteen. Toinen tavoite oli tutkia, miten yksilön kaatumisriski näyttäytyy eri kaatumisriskimittareissa. Työssä arvioitiin Disease State Fingerprint -visualisointimenetelmän käytettävyyttä eri kaatumisriskimittareiden vertailussa. Menetelmän avulla pystyttiin tunnistamaan ne mittarit, joilla voitiin parhaiten erottaa tutkimusjoukon kaatujat ei-kaatujista, sekä osoittamaan, miten yksilön kokonaiskaatumisriski koostuu eri tekijöistä. Kolmas tavoite oli tutkia, miten puettavia kiihtyvyysantureita voidaan hyödyntää yksilön kaatumisriskin arvioinnissa. Analyysit pohjautuivat kolmeen datasettiin, jotka oli kerätty yhteensä 111 henkilöstä. Tulokset osoittavat, että puettavan kiihtyvyysanturin signaaleista laskettuja piirteitä voidaan käyttää henkilön tasapainon arviointiin. Lisäksi tulokset osoittavat, että kiihtyvyyteen pohjautuvat piirteet saattavat tunnistaa tasapaino-ongelmia jopa perinteisiä kliinisiä mittareita aiemmin. Saatuja tuloksia voidaan hyödyntää menetelmien validointitutkimuksen sekä käyttöönoton suunnittelemiseksi ja toteuttamiseksi.

Preface

The research work reported in this thesis was carried out at VTT Technical Research Centre of Finland Ltd, where I started as a research trainee in 2005. The same year I started working on my Master’s thesis on accelerometry-based balance assessment, which also became the topic of my PhD thesis. I have been fortunate in being able to work in variety of national and international projects funded by VTT, Tekes – the Finnish Funding Agency for Innovation, and EU, where I could do research on interesting topics, and also advance my thesis. I would also like to thank Yliopiston Apteekin rahasto Fund for funding my work.

Firstly, I would like to express my gratitude to my supervisors. Thank you, Professor Tapio Seppänen for your support and invaluable guidance in compiling and finalizing this thesis. Thank you, Professors Timo Jämsä and Raija Korpelainen for sharing your expertise, and also for the opportunity to work part time as a PhD student in GASEL-project at the University of Oulu during 2014–2016. I would like to thank Dr. Jani Mäntyjärvi at VTT, first of all for hiring me as a research trainee back at 2005, and for your guidance during these years.

I would like to thank University of Oulu Graduate School and the members of my follow-up group, Professor Minna Isomursu, Professor Jarmo Reponen, and Dr. Ville Könönen for their support and comments to my thesis. I would also like to thank the pre-examiners Professors Jari Viik from the Tampere University of Technology and Pasi Karjalainen from the University of Eastern Finland for their valuable comments that helped me to improve my thesis.

I would like to thank my superiors and colleagues at VTT, who I have been working with throughout these years. I have been privileged for being able to work in great teams with skilful experts in Oulu, Tampere, Espoo and Kuopio. Especially, I would like to thank my former team manager Mr. Johan Plomp for being so supportive and enabling us to work in such interesting projects. The most important research project for this thesis was Ageing in Balance, supported by Active and Assisted Living (AAL) Programme during 2012–2015. Most of the work of this thesis was carried out in that project, or is based on data collected in it. Therefore, I would like to express my deepest gratitude for the project manager of Ageing in Balance, co-author, my colleague, and dear friend Mrs. Milla Immonen. Without your support I would not have been able to accomplish this thesis. I am also very grateful for Dr. Miikka Ermes for his support and practical guidance in data analytics, as well as, writing the articles. I would also like to express my gratitude to all the other co-authors of the articles, especially Mr. Jouni Kaartinen, Mr. Mikko Lindholm, and Mr. Juho Merilahti for your contribution. Thank you, Ms. Salla Muuraiskangas for being such a great office roommate and friend for many years and for your support at work and beyond. Besides being amazing colleagues, I would like to thank Mrs. Anna Sachinopoulou, Dr. Marja Harjumaa, and Dr. Tiia Ojanperä for being such good friends.

I am deeply thankful to my family and friends. My parents, Jouko and Päivi, thank you for believing in me and for your endless support in my work and life. My sister Hanna, thank you for always being there and encouraging me with everything I do. I am also very grateful for my parents-in-law, friends and neighbours for helping me to maintain balance between work and life.

Finally, my most sincere and loving thanks I owe to my husband Mikko and our dear children Neea and Niko. Thank you for standing by me and supporting me all these years. The words are not enough to express how precious you are to me.

Oulu, September 2017

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Academic dissertation

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List of publications

This thesis is based on the following original publications which are referred to in the text as Papers I–VI. The publications are reproduced with kind permission from the publishers.

I. Similä, H., Immonen, M., Gordillo, C. G., Petäkoski-Hult, T., & Eklund, P. (2013). Focus Group Evaluation of Scenarios for Fall Risk Assessment and Fall Prevention in Two Countries. In C. Nugent, A. Coronato, & J. Bravo (Eds.), Ambient Assisted Living and Active Aging: 5th International Work-Conference, IWAAL 2013, Carrillo, Costa Rica, December 2-6, 2013, Proceedings (pp. 39–46). Cham: Springer International Publishing Switzerland.

II. Similä, H., Kaartinen, J., Lindholm, M., Saarinen, A., & Mahjneh, I. (2006). Human balance estimation using a wireless 3D acceleration sensor network. In 2006 International Conference of the IEEE Engineering in Medicine and Biology Society (pp. 1493–1496). New York Aug. 30 2006-Sept. 3 2006.

III. Similä, H., Mäntyjärvi, J., Merilahti, J., Lindholm, M., & Ermes, M. (2014). Accelerometry-based berg balance scale score estimation. IEEE Journal of Biomedical and Health Informatics, 18(4), 1114–1121.

IV. Similä, H., & Immonen, M. (2014). Disease State Fingerprint for Fall Risk Assessment. In 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (pp. 3176–3179). Chicago 26-30 Aug. 2014.

V. Similä, H., Immonen, M., Merilahti, J., & Petäkoski-Hult, T. (2015). Gait analysis and estimation of changes in fall risk factors. In 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (pp. 6939–6942). Milan 25-29 Aug. 2015.

VI. Similä, H., Immonen, M., & Ermes, M. (2017). Accelerometry-based Assessment and Detection of Early Signs of Balance Deficits. Computers in Biology and Medicine, 85, 25–32.

Abbreviations

3D	Three-Dimensional
ABC	Activities-specific Balance Confidence
ADL	Activities of Daily Living
ANN	Artificial Neural Network
AST	Alternate-Step-Test
AUC	Area Under Curve
BBS	Berg Balance Scale
BMI	Body Mass Index
CoM	Centre of Mass
DSF	Disease State Fingerprint
DSI	Disease State Index
FES-I	Falls Efficacy Scale-International
FFT	Fast Fourier Transform
FRAT	Falls Risk Assessment Tool
FROP-Com	Fall Risk for Older People in the Community
g	Gravitational acceleration
GDS	Geriatric Depression Scale
IMU	Inertial Measurement Unit
kNN	k-Nearest-Neighbour
MMSE	Mini-Mental State Examination
OSF	Official Statistics Finland
PCA	Principal Component Analysis
POMA	Performance-Oriented Mobility Assessment

PPA	Physiological Profile Assessment
RMS	Root Mean Square
ROC	Receiver Operating Characteristics
SD	Standard Deviation
SFFS	Sequential Forward Floating Selection
SFS	Sequential Forward Selection
SMA	Signal Magnitude Area
SOM	Self-Organizing Map
STS-5	Sit-To-Stand five times
SVM	Support Vector Machine
THL	National Institute for Health and Welfare (Terveyden ja hyvinvoinnin laitos)
TUG	Timed-Up-and-Go
WHO	World Health Organization

Contents

1. Introduction

1.1 Background

Falls are a major health risk that diminishes the quality of life among older people and increases health services costs. Every third person over 65 years old falls at least once each year (Lord, Sherrington, & Menz, 2001) and the number of falls increases with age and frailty level (World Health Organization, 2007). Falls may lead to death and serious injuries, e.g. in a study by Parkkari et al. (1999), 98% of hip fractures were caused by falls, not to mention the negative effect on the quality of life of a person who has fallen (Salkeld et al., 2000). In the year 2000 in the U.S., fall-related, non-fatal injuries produced $19 billion in direct medical costs through hospitalizations, emergency department visits and outpatient treatment (Stevens, Corso, Finkelstein, & Miller, 2006). Falls are a multifactorial problem and usually they are the result of interactions between multiple intrinsic and extrinsic risk factors (Rubenstein & Josephson, 2006).The most effective fall prevention strategies use multidimensional fall risk assessment combined with targeted interventions (Rubenstein & Josephson, 2006). Typically, a person is assessed for e.g. history of falls, balance, mobility, physical functioning, muscle strength, number of drugs in use, and cognitive functions (Perell et al., 2001; Scott, Votova, Scanlan, & Close, 2007). However, it is not easy to select which assessment scales to use (Perell et al., 2001) and regular fall risk assessments would require significant resources from health care organizations (Ejupi, Lord, & Delbaere, 2014). Thus, it is important to develop new methods to recognize people at risk cost-effectively and early enough so the preventive actions can be taken.

A variety of assessment scales are developed for assessing the static and dynamic balance of a person (Ambrose, Paul, & Hausdorff, 2013). One of the commonly used methods is recording the time it takes to walk a certain distance, e.g. four metres (Quach et al., 2011), or measuring the distance walked in six minutes (Steffen, Hacker, & Mollinger, 2002). The Timed Up-and-Go (TUG) (Podsiadlo & Richardson, 1991) test includes standing up from a chair, walking three metres, turning around, walking back to the chair and sitting down on the chair again. Furthermore, as an example of a more versatile test the Berg Balance Scale (BBS) (Berg, Wood-Dauphinee, Williams, & Gayton, 1989) has 14 tasks testing different aspects of postural balance and mobility. All of these balance tests are conventionally performed under supervision, requiring a professional scoring the tasks or taking the time. Three-dimensional accelerometry enables unobtrusive long-term monitoring of human movements in unsupervised conditions (Mathie et al., 2004) and thus provides an opportunity for objective fall risk estimation in free-living situations (Narayanan et al., 2010) without the need for a health care professional's presence. Some studies suggest that body-worn kinematic sensors may even be more accurate than the standard fall-risk metrics. For example, a recent study by van Schooten et al. (2015) suggests that by combining accelerometry-based gait features with traditional questionnaires, prospective falls can be estimated more accurately than with questionnaires or gait features alone. Typically, two types of inertial sensors are used in fall risk assessment studies: gyroscopes, that measure angular velocity, or accelerometers, that measure linear acceleration, or a combination of the two. However, a majority (70%) of the studies utilize only accelerometers (Howcroft, Kofman, & Lemaire, 2013). There is strong evidence that falls can be prevented with appropriate interventions (Gillespie, Robertson, & Gillespie, 2012). Prospective fall risk detection enables initiation of preventive interventions early enough to ensure their effectiveness.

1.2 Research problem and objectives

This work includes a literature review on the factors causing falls among older adults and how the fall risk is assessed in current practice. The objective of this thesis was to develop new methods and data analysis algorithms for fall risk assessment utilizing data especially from body-worn accelerometers. The fundamental target of the research was to attain methods to prospectively estimate the increase in individual fall risk.

Research questions:

1. How do end-users perceive current and future fall risk assessment and fall prevention technologies?

   With this research question the end-user perspective was studied and understanding of the technology application context is gained. The aim was also to understand target users' willingness to adopt the technologies under development into everyday use.

2. How is an individual's fall risk manifested through different assessment scales?

   This research questions aims to give insight into how different fall risk assessment scales currently used in the health care practice are able to capture individual fall risk and how the differences between individuals can be seen in these scales.

3. How can body-worn accelerometry be utilized in assessment of individual fall risk?
   a. How can balance ability be estimated from an acceleration measurement?
   b. How can prospective changes in fall risk factors be estimated from an acceleration measurement?

   The third research question is twofold. First, the aim was to investigate how well data analytics based on body-worn accelerometry can be used to estimate balance of a person and give comparable results to clinically used balance assessment scales. Secondly, the aim was to study whether early signs of deterioration in balance can be detected from accelerometry data and prospectively estimate the decrease in balance assessment scales after a certain period of time.

1.3 Research scope and approach

The objectives of the thesis are approached by investigating the data collected from test subjects in order to evaluate individual fall risk focusing primarily on quantitative processing and analysis of the acceleration signal measured by body-worn sensors. The ability to move and perform certain physical tasks is highly indicative of a person's fall risk and the acceleration signal measured while performing those tasks is supposed to capture relevant information about the fall risk. Furthermore, a qualitative content analysis approach is applied to understand how the proposed solutions are perceived by the possible future users.

The original publications are based on four data sets. Paper I is based on questionnaire and semi-structured discussion data from 58 subjects collected in focus groups organized in two countries in order to evaluate fall risk assessment and fall prevention-related scenarios. 29 subjects (aged 63–93 years) participated in four focus group discussions in Finland and 29 subjects (aged 56–96 years) participated in four focus groups in Spain.

The three-dimensional acceleration signals used in the analysis were all captured while the subjects performed specific tasks, such as a balance test, or during walking under supervised condition. In each study the sensor was attached to the lower back, near the Centre of Mass (CoM). Paper II is based on a data set collected from eight patients with a balance-affecting condition and seven healthy controls. Paper III is based on a data set collected from 54 subjects from three groups: 15 neurological patients, 20 older adults, and 19 healthy young persons. Papers V and VI are based on data set collected from 42 older adults.

Paper IV is based on fall risk assessment data, other than accelerometry, of the same 42 older adults as in Papers V and VI. Paper IV applies an algorithm originally developed for a different application field, i.e. early detection of Alzheimer's disease, into fall risk assessment. It allows visual inspection of several fall risk assessment scales at once, both on an individual and group level, and facilitates the comparison of different scales.

The objective of Papers II and III was to develop algorithms for balance assessment of a person using an acceleration signal measured during walking. The objective of Papers V and VI was to progress into developing algorithms that prospectively estimate the fall risk of a person by predicting decline in traditional balance assessment scales in the future based on acceleration measurement. In both approaches the first part of acceleration signal processing is to extract features from the raw signal that are expected to contain some relevant information about the phenomenon under investigation. Second, the features are studied to find out which of them are significant in identifying the persons with certain characteristics according to the reference measure, i.e. balance or fall risk in this case. The following figure summarises the approaches of each publication and how they relate to the compilation.

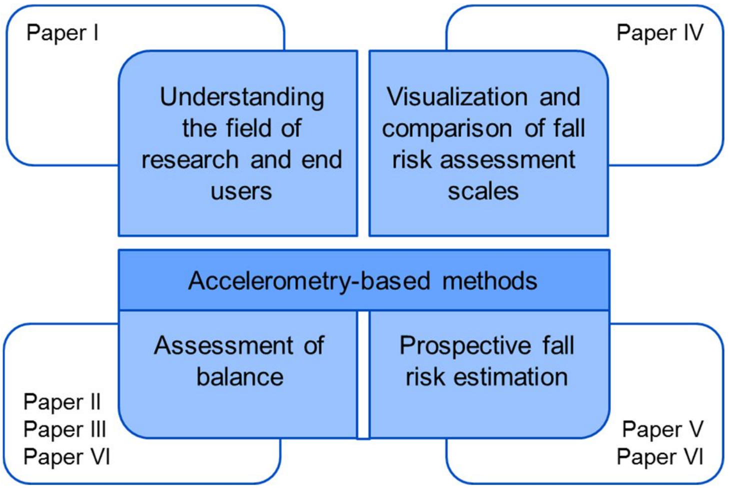

Figure 1. Grouping of the original publications according to research questions.

1.4 Author's contributions

In Paper I the author was the main responsible for the scenario about self-monitoring of fall risk and commented also the other scenarios. The author participated in the focus groups as one of the moderators and was responsible for the data analysis and the corresponding author of the publication. All the authors of the paper participated in deriving the scenarios. Milla Immonen, Patrik Eklund and Tuula Petäkoski-Hult acted as moderators in the focus groups in Finland and Carlos Garcia Gordillo was the main responsible for organizing the corresponding focus groups in Spain.

In Paper II the author participated in data collection with Ari Saarinen and was the main person responsible for the data analysis and writing of the paper. Jouni Kaartinen coordinated the study design and implementation. Ari Saarinen and Ibrahim Mahjneh were the medical experts of the study. Mikko Lindholm was responsible for the acceleration sensor tilt normalization algorithm, which the author utilized in the data analysis.

In Paper III the author was the main person responsible for the data analysis and writing of the paper. Juho Merilahti and Miikka Ermes were responsible for designing and implementation of the data collection. Jani Mäntyjärvi and Miikka Ermes were the supervisors of the data analysis. Mikko Lindholm was responsible for the gait pattern extraction algorithm utilized in the data analysis.

In Papers IV, V and VI the author was the main person responsible for the design and implementation of the data collection together with Milla Immonen and was primarily responsible for the data analysis and writing of the papers. In Paper IV the author was responsible for applying and testing of an existing data analysis algorithm in a novel context, i.e. fall risk assessment. Tuula Petäkoski-Hult participated in preparation of the study and data collection, and Juho Merilahti participated in data collection. Miikka Ermes was the supervisor in data analysis for Paper VI.

2. Literature review

2.1 Older people and falls

In a global perspective, as fertility declines and life expectancy rises, the proportion of people aged 60 years or more is rapidly increasing (United Nations Department of Economic and Social Affairs Population Division, 2015). The population is aging throughout the world and, for example, in Finland it is estimated that in 2060 28.8% of population will be more than 65 years old while in 2010 it was 17.5% (Official Statistics of Finland (OSF), 2015).

Each year, 28–35% of people over 65 years old experience a fall and the percentage of fallers increases with age and frailty level. The frequency of falls is even higher in nursing homes, where 30–50% of older people living in long-term care institution fall each year (World Health Organization, 2007). A common consensus on a definition of a fall is still lacking. The definition by the Kellogg International Working Group on prevention of falls in the elderly defines a fall as "an unintentionally coming to the ground or some lower level as a consequence of sustaining a violent blow, loss of consciousness, sudden onset of paralysis as in stroke or an epileptic seizure" (Gibson, Andres, Isaacs, Radebaugh, & Worm-Petersen, 1987). One commonly used definition by the World Health Organization (WHO) defines a fall more broadly as "inadvertently coming to rest on the ground, floor or other lower level, excluding intentional change in position to rest in furniture, wall or other objects" (World Health Organization, 2007). It does not specify what caused the fall and thus it is not limited to any specific type of fall.

Falls may have serious consequences on a person's health and quality of life. More than 50% of injury-related hospitalizations of people over 65 years old are caused by falls (World Health Organization, 2007). In a study by Parkkari et al. (1999) 98% of hip fractures were the result of a fall and subsequent impact on the greater trochanter of the proximal femur. Falls are also major contributors to immobility and premature nursing home placement (Rubenstein, 2006). According to Vellas et al. (1997) one third of people who have fallen develop fear of falling again, which is associated with balance, gait and cognitive disorders and thus decreases the level of mobility. Furthermore, falls cause mortality and a majority of accidental falls leading to death occur for people over 65 years (Official Statistics of Finland (OSF), 2011). For example in Finland, 1390 people over 65 years old died in fatal accidents in 2009 and 70% of those were caused by falls (Official Statistics of Finland (OSF), 2011).

2.2 Fall risk factors

A fall risk factor is defined by Rubenstein & Josephson (2006) as “a characteristic that is found significantly more often in individuals who subsequently experience an adverse event than in individuals who do not experience the event”. Falls are usually multifactorial in their origin and one single fall risk factor behind a fall cannot be identified (Rubenstein & Josephson, 2006). Furthermore, risk of falling increases with the number of risk factors possessed by the person (Tinetti, Speechley, & Ginter, 1988). Taxonomy of fall risk factors vary between studies, but often the risk factors are divided into intrinsic and extrinsic risk factors (Ambrose et al., 2013; Bueno-Cavanillas, Padilla-Ruiz, Jimeâ Nez-Moleoâ N, Peinado-Alonso, & Gaâ Lvez-Vargas, 2000; Cesari et al., 2002; Perell et al., 2001; Rubenstein & Josephson, 2006). Intrinsic risk factors refer to, e.g. psychosocial and demographic factors, such as advanced age, postural instability, sensory and neuromuscular factors, medical factors, and drugs (Lord et al., 2001; Rubenstein & Josephson, 2006). Extrinsic factors on the other hand refer to environmental hazards and poor footwear, as examples (Lord et al., 2001; Rubenstein & Josephson, 2006). The intrinsic and extrinsic fall risk factors are summarized in Figure 2. According to Rubenstein et al. (Rubenstein & Josephson, 2006) 25–45% of the falls among older adults are accidental or triggered by environmental hazards. Analysis of fall circumstances and symptoms near the time of falling may point to a specific aetiology or differential diagnosis. For example, a sudden rise from a lying or sitting position may induce orthostatic hypotension, or a trip or slip may be caused by gait, balance or vision disturbance or an environmental hazard. Although, a person having experienced a fall may have poor recollection of the event him/herself and reports from witnesses are important (Rubenstein, 2006).

Intrinsic fall risk factors

- Gait and balance impairment
- Vestibular dysfunction
- Medical condition
- Drugs
- Cognitive impairment
- Vision problems
- Poor muscle strength
- Fear of falling

Extrinsic fall risk factors

- Environmental hazards
- Poor footwear

Figure 2. Intrinsic and extrinsic fall risk factors.

2.2.1 Intrinsic fall risk factors

2.2.1.1 Balance and gait

Postural control requires integration of several sensorimotor processes and resources for perceiving body orientation in space, interpreting sensory information, coordinating movement strategies to maintain stance position, control the centre-of-mass (CoM) dynamics during gait, cognitive processing of the postural task, and biomechanical constraints for controlling the CoM (Horak, 2006). The human vestibular system consists of three components: a peripheral sensory apparatus, a central processor, and a mechanism for motor output (Hain & Helminski, 2007).

The peripheral vestibular system is located in the inner ear and it consists of membranous and bony labyrinths, and the motion sensors called “the hair cells”. The bony labyrinth has three semi-circular canals, the cochlea, and a central chamber, the vestibule, all filled with perilymphatic fluid. The membranous labyrinth, filled with endolymphatic fluid, is suspended within the three canals of bony labyrinth and has the two otolith organs, the utricle and saccule, inside the vestibule. One end of each semi-circular canal is widened to form an ampulla. The ampullae and the otolith organs contain the specialized hair cells that sense head motion, gravity and linear acceleration. Due to the orientation and differences in their fluid mechanics, the canals and otolith organs respond selectively to head motion in a particular direction, and to angular and linear accelerations (Hain & Helminski, 2007). Vestibular dysfunction can cause symptoms of dizziness, such as vertigo and imbalance, which can culminate in a fall in some cases (Agrawal, Carey, Della Santina, Schubert, & Minor, 2009).

Normal human gait can be defined as “a method of locomotion involving the use of two legs, alternately, to provide both support and propulsion at least one foot being in contact with the ground at all times”. The gait cycle is considered as a time interval between two successive occurrences of initial contact of one foot, for example the right foot. The gait cycle constitutes two phases: stance phase, where the foot is on the ground, and swing phase, where the foot is in the air. The stance phase has four periods starting from initial contact: 1) loading response until the opposite toe lifts off the ground, 2) mid-stance until the heel starts to rise, 3) terminal stance until the opposite heel touches the ground, and 4) pre-swing until the toe lifts off the ground and the swing phase begins. The swing phase has three stages: 1) initial swing until the feet become adjacent to each other, 2) mid-swing until the tibia of the leg is in a vertical position, and 3) terminal swing until the heel touches the ground again (subsequent initial contact). (Whittle, 2007)

Spatial and temporal characteristics of the different periods of the gait cycle are often studied to give insight on a person’s dynamic postural control. Advanced age affects the motor skills of a person and causes changes in gait. Gait and balance disorders affect 20–50% of people over 65 years old (Rubenstein & Josephson, 2006). It has been observed that older people have faster horizontal heel contact velocity, shorter step length and slower transitional acceleration of the whole body CoM compared to younger people (Lockhart, Woldstad, & Smith, 2003). Increased gait variability has been associated with history of falls (Toebes, Hoozemans, Furrer, Dekker, & van Dieën, 2012) and it also indicates increased prospective fall risk among community-living older adults (Hausdorff, Rios, & Edelberg, 2001).

2.2.1.2 Medical condition and drugs

Prevalence of chronic diseases increases with age and it is increasingly common for older people to have multiple medical conditions at the same time (Salive, 2013). Medical conditions often require medication treatment, which can themselves be a risk factor for falls. Especially bentzodiazepines, antidepressants and antipsychotics were found to be associated with an increased risk of falling (Hartikainen, Lönnroos, & Louhivuori, 2007) and the risk further increases with use of polypharmacy if at least one drug known to increase falling risk is in use (Ziere et al., 2005). Parkinson’s disease is a degenerative disorder that affects the motor system. Risk of falling increases with disease severity and in particular previous falls, disease duration, dementia, and loss of arm swing were found as independent predictors of falling in idiopathic Parkinson’s disease patients (Wood, Bilclough, Bowron, & Walker, 2002). Other medical factors associated with increased risk of falling are, for example, stroke (Forster & Young, 1995), depression (Whooley et al., 1999), arthritis (Campbell, Borrie, & Spears, 1989), foot problems (Menz, Morris, & Lord, 2006a), and urinary incontinence (Tromp et al., 2001).

2.2.1.3 Cognitive impairment

Cognitive impairment is a psychological factor that affects 5–15% of persons over 65 years old and it almost doubles the risk of falling (Rubenstein & Josephson, 2006). Even subtle deficits in executive function was found to be associated with increased risk of falling and fall injuries (Muir, Gopaul, & Montero Odasso, 2012). Confusion and cognitive impairment may refer to an underlying systemic or metabolic process or dementing illness. E.g., dementia can impair judgement, visuospatial perception, and orientation ability, and thus increase the risk of falls (Rubenstein & Josephson, 2006).

2.2.1.4 Vision problems

Visual acuity and contrast sensitivity decline with age (Lord, Clark, & Webster, 1991). Problems with seeing objects at close range or reading small print is compensated with multifocal glasses, which doubles the risk of falling (Reed-Jones et al., 2013). Furthermore, restricted vision and reduction in visual processing speed increase response time when facing external obstacles, and thus increase the risk for trips, slips and falls (Reed-Jones et al., 2013). According to Ray et al. (2008), restricted vision affects negatively overall postural stability and individuals with vision loss employ more hip strategy, i.e. bend the upper body forward, to maintain their balance.

2.2.1.5 Poor muscle strength

Muscle strength declines rapidly in old age. In a study by Goodpaster et al. (2006) the annual decline in muscle strength was 2.6% to 4.1% among people aged 70 to 79 years. Moreland et al. (2004) concluded in their review that especially lower extremity muscle weakness is a significant risk factor for falls. Pijnappels et al. (2008) suggest that the assessment of capacity to generate maximum extension force by the whole leg can be used to distinguish between fallers and non-fallers.

Vitamin D has been shown to have a direct effect on muscle strength and function, and thus is associated with frailty and falls (Halfon, Phan, & Teta, 2015). According to a review by Halfon et al. (2015) vitamin D supplementation has contributed to a reduction of falls in several studies with older adults..

2.2.1.6 Fear of falling

Fear of falling is a psychological factor and a major risk factor for falling (Ambrose et al., 2013; Yardley et al., 2005). One third of older people that fall develop a fear of falling again (Vellas, Wayne, Romero, Baumgartner, & Garry, 1997), and up to 40% of people who are afraid of falling will restrict their activities of daily living (Ambrose et al., 2013). This in turn may lead to functional decline, social isolation and decreased quality of life (G. A. R. Zijlstra et al., 2007).

2.2.2 Extrinsic fall risk factors

Environmental hazards at home and in the community are often reported as causes of falls, especially related to trips and slips, although the primary reason seems to be intrinsic rather than extrinsic (Lord et al., 2001). The falls caused by environmental hazards are many times a result of interactions between hazards or hazardous activities and increased individual susceptibility from accumulated effects of age and disease (Rubenstein & Josephson, 2006). Some of the general environmental fall risk factors reported are, e.g., slippery floors or other surfaces, rugs, pets, inappropriate furniture, stairs too steep or without handrails, obstacles on walkways, crowds, certain weather conditions (leaves, snow, ice, rain), brief cycles of traffic lights, and lack of places to rest outdoors (Lord et al., 2001). Poor footwear, such as high-heel shoes, can increase the risk of falling (Menant, Steele, Menz, Munro, & Lord, 2008). Walking barefoot or wearing socks only indoors has been shown to be associated with risk of falling (Menz, Morris, & Lord, 2006b).

2.3 Fall risk assessment

Fall risk assessment is done on different levels and with different methods depending on target population (Rubenstein & Josephson, 2006). In general, tools assessing intrinsic characteristics of the patient are the most appropriate and efficient in the acute care setting. In an outpatient setting, on the other hand, the focus should be primarily on functional status as in mobility and balance assessment. In the extended care setting nearly every patient is at high risk for falls and universal precautions for fall prevention may be the most efficient (Perell et al., 2001). It is not always easy for a health care professional to decide which assessment scales to use, and thus there are several studies that aim to compare the outcomes of some commonly used assessment scales (Lajoie & Gallagher, 2004; Scott et al., 2007; Tiedemann, Shimada, Sherrington, Murray, & Lord, 2008). Perell et al., (2001) recommend the following criteria for choosing the most appropriate assessment tool: “high sensitivity, specificity, and interrater reliability; similarity of patient population to ones in which the instrument was developed or studied; written procedures explicitly outlining appropriate use of the form; reasonable time required to administer the scale; and established thresholds identifying when to initiate interventions.”. Furthermore, a distinction should be made whether the assessment scale is meant for predicting the possibility of a fall in the future, or does it assess the presence or magnitude of a certain risk factor. The following subsections review some of the most common fall risk assessment tools. Typically, an assessment tool addresses more than one particular intrinsic or extrinsic risk factor, or several tools are used in combination. The description of tools is divided based on the target of the assessment into multifactorial, postural control and mobility, physiological factors, psychological factors and other risk factors.

2.3.1 Multifactorial fall risk assessment tools

The Downton Index is an example of a fall risk assessment tool that takes into account several risk factors and, as an example, it has been validated among patients in stroke rehabilitation (Nyberg & Gustafson, 1996) showing moderate association between predicted risk and the observed outcome regarding falls. The fall prediction sensitivity was 91%, but the specificity was limited to 27% (Nyberg & Gustafson, 1996). The Downton index is a sum of 11 risk factors under the following categories: previous falls, medication, sensory deficits, mental state, and gait. A score of 3 or more on a range 0–11 indicates high risk of falls (Downton, 1993).

Fall Risk for Older People in the Community (FROP-Com) is a tool that covers 13 risk factors in 26 questions with scoring from 0 to 3. The total score ranges from 0 to 60, with higher scores indicative of greater falls risk. In a sample of high-risk older people the FROP-Com was able to predict 71.3% of fallers and 56.1% of non-fallers. (Russell, Hill, Blackberry, Day, & Dharmage, 2008) Russel et al. (2009) have further developed a shorter version of the test for initial screening in time-limited situations. It showed a sensitivity of 67.1% and specificity of 66.7% in predicting falls of community-dwelling older people. The logistic regression analysis resulted in three risk factors in the FROP-Com Screen tool: number of falls in the past 12 months, whether the person requires assistance to perform domestic activities of daily living (ADL), and observation of the person's balance. All three items are scored 0–3. A score of more than 4 points indicates high risk of falling (Russell et al., 2009).

Falls Risk Assessment Tool (FRAT) includes two parts: the first one administrated by clinical or non-clinical staff for identification of those at higher risk of falling and the second for clinical staff for guidance with regard to further assessment, referral options and intervention for those identified as high risk. Part 1 has five questions about previous falls, taking four or more medications per day, diagnosis of stroke or Parkinson's disease, balance problems, and ability to rise from a chair without using arms. Presence of three or more risk factors was indicative of fall risk with a positive predictive value of 0.57. The first two items of the second part are the same as in part 1; balance and gait assessment are covered in more depth and testing for postural hypotension was included to finally cover four risk factor areas (Nandy et al., 2004).

The assessment tools introduced above are not the complete list of tools developed and used in clinical practice. What is common between these scales is that they all ask about the falls history. In fact, the National Institute for Health and Welfare (THL) in Finland recommends for a health care professional that every time they see an older person they should ask "Have you fallen during the last 12 months?" (Pajala, 2012). Follow-up measures are determined based on the answer. Furthermore, each of the scales somehow includes evaluation of balance or gait, either by self-report or observation.

2.3.2 Postural control and mobility assessment

Postural stability when standing is usually tested by observing a person performing a certain stability task. It can be a measure of spontaneous postural sway during standing (Maki, Holliday, & Topper, 1994). A more challenging task is to have a person stand with their feet together (Kirby, Price, & MacLeod, 1987), eyes closed (Lord, Rogers, Howland, & Fitzpatrick, 1999) or on one foot (Vellas, Wayne, Romero, Baumgartner, Rubenstein, et al., 1997). The more challenging the stability task is, the stronger its evidence in indicating increased fall risk (Lord et al., 2001). Postural stability can also be challenged by reaching forward with feet fixed on place and measuring the maximum distance the arms can reach (Duncan, Weiner, Chandler, & Studenski, 1990). In addition, the subject's sensory or motor systems responses to external stimuli can be evaluated by external perturbation (Lord et al., 2001), which is important in preventing falling in such situations. Different devices have been developed for objective assessment of postural balance, for example, a sway meter or posturography apparatus (Lanska, 2002), or a force platform (Piirtola & Era, 2006).

Lord et al. (2001) describe a choice stepping reaction test that measures a person's 1) perception of a postural threat, 2) selection of an appropriate corrective response, and 3) proper response execution. The subjects stand on a platform containing four panels that are illuminated in random order. The subjects are instructed to step on the illuminated panel as quickly as possible. The people with a history of falls had significantly increased choice reaction stepping times compared to the people with no history of falls (Lord et al., 2001).

Another example of a stepping test is an alternate-step-test (AST), where the subject alternatively places the entire left and right foot onto a step 18 cm in height as fast as possible, eight times (Tiedemann et al., 2008). In a comparative study by Tiedemann et al. (2008), where eight functional mobility tests were compared, the AST was the second most useful test for discriminating fallers from non-fallers by means of validity, reliability and feasibility. They suggested a cut-off point of 10 seconds for discriminating multiple fallers from non-multiple fallers. The most useful test in that study was sit-to-stand five times (STS-5). In STS-5 the subjects are instructed to fully stand up from a chair 5 times as quickly as possible and the examiner records the time for completing the repetitions. Whitney et al. (2005) suggest that 14.2 seconds is an optimal cut-off score for identifying older people with balance disorders (S. L. Whitney et al., 2005).

TUG is an example of a test that combines multiple tasks (Podsiadlo & Richardson, 1991). In the TUG test the subject is first asked to sit on a chair. When that start command is given; the subject stands up, walks over the three-metre marker (e.g. piece of tape on the floor), turns around, walks back to the chair and sits down again. The time of 13.5 seconds is suggested as a cut-off point for identifying fallers from non-fallers (Shumway-Cook, Brauer, & Woollacott, 2000). Although the TUG is widely used as a screening tool, a more recent meta-analysis showed that TUG alone has a limited ability to predict falls in community dwelling older adults (Barry, Galvin, Keogh, Horgan, & Fahey, 2014).

The Performance-Oriented Mobility Assessment (POMA) tool developed by Tinetti (Tinetti, 1986) has two parts, balance and gait, with specific tasks evaluated based on visual assessment on a scale 0 to 2 points. The overall balance score range is 0–16 and gait score 0–12. Patients with a total score lower than 19 have a high risk of falling, 19–23 moderate fall risk and a score of 24 or more indicates low risk of falling.

The BBS constitutes 14 tasks that are increasingly demanding; sitting to standing, standing unsupported, sitting unsupported, standing to sitting, transfers, standing with eyes closed, standing with feet together, reaching forward with outstretched arm, retrieving object from floor, turning to look behind, turning 360 degrees, placing alternate foot on stool, standing with one foot in front, standing on one foot (Berg et al., 1989). Each task is scored 0–4, four meaning task execution according to instruction without problems, resulting in a maximum score of 56 points. Although a score of 45 is often recommended as a cut-off score for identifying people at risk of falling, it rather discriminates between people at risk for multiple falls instead of any fall (Muir, Berg, Chesworth, & Speechley, 2008). Muir et al. (2008) recommend that instead as a dichotomous scale the BBS should be used in multilevel form with likelihood ratios, as it preserves the gradient of risk across the whole range of scores. Furthermore, they emphasize the multifactorial nature of fall risk estimation and suggest the balance assessment through BBS to be integrated with other fall risk information to predict future falls.

Gait speed is an often-used method for assessing functional capacity of a person. The distance for gait speed assessment is usually four or six metres (Abellan Van Kan et al., 2009). Older people can be categorized as slow, intermediate, or fast walkers using cut-off points of 0.6 and 1.0 ms^{-1}, respectively, and there are several studies that have found an association between slower walking speed and falls (Abellan Van Kan et al., 2009). Gait speed has also been shown to be associated with other adverse outcomes and survival of older adults (Studenski et al., 2011). Mortaza et al. (2014) reviewed several studies that have investigated the ability of spatio-temporal parameters of gait in predicting falls of older people. The results showed a tendency that older people who have fallen have a slower walking speed and cadence, longer stride time, double support duration, shorter stride and step length, wider step width and more variability in the spatio-temporal parameters of gait. However, the spatio-temporal analysis alone is not an adequate predictor of falls in older people (Mortaza, Abu Osman, & Mehdikhani, 2014).

2.3.3 Physiological factors

Physiological Profile Assessment (PPA) combines several aspects of individual fall risk. The PPA includes tests for vision, peripheral sensation, lower limb strength, reaction time and body sway. Visual acuity is measured using a letter chart with high- and low-contrast letters at a three-metre distance. The size of the letters is smaller on each line and the score for the test depends on the lowest line on which the subject can correctly read the letters. In the contrast sensitivity test the subject is asked to identify the orientation of an edge between two areas on twenty circular patches that have reducing contrast. The visual field dependence test assesses indirectly vestibular function by placing vision in conflict with a rotating visual stimulus while the subject is asked to align a straight edge to the true vertical position. Peripheral sensation tests include 1) test for tactile sensitivity by touching the subject's ankle with filaments with varying diameter, 2) vibration sense measurement with an electronic vibration generator, and 3) proprioception test by measuring the difference in aligning the lower limbs while the subject is seated with eyes closed. The maximal isometric muscle force is measured for knee flexors, knee extensors and ankle dorsiflexors. Reaction times of a finger and foot for a light stimulus are assessed with an electronic timer. Postural sway is assessed with a sway meter that measures displacement of the body at the waist level. The test is performed four times for 30 seconds, if possible, on a firm surface, and on a 15-cm-thick medium-density foam rubber mat, both with the subject's eyes open and eyes closed. The screening version of the PPA contains five of the abovementioned tests: edge contrast sensitivity for vision, proprioception for peripheral sensation, knee extension force for lower-extremity force, finger reaction time, and body sway on a medium-density rubber mat (Lord, Menz, & Tiedemann, 2003).

Muscle strength alone, especially in the lower body, has also been shown to predict falls in older adults (Moreland et al., 2004). The methods for muscle strength measurement vary from timed chair stands to dynamometer devices (Moreland et al., 2004).

2.3.4 Psychological factors

The Falls Efficacy Scale-International (FES-I) is a questionnaire with 16 items about a person's concerns about falling while doing specific everyday activities, such as cleaning the house, preparing meals, taking a bath, walking in different situations, etc. (Yardley et al., 2005). Each item is answered on a four-point scale from 1="Not at all concerned" to 4="Very concerned". A score of more than 23 (range 16 to 64) is suggested as a cut-off point for indicating high concern about falling (Delbaere et al., 2010). Another test for fear of falling is the Activities-specific Balance Confidence (ABC) scale (Powell & Myers, 1995). It has also 16 items inquiring the level of self-confidence on not losing balance or become unsteady while doing specific everyday activities. The answer is given as a percentage from 0% to 100% (as full ten-point increments). The total ABC score is an average rating of all 16 items. A score of 67% is suggested as a cut-off point for predicting geriatric fallers (Lajoie & Gallagher, 2004).

Mini-Mental State Examination (MMSE) is a scale intended for short-term memory and cognitive state assessment. It has tasks that require vocal responses to questions that cover orientation, memory and attention. In addition, there are tasks that test the subject's ability to name objects, follow verbal and written commands, write a sentence spontaneously, and copy a complex polygon showed to them. The maximum score of the test is 30 (Folstein, Folstein, & McHugh, 1975). If the score is 24 or less, the result is considered deviant (Pajala, 2012).

The Geriatric Depression Scale (GDS) is a tool with 15 questions each scored as 1 or 0 points. The questions ask about the subject's feelings, such as satisfaction with life, emptiness, happiness, etc., over the past week. A score of more than 5 points is suggestive of depression and a score of 10 or more points is almost always indicative of depression (Kurlowicz & Greenberg, 2007).

2.3.5 Assessment of other risk factors

Other assessments associated with fall risk that are suggested for use are, for example, environmental checklists that infer to eliminate home hazards, such as loose or frayed rugs, trailing electrical cords, and unstable furniture, or ensure adequate lightning, bathroom grab rails, etc. (Rubenstein, 2006). Furthermore, nutrition, alcohol, medication and specific medical conditions are often part of comprehensive fall risk assessment (Pajala, 2012). The following figure (Figure 3) summarizes the different fall risk assessment scales referred to in this thesis.

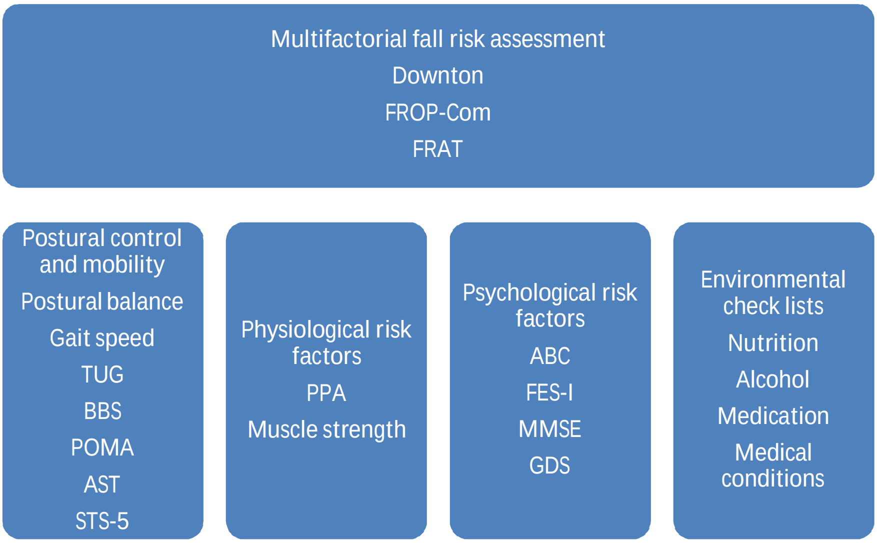

Figure 3. Summary of fall risk assessment scales.

2.4 Accelerometry-based postural control and balance assessment

Body-worn sensors have been increasingly applied in fall risk screening and assessment, as they are inexpensive, small, portable, and can provide movement information during daily-life tasks. Typically, accelerometers, gyroscopes or their combination are used for sensing body movements. The accelerometers alone are used in the majority of the fall risk assessment studies, i.e. in 70% of the studies reviewed by Howcroft et al. (Howcroft et al., 2013). In a more specific movement analysis, e.g., assessment of kinematic gait parameters a whole Inertial Measurement Unit (IMU) containing accelerometer, gyroscope, and magnetometer provides higher detection accuracy of gait events (Caldas, Mundt, Potthast, Buarque de Lima Neto, & Markert, 2017). However, this literature review focuses specifically on accelerometry-based methods. The most common sensor location is to place it on the lower back, near the CoM, while assessing certain activities, such as level walking, TUG, STS, AST, etc. Other locations sensors are used are the head, upper back, sternum, shoulder, elbow, wrist, hip, thigh, knee, shank, ankle, and foot (Howcroft et al., 2013).

In general, the signals produced by the wearable sensors are often preprocessed, e.g. filtered, and a set of features are extracted from them. The features are further utilized by machine learning methods to form a classification or regression model to assess the fall risk or estimate the probability of falls. The model typically tries to classify subjects into high fall risk and low fall risk groups, or fallers and non-fallers, or to calculate a certain risk estimate. If previous falls, or fall history are used as a reference in model specification, the resulting model is retrospective, as it aims to classify subjects based on their experienced falls. More recently the research has moved more and more towards development of prospective fall risk estimation, where fall incidents after, e.g. one year, are used as the reference (Shany, Wang, Liu, Lovell, & Redmond, 2015).

Howcroft et al. (2013) reviewed studies that applied inertial sensors in fall risk assessment. Their findings showed that 15% of studies classified subjects according to prospective falls occurrence data, 30% using retrospective falls history, and 32.5% used clinical assessment as their reference. The rest used a combination of retrospective falls occurrence and clinical assessments. According to the review, the accuracy of the predictive models varied between 62–100% (Howcroft et al., 2013). However, Palumbo et al. (2015) suggest that the theoretical maximum accuracy of an ideal prognostic tool would not be more than 81% (Palumbo, Palmerini, & Chiari, 2015). This implies that the methods used in the studies achieving prominently high prediction accuracies should be critically inspected (Shany et al., 2015).

2.4.1 Acceleration sensor

The accelerometer's operation is based on Hooke's law, where a mass responds to acceleration by causing a spring or an equivalent component to stretch or compress proportionally to the measured acceleration. The accelerometers may be based on piezoelectric, piezoresistive, or variable capacitance methods of transduction. It should be noted that the accelerometers sense the gravitational acceleration in addition to movement-related acceleration, and the resulting signal is a sum of the two. In triaxial devices, that measure three-dimensional (3D) acceleration, there are three sensitive axes mounted orthogonally to one another (Shany, Redmond, Narayanan, & Lovell, 2012). It can be assumed that the human body movements are contained within frequency components below 20 Hz (Karantonis, Narayanan, Mathie, Lovell, & Celler, 2006), and with a sampling rate of 30 Hz one can capture

99% percent of the signal power in gait (Antonsson & Mann, 1985). Human activity recognition applications have worked well with an accelerometer sensitivity of ±2g (g denoting gravitational acceleration of 9.81 ms^{-1}) (Bao & Intille, 2004), although daily physical activities may produce accelerations up to 10g measured at the waist level (Jämsä, Vainionpää, Korpelainen, Vihriälä, & Leppäluoto, 2006).

2.4.2 Signal pre-processing and feature extraction

Before feature extraction the raw signals provided by accelerometers are often filtered to remove noise and to separate body acceleration from gravitational acceleration. For example, a low pass filter with a cut-off frequency at 0.25 Hz has been applied to separate the gravity component of the acceleration (Karantonis et al., 2006; Liu et al., 2011). The gravitational component can be utilized in determining the postural orientation of a subject (Shany et al., 2012), while the other component, obtained by subtracting the gravity component from the original signal, contains the accelerations produced by body motions (Karantonis et al., 2006). Feature extraction may be applied separately to all three signals, *x*, *y*, and *z*, measured by the 3D accelerometer, representing anteroposterior, mediolateral, and vertical directions of movement, or to resultant acceleration, which is a squared sum of the three signals. Resultant acceleration is calculated as

$$a(t) = \sqrt{\left(a_x(t)\right)^2 + \left(a_y(t)\right)^2 + \left(a_z(t)\right)^2} \qquad (1)$$

where a_x, a_y, and a_z represent accelerations of the *x*, *y* and *z* axes, respectively.

Howcroft et al. (2013) identified 130 distinct features calculated from the inertial sensor data (some of them extracted also from gyroscope signals) that were applied in fall risk assessment. According to their categorization 7.7% were position and angle, 11.5% angular velocity, 20% linear acceleration, 3.8% spatial, 23.1% temporal, 3.8% energy, 15.4% frequency and 14.6% other type of features. They listed 13 features that were found to be significant covariates in more than one study: 1) mediolateral and anteroposterior postural sway length; 2) mediolateral and anteroposterior sway velocity; 3) ratio of mean squared modulus of postural sway; 4) standard deviation (SD) of anteroposterior acceleration; 5) root mean square (RMS) amplitude of vertical linear acceleration; 6) gait speed; 7) sit-to-stand transition duration; 8) dominant Fast Fourier Transform (FFT) peak parameters derived from lower back linear acceleration signals; 9) ratio of even to odd harmonic magnitudes derived from head, upper back, and lower-back linear acceleration signals; 10) area under the first six harmonics divided by the remaining area for lower-back linear acceleration signals; 11) ratio of the first four harmonics to the magnitude of the first six harmonics for lower-back linear acceleration signals; 12) maximum Lyapunov exponent of angular velocity signal; and 13) discrete wavelet transform parameters from lower-back angular velocity and linear acceleration signals and sternum linear acceleration signals (Howcroft et al., 2013). In a study by Narayanan et al. (2010)

several temporal and energy-related features were evaluated for fall risk assessment. Besides duration between successive time markers of the AST test, they obtained a normalized SD of AST time differences and STS-5 dissimilarity of sit-to-stand cycles as predictors in their fall risk model (Narayanan et al., 2010). Liu et al. (2011) expanded the study further by adding frequency domain features to the pool of features and were able to improve the correlation between accelerometry-based estimates and clinical fall risk assessment.

Accelerometry-based gait analysis has been applied to fall risk assessment by many researchers. In fact, walking was the most frequently (in 45% of the reviewed studies) assessed activity for inertial-sensor-based fall risk assessment (Howcroft et al., 2013). Features extracted from gait signal have been, e.g., gait speed, number of steps, cadence, step time, step length, step-time asymmetry, stance time, step and stride regularity/variability, amplitude and width at the dominant frequency in the power spectral density, harmonic ratio, inter-stride amplitude variability, and RMS of the accelerometer data (Bautmans, Jansen, Van Keymolen, & Mets, 2011; Menz, Lord, & Fitzpatrick, 2003a; Mortaza et al., 2014; Senden, Savelberg, Grimm, Heyligers, & Meijer, 2012; Weiss et al., 2013). Many of these features require step detection from the acceleration signal. An often-used method is peak detection from anteroposterior acceleration, since the peak acceleration coincides with the foot contact phase of the gait cycle (W. Zijlstra & Hof, 2003). Figure 4 shows an example of one subject's acceleration during gait.

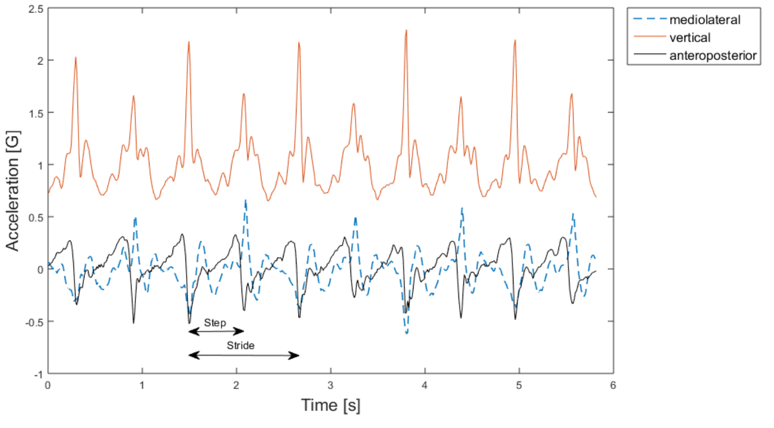

Figure 4. Example of gait acceleration measured in mediolateral, vertical and anteroposterior directions with an accelerometer attached to the lower back near the CoM. Intervals representing one step and one stride are indicated with double arrows in the figure.

2.4.3 Fall risk estimation

Building of a model for fall risk estimation has three main steps: 1) selecting the features to be used in the model; 2) training of the selected model with the training data set; and 3) validating the model with the test data set. There are several methods used in the literature for each of the steps. The feature selection should be performed only with the training data set, although due to the limited available data sets it is not often realized in many of the studies in this field (Shany et al., 2015).

2.4.3.1 Feature selection

Two commonly used feature selection methods are sequential forward selection (SFS) (A. W. Whitney, 1971) and sequential forward floating selection (SFFS) (Pudil, Novovicová, & Kittler, 1994). The SFS algorithm starts with an empty feature subset. During each step, all the remaining features, not yet selected, are considered and the feature that gives the best score on the selection criteria is included. Selection criteria can be, e.g., a distance measure or a classification result. The step is repeated with the remaining feature pool as long as a predetermined number of features has been selected, or the threshold set for minimum improvement of the selection criteria score is not reached anymore. The SFS has a nesting effect that can be avoided with the SFFS algorithm. In the SFFS algorithm, after the inclusion of one feature, a backtracking phase begins, where features can be excluded. The least significant feature in the selected feature pool is determined. If it is the last one added, the algorithm goes back to selecting a new feature by SFS. Otherwise the least significant feature is excluded and moved back to the set of available features and conditional exclusion is continued. Exclusion is carried out for as long as better feature subsets of the corresponding sizes are found. After that, the cycle starts all over again with SFS, and is repeated until the previously defined subset size is reached.

If the number of extracted features is high and the sample size is limited it may lead to a situation where the classification algorithm learns the data at hand very well, but has much lower performance when used with other data. Dimensionality reduction methods may be used to avoid overfitting the classification algorithm and the following are just couple of examples of such methods. For example, a correlation matrix can be used to find features that are highly correlated with each other and thus are good candidates to be merged (Duda, Hart, & Stork, 2001). Also, Principal Component Analysis (PCA) has been applied to extract new features that account for most of the data variability and they are used to find a reduced set of features from the original pool that correlate with the principal components (Palmerini, Mellone, Rocchi, & Chiari, 2011).

2.4.3.2 Modelling, classification and clustering of fall risk

Different methods have been applied to derive a model for fall risk assessment, fall prediction or distinguishing fallers from non-fallers. From the papers included in the review by Howcroft et al. (2013), 65% used regression models, 15% decision trees, 10% support vector machines (SVM), 10% cluster analysis, and 25% other classifiers such as the Bayesian classifier. 30% of the reviewed studies used more than one method. The highest levels of sensitivity and specificity were 91.3% and 83.3% for retrospective fall history and, respectively, the levels were 74% and 82% for the prospective falls estimation. However, half of the studies did not have separate data sets for model training and validation, which limits the applicability of the results in a wider population (Howcroft et al., 2013; Shany et al., 2015).

Regression analysis aims to find the relationship between one or more independent variables (predictors) and the dependent variable. In logistic regression modelling the outcome, i.e. the dependent variable, is binary and can have two values, e.g. faller vs. non-faller. Furthermore, the generalized linear models use linear methods, but allow also a nonlinear relationship between a response and predictors (McCullagh & Nelder, 1989). A regression model for an outcome S is expressed as

$$S = w_0 + w_1 X_1 + \cdots + w_N X_N \tag{2}$$

where w_i is the weight for predictor X_i.

In a classification problem the outcome classes are known beforehand. The Bayesian classifier uses prior probabilities of the features to derive posterior probabilities of a new sample belonging to each of the outcome classes and the class with the highest probability (or the lowest probability of error) is selected. The method applies Bayes' formula

$$P(\omega_j|\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\omega_j)P(\omega_j)}{p(\boldsymbol{x})} \tag{3}$$

where $P(\omega_j|\boldsymbol{x})$ is the posterior probability of an outcome to belong to class ω_j, when a feature vector has values $\boldsymbol{x}$. $P(\omega_j)$ is the prior probability of class ω_j, $p(\boldsymbol{x}|\omega_j)$ is the likelihood of ω_j with respect to $\boldsymbol{x}$, and $p(\boldsymbol{x})$ is the evidence (or the scale factor) for stating the probability of $\boldsymbol{x}$. The often-used simple naïve Bayesian classifier takes the assumption that the input features are conditionally independent given the class (Duda et al., 2001).

The minimum-distance classifier is one form of representing classification algorithm. It calculates the Euclidean distance $\|\boldsymbol{x} - \mu_i\|$ between the sample vector $\boldsymbol{x}$ and mean vectors μ_i, representing ideal vectors of each of the classes. The class to which the distance is smallest is selected. The k-nearest-neighbor (kNN) classifier calculates the distance to all training data set points. The resulting class for the sample under investigation is assigned based on a majority vote of the known classes of the k-nearest points. The performance of the kNN classifier relies on selection of the distance metric, e.g. Euclidean or Manhattan distances may be used (Duda et al., 2001).

The decision tree forms a widening tree structure, where the attribute is tested in each node against a rule and the following branch is selected based on the result. The final leaves of the tree represent the different classes. The number of layers in a tree depends on the application.

The SVM method maps the original data into a higher dimensional feature space, and then finds the optimal hyperplane that separates all the data points of one class from those of the other class. The optimal hyperplane is selected so that it has the maximum distance from the training samples representing different classes (Gunn, 1998).

The cluster analysis differs from classification in that the outcome classes are not necessarily determined beforehand. In cluster analysis the samples are grouped so that samples similar to each other form a group. Several clustering techniques exist, for example, k-means clustering where the aim is to group the data samples into k clusters. The cluster is assigned by finding the nearest mean, i.e. the prototype vector representing a cluster. These methods can also be used for unsupervised feature extraction as the training data may be unlabelled and the labels are given to the groups found in the data (Duda et al., 2001). An example of an unsupervised artificial neural network (ANN) method is a self-organizing map (SOM) that is especially useful for visualizing low-dimensional views of high-dimensional data. It uses method of competitive learning where a distance of the input vector to all the weight vectors is computed. The weights of the best matching reference vector and its neighbours are tuned closer to the input vector. The size of the neighbourhood set and the adaptation coefficient decrease monotonically over time, eventually resulting in a topologically organized representation of the data (Kohonen, 1990).

The classification methods described above are the most typically used in fall risk estimation studies, but also other classification techniques exist, such as fuzzy classifiers (Duda et al., 2001) and the random forest classifier that is used, e.g. in activity recognition applications (Casale, Pujol, & Radeva, 2011).

2.4.3.3 Model validation

In the ideal situation, the fall risk model training, i.e. the feature selection, model selection, fitting and hyperparameter tuning, are performed with a training data set and the obtained model is validated with another independent data set. However, in many cases the data available for building and validating a model is limited. It may lead to a situation where the model has learned the present data set well, but is not generalizable to other data sets.

The classifier performance is often evaluated based on prediction accuracy, sensitivity and specificity. Accuracy is the percentage of correctly predicted outcomes. Sensitivity of a model is the proportion of positives that are correctly identified, e.g., in fall risk estimation context subjects correctly classified as having increased fall risk. Specificity is the proportion of negatives correctly identified, respectively. In the holdout method the data set is randomly divided into training and testing sets, e.g. 2/3 of the data is used for training and 1/3 for testing, respectively. In the cross-validation method the data set is divided into *k* subsets (folds). The classifier is trained for each subset on the union of all the other subsets. The error rate of the classifier is the average of the error rates for each subset. When the size of the subset is one, the method is called leave-one-out validation and it is a special case of cross-validation (Kotsiantis, 2007). In repeated cross-validation the cross-validation is done multiple times with the same data, e.g. ten-times ten-fold cross-validation have been applied (Marschollek et al., 2008).

The Receiver Operating Characteristics (ROC) and Area Under Curve (AUC) methods can be applied to evaluate classifier performance. The ROC plot represents the sensitivity vs. 1 – specificity for the range of decision thresholds and thus provides a complete picture of test accuracy in discriminating between two outcomes (Zweig & Campbell, 1993). The AUC is determined as the area under the ROC curve and gives a single measure of a classifier performance (Bradley, 1997). The closer the AUC is to the value of one, the better the classifier performance.

3. Research contributions

3.1 Description of the data

The publications utilize four datasets summarized in Table 1. The data collection protocols and methods are described in more detail in the following sections.

3.1.1 Scenario evaluation in focus groups (Paper I)

Five different scenarios describing possible future technologies for fall risk assessment and fall prevention were jointly created with the research partners, having backgrounds in, e.g. in mathematics, economics, medicine and software engineering. Four focus group interviews, with 5–10 older adult participants in each, were organized in Tampere, Finland (N=29 in total, aged 63–93 years, mean±SD 73.6±7.4 years) and four in Madrid, Spain (N=29 in total, aged 56–96 years, mean±SD 73.0±9.7 years). The recruited voluntary participants in Finland were residents of privately owned senior houses. In Spain, two of the groups were with hospital patients and the other two with independently living older adults.

After a short introduction to the project, the participants were asked to fill in a background questionnaire (demographics, current usage and attitudes towards technology, falls history, possible conditions affecting balance, etc.). The scenarios were explained to the participants one by one with a picture or a sketch further explaining the situation. The main features of the scenarios are represented in Table 2. After the explanation the participants evaluated the scenario for its credibility, usefulness, ease of use, adoptability, ethicality and desirability, on a five-point Likert scale from strongly agree to strongly disagree (Likert, 1932). In addition, the participants' willingness to pay for such solutions was investigated. In a semi-structured discussion before and after the scenario evaluation, the participants were asked about their current knowledge of fall risks and perceptions on fall prevention activities.

Table 1. Four datasets used in Papers I–VI.

Data	No of participants	Age (mean±SD)	Target group	Reference fall risk assessment scales
Focus group scenario evaluation (Paper I)	N=29	63–93 years (73.6±7.4 years)	Senior house residents, Finland	falls history self-rated balance medical condition
	N=29	56–96 years (73.0±9.7 years)	Hospital patients and independently living older adults, Spain	
Accelerometer data for balance assessment (Paper II)	N=8	49–77 years (58.3±9.0 years)	Patients with balance affecting condition	10m walk sit-to-stand BBS medical condition
	N=7	20–81 years (61.7±22.2 years)	Controls	
Accelerometer data for balance assessment (Paper III)	N=15	40–68 years (55.2±7.3 years)	Neurological patients	walk (>10m) BBS medical condition
	N=20	67–87 years (76.8±5.6 years)	Older adults	
	N=19	21–36 years (27.5±4.4 years)	Healthy young persons	
Comprehensive fall risk assessment, one-year follow-up, prospective fall risk assessment (Papers IV, V, VI)	N=42	64–85 years (74.2±5.6 years)	Independently living older adults	medical condition, falls history, medication, physical activity, ABC, GDS, MMSE, sensory functions, nutrition, alcohol consumption, Romberg test (balance platform), walk (>20m), BBS, TUG, STS-5, grip strength, lower body muscle strength (leg adductor/abductor and extensor/flexor)

Table 2. Fall risk assessment and fall prevention-related scenarios evaluated in focus groups (adapted from Paper I).

<table>
<tr><td>Scenario A: Fall risk assessment and prescribing of fall prevention interventions</td><td>Actors
Elsa, 80 years, living at home
Doctor, physiotherapist, nurse
Elsa’s daughter</td></tr>
<tr><td colspan="2">Main features
doctor, physiotherapist, Elsa herself and Elsa’s daughter fill-in fall risk assessment scales
combined fall risk estimate based on all the scales and tests
guidance for fall prevention based on test results
follow-up</td></tr>
<tr><td>Scenario B: Self-monitoring of falls risk</td><td>Actors
Lisa, 65 years, living at home</td></tr>
<tr><td colspan="2">Main features
guidance through home terminal device to perform certain physical tasks wearing an activity monitor
fall risk calculation
statistics and exercise guidance based on results
data transfer to central database (for doctors, etc.)</td></tr>
<tr><td>Scenario C: Active fall prevention</td><td>Actors
Helmi, 82 years, living at home with her husband and dog
Physiotherapist</td></tr>
<tr><td colspan="2">Main features
intelligent equipment at the gym
personal ID card, that can be inserted into the gym devices, for viewing exercise plans and automatic follow-up
data transfer to the home computer with the ID card</td></tr>
<tr><td>Scenario D: ADL monitor & fall prevention system</td><td>Actors
David, normal healthy person, 65–75 years
General Practitioner</td></tr>
<tr><td colspan="2">Main features
monitoring of activities of daily living (partly automatic, partly self-registered) through home system (PC, webcam, smartphone)
proposing physical and mental exercises based on ADL assessment
alert for deterioration trend and prompt for a visit to the general practitioner</td></tr>
<tr><td>Scenario E: Fall prevention by building confidence, physical exercise and social support</td><td>Actors
Aino and Reino,
a retired couple, 75–80 years</td></tr>
<tr><td colspan="2">Main features
intervention club (a group of older adults who want to prevent falls) all having a home device (e.g. tablet)
exercise guidance and information videos (motivation, safety, etc.)
monitoring of performed exercises
peer support by other club members via the device: comparison of results, discussions, motivation</td></tr>
</table>

3.1.2 Accelerometer data collection for balance assessment (Papers II and III)

Paper II used data from the study where eight patients (aged 49–77 years, with mean±SD of 58.3±9.0 years) with a balance affecting condition and seven healthy controls (aged 20–81 years, with mean±SD of 61.7±22.2 years) were recruited for balance assessment. The subjects wore five wireless 3D acceleration sensors, one at the lower back near the CoM (±2g, Analog Devices, 33Hz), two on the outsides of the knees (±2G, Analog Devices, 41.25Hz) and two on the outsides of the ankles (±2g, Analog Devices, 41.25Hz). The subjects performed balance and mobility tests under the supervision of a trained physical therapist while wearing the sensors. The tests included 10m walk test, standing up from a chair, and the BBS. The data from the lower back sensor during the walking test were analysed in Paper II.

For Paper III, 54 subjects were recruited for the study, for three groups: 15 neurological patients (aged 40–68 years, with mean and SD of 55.2±7.3); 20 older adults (aged 67–87 years, with mean±SD 76.8±5.6); and 19 healthy young persons (aged 21–36 years, with mean±SD = 27.5±4.4). The neurological patients had diagnosis of cerebrovascular disease, head injury, central nervous system inflammatory disease, or disease of nervous system, such as Parkinson's disease. The participants performed BBS and walk tests (corridor at least 10 metres long) under a physiotherapist's supervision while wearing a 3D accelerometer (8 bit, 75 Hz, Alive Heart Monitor, from Alive Technologies, Queensland, Australia) at the lower back near the CoM. The data were annotated by a researcher on the site by marking each task's starting and ending with computer software synchronized with the sensor.

3.1.3 Comprehensive fall risk assessment data collection at baseline and one-year follow-up (Papers IV, V and VI)

Fourty-two independently living older adults (aged 64–85 years, mean±SD age 74.2±5.6 years) were recruited for the study. The participants went through a comprehensive fall risk assessment procedure at baseline and after a 12-month follow-up. The testing procedure comprised five parts: 1) background questionnaire, 2) interview, 3) balance platform assessment with Kinect recording, 4) physical balance and walk tests with an activity monitor, and 5) muscle strength measurements. The participants filled in a background questionnaire prior to the tests (demographics, health status, medication usage, physical activity, falls during last 12 months, ABC scale (Powell & Myers, 1995), and GDS (Kurlowicz & Greenberg, 2007)). In the interview the participants were assessed for Mini-Mental State Examination (MMSE) (Folstein et al., 1975), sensory functions, nutrition, alcohol consumption, and motivators and barriers for physical exercise. Static balance of the subject was assessed in the baseline and final assessments with the Romberg test, where the person stood for 30s with eyes open on the balance platform (Balance Trainer BT4, HURLabs, http://www.hurlabs.com) and then repeated the same with eyes closed. A depth camera (Microsoft Kinect, www.microsoft.com) was recording simultaneously about three metres behind and orthogonally to the balance platform.

The physical balance and walk tests were supervised by a physiotherapist or a researcher and the subjects wore two accelerometers (±16g, 100Hz, GCDC X16-2, www.gcdataconcepts.com) attached with special belts. One sensor was at the lower back near the centre of mass and the other in the front on the right side. A researcher manually annotated the beginning and ending of each task with computer software, that was synchronized with the accelerometers. The assessment scales included were BBS (Berg et al., 1989), TUG (Podsiadlo & Richardson, 1991), STS-5 (i.e. time it takes to perform five repetitions) and corridor walking, which was performed twice in a corridor of over a 20-metre-long distance. In addition to grip strength, lower body muscle strength was measured from leg adductor/abductor and extensor/flexor.

3.2 End-user perceptions on fall risk assessment and fall prevention technologies

This section answers to the first research question: “How do end-users perceive current and future fall risk assessment and fall prevention technologies?” Understanding the context of use and discovering user needs are crucial for successful adoption of new technologies. By involving the real end-users in the development already at the early phases gives such insight and helps to set requirements for research and development. Paper I combined qualitative content analysis of focus group discussions and quantitative rating of fall risk assessment and fall prevention related scenarios. All five scenarios received positive scores in terms of goodness grades, which combines the assessments for credibility, usefulness, ease of use, adoptability, ethicality and desirability on a scale from -50 to 50 (Kenttä, Merilahti, Petäkoski-Hult, Ikonen, & Korhonen, 2007). Figure 5 represents the goodness grades calculated for each scenario.

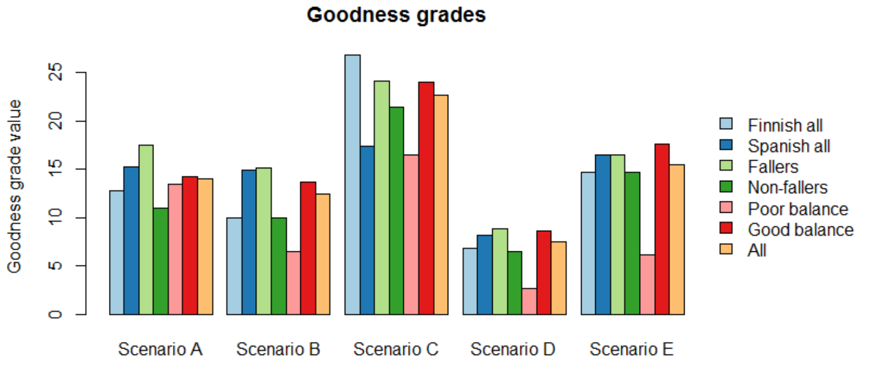

Figure 5. Average goodness grade values per scenario by different groups of respondents.

The scenario introducing intelligent gym equipment received the highest scores both in Finland and Spain, and especially in Finland it was clearly the most interesting one for the participants, with a goodness grade of 26.8. Also the peer support functionalities were valued by the participants. Out of 58 participants, 28 had experienced one or more falls during the last year, and 30 did not have any falls. Eleven participants rated their balance as poor and 47 participants moderate to very good. In general, the persons that had experienced a fall during the last year rated all the scenarios higher, but, on the contrary, those who rated their balance poorer gave lower scores for all the scenarios on average. The lowest score of 2.8 was given by the persons with poor self-rated balance for the scenario including monitoring of daily activities.

Besides answers to the scenario-related questionnaires, the views of the focus group participants were reflected on their comments during the discussion. They considered the external fall risk factors as the most important causes of falls, although they realized that also intrinsic factors, such as poor muscle strength, dizziness, low blood pressure, fear of falling and cerebral infarction may cause falls. According to the focus group participants, the most important actions to prevent falls were 1) education and structured information about fall risks, 2) removal of environmental risk factors such as poor footwear and rugs, and 3) balance and muscle strength training. The Finnish participants seemed to be well aware of the topic of fall prevention, but some of them considered that it does not concern them yet. The participants expressed varying opinions on who should pay for these kinds of technologies, whether it should be the municipality or the older users themselves, and how expensive the solutions will be. The terminology, such as “computer” used in the focus groups led to ambivalence among the participants.

3.3 Comparison and visualization of fall risk assessment scales

This section answers to the second research question: "How is an individual's fall risk manifested through different assessment scales?" Currently, the fall risk assessment practices vary substantially and there is no standard set of assessment scales used by all health care providers. Furthermore, as research has shown, there are a variety of factors that can cause a fall and often a different combination of several risk factors can be identified on an individual level. Paper IV applies the Disease State Index (DSI) algorithm and Disease State Fingerprint (DSF) visualization method proposed by Mattila et al. (2011) in the context of fall risk assessment. The method allows inspection of several assessment scale results at once, revealing the most sensitive scales in the population in question and projecting the individual fall risk in a holistic way.

The DSI is a scalar index value from 0 to 1, indicating the state of fall risk of a person in this case. An increasing DSI value indicates increasing similarity to the risk population. The DSI value determination starts from an individual measurement level, such as a leg adductor muscle strength measurement. The DSI for each individual measurement is obtained by comparing that measurement value to previously known training data using a fitness function. Fitness function gives the DSI value for that measurement revealing which population, fallers or non-fallers, the value fits best. The relevance of each variable is computed using the training data. It indicates how well a variable is able to discriminate between the known faller and non-faller populations. The composite DSI value, such as lower body muscle strength, is obtained as an arithmetic mean of individual measurements weighted by their relevance values. The composite DSI values from lower branch are then used for evaluating the relevance and fitness functions for the next step, finally merging into a total DSI value (Mattila et al., 2011).

In Paper IV the study population was divided based on self-reported history of falls during the last year into fallers and non-fallers. Eleven out of 42 subjects reported having fallen at least once during the last year and 31 had no falls. The tree structure for the DSF algorithm consisted of 32 features. The balance platform features were selected from the parameters given by the balance platform device and they were grouped under three branches: Romberg quotient, parameters measured during the eyes open test, and the same parameters measured during the eyes closed test. Grip strength of right and left hands were grouped under upper body muscle strength and all the lower body muscle strength measurements were grouped together, respectively.

Figure 6 represents two example cases, one with history of falls and one with no falls during the last year. The size of the node boxes shows the relative relevance of each feature in differentiating fallers and non-fallers. The nodes are organized according to descending relevance. The colour and number beside the box indicates the similarity of the subject assessment to the positive (fallers) class. Red colour refers to fallers and blue to non-fallers.

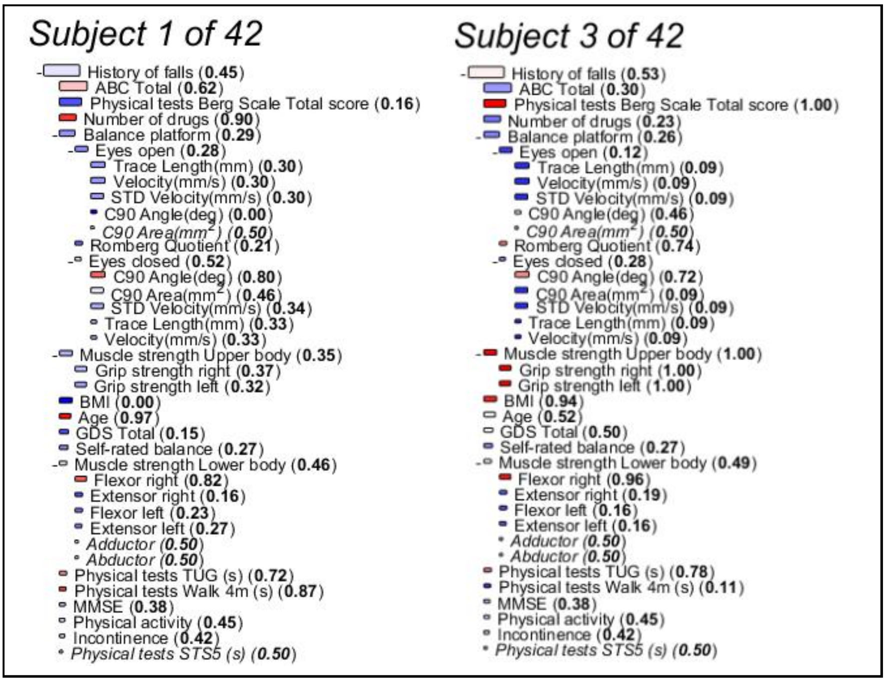

Figure 6. Example DSF visualizations for two subjects. Subject 1 has not fallen during the last year and subject 3 fell once last year.

The example visualizations in Figure 6 show that the ABC total score, BBS total score and number of drugs in use are the most relevant measurements and differ the most between the fallers and non-fallers. The relevance of ABC and BBS in inspecting retrospective falls have been proven by other studies as well. The ABC scale assesses how confident a person is in maintaining balance while performing daily activities. A lower score on the ABC scale implies increased fear of falling and people having experienced a fall before have a lower ABC score (Lajoie & Gallagher, 2004). In a study by Shumway-Cook et al. (1997) the BBS was found to be the best in discriminating fallers from non-fallers, where two or more falls during the last six months was used as a criterion for a faller status (Shumway-Cook, Baldwin, Polissar, & Gruber, 1997). They did not find a significant difference in MMSE result or walking speed between fallers and non-fallers, and these assessment scales showed a low relevance also by DSF.

The DSF demonstrates that overall fall risk of an individual constitutes a different combination of risk factors and both of the example cases have individual assessments that refer to the opposite class. For example, Subject 3, with a history of falls, has an increased fall risk according to the BBS test result, but many others, such as ABC score and number of drugs in use, indicate otherwise. The results for Subject 1, on the other hand, show the opposite with those measures.

Although the main objective of Paper IV was to compare and visualize the different assessment scale results, the DSI was also tested as a supervised classifier. The classifier was evaluated with the leave-one-out cross-validation method for sensitivity and specificity in separating fallers from non-fallers. The obtained sensitivity and specificity of classification were 54.5% and 64.5%, respectively. The classification of subjects based on their ABC score was also tested with the same three structures. Although, in that case the ABC score was replaced by the history of falls as one of the leaf variables in the DSI. The ABC score of 80% was used as a cut-off, since a score of ≥80% was considered as indicating good functional capabilities (Myers, Fletcher, Myers, & Sherk, 1998). In the study group, 35 subjects scored 80% or more and seven had a score below that. The sensitivity and specificity of the DSI classifier to discriminate subjects with an ABC total score lower than 80% were 71.4% and 88.6%, respectively.

3.4 Accelerometry-based postural control and balance assessment

This section answers to the third research question: "How can body-worn accelerometry be utilized in assessment of individual fall risk?" The third question has two parts a) "How can balance ability be estimated from an acceleration measurement?" and b) "How can prospective changes in fall risk factors be estimated from an acceleration measurement?" As explained in Chapter 2.4, the accelerometry has been suggested as a means for inexpensive, objective and sensitive fall risk assessment that adds to or even enhances the traditional assessment scales. There is a need for data analysis methods that transforms the raw signals produced by accelerometers into meaningful information about a person's fall risk. The data analysis methods accompany information about the measurement protocol, i.e. where and how the sensor should be placed, and what are the most relevant activities to be analysed.

3.4.1 Assessment of current balance

Paper II demonstrated that the wireless 3D acceleration sensor network setup tested was feasible for balance assessment. With the study sample, the patients with a balance-affecting condition proved to have larger step time variability and lateral displacement amplitude, and smaller vertical displacement amplitude of the lower back acceleration sensor, than the control subjects. Figure 7 represents the feature value distributions for the two groups.

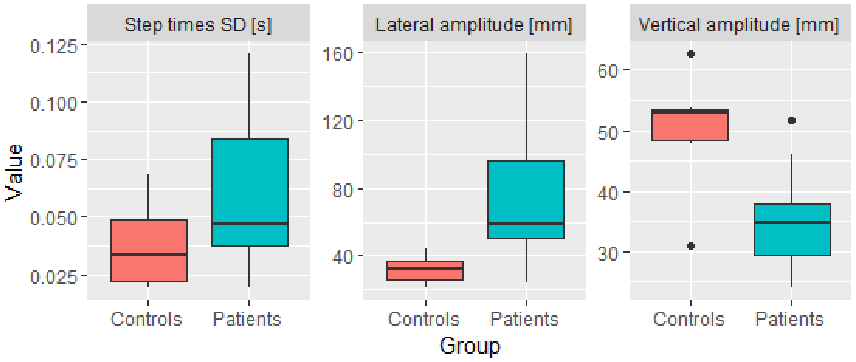

Figure 7. Distributions of accelerometry-based standard deviation (SD) of step times, lateral displacement amplitude and vertical displacement amplitude values for Patients and Controls separately. The box represents the range between the first and third quartile of the sample with a median value marked with a line. The whiskers extend to the highest and lowest values that are within 1.5 times the box range outside the box borders. The dots represent the outliers beyond the whiskers.

According to Menz et al. (2003), older people adopt a more conservative gait pattern as a compensatory strategy to stabilize their balance while walking, which can be seen as smaller magnitude of accelerations at the head and pelvis, reduced velocity and step length, and increased step timing variability. Also in Paper II study sample, the SD of step times was larger in the patient group. Vertical displacement was smaller in the patient group and lateral displacement was larger, respectively. Increased lateral pelvic displacement has been found to be associated with slower walking speed (Dodd & Morris, 2003).

The three features calculated in Paper II were tested for their ability to distinguish patients from controls with SOM clustering and fuzzy classification methods. The readily available SOM toolbox for Matlab was used to perform SOM clustering and visual inspection of the data ("SOM Toolbox 2.0," 2005). The resulting visualization is a two dimensional grid of nodes that model the higher-dimensional observations. The grid visualization depicts the similarities among the data, as the nodes with similar models are closer to each other than the dissimilar ones. In Paper II, the resulting clustering map was organized so that most of the patient subjects were gathered at the opposite end of the map than the control subjects, indicating similarity within the groups.

In fuzzy classification, membership functions were determined with the training data for the two reference classes and for the three features separately. The obtained degrees of memberships from the three features are summed to get the total degree of membership for both classes: Patients and Controls. The classification results showed that 6/8 (75%) of the patients were correctly classified as patients, and 4/6 (67%) of the controls were classified as controls, respectively.

Paper III introduced a method for estimating the BBS score from an accelerometer measurement. The estimation was performed by evaluating similarity between subjects' acceleration patterns measured during 1) different BBS tasks and 2) gait. Acceleration patterns measured during nine BBS tasks were selected for further analysis: *sit to stand*, *stand without support*, *stand to sit*, *stand eyes shut*, *stand feet together*, *reaching*, *picking up an object*, *look behind*, and *tandem standing*. The BBS score was estimated with combinations of one, two, and three tasks to determine which tasks lead to the best estimation result. Resultant acceleration during a particular task was used for pattern comparison. The subjects' data were normalized to the average length of that task by resampling or decimation to enable waveform comparison. In the gait-based BBS score estimation a unique 3D gait pattern was constructed for each subject. The procedure for this individual signature gait pattern creation was introduced by Mäntyjärvi et al. (Mäntyjärvi, Lindholm, Vildjiounaite, Mäkelä, & Ailisto, 2005). It combines a representation of a person's gait acceleration in medio-lateral, vertical and antero-posterior directions including one stride, i.e. steps with right and left leg.

Three different similarity measures were tested in both BBS task and gait pattern comparisons: Euclidean distance, correlation coefficient, and Tanimoto coefficient. The BBS score estimate for a person was determined as an average of BBS scores of the three nearest neighbouring subjects' that have the most similar acceleration patterns using leave-one-out cross-validation. The sample was divided into high and low fall risk groups, based on their BBS score (high fall risk with BBS score 49 or less). Table 3 represents the best classification results with both BBS tasks and gait pattern-based methods.

Table 3. The best classification results with three BBS tasks and gait pattern using the Tanimoto coefficient as a similarity measure

	BBS tasks ***stand to sit*** ***reaching*** ***picking up object***		**Gait pattern**	
Area Under Curve (AUC)	0.842		0.889	
	Low fall risk BBS > 49	**High fall risk BBS ≤ 49**	**Low fall risk BBS > 49**	**High fall risk BBS ≤ 49**
Low fall risk BBS > 49	62.1	37.9	96.6	3.4
High fall risk BBS ≤ 49	10.5	89.5	22.2	77.8

Confusion matrices with respect to low- and high-fall-risk groups are presented as a percentage (%) of correctly classified subjects.

The Tanimoto coefficient provided with the best results, when compared to the ones obtained with Euclidean distance and correlation coefficient. The study showed that the selection of a similarity measure has an effect on the results, but further studies are needed to analyse the significance of the impact and verify the optimal choice for the algorithm. The similarity comparison of acceleration patterns measured during different BBS tasks indicated that the most useful tasks for estimating the BBS total score were “stand to sit”, “reaching” and “picking up object”. The similarity comparison of the gait patterns resulted in highest AUC value of 0.889. The accuracy in identifying subjects with high fall risk was 77.7% and 96.6% with low fall risk, respectively. The BBS tasks-based method was more accurate in identifying subjects with high fall risk with an accuracy of 89.5%.

As reviewed in Chapter 2.2.1 postural control requires integration of several sensorimotor processes and resources, and the more complex the task at hand is, the more attentional requirements are required (Lajoie & Gallagher, 2004). The individual BBS tasks assess a certain aspect, such as co-ordination or muscle strength. Gait, on the other hand, is a more complex task capturing a wider range of postural control requirements. The number of BBS tasks in the estimation was limited to three, thus possibly omitting some of the other important aspects of balance. This might also partly explain the better overall BBS score estimation results of the gait-based method.

3.4.2 Prospective fall risk assessment

Paper V was an explorative study were 11 gait features were investigated for their correlation to decline in nine fall risk assessment scales during a one-year follow-up. The features were calculated from the resultant acceleration measured from the lower back during walking. Table 4 summarizes the features that differed significantly between subjects whose assessment scale result decreased during follow-up and subjects having the same or improved result.

Several of the features were significantly different between subjects that had 1) decreased and 2) similar or improved results in the ABC total score, BBS score, GDS score and STS-5 test. Average, SD and minimum-maximum range of signal vector magnitude and average peak acceleration were the most promising gait features in separating subjects with negative and positive change in ABC and BBS scales. There were no significant associations with gait features and changes in MMSE, TUG, left hand grip strength and falls during the follow-up period. However, it should be noted that the analysis in Paper V did not take into account the type of falls and possible accidental falls were not excluded. Out of 36 subjects seven reported having fallen once and two had fallen twice.

Table 4. Features that differed significantly ($p < 0.05$, Kruskal Wallis one-way ANOVA, marked with X) between subjects whose assessment scale result decreased during one year and subjects whose result improved or stayed the same.

	Assessment scale								
Features	ABC	BBS	GDS	STS-5	Grip strength right [kg]	Grip strength left [kg]	MMSE	TUG	Falls (12 months follow-up)
Average of signal vector magnitude (resultant acceleration) [G]	X	X							
SD of resultant acceleration [G]	X	X							
Range between minimum and maximum of resultant acceleration [G]	X	X							
Average step time [s]	X			X					
Average stride time [s]	X			X					
SD of step times [s]			X						
SD of stride times [s]									
Asymmetry between (a and b) step times			X						
Average peak acceleration (resultant acceleration) [G]	X	X			X				
SD of peak accelerations (resultant acceleration) [G]									
Asymmetry between (a and b) peak accelerations (resultant acceleration)			X						

Often the gait acceleration features have been investigated in cross-sectional studies for their correlation to contemporary fall risk assessment scale results. SD of stride times has previously been found associated with the current result of many fall risk assessment scales. Increased variability was correlated with poor health status and decreased performance in several balance and functional tests, such as number of medications, MMSE, grip strength, TUG, and confidence in one's ability to perform activities without falling (Hausdorff, Rios, & Edelberg, 2001). Hausdorff et al. (2001) state that stride-to-stride variability may not be completely independent of neuropsychologic function and fear of falling. In Paper V, on the other hand, the SD of stride times was not significantly associated with change in those scales. However, there were several other features associated, for example, with change in ABC scale that is also a measure of self-confidence in performing daily activities without losing balance.

SD of step times was associated with change in GDS, as were asymmetries between right and left step times and peak accelerations. Depression (assessed by GDS) has been found to be associated with falls and fractures. In a study by Whooley et al. (1999), older women with depression had a greater frequency of falls (70%) than women without depression (59%).

Paper V demonstrated that associations between accelerometry-based gait features and changes in clinical fall risk assessment scales may be found. The results served as encouragement for further investigation and analysis carried out in Paper VI.

The purpose in Paper VI was to analyse whether features extracted from waist acceleration measured during walking would be able to predict decline in balance during a one-year follow-up. The paper addressed the objective by presenting generalized linear models for 1) estimating the result of three selected reference measure: BBS, TUG and 4-metre walk tests and 2) predicting decline in balance, measured as decrease in BBS total score and BBS sub-component one leg stance.

The acceleration signal was first low-pass filtered (3rd order elliptic infinite impulse response filter, cut-off at 0.25Hz, passband ripple 0.01 dB, stopband at -100 dB) to separate acceleration components due to gravity and body motion. Four signals, body accelerations in mediolateral (x), vertical (y), and anteroposterior (z) directions, and resultant acceleration, were used for feature extraction. A total of 43 different features were calculated. The features included basic features, such as SD and signal range, temporal gait features utilizing step detection, resultant acceleration amplitude features and harmonics ratio features were derived from the signal frequency spectrum. Age and Body Mass Index (BMI) were inserted as control variables. The SFFS feature selection method with ten-fold cross-validation was applied to derive the models for estimation and prediction.

Ten models were generated in each round of ten-fold cross-validation. The same features were repeatedly selected as predictors in the models for estimating the reference scale results. That indicates that those features presumably contain higher predictive value over the other features. Signal Magnitude Area (SMA), first six harmonics ratio to the remaining spectrum of mediolateral acceleration, and ratio of even harmonics to odd harmonics of antero-posterior acceleration were the most frequently selected features for estimating the BBS score, SMA being the most predictive. A positive SMA estimate value indicates that the larger the SMA, the larger the BBS score estimate. SMA represents the amount of acceleration induced to the sensor. It is suggested that older people adopt a more conservative gait pattern as a compensatory strategy to stabilize their balance while walking, which leads to smaller magnitudes of accelerations at the head and pelvis (Menz et al., 2003b), and thus smaller SMA.

The third harmonic ratio to the first six harmonics of resultant acceleration and average of resultant acceleration were the most predictive of TUG time. The regular gait is dominated by the second harmonic representing the step frequency (Menz et al., 2003a). Thus, the third harmonic represents a periodicity of higher frequency than that of step frequency. The larger value of the third harmonic ratio might reflect a less smooth gait, since it was also associated with longer time in TUG. Resultant acceleration represents the amount of total acceleration in three dimensions measured by the sensor. Larger value of the feature average resultant acceleration was associated with shorter TUG time, which might indicate a less conservative gait pattern and thus presumably faster movement.

Average step time, average stride time and standard deviation of mediolateral acceleration were selected most often in the four-metre walk time estimation model. Average step and stride times are presumably highly correlated with each other. In fact, when both features were selected in four folds, the estimate value was multiple times higher for both of them but with the opposite sign. This indicates that the effect of the other feature was compensated by deducting the other, and only one of the features should be included in the analysis. Table 5 summarizes the obtained results.

Table 5. Mean normalized RMSE values for estimating the reference scale result, the most frequently selected features and the mean estimate values.

Reference scale	**Mean NRMSE**	**Most frequently selected features (number of folds selected in)**	**Mean estimate value (minimum – maximum**
BBS score	0.28	Signal magnitude area, SMA (9)	0.82(0.58–1.15)
		First six harmonics ratio to remaining spectrum of mediolateral acceleration (5)	0.92(0.82–1.05)
		Ratio of even harmonics to odd harmonics of antero-posterior acceleration (4)	-0.76(-0.98–(-0.60))
TUG time [s]	0.18	Third harmonic ratio to first six harmonics of resultant acceleration (10)	1.19(0.99–1.31)
		Average of resultant acceleration (8)	-0.87(-1.01–(-0.66))
4-metre walk time [s]	0.22	Average step time (10)	0.40(0.27–0.53)*
		Standard deviation of mediolateral acceleration (4)	-0.36(-0.44–(-0.23))
*** estimate in six folds, where *average stride time* was not selected as a predictor**			

The BBS test has 14 tasks with increasing difficulty and the final components are considered the most challenging (Berg et al., 1989). In Paper VI, the subjects were categorized as “balance declined” if their 1) BBS total score decreased or 2) score in BBS sub-component one leg stance (task 14) decreased during the follow-up period. Standard deviation of vertical acceleration was selected in every round of ten-fold cross-validation for predicting decline in BBS total score and one leg stance. It was also previously found to be associated with prospective falls (van Schooten et al., 2015). Standard deviation is a measure of dispersion in the data relative to the mean. In Paper VI, the standard deviation is equal to RMS, since the gravitational acceleration was removed from the three dimensional accelerations resulting in signals with a zero mean (Menz et al., 2003a). Vertical RMS has also been found to be strongly correlated (r=0.60) with the Tinetti scale (also known as POMA) and it had good discriminative power in differentiating subjects with a Tinetti score of ≤ 24 and score of > 24 with an AUC of 0.81 (Senden et al., 2012). Table 6 summarizes the obtained results. Figure 8 represents the ROC plots for the combined output of ten-fold cross-validation for predicting subjects with decline in BBS total score and one leg stance during one-year follow-up.

Table 6. Mean classification accuracy, most frequently selected features, mean estimate values and AUCs of models predicting decline in balance.

Measure of decline in balance	Mean classification accuracy [%]	Most frequently selected features (number of folds selected in)	Mean estimate value (minimum - maximum	AUC
BBS total score	69.2	Standard deviation of vertical acceleration (10)	-1.68 (-3.04–(-1.41))	0.78
One leg stance (BBS task 14)	78.5	Standard deviation of vertical acceleration (10)	-3.77 (-5.89–(-2.75))	0.82

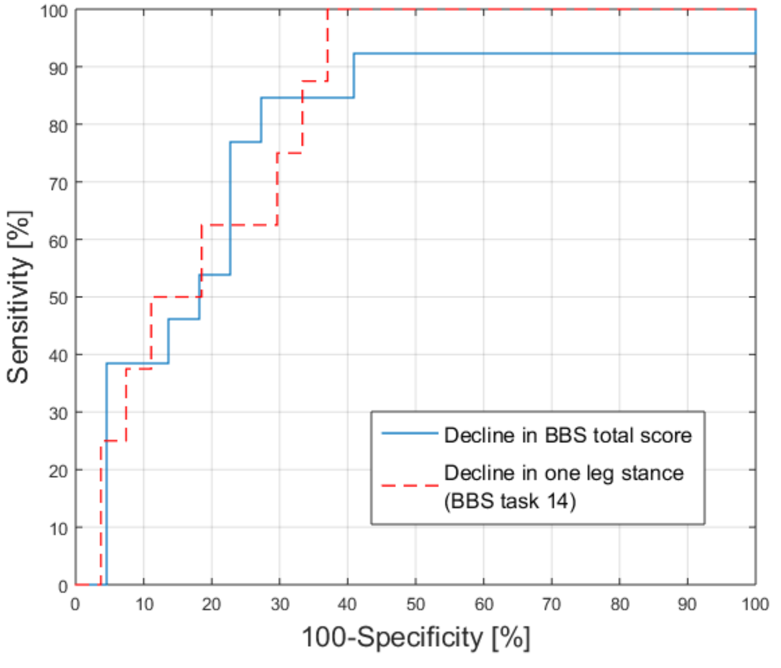

Figure 8. ROC curves for predicting decline in BBS total score, and one leg stance during a one-year follow-up.

It was expected that different sets of features were selected for different models, since the selected reference scales include aspects that measure different characteristics of balance. Age and BMI were not selected as predictors in any of the models. This suggests that gait features contain additional information about balance, and age alone does not explain all the changes in balance ability. In comparison, van Schooten *et al.* (2015) reported that their falls prediction model AUC rose from 0.68 to 0.82 when gait parameters were added to the traditional questionnaires, grip strength and trail making test data. In Paper VI, several acceleration spectra-based features were associated with BBS, TUG and 4-metre walk test, which suggests that the frequency spectrum of human movement acceleration contains valuable information with regard to balance assessment. The same conclusion was drawn by Liu et al., (2011) in their study of accelerometry-based PPA fall risk score estimation. When frequency spectra-based features were supplemented to temporal and energy-related features the correlation of estimation rose from r=0.81 to r=0.96.

4. Discussion

4.1 End-user perceptions on fall risk assessment and fall prevention technologies

The first research question was: "How do end-users perceive current and future fall risk assessment and fall prevention technologies?" The results of Paper I focus groups imply that the acceptance of a new technology solution is higher if the solution is familiar to a person and it can be easily integrated into current daily activities. Most of the Finnish focus group participants were actively going to the gym and they rated the scenario with intelligent gym equipment the highest. Furthermore, the participants named muscle strength training as one of the most important actions to prevent falls. Similar observations were made by Mercer et al. (2016) in their study on acceptance of wearable activity trackers among people over 50 years old. At the time of study the wearable activity trackers were an emerging technology and the participants felt that the activity trackers were too new to be comfortable with (Mercer et al., 2016).

Peoples' prior experiences and beliefs, e.g. self-efficacy, have an effect on their attitudes towards new technologies. In Paper I, people with a history of falls seemed to be more interested in fall prevention than non-fallers, as they usually gave better ratings to the proposed scenarios. At the same time, people who rated their balance better evaluated the scenarios higher than people with poor self-rated balance. This slightly conflicting finding may arise from the fact that people with poor balance expect to have difficulties in performing physical activities that were part of most of the scenarios. Older people might also fear the normal responses of physical exercises, such as shortness of breath, and fear of getting injured and thus limiting their physical activity (Stevens, Noonan, & Rubenstein, 2010).

Older people often do not want to admit their vulnerability and recognize they have increased fall risk. They acknowledge the extrinsic fall risk factors rather than the intrinsic ones. In addition to focus group interviews in Paper I, this conception was perceived by other studies as well (Robinovitch et al., 2013; Stevens et al., 2010). The fallers might want to rationalize the falls as having an external, unavoidable cause, so that they are not perceived as vulnerable (Robinovitch et al., 2013).

4.2 Comparison and visualization of fall risk assessment scales

The second research question was: "How is an individual's fall risk manifested through different assessment scales?" Paper IV presented a method for comparing and visualizing the results of different fall risk assessment scales at once utilizing DSI and DSF methods. As explained in Chapter 2.2 individuals have a different combination of risk factors contributing to the overall fall risk. This could be seen also in the study population in Paper IV through DSF visualization. This is important to realize when selecting the assessment scales in practice, so that they capture all relevant aspects of fall risk.

The visualization in Paper IV gives an indication of which assessment scales differ the most between fallers and non-fallers among relatively well-functioning older people. However, the use of DSI as a classification method provided rather low sensitivity and specificity with this sample. The DSI method is based on distributions of faller and non-faller training data, and thus would require a representative training set from both populations. In Paper IV the sample size was small and all the subjects were in quite good physical condition resulting in highly overlapping distributions of the fall risk assessment data. Furthermore, self-reported falls information during the last year was used as a reference. According to a study by Mackenzie et al. (2006) with 264 subjects over the age of 70 years, retrospective self-reported fall rates may be under-reported. The sensitivity of recalling the falls from the previous six months was only 56% (Mackenzie, Byles, & D'Este, 2006). Also in Paper IV, any possible accidental falls were not excluded and the person was considered a faller already when there was one fall during the last year. The deficiency in training data presumably was reflected as low sensitivity and specificity of classification results.

The DSI method's advantage is in that it supports different types of tests and variables. It provides a large amount of data about the individual back to the clinician in a way that the clinician is able to concentrate on important information and ignore irrelevant information (Mattila et al., 2011). That would be especially beneficial for clinicians with less experience, since they are often unaware of existing fall risk assessment scales and how to select the appropriate ones (Perell et al., 2001). Further study with a larger sample utilizing the DSF method is needed, possibly with several subgroups representing older people with different levels of fall risk. Also, the selection of a tree structure influences the results and needs to be studied further.

4.3 Accelerometry-based postural control and balance assessment

4.3.1 Assessment of current balance

The third research question was: "How can body-worn accelerometry be utilized in assessment of individual fall risk?" In more specifically question 3a asked: "How can balance ability be estimated from an acceleration measurement?" Through papers

II, III and VI, different methods are introduced to derive accelerometry-based balance assessment that is compared to the current status as measured by clinical assessment scales. In Paper II, the sensor displacement trajectory was calculated by double-integrating the acceleration signal. The offset was corrected at each point by subtracting an average of two consecutive steps, one step before and one step after the point in question. The offset correction method used may have attenuated the actual position trajectory peaks. Sensor fusion, e.g., an accelerometer and gyroscope might overcome this problem and more accurate position information could be obtained.

In Paper III, two methods for estimating the BBS score of a person were introduced. The BBS score estimation based on gait patterns worked better compared to the BBS tasks based method. It is reasonable, since maintaining balance during gait represents considerable challenges to the postural control system and the gait patterns change with age due to declines in sensory functions and muscle strength (Lord et al., 2001). The individual BBS tasks, on the other hand, assess more specific aspects of balance. The analysis of the acceleration patterns during BBS tasks gave an indication of which BBS tasks are best able to categorize people into high and low fall risk groups. If sufficient balance estimation would be achieved with a smaller number of tasks, it would reduce the time required to administer testing. Since the proposed method assesses the similarity between the subjects, a comprehensive pool of reference data would be needed in order to achieve a proper estimate for a subject's BBS score. Based on classification results, the method in its current form could be applied for rule-out purposes, i.e. to confirm that fall risk has not increased, as it has higher sensitivity for detecting persons with low fall risk. The data set in Paper III was skewed toward higher BBS scores, presumably causing the tendency to overestimate especially the lower BBS score estimates.

The methods introduced in Papers II, III and VI rely on manually annotated acceleration data. However, there are several studies demonstrating walking activity detection from an accelerometry measurement (e.g. Karantonis et al., 2006; Könönen, Mäntyjärvi, Similä, Pärkkä, & Ermes, 2010), and thus showing the potential of transferring these methods into real-world, long-term monitoring applications. Moreover, the approach used in Paper III to construct the individual gait pattern for comparison process is not yet fully automatic and needs also to be improved to enhance its applicability in real environment solutions.

4.3.2 Prospective fall risk assessment

The research question 3b was: "How can prospective changes in fall risk factors be estimated from an acceleration measurement?" In order to prevent falls, it is crucial to detect balance problems early enough and thus estimate prospective fall risk more accurately. Papers V and VI showed that accelerometry has potential in detecting early signs of balance deficits. Gait acceleration analysis presumably can reveal more subtle changes in physical functioning that are not yet seen by the traditional clinical fall risk assessment scales.

Paper V was a first attempt to investigate simple gait features and their association with decline in clinical assessment scales after one year. A significant association was found between gait features and several assessment scales. The significant gait features differed between the assessment scales, which is expected as the assessment scales measure different fall risk factors. The results infer that gait contains information about multiple fall risk factors.

Paper IV showed that the ABC score was the best assessment scale able to differentiate between fallers and non-fallers based on history of falls information. The decline in the ABC score suggests that the person is less certain that they will maintain their balance while performing activities of daily living and thus is more prone to falls (Pajala, 2012). Further analysis of the same data set in Paper V indicated that several calculated gait features were associated with the decline in the ABC score after one year. The results of Papers IV and V are interesting and encouraging for future investigations to validate these findings with a larger sample.

The selected features were different for the estimation of balance assessment scale result and for prediction of decline in balance in Paper VI. van Schooten et al. (2015) reported similar findings that different gait characteristics were associated with retrospective falls and prospective falls. This suggest that the sensor-based algorithms that are supposed to prospectively predict future falls or weakening of physical condition should be developed and validated on prospective data.

Paper VI constructed two regression models for predicting decline in balance during a one-year follow-up. The prediction of change was inspected as a binary value: decline vs. no decline. This approach did not take into account the amount of decrease in BBS scores. A decrease of one point or more in BBS total score, and in the one leg stance for the second model, was considered as a decline in balance. The study sample was considered too narrow for predicting the actual decrease. Sheehan et al. (2014) predicted decline in balance with baseline quantitative TUG parameters, and resulted in AUC values of 0.7 and 0.8 for predicting decline of four or more points in total BBS score and two or more points in the one leg stance, respectively. The AUC values in Paper VI were, however, corresponding, since AUC was 0.78 for predicting decline in total BBS and 0.82 for predicting decline in one leg stance. The results of this study suggest that a decline as subtle as one point in BBS might be predictable with gait accelerometry.

The accelerometry-based methods presented here assess principally the postural control and mobility of a person, which represent a part of intrinsic fall risk factors and thus do not cover the entire risk of future falls. Also the reference clinical measures, such as TUG and BBS, display uncertainty in prediction of future falling. TUG was selected as a reference measure in Paper VI, since it is widely used to assess the mobility of an older population. However, there are several counter arguments for its ability to predict falls. Barry et al. reviewed that TUG score alone does not adequately encompass multiple fall risk factors and it needs to be complemented with other assessments to improve its prediction accuracy (Barry et al., 2014). In a one-year follow-up study by Lin et al. (2004), TUG was also found to not be responsive to falls, although it had a small but clinically meaningful responsiveness to decline in activities of daily living performance, which require balance ability.

The DSF visualization in Paper IV inferred also that in the study population the TUG score was not substantially different between subjects with history of falls and non-fallers.

According to Muir et al. BBS is inadequate for identifying the majority of people at risk of falling, although it has a good discriminative ability to predict multiple falls (Muir et al., 2008). However, a decrease in assessment scales measuring postural control and mobility is an important indication of decline in physical functioning and should lead to preventive actions. Thus, estimating balance and other fall risk factors might prove to be a more coherent reference for developing prediction instead of falls. As explained in Chapter 2.2, falls are caused by a multitude of reasons, which makes them difficult to predict. It seems that it may be more accurate to estimate a decrease in balance than actual future fall events.

4.4 Study limitations and future prospects

The mutual limitation in Papers II–VI was the rather small sample size ranging from 15 to 54 subjects, which limits the generalizability of the results. It is the topic of future studies to evaluate the clinical validity of these models with a larger data set. Also the data used in the analyses were collected under a supervised condition, which measures the performance at that specific moment. Acceleration measurement during daily life could provide a more reliable balance and mobility assessment. Weiss et al. (2013) have demonstrated that accelerometry-based gait features from daily activity monitoring provide valuable information for the fall risk assessment. They found mild to moderate correlations between at-home gait features and in-laboratory fall risk assessment scales, such as BBS and TUG (Weiss et al., 2013).

It should also be noted that the feature pool used for deriving the prediction models in Paper VI was large and possibly contained redundant features. Some of the calculated features might have been highly correlated with each other and initial feature selection, e.g. by correlation or PCA, could be applied to reduce dimensionality.

The results presented in Papers I–VI are indicative that a simple walk test with wearable monitoring has a potential for identifying people with early signs of balance deficits. It could be applied, for example, as a supervised quick screening test or integrated as part of a long-term activity monitoring solution. However, before the accelerometry methods proposed are ready to be integrated in real consumer products, a rigorous validation should be made. The validation should be done with an external prospective data set that is representative of the older population. The effect of measurement context should also be investigated in the future to determine whether the same data analysis methods are applicable for the data collected in real-world settings.

5. Conclusions

In this thesis, data analysis methods for fall risk assessment of older adults were proposed. Three research objectives were addressed though six original publications. The end-user perceptions and understanding of technology context were obtained through focus group scenario evaluations. Different fall risk assessment scales were compared and visualized utilizing DSI and DSF methods that were novel to this application field. Three data sets with body acceleration measurement were used in developing methods for assessment of current balance and prediction of decline in balance during a one-year follow-up.

The first research question asked how do end-users perceive current and future fall risk assessment and fall prevention technologies. Fall risk assessment and fall prevention scenario evaluation with older people showed that new technologies introduced to the end-users should not be too different from the ones they are currently familiar with. Also people's prior experience and self-efficacy presumably affect the acceptance of new solutions.

The second research question asked how an individual's fall risk is manifested through different assessment scales. The DSF visualization method demonstrated that visualization of an individual's fall risk factors is important, especially for the clinician to gain a comprehensive understanding of a specific person's fall risk. People may have different combinations of fall risk factors that affect total fall risk. The method also showed which assessment scales differ the most between the persons at risk and persons without risk.

The third research question asked how body-worn accelerometry could be utilized in the assessment of individual fall risk. The results showed that accelerometry-based gait analysis could be applied in assessing the postural control and mobility of a person. This thesis brought up potentially relevant gait features that are associated with static and dynamic balance ability. Furthermore, the results indicated that accelerometry has the potential to detect early signs of balance deficits.

The results of this thesis can be used as a basis for future studies, where the findings can be validated with larger data sets. Also, other reference scales not used in the analyses should be investigated, since the methods are likely to be generalizable to other measures of balance as well.

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PAPER I

Focus Group Evaluation of Scenarios for Fall Risk Assessment and Fall Prevention in Two Countries

Ambient Assisted Living and Active Aging: 5th International Work-Conference, IWAAL 2013, Carrillo, Costa Rica, December 2–6, 2013, Proceedings (pp. 39–46).

Focus Group Evaluation of Scenarios for Fall Risk Assessment and Fall Prevention in Two Countries

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Abstract. Information and communication technologies (ICT) provide means for developing new tools for preventing falls. To enhance adherence to fall prevention interventions, end users need to be engaged from the early phases of the development process. This paper reports the focus group evaluation of five scenarios related to fall risk assessment and fall prevention. There were four focus groups with older adults in both Finland and Spain; 58 participants in all. The most interesting features for the interviewees were usage of intelligent gym equipment, the possibility of peer support and multi-factorial fall risk assessment. The scenario with intelligent gym equipment rose above the others among Finnish participants, while the scenarios were ranked more evenly by Spanish correspondents. The analysis showed that a personal history of falls and a connection to current habits and routines affected the reception of the proposed solutions.

Keywords: fall risk, fall prevention, older adults, ambient assisted living.

1 Introduction

One third of people over the age of 65 fall at least once each year [1]. Falls have a negative effect on a person's quality of life, as they may lead to serious injuries and added fear of falling again, not to mention the increased health care costs [2]. In order to prevent falls efficiently, the fall risk of a person needs to be assessed. As an example, clinically proven assessment scales such as the Berg Balance Scale [3] and Physiological Profile Assessment [4] test postural control and physical functions. Furthermore, the Downton Index [5] also considers previous falls, medication, sensory deficits and mental state to constitute a fall risk index, to mention but a few examples.

According to Gillespie et al. [6], these interventions are likely to be effective, whether targeting multiple risk factors or taking a more specific approach, such as

C. Nugent, A. Coronato, and J. Bravo (Eds.): IWAAL 2013, LNCS 8277, pp. 39–46, 2013.

combined muscle strength and balance training. Optimal approaches involve interdisciplinary collaboration [7]. Individually tailored interventions are found to be especially beneficial in preventing falls [6]. Information and communication technologies (ICT) provide means for developing new tools for fall prevention. In order for interventions to be effective, it is of the utmost importance for the target user to comply with the program. For example, in a fall prevention study in Australia, only 21% of the 5,681 study participants did balance or strength training and just 3% did both following the recommendation of exercising two days a week [8]. Developers must acknowledge the barriers and motivators for physical exercise that older people perceive [9], in order to improve the adherence of such interventions. Thus it is key to engage end users from the earliest stages of the development process.

The aim of our research is to iteratively develop and evaluate tools for fall risk assessment and fall prevention. This paper reports the results from a cross-cultural focus group evaluation of five functional scenarios of the prospective system with older adults in two countries: Finland and Spain.

2 Methods

2.1 Scenarios

The scenarios are narrative stories that explain the functionalities and flow of events of the system from the end-users' point of view. Five different scenarios were jointly created by the research partners, who have backgrounds in fields such as mathematics, economics, medicine and software engineering. Short descriptions of the main features are explained in Table 1.

Table 1. Main Features of the Evaluated Scenarios

Scenario	Users	Main features
A: Fall risk assessment and prescription of fall prevention interventions	Elsa, 80 years old, living at home Doctor, physical therapist, nurse Elsa's daughter	- doctor, physical therapist, Elsa and Elsa's daughter fill in fall risk assessment scales - combined fall risk estimate based on all the scales and tests - guidance for fall prevention based on test results - follow-up
B: Self-monitoring of fall risk	Lisa, 65 years old, living at home	- guidance through home terminal device to perform certain physical tasks while wearing an activity monitor - fall risk calculation - statistics and exercise guidance based on results - data transfer to central database (for doctors etc.)
C: Active fall prevention	Helmi, 82 years old, living at home with her husband and dog Physical therapist	- intelligent equipment at the gym - personal ID card that can be inserted into apparatuses at the gym for viewing of exercise plans and automatic follow-up - data transfer to the home computer with the same ID card

Table 1. (*continued*)

D: ADL monitor & fall prevention system	David, normal healthy person, 65-75 years old General practitioner	- monitoring of activities of daily living (partly automatic, partly self-registered) through home system (PC, webcam, smartphone) - proposing physical and mental exercises based on ADL assessment - alert in case of deterioration trend and prompt for a visit to the general practitioner
E: Fall prevention by building confidence, physical exercise and social support	Aino and Reino, retired couple, 75-80 years old	- intervention club (a group of older adults who want to prevent falls) all provided with a home device (e.g. tablet) - exercise guidance and information videos (motivation, safety, etc.) - monitoring of exercises performed - peer support by other club members via the device: comparison of results, discussions, motivation

2.2 Focus Group Evaluation

Four focus group interviews, with 5-8 older adult participants in each, were organized in Tampere, Finland (N=29 in total, aged 63-93 years, mean 74 years). The recruited voluntary participants were residents of privately owned senior houses. Furthermore, four focus group interviews, with 5-10 older adult participants, were organized in Madrid, Spain (N=29 in total, aged 56-96 years, mean 73 years). Two of the groups were of patients at the Hospital La Fuenfría; a third group's participants were independently living senior citizens, members of the Cultural Centre in the town of Cercedilla (Madrid), and a fourth group were also independently living older people attending the Primary Care Centre of Monterrozas in Las Rozas (Madrid).

After a short introduction to the project, the participants were asked to fill in a background questionnaire about demographics, current usage and attitudes towards technology, fall history and possible conditions affecting their balance. The scenarios were explained one by one, while a picture or a sketch elucidating the story was shown to the participants. After each scenario the interviewees filled in a questionnaire with six aspects adopted from Ikonen et al. [10]: credibility, usefulness, ease of use, adoptability, ethicality and desirability. Each aspect was rated on a five-point Likert scale; strongly agree, agree, undecided, disagree and strongly disagree. In addition, a willingness to pay option was included in the questionnaire for each scenario in the Spanish focus groups, whereas in the Finnish focus groups this topic was covered in the discussion.

The moderators encouraged the participants to freely discuss the scenarios in order to elicit open comments and gather possible improvement ideas. Through semi-structured discussion before and after the scenario evaluation, the participants were asked about their current knowledge of fall risks and perceptions on fall prevention activities. The discussions were recorded for later analysis.

2.3 Data Analysis

To compare the different scenarios a Goodness Grade, applied from Kenttä et al. [11], was calculated for each scenario. The answers for the Likert items were translated into numerical form from -2 to 2, with 2 representing the answer "strongly agree" and

-2 “strongly disagree”, respectively. The sum of all the answers for the same question is adjusted for answer frequency to that particular question. The results are presented as percentages from -50 to 50.

The focus group recordings were examined to collect the comments emerging during the scenario evaluation and the semi-structured discussions.

It is also important to note that the Likert items represent individual ‘attitude’ or ‘opinion’ with respect to a statement. The statement can be apparently logical, even close to a formal predicate in first-order logic, but the specific Likert item selected should not necessarily be seen as an objective truth value that the individual attaches to the statement. Some responders in a population might have a stronger background for logical thinking, some a weaker one. This means, on the one hand, that responses are not always comparable and, on the other, that transference from Likert items and scales to other items and scales must be done with the utmost care. Furthermore, test groups responding with Likert items are usually not given any detailed guidelines, e.g. concerning the difference between ‘agree’ and ‘strongly agree’.

2.4 Statistical Power

Hypothesis testing is comparing mean values for population groups. If the mean values are closer to being the same, we are closer to the ‘truth’ concerning the null hypothesis, i.e., closer to ‘not significant’, which means we have not found enough evidence against the null hypothesis. Conversely, ‘significance’ means having found evidence against the null hypothesis, i.e., there is a ‘significant’ difference in the mean values. Note, however, that “no evidence for difference” is not the same as “no difference”.

In our paper, the sample size is rather small relative to conventional ways of providing power calculations, which focus on type II error, i.e., false negatives. However, the sample size is not “too small” to provide some discussions and reach some conclusions, e.g. about differences in means.

Suppose we aim at a statistical significance level of 0.05 with 80% power. Then the sample size, using Altman’s monograms [12], should be

$$n = \frac{2}{d^2} \times c_{0.05;80\%} \tag{1}$$

in each arm of the trial, where the standardized difference is the ratio between difference in mean and standard deviation

$$d = \frac{(mean_1 - mean_2)}{\sqrt{\frac{(var_1 + var_2)}{2}}}. \tag{2}$$

As an example, consider the sample divided into two fairly equal-sized groups. As $c_{0.05;80\%} = 7.9$ and the groups’ answers have a difference in means of close to 0.5 and variances close to 1, according to (1) and (2), we obtain an ideal sample size of n = 63. I.e., we are fairly close the ideal sample size for a typical hypothesis testing. These observations also show how extended tests can be performed.

3 Results

3.1 Questionnaire Results

At least one of the six aspects (credibility, usefulness, ease of use, adoptability, ethicality and desirability) was evaluated by all the focus group participants for scenarios A and B. In addition, some participants did not evaluate all the scenarios resulting in response rates of 87.9%, 89.7%, and 86.2% for scenarios C, D, and E respectively. The first Spanish group with five people was not presented with scenarios C, D and E.

Fig. 1 presents the overall and separate goodness grades for Finland and Spain for each scenario. On a scale from -50 to 50, scenario C scored the highest total goodness grade of 22.6, as it did in both countries separately. In Finland, scenario C was clearly the best received, with a score of 26.8, whereas in Spain the ratings were more even.

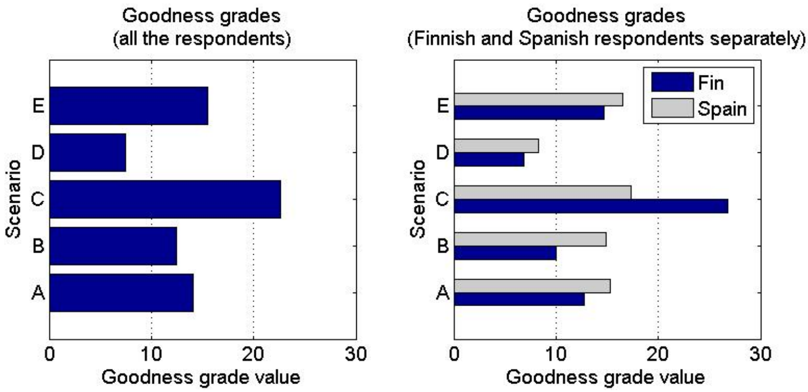

Fig. 1. Left: Goodness grades among all respondents (N=58). Right: Goodness grades among Finnish (N=29) and Spanish (N=29) interviewees separately.

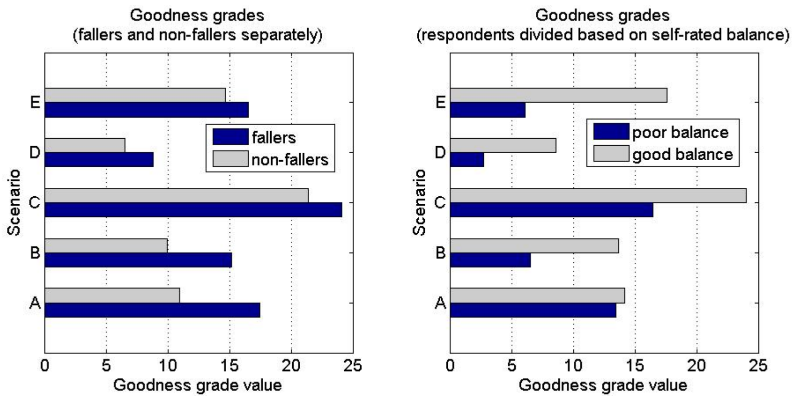

Fig. 2. Left: Goodness grades among subjects based on number of falls during the last year; one or more falls (N=28) and zero falls (N=30). Right: Goodness grades among subjects based on self-rated balance; poor or very poor (N=11) and moderate to very good (N=47).

28 of 58 focus group participants had fallen at least once during the previous year and 64.3% of those still rated their balance as moderate or better, and 32.1% as good or very good. Fig. 2 illustrates how people with a history of falls rated each scenario compared to non-fallers, and how people with poor self-rated balance answered compared to people with good self-rated balance.

There was a clear correlation between the desirability to use an ICT-based fall prevention system and current computer use. Using the average of all answers to the questionnaire, the mean to the question "I would like to use it" among those using a computer is 2.38 while the mean among those not using a computer is 2.97 (5 representing absolute rejection and 1 absolute willingness). The difference in mean is therefore 0.59.

Willingness to pay was introduced separately for each scenario in the Spanish questionnaire. The results correspond with the qualification given to each scenario. The first number denotes average points for all seven questions, and the second number is the average for the willingness to pay question: A 2.5/3.1; B 2.5/3.0; C 2.4/2.6; D 2.7/3.1; E 2.4/3.0 (5 representing absolute rejection and 1 absolute willingness).

3.2 Qualitative Data Results

According to participants in both countries, external factors were by far the most important cause of falling, i.e. slippery roads, bad footwear and rugs. Intrinsic factors that were mentioned included poor muscle strength, dizziness, low blood pressure, fear of falling and cerebral infarction.

Focus group participants considered education important, i.e. sharing information about fall risks and fall prevention either among their peers or by professionals. Finnish interviewees called the topic of fall prevention very well known by them, although some people considered that it doesn't apply to them at this point. On the other hand, the Spanish older adults complained about a lack of structured information about falls before they or people in their near circle fall. In addition to proper footwear and environmental modifications, such as removing rugs, many of the respondents suggested balance exercises and strength training as means for preventing falls.

Opinions on willingness to pay for these kinds of solutions differed. Some considered them useful and said they would pay at least some money themselves while others were not willing to pay at all. Some people were worried that it wouldn't be possible on their low retirement allowance. They said the municipality should be responsible for the costs, since using these kinds of systems can reduce health care expenses.

Many of the participants expressed an interest in participating in the development in the later stages of the project as field trial users of the future system. Scenario C was the most attractive to focus group participants. Comments included: "It is the most feasible" and "most usable in real life". The social aspect of scenario E was found positive by many. They valued the peer support and cooperation features. However, there were some that thought they might feel pressured when it came to comparing their own performance with others.

The usage of the word “computer” in the scenarios caused ambivalence among some users who did not currently own a computer. Some suspected that the proposed solutions could not be implemented in real life. There were worries about who would carry out the fall risk evaluations and how much they would cost.

4 Discussion

The overall goodness of all scenarios was positively evaluated, since there were no negative grades on the scale from -50 to 50. The three best-liked scenarios, those introducing intelligent gym equipment, peer support, and multi-factorial fall risk assessment, were the same in both countries, Finland and Spain. In Finland, scenario C rose clearly above the others. One contributory factor may be that it was the most familiar to many of the Finnish interviewees, since most of them were actively going to gym already. Scenario D, with the lowest goodness grade in both countries, may have been too technical for many and difficult to understand. It contained several different features and perhaps should have been broken down into smaller sub-scenarios. In addition, it should be noted that the personality of the moderator may have had an effect on the results, as participants were divided into subgroups led by different moderators.

Interestingly, people with a history of falls usually gave better ratings to the proposed scenarios than non-fallers. This could indicate that people who have fallen before are, on average, keener on fall prevention. At the same time, people who rated their balance better evaluated all the scenarios better than people with poor self-rated balance. This might arise from the fact that, for people with poor balance, it is difficult to perform the physical activities that are part of most scenarios. Also Stevens et al. [13] reported that older adults often believe themselves to be too old or frail for physical exercise.

The participants were quite well aware of fall risks, which may be due to the fact that they were recruited on a voluntary basis, implying that only people interested in fall prevention participated. Similarly to Stevens et al. [13], the first responses to the question on causes of falls usually related to extrinsic factors rather than intrinsic factors.

There were some interviewees in the focus groups that did not currently own computers, which caused some confusion for them. However, the situation will presumably be different in the future, since older adults ten years from now will most probably be used to working with computers.

In future work, evaluation results will be used for system requirement specifications. Similar focus group interviews will also be organized with professional end users, e.g. physical therapists, doctors and other caregivers. Furthermore, it would be interesting to evaluate the same scenarios at the end of the project to observe possible changes in older adults’ perceptions and attitudes towards the presented ideas.

Acknowledgments. This study was conducted under the Ageing in Balance project, which is a part of the European Ambient Assisted Living Joint Program (AAL JP). The authors would like to thank all the focus group participants and especially YH Kodit Oy and Kotosalla foundation in Finland, and Cercedilla Town Hall and Centro de Salud Monterrozas in Spain for their contribution.

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PAPER II

Human balance estimation using a wireless 3D acceleration sensor network

International Conference of the IEEE Engineering in Medicine and Biology Society (pp. 1493–1496).
New York, Aug. 30 2006 – Sept. 3 2006.

Proceedings of the 28th IEEE
EMBS Annual International Conference
New York City, USA, Aug 30-Sept 3, 2006

Human Balance Estimation using a Wireless 3D Acceleration Sensor Network

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Abstract—**Balance and gait are a consequence of complex coordination between muscles, nerves, and central nervous system structures. The impairment of these functions can pose serious threats to independent living, especially in the elderly. This study was carried out to evaluate the performance of a wireless acceleration sensor network and its capability in balance estimation. The test has been carried out in eight patients and seven healthy controls. The Patients group had larger values in lateral amplitudes of the sensor displacement and smaller values in vertical displacement amplitudes of the sensor. The step time variations for the Patients were larger than those for the Controls. A fuzzy logic and clustering classifiers were implemented, which gave promising results suggesting that a person with balance deficits can be recognized with this system. We conclude that a wireless system is easier to use than a wired one and more unobtrusive to the user.**

I. Introduction

MAINTAINING balance while walking and performing other everyday activities has a great impact on quality of life. Disorders of balance and gait have serious consequences, since falling can cause serious injuries or even death. In Finland, falling has been estimated to cause the death of more than one thousand persons annually among people over 50 years old [1]. Preventive measures could reduce the risk of falling by 20 – 40 % [1].

Nowadays, balance and gait evaluations usually depend on visual objective estimation or on expensive laboratory equipment, such as a force platform or video camera system. A wireless acceleration sensor network provides for a reasonably priced ambulatory measurement system that is unobtrusive to the user.

II. Methods

A. Wireless Sensor Network

A fundamental part of this measurement system is a SoapBox (Sensing, Operating and Activating Peripheral Box). Five SoapBoxes are used to implement an acceleration sensing wireless body area network (WBAN) (see Fig. 1). A SoapBox is a flexible and reusable platform for several applications in ubiquitous computing. The matchbox-sized SoapBox module has a processor, five sensors and wireless and wired communication capabilities. Although the SoapBox includes several types of sensors, only the 3D acceleration sensor is used in this application. The acceleration sensor is constructed of two +/-2g Analog Devices (ADXL202JE) [2], [3].

The WBAN arrangement in this research consists of one central SoapBox and four remote SoapBoxes. The remote SoapBoxes measure 3D acceleration at a 41.25 Hz sampling rate and the central SoapBox has a sampling rate of 33 Hz. The central node receives the data from the remote nodes wirelessly using a 1 mW licence free 868.35 MHz radio (RF Monolithics TR1001). A time division multiple access (TDMA) based medium access control (MAC) protocol is used for data transfer. The central node forwards both its own and the received data to a Nokia Series 60 mobile phone. This time a Bluetooth connection (F2M01 serial-to-Bluetooth adapter) is used for data transfer [2], [3].

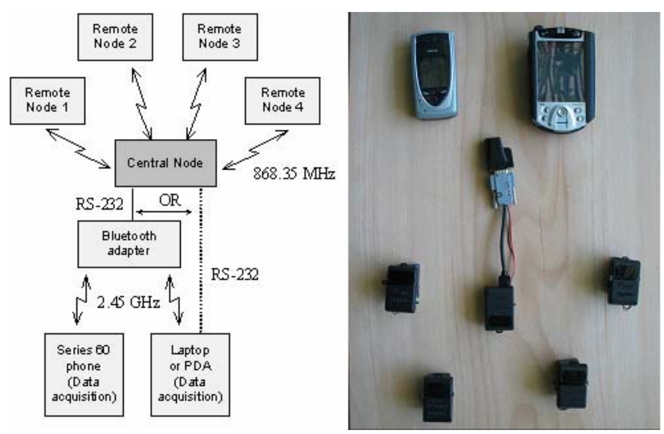

Fig. 1. The overall network topology and device setup.

A MotionLogger (Series 60 Symbian [4] application) is created on the mobile phone for storing the WBAN data. An annotation feature is added to help distinguish between different events in the data at the data processing phase. The user adds an annotation label to the data, which stands as a mark for the starting point or ending point of a certain event. The measured data is transferred to a PC via a Bluetooth connection.

B. Measurements

The system was tested by executing balance and mobility

Manuscript received April 21, 2006. This work was supported in part by Tekes, the Finnish Funding Agency for Technology and Innovation and VTT, Technical Research Centre of Finland.

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tests at the Rokua and Kajaani Rehabilitation Centres under the supervision of a trained physical therapist. The test subjects performed several tasks, for example, walking 10m as fast as possible, standing up from a chair, Berg's balance test etc. wearing the wireless sensor network. The SoapBox sensors are attached with five specially made rubber bands, where a pocket for the SoapBox and its battery is sewed to each band. The rubber bands are fastened into place with a two-sided adhesive sticker, which is sewed to the rubber band so that it doesn't lose its elasticity. One sensor is placed on the lower back at approximately the height of the centre of mass. Two of the sensors are attached to the outsides of the knees and two to the outsides of the ankles. The purpose is to align the sensor axes so that when a person is standing in an upright position, one axis is pointing to the side, one axis backward or forward and one axis up or down.

We have included eight patients and seven healthy controls in this study (Table I). The study was carried out in all subjects after informed consent and in agreement with the Helsinki declaration. The subject qualifies as a patient if he/she has an illness that may affect his/her balance. The results of the 10-meter walk task are presented.

TABLE I
BACKGROUND INFORMATION OF THE TEST SUBJECTS

Subject Patient (P)/ Control (C)	Male (M)/ Female (F)	Age (years)	Diagnosis
P1	M	51	MS, spastic, ataxia
P2	M	55	Dystonia, backwards falling attacks
P3	F	77	Left falling attacks occasionally, left hearing deficiency
P4	F	49	Rheumatism, shortening of right leg (3cm), stiff right ankle, artificial joint in both hips and left knee
P5	F	55	Rheumatism, shortening of right leg (3cm), knee valgus, stiff ankle, left knee instability, artificial joint in both hips and left knee
P6	F	54	Left hemiplegia
P7	M	61	Mild left leg paralysis
P8	M	64	Right hemiplegia, ankle support, stick
C1	M	81	-
C2	M	80	-
C3	F	79	-
C4	F	67	-
C5	F	20	-
C6	M	56	-
C7	M	49	-

C. *Tilt Normalization*

Tilt normalization is performed for the hip sensor. The sensor axes are rotated so that the up – down axis is in the same direction as the gravitational force. This algorithm, adopted from [5], only corrects the average tilt due to inaccurate attachment of the sensor or different body shapes, not the dynamic tilt caused by human movements. The same tilt normalization method was found useful in user-independent gesture recognition in [5].

D. *Parameters*

As stated in [6] and [7], a person can be identified from the gait data measured using accelerometers. Thus, it is reasonable to believe that disorders affecting balance of gait are also noticeable from the acceleration data measured while walking. The human gait has been studied several times before in the context of balance estimation using different types of measurement systems. One example is Hausdorff *et al* [8], who investigated gait variability and its relationship to fall risk among older adults using force-sensitive insoles. This approach is now applied to the accelerometer-based system. A hip sensor placed on the lower back is most suitable for detecting time variables of gait, since it contains information from both legs (right and left leg). Heel strikes cause peaks in the vertical acceleration signal measured from the hip. The maximum peaks are detected from the data, and the step times are calculated using the time span between the peaks. A standard deviation of the step times within a data clip is calculated.

The amplitude values of the position trajectories of the sensor are also interesting. As Dodd *et al* [9] investigated lateral pelvic displacement (LPD) in stroke patients, this research also studies the same feature and its relationship to the balance and stability of walking. Position trajectory of the sensor is calculated for the walking data by double-integrating the acceleration signal. An offset fluctuation is diminished by calculating a correction curve, which is then subtracted from the integral. The correction curve is obtained by calculating an offset value for every point, which is an average of two consecutive steps that is, one step before and one step after the point in question. The underlying assumption when calculating the position trajectory of the sensor during gait is that, on a level surface, the accelerations in lateral and vertical directions should have a zero mean value. The correction curve may somewhat attenuate real transitory peaks in position trajectory. Similarly, the swinging and slight deflection of the sensor during walking makes the absolute values of the position partly indicative, but differences between position trajectories of different persons can still be distinguished. Maximum and minimum amplitudes in the lateral position trajectory represent displacements to the right and left. The total amplitude value is a sum of average right and average left amplitudes, that is, an average of total lateral amplitude of the sensor. The total vertical displacement amplitudes are also investigated where the averages of up and down amplitudes are combined.

E. *Subject Classification*

The subject classification utilizes the self-organizing map (SOM) clustering [10] and fuzzy logic methods. The clustering is carried out with algorithms implemented in the

SOM toolbox from [11]. Prior to clustering, the variables are normalized using the toolbox's functions so that their variance is set to unity and their mean to zero. This ensures equal emphasis on every variable regardless of their numerical range. In the fuzzy logic analysis, the leave-one-out method is used to obtain membership functions for the two groups Patients and Controls. For the subject left out, the degrees of membership are determined from the functions obtained with the other subject's parameters. The four nearest to the median values of the Patients are used to define the membership function for that group. The average value of them is set to 1 and the minimum and maximum values to 0, which results in a membership function shaped like a triangle. The membership function for the Controls is evaluated similarly. The degree of membership of the subject in both groups is determined with the membership functions for every three variables separately. The total degree of membership is obtained by adding all three degrees of membership values in the Patients group and all three degrees of membership values in the Controls group. Thus, the maximum total degree of membership in a group can be three. The subject is classified as belonging to the group in which it has the larger degree of membership.

III. Results

Vertical acceleration of the hip sensor during walking is used in the evaluation of time values. Fig. 2 presents standard deviations of the step times for both Patients and Controls.

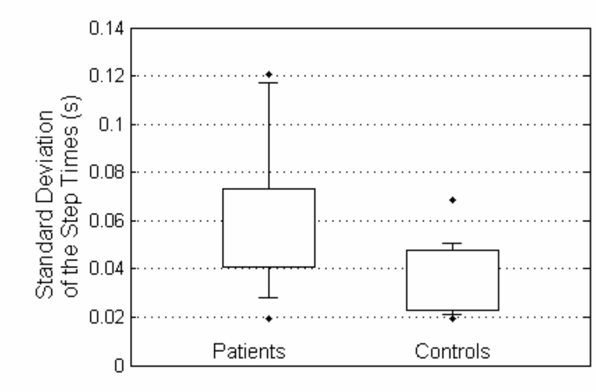


Fig. 2. Standard deviations of the step times evaluated from the acceleration measured from the hip during walking. The white boxes contain the four nearest to the median values of the Patients (n=8) and the three nearest to the median values of the Controls (n=7). Line markers represent the next values under and above the box. The dots represent the smallest and largest values in both groups.

Fig. 3. presents lateral and vertical displacement amplitudes of the hip sensor during walking in both subject groups. The lateral amplitude value used is a sum of average right and average left amplitudes. On the other hand, the averages of up and down amplitudes for the vertical displacement are combined.

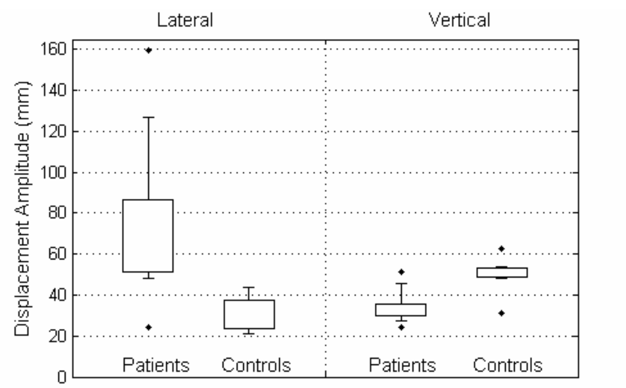
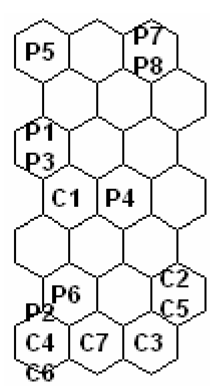


Fig. 3. Lateral and vertical displacement amplitudes of the hip sensor measured during walking. The white boxes contain the four nearest to the median values of the Patients (n=8) and Controls (n=6) in lateral direction, and the four nearest to the median values of the Patients (n=8) and the three nearest to the median values of the Controls (n=7) in vertical direction. The line markers represent the next amplitude values under and above the box. The dots represent the smallest and largest values in the group. (Control subject C6's walking sample was too small for lateral position assessment, thus it was left undefined.)

The parameters "standard deviation of the step times", "total amplitude of the lateral position of the hip sensor" and "total amplitude of the vertical position of the hip sensor" are taken into subject classification analysis. The clustering is carried out for subjects P1 – P8 and C1 – C7. The plot in Fig. 4a) illustrates how the subjects are distributed on the map. The fuzzy logic analysis is carried out for subjects P1 – P8 and C1 – C7, excluding subject C6, since it does not have values for all three parameters. The results for the fuzzy classification are found in Fig. 4b).



a)

Subject	Result (P → Patient, C → Control)
P1	P
P2	C
P3	P
P4	P
P5	P
P6	C
P7	P
P8	P
C1	P
C2	C
C3	C
C4	No result
C5	C
C7	C

b)

Fig. 4. a) The subject distribution on the clustering map. b) The fuzzy classification of the subjects into two groups Patients (P) and Controls (C).

IV. Discussion

Standard deviations calculated from the step times show a difference between Patients and Controls. The larger standard deviation in this context means a more irregular gait. The results are consistent with those previously reported [8], even though the distance walked was shorter in this testing arrangement. Lateral displacement amplitudes of the Patients are also greater than those of the Controls, which is concordant with the data recently reported [9]. A difference between the two groups can also be found in vertical displacement amplitudes.

The clustering and fuzzy logic methods provide similar results. Subject C1 is closer to the Patients cluster and it was also declared a Patient in the fuzzy logic analysis. The age of subject C1 might have had some effect on his gait, thus bringing him closer to the Patients group, as the incidence of falls increases markedly with age. In addition, subjects P2 and P6 are more in the Controls cluster than in the Patients one, and they were declared Controls with the fuzzy logic classifier as well. Patient P6 has left hemiplegia, which is mostly emphasized in the left arm. This explains why the illness does not affect the patient's gait very much. Patient P2 has an illness, which causes backwards falling attacks. According to a medical assessment, the person walks with his slightly spastic legs straight forward without any abnormal sway between the falling attacks. Two clusters can still be separated, one with more Patients in it and the other with more Controls in it, and the results are comparable with the ones obtained using the fuzzy logic method.

To improve the testing arrangement, the walking distance could be longer than 10 metres e.g. 50 metres depending on the condition of the subjects. More subjects could also be used in the study. It could also be useful to divide the subjects into more specific groups, such as subjects with a high fall risk, subjects with a moderate fall risk, and subjects with no fall risk. This kind of five-sensor system provides a large amount of data. Including the sensor data obtained from the knee and ankle sensors to the data analysis would provide more accurate results. For example, different phases of the gait cycle can be studied further to obtain information about the rhythmics of the gait. The dynamical tilt of a sensor can be reached with additional sensors, e.g. gyroscopes, making it possible to calculate the temporary 3D position of the acceleration sensor. This in turn enables definition of the continuously changing offset values of the acceleration signals caused by the gravity, and thus substantially improves the estimation of the position trajectory during the gait.

All in all, the parameters calculated from the walking data appeared to have dependence to balance even with quite a small test subject group. A reliable classifier was also introduced for identifying subjects with balance deficits. This provides a method for creating a new ambulatory on-line balance analyzer tool for doctors and physical therapists. The balance analyzer could be used in addition to a physical examination or home health care as a means of detecting balance deficits at an early stage and identifying the need for fall-preventive measures.

ACKNOWLEDGMENT

VTT would like to thank the staff of Rokua and Kajaani Rehabilitation Centres for their valuable work concerning the test measurements and Ari Saarinen in particular for his contribution to this study.

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PAPER III

Accelerometry-based berg balance scale score estimation

IEEE Journal of Biomedical and Health Informatics,
18(4), 1114–1121.

Accelerometry-Based Berg Balance Scale Score Estimation

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***Abstract*—The objective of the study was to investigate the validity of 3-D-accelerometry-based Berg balance scale (BBS) score estimation. In particular, acceleration patterns of BBS tasks and gait were the targets of analysis. Accelerations of the lower back were measured during execution of the BBS test and corridor walking for 54 subjects, consisting of neurological patients, older adults, and healthy young persons. The BBS score was estimated from one to three BBS tasks and from gait-related data, separately, through assessment of the similarity of acceleration patterns between subjects. The work also validated both approaches' ability to classify subjects into high- and low-fall-risk groups. The gait-based method yielded the best BBS score estimates and the most accurate BBS-task-based estimates were produced with the *stand to sit*, *reaching*, and *picking object* tasks. The proposed gait-based method can identify subjects with high or low risk of falling with an accuracy of 77.8% and 96.6%, respectively, and the BBS-task based method with corresponding accuracy of 89.5% and 62.1%.**

***Index Terms*—Berg balance scale (BBS), fall-risk assessment, gait analysis.**

I. Introduction

EVERY third person over 65 years of age falls at least once every year [1], and, for example, falling or stumbling was the accident most commonly leading to death among both men and women in Finland in 2010 [2]. Locomotion requires muscle strength and balance. Problems with balance cause changes in gait, such as decelerating one's walking and shortening one's steps [3] to compensate for poor balance. One traditional method of balance assessment is the Berg balance scale (BBS) [4], a performance-oriented measure of balance that involves 14 tasks. Performance of each task is scored on a scale of 0–4, making the maximum possible score 56. According to Shumway-Cook *et al.* [5], people with a score lower than 49 show increased risk of falling, while those with a score over 49 have low fall risk. The BBS scale is based, however, on subjective assessment by, for example, a physiotherapist and yields information about balance at that particular moment, so it is unsuitable for continuous fall-risk estimation in free-living situations.

Manuscript received April 29, 2013; revised August 22, 2013; accepted October 24, 2013. Date of publication November 6, 2013; date of current version June 30, 2014. This work was funded by Tekes (the Finnish Funding Agency for Technology and Innovation), Pikosystems Oy, TietoEnator Oyj, YH Länsi Oy, UPM-Kymmene Oyj, Turun Ortofysio Oy, ArctiCare Technologies Oy, Suomen Ensiapupalvelu, and VTT Technical Research Centre of Finland.

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Digital Object Identifier 10.1109/JBHI.2013.2288940

As reviewed by Shany *et al.* [6] and Scanail *et al.* [7], wearable sensors are increasingly being used for human gait and balance assessment. Typically, one or more accelerometers and/or gyroscopes are used. Data-analysis methods and algorithms have been developed for such purposes as activity recognition [8], fall detection [9], gait analysis [10], and fall-risk estimation [11]. Studies that aim at distinguishing fallers from nonfallers, or between people with high and low fall risk, via sensor data usually compare the results with those of standard clinical fall-risk assessment scales such as the BBS [12], timed up-and-go (TUG) [13], or physiological profile assessment [11]. They show that analysis of sensor data can provide comparable results relative to the clinical measures [6], [7].

Three-dimensional accelerometry enables unobtrusive long-term monitoring of human movements in unsupervised conditions [14] and thus provides an opportunity for objective fall-risk estimation in free-living situations [11] without the need for a health-care professional's presence. Some studies suggest that body-worn kinematic sensors may even be more accurate than the standard fall-risk metrics. For example, Greene *et al.* [15] reported a mean accuracy of 76.8% in contrast to the 61.4% of BBS testing and 60.6% of TUG in discriminating persons with a history of falls. It was also indicated by Doheny *et al.* [16] that accelerometry might improve discrimination between fallers and nonfallers from that of the standard clinical measure five times sit-to-stand (STS-5).

Growing health-care impacts and costs of demographic ageing serve as motivation to develop methods for recognizing individuals with increased fall risk more accurately and earlier, since this is an important element in the selection of the evidence-based interventions with the greatest chance of a positive outcome [17]. Earlier detection of balance problems enables cost-effective targeting of fall-prevention actions to the right people, early enough. For example, improvements in muscle strength can compensate somewhat for balance deficits and diminish difficulties in moving [3].

In the research described here, the aim was to explore the use of accelerometry in estimating the BBS score and, thus, facilitate development of methods for estimating a person's fall risk objectively and unobtrusively during daily activities. In particular, the similarity (or distance) between different BBS tasks and gait-related acceleration trajectories were studied. Duda *et al.* [18] state that in some cases general Euclidean distance may or may not be meaningful, and it is hard to base choice of a metrics on prior knowledge about the distributions. Therefore, another objective was to examine whether the selection of a similarity measure has an impact on the results. Fifty-four subjects from three groups—neurological patients, older adults, and healthy young persons—were studied and a method for estimating a person's BBS score is proposed here.

II. Methods

A. Data Collection

The test protocol included a BSS test [4], which was explained to the participants and evaluated by a physiotherapist, and at least a 10-m walk back and forth in a corridor at one's own pace in one's preferred footwear. The BBS test is used by the health-care professionals at participating university hospital as part of their care process for evaluation of balance deficits. Alongside the self-reported history of imbalance, it has been reported to predict falling with a sensitivity of 91% and specificity of 82% [5]. Kinetic data were collected during the tests with a 3-D accelerometer (8 bit, 75-Hz alive heart monitor, from Alive Technologies, of Queensland, Australia). It is often recommended that the sensor be attached at waist level, near the center of mass [6]. To ensure comparability between the individual results, sensor placement was kept as uniform as possible; the sensor was attached to the person's lower back (lumbar spine) with a tight elastic belt as described in [19]. Each task's start and end moments were marked by a researcher on the site with computer software [20] to an accuracy of 1 s. The annotation entries were checked manually afterward to verify their correctness.

The BBS consists of 14 physical tasks, such as *transfer from sitting to standing position*, *standing eyes shut*, and *picking up an object from the floor* [4], all normally part of daily activities. Each task performance is assigned 0–4 points by a professional observer, to give a total score of 0–56. The maximum score of 56 indicates that there is no increased risk of falling. For example, the full score of four points is given for the BBS task *transfer from standing to sitting position* when the person is able to sit down on the chair without using his or her arms for assistance. The score is reduced as the amount of help the person gets from his or her arms, his or her legs, or the supervisor increases. Use of the arms and/or legs in execution of the task affects the speed and trajectories of the body. It can also be expected to influence the signals captured by an accelerometer attached to the body—e.g., altering the signal form.

B. Subjects

Fifty-four subjects were recruited for the study, for three groups: 15 neurological patients (aged 40–68 years, with mean and standard deviation (std) of 55.2 $\pm$ 7.3); 20 older adults (aged 67–87 years, with mean+std 76.8 $\pm$ 5.6); and 19 healthy young persons (aged 21–36 years), with mean+std $=$ 27.5 $\pm$ 4.4. Seven of the patients had a diagnosis of cerebrovascular diseases (ICD-10 I60–I69), one of injuries to the head (ICD-10 S00-S09), one of inflammatory disease of the central nervous system (ICD-10 G00-G09), and six of diseases of nervous system (ICD-10 G20-G26), of which the most had a Parkinson's disease. Accelerometer data from five persons were lost due to technical problems, resulting in inclusion of 19 subjects in the older adults group, 13 in the neurological patients group and 17 in healthy young persons' group. The same physiotherapist evaluated all the participants and the tests situations were as identical as possible. The study was accepted by the ethical committee of the hospital district. Preliminary analysis of differences in accelerometer signal features between the subject groups are reported in [12].

C. Data Analysis

The first goal of the data analysis was to develop a method for estimating the BBS score of a person on the basis of the accelerometer data recorded 1) during performance of the BBS tasks and 2) on gait. Both approaches were validated in terms of their ability in classifying subjects into high- and low-fall-risk groups. The second goal was to determine which of the BBS tasks provide the best results and to compare the estimated BBS scores between the subject groups.

D. Preprocessing of Data

The data analysis was carried out in the Matlab (from MathWorks, Inc.; Natick, MA, USA) programming environment. Nine tasks from the BBS were selected for further analysis. The tasks excluded, among them *stool stepping*, involve periodic movements or movements that fewer test subjects were able to perform. For example, only 39 subjects were able to execute the *standing on one foot* task, so its inclusion in the analysis would have complicated interpretation of the results. These tasks were selected: *sit to stand*, *stand without support*, *stand to sit*, *stand eyes shut*, *stand feet together*, *reaching*, *picking up an object*, *look behind*, and *tandem standing*. The BBS estimation was analyzed for combinations of one, two, and three tasks, for determination of which tasks lead to the best BBS score estimation result. There would be 1001 distinct combinations of four tasks out of nine, so the set size was limited to three tasks in this case. With the exception of one subject in the neurological-patient group for the *stand to sit* task, data existed for all nine tasks selected for all 49 test subjects.

The data in the x, y, and z dimensions measured during the BBS tasks and the gait were identified on the basis of manual annotations. In the BBS-task-based approach, the resultant acceleration was calculated for these data samples according to (1), where a_x is acceleration in the medio-lateral, a_y the vertical, and a_z the anterior–posterior planes:

$$a_{\mathrm{res}}\left[n\right] = \sqrt{\left(a_x\left[n\right]\right)^2 + \left(a_y\left[n\right]\right)^2 + \left(a_z\left[n\right]\right)^2}. \qquad (1)$$

The average signal length was calculated for each task, and each subject's data were normalized to the average for the relevant task via resampling of the signal by means of either interpolation or decimation. This procedure enabled comparison of waveforms between subjects. Two example cases are illustrated in Fig. 1. Furthermore, to reduce the noise effect, the resulting signals were filtered with a five-point floating average filter.

In the gait-based approach, the data were preprocessed according to Mäntyjärvi *et al.* [21], to construct a unique 3-D gait pattern for each subject. While they used only two dimensions of the 3-D data, this paper uses all three dimensions. The

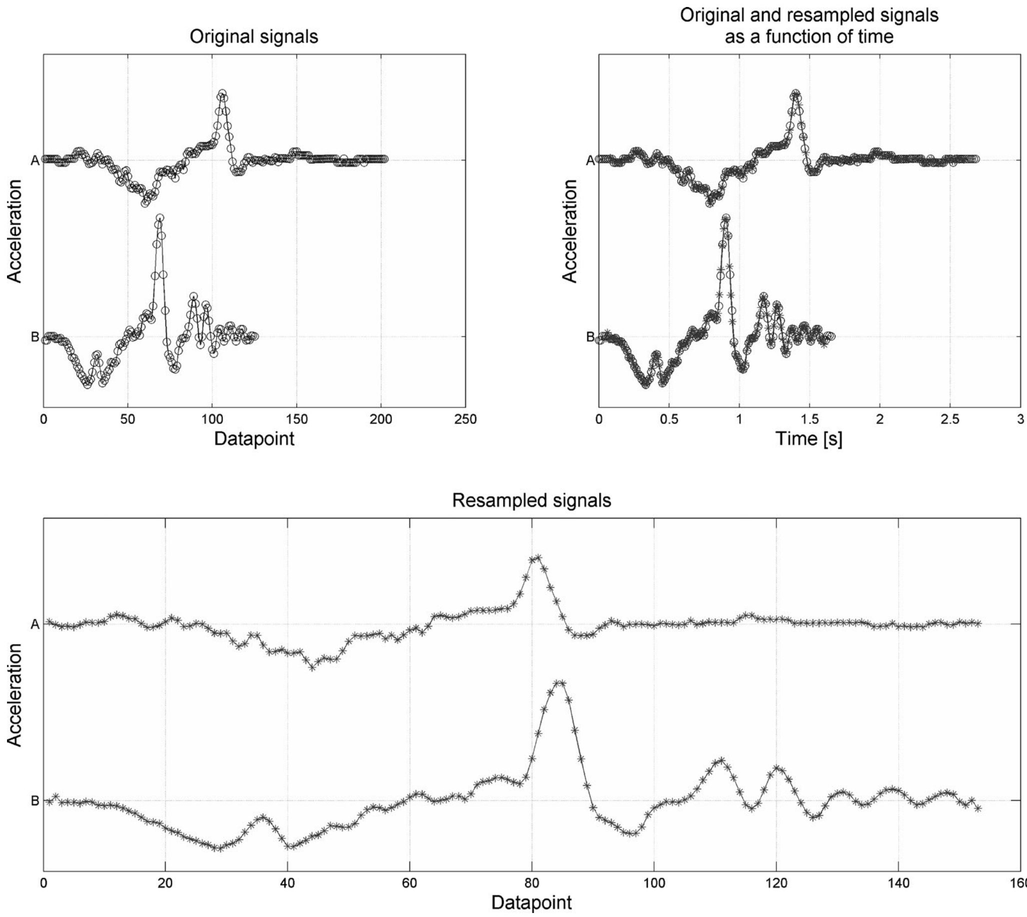

Fig. 1. Examples of the data resampling for two cases, denoted as A and B. The upper left picture illustrates the original signals. (a) Image in the upper right features original and decimated signals, in which the number of data points is reduced from 202 to 153, and (b) original and interpolated signals, in which the number of data points is increased from 125 to 153. Circles represent the original samples, and the resampled signals are plotted with asterisks ($*$). The resampled signals for A and B are plotted together at the bottom. The data were obtained during the *stand to sit* task.

procedure was similar otherwise. Data sequences representing step pairs were separated out from the gait data. Visual inspection was applied during the process, to verify that the step pairs had been detected correctly and that at least two separate pairs were found for each subject. The test subject in question was omitted from the gait-pattern examination if the step pairs were not detectable; resulting in 47 subjects in gait-based BBS score estimation. Intercorrelation of the signals representing the steps of a specific subject was calculated for all three dimensions, with a sliding window, to reveal the 60% of pairs that correlated best. The aim was to discover the step pairs that represent the typical gait pattern for the relevant person. With this procedure, extraordinary steps due to turning, swaying, etc., are omitted. The selected step pairs were averaged for each three dimensions separately and concatenated to form a person's signature gait pattern. The left–right or right–left order of steps is taken into account by creation of two gait patterns for each subject, which represent both left–right and right–left combinations without determination of which is which.

E. BBS Score Estimation

In the first part of the analysis, leave-one-out cross-validation was applied for calculation of the BBS estimate for each subject. In addition to distance between two samples, other metrics can be used to measure the similarity of two vectors [18]. Since different similarity measures suit better for various types of data, three similarity measures were tested, to compare the person's preprocessed data samples to the other subjects' corresponding ones. The experiments were done using basic measures such as Euclidean distance (2) and correlation coefficient (3), and Tanimoto coefficient (4), which combines them both in operation. The aim here was to find out whether the selection of the metrics used has a significant impact on the results.

$$d(\mathbf{a},\mathbf{b}) = \left(\sum_{k=1}^{d} |a_k - b_k|^2\right)^{1/2} \tag{2}$$

$$r_{ab} = \frac{\sum_{k=1}^{d} (a_k - a_{\mathrm{mean}})(b_k - b_{\mathrm{mean}})}{\sqrt{\sum_{k=1}^{d} (a_k - a_{\mathrm{mean}})^2 \sum_{k=1}^{d} (b_k - b_{\mathrm{mean}})^2}} \tag{3}$$

$$s(\mathbf{a},\mathbf{b}) = \frac{\mathbf{a}^t\mathbf{b}}{\mathbf{a}^t\mathbf{a} + \mathbf{b}^t\mathbf{b} - \mathbf{a}^t\mathbf{b}}. \tag{4}$$

Sample vectors from two subjects are denoted as **a** and **b**, a_k and b_k are the kth sample of vectors **a** and **b**, and a_{mean} and b_{mean} are the mean of **a** and of **b**, respectively.

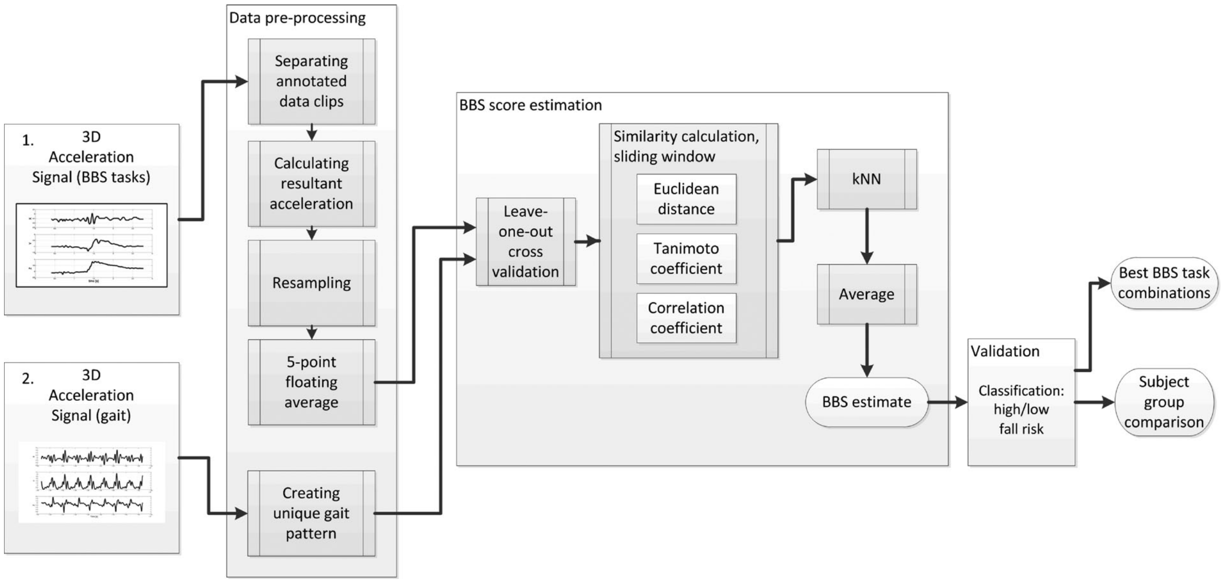

Fig. 2. Data-analysis process for BBS tasks and gait-related acceleration signals.

The k-nearest-neighbor classification with a k value of 3 was applied for selection of the three most similar reference subjects for the test subject under evaluation. That is, the three subjects with the greatest similarity or smallest distance to the subject in question were selected. A 1-s sliding window (based on the original sampling frequency) was used to eliminate possible deviations in annotation markers. The greatest similarity or smallest distance from that window was selected to represent the similarity to, or distance from, the relevant reference subject. An average of the real BBS scores of those three neighboring subjects was used as a BBS estimate. In case the estimation is based on data from more than one BBS task, the estimates for individual tasks are averaged over all tasks selected.

F. Validation

The estimated BBS scores were used for classification of the subjects into high- and low-fall-risk groups. With the real BBS scores, a cut-off score of 49 [5] was used for determination of the reference classes. A frequently used method of investigating the sensitivity and specificity of a classifier, receiver operating curve (ROC), was applied. Area under curve (AUC) was calculated for each ROC, to aid in comparison of results and determination of the best task combinations. The data-analysis process is illustrated in Fig. 2.

III. Results

The task combinations that produced the highest AUC values with one, two, and three tasks and the gait-based results are presented in Table I. The estimated BBS scores differed significantly (one-way ANOVA, Kruskal Wallis test $p < 0.05$) between subjects with low and high fall risk for all other cases except the task *stand to sit*, for which Euclidean distance was employed as a similarity measure.

In the BBS-task-based estimation, each time a task was added to the algorithm the AUC value increased and the recognition of subjects with a high risk of falling was improved. The best results were obtained with the tasks *stand to sit*, *reaching*, and *picking object*. The gait-based estimates produced higher AUC values than did BBS-task-based analysis. The highest AUC values were obtained with Tanimoto coefficient as a similarity measure in both approaches.

The distributions of the estimated and real BBS scores in the subject groups; healthy young people, older adults, and neurological patients are shown as boxplots in Fig. 3. The boxplots represent estimated BBS scores with different similarity measures calculated with the combinations of three tasks shown in Table I and the gait-based method.

The distributions of gait-based BBS estimates between subject groups are more similar to the real BBS score distributions than to the ones obtained with the three BBS tasks. Furthermore, the BBS-task-based estimates tend to have wider distributions in the healthy-young-adult group and narrower distributions in the older adult and patient groups in comparison to the real BBS scores. In all cases, the mean of healthy-young-adults' BBS score differed significantly from the means for the other two groups ($p < 0.001$).

The estimated BBS values are plotted against the real BBS scores in Fig. 4 for the three subject groups; Tanimoto coefficient is used here as a similarity measure with the combination of the best three tasks (according to AUC analysis) and the gait-based method, since it produced the highest AUC values.

The total estimation error was smaller for gait-based BBS score estimation than for the BBS-task based method. The algorithm tends to overestimate the lower BBS scores under both approaches.

IV. Discussion

The aim of the research described here was to develop an accelerometry-based method for estimating the BBS score by using 1) combinations of data obtained during different BBS

TABLE I
CONFUSION MATRIX FOR THE BEST CLASSIFICATION RESULTS (HIGHEST AUC VALUES) WITH RESPECT TO LOW- AND HIGH-FALL-RISK GROUPS FOR ONE, TWO, AND THREE BBS TASKS AND THE GAIT-BASED METHOD WITH THREE SIMILARITY MEASURES

Real BBS scores	Estimated BBS scores **Euclidean distance**		**Tanimoto coefficient**		**Correlation coefficient**	
One task	task: *stand to sit* AUC = 0.6597		task: *stand to sit* AUC = 0.7967		task: *stand to sit* AUC = 0.7577	
	Low fall risk BBS > 49	High fall risk BBS ≤ 49	Low fall risk BBS > 49	High fall risk BBS ≤ 49	Low fall risk BBS > 49	High fall risk BBS ≤ 49
Low fall risk BBS > 49	69.0	31.0	72.4	27.6	89.7	10.3
High fall risk BBS ≤ 49	47.4	52.6	26.3	73.7	57.9	42.1
Two tasks	tasks: *stand to sit* *picking object* AUC = 0.7868		tasks: *stand to sit* *picking object* AUC = 0.8303		tasks: *stand to sit* *look behind* AUC = 0.7995	
	Low fall risk BBS > 49	High fall risk BBS ≤ 49	Low fall risk BBS > 49	High fall risk BBS ≤ 49	Low fall risk BBS > 49	High fall risk BBS ≤ 49
Low fall risk BBS > 49	69.0	31.0	65.5	34.5	89.7	10.3
High fall risk BBS ≤ 49	26.3	73.7	21.1	79.0	47.4	52.6
Three tasks	tasks: *stand to sit* *stand eyes shut* *picking object* AUC = 0.8140		tasks: *stand to sit* *reaching* *picking object* AUC = 0.8421		tasks: *stand to sit* *picking object* *look behind* AUC = 0.8167	
	Low fall risk BBS > 49	High fall risk BBS ≤ 49	Low fall risk BBS > 49	High fall risk BBS ≤ 49	Low fall risk BBS > 49	High fall risk BBS ≤ 49
Low fall risk BBS > 49	65.5	34.5	62.1	37.9	93.1	6.9
High fall risk BBS ≤ 49	21.1	79.0	10.5	89.5	47.4	52.6
Gait pattern	AUC = 0.8410		AUC = 0.8889		AUC = 0.8793	
	Low fall risk BBS > 49	High fall risk BBS ≤ 49	Low fall risk BBS > 49	High fall risk BBS ≤ 49	Low fall risk BBS > 49	High fall risk BBS ≤ 49
Low fall risk BBS > 49	89.7	10.3	96.6	3.5	96.6	3.5
High fall risk BBS ≤ 49	44.4	55.6	22.2	77.8	27.8	72.2

A bbs score of 49 is used as a threshold value. The results are presented as percentages (%).

tasks and 2) the gait patterns. The approach was validated with groups of real subjects: the neurological patients, older adults, and healthy young persons. The results with the current dataset indicate that the gait-based BBS estimation outperforms the BBS-task-based estimation. Table I shows that if a threshold of 49 is used also for the estimates to divide the subjects into high- and low-fall-risk groups, the accuracy of identification of people with low risk of falling is very high using gait-based estimates. However, it might often be more important to identify those people with high fall risk. Although the table suggests that this would be done more accurately with the BBS-task-based method, the higher AUC value indicates better classification performance for the gait-based method. It should be noted, that the classifier is not adjusted here, as the classification is based on the same threshold value for the BBS estimates and the reference BBS scores. The gait-based BBS estimation might work better, since problems in balance cause changes in gait [3], while each of the BBS tasks assess only a certain feature such as coordination or muscle strength. By having only three tasks included in the estimation of BBS score, some of the other important aspects of balance may be omitted. This study also shows that the selection of similarity measure has an effect on the results; however, further studies are needed, to analyze how significant the impact is and which similarity measure would be the optimal choice for the algorithm.

The most significant BBS tasks for the algorithm presented in this paper are *stand to sit*, *reaching*, and *picking object*, which yield the best BBS score estimates with Tanimoto coefficient. These tasks require lower body muscle strength and coordination, which are good indications of balance. Our finding that *stand to sit* was an important determinant of a person's balance is consistent with results of previous studies. According to Tiedemann *et al.* [22], multiple-fallers show significantly worse performance in the STS-5 test, in which *stand to sit* is part of the movement, than nonmultiple-fallers do, with a sensitivity of 66% and specificity of 55% for separation of the two groups. In addition, Doheny *et al.* [16] report several parameters, such as mean sit-to-stand time, jerk, and spectral edge frequency derived from acceleration signals measured during the STS-5 test, that differ significantly between fallers and nonfallers. The

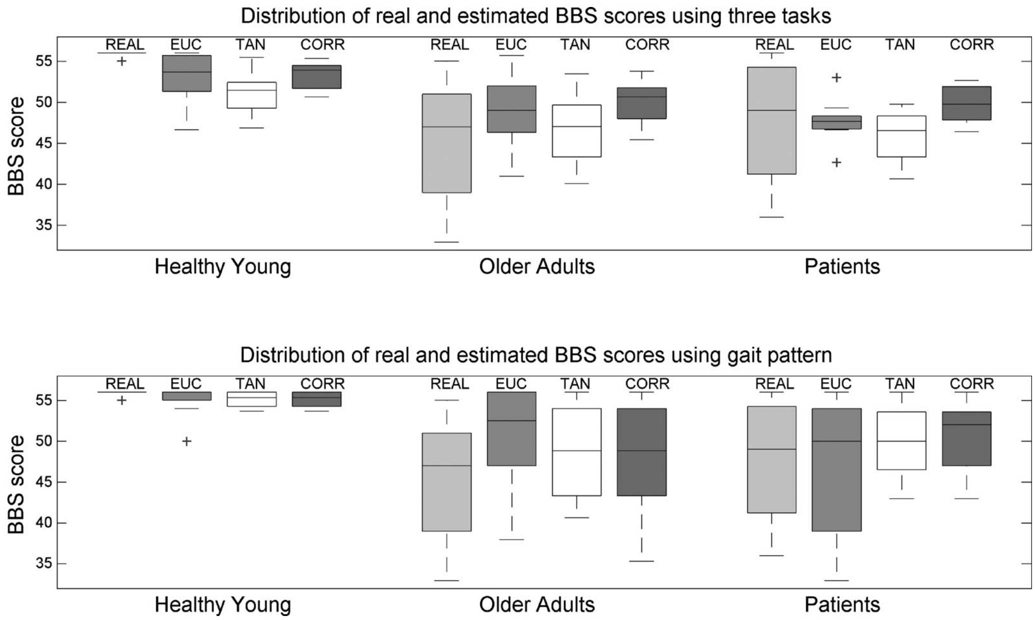

Fig. 3. Distributions of the real and estimated BBS scores in the subject groups: healthy young people, older adults, and neurological patients. The estimated BBS scores were calculated with the three tasks producing the highest AUC values (see Table I) and gait data with all three similarity measures.

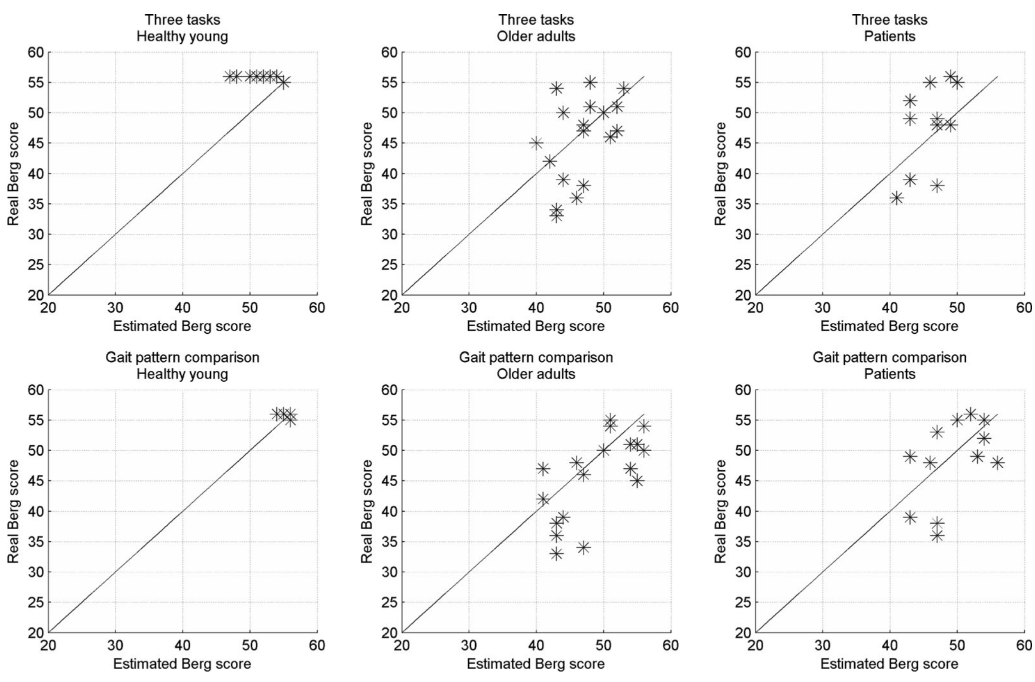

Fig. 4. Estimated versus real BBS scores for the three subject groups: healthy young persons, older adults, and neurological patients. The top three diagrams represent the results for three tasks: *stand to sit*, *reaching*, and *picking object*, with Tanimoto coefficient as a similarity measure, and the bottom three are obtained via the gait-based method, again with Tanimoto coefficient as a similarity measure. The mean and standard deviations of the estimation error for the three tasks are 4.94 ± 2.38, 4.63 ± 3.89, and 5.08 ± 3.00 score points, for healthy young people, older adults, and neurological patients, respectively, resulting in total mean error of 4.85 ± 3.14 points. The corresponding mean-error figures for the gait-based method are 0.88 ± 0.86, 4.94 ± 3.51, and 5.17 ± 3.01 score points, and the total mean error is 3.53 ± 3.32 points.

BBS tasks of *reaching* forward and *picking up an object from the floor* test the ability to shift one's center of gravity. However, the functional-reach test alone—i.e., reaching only in the forward direction—does not give results comparable to those with BBS [23], [24], but, for example, in [23] reports significant correlation between the multidirectional-reach test and BBS results. Similarly, our results in Table I indicate that with *reaching* forward added in alongside the tasks *stand to sit* and *picking object*, the identification of people with high fall risk shows particular improvement, from 79% to 89.5%.

The distributions of the estimated BBS scores show that the BBS-task-based method produces estimates that have more unified distributions across subject groups, also resulting in individual estimates with less variance relative to each other. This is probably because of the way the algorithm handles averaging over the various tasks—i.e., the estimate is based on only three of the 14 BBS tasks, and a person may have been able to perform those yet had problems with some of the other tasks. In addition, the dataset obtained includes too few people with different balance abilities, and thus quite different BBS scores, for revealing fully similar subjects. The neurological patients in this study are an especially heterogeneous group, making for fewer points of comparison in that set. This is indicated also by the estimation error, as it is smallest in the healthy-young-person group and largest for the neurological-patient group. The tendency of the algorithm to overestimate especially the lower BBS scores presumably is caused by the fact that the dataset is skewed toward higher BBS scores as it features more people with high BBS scores than with lower ones. The results shown here are based on this particular dataset, and more data are needed if reproducibility of the results is to be ensured.

In our approach, the unique gait pattern for a subject is constructed through averaging of the stride-length segments of the data. Bautmans *et al.* [25] state also that reliability of gait features for purposes of identifying subjects with increased fall risk is improved when the process uses the mean of two walks instead of a single walk. However, the data preprocessing to create the unique gait patterns is more complicated than for nonperiodic movements such as *stand to sit* transfer, and in this case visual inspection was required, to ensure the correctness of the preprocessed signal.

It should be noted that clinical measures such as BBS, when used as a reference measure, themselves display uncertainty in prediction of future falling. For example, Muir *et al.* [26] state that BBS is inadequate for identifying the majority of people at risk of falling; however, it has good discriminative ability to predict multiple falls. As the clinical fall-risk assessment scales in current use have limitations with regard to their sensitivity and specificity also, it would benefit our approach to have actual history of falls as reference data and, on the other hand, long-term follow-up studies for prospective analysis of fall risk. The current method could be used as a first indicator of balance problems and for recommendation of seeking further assessment. In addition, since the method estimates the fall risk by finding the most similar subjects from the reference dataset, with a larger dataset in the future, the background information of those subjects might provide some idea of the underlying physiological complications.

The data used in this paper were collected in supervised conditions. Accordingly, one aim for future work is to investigate whether fall-risk estimate can be computed from data obtained in unsupervised conditions—i.e., whether the movement data corresponding to clinical balance tests such as the BBS and gait tests could be recognized from the real-life data and used in calculation of a fall-risk estimate for a person. Furthermore, it is of interest for us to study how this kind of long-term measurement could be integrated into current health-care processes. Such a solution would have clear benefits in fall-risk management and fall prevention, as the fall risk could be continuously and unobtrusively evaluated with the aid of low-cost sensors, enabling early interventions to decrease the risk more efficiently.

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PAPER IV

Disease State Fingerprint for Fall Risk Assessment

36th Annual International Conference
of the IEEE Engineering in Medicine and Biology Society
(pp. 3176–3179). Chicago, 26–30 Aug. 2014.

Disease State Fingerprint for Fall Risk Assessment

Heidi Similä, and Milla Immonen

Abstract— **Fall prevention is an important and complex multifactorial challenge, since one third of people over 65 years old fall at least once every year. A novel application of Disease State Fingerprint (DSF) algorithm is presented for holistic visualization of fall risk factors and identifying persons with falls history or decreased level of physical functioning based on fall risk assessment data. The algorithm is tested with data from 42 older adults, that went through a comprehensive fall risk assessment. Within the study population the Activities-specific Balance Confidence (ABC) scale score, Berg Balance Scale (BBS) score and the number of drugs in use were the three most relevant variables, that differed between the fallers and non-fallers. This study showed that the DSF visualization is beneficial in inspection of an individual's significant fall risk factors, since people have problems in different areas and one single assessment scale is not enough to expose all the people at risk.**

I. Introduction

One third of people over 65 years old fall at least once each year [1] and the number of falls per year increases with age and frailty level [2]. Furthermore, the world's population is ageing with speed and the number of people aged 65 or older is expected to grow from an estimated 524 million in 2010 to nearly 1.5 billion in 2050 [3]. Falls have serious consequences, because they cause mortality, morbidity, reduced functioning, and premature nursing home admission [4]. Hip fracture is one of the most time and money consuming, quality of life changing consequences of falls. For example during the years 1996–2008 in Finland (population 5 million) approximately 7000 hip fractures occurred per year. The care expenses and consequential expenses are very high after a hip fracture and the quality of life of fallers dramatically drop after an injuring fall. The cost of the first year after the hip-fracture was 14 400€ in 2003 in Finland. If the patient needed to move from home into institutional care after the fracture, the cost for the care was 35 700€ for the first year [5]. Society and individuals need to take preventive actions against falls. Falls can be prevented with interventions targeting multiple risk factors or taking a more specific approach, such as combined muscle strength and balance training [6].

There are several intrinsic and extrinsic factors contributing to a person's fall risk, e.g. balance ability, muscle strength, dizziness, posture, gait, drugs, environmental and cognitive impairment, medical factors, poor footwear, etc. All of these can be seen as individual risk factors. However, it is hard to find a single risk factor that is a cause of a fall and it is unlikely that one assessment measure would have excellent accuracy to predict falls [7]. More commonly there are several simultaneous factors behind the fall.

Even with a comprehensive fall risk assessment that incorporates several scales it is not easy to form a detailed overview of a person's health status and prevailing fall risk factors. As Perell et al. point out in their analytic review of fall risk assessment scales [8], the clinicians have difficulties in selecting the most appropriate assessment scale or they lack knowledge of them. They list the assessment scales with diagnostic abilities from separate studies. However, it doesn't provide information of the scales' reliability and validity within the same subjects. Different scales with same subjects were compared e.g. in [9] and [10] in which a logistic regression models were derived with most predictive variables from several scales.

This paper presents a novel application of Disease State Fingerprint (DSF) algorithm [11] to a holistic visualization of fall risk factors. It allows identification of particular areas with needs for improvement on an individual level as well as comparison of groups with different characteristics, such as people with falls history and people with no falls. The fingerprint visualization can also be used to determine which assessment scales or fall risk factors are significant for the person or population in question. In addition, the DSF is used as a supervised classifier to identify persons at risk based on their data. The algorithm is tested with fall risk assessment data from 42 older adults.

II. Methods

A. Data collection

An extensive fall risk assessment is performed for 42 older adults in two locations in Finland. 27 test subjects are recruited among residents of a senior house in Tampere. Residents apply for an apartment by themselves and are in relatively good economic position. Their background and work history varies a lot, thus they are well representative of the population of interest. All the residents have free access to gym, which may have an effect on their initial physical condition. The participants are recruited to the study by the senior house's service counselor. Furthermore, 15 subjects are recruited in Oulu from a physical exercise group led by a physiotherapist in a local seniors' gym. The inclusion criteria for the study are age 64 years or more, living independently,

This work was supported in part by Tekes, the Finnish Funding Agency for Technology and Innovation, and the Ambient Assisted Living Joint Program (AAL-JP).

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don't have cognitive incapability and is able to perform simple physical exercises independently. Person is excluded from the study if he/she is wheelchair or bed bound or has a medical condition or functionality deficit that prevent from doing simple physical exercises. The participants are recruited on voluntary basis and result with 42 subjects; one male and 41 females. This study was approved by the local Ethics Committee of Human Sciences.

The fall risk assessment consist of following parts: 1) background questionnaire, 2) interview, 3) balance platform assessment with Kinect recording, 4) physical balance and walk tests with an activity monitor, and 5) muscle strength measurements.

Before the tests the participants are given an information sheet about the study and they receive a background questionnaire they fill in beforehand at home. The questionnaire asks about age, gender, height, weight, falls during last 12 months, self-rated balance, incontinence, medication usage, physical activity and it includes scales Activities-specific Balance Confidence (ABC) [12] and Geriatric Depression Scale (GDS) [13].

The participants signed an informed consent when coming to the interview carried out by a researcher. The interview is based on the IKINÄ report [12] and its purpose was to enquire those aspects of fall risk that were not included in the background questionnaire, such as questions about sensory functions and Mini-Mental State Examination (MMSE) [15]. In addition, there were questions about nutrition, alcohol consumption, motivators and barriers for physical exercise, daily behavior, and own evaluation of fall related environmental hazards. After the interview standing balance is tested on a balance platform (Balance Trainer BT4, HURLabs, http://www.hurlabs.com) following the protocol of the Romberg test, i.e. first the person stands 30s with eyes open on the balance platform and then repeats the same with eyes closed. The balance platform has four force sensitive sensors in each of its corner and it incorporates calculation of several parameters such as Romberg quotient, trace length of sway, velocity and area of movement, etc. A depth camera (Microsoft Kinect, www.microsoft.com) is placed about three meters behind and orthogonally to the balance platform in order to study whether it can be used to detect possible sway during the standing tests.

Physical balance and walk tests are led by a physiotherapist in Tampere and by a physiotherapy student in Oulu. The tests include Berg Balance Scale (BBS) [16], Timed Up and Go –test (TUG) [17], five times sit to stand test (STS-5), i.e. time it takes to perform five repetitions, and corridor walking, which includes 4m walking speed assessment. The walk test is performed twice in a corridor of over 20 meters long. During the balance and walk tests the test subjects wore two accelerometers (GCDC X16-2, www.gcdataconcepts.com), one at the lower back near the center of mass and the other in front at the waist level. The sensors were attached with special belts that were adjustable to each person's circumference. A researcher annotated the acceleration measurement by marking each test and subtask with a computer that was synchronized with the accelerometers. The data produced by the accelerometers are used for more detailed movement analysis later on.

In Tampere the lower body muscle strength was measured with gym equipment and HUR performance recorder. The performance recorder is attached to the gym device, where it measures maximum force produced by the user. The specific muscles are leg adductor/abductor and extensor/flexor. After a few minutes warm up with a stationary bike, maximum force produced by each of the four muscles is measured three times. The maximum value is taken into account. In Oulu the same maximum force test was not possible due to available gym equipment. Thus the lower body muscle strength is measured without performance recorder as repetition test [18]. The aim was to find a load (in kilograms) for each muscle, so that the subject is able to perform 3-5 repetitions with the gym device. The devices are the same as in Tampere, i.e. leg adductor/abductor and extensor/flexor. The maximum force can then be estimated according to [19]. The upper body muscle strength was measured by grip strength test with the same hydraulic hand dynamometer by all the subjects. The test was performed three times with both hands and the best result was taken into account. The muscle strength tests were supervised by a researcher or a physiotherapy student. After the whole fall risk evaluation all the participants were given a feedback sheet with main results and interpretation based on their age group averages.

The following table summarizes the main characteristics of the test subjects.

TABLE I. SAMPLE CHARACTERISTICS AND GROUPS

N	Age [years] *(Mean±std)*	*BBS score* *(Mean±std)*	**Grouping methods**			
			Fall Incidents		***ABC Total score***[a]	
			Yes	***No***	***< 80%***	***≥80%***
42	64-85 (74,17±5,57)	34-56 (53±3.64)	11	31	7	35

a. ABC groups divided according to [20], where ABC functional rating was as follows: ABC <50% means poor, <80% moderate and ≥80 % good functional capabilities.

B. Data analysis

The Disease State Fingerprint (DSF) visualization and its underlying Disease State Index (DSI) methods developed by Mattila et al. [11] were applied to the data. The input data to the DSF algorithm should have two classes, e.g. fallers and non-fallers. The feature data is organized as a tree with selected number of leaves under the root. The provided DSI value indicates the proportion of data matching to the profile of positive cases in the model. In the case with fallers vs. non-fallers the positive case means a faller. The DSI values are used for creating a tree visualization of the analysis results, where nodes' sizes show the relative relevance of each feature and colors indicate similarity to the positive (red) and control (blue) classes. More detailed explanation of the algorithm can be found in [11].

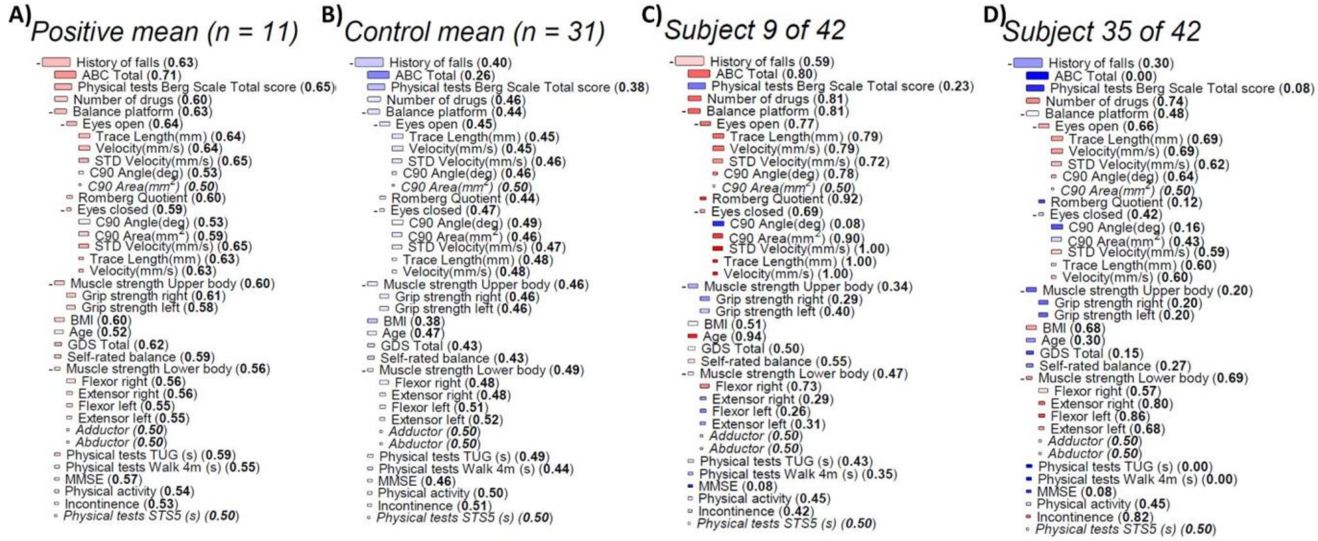

Figure 1. DSF visualizations for A) mean of fallers group, B) mean of non-fallers group, C) example case from fallers group, and D) example case from non-fallers group. The tree visualizations are opened to show all the 32 used features. All the available items from balance platform and the individual questions from ABC, BBS and GDS scales are not included besides the total scores. The size of the node boxes show the relative relevance of each feature and the numbers indicate the similarity to the positive (fallers) class.

The DSF is used as a supervised classifier with leave-one-out cross validation method to investigate the ability of DSI value in separating fallers from non-fallers. A DSI value over 0.5 suggests the subject belongs to the fallers group and below 0.5 refers to the non-fallers group respectively. Furthermore, different grouping criteria is tested by applying the total score from ABC test, and more specifically the level of physical functioning, to form the two reference classes.

When also the individual questions or tasks are included from ABC, BBS and GDS scales, the total number of features considered in this analysis is 103.

III. Results

The DSF visualization for fallers (positive) and non-fallers (control) group means are presented in Fig. 1 with example cases from both groups. The *ABC total score* followed by *BBS total score* and *number of drugs in use* were the three most relevant features, that differed the most between the two classes. The visualizations of the example cases C) and D) show that both have individual assessment results that refer to the opposite class. For example the subject in Fig. 1 C) had *BBS total score* similar to the non-fallers' group, while *ABC total score*, *number of drugs in use* and *overall balance platform leaf value* features were comparable with the fallers' group results.

Classification of subjects into fallers and non-fallers based on their resulting DSI value and the leave-one-out cross validation method yielded sensitivity of 54.5% and specificity of 64.5%. When the subjects were divided into two groups based on the ABC result, the classification results with the same features as in Fig. 1, except replacing *ABC total* from the leaves with *history of falls*, gives sensitivity of 71.4% and specificity of 88.6%.

When testing the individual items from different scales all the 103 features were inserted to the DSF directly under the root to investigate which of them differ the most between the groups of fallers and non-fallers. The ten most relevant features were mostly from ABC questionnaire: 1) *ABC question 5*, 2) *ABC total score*, 3) *ABC question 13*, 4) *ABC question 10*, 5) *BBS task 11*, 6) *ABC question 4*, 7) *ABC question 9*, 8) *BBS total score*, 9) *ABC question 15*, and 10) *Balance platform Eyes closed Standard deviation in X direction*. Classification with this tree structure resulted in sensitivity of 54.5% and specificity of 80.6%.

IV. Discussion

This paper presented a novel application of DSF in fall risk analysis. A clear benefit and potential of the DSF visualization is that it allows inspection of multiple assessment scales and factors at a glance. In addition, it enables detection of significant factors for the individual, as it became evident also in this study sample that the assessment scales indicating fall risk for one person might not reveal the risk for the other. This confirms the fact that people have problems in different areas and one single assessment scale is not enough to expose all the people at risk. The visualization method represented here allows rapid interpretation of large amount of data and can be utilized in selecting the most relevant assessment scales.

The results with this study sample indicated that the *BBS total score* was the second most relevant feature in separating fallers from non-fallers. Similar results were achieved in [9] and [10], where regression analysis was used to form a model for either predicting falling or separating fallers from non-fallers. Furthermore the *ABC total score*, that was the most relevant in our study, was also found significant in [10]. However, when investigating individual items of the ABC scale, the most relevant questions were not the same. In this study, question 5 (confidence when standing on tiptoes and reaching for something above head) was the most relevant item from the ABC scale, and also from the whole set of included features. Whereas, the question 1 (walking around the house) was the most significant in study [10]. The test subjects in this study were in relatively good physical condition, due to which they might generally feel confident when walking around the house and the difficulties come up with more difficult tasks, such as described in question 5. This is important finding, since developing technologies for early risk detection is more crucial in the current ageing population; we need to find out more accurate discriminating factors earlier to start early prevention.

The DSF can be utilized with different grouping criteria of subjects, as was demonstrated with the ABC scale result. This grouping yielded the highest sensitivity and specificity of classification, but more data is needed to validate the results. The small sample size and relatively good condition of all of them affects especially the classification results, since two clearly divergent groups cannot be distinguished based on the data. Another interesting grouping criteria could be e.g. the total BBS score. Although the current sample has relatively high BBS scores with the average of 53 out of 56 points, it appeared to differ between the fallers and non-fallers.

This research had some limitations, which need to be taken into account when exploiting the results. The limited number of subjects were in relatively good physical condition and the group of fallers was clearly smaller compared to non-fallers. In order to verify the method's ability to estimate true fall risk, follow-up data from actual fall incidents after the baseline assessment should be collected. In addition, the classification performance of the algorithm should be compared to other commonly used approaches. The objective of our future work is to utilize also the accelerometer and depth camera data by studying how different sensor features correlate to the total fall risk, different clinical assessment scales and individual fall risk factors with the DSF algorithm. The same subjects will be invited to follow-up assessment to study possible changes in their condition and thus in different measures.

ACKNOWLEDGMENT

The authors would like to thank Kotosalla foundation, YHKodit Oy and Fysiocenter Gym in Tampere for providing the test facilities, and physiotherapist/service counselor Kirsta Rantanen for recruiting the test persons in Tampere. The authors would also like to thank physiotherapist students Mirella Hietaniemi and Sari Saikkonen of Oulu University of Applied Sciences for their assistance, physiotherapist Leena Lång of SeniorKunto for recruiting the participants in Oulu and providing the test facilities with Oulun VillaMetsola Oy. The authors would like to thank HURLabs for providing the test devices and AAL JP Ageing in Balance project partners for cooperation.

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PAPER V

Gait analysis and estimation of changes in fall risk factors

37th Annual International Conference of
the IEEE Engineering in Medicine and Biology Society
(EMBC) (pp. 6939–6942). Milan, 25–29 Aug. 2015.

Gait Analysis and Estimation of Changes in Fall Risk Factors

Heidi Similä, Milla Immonen, Juho Merilahti, and Tuula Petäkoski-Hult

Abstract— **Falls are a major problem for older adults. A continuous gait monitoring that provides fall risk assessment would allow timely interventions aiming for preventing falls. The objective of this work was to find out whether gait variables calculated from the acceleration signal measured during walk task in the baseline assessment can predict changes in commonly used fall risk assessment scales after 12 months follow-up. Forty two subjects were measured during walk test with a triaxial acceleration sensor worn on a waist belt at the lower back near the centre of mass. The fall risk was assessed using a test protocol, which included several assessment methods. Gait analysis was able to predict a decline in ABC, BBS and GDS total scores and slower time in STS-5 after twelve-months follow-up. A subsequent study is needed to confirm the model's suitability for data recorded in everyday lives.**

I. Introduction

Every third person over 65 years old fall at least once each year [1] and the number of falls per year increases with age and frailty level [2]. Falls are multifactorial problem and often there are several factors causing the fall, thus a comprehensive fall risk assessment requires using a combination of several fall risk assessment scales. [3] Typically a person is assessed for e.g. balance, physical functioning, muscle strength, number of drugs in use, and cognitive functions. Regular fall risk assessments would require a lot of resources from the health care organizations [4].

The fall prevention actions such as physical exercising interventions are more effective when they are started early enough. This means that fall risk has to be identified earlier. Body-worn accelerometers are often used for developing methods for objective fall risk assessment and gait analysis. As an example, Aminian et al. [5] showed that accelerometers can be used for analyzing gait improvement after hip surgery. According to a recent review by Montaza et al. [6] variables such as step length, gait speed, stride length, stance times and variability in spatio-temporal gait parameters have been shown to differ between fallers and non-fallers. Furthermore, currently more studies aim at going for unsupervised measurements, where physical activity data is gathered in real-life situation representing more genuine performance [7, 8]. Often sensor-based fall risk estimation studies use cross-sectional data i.e. previous falls in developing the data analysis algorithms, however they may not have the same predictive ability with the prospective data [9].

In this paper, the ability of accelerometer-based gait variables to estimate changes in typically used fall risk assessment scales after one-year follow-up is studied. The objective is to investigate whether simple walk test could indicate future decline or deterioration in physical or cognitive functioning of a person and whether it can estimate the falls within the next 12 months.

II. Methods

A. Data Collection

For this study 42 older adults (aged 64-85 years, mean age 74.17±5.57 years) were recruited on voluntary basis from two locations in Finland. 27 test subjects were recruited among residents of a senior house in Tampere and 15 subjects were recruited from a senior physical exercise group in Oulu. The inclusion criteria for the study were age 64 years or more, living independently, no cognitive incapability and is able to perform simple physical exercises independently. All participants signed an informed consent and this study was approved by the local Ethics Committee of Human Sciences.

The 42 participants, one male and 41 female, went through a comprehensive baseline fall risk assessment consisted of following parts: 1) background questionnaire, 2) interview, 3) balance platform assessment with Kinect recording, 4) physical balance and walk tests with an activity monitor, and 5) muscle strength measurements. Prior to the tests the participants were given an information sheet about the study and they received a background questionnaire to be filled in beforehand at home. The questionnaire asked e.g. about demographics, health status, medication usage, physical activity, falls during last 12 months, and it included Activities-specific Balance Confidence (ABC) [10] and Geriatric Depression Scale (GDS) [11] scales.

The interview was based on [3] and it included questions e.g. about sensory functions, nutrition, alcohol consumption, motivators and barriers for physical exercise, and Mini-Mental State Examination (MMSE) [12]. The balance platform assessment (Balance Trainer BT4, HURLabs, http://www.hurlabs.com) followed the protocol of the Romberg test, i.e. first the person stands 30s with eyes open on the balance platform and then repeats the same with eyes closed, while a depth camera (Microsoft Kinect, www.microsoft.com) was placed about three meters behind and orthogonally to the balance platform.

The physical balance and walk tests included Berg Balance Scale (BBS) [13], Timed Up and Go –test (TUG) [14], five times sit to stand test (STS-5), i.e. time it takes to

This work was supported in part by Tekes, the Finnish Funding Agency for Technology and Innovation, and the Ambient Assisted Living Joint Program (AAL-JP).

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perform five repetitions, and corridor walking. The walk test was performed twice in a corridor of over 20 meters long. During the balance and walk tests the test subjects wore two accelerometers (GCDC X16-2, www.gcdataconcepts.com) at the waist level attached with special belts. One was at the lower back near the centre of mass and the other in front on the right side. The acceleration measurement was manually annotated by marking each test and subtask with a computer that was synchronized with the accelerometers.

The lower body muscle strength was measured from leg adductor/abductor and extensor/flexor after a few minutes warm up. HUR performance recorder measuring maximum force was connected to the gym device in Tampere. It was not compatible with the available gym equipment in Oulu, thus the lower body muscle strength was measured there as a repetition test [15] and the maximum force was estimated according to [16]. The grip strength was measured with the same hydraulic hand dynamometer by all the subjects.

The test subjects were invited twice to the follow-up fall risk assessment tests. The second one, i.e. midterm assessment, included all the same tests as in the baseline assessment except for the balance platform test. The third and the final assessment was exactly the same as the baseline assessment. The time spans between the tests were 9-12 months in Tampere and 4-8 months in Oulu (see Table I). After each of the assessment the participants were given a feedback sheet with main results and interpretation based on their age group averages.

TABLE I. THE FALL RISK ASSESSMENTS. NUMBER OF SUBJECTS AND THE TIMELINE (M0 REFERS TO MONTH 0, I.E. START OF FIRST TESTS)

	Baseline assessment	**Midterm assessment**	**Final assessment**
Tampere	N = 27 M0	N = 22 M12-M13	N = 19 M21
Oulu	N = 15 M9	N = 14 M17	N = 14 M20-M21
Total	N = 42	N = 36	N = 33

The first analysis of the baseline assessment data is reported in [17]. The test group was divided into three groups: technology intervention, paper intervention and control groups. All groups went through similar testing procedures. Technology group received a touch-screen PC at home, with exercise reminders and guidance and paper group received paper printed instructions to exercise. Control group did not receive instructions to exercise. This paper deals with all test persons and differences between groups will be analysed in further studies.

B. Data Processing and Analysis

The objective of this work was to find out whether gait variables calculated from the acceleration signal measured during walk task in the baseline assessment can predict changes in commonly used fall risk assessment scales after 12 months follow-up. The data analysis was carried out in Matlab (from MathWorks, Inc.; Natick, MA, USA) programming environment. The sensor attached to the lower back was selected for the analysis. For the conformity of the analysis the midterm assessment results were used for the Tampere subjects and the final assessment results were used for the Oulu subjects. Thus the follow-up period is uniform approximately 12 months for all the subjects. This results in total of 36 subjects in this analysis.

The acceleration data from the walk task was separated based on manual annotations. The first of the two corridor walks was selected. Each data clip was visually inspected to ensure correct cut-off points. A resultant acceleration was calculated of the three dimensional data according to (1), where a_x is acceleration in the medio-lateral, a_y the vertical, and a_z the anterior–posterior planes.

$$a_{res}[n] = \sqrt{(a_x[n])^2 + (a_y[n])^2 + (a_z[n])^2} \quad (1)$$

The following variables were extracted from the resultant acceleration signal: mean and standard deviation of acceleration and difference between maximum and minimum accelerations during the walk test. The peaks, i.e. the acceleration value and the corresponding time instances, representing the steps in the resultant acceleration signal were detected and visually inspected for their correctness. The first and the last two of the detected steps were excluded from the analysis to decrease the effect of speed up and slow down phases of gait. The following temporal gait variables were calculated for the steps data: mean step/stride lengths (in seconds), step/stride time variability (standard deviation of step/stride lengths), and step asymmetry between right and left as in [18]. Furthermore, mean, standard deviation and asymmetry were calculated for the peak accelerations.

The above mentioned gait variables were inspected with one-way ANOVA (Kruskal Wallis test) whether they differ significantly between the test subjects that deteriorated their scores or performance in 12 months follow-up test and those who improved or maintained their level. Similarly to [6], Cohen's d was used as a measure of effect size (ES). The assessment scales in this analysis were total scores of ABC, GDS, MMSE, and BBS, times in TUG and STS-5 tests, and grip strength right/left hands. Higher score does not automatically mean improved results, e.g. score of 0 in GDS means there is no signs of depression. In addition, the gait variables were examined whether they differ between fallers and non-fallers. The person was considered as a faller if he/she had fallen at least once within the follow-up period.

III. RESULTS

Table II summarizes the results of how many subjects decreased their scores or performed worse, and how many improved or maintained their level in the follow-up fall risk assessment. The last two columns show the average magnitude of positive and negative changes on that particular scale.

The results in Table III show that 6 out of 11 baseline gait variables differed significantly between subjects with lower and subjects with higher/same total score in ABC scale after 12 months and there were also several significant variables associating with change in GDC total score, BBS total score and STS-5 tests and one with right hand grip strength. The effect sizes for these parameters were between 0.7–1.0.

TABLE II. NUMBER OF SUBJECTS IN GROUPS HAVING POSITIVE OR NEGATIVE CHANGE AND MEAN±STD OF THE CHANGE IN FALL RISK ASSESSMENT SCALES RESULT AFTER 12 MONTHS FOLLOW-UP.

Assessment scale	**Number of Subjects**		**Change mean±std**	
	Decreased	***Improved or same***	***Decreased***	***Improved or same***
ABC (0-100 points)	23	13	-8.72±8.94	4.90±9.66
GDS (0-15 points)	27	9	0.74±1.23	-1.33±0.5
MMSE (0-30 points)	9	27	-1.56±0.88	0.89±0.97
BBS (0-56 points)	13	23	-2.23±1.36	1.13±1.69
TUG (s)	25	11	1.39±1.13	-2.07±2.61
STS-5 (s)	15	21	1.97±1.63	-2.83±2.56
Grip strength right (kg)	18	18	-3.07±2.25	1.59±1.62
Grip strength left (kg)	21	15	-2.87±2.26	2.16±3.31

There were no significant association between the gait variables and change in MMSE total score, TUG time and left hand grip strength, or falls during the 12 months follow-up. Nine subjects had experienced at least one fall and more precisely seven of them had fallen once and two had had two falls. The Fig. 1 illustrates the gait variable distributions for fallers and non-fallers separately.

IV. DISCUSSION

The results indicate that the gait variables extracted from the accelerometer signal differ between subjects who had lower scores after one year in several assessment scales typically used as part of fall risk assessment. Especially mean, standard deviation and min-max range of acceleration during walking, and mean peak acceleration were the most promising gait variables with high effect sizes to estimate change in ABC and also in BBS total scores. Decline in ABC total score shows that the person is less certain of his functional capability than before and has increased risk of falling [3]. Based on these results, decline in ABC score may be predictable from gait, which would enable earlier intervention to better maintain the functional capability.

There were no significant association in gait variables and changes in assessment scales MMSE and TUG. Similarly, in a cross-sectional analysis of Bautmans et al [18], the accelerometry-based step time variability did not correlate with the results of those scales. With this study sample the gait variables did not differ significantly between fallers and non-fallers, although differing trends can be seen in Fig. 1. As a comparison Hausdorff et al. [19] reported significant increase in gait variability with fallers compared to non-fallers after one-year follow-up. It should be noted that in this analysis the person was considered a faller if there were at least one fall during the follow-up period. Often used approach is to analyze multiple fallers, e.g. [20], but in this sample, only two persons had more than one fall during the follow-up.

In addition to small sample size there are limitations that may have an effect to these results. First, in this study setup the test subjects were divided in three groups, with two of them receiving exercise instructions either via technology tools or paper. However, all these groups were pooled into one for this analysis. The subjects receiving any intervention may have better assessment result in the follow-up particularly due to the intervention. Secondly, all the test subjects were quite active and in good physical condition, also in the control group.

In future work we will analyze the different groups separately and consider the level of physical activity as a grouping criterion. Furthermore, we will include accelerometer data from midterm and final assessments into the analysis. These results are promising that such a simple walk test or even unobtrusive gait recording during everyday lives could be used e.g. as a screening tool to prompt for a

TABLE III. SIGNIFICANCE AND EFFECT SIZE OF GAIT VARIABLES IN SEPARATING SUBJECTS WITH POSITIVE OR NEGATIVE CHANGE IN FALL RISK ASSESSMENT SCALES

Assessment scale	**Gait variable with corresponding p-value and effects size (in parentheses)** (p-values below 0.05 are highlighted with dark background color)										
	mean total acc	***std total acc***	***min-max***	***mean step length***	***std step length***	***mean stride length***	***std stride length***	***step time asymmetry***	***mean peak acc***	***std peak acc***	***peak acc asymmetry***
ABC total	0.006 (0.9)	0.008 (0.9)	0.020 (0.8)	0.026 (0.8)	0.772 (0.1)	0.024 (0.8)	0.426 (0.3)	0.156 (0.5)	0.014 (0.8)	0.120 (0.5)	0.844 (0.1)
GDS total	0.432 (0.3)	0.202 (0.5)	0.521 (0.3)	0.825 (0.1)	0.048 (0.8)	0.822 (0.1)	0.985 (0.0)	0.049 (0.8)	0.649 (0.2)	0.381 (0.3)	0.026 (0.8)
MMSE total	0.610 (0.2)	0.899 (0.0)	0.894 (0.1)	0.487 (0.3)	0.793 (0.1)	0.480 (0.3)	0.912 (0.0)	0.666 (0.2)	0.807 (0.1)	0.916 (0.0)	0.853 (0.1)
BBS total	0.013 (0.8)	0.003 (1.0)	0.009 (0.9)	0.445 (0.3)	0.954 (0.0)	0.443 (0.3)	0.562 (0.2)	0.831 (0.1)	0.024 (0.8)	0.163 (0.5)	0.858 (0.1)
TUG (s)	0.505 (0.2)	0.716 (0.1)	0.730 (0.1)	0.824 (0.1)	0.155 (0.5)	0.829 (0.1)	0.253 (0.4)	0.090 (0.6)	0.640 (0.2)	0.466 (0.3)	0.547 (0.2)
STS-5 (s)	0.123 (0.5)	0.287 (0.4)	0.519 (0.2)	0.035 (0.7)	0.265 (0.4)	0.036 (0.7)	0.650 (0.2)	0.383 (0.3)	0.992 (0.0)	0.587 (0.2)	0.571 (0.2)
Grip strength right (kg)	0.464 (0.2)	0.265 (0.4)	0.095 (0.6)	0.813 (0.1)	0.265 (0.4)	0.811 (0.1)	0.334 (0.3)	0.074 (0.6)	0.033 (0.7)	0.470 (0.2)	0.265 (0.4)
Grip strength left (kg)	0.959 (0.0)	0.863 (0.1)	0.457 (0.3)	0.704 (0.1)	0.123 (0.5)	0.704 (0.1)	0.345 (0.3)	0.054 (0.6)	0.327 (0.3)	0.362 (0.3)	0.846 (0.1)
Falls (12 months follow-up)	0.303 (0.4)	0.091 (0.7)	0.411 (0.3)	0.147 (0.6)	0.490 (0.3)	0.152 (0.6)	0.800 (0.1)	0.161 (0.5)	0.493 (0.3)	0.280 (0.4)	0.240 (0.5)

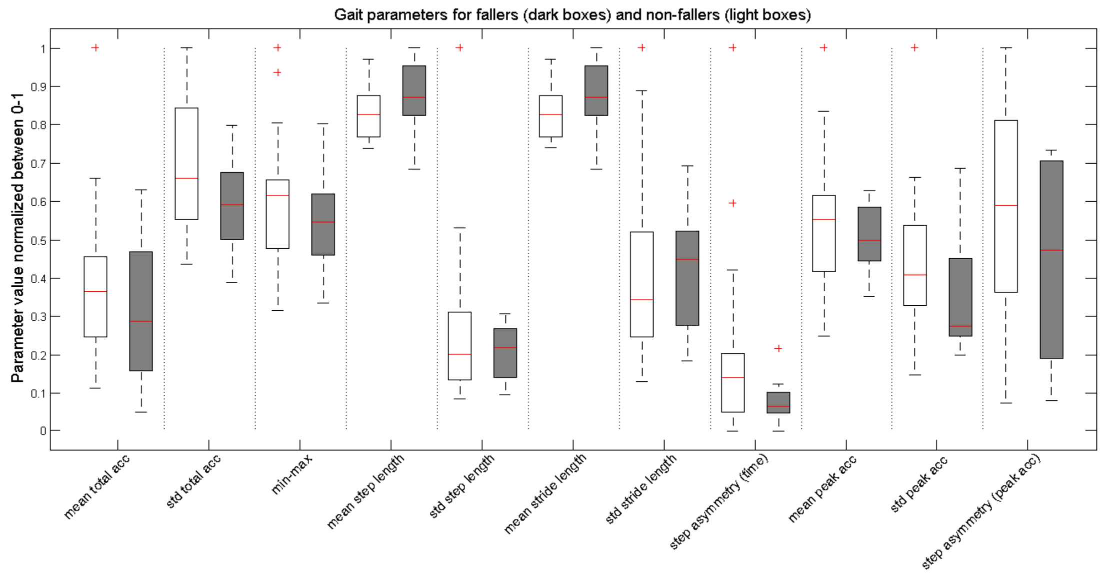

Figure 1. Gait variable distributions for fallers (dark boxes) and non-fallers (light boxes). Values are normalized between 0-1 for the visualization.

more thorough clinical evaluation for the persons with increased risks. However, a larger study with more test subjects is needed to validate these results.

Acknowledgment

The authors would like to thank Kotosalla foundation, YHKodit Oy and Fysiocenter Gym in Tampere and SeniorKunto and Oulun VillaMetsola Oy in Oulu for providing the test facilities. The authors would like to thank HURLabs for providing the test devices and AAL JP Ageing in Balance project partners for cooperation.

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PAPER VI

Accelerometry-based Assessment and Detection of Early Signs of Balance Deficits

Computers in Biology and Medicine, 85, 25–32.

Computers in Biology and Medicine 85 (2017) 25–32

Contents lists available at ScienceDirect

Computers in Biology and Medicine

journal homepage: www.elsevier.com/locate/compbiomed

Accelerometry-based assessment and detection of early signs of balance deficits

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ARTICLE INFO

Keywords:
Fall risk assessment
Accelerometry
Gait analysis
Berg Balance Scale
Timed-up-and-go

ABSTRACT

Falls are the cause for more than half of the injury-related hospitalizations among older people. Accurate assessment of individuals' fall risk could enable targeted interventions to reduce the risk. This paper presents a novel method for using wearable accelerometers to detect early signs of deficits in balance from gait. Gait acceleration data were analyzed from 35 healthy female participants (73.86 ± 5.40 years). The data were collected with waist-mounted accelerometer and the participants performed three supervised balance tests: Berg Balance Scale (BBS), Timed-Up-and-Go (TUG) and 4 m walk. The follow-up tests with the same protocol were performed after one year. Altogether 43 features were extracted from the accelerometer signals. Sequential forward floating selection and ten-fold cross-validation were applied to determine models for 1) estimating the outcomes of BBS, TUG and 4 m walk tests and 2) predicting decline in balance during one-year follow-up indicated as decline in BBS total score and one leg stance. Normalized root-mean-square errors (RMSE) of the assessment scale result estimates were 0.28 for BBS score, 0.18 for TUG time, and 0.22 for 4 m walk test. Area under curve (AUC) was 0.78 for predicting decline in BBS total score and 0.82 for one leg stance, respectively. The results suggest that the gait features can be used to estimate the result of a clinical balance assessment scale and predict decline in balance. A simple walk test with wearable monitoring could be applicable as an initial screening tool to identify people with early signs of balance deficits.

1. Introduction

Falls are a significant risk to the health of the older population. Based on WHO report, 28–35% of people aged over 65 years experience at least one fall each year [1]. Falls are the cause for more than 50% of injury-related hospitalizations among older people. They have been estimated to cost US$ 3611 per a fall injury episode in Finland and Australia [1]. Thus, effective measures to prevent falls and identify people at risk of falling are needed. It is important to assess fall risk at an individual level, since different people have problems in different areas that compound to the overall fall risk [2]. Falls may be a result of intrinsic factors such as advanced age, postural instability, sensory and neuromuscular factors, medical factors, and drugs, or extrinsic factors such as environmental hazards or poor footwear [3,4].

Gait and balance deficits affect 20–50% of older adults and they have been found as significant risk factors for falls [4]. Maintaining balance during walking represents a challenge to musculoskeletal and sensory systems. Since ageing is associated with decline in both of these systems, it also causes changes in gait patterns, such as increased stride-to-stride variability in gait parameters, e.g. cadence, stride length, and gait speed. These parameters have been associated with postural instability and falling [3]. Performance-based assessment scales, such as Tinetti scale [5], Berg Balance Scale (BBS) [6], and Timed-Up-and-Go (TUG) test [7], are typically used in clinical practice. They have been developed for assessing mobility, and static and dynamic balance abilities of a person. However, many of these clinical balance tests have limitations especially among higher functioning older adults. For example, the BBS score was not predictive of falls and it had a ceiling effect for persons with better functional ability [8]. Furthermore, the performance-based tests depend on professional supervision and thus require resources to administer.

Ambulatory movement monitoring with inertial sensors can bring further insights into analysis of balance and mobility. Gyroscopes and accelerometers are inertial sensors that measure angular velocity and linear acceleration of body segments. There are several studies demonstrating the potential of inertial sensor parameters in estimating fall risk of a person [9] and accelerometry is claimed to be able to capture more subtle changes in gait than the subjective balance

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http://dx.doi.org/10.1016/j.compbiomed.2017.04.009
Received 3 February 2017; Received in revised form 12 April 2017; Accepted 12 April 2017

assessment scales [10]. Accelerometry have been shown to be able to discriminate between fallers and non-fallers (e.g. [11–13]) using retrospective falls history data. However, the same algorithms may not be able to predict future falls [14] and thus recent studies have focused more on prospective fall risk assessment (e.g. [15–17]). Greene et al. demonstrated that inertial sensor based method was able to predict future falls with an accuracy of 79.69% compared to the accuracies of 59.43% and 64.30% for TUG and BBS respectively in a 2-year follow-up study [18]. When accelerometry-based gait features are combined with traditional questionnaires, prospective falls may be predicted more accurately than with questionnaires or gait features alone. In a study by van Schooten et al., the falls prediction model AUC rose from 0.68 to 0.82 when gait parameters were added to the traditional questionnaires, grip strength and trail making test data [17].

Currently, there are not many studies that aim to estimate decline in balance from inertial sensor measurement. One such example is from Sheehan *et al.* where they investigated quantitative TUG parameters to estimate decline as measured by change in BBS total score, and its sub-components [19]. Inertial sensor-based gait analysis, however, would not necessarily require performance of any specific task, such as TUG, or supervision by health care professional. Daily-life gait analysis has already been shown to have potential in identifying individuals with increased fall risk [17]. The objective of this study was to develop models for estimating decline in balance using accelerometry-based gait features. We hypothesize that the gait acceleration measurement is more sensitive in detecting early changes in balance that are not yet recognized by traditional assessment scales. With the models we estimated 1) the result of three selected reference measures; BBS, TUG and 4 m walk tests, commonly used in clinical practice, and 2) decline in balance during one-year follow-up indicated as negative change in BBS test.

2. Methods

2.1. Data collection

2.1.1. Subjects

We recruited 42 volunteer older adults (one male, 41 female, aged 64–85 years, mean ± std 74.17 ± 5.57 years) to participate in this study. Twenty-seven of the test subjects were residents of a senior house in Tampere, Finland, and 15 subjects were members of a senior physical exercise group in Oulu, Finland. The criteria for inclusion were: the subject should be living independently, have no cognitive incapability and is able to independently perform simple physical tasks. This study was approved by the Ethics Committee of Human Sciences at the University of Oulu. Prior to the tests the subjects were given an information sheet about the study and they signed an informed consent.

2.1.2. Fall risk assessment

The fall risk assessment procedure composed of five parts: 1) background questionnaire, 2) interview, 3) balance platform assessment with Kinect recording, 4) physical balance and walk tests with an activity monitor, and 5) muscle strength measurements. The guidelines for extensive fall risk assessment proposed by Pajala et al. [20] were followed in planning the assessments.

The background questionnaire, which the participants filled in prior to the tests, asked about demographics, health status, medication usage, physical activity, any falls during last 12 months and it included Activities-specific Balance Confidence (ABC) [21] and Geriatric Depression Scale (GDS) [22] scales. The background questionnaire data was complemented with an interview including questions about sensory functions, nutrition, alcohol consumption, and motivators and barriers for physical exercise, and Mini-Mental State Examination (MMSE) [23]. Also more specific details about reported falls where inquired, such as time of day, location, reasons, and consequences of the fall. Static balance of the subject was assessed with the Romberg test, where the person stands 30 s with eyes open on the balance platform (Balance Trainer BT4 from HURLabs, http://www.hurlabs.com) and then repeats the same with eyes closed. There was a depth camera (Microsoft Kinect, www.microsoft.com) recording simultaneously about three meters behind and orthogonally to the balance platform. The balance platform and depth camera assessments were not analyzed further in this paper.

The physical balance and walk tests, supervised by a physiotherapist or a researcher, consisted of Berg Balance Scale (BBS) [6], Timed Up and Go –test (TUG) [7], five times sit to stand test (STS-5), i.e. time it takes to perform five repetitions, and corridor walking, which was performed twice in a corridor of over 20 m long. The subjects wore two accelerometers (GCDC X16-2, www.gcdataconcepts.com, sampling rate 100 Hz, range ± 16 G), while performing the balance and walk tests. One sensor was fixed to the centre of lower back between L3-L5 vertebrae using an elastic belt. The other sensor was attached with a separate belt at front side of the body on right hip. The sensors were attached by the same researcher for all the subjects in order to ensure uniform positioning. A researcher observed the tests and manually annotated the beginning and ending of each test and possible subtasks with a computer software. The real time clock embedded in the accelerometers were synchronized with the computer clock at the beginning of each test session. The analyzes of this paper were performed using the signals only from the lower back sensor.

Lower body isometric muscle strength was measured from leg adductor/abductor and extensor/flexor three times for each leg with a performance recorder (Performance Recorder PR1 from HURLabs, http://www.hurlabs.com) connected to a gym device in Tampere. In Oulu, the performance recorder was not compatible with the available gym equipment, thus a repetition test protocol was applied. The goal of the test was to find the maximum weight, with which the person was able to perform 4–6 repetition maximums (RM) in order to estimate the 1RM weight for the muscles under investigation [24]. Lower body muscle strength measurements, however, were not further analyzed in this paper. The grip strength was measured three times for right and left hand separately using hydraulic hand dynamometer (Saehan Hydraulic Hand Dynamometer, www.msd-europe.com). The subject warmed up a few minutes with stationary bicycle before the muscle strength measurements.

2.1.3. Follow-up assessments

The subjects went through a comprehensive fall risk assessment three times with a time span from 4 to 12 months between the assessments. The fall risk assessment protocol was the same at all three time points, except that the balance platform test was not included in the second, i.e. midterm assessment. Each time the participants were given a feedback sheet with main results and interpretation based on their age group averages. The subjects in Tampere had their midterm assessment 12–13 months and the final assessment 21 months after the baseline assessment. In proportion, in Oulu the midterm assessment was eight months and final assessment 12 months after the baseline assessment. In order to have equal period between data collections, this paper takes into further analysis the baseline assessment data from all subjects, and midterm assessment data from Tampere subjects and final assessment data from Oulu subjects. This results in 12-months follow-up period for all the subjects in this analysis.

2.1.4. Intervention

The subjects were randomly divided into three groups after the baseline fall risk assessment by randomizing the order of subject ID numbers and dividing the result into three groups. One group was given home technology tools that were iteratively developed within this study. The home system included touch screen PC with an exercise software for supporting fall prevention at home and an accelerometer for monitoring activity. The exercise software enabled personalized exercise program with a set of video exercises, reminders for the exercises, exercise monitoring on a diary and using accelerometer as a step counter. The home terminal was also used to display timed questionnaires e.g. about sleep quality and mood. The second group was given similar exercises on a traditional paper format and a paper diary for tracking the exercises. The third group participated only in the assessments. This paper presents secondary analysis of the study where the analyses are not conducted based on these groups but the fall risk assessment data of all subjects is employed. The preliminary analysis on this data is reported in [25].

2.2. Data analysis

The data analysis was carried out using Matlab version R2015a (Mathworks Inc., Natick, MA, USA) and IBM SPSS Statistics for Windows version 22.0 (IBM Corp., Armonk, NY, USA).

The BBS test has 14 tasks, i.e. sub-components, with increasing difficulty and the final components are considered the most challenging [6]. Sheehan *et al.* categorized their study participants as "balance declined" and "balance not-declined" using BBS total score and sub-component scores for tandem stance (task 13) and one leg stance (task 14) [19]. Respectively, in this study, the subjects were categorized as "balance declined" if their 1) BBS total score decreased or 2) score in one leg stance (task 14) decreased at least one point during the follow-up period. The group differences in baseline characteristics were analyzed using Mann-Whitney *U* test. Age and Body Mass Index (BMI) were added as control variables in the analysis to find out whether those variables alone could explain the decline in balance.

Acceleration data measured during corridor walking with a sensor attached to the lower back were separated for further analysis based on manual annotations. The corridor, where the walk test was performed, had tape markers on the floor couple of meters after the beginning and before the end of the corridor. The annotation markers were placed on the acceleration signal once the subject crossed the tape markers. Additional two seconds were removed from the beginning and end of the data in order to ensure normal steady walk data in the analysis. A low pass filtering (3rd order elliptic infinite impulse response filter, cut-off at 0.25 Hz, passband ripple 0.01 dB, stopband at −100 dB [26]) was applied to separate acceleration components due to gravity and body motion. Body accelerations in mediolateral (x), vertical (y), and anteroposterior (z) directions were gained by subtracting the filtered signals from the original accelerations. In addition, resultant acceleration, also referred as signal vector magnitude, was calculated from the three axis according to (1), where a_{RES} is the resultant acceleration, a_x is body acceleration in the mediolateral, a_y the vertical, and a_z the anterior–posterior planes, resulting in four signals in feature extraction.

$$a_{RES}[n] = \sqrt{(a_x[n])^2 + (a_y[n])^2 + (a_z[n])^2} \tag{1}$$

2.2.1. Acceleration feature extraction

Peaks in the vertical pelvis acceleration coincide with heel strikes [27]. The algorithm for peaks detection was the following 1) calculation of 10-point moving average of the vertical acceleration, 2) detecting crossings of a threshold of 0.15 times the maximum value of the signal under investigation (the threshold value was determined through trial and error), 3) detection of the local maxima in the original signal between indices of consecutive threshold crossings, and 4) visual inspection of detected steps (plotting the original signal with detected steps and manual removal/addition of peak indices if necessary). Step time is the time between two consecutive peaks and stride time is the time of two consecutive steps. Mean and standard deviation of step times in seconds, and of stride times respectively, were calculated. Step frequency during walking test was determined by detecting the dominant peak in the vertical acceleration frequency magnitude spectrum obtained by fast Fourier Transform (FFT) algorithm. Step time asymmetry between right and left steps was determined according to (2) similarly as in [12].

$$steptimeasymmetry = \frac{\begin{pmatrix} meanstep \\ timeleg1 \end{pmatrix} - \begin{pmatrix} meanstep \\ timeleg2 \end{pmatrix}}{meansteptimesbothlegs} \tag{2}$$

Absolute value of step time asymmetry is taken into further analysis, since step times are identified so that every other step is taken by leg1 and every other by leg2, and not left and right specifically. Summed magnitude area (SMA) of the three axis was calculated as

$$SMA = \sum_{n=1}^{K} [|a_x[n]| + |a_y[n]| + |a_z[n]|], \tag{3}$$

where K is the total number of samples in the data.

For the spectral features, in order to minimize spectral leakage, the signals were multiplied with a Hanning window prior to calculation of a discrete Fourier transform, similarly as in [28]. The fundamental frequency of walking is the full gait cycle constituted of two steps [29]. Thus the first fundamental harmonic frequency was determined by finding the maximum peak in spectrum near the stride frequency. The next harmonics from second to sixth were determined as multiples of the fundamental frequency. The area under the first six harmonics was calculated as a sum of areas under bands of 0.3 Hz around each harmonic as proposed by Liu et al. [28]. The frequency features were calculated as ratio of first six harmonics to area under remaining spectrum, and ratios of harmonics one to four to all six harmonics. In addition, ratio of even and odd harmonics was calculated.

Basic features include mean value for resultant acceleration (a_{RES}), and standard deviation and maximum-minimum range for all signals. For the resultant acceleration the amplitudes of peaks representing steps were detected. Mean and standard deviation of the amplitudes were calculated. Amplitude asymmetry between right and left steps was determined similarly as step time asymmetry. Table 1. summarizes the calculated features.

2.2.2. Estimation of Assessment Scale Result

Generalized linear models were determined to estimate BBS, TUG and 4 m walk test results at baseline with baseline gait features. Generalized linear models use linear methods, but allow also nonlinear relationship between a response and predictors [30]. Sequential forward floating selection (SFFS) method [31] and stratified 10-fold cross-validation methods were applied to obtain significant features in the models. The criteria for adding a feature were 1) the feature is significant at a level $p < 0.05$ and 2) it minimizes the root-mean-square error (RMSE) of the estimation. In this study, models for estimating BBS, TUG and 4 m walk test results were determined. The estimates were rounded to the accuracy of original measurement, i.e. the BBS score estimate is rounded to nearest integer with maximum value of 56, and TUG and 4 m walk times were rounded to precision of 0.01 s. Normalized RMSE values were determined to evaluate the model performance. The final model was achieved when no more features could be added.

2.2.3. Prediction of decline in balance

Secondly, generalized linear models were determined to distinguish between subjects that had a decline in balance and subjects that had no decline in balance during the one-year follow-up. The SFFS method [31] and stratified 10-fold cross-validation methods were applied to obtain significant features in the models. The criteria for adding a feature were 1) the feature is significant at a level $p < 0.05$ and 2) it

Table 1
List of features calculated from the gait acceleration (no. 1–43) and the two control variables (no. 44–45).

No.	Name	Description
1	stepFreq	Step frequency [steps/second]
2	SMA	Signal magnitude area [G]
Frequency features		
3	harmonicsratioX	1st 6 harm. ratio to remaining spectrum X-axis
4	hr1X	1st harm. ratio to all harm. X-axis
5	hr2X	2nd harm. ratio to all harm. X-axis
6	hr3X	3rd harm. ratio to all harm. X-axis
7	hr4X	4th harm. ratio to all harm. X-axis
8	hreoX	ratio of even harm. to odd harm. X-axis
9	harmonicsratioY	1st 6 harm. ratio to remaining spectrum Y-axis
10	hr1Y	1st harm. ratio to all harm. Y-axis
11	hr2Y	2nd harm. ratio to all harm. Y-axis
12	hr3Y	3rd harm. ratio to all harm. Y-axis
13	hr4Y	4th harm. ratio to all harm. Y-axis
14	hreoY	ratio of even harm. to odd harm. Y-axis
15	harmonicsratioZ	1st 6 harm. ratio to remaining spectrum Z-axis
16	hr1Z	1st harm. ratio to all harm. Z-axis
17	hr2Z	2nd harm. ratio to all harm. Z-axis
18	hr3Z	3rd harm. ratio to all harm. Z-axis
19	hr4Z	4th harm. ratio to all harm. Z-axis
20	hreoZ	ratio of even harm. to odd harm. Z-axis
21	harmonicsratioRES	1st 6 harm. ratio to remaining spectrum resultant acceleration (a_{RES})
22	hr1RES	1st harm. ratio to all harm. a_{RES}
23	hr2RES	2nd harm. ratio to all harm. a_{RES}
24	hr3RES	3rd harm. ratio to all harm. a_{RES}
25	hr4RES	4th harm. ratio to all harm. a_{RES}
26	hreoRES	ratio of even harm. to odd harm. a_{RES}
Basic features		
27	meanRES	average of signal vector magnitude [G]
28	stdX	standard deviation of X-axis [G]
29	stdY	standard deviation of Y-axis [G]
30	stdZ	standard deviation of Z-axis [G]
31	stdRES	standard deviation of a_{RES} [G]
32	minmaxX	max - min range of X-axis [G]
33	minmaxY	max - min range of Y-axis [G]
34	minmaxZ	max - min range of Z-axis [G]
35	minmaxRES	max - min range of a_{RES} [G]
Temporal gait features		
36	mean_step_time	average step time [seconds]
37	std_step_time	standard deviation of step times [seconds]
38	mean_stride_time	average stride time [seconds]
39	std_stride_time	standard deviation of stride times [seconds]
40	asymmetry1	asymmetry between (a and b) step times x 100 [%]
Resultant acceleration amplitude features		
41	mean_amplitude	average peak amplitude (detected steps) in a_{RES} [G]
42	std_amplitudes	standard deviation of peak amplitudes in a_{RES} [G]
43	asymmetry2	asymmetry between (a and b) step amplitudes in a_{RES} x 100 [%]
Control variables		
44	Age	subject age [years]
45	BMI	subject BMI [kg/m^2]

maximizes the classification result as evaluated by the highest area under curve (AUC) with the training set. In this study, models were determined for predicting decline in 1) BBS total score and 2) score in BBS one leg stance task.

To compare the classification performances Receive Operating Curve (ROC) and AUC were evaluated. The ROC plot represents the sensitivity vs. 1 − specificity for the range of decision thresholds and thus provides a complete picture of the test accuracy in discriminating between the two outcomes [32]. The AUC is determined as the area under the ROC curve and gives a single measure of a classifier performance [33]. The closer the AUC is to value of one, the better the classifier performance.

3. Results

From the original sample of 42 subjects 35 completed the study protocol and were included in the analysis. Three from the original sample were not reached, two withdrew because of health reasons, one moved to another place and the only male subject was not included. Table 2. represents the baseline characteristics of the test subjects associated with decline in balance. The 4 m walk time was lost for one subject, thus all the following results regarding the walk test include 34 subjects.

The BBS baseline tests show that all the subjects were above the threshold of 49 points or more, which indicates they did not have decreased balance ability [34]. Four subjects had TUG time more than 12 s that is considered to indicate problems in individual's ambulatory abilities [35]. All the subjects walked 4 m with a time less than 4.82 s which gives full points in Short Physical Performance Battery (SPPB) test according to [20].

3.1. Estimation of assessment scale result

The feature selection was performed for estimating the result of BBS, TUG and 4 m walk time with generalized linear models. Ten-fold cross-validation yielded ten models for each reference scale. Table 3. presents selected features, estimate values, confidence intervals and *p*-values of the predictors, and normalized RMSE in each ten folds.

The features most frequently selected in the ten-fold cross-validation rounds for estimating BBS score were *SMA* (in nine rounds), *first six harmonics ratio to remaining spectrum of mediolateral acceleration* (in five rounds), and *ratio of even harmonics to odd harmonics of antero-posterior acceleration* (in four rounds). *Third harmonic ratio to first six harmonics of resultant acceleration* was selected in all ten rounds of TUG time estimation, and *average of resultant acceleration* was selected in eight rounds, respectively. *Average step time* was selected in all rounds as a predictor of 4 m walk time. *Average stride time* and *standard deviation of mediolateral acceleration* were selected in four rounds.

Fig. 1. represents the estimated values of BBS score, TUG time and 4 m walk time compared with the corresponding measured assessment scale result. Mean normalized RMSE of estimation in ten folds was 0.28 for BBS score, 0.18 for TUG time, and 0.22 for 4 m walk time, respectively.

3.2. Prediction of decline in balance

Generalized linear models were determined by SFFS and ten-fold cross-validation methods to predict decline in BBS total score and one leg stance (BBS task 14). Table 4. presents selected features, estimate values, confidence intervals and *p*-values of the predictors, and the accuracy of classification in each ten folds.

Standard deviation of vertical acceleration was selected in each cross-validation round for predicting decline in both BBS total score and one leg stance. Mean accuracy of classification was 69.2% for decline in BBS total score and 78.5% for decline in one leg stance. Fig. 2. represents the ROC plots for the classification. AUC was 0.78 for predicting decline in BBS total score and 0.82 for predicting decline in one leg stance. At the sensitivity level of 80%, the specificities were 73% and 67% for predicting decline in BBS total score and one leg stance respectively.

4. Discussion

The purpose of this study was to analyze whether features extracted from waist acceleration measured during walking can be used to estimate the result of three reference balance assessment scales and to detect early signs of decline in balance. In ten-fold cross-validation the same features were repeatedly selected as predictors in the models

Table 2
Baseline characteristics for the test subjects in total sample, and in groups dichotomized into decline/no decline in balance.

	Total sample (n =35)	Decline in total BBS (n =13)	No decline in total BBS (n =22)	Decline in BBS task 14 (one leg stance) (n =8)	No decline in BBS task 14 (one leg stance) (n =27)
BBS score	54(49–56)	54(50–56)	54(46–56)	53.50(50–56)	54(49–56)
TUG [s]	9.55(2.28)	10.46(2.15)*	9.01(2.23)	10.43(2.42)	9.29(2.22)
Walk 4 m [s]	3.03(0.59) (n = 34)	3.37(0.61)* (n = 12)	2.85(0.51)	3.50(0.70) (n = 7)	2.91(0.51)
Age [years]	73.80(5.41)	75.92(5.31)	72.55(5.18)	75.00(5.53)	73.44(5.43)
BMI [kg/m^2]	26.52(3.86)	26.95(5.37)	26.27(2.73)	28.68(5.92)	25.88(2.86)
Height [cm]	160.03(6.12)	157.77(3.75)	161.36(6.90)	157.00(3.42)	160.93(6.50)
Weight [kg]	68.24(9.76)	69.98(12.81)	67.20(7.58)	75.23(13.47)	66.17(7.50)
ABC score	87(20.47)	85.15(20.36)	88.10(20.94)	80.16(25.06)	89.03(18.98)
MMSE score	28(24–30)	28(24–30)	28.5(25–30)	28.5(24–30)	28(25–30)
Grip strength [kg]	25.63(4.99)	24.67(4.11)	26.19(5.46)	26.15(2.21)	25.47(5.59)
Self-reported history of falls yes/no	8/27	2/11	6/16	0/8	8/19

Data expressed as mean(standard deviation) and median(minimum-maximum).
* Significant difference between groups at the level of $\alpha < 0.05$, Mann-Whitney *U* Test.

for estimating BBS, TUG and 4 m walk test results. That indicates that those features presumably contain higher predictive value over the other features. The selected reference assessment scales partly measure similar characteristics of static and dynamic balance, but also include aspects that measure different characteristics. Thus, it was expected that different set of features was selected for different models. Features determined from mediolateral, antero-posterior and resultant accelerations were the most significant in estimating the assessment scale results at baseline, whereas vertical acceleration, standard deviation of vertical acceleration in particular, seemed to be more predictive of decline in balance.

The feature SMA, i.e. signal magnitude area, represents the amount of acceleration induced to the sensor and it was found a significant predictor of BBS score in nine cross-validation rounds. Positive feature estimate value indicates that the larger the SMA, the larger the BBS score estimate. The finding is consistent with the literature, since it is suggested that older people adopt a more conservative gait pattern as a compensatory strategy to stabilize their balance while walking, which leads to smaller magnitude of accelerations at the head and pelvis, reduced velocity and step length, and increased step timing variability [36]. Resultant acceleration represents the total acceleration of all three dimensions measured by the sensor during movement. Therefore, larger value of that feature should indicate a less conservative gait pattern and thus presumably faster movement. The results show that, in fact, larger value of average resultant acceleration was associated with shorter TUG time. Third harmonic ratio to first six harmonics of resultant acceleration was the most predictive of TUG time. The third harmonic represents a periodicity of higher frequency than that of step frequency, since the regular gait is dominated by the second harmonic representing the step frequency [27]. In this study, larger value of third harmonic ratio indicated longer time in TUG, and might reflect a less smooth gait. Furthermore, it is not very surprising that average step time was a significant predictor of baseline 4 m walk time in all cross-validation rounds. Average stride time is presumably highly correlated with average step time and, in fact, when both features were selected, the estimate value was quite high for both of them with opposite sign. This indicates only one of the features should be included in the analysis.

Standard deviation is a measure of dispersion in the data relative to mean. Since the gravitational acceleration was removed from the three dimensional accelerations the resulting signals have zero mean, and thus the standard deviation is equal to root mean square (RMS) as explained in [27]. Senden et al. found strong and significant correlation (r=0.60) between vertical acceleration RMS and the Tinetti scale [10]. In their study, the vertical RMS had also good discriminative power in differentiating subjects with Tinetti score of ≤24 and subjects with score of > 24 with AUC of 0.81. Moreover, van Schooten *et al.* found vertical standard deviation associated with prospective falls [17]. In this study the same feature, i.e. vertical standard deviation, was selected in every 10 folds as a predictor for estimating decline in total BBS and decline in one leg stance.

Liu et al. reported considerable improvement in accelerometry-based Physiological Profile Assessment (PPA) fall risk score estimation when temporal and energy-related features were supplemented with frequency spectra-based features from correlation of r=0.81 to r=0.96 [28]. However, the large number of features (N=126) relative to sample size and feature selection methodology applied suggest the obtained models may be overfitted. In any case, in this study, several acceleration spectra-based features were found associated with BBS, TUG and 4-meters walk test, and were selected by the SFFS method in the regression models for estimating the results of those scales. These results suggest that frequency spectrum of human movement acceleration contains valuable information with regard balance assessment. The control variables, age and BMI, were not selected as predictors in any of the models suggesting that gait features contain additional information about balance and age alone does not explain all the changes in balance ability in this study sample. To summarize the most important parameters of gait regarding to balance assessment, the amount of acceleration in three dimensions measured by the sensor during walking, SMA and average resultant acceleration in particular, were associated with performance in BBS and TUG tests. The smoothness of gait, quantified as the third harmonic ratio to first six harmonics of resultant acceleration, was the most important predictor of time in TUG test. Average step and stride times were expectedly associated with 4 m walk time. Standard deviation of vertical acceleration was a significant predictor of decline in both BBS total score and one leg stance task during one-year follow-up.

In a study by Sheehan *et al.*, baseline quantitative TUG parameters were able to predict decline in total BBS score and one leg stance with AUC values of 0.7 and 0.8 respectively [19]. Corresponding results were achieved in this study, since AUC was 0.78 for predicting decline in total BBS and 0.82 for predicting decline in one leg stance. Although, in this study, the decline of one point is used as a cut-off for classifying subject as having declined balance during follow-up, while Sheehan *et al.* used cut-off of two points in one leg stance and four points in total BBS score [19]. The results of this study suggest that decline as subtle as one point in BBS might be predictable with gait accelerometry.

There are some limitations in this study. The number of subjects was rather low and the analysis here did not take into account the intervention some of the subjects were exposed to. However, all the test

Table 3
Results from the ten-fold cross-validation of assessment scale result estimation for BBS, TUG and 4 m walk. Selected features, estimate values, confidence intervals, and *p*-values of the predictors, and normalized RMSE in each ten folds are represented.

Fold	NRMSE	Selected features	Estimate	95% Confidence interval		*p*-value
BBS						
1	0.28	2	1.15	0.55	1.74	0.00
		3	0.87	0.31	1.43	0.00
		20	−0.72	−1.27	−0.17	0.01
2	0.33	2	0.83	0.37	1.28	0.00
		3	0.82	0.25	1.39	0.01
		20	−0.98	−1.58	−0.39	0.00
		1	−0.54	−1.01	−0.06	0.03
		8	0.59	0.06	1.12	0.03
		15	0.64	0.01	1.26	0.05
3	0.16	2	0.75	0.11	1.40	0.02
4	0.28	3	1.05	0.44	1.66	0.00
		8	0.90	0.26	1.54	0.01
		2	0.71	0.05	1.37	0.04
5	0.30	3	0.97	0.36	1.57	0.00
		2	0.74	0.19	1.28	0.01
		20	−0.60	−1.17	−0.03	0.04
6	0.50	4	−1.16	−1.75	−0.58	0.00
		6	−0.77	−1.33	−0.22	0.01
		2	0.58	0.08	1.08	0.02
7	0.25	2	0.80	0.16	1.43	0.02
8	0.31	27	1.15	0.48	1.82	0.00
		1	−0.74	−1.45	−0.04	0.04
9	0.31	2	0.83	0.24	1.42	0.01
10	0.12	2	0.96	0.39	1.52	0.00
		3	0.89	0.31	1.47	0.00
		20	−0.75	−1.34	−0.16	0.01
TUG						
1	0.28	28	−1.13	−1.74	−0.51	0.00
		24	1.20	0.63	1.77	0.00
		25	−0.69	−1.22	−0.17	0.01
		39	0.79	0.25	1.32	0.01
		37	−1.09	−2.02	−0.17	0.02
2	0.23	24	1.06	0.48	1.65	0.00
		27	−0.66	−1.20	−0.11	0.02
		25	−0.59	−1.16	−0.03	0.04
3	0.15	24	1.25	0.63	1.87	0.00
		27	−0.85	−1.47	−0.24	0.01
4	0.31	24	1.16	0.75	1.58	0.00
		36	3.95	1.93	5.97	0.00
		22	1.04	0.63	1.46	0.00
		39	0.88	0.48	1.28	0.00
		37	−0.55	−0.97	−0.14	0.01
		1	2.60	0.50	4.71	0.02
5	0.07	24	1.23	0.57	1.89	0.00
		27	−0.94	−1.60	−0.28	0.01
6	0.10	24	1.18	0.56	1.80	0.00
		27	−0.94	−1.55	−0.33	0.00
7	0.15	24	1.31	0.69	1.93	0.00
		27	−0.95	−1.57	−0.33	0.00
8	0.22	24	0.99	0.39	1.59	0.00
		27	−0.74	−1.34	−0.15	0.02
9	0.13	24	1.30	0.68	1.91	0.00
		27	−0.87	−1.48	−0.25	0.01
10	0.14	24	1.18	0.58	1.78	0.00
		27	−1.01	−1.58	−0.44	0.00
		25	−0.62	−1.23	−0.01	0.05
BBS						
1	0.28	36	24.91	8.25	41.58	0.00
		38	−24.57	−41.24	−7.89	0.01
2	0.19	36	16.39	1.82	30.97	0.03
		28	−0.44	−0.65	−0.22	0.00
		30	0.36	0.14	0.59	0.00
		38	−15.93	−30.49	−1.38	0.03
3	0.27	36	0.27	0.11	0.43	0.00
		27	−0.23	−0.39	−0.08	0.00
		25	−0.17	−0.30	−0.04	0.01
4	0.24	36	0.31	0.16	0.47	0.00
		28	−0.23	−0.38	−0.07	0.01
5	0.16	36	0.44	0.27	0.61	0.00
		28	−0.40	−0.63	−0.17	0.00
		30	0.36	0.09	0.62	0.01
6	0.23	36	0.41	0.26	0.56	0.00
		28	−0.37	−0.55	−0.19	0.00
		34	0.28	0.10	0.47	0.00
7	0.33	36	0.53	0.38	0.69	0.00
		26	−0.19	−0.34	−0.04	0.02
8	0.19	36	18.56	1.51	35.61	0.03
		27	−0.21	−0.39	−0.03	0.03
		38	−18.23	−35.26	−1.19	0.04
9	0.21	36	0.44	0.29	0.60	0.00
10	0.15	36	21.97	3.64	40.31	0.02
		38	−21.57	−39.91	−3.22	0.02
		4	0.15	0.01	0.29	0.04

subjects were quite active in all, technology, paper and control groups, and they participated in the same exercise groups outside this study. Thus, it is arguable to treat them here as one sample set. It should also be noted that the three assessments did not have same delay for all the subjects. Although, a follow-up period of one year was employed for all the subjects in the analysis of this paper, some of the subjects had one additional assessment before the follow-up assessment. Exposure to intervention and additional testing may have encouraged some subjects to exercise more and improve their physical functioning during the follow-up period. Furthermore, the study sample consisted only of female subjects, and the generalizability of the results for males needs to be verified. The prediction of change in BBS total score and one leg stance were inspected as a binary value: decrease vs. no decrease. The approach chosen does not take into account the amount of decrease, since the study sample was considered too narrow for predicting the actual decrease. Future studies should investigate whether predicting actual decrease is feasible and what is the magnitude of change that is clinically significant. The available data set cannot be used for rigorous validation of the methods and a comprehensive validation is an objective of the future studies.

Accelerometry-based fall risk assessment has a great potential in improving clinical practices. If an instrumented walk test would provide comparable or better balance assessment results to the reference measures, it would save time in health care appointment. Furthermore, since gait analysis could be incorporated in everyday life [17], it provides with a possibility to long-term monitoring of balance

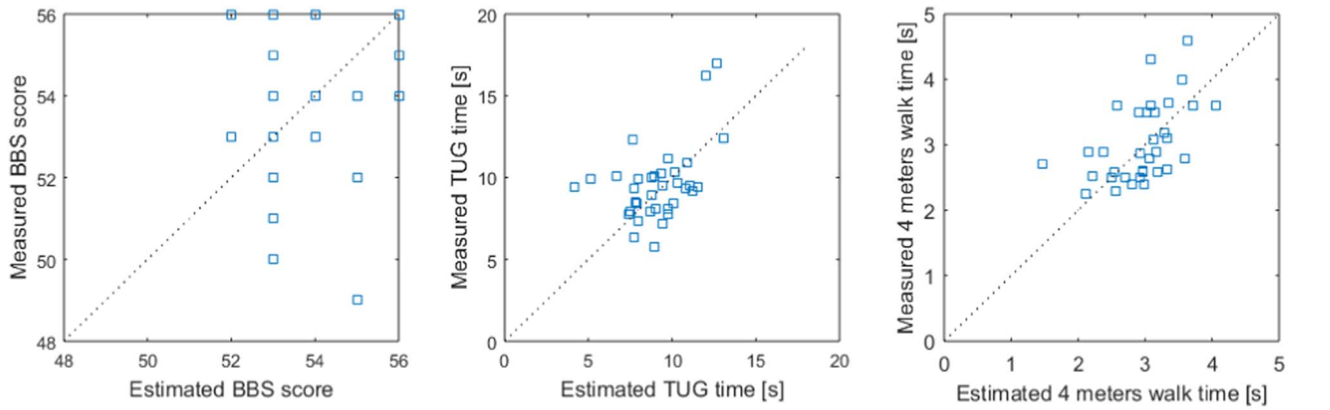

Fig. 1. Correlation plots for estimated and measured BBS score, TUG time and 4 m walk time. The estimated assessment scale value represents the result of generalized linear model with selected accelerometry-based gait features.

Table 4
Results from the ten-fold cross-validation of predicting decline in BBS total score and one leg stance (BBS task 14). Selected features, estimate values, confidence intervals, *p*-values of the predictors, and accuracy of classification in each ten folds are represented.

Fold	Accuracy of classification [%]	Selected features	Estimate	95% Confidence interval		*p*-value
Decrease in BBS total score						
1	50	29	−1.41	−2.65	−0.16	0.02
2	75	29	−1.51	−2.81	−0.20	0.02
3	75	29	−1.42	−2.62	−0.22	0.02
4	50	29	−1.62	−2.92	−0.32	0.01
5	75	29	−1.51	−2.72	−0.29	0.01
6	100	29	−1.44	−2.69	−0.19	0.02
7	100	29	−1.42	−2.64	−0.20	0.02
8	33	29	−3.04	−5.42	−0.66	0.01
9	67	29	−1.99	−3.42	−0.57	0.00
		25	−1.40	−2.73	−0.07	0.03
10	67	29	−1.47	−2.73	−0.22	0.02
Decrease in one leg stance (BBS task 14)						
1	75	29	−3.04	−5.77	−0.31	0.02
2	50	29	−5.70	−11.27	−0.14	0.04
3	100	29	−2.75	−5.40	−0.09	0.03
4	75	29	−4.84	−9.54	−0.13	0.04
		8	−2.37	−4.78	0.04	0.04
5	50	29	−2.80	−5.25	−0.35	0.02
6	67	29	−5.89	−11.99	0.20	0.05
		8	−2.76	−5.59	0.06	0.05
7	67	29	−2.80	−5.29	−0.32	0.02
8	67	29	−3.90	−7.20	−0.60	0.02
		30	1.41	−0.02	2.85	0.04
9	67	29	−3.49	−6.61	−0.37	0.02
10	100	29	−2.88	−5.37	−0.38	0.02

with higher sensitivity to short-term fluctuations in balance. The actual fall incidents are caused by multitude of reasons and often by extrinsic factors. Also, because the clinical assessment scales currently in use have a ceiling effect among higher functioning older people, estimating balance and fall risk might prove to be more coherent reference for developing prediction instead of falls. These results can be used as a basis for further studies to verify the clinical importance of these findings, and also to investigate possible predictive ability of the gait features with regard to other assessment scales not inspected here. The results suggest that simple walk test with wearable monitoring could be applied, for example, as an initial screening tool to identify people with early signs of balance deficits and they could be directed to further testing.

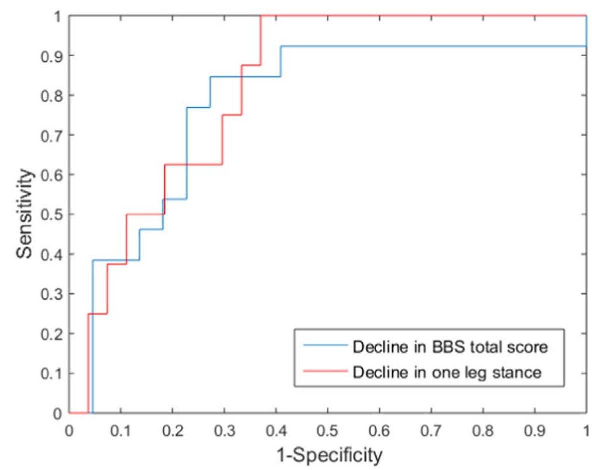

Fig. 2. ROC plots for combined output of ten-fold cross-validation for predicting subjects with decline in BBS total score and one leg stance (BBS task 14) during one-year follow-up. The prediction of decline was determined by generalized linear model with selected accelerometry-based gait features.

Conflict of interest

The authors declare that there are no conflicts of interest.

Acknowledgement

This study was approved by the Ethics Committee of Human Sciences at the University of Oulu (statement 2/2014), This work was partly funded by Tekes - the Finnish Funding Agency for Innovation as part of projects Ageing in Balance (AAL-2011-4-Ageing in Balance) and Digital Health Revolution (40122/14). The authors would like to thank all the study participants and Professor Tapio Seppänen for his input in data analysis methodology.

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Series title and number

VTT Science 163

Title	**Assessing fall risk of older adults using accelerometry-based methods**
Author(s)	Heidi Similä
Abstract	Falls pose a serious threat to older people, since they may lead to severe injuries, reduced quality of life and increased health care costs. Every third person over 65 years old falls at least once each year, and the number of falls increases with age and frailty level. Falls are multifactorial by nature and a person can have several risk factors contributing to a fall. A variety of assessment scales have been developed for assessing fall risk factors and estimating the probability of future falls. These are typically administrated by a health care professional. However, selection of an assessment scale with high enough sensitivity and specificity and reasonable administration time can be difficult. The goal of this thesis was to develop new methods for fall risk assessment utilizing accelerometry-based movement sensing, which enables objective detection and assessment of a person's balance deficits. The first objective was to investigate the perceptions of prospective end-users of new technologies via focus group interviews. The analysis showed that familiarity, prior experience and self-efficacy presumably affect the acceptance of new solutions. The second objective was to investigate how an individual's fall risk is manifested through different assessment scales. The Disease State Fingerprint visualization method was examined for its potential in comparing different fall risk assessment scales. It was found useful in discovering the most relevant assessment scales for separating fallers from non-fallers in the study population, and for presenting how the overall fall risk of an individual is constituted. The third objective was to study how body-worn accelerometry could be utilized in the assessment of individual fall risk. For the third objective, three data sets were collected from a total of 111 subjects. The results showed that features derived from the body-worn accelerometer signals could be used for assessment of a person's balance. Furthermore, they seem to be able detect balance deficits even earlier than the traditionally used clinical assessment scales. The results provide a basis for studies validating these methods and further transferring them into practice.
ISBN, ISSN, URN	ISBN 978-951-38-8573-1 (Soft back ed.) ISBN 978-951-38-8572-4 (URL: http://www.vttresearch.com/impact/publications) ISSN-L 2242-119X ISSN 2242-119X (Print) ISSN 2242-1203 (Online) http://urn.fi/URN:ISBN:978-951-38-8572-4
Date	November 2017
Language	English, Finnish abstract
Pages	71 p. + app. 48 p.
Name of the project	
Commissioned by	
Keywords	Balance, wearable sensors, machine learning, gait analysis
Publisher	VTT Technical Research Centre of Finland Ltd P.O. Box 1000, FI-02044 VTT, Finland, Tel. 020 722 111

Julkaisun sarja ja numero

VTT Science 163

Nimeke	**Ikääntyneiden kaatumisriskin arviointi kiihtyvyysanturipohjaisilla menetelmillä**
Tekijä(t)	Heidi Similä
Tiivistelmä	Kaatumiset ovat uhka ikääntyneille, koska ne voivat aiheuttaa vakavia vammoja, heikentää elämänlaatua ja lisätä terveydenhuollon kustannuksia. Joka kolmas yli 65-vuotias kaatuu vähintään kerran vuodessa, ja kaatumisten lukumäärä kasvaa iän ja heikentyneen kunnon myötä. Kaatumiset voivat johtua lukuisista eri tekijöistä, ja yhden kaatumisen taustalla voi vaikuttaa useita riskitekijöitä. Kaatumisriskitekijöiden ja kaatumisten todennäköisyyden arviointiin on kehitetty useita erilaisia mittareita, joita käyttävät tyypillisesti terveydenhuollon ammattilaiset. Käytettävän mittarin valinta ei ole helppoa, sillä mittarin tulisi olla sensitiivinen ja spesifinen ja arviointi tulisi voida suorittaa kohtuullisessa ajassa. Tämän väitöstyön päätavoitteena oli kehittää uusia menetelmiä kaatumisriskin arvioimiseksi hyödyntämällä kiihtyvyysanturipohjaista liikkeenmittausta, joka mahdollistaa henkilön tasapaino-ongelmien tunnistamisen objektiivisesti. Ensimmäinen tavoite oli selvittää fokusryhmähaastattelujen avulla, miten loppukäyttäjät kokevat nykyiset ja tulevaisuuden kaatumisriskin arviointiin ja kaatumisten ennaltaehkäisyyn suunnatut teknologiat. Aineiston analyysi osoitti, että aiheeseen liittyvä tuttuus, aiempi kokemus sekä minäpystyvyys oletettavasti vaikuttavat uusien ratkaisujen hyväksyttävyyteen. Toinen tavoite oli tutkia, miten yksilön kaatumisriski näyttäytyy eri kaatumisriskimittareissa. Työssä arvioitiin Disease State Fingerprint -visualisointimenetelmän käytettävyyttä eri kaatumisriskimittareiden vertailussa. Menetelmän avulla pystyttiin tunnistamaan ne mittarit, joilla voitiin parhaiten erottaa tutkimusjoukon kaatujat ei-kaatujista, sekä osoittamaan, miten yksilön kokonaiskaatumisriski koostuu eri tekijöistä. Kolmas tavoite oli tutkia, miten puettavia kiihtyvyysantureita voidaan hyödyntää yksilön kaatumisriskin arvioinnissa. Analyysit pohjautuivat kolmeen datasettiin, jotka oli kerätty yhteensä 111 henkilöstä. Tulokset osoittavat, että puettavan kiihtyvyysanturin signaaleista laskettuja piirteitä voidaan käyttää henkilön tasapainon arviointiin. Lisäksi tulokset osoittavat, että kiihtyvyyteen pohjautuvat piirteet saattavat tunnistaa tasapaino-ongelmia jopa perinteisiä kliinisiä mittareita aiemmin. Saatuja tuloksia voidaan hyödyntää menetelmien validointitutkimuksen sekä käyttöönoton suunnittelemiseksi ja toteuttamiseksi.
ISBN, ISSN, URN	ISBN 978-951-38-8573-1 (nid.) ISBN 978-951-38-8572-4 (URL: http://www.vtt.fi/julkaisut) ISSN-L 2242-119X ISSN 2242-119X (Painettu) ISSN 2242-1203 (Verkkojulkaisu) http://urn.fi/URN:ISBN:978-951-38-8572-4
Julkaisuaika	Marraskuu 2017
Kieli	Englanti, suomenkielinen tiivistelmä
Sivumäärä	71 s. + liitt. 48 s.
Projektin nimi	
Rahoittajat	
Avainsanat	Tasapaino, puettavat anturit, koneoppiminen, kävelyanalyysi
Julkaisija	Teknologian tutkimuskeskus VTT Oy PL 1000, 02044 VTT, puh. 020 722 111

VTT SCIENCE 163

Assessing fall risk of older adults using...

Assessing fall risk of older adults using accelerometry-based methods

More than one third of older people fall each year. Falls can be prevented with correct and timely intervention, but there is a need for more accurate fall risk assessment methods that enable early detection of increased risk. Variety of clinical assessment scales exist, but it can be challenging to choose which assessment scales to use. Furthermore, there may be multitude of factors causing a fall of an individual.

This thesis introduces accelerometry-based movement monitoring methods to detect and assess balance problems. The methods analyze gait acceleration data measured with a waist-mounted sensor during walking. The features extracted from gait acceleration provide results comparable to clinical assessment scales. The results indicate that the accelerometry-based features may even detect balance problems earlier than the traditional scales. This thesis applies a visualization method for comparing different assessment scales and representing the factors constituting the fall risk of an individual. The older people are also involved in the development of technologies through focus group interviews to enhance the acceptability of new solutions.

ISBN 978-951-38-8573-1 (Soft back ed.)
ISBN 978-951-38-8572-4 (URL: http://www.vttresearch.com/impact/publications)
ISSN-L 2242-119X
ISSN 2242-119X (Print)
ISSN 2242-1203 (Online)
http://urn.fi/URN:ISBN:978-951-38-8572-4