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New Sensor-Based Methods for Clinical and In-Home Assessment of Fall Risk in Older People

DISSERTATION

submitted in partial fulfillment of the requirements for the degree of

Doctor of Technical Sciences

by

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Registration Number 0626078

to the Faculty of Informatics

at the Vienna University of Technology

Advisor: Dr. Kim Delbaere, Prof. Stephen Lord, Prof. Wolfgang Zagler

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Vienna, 30th November, 2015

Andreas Ejupi

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an der Fakultät für Informatik

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I hereby declare that I have written this Doctoral Thesis independently, that I have completely specified the utilized sources and resources and that I have definitely marked all parts of the work - including tables, maps and figures - which belong to other works or to the internet, literally or extracted, by referencing the source as borrowed.

Vienna, 30th November, 2015

Andreas Ejupi

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Publications

This thesis is partially based on the following publications:

Chapter 2:

A. Ejupi, S. R. Lord, and K. Delbaere, "New methods for fall risk prediction." *Current Opinion in Clinical Nutrition and Metabolic Care*, vol. 17, no. 5, pp. 407–411, 2014

Chapter 4:

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Chapter 5:

A. Ejupi, M. Brodie, Y. J. Gschwind, S. R. Lord, and K. Delbaere, "Kinect-based choice reaching and stepping reaction time tests for clinical and in-home assessment of fall risk in older people: a prospective study," *European Review of Aging and Physical Activitiy*, 2015, in press

Chapter 6:

A. Ejupi, M. Brodie, Y. J. Gschwind, D. Schoene, S. R. Lord, and K. Delbaere, "Choice Stepping Reaction Time test using Exergame technology for fall risk assessment in older people," in *Conference Proceedings IEEE Engineering in Medicine and Biology*, 2014, pp. 6957–6960

Chapter 7:

A. Ejupi, M. Brodie, S. R. Lord, J. Annegarn, S. J. Redmond, and K. Delbaere, "Wavelet-Based Sit-To-Stand Detection and Assessment of Fall Risk in Older People Using a Wearable Pendant Device," *IEEE Transactions on Biomedical Engineering*, 2015, manuscript submitted for publication

Chapter 8:

A. Ejupi, Y. J. Gschwind, T. Valenzuela, S. R. Lord, and K. Delbaere, "A Kinect and inertial sensor-based system for the self-assessment of fall risk: a home-based study in older people," *Human Computer Interaction*, 2015, advance online publication

Other publications by the author of this thesis related to the topic:

A. Ejupi, J. Oberzaucher, F. Werner, and W. Zagler, "Development of a fall detection model for an instrumented insole," in *International Conference on Information Communication Technologies in Health*, 2012

K. Kreiner, H. De Rosario, C. Gossy, A. Ejupi, and M. Drobics, "Play Up! a Smart Knowledge-Based System using Games for Preventing Falls in Elderly People," in *Proceedings of the eHealth Conference*, 2013, pp. 243–248

Y. J. Gschwind, S. Eichberg, H. R. Marston, A. Ejupi, H. de Rosario, M. Kroll, M. Drobics, J. Annegarn, R. Wieching, S. R. Lord, K. Aal, and K. Delbaere, "ICT-based system to predict and prevent falls (iStoppFalls): study protocol for an international multicenter randomized controlled trial." *BMC Geriatrics*, vol. 14, no. 91, 2014

H. R. Marston, A. Woodbury, Y. J. Gschwind, M. Kroll, D. Fink, S. Eichberg, K. Kreiner, A. Ejupi, J. Annegarn, H. D. Rosario, A. Wienholtz, R. Wieching, and K. Delbaere, "The design of a purpose-built exergame for fall prediction and prevention for older people," *European Review of Aging and Physical Activitiy*, 2015, in press

Y. J. Gschwind, S. Eichberg, A. Ejupi, H. de Rosario, M. Kroll, H. R. Marston, M. Drobics, J. Annegarn, R. Wieching, S. R. Lord, K. Aal, D. Vaziri, A. Woodbury, D. Fink, and K. Delbaere, "ICT-based system to predict and prevent falls (iStoppFalls): results from an international multicenter randomized controlled trial," *European Review of Aging and Physical Activitiy*, 2015, in press

Y. J. Gschwind, D. Schoene, S. R. Lord, A. Ejupi, T. Valenzuela Artaega, K. Aal, A. Woodbury, and K. Delbaere, "The effect of sensor-based exercise at home on functional performance associated with fall risk in older people - a comparison of two exergame interventions," *European Review of Aging and Physical Activitiy*, 2015, in press

For a full list of publications see `http://www.ejupi.at/publications`.

Abstract

Background. Falls are common in older people and are becoming an increasing burden on society as the population ages. An accurate assessment of fall risk could assist to identify individuals at increased risk and would enable appropriate intervention before a fall occurs. To date, the methods used to assess fall risk often lack accuracy and objectivity, require expensive equipment and specialized knowledge, and are limited to the clinical setting.

Objective. The main objectives of this thesis were the development and evaluation of new sensor-based methods to accurately assess fall risk in both clinical and home settings. These new methods included the Microsoft Kinect, a low-cost consumer depth camera, and a pendant-style wearable sensor (Philips Research), comprising of an accelerometer and barometric air pressure sensor.

Methods. A Kinect-based system (also referred to as the iStoppFalls assessment) for the assessment of balance, strength and reaction time through a program on the television was developed. The feasibility and validity of the Kinect-based system and wearable sensor to assess fall risk in community-living older people was investigated across three studies:

In the first study, 94 older people were assessed on a Kinect-based five-times-sit-to-stand, choice stepping and choice reaching reaction time test in a clinical setting. Signal processing algorithms were developed to quantify performance on these tests by extracting temporal and spatial measurements from the Kinect skeleton data. The convergent validity of these measurements was established against traditional clinical tests and the ability to differentiate between people who are at risk for falls from people who are not at risk was investigated.

In the second study, 119 older people were asked to perform typical daily activities, including postural transitions (an indicator for fall risk), while wearing the pendant device. A signal processing algorithm, based on wavelet transformations of the accelerometer and barometric air pressure sensor data, was developed to automatically detect and assess sit-to-stand movements during daily activities.

In the third study, the long-term use of the Kinect-based system and wearable sensor was investigated in the homes of 62 older people over a four months study period. Participants were asked to independently perform at least one assessment session each month and to wear the pendant during the day. Interviews were conducted to investigate user experience and design guidelines for future home-based assessments were developed.

Results. The Kinect-based system and the wearable sensor could be used to assess fall risk in older people in a clinical setting. Further, it was feasible to use both methods in an unsupervised home setting.

Fallers performed significantly worse than non-fallers on the Kinect-based tests ($p < 0.05$). The proposed algorithms accurately detected these performance differences in the sensor data, supporting good discriminant validity of this new method.

The wearable sensor based on the proposed algorithm accurately detected sit-to-stand movements through the monitoring of activities of daily life (sensitivity: 93.1 - 98.9%, false positive rate: 0 - 2.9%) and differentiated significantly between the fallers and non-fallers ($p < 0.05$).

In total, 241 Kinect-based assessments were independently performed by the participants at home. The wearable sensor was worn for a total of 39,803 hours. Most participants felt positive about their experience and could see themselves continuing with the Kinect-based assessment or to wear the pendant device on a regular basis to monitor their fall risk.

Conclusion. The findings of this thesis suggest the feasibility of these new sensor-based methods in both clinical and home settings. In future, these methods could be used as an accurate, objective, easy to administer and inexpensive alternative or complement to traditional clinical fall risk tests, and could also provide health care professionals more detailed information about their patient's daily risk of falling at home.

Kurzfassung

Problemstellung. Stürze sind die häufigsten Unfälle älterer Menschen. Deren Folgen stellen eine große Herausforderung für das Gesundheitswesen dar. Aufgrund des demografischen Wandels und der damit verbundenen alternden Gesellschaft gewinnt die Thematik zunehmend an Bedeutung. Eine exakte Sturzrisikoerfassung zur Identifikation älterer Personen mit erhöhtem Sturzrisiko würde rechtzeitige Präventionsmaßnahmen ermöglichen. Derzeitige Verfahren zur Bestimmung des Sturzrisikos sind oftmals unpräzise, abhängig von subjektiven Interpretationen, benötigen spezielle Apparaturen (und Expertenwissen) und sind auf einen Einsatz im Labor oder in speziellen geriatrischen Kliniken beschränkt.

Zielsetzung. Ziel dieser Arbeit war die Entwicklung und Evaluierung neuer sensorbasierter Verfahren zur Sturzrisikobestimmung, die in Zukunft sowohl in klinischen als auch in häuslichen Settings eingesetzt werden können. Zum Einsatz kamen Microsoft Kinect, ein kostengünstiger visueller Tiefensensor, und ein tragbares Gerät (Philips Research), bestehend aus einem Beschleunigungssensor und Luftdrucksensor.

Methoden. Ein sensorbasiertes Assessment-Werkzeug zur Ermittlung der körperlichen Leistungsfähigkeit wurde entwickelt. Die Tests konnten mithilfe eines herkömmlichen Fernsehers und dem Kinect-Sensor in einer virtuellen Testumgebung durchgeführt werden. Das Kinect-basierte Testsystem und der tragbare Sensor wurden in drei Studien hinsichtlich des Einsatzes zur Ermittlung des Sturzrisikos älterer Personen untersucht.

In der ersten Studie wurden 94 Probanden mit dem Kinect-basierten System in einem klinischen Setting getestet. Dabei absolvierten die Probanden Tests zur Messung des Kraft-, Balance- und Reflexverhaltens. Algorithmen wurden entwickelt um aus den Sensordaten der Microsoft Kinect Performanz-Indikatoren zu erstellen. Die Konvergenzvalidität dieser Messergebnisse wurde mithilfe von Referenztests (Goldstandard) überprüft. Zusätzlich wurde untersucht, ob man mithilfe der sensorbasierten Messwerte zwischen Personen mit erhöhtem Sturzrisiko und weniger gefährdeten Personen unterscheiden kann (Diskriminanzvalidität).

In der zweiten Studie wurden alltägliche Aktivitäten von 119 Probanden mit dem tragbaren Sensor aufgezeichnet. Ein Beispiel für eine solche Alltagsbewegung ist das Aufstehen von einem Stuhl, das einen Rückschluss auf das Sturzrisiko einer Person erlaubt. Dazu wurde ein Algorithmus entwickelt, der basierend auf Wavelet-Transformationen der Beschleunigungs- und Luftdrucksensordaten das Aufstehen von einem Stuhl erkennen und die Bewegungsausführung bewerten kann.

In der dritten Studie wurde der mögliche Langzeiteinsatz (über vier Monate) des Kinect-basierten Systems und des tragbaren Sensors in der häuslichen Umgebung getestet. An der Studie beteiligten sich insgesamt 62 Probanden, die sich dazu bereit erklärten zumindest einmal pro Monat ein Kinect-basiertes Assessment selbständig durchzuführen, sowie den tragbaren Sensor täglich während der gesamten Studiendauer zu verwenden. Die Erfahrungen und Erzählungen der Probanden wurden mithilfe von Interviews am Ende der Studie festgehalten. Darauf aufbauend wurden Guidelines für zukünftige sensorbasierte Verfahren zur Sturzrisikoerfassung im häuslichen Setting erarbeitet.

Ergebnisse. Diese Arbeit zeigt, dass es möglich ist mithilfe des Kinect-basierten Systems zwischen sturzgefährdeten und weniger sturzgefährdeten Personen zu unterscheiden. Die auf Basis der entwickelten Algorithmen extrahierten Messwerte zeigten eine ausgezeichnete Konvergenzvalidität und waren signifikant unterschiedlich zwischen den sturzgefährdeten und weniger sturzgefährdeten Personen ($p < 0.05$).

Ein weiteres Resultat dieser Arbeit ist die Möglichkeit Aufstehbewegungen (während alltäglicher Bewegungen) mithilfe des entwickelten Algorithmus und tragbaren Sensors zu detektieren (Sensitivität: 93.1 – 98.9%, Falsch-Positiv-Rate: 0 – 2.9%). Das entwickelte Verfahren konnte erfolgreich zwischen sturzgefährdeten und weniger sturzgefährdeten Personen unterscheiden ($p < 0.05$).

Die Ergebnisse der Langzeitstudie zeigen, dass sowohl das Kinect-basierte System als auch der tragbare Sensor im häuslichen Setting verwendet werden können. Insgesamt wurde das Kinect-basierte Assessment 241-mal zur Ermittlung des individuellen Sturzrisikos durchgeführt. Der tragbare Sensor wurde für eine Gesamtdauer von 39.803 Stunden verwendet. Die meisten Teilnehmer äußerten sich positiv über die verwendeten Geräte und könnten sich vorstellen, diese auch zukünftig über die Studiendauer hinaus regelmäßig zu verwenden.

Schlussfolgerung. Zusammengefasst kann festgehalten werden, dass die entwickelten sensorbasierten Verfahren zur Sturzrisikoerfassung älterer Personen im klinischen als auch im häuslichen Setting verwendet werden können. Zukünftig könnten diese Verfahren als exakte, objektive, einfach anwendbare und kostengünstige Alternativen zu bisherigen klinischen Tests zum Einsatz kommen. Besonders die sensorbasierte Sturzrisikoerfassung außerhalb des klinischen Settings ist vielversprechend und kann Ärzten, Therapeuten und den betroffenen Personen selbst helfen, das individuelle Sturzrisiko regelmäßig festzustellen.

Contents

CHAPTER 1

Introduction

Age is an issue of mind over matter. If you don't mind, it doesn't matter.

Mark Twain

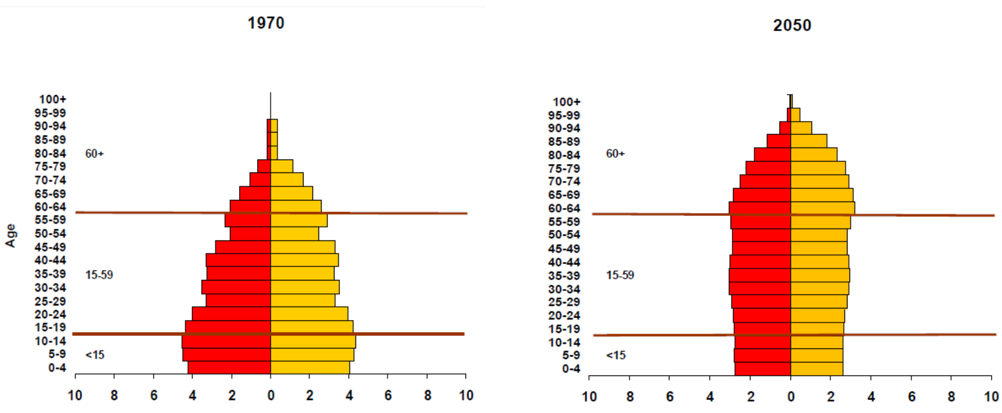
1.1 Falls in Older People

Falls remain an important problem in older people and are becoming an increasing burden on society as the population ages. A fall is commonly defined as *"an unexpected event in which the person comes to rest on the ground, floor, or lower level"* [13]. Yearly fall rates vary between 30% for those aged 65+ years to 50% for those aged 85+ years.

Because of demographic changes the issue with falls will be even more important in future. In 2000, 605 million people were 60+ years old. The World Health Organization estimates that by 2050, two billion people will be 60+ years and predicts a substantial change in the population profile, where this cohort will be the fastest growing group in the next decades (Figure 1.1) [14]. Figure 1.2 illustrates a projection of the estimated population by country in 2050.

Falls are the leading cause of injury-related hospitalization in old age [17]. About 37.3 million falls require medical attention and 424,000 people die from fall-related injuries every year worldwide [14]. The major causes for injury-related hospitalization are hip fractures, head and upper limb injuries [18]. The mean duration of a hospital stay because of a fall varies from four to 20 days [18]. A fall often initiates a vicious cycle which is difficult to break and may lead to a post-fall syndrome that includes loss of autonomy, confusion, immobility, depression and a restriction of daily activities [18].

Falls are the most expensive injury among older people. Costs related to falls can be categorized in direct and indirect costs. Direct costs include expenses for treatment and rehabilitation (e.g. doctor visits, diagnostic tests, medication, hospital care) and indirect costs are quantified as societal productivity losses (e.g. loss of income) of caregivers and patients [18, 19]. In a recent review, the total economic costs related to falls were estimated with US $23.3 billion annually in the United States [20]. The mean costs of a



(a) (b)

Figure 1.1: Population pyramids of more developed regions in (a) 1970 and (b) 2050 [15].

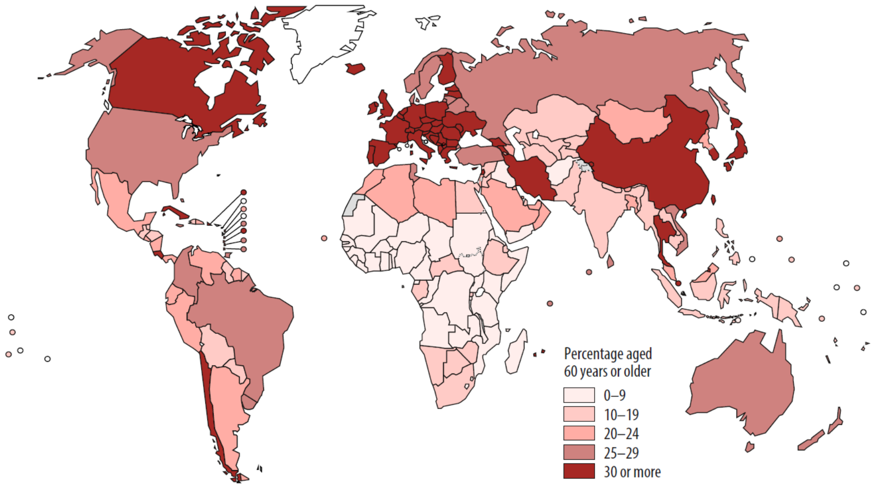


Figure 1.2: Proportion of population aged 60 years or older, by country, 2050 projections [16].

fall ranged from US $3,476 per faller to US $10,749 per injurious fall, and US $26,483 per fall requiring hospitalization [20]. In New South Wales, Australia, the lifetime treatment and care costs of fall-related injuries were estimated at AU $558.5 million annually [21]. In Europe, annually costs related to falls were estimated with US $1.6 billion in the United Kingdom [20].

About 50% of the falls in community-living older people occur within their homes or surrounding areas [22, 23], and people of advanced age and people with limited mobility are particularly more likely to fall at home [24]. The majority of falls occur on a level surface and in situations where people undertake their normal daily activities [19]. It has recently been reported that in frail older people the top three activities associated with falls are forward walking, standing quietly and sitting down [25].

1.2 Risk Factors for Falls

Falls are complex and most falls occur as a result of a combination of multiple risk factors. In general, the literature distinguishes between intrinsic (e.g. functional and health related) and extrinsic (e.g. environmental) risk factors [26]. Falls are related to a variety of physiological risk factors with physical inactivity [27, 28], poor balance [29, 30], impaired gait [31,32], muscle weakness [27,33] and slow reaction times [34–36] consistently reported. Neuropsychological risk factors include depression [37, 38], fear of falling [39] and poor executive functions [38, 40]. Examples for environmental risk factors are dim lighting, slippery surfaces, obstacles and tripping hazards.

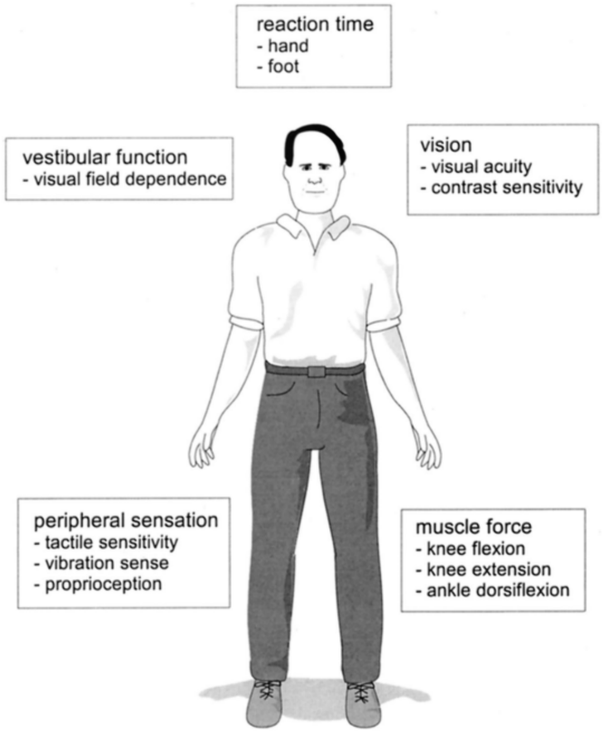


Figure 1.3: Systems involved in the maintenance of postural stability [19].

Balance

Figure 1.3 illustrates the factors involved in the maintenance of human stability. Several studies have shown that postural control declines with age [41, 42]. Maintaining upright posture (i.e. static balance) and stability during the execution of movements (i.e. dynamic balance) are important functions of the postural control system [43]. Therefore, poor static and dynamic balance have been identified as risk factors of falls [29, 30].

Strength

Skeletal muscle mass and quality decline with age leading to a deficit in muscle function [44]. Muscle strength (i.e. the ability to generate force) and muscle power (i.e. the ability to generate this force rapidly) have been associated with falls [33] [45]. Furthermore, there is evidence for the contribution of muscle strength and power to balance performance in older people [44].

Reaction time

Quick protective reactions that involve reaching or stepping movements are also important to avoid falls [46] and to reduce the risk of injuries [47, 48]. It has been reported, that fallers have slower reaction times than non-fallers [34–36].

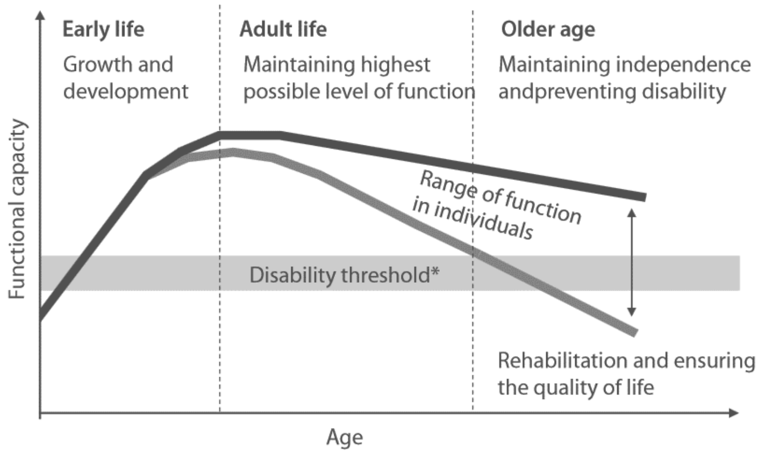


Figure 1.4: Decrease of functional capacity over lifetime [18].

1.3 Prevention of Falls

There is evidence that falls in older people can be prevented [49, 50]. Figure 1.4 illustrates the decrease of functional capacity over lifetime. The goal of active and healthy ageing is to slow down this degenerative process and in consequence reduce the risk of falling. Recent findings indicate that multiple-component exercise programs, usually containing balance and strength training exercises, and multifactorial interventions integrating assessment with individualized treatment are effective in preventing falls [49].

Studies have shown that a reduced intake of inappropriate medications and a gradual withdrawal of psychotropic medications are effective methods in fall prevention [49, 51]. Improving home safety (i.e. the assessment and elimination of environmental hazards) has shown to be effective when carried out by occupational therapists [49, 52]. Further, vitamin D supplementation in people with lower vitamin D levels, insertion of pacemakers in people with carotid sinus hypersensitivity and anti-slip shoe devices worn in icy conditions have been demonstrated to reduce falls [49].

1.4 Fall Risk Assessments

Fall risk assessments have been developed to determine the individual likelihood to fall. An accurate identification can increase the chance of selecting an appropriate prevention or treatment strategy, targeted to meet the needs of the individual older person [18]. Furthermore, regularly repeated fall risk assessments can guide and help to measure the success of fall intervention programs.

Fall risk tests should be simple, valid, reliable, inexpensive, short to administer and provide quantitative outcome measurements [35]. Numerous tests of balance, strength, reaction time and mobility have been developed in the past and found to be associated with an increased risk of falling.

Balance

In clinical settings, balance assessments are widely used to assess fall risk. In most of these tests participants are asked to maintain their balance for a specific duration (e.g. 10 seconds) in various stance positions (e.g. semi-tandem, near-tandem, full tandem) [29]. The main outcome measurement is a success or failure with respect to whether the participant is able to hold the stance without moving the feet or requiring additional support. More sophisticated methods measure the amount of sway during these tests with a sway meter [35] or a force platform [52]. The Timed Up and Go [53] is another widely used test to assess functional mobility. The outcome of this test, the stop-watch measured time that a participant takes to rise from a chair, walk three meters, turn around, walk back to the chair, and sit down, has been associated with falls [54].

Strength

The sit-to-stand test with five repetitions is commonly used in clinical settings to assess functional lower extremity muscle strength, which has been related to falls [55–57]. Further, poor performance on the five-times-sit-to-stand-test is associated with impaired balance [58, 59], reduced reaction time and other factors such as pain and vitality [58]. Performance is measured in seconds, as the total time from the initial seated position to the final seated position after completing five stands, with a stop-watch. Other widely used strength indicators are isometric knee extension strength measured with spring or strain gauges and handgrip strength [35, 60].

Reaction time

Many studies have reported that reaction time increases significantly with age [43, 46, 61] and that a slower reaction time is related to a higher risk of falling [34, 36]. Simple and choice reaction times with finger- or foot-press responses have been measured with electronic timers and switches in the laboratory [34, 35]. Studies have examined voluntary reaction times and the responses to balance perturbations in older people [34, 43, 62].

Fall risk assessment tools aim to predict the individual fall probability by combining single measurements. The Physiological Profile Assessment (PPA) estimates the likelihood to fall based on tests which assess sensorimotor abilities: 1) sway when standing on medium-density foam with eyes open, 2) knee extension strength, 3) hand reaction time, 4) contrast sensitivity and 5) peripheral sensation [35]. The Berg Balance Scale [63], Tinetti Performance Oriented Mobility Assessment [64], Balance Evaluation Systems Test [65] and the Short Physical Performance Battery [66] are other examples of fall risk assessment tools.

1.5 Aim of the Thesis

To date, the methods used to assess fall risk are often described as subjective and inaccurate [67]. Because of limited health care resources, objective test equipment (e.g. force platforms or electronic walkways) and expertise to perform these assessments are not always available. It is possible that clinical tests are only moderately predictive of falls because such assessments are a one-time snapshot performed under ideal circumstances dissimilar to those that would lead to falls in an older person's daily environment. Accurate, objective, inexpensive and easy to administer tests which can be undertaken regularly to assess fall risk are required.

Recent technological advances in low-cost and portable measurement instruments hold promise for improved assessments in both supervised clinical and unsupervised home settings. An assessment conducted at home has several advantages over a clinical assessment. It is more convenient and provides easy access for people living in rural and remote areas with limited access to proper health care. The assessment is conducted in a person's natural environment which might lead to more accurate and representative results of a person's performance.

The main aim of this thesis was to develop and evaluate new sensor-based methods to accurately assess fall risk in both clinical and home settings. The feasibility of the Microsoft Kinect (a low cost consumer depth camera) and a wearable sensor (Philips Research) were investigated in this regard. The main research questions of this thesis as summarized as follows:

1. Can physical tests of balance, strength and reaction time measured using a Kinect-based system assess fall risk in older people?
2. Can the monitoring of activities of daily life using a wearable sensor assess fall risk in older people?
3. Can assessments of fall risk be undertaken with the Kinect-based system and wearable sensors by older people unsupervised at home?

1.6 Thesis Outline

This thesis describes a series of studies on the development and evaluation of new sensor-based methods to assess fall risk. The present work is organized in the following chapters:

Chapter 1 provides an introduction to the problem of falls in older people. The demographic change, injuries and costs related to falls, risk factors for falls, intervention strategies, and examples of traditional fall risk tests are discussed.

Chapter 2 collates the findings of recent studies that have developed and evaluated sensor-based methods to assess fall risk. Research gaps were identified which this thesis attempts to address.

Chapter 3 presents a Kinect-based system (also referred to as the iStoppFalls assessment) for directed routine assessments and a wearable sensor for monitoring daily activities. This chapter describes the details of three studies to investigate the feasibility and validity of these new sensor-based methods to assess fall risk in older people.

Chapter 4 describes a study on the development and evaluation of a Kinect-based five-times-sit-to-stand test. A signal processing algorithm was proposed to automatically quantify performance on the test based on the skeleton data from the Kinect sensor. The validity of the extracted sensor-based measurements to differentiate between people who are at risk for falls from people who are not at risk for falls, the convergent validity compared to traditional clinical fall risk measurements, and the preliminary feasibility to administer the test in the home setting were investigated in 94 community-living older people.

Chapter 5 describes the development and evaluation of Kinect-based choice stepping and reaching reaction time tests. Signal processing algorithms were presented to automatically extract temporal and spatial measurements. The discriminant and convergent validity of these measurements and the preliminary feasibility to administer the tests in the home setting were investigated.

Chapter 6 describes the feasibility to complement the Kinect measurements with data derived from a body-worn inertial sensor in the choice stepping reaction time test.

Chapter 7 describes a study on the accuracy of a wearable sensor to detect and assess sit-to-stand movements during activities of daily living. A signal processing algorithm was proposed using wavelet transformations of accelerometer and barometric air pressure sensor data. The detection accuracy and discriminant validity of the algorithm was evaluated in 94 older people performing sit-to-stand movements as part of a clinical assessment and 25 older people performing typical daily activities in a free-living assessment.

Chapter 8 describes a four-month study on the long-term use of the Kinect-based system and the wearable pendant device in the homes of 62 older people. Participants were asked to perform at least one assessment session each month and to wear the pendant during the day. Interviews were conducted with participants to investigate user experience and design guidelines for future home-based assessments were developed.

Chapter 9 summarizes and concludes the findings of this thesis, presents potential applications for these new sensor-based methods and makes recommendations for future topics of research.

CHAPTER 2

State of the Art (Sensor-Based Methods)

Summary

Background. An accurate identification of fall risk can assist in the selection of an appropriate prevention or treatment strategy. Because of limited health care resources, regular and objective fall risk assessments are not practical in a clinical setting on a large scale.

Objective. Recent research explored technological methods for the accurate and objective assessment of fall risk. This review collates the findings of recent studies that have used sensor-based methods to assess fall risk and identifies research gaps which this thesis attempts to address.

Methods. Databases were searched for literature published between January 2012 and December 2014. Articles were included based on the following criteria: 1) a technology-based method was used to assess fall risk, 2) the paper reported results on the comparison of fallers and non-fallers, 3) the total sample size was 30 or more, 4) participants were healthy community-dwelling older people, 5) the average age of participants was 60 years or over and 6) the paper was published in English.

Results. Sixteen studies met the inclusion criteria. Wearable and stationary sensor devices have been used to assess balance, stepping reaction time, functional mobility, gait and physical activity. Sensor-based parameters could be identified and research has provided preliminary evidence that these measurements can discriminate between fallers and non-fallers. However, studies used varying definitions of fallers and time frames with only one study using the gold standard prospective method of recording falls. The sample sizes of the majority of studies were too small to provide any definitive conclusion regarding accuracy of using these new methods for classifying fallers and non-fallers. All but four studies were conducted in a laboratory setting and therefore, do not provide any information regarding the feasibility of using these new technologies outside this setting (e.g. in daily life settings).

Conclusion. The findings indicate a need to develop and evaluate objective, less expensive and easy to administer assessment tests for clinical and home settings to enable the accurate identification of fall risk. Two sensor-based methods were identified as valuable to investigate within this thesis: 1) directed routine assessments (e.g. by using the Microsoft Kinect) and 2) monitoring of daily activities (e.g. by using wearable sensors).

2.1 Introduction

Fall risk assessments have been developed to determine the individual likelihood to fall. An accurate identification can increase the chance of selecting an appropriate prevention or treatment strategy, targeted to meet the needs of the individual older person. Fall risk is generally assessed in a clinical setting. The assessments are often described as subjective, variable in administration and therefore only weakly associated with falls. Because of limited health care resources, objective test equipment and expertise to perform these assessments are not always available. Additionally, assessments have been described as one-time snapshots under ideal circumstances dissimilar to those that would lead to falls in an older person's daily environment.

Technological advances have enabled less expensive, easy to administer and accurate ways to quantify physical fall risk in clinical practice and in the homes of older people. Furthermore, technology might enable more continuous monitoring while people are performing unsupervised directed routines or simply undertaking their daily activities at home. This review collates the findings of recent studies that have used such new technological approaches for fall risk assessment.

2.2 Literature Search and Selection Criteria

The literature was searched using "Pubmed", "Scopus" and "IEEE Xplore" databases. The following primary search terms were entered: "falls", "assessment", "sensor-based assessment", "accelerometer", "gyroscope" and "inertial sensor". Articles were included based on the following criteria: 1) a new technology-based method was used to assess fall risk, 2) the paper reported results on the comparison of fallers and non-fallers, 3) the total sample size was 30 or more, 4) participants were healthy community-dwelling older people, 5) the average age of participants was 60 years or over and 6) the paper was published in English between January 2012 and December 2014 (Figure 2.1).

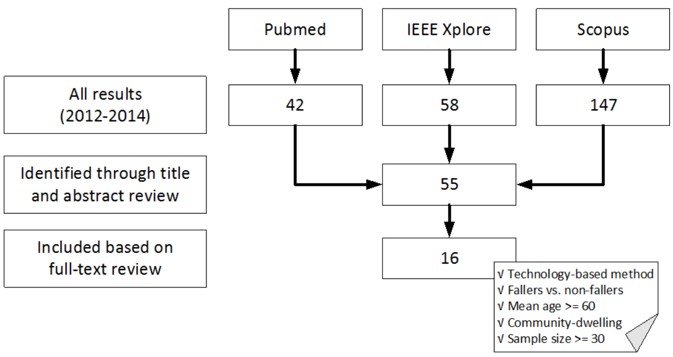


Figure 2.1: Study selection process.

2.3 Search Results

A total of 16 studies were identified [28, 68–82]. Study populations, description of the fall discrimination measure and main findings are summarized in Table 2.1. The sample sizes ranged from 39 [73] to 1680 [28]. Mean age of the participants varied from 62 [74] to 88 years [83]. The outcome measure of falls was measured differently across studies, with one study stratifying for fall risk using the Tinetti scale [75], 11 studies used a retrospective recall over 12 months [28, 70, 71, 73, 74, 76, 78–81, 83], one study used a retrospective recall over two years [72], two studies used a retrospective recall over five years [68, 69], and one study used prospective fall diaries over 12 months [77]. Fallers were defined as having at least one fall in the study period in 10 studies [68, 70–72, 74, 76, 77, 80, 81, 83] and as at least two falls in five studies [28, 69, 73, 78, 79].

Two studies examined postural sway [68, 69], two studies examined choice stepping reaction time [70, 71], two studies examined functional mobility [72, 73], eight studies examined gait [74–81], one study examined physical activity [28], and one study examined physical activity in combination with sleep patterns [83].

Twelve studies reported on laboratory assessments [68–77, 79, 80] and four on home-based assessments [28, 78, 81, 83]. Thirteen studies used inertial sensors to acquire the data [28, 68, 72–81, 83], two studies used pressure sensors [69, 71] and one study used a laser infrared sensor [70].

Table 2.1: Summary of included studies with more than 30 older participants (mean age > 60 years).

Study	**Study design and population**	**Study period and falls measure**	**Fall prediction measure**	**Main finding of the study**
Doheny et al., 2012 [68]	Community-dwelling, n=110, mean age 73 years (SD=6), 56 fallers	Retrospective recall over 5 years *Fallers:* at least one fall	*Overall measure:* postural sway *Device:* inertial sensor, attached to lower back *Assessment:* Centre of Mass displacement in comfortable and semi-tandem stance position with eyes open, for 35 and 40 seconds *Setting:* laboratory	Significant ($p<.05$) difference between fallers and non-fallers on sway range, length, velocity and Root Mean Square acceleration
McGrath et al., 2012 [69]	Community-dwelling, n=120, mean age 74 years (SD=6), 65 fallers	Retrospective recall over 5 years *Fallers:* at least two falls, or one fall with specific criteria	*Overall measure:* postural sway *Device:* portable pressure sensor matrix *Assessment:* Centre of Pressure excursions in semi-tandem and narrow stance, with eyes open and eyes closed, for 30 seconds *Setting:* laboratory	Significant ($p<.05$) difference between fallers and non-fallers on sway length, velocity and frequency, especially in eyes closed condition
Nishiguchi et al., 2013 [70]	Community-dwelling, n=152, mean age 74 years (SD=5), 41 fallers	Retrospective recall over 12 months *Fallers:* at least one fall	*Overall measure:* stepping *Device:* infrared laser sensor, positioned in front of the participant *Assessment:* temporal and spatial parameters in four-square choice stepping test *Setting:* laboratory	Significant ($p<.05$) difference between fallers and non-fallers in reaction time and step time
Schoene et al., 2013 [71]	Community-dwelling, n=103, mean age 80 years (SD=5), 29 fallers	Retrospective recall over 12 months *Fallers:* at least one fall	*Overall measure:* stepping *Device:* sensor-based dance pad *Assessment:* stepping performance in stepping test with high attention component *Setting:* laboratory	Significant ($p<.05$) difference between fallers and non-fallers in total step time and number of step errors

Study	**Study design and population**	**Study period and falls measure**	**Fall prediction measure**	**Main finding of the study**
Greene et al., 2012 [72]	Community-dwelling, n=226, mean age 72 years (SD=7), 83 fallers	Retrospective recall over 24 months *Fallers:* at least one fall	*Overall measure:* functional mobility *Device:* two inertial sensors, attached to the left and right shanks *Assessment:* accelerations and angular velocities in Timed Up and Go test *Setting:* laboratory	Model using accelerometer- and gyroscope-derived parameters classified fallers from non-fallers with 79% accuracy (mean 95% CI: 77.09–82.34)
Doheny et al., 2013 [73]	Community-dwelling, n=39, age range 61-88, 19 fallers	Retrospective recall over 12 months *Fallers:* at least two falls, or one fall requiring medical attention	*Overall measure:* functional mobility *Device:* two inertial sensors, one attached to thigh, other positioned above sternum *Assessment:* accelerations in Five-Times-Sit-to-Stand test, intraday test-retest reliability *Setting:* laboratory	Model using statistically reliable (ICC>0.7) accelerometer-derived parameters classified fallers from non-fallers with 74% accuracy, 80% specificity and 69% sensitivity
Toebes et al., 2012 [74]	Community-dwelling, n=134, mean age 62 years (SD=6), 44 fallers	Retrospective recall over 12 months *Fallers:* at least one fall	*Overall measure:* gait *Device:* inertial sensor, attached to trunk *Assessment:* 12-17 minutes treadmill walking *Setting:* laboratory	Significant ($p<.05$) associations between gait variability and short-term local dynamic stability with fall history
Senden et al., 2012 [75]	Community-dwelling, n=100, mean age 77 years (SD=6), 50 fallers	Stratified for fall risk using the Tinetti scale *Fallers:* Tinetti score ≤ 24	*Overall measure:* gait *Device:* inertial sensor, attached to lower back *Assessment:* 20 meter walks *Setting:* laboratory	Significant ($p<.05$) difference between participants with high risk and low risk of falling on walking speed, step length and RMS vertical accelerations

Study	Study design and population	Study period and falls measure	Fall prediction measure	Main finding of the study
Riva et al., 2013 [76]	n=131, mean age 62 years (SD=6), 42 fallers	Retrospective recall over 12 months *Fallers:* at least one fall	*Overall measure:* gait *Device:* inertial sensor, located on trunk below shoulder blades *Assessment:* nonlinear stability measurements, not dependent on step detection, when walking on a treadmill *Setting:* laboratory	Significant (p<.05) associations between multi-scale entropy (indicator of complexity of gait kinematics), and recurrence quantification analysis measures with fall history
Doi et al., 2013 [77]	Community-dwelling, n=73, mean age 81 years (SD=7), 16 fallers	Prospective study over 12 months *Fallers:* at least one fall	*Overall measure:* gait *Device:* two inertial sensors, attached to lower and upper trunk *Assessment:* stability measurements, in 10 m walk *Setting:* laboratory	Significant (p<.05) difference between fallers and non-fallers on harmonic ratio measurement (indicator for smoothness and stability of trunk movements)
Weiss et al., 2013 [78]	Community-dwelling, n=71, mean age 78 years (SD=5), 32 fallers	Retrospective recall over 12 months *Fallers:* at least two falls	*Overall measure:* gait *Device:* inertial sensor, attached to lower back *Assessment:* three days of unsupervised activities of daily living *Setting:* continuous, in-home	Significant (p<.05) difference between fallers and non-fallers in step-to-step variability, measured as amplitude of dominant frequency in power spectral density
Cui et al., 2014 [79]	Community-dwelling, n=81, age range 65-90, 39 fallers	Retrospective recall over 12 months *Fallers:* at least two falls	*Overall measure:* gait *Device:* inertial sensor, attached to lower back *Assessment:* one minute walking under different conditions, 1) normal walking, 2) normal walking with a harness and 3) walking through an obstacle course with a harness *Setting:* laboratory	Significant (p<.05) difference between fallers and non-fallers in step stability, measured as a ratio of intrinsic mode functions using the empirical mode decomposition method

Study	**Study design and population**	**Study period and falls measure**	**Fall prediction measure**	**Main finding of the study**
Brodie et al., 2014 [80]	Community-dwelling, n=96, mean age 80 years (SD=4), 35 fallers	Retrospective recall over 12 months *Fallers:* at least one fall	*Overall measure:* gait *Device:* inertial sensor *Assessment:* 20 meter walks *Setting:* laboratory	Fallers walked slower and had less lateral harmonic stability, measured by the 8-step medio-lateral harmonic ratio, than non-fallers (RR: 0.19, 95% CI: 0.06-0.57)
Rispens et al., 2014 [81]	Community-dwelling, n=110, mean age 78 years (SD=8), 58 (est.) fallers	Retrospective recall over 12 months *Fallers:* at least one fall	*Overall measure:* gait *Device:* inertial sensor, attached to lower back *Assessment:* 14 days of unsupervised activities of daily living *Setting:* continuous, in-home	Significant ($p<.05$) associations between the spectral power, local dynamic stability, local dynamic stability per stride, gait smoothness (index of harmonicity), amplitude and slope of the dominant frequency with fall history
Jefferis et al., 2014 [28]	Community-dwelling, n=1680 (men), age range 71-92, 185 fallers	Retrospective recall over 12 months *Fallers:* at least two falls	*Overall measure:* physical activity *Device:* inertial sensor, attached to hip *Assessment:* seven days of unsupervised activities of daily living *Setting:* continuous, in-home	Fallers were less active than non-fallers, measured in steps per day, minutes spent in light activities, minutes spent in moderate to vigorous activities and minutes of sedentary behaviour than non-fallers
Anderson et al., 2014 [83]	Community-dwelling, n=421 (men), age range 87-89, 156 fallers	Retrospective recall over 12 months *Fallers:* at least one fall	*Overall measure:* physical activity and sleep *Device:* inertial sensor, attached to wrist *Assessment:* five to seven days of unsupervised activities of daily living *Setting:* continuous, in-home	Significant ($p<.05$) association between impaired sleep-wake cycles, measured as the differences between the least and most active periods, with fall history

2.4 Findings and Discussion

This literature review examined new technological advances in the area of fall risk assessment in older people. Large epidemiological studies have identified a range of important risk factors for falling, with impairments in balance, strength, mobility and slow reactions showing strong associations with falls. The identified studies give an insight into which technologies are feasible for use in older people and how measurement outcomes derived from these technology-based assessments are likely to assist in the assessment of fall risk in the future.

2.4.1 Assessment of Physiological Fall Risk Measurements

Balance

The ability to maintain postural stability and an increased postural sway has been associated with falls [29, 30]. Objective balance measurements using gold standard measures such as force platforms are expensive, require expertise to administer and are therefore not always practicable in clinical settings. The availability of low-cost and commercially-available sensors (e.g. inertial sensors, Wii Balance Board) make it more feasible to conduct regular balance assessment in clinical practice or in people's homes. Within the review period, one study was published measuring static balance with an inertial sensor [68] and one using a pressure sensor matrix [69] during different stances. Both systems were feasible for use in older adults, and indicated postural sway during quiet stance was significantly increased in fallers compared to non-fallers [68, 69].

However, these tests were conducted in a supervised laboratory setting. Future work is required to develop easy to administer, accurate and safe tests of static and dynamic balance which can be conducted in a clinical setting and in the homes of older people on a regular basis.

Reactions

Quick protective reactions that involve reaching or stepping movements are important to avoid falls [46] and to reduce the risk of injuries [47, 48]. In the reviewed papers, one study assessed stepping performance using an infrared laser sensor in combination with a step mat [70] and one using a pressure sensor-based mat [71]. Both studies confirmed that fallers had slower reaction times and total step times when compared to non-fallers [70, 71]. The pressure sensor-based system further demonstrated to be an effective home-based method for improving stepping ability and balance in older people [84]. The requirement of a physical mat in both studies could be seen as an advantage as it provides real targets during stepping.

However, step mats also pose a potential trip hazard, require time to set up and limit movements to the pre-defined fields. In addition to stepping movements, upper-limb responses are important to prevent a fall and to reduce risk of injuries [46, 47]. No research exists on upper-limb reaction time tests using low-cost sensor-based approaches.

Future work should investigate the potential of novel reaction time tests for lower- and upper-limb movements and their associations to falls.

Functional Mobility

The Five-Times-Sit-to-Stand test is often used as a proxy measure for functional mobility and lower limb strength [55, 56]. In clinical practice, a measure of total time required to complete this test is used as a marker for fall risk, with a slower time indicative of a higher risk of falling. The use of inertial sensors makes it possible to further quantify the smoothness of the sit-to-stand transitions [73, 85, 86]. A small study suggested that this method can classify fallers and non-fallers with good accuracy [73]. The Timed Up and Go (TUG) test is a measurement of balance, gait speed and functional abilities [53]. In the test participants are asked to rise from a chair, walk three meters, turn around, walk back and sit down on the chair. Within the review period, one study used inertial sensors to derive temporal gait, spatial gait, angular velocity and turn parameters from the participant's movements during the test [72]. The findings indicated good accuracy in classifying fallers from non-fallers.

The results of these traditional fall risk tests conducted in the laboratory were promising. Future work should focus on novel ways to transfer these clinical tests from the laboratory into the homes of older people by using a directed routine approach or by monitoring movements (e.g. sit-to-stand transitions) during daily life activities.

Gait

Slower gait speed and reduced gait stability have been associated with falls in older people [19, 31]. Research is increasingly exploring the use of inertial sensors to assess gait [74–81], eliminating the need for more expensive electronic walkways or camera-based systems. However, a remaining challenge in the measurement of spatio-temporal and stability gait measures using inertial sensors is the accurate detection of steps [76]. Within the review period, several papers focused on nonlinear analysis techniques that do not require step detection, i.e. using harmonic ratios as an indicator for smoothness and stability of trunk movements [74, 77, 80, 81], or using multiscale entropy as an indicator of gait complexity [76]. Preliminary results suggested that these new gait measures can detect differences between fallers and non-fallers [74–81]; findings that will facilitate assessment of gait data during daily life.

The majority of reviewed papers focussed on gait in relation to falls in older people. This is reasonable as forward walking has been identified as the main activity associated with falls [25]. However, only two studies assessed gait outside of the laboratory [78, 81]. These studies monitored gait continuously for three [78] to 14 [81] days during daily life using a body worn inertial sensor attached to the lower back. Future work should focus on the assessment of gait characteristics in daily life gait.

Physical Activity

Limited mobility and reduced physical activity have been associated with increased risk of falls [60, 87]. Within the review period, two studies focused on the measurement of physical activity levels of up to seven days during daily life [28, 83]. One large study analysed the time spent in light, moderate, vigorous activities and minutes of sedentary behaviour [28]. The other study focussed on sleep-wake cycles [83]. The findings indicate that fallers were less active and were more likely to have impaired sleep-wake cycles than non-fallers [28, 83]. However, a recent review concluded that the methods used to assess physical activity are still at an early stage of development and emphasized the need for standardized activity monitoring protocols [88].

2.4.2 Use of Technology

In the review period, body-worn and stationary devices were used to assess fall risk in the laboratory and home setting. Thirteen studies used wearable inertial sensors to quantify participant's movements [28, 68, 72–81, 83]. Wearable technology holds great promise for its applications in fall prevention, because it allows continuous monitoring of daily activities. Within the review period, two studies assessed gait characteristics [78, 81] and two studies assessed physical activity levels [28, 83] with wearable inertial sensors in a home setting. Future work should further explore the feasibility of wearable devices to assess fall risk outside of the laboratory.

Microsoft Kinect

The Microsoft Kinect, a low-cost three-dimensional depth sensor, was not used in any study matching the review criteria. The Kinect has gained popularity in recent years and has been used in various fields, for example in rehabilitation [89, 90] or robotics [91]. The advantages of a Kinect-based system can be summarized as 1) easy to set up - no further physical equipment is needed, 2) safe - no additional trip hazards, 3) inexpensive - the Microsoft Kinect is a widely available consumer device and 4) fairly accurate [92, 93] - enables whole body tracking of participants' movements.

Nine studies were identified, mainly pilot and feasibility studies, using the Kinect in a broader context of fall prevention over the last three years [94–102]. The sample sizes were small; only two studies evaluated the developed Kinect-based tests with more than 30 participants [94, 95]. Discriminative validity to identify fallers was only assessed in one study, based on retrospective fall data [95]. No study used the gold standard prospective method of recording falls and all but one study were conducted in the laboratory.

One study showed that a test based on Tai Chi exercises and solving Sudoku puzzles [94] was able to assess dual task abilities which have been associated with falls in older people [103]. Another study used the Kinect in combination with a Wii balance board and two Wii motion controllers to assess performance during standing tasks in a cohort of Tango club dancers and hospitalized people [95]. The developed model classified fall risk with an accuracy of 89%. The Kinect has been used to assess gait characteristics in the laboratory [96]. The study showed that the Kinect is accurate compared to an electronic walkway system [96]. Another study demonstrated the feasibility of the Kinect to continuously assess gait at home. In this study, the Kinect was mounted to the wall below the ceiling [97, 98]. Further, the Kinect has been used for the automatic analysis of the TUG test [99, 100] and to quantify static and dynamic balance performance [101, 102].

Future research is warranted to examine the feasibility of the Kinect to assess fall risk in clinical and home settings. The sensitivity of measurements derived from the Kinect sensor data to differ between older fallers and non-fallers should be investigated

2.4.3 Laboratory vs. Home-Based

An assessment conducted at home has several advantages over a clinical assessment: 1) it provides a convenient and easy accessible solution for people living in remote areas, 2) it might lead to more representative results, 3) it helps to monitor changes of fall risk over time and 4) it empowers people to take an active role in their own health management [104–106]. A recent report of expert opinions encourage the development of home-based assessments [107]. However, sociological and technological challenges emerge when using health technology in private homes, affecting the acceptance of technology, especially with users in older age [105, 108, 109]. It has been reported, that older people had difficulty in recognizing the advantages of home-based health systems before they used them [105, 110]. In order to increase user acceptance, there has to be a clear benefit for older people to use a home-based technology [111]. The technology has to fit the routines of daily life and has to allow people to continue with the activities they like [112]. In addition, it is important to consider the available space, purpose of rooms, use of existing technology (e.g. television), and individual preferences when deploying health technology in private homes [113].

The technology has to be simple to use and reliable. Not only the reliability of the technology itself, but also the reliability of measurements taken by the people in their homes is important. The accuracy of the measures can be compromised because people do not adhere to the rules required for a particular measurement or because of the lack of contextual information [114]. Education is important to ensure that people can interpret and understand the meaning of the measurements [114]. Visualizations can help to enhance the understanding and support self-reflection. Some examples supported by older people include icons (e.g. smiley faces), bar charts, line charts, speedometer and text. Ian Li et al. [115] found that people were interested in data that revealed the current status, the current status compared to the individual goal and the history of data over time.

Another challenge is to motivate people to use home-based health technology regularly. Grönvall et al. [114] identified three different sources of motivation. First, people want to enhance their independence. Second, people have a general interest in their own health. Third, people are motivated to stay healthy and independent in their activities of daily life.

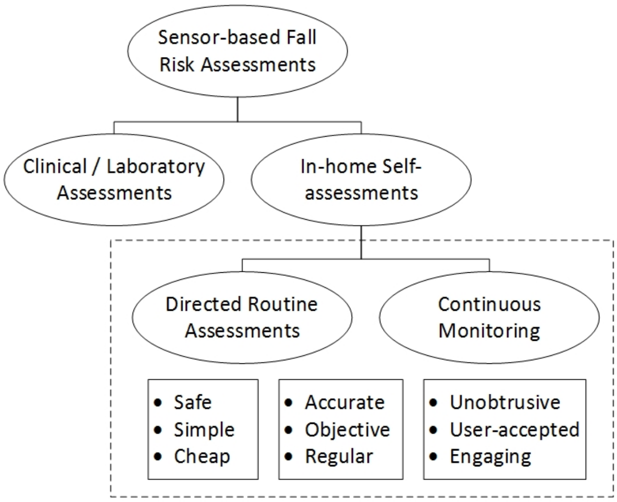


Figure 2.2: Application areas of sensor-based fall risk assessments and requirements for in-home self-assessments.

However, the majority of studies in the review period were conducted in a laboratory setting and therefore, do not provide any information regarding the feasibility of using these new technologies in daily life settings. Future research should focus on the development of novel approaches to measure fall risk at home under consideration of the necessary design requirements, through use of a directed routine assessment or by means of monitoring daily life activities (Figure 2.2).

2.4.4 Methodological Limitations

The included studies used different approaches to discriminate between fallers and non-fallers – i.e. varying definitions of fallers and time frames – with only one study using a prospective method of recording falls. The sample sizes of the majority of studies were too small to provide any definitive conclusion regarding accuracy of using these new methods for classifying fallers and non-fallers.

2.5 Conclusion

Recently, sensor-based fall risk assessments have been developed and research has provided preliminary evidence that these assessments can discriminate fallers from non-fallers. The applied sensors are inexpensive, fairly accurate and portable which would enable their use in a laboratory and home settings. Assessments conducted at home have several advantages over assessments conducted in the clinics. Two approaches to assess fall risk in both clinical and home settings were identified as valuable to further investigate. First, preliminary studies have used wearable sensors (e.g. inertial sensors) to monitor activities that people might perform in their daily life. Another approach would be to monitor fall risk through regularly repeated (e.g. monthly) directed routine assessments. The Microsoft Kinect, a low-cost consumer device, has been identified as particularly suitable for such an application. However, no high quality studies using the Kinect could be identified within the review period.

Further studies are required to validate these findings and to assess fall risk through use of a directed routine using the Kinect or by means of continuous monitoring using a wearable sensor, so as to enable the accurate identification of fall risk and use this information to target interventions accordingly. The feasibility of these new methods should be investigated in both clinical and home settings in older people.

CHAPTER 3

Materials and Study Protocol

Summary

Background. The literature review revealed that there is a need for accurate, objective, low-cost and easy to administer fall risk assessment tests, which can be used in both clinical and home settings. Two methods have been identified as suitable in this regard: 1) sensor-based directed routine assessments and 2) sensor-based monitoring of normal daily activities.

Objective. This chapter presents the details of a Kinect-based system for directed routine assessments and a wearable sensor for the monitoring of daily activities. The protocol of three studies conducted to explore the feasibility and validity of these new sensor-based methods are described in this chapter.

Results. The Kinect-based system (also referred to as the iStoppFalls assessment) comprised of 1) the Microsoft Kinect, 2) a Personal Computer, 3) an assessment software and 4) a TV set-top-box as the main components. The assessment software, developed in C++ using Microsoft DirectX for game programming and the Microsoft Kinect SDK, included physical tests for the assessment of balance, strength and reaction time. The wearable pendant device (Philips Research) comprised of a three-dimensional accelerometer and a barometric air pressure sensor. The pendant was attached to a lanyard and could be freely worn around the neck during the day.

In a first study, older people were assessed on a Kinect-based five-times-sit-to-stand, choice stepping and choice reaching reaction time test. In a second study, older people were asked to perform typical daily activities, including postural transitions, while wearing the pendant device. In a third study, the long-term use of the Kinect-based system and the wearable sensor was investigated in the homes of older people.

3.1 Introduction

The literature review indicated that stationary (e.g. Microsoft Kinect) and wearable (e.g. inertial sensors) devices are suitable for directed routine assessments and for the monitoring of normal daily activities. This chapter presents the details of a Kinect-based system (also referred to as the iStoppFalls assessment) and a wearable sensor, as well as the details of three studies which have been conducted to explore the feasibility and validity of these new sensor-based methods.

3.2 Kinect-Based System

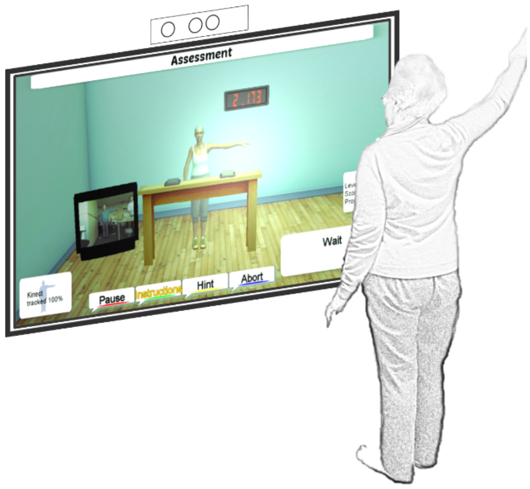
A screening tool which relies on motion capture technology to assess fall risk was developed in collaboration with content experts from Neuroscience Research Australia and German Sport University Cologne, as well as digital game experts from Kaasa Health and other partners from the iStoppFalls consortium [116]. Within this thesis the focus was on the development of signal processing algorithms and evaluation of the Kinect-based system to assess fall risk in community-living older people.

The system guided the participants through the assessment tests by means of a directed routine and measured participants' performance with an optical sensor (i.e. Microsoft Kinect). The assessment tests were based on traditional clinical tests for the measurement of balance, strength and reaction time and were designed using a exergame approach (i.e. full-body interaction).

Recent research and development focused on exergames to promote physical fitness among younger [117, 118] and older people [82, 119–122]. Exergames have been investigated for improving balance [121, 123], strength [119] and stepping [84, 119] performance. Further, exergames have been used for rehabilitation after a stroke [124], in children with cerebral palsy [125], in people with Parkinson's disease [126], and as a tool to measure general physical health [127]. It has been suggested that exergames are fun and motivating [82] and a convenient solution to exercise at home for older people [122]. Exergaming has shown a positive effect on emotional and physical well-being [128, 129] and people tend to forget that they are doing something physically challenging while playing [82]. However, authors of several studies argued that commercially available games can put older people at risk because they are not designed for their level of physical abilities [119, 130]. The functional limitations (e.g. range of motion) and lack of technological experience should be considered when designing digital assessment tests for older people [131].

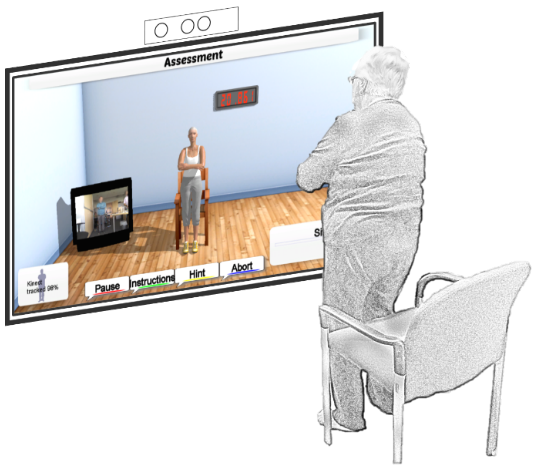
During the iStoppFalls assessment tests participants saw themselves represented as an avatar in a virtual test environment (Figure 3.1). Previous studies have shown that people's behaviour in virtual environments is significantly related to their visual representations [132] and that avatars improve the interaction between older people and computers [133].

(a)



(b)

(c)



(d)

Figure 3.1: The (a) balance test, (b) reaching reaction time test, (c) stepping reaction time test and (d) five-times-sit-to-stand test.

(a) (b) (c)

Figure 3.2: Base of support during balance tests for (a) semi-tandem stance, (b) near-tandem stance and (c) full tandem stance. Adapted from [9].

3.2.1 Kinect-Based Static Balance Tests

The balance test required participants to stand for up to 30 seconds without holding on to a support or moving their feet while standing in three different feet positions (Figure 3.2): 1) semi-tandem stance, with the side of the heel of one foot touching the great toe of the other, 2) near-tandem stance, with the great toe of the back foot about 2.5 cm behind and 2.5 cm to the side of the heel of the front foot and 3) full-tandem stance, with the heel of one foot in front of and touching the toes of the other foot (Figure 3.1a). Previous studies have reported that poor performances in these tests are associated with an increased risk of falling.

3.2.2 Kinect-Based Five-Times-Sit-To-Stand Test

Studies have reported that reduced lower extremity muscle strength is associated with an increased risk of falling and therefore a test based on the five-times-sit-to-stand-test was developed (Figure 3.1d). For this test participants were asked to stand up and sit down from a standard height chair five times as quickly as possible with their arms folded across the chest.

3.2.3 Kinect-Based Choice Reaching and Stepping Reaction Time Tests

Previous studies have reported that slow reaction times are a significant predictor of falls. Two choice reaction time tests were developed: 1) a stepping reaction time test (Figure 3.1c) and 2) a reaching reaction time test (Figure 3.1b). For these tests participants saw two lights (one to the left and one to the right side of the avatar), which flashed in random order (20 repetitions). In the stepping reaction time test, participants were instructed to take a step onto the flashing light as quickly as possible (left leg to the left light or right leg to the right light). In the reaching reaction time test, participants were asked to lift their arm to the flashing light (left arm to the left light or right arm to the right light).

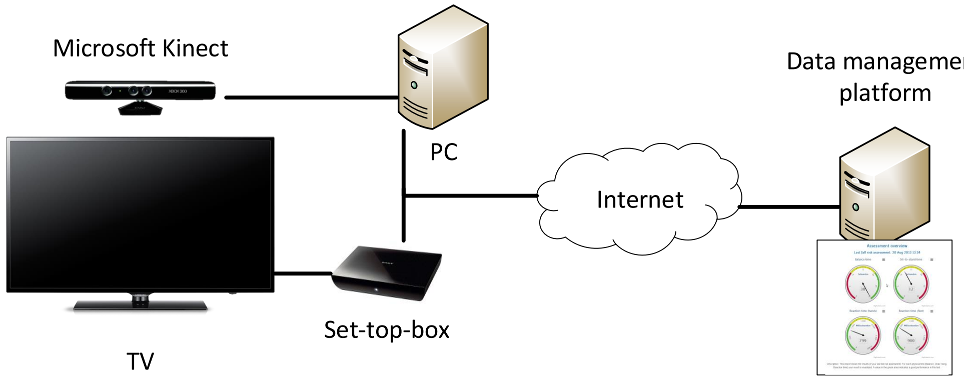


Figure 3.3: Architecture of the Kinect-based system.

3.2.4 Questionnaires

The 10-item iconographical Falls Efficacy Scale [134] was used to assess concern about falling using pictures. In addition, questions about general medical health were included:

- *"Have you had one or more falls in the previous 12 months?"*
- *"How many medications do you take each day?"*
- *"Do you currently take any medications to help you sleep?"*
- *"Do you wear multifocal glasses outside your home?"*
- *"Do you have painful feet?"*

Participants were allowed to skip the questionnaires if nothing had changed since the last time they completed them.

3.2.5 Hardware and Software

The main components of the iStoppFalls assessment were: 1) the Microsoft Kinect sensor for Windows, 2) a Personal Computer, 3) an assessment software and 4) a TV set-top-box (Figure 3.3). Optionally, the system could be connected to a web-based data management platform which stored the test results and automatically generated performance reports for the participants and their carers.

The PC was responsible for the execution of the assessment software and the data exchange with the Microsoft Kinect. The set-top-box, which was connected to the TV, served as a gateway and user-friendly remote control for the assessment software.

Microsoft Kinect

In recent years, interactive game devices such as the Nintendo Wii, PlayStation Move and the Microsoft Xbox Kinect have become increasingly popular and have made low-cost motion capture technology available for private use. In 2012, Microsoft released its version of the Xbox Kinect sensor for Windows. The Kinect is a consumer device which can measure three-dimensional motion of a person (Figure 3.4). Skeletal data of anatomical landmarks (in world coordinates) can be recorded using the Microsoft Kinect Software Development Kit for Windows with a frequency of 30 Hz. Therefore, it generates a depth map and estimates the position and posture of human body parts (Figure 3.5). For generating the depth map it uses the principle of structured light [135]. The Microsoft Kinect has a spatial resolution of 0.3 cm and depth resolution of 1 cm at 2 m distance from the sensor [92]. The Kinect projects a known pattern (i.e. speckle pattern) to the scene using infrared laser light (Figure 3.6). The depth of an object is estimated from the deformation of that pattern. Based on the depth map the human pose is predicted by using a machine learning algorithm [136]. For the assessment system skeletal data of anatomical landmarks (in world coordinates) were recorded using the Microsoft Kinect Software Development Kit for Windows.

PC and Software

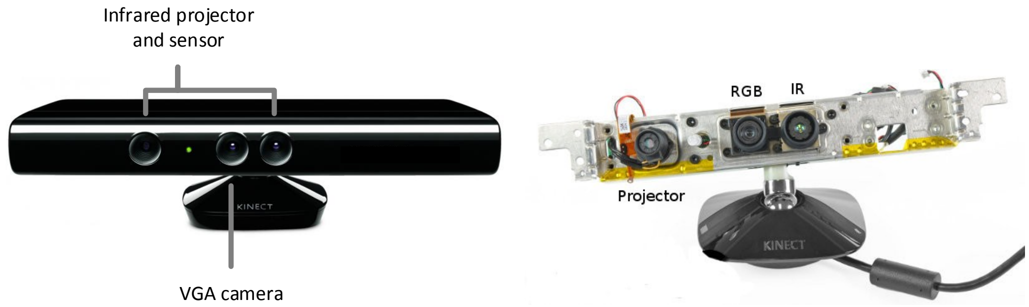
The assessment software runs on a computer (Model: Shuttle XPC-XG41 [140]) with the Microsoft Windows 7 (64bit) operating system. The software program rendered the real-time avatar movements, stored the raw Kinect sensor data to the PC, displayed the test instructions, provided a start countdown and presented instant performance feedback (Figure 3.7). The program was developed in C++ using Microsoft DirectX for game programming and the Microsoft Kinect SDK [141] for the communication with the Kinect sensor.

TV Set-Top-Box

The set-top-box (Model: Sony NSZ-GS [142]) was connected to the PC and TV. On the set-top-box an android-based application was used to start the assessment tests and access the performance reports (Figure 3.8). Users could navigate using the set-top-box remote control (Figure 3.9).

Data Management Platform

The data management platform provided data storage and produced the reports based on the transmitted assessment data from the PC. Further, it provided a web-based interface for researchers/relatives/physicians/other carers to monitor the participant's progress (Figure 3.10). The platform was developed based on the open-source framework Django [143] because of its simplicity and support for rapid prototyping of applications.



(a) (b)

Figure 3.4: Details of the Microsoft Kinect (a) with enclosure and (b) without enclosure [137].

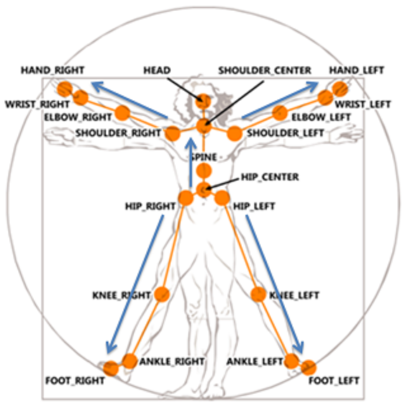
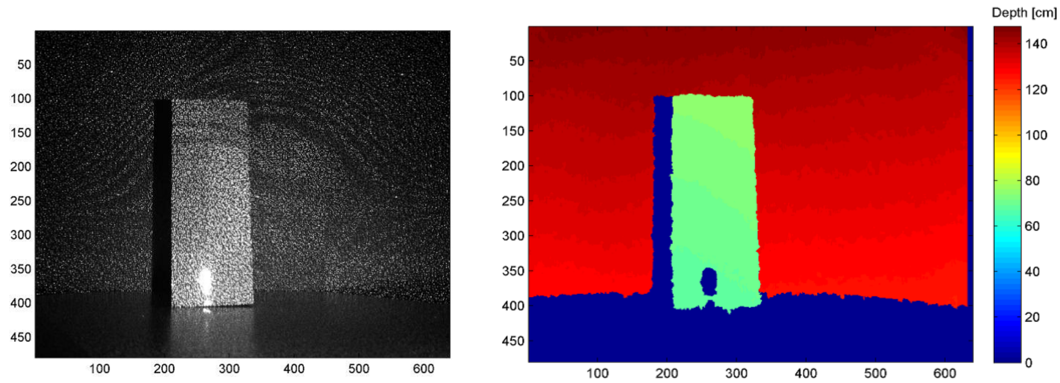


Figure 3.5: Skeleton information on twenty joints of the user's body tracked with the Microsoft Kinect [138].



(a) (b)

Figure 3.6: (a) Infrared image of the pattern of speckles projected on a sample scene and (b) the corresponding depth image [139].

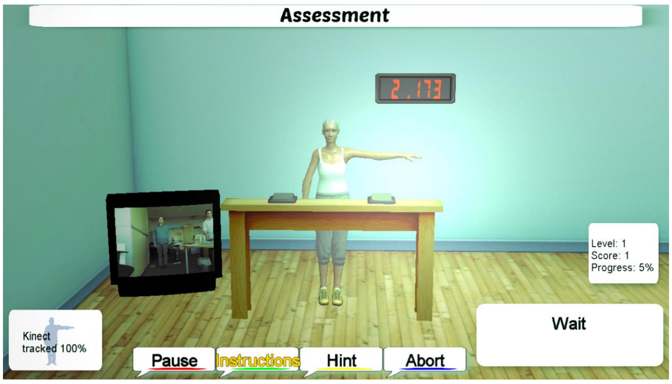


Figure 3.7: The assessment software with the reaching reaction time test.

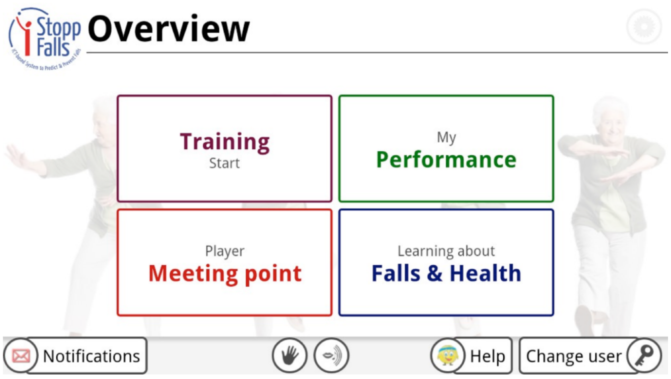


Figure 3.8: Android-based application running on the set-top-box. Participants were able to start the assessment tests and to look at their performance reports within the application.

Figure 3.9: Participants used this remote control to interact with the system and start the assessment tests [142].

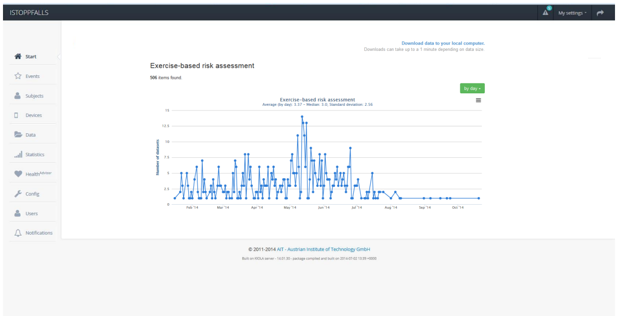


Figure 3.10: Web interface of the data management platform to access test statistics by relatives, physicians or other carers.

3.2.6 User Feedback

In a semi- or unsupervised setting clear and simple test instructions are important. The assessment software provided on-screen instructions, using a combination of text, pictures and videos at the beginning of each test (Figure 3.11).

Constant feedback about physical performance and improvements have been identified as important for keeping participants engaged into fall prevention programs [144–146]. The iStoppFalls assessment provided immediate feedback during the tests, the option to review the last test score (Figure 3.12a) and graphics using line charts of a long-term progress (Figure 3.13). The user feedback from the physical tests included the average reaction time, five-times-sit-to-stand time and an overview of the balance abilities in the different stance positions. In addition, the individual fall risk was estimated based on a scoring system (Quickscreen ©; Neuroscience Research Australia) which combined the results of the questionnaires and physical tests measured with the Kinect (Figure 3.12b). All user reports were HTML-based documents generated by the data management platform using the JavaScript library Highcharts [147]. Participants were able to access the reports on their TV screens at any time.

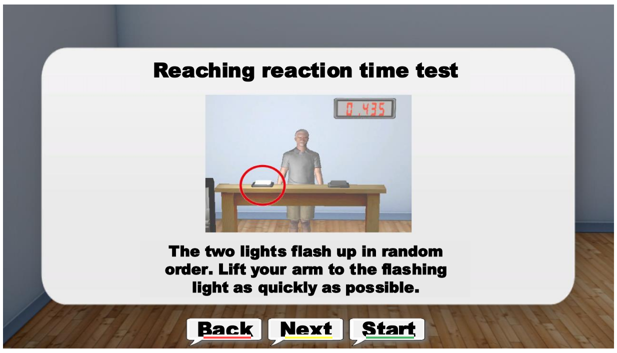
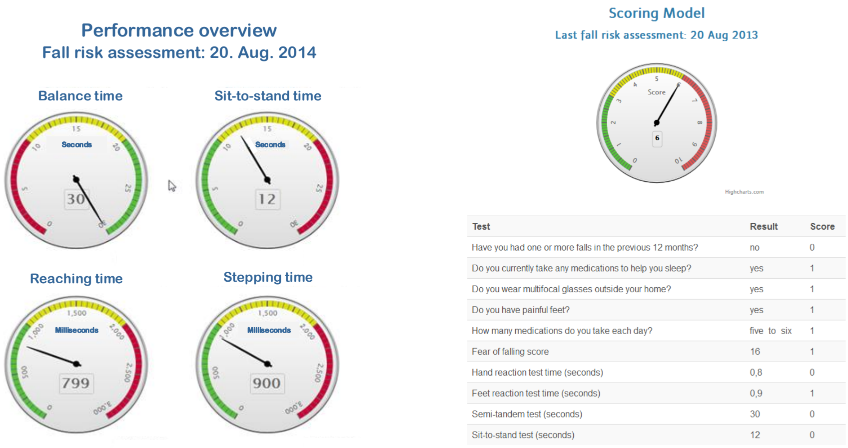


Figure 3.11: Test instructions for the reaching reaction time test.



(a) (b)

Figure 3.12: (a) Performance report of the last assessment session and (b) fall risk score based on the Kinect-based tests and questionnaires.

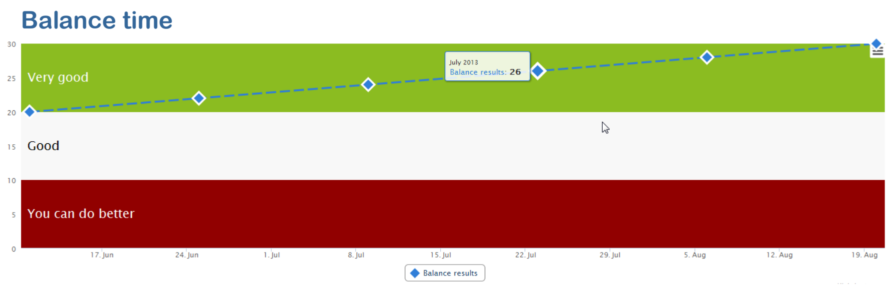


Figure 3.13: Long-term performance over the last two months on the balance test.

3.3 Wearable Sensor

Within the iStoppFalls project, an inertial pendant device (Figure 3.14) was developed by Philips Research. The matchbox-sized (dimension: 6.5 x 4.0 x 1.2 cm, weight: 40 g) device comprised of a three-dimensional accelerometer (Analog Devices ADXL362, range of ± 8G, sampling rate 50Hz) and a barometric air pressure sensor (Measurement Specialties MS5611, range of 10 to 1200 hPa, altitude resolution 10 cm, sampling rate 25Hz). The participants were asked to wear the pendant device attached to a lanyard around their necks during the experiments (Figure 3.15). The pendant device was able to record data for 2.5 days without battery recharging. Data were stored locally on a MicroSD card or were streamed to a nearby computer via Bluetooth.

(a)

(b)

Figure 3.14: (a) Rendering of the wearable inertial pendant device [148] and (b) comparison of the size of the pendant device to a two euro coin.

Figure 3.15: The pendant device worn above clothing.

3.4 Study Protocol

Three studies were conducted to evaluate the feasibility of the Kinect-based system and the wearable pendant device to assess fall risk in the clinical and home settings.

3.4.1 Evaluation of Kinect-Based System

Participants

Ninety-four community-dwelling older people, living in retirement villages in the area of Sydney, Australia, participated in this study. The inclusion criteria were: living in the community, aged 65 years or older and being ambulant with or without the use of a walking aid. The exclusion criteria were: being medically unstable, suffering from major cognitive impairment (Mini-Cog <3), neurodegenerative disease or colour blindness.

Written informed consent was obtained from all participants prior to data collection. The study was approved by the University of New South Wales Human Studies Ethics Committee.

Protocol

Participants were assessed on the Kinect-based tests in the following order (Figure 3.16):

1. Static balance tests
2. Reaching reaction time test
3. Stepping reaction time test
4. Five-times-sit-to-stand test

The balance tests measured the ability of a person to stand for 30 seconds during different tests conditions (Figure 3.16a). Participants were asked to face the TV, keep their arms by their sides and try not shift their feet. Participants put either foot in front, whichever was more comfortable for them. All tests were performed without shoes to avoid any bias because of different types of shoes. The instructions were as following:

1. *"These tests will help us to assess your balance during standing."*
2. *"First, I will show you the movements then I want you to perform it."*
   a) Comfortable stand:
      - *"We will start with the comfortable stand."*
      - *"I would like you to stand as it is comfortable for you for 30 seconds."*

   b) Semi-tandem:
      - *"I would like you to stand with the side of the heel of one foot touching the big toe of the other foot for 30 seconds."*
      - »Demonstrate correct position«

   c) Near-tandem:
      - *"I would like you to stand with the great toe of the back foot about 2.5 cm behind and 2.5 cm to the side of the heel of the front foot for 30 seconds."*
      - »Demonstrate correct position«

   d) Tandem:
      - *"I would like you to stand with the heel of one foot in front of and touching the toes of the other foot for 30 seconds."*
      - »Demonstrate correct position«

(a) (b) (c) (d)

Figure 3.16: Female participant performing (a) balance test, (b) reaching reaction time test, (c) stepping reaction time test and (d) five-times-sit-to-stand test.

3. *"Before the test starts there will be a countdown of five seconds."*

4. *"You should hold on the chair until the countdown is over."*

5. *"After the countdown: release the chair, keep your arms by your sides and try not to shift your feet for 30 seconds."*

The choice reaching reaction time test involved two buttons shown in the virtual test environment (Figure 3.16b). The buttons flashed up in random order and participants had to turn them off by moving the hand over it as quickly as possible. Participants were instructed as following:

1. *"This test will help us to assess your reaction time."*

2. *"You will see two buttons on a virtual table on the TV screen. The left or right button will flash up and you have to move your arm to the side of the active button. After you moved your arm keep it by your side again."*

3. *"First, I will show you the movement then I want you to perform it."*

4. »Demonstrate correct movement«

5. *"There will be a countdown of five seconds again."*

6. *"After the countdown try to be as quickly as possible."*

The choice stepping reaction time test was similar designed to the reaching reaction time test, but the two flashing buttons were placed on a virtual floor and participants had to take a step to the side to turn them off (Figure 3.16c). Participants were instructed as following:

1. *"This test will help us to assess your reaction time."*

2. *"You will see two buttons on a virtual floor on the TV screen. The left or right button will flash up and you have to step on the side of the active button. After you move step back again."*

3. *"Make sure to take a full step to the side (with some weight shifting)."*

4. »Demonstrate correct movement«

5. *"There will be a countdown of five seconds again."*

6. *"After the countdown try to be as quickly as possible."*

The five-times-sit-to-stand test measured the ability of a person to rise from a chair repeatedly (Figure 3.16d). Participants were asked to stand up and sit down from a chair five times as quickly as possible with their arms folded across their chest. Participants were instructed as following:

1. *"This test will help us to assess your strength abilities during chair rises."*
2. *"I would like you to sit on the chair, keeping your arms folded across your chest."*
3. *"There will be a countdown of five seconds. Wait for the countdown."*
4. *"After the countdown stand up and sit down as quickly as possible five times in a row."*
5. »Demonstrate correct movement«
6. *"Do not forget to keep your arms folded across your chest and try to be as quickly as possible."*
7. *"The test will end automatically after five times when you sit on the chair again."*

In addition, participants were assessed on the Physiological Profile Assessment (PPA) [35] as a gold standard reference to the Kinect-based assessments. The PPA is based on tests which assess sensorimotor abilities: balance (sway when standing on a medium-density foam with eyes open; Figure 3.17a), lower-extremity muscle strength (knee extension; Figure 3.17b), hand reaction time (Figure 3.17c), contrast sensitivity (Melbourne Edge Test) and peripheral sensation (proprioception). Additionally, the Attention Network Test (ANT) [149] to measure choice reaction time was conducted. The ANT is a computer-based test where participants had to determine whether a central arrow point to the left or right and to press the corresponding button on a PC-keyboard as quickly as possible.

During a face-to-face interview the number of self-reported falls in the past 12 months was recorded. In addition, participants were followed-up for six months and asked to report their falls with monthly falls calendars. Follow-up telephone interviews were conducted if participants failed to return their calendars. A fall was defined as an *"unexpected event in which the person comes to rest on the ground, floor, or lower level"* [13].

Test Setup

The Figures 3.18 and 3.19 illustrate the test setup. The Kinect sensor was placed in front of the TV screen at a height of 80 cm and a distance of 2 m from the participants. A standard height chair was used in the five-times-sit-to-stand test (Figure 3.19a) and as a support to hold on in the other tests (Figure 3.19b). All assessments were video recorded with two video cameras (i.e. front and side view) to assist with the interpretation of any unusual patterns in the data during the data analysis process.

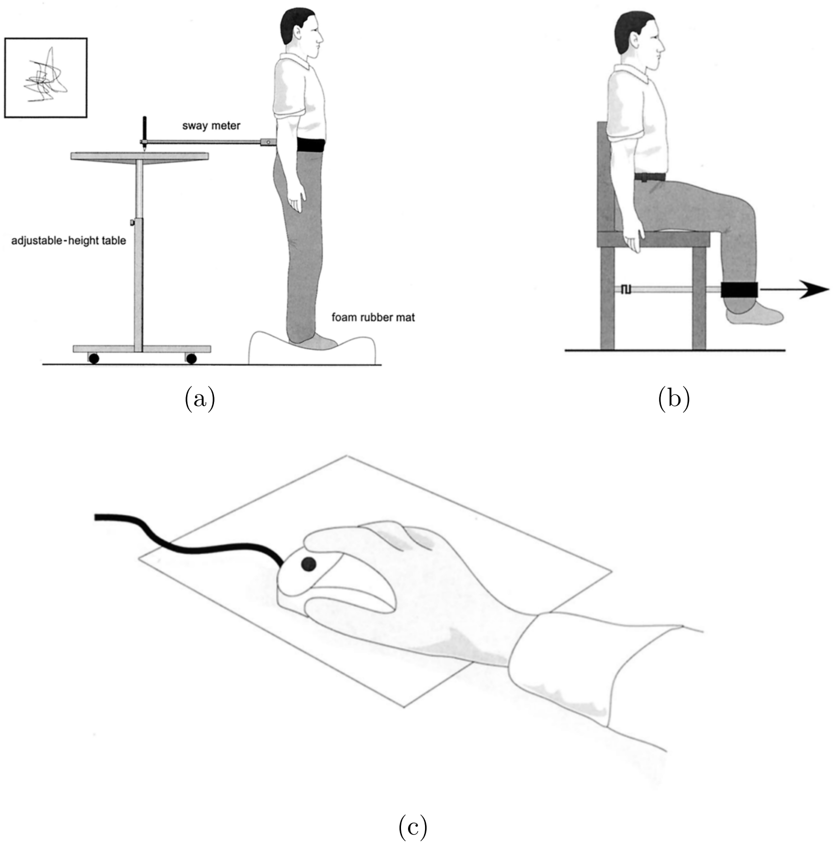


Figure 3.17: (a) Postural sway test standing on a foam rubber mat, (b) Muscle force test (knee extension) and (c) Hand reaction time test [35].

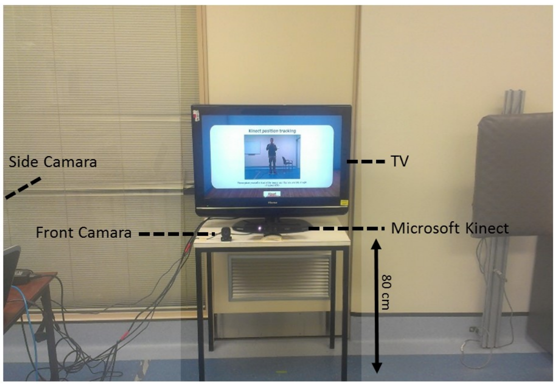
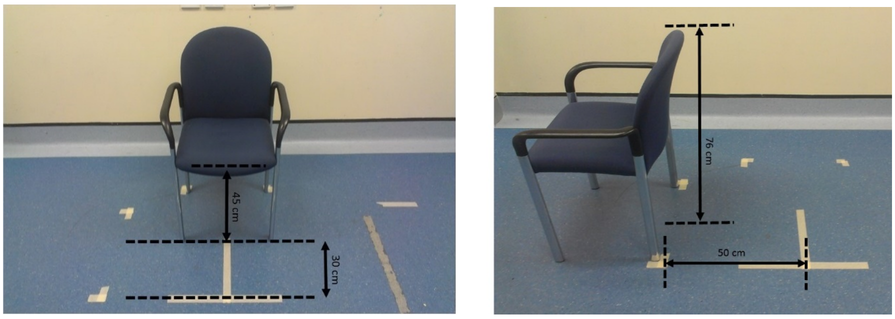


Figure 3.18: Test setup in the Kinect-based system evaluation study.



(a) (b)

Figure 3.19: Chair placement during the (a) five-times-sit-to-stand test and b) balance, reaching and stepping tests.

3.4.2 Evaluation of Wearable Sensor

Participants

A total of 119 community-dwelling older people living in Sydney, Australia participated in this study. Participants took part in a free-living (n=25) or clinical assessment (n=94). The inclusion and exclusion criteria were the same as in the Kinect-based study. Written informed consent was obtained from all participants and the study was approved by the University of New South Wales Human Studies Ethics Committee. This study was performed in collaboration with researchers of the Graduate School of Biomedical Engineering, University of New South Wales, who conducted the free-living assessments.

Protocol

The free-living assessment comprised 30 minutes of daily activities that people might perform in their home environment while wearing the pendant device around their necks without further restrictions. Free-living activities were semi-structured; participants performed several tasks (including eight sit-to-stand movements) in a given order, but were not given specific instructions about how to complete each task. Tasks included: sitting down on soft and hard chairs, lying down on a sofa, switching power outlets at floor level and light switches at shoulder level. In one of the tasks, participants were asked to go to a kitchen bench, pour themselves a cup of water, carry the cup to a table, pull a chair out, sit down, drink from the cup, return to the kitchen bench, and wash their cup in a sink. Other tasks included bending to put rubbish in the bin, walking through corridors, walking between rooms, moving about within a room, taking the elevator and walking up and down stairs.

In the clinical assessment, participants were asked to follow a standardized protocol while wearing the pendant device at the height of their chest and under their clothes. Participants performed the following routine in which they had to stand up from a chair (height: 45 cm), walk 10 m and sit down again at their normal comfortable speed. During

Figure 3.20: Installation of the Kinect-based system in a private home.

a face-to-face interview the number of self-reported falls in the past 12 months was recorded.

3.4.3 Home Study

Participants

A total of 62 community-dwelling older people participated in this study. Participants were distributed across three study sites in Cologne (n=22), Valencia (n=21) and Sydney (n=19). The study was conducted in collaboration with researchers from the Institute of Sport Gerontology, German Sport University Cologne and the Biomechanics Institute of Valencia, who were responsible for the data collection in Cologne and Valencia respectively. The inclusion and exclusion criteria were the same as in the Kinect-based study. Ethical approval was authorized by the ethics committees of the German Sport University Cologne, the Polytechnic University of Valencia, and the Human Research Ethics Committee of the University of New South Wales.

Protocol

The Kinect-based system and the wearable sensor were deployed into the homes of the participants (Figure 3.20). Participants were instructed on how to perform the Kinect-based tests, completed an assessment (i.e. standing balance, sit-to-stand and reaction time tests) semi-supervised during the initial installation and were asked to perform the tests at least once per month on their own. In addition, participants were asked to wear the pendant device as often as possible during the day.

CHAPTER 4

Kinect-Based Five-Times-Sit-To-Stand Assessment

Summary

Background. Studies have reported that reduced lower extremity muscle strength is associated with an increased risk of falling and therefore a test based on the traditional five-times-sit-to-stand test was developed. For this test participants were asked to stand up and sit down from a standard height chair five times as quickly as possible with their arms folded across the chest.

Objective. The main objectives of this study were to 1) develop an algorithm to quantify performance on the new Kinect-based five-times-sit-to-stand test and 2) examine the feasibility of this test to differentiate between people who are at risk for falls from people who are not at risk. Further, it has been preliminary explored whether this test can be used for supervised and unsupervised in-home fall risk assessments.

Methods. A total of 94 community-dwelling older adults were assessed on the Kinect-based five-times-sit-to-stand test in a clinical setting and 20 participants were tested in their own homes. A signal processing algorithm was developed to extract timing and speed related measurements from the Kinect-based sensor data to discriminate between fallers and non-fallers. The associations of these measurements to traditional clinical fall risk tests and the results of supervised and unsupervised in-home assessments were examined.

Results. Fallers were significantly slower than non-fallers on the developed Kinect-based measures. The mean velocity of the sit-to-stand transitions discriminated well between the fallers and non-fallers based on 12 months retrospective fall data. The Kinect-based measures collected in the laboratory correlated strongly with those collected in the supervised ($r = 0.704 - 0.832$) and unsupervised ($r = 0.775 - 0.931$) in-home assessments.

Conclusion. The Kinect-based five-times-sit-to-stand test was feasible to administer in older people. The proposed algorithm successfully differentiated between fallers and non-fallers based on the extracted performance measures. The strong correlations between the clinical and in-home assessments suggest the validity of the test to assess fall risk in the home setting.

4.1 Introduction

The sit-to-stand test with five repetitions (5STS) is a functional test that is commonly used in clinical settings to assess fall risk [55, 56]. In the test, the person is asked to stand up and sit down from a chair five times as quickly as possible with their arms folded. Previous studies have shown that performance on the 5STS is associated with reduced lower extremity muscle strength [58], impaired balance [58, 59, 150], reduced reaction time and psychological factors such as pain and vitality [58]. Studies have shown that the 5STS performance is slower in frailer populations and people with balance disorders [59]. Performance is usually measured in seconds, as the total stop-watch measured 5STS time from the initial seated position to the final seated position after completing five stands. A 5STS time longer than 12s-15s has been associated with a higher risk of falling [55, 57], but there is no general agreement on the threshold that should be used to identify fallers.

Recent research has used inertial sensors, especially accelerometer and gyroscopes to quantify sit-to-stand performance in the laboratory [73, 85, 151]. The new generation of sensors is small, portable and inexpensive, and may be used also outside of the laboratory.

In this study, the feasibility of the Microsoft Kinect a low-cost, portable and marker-free computer vision sensor in a directed routine 5STS test ("Kinect-based 5STS") was examined. Previously, the Kinect has demonstrated good accuracy compared to a gold standard Vicon motion analysis system for the five-times-sit-to-stand test [92]. It has been hypothesized that a detailed analysis of the participants' movements during the Kinect-based 5STS discriminates well between fallers and non-fallers and will show stronger associations with established clinical fall risk measures when compared to the standard stop-watch measured 5STS time. Secondly, it has been investigated whether the Kinect-based 5STS can be used for supervised and unsupervised in-home assessments.

4.2 Methods

4.2.1 Participants

A total of 94 community-dwelling older adults living in retirement villages in Sydney, Australia participated in this study. The sample was recruited from two randomized controlled trials, 41 people were control group participants in the SureStep interactive step training trial and 53 were control or intervention group participants in the iStoppFalls trial [9]. The in-home assessments were conducted with the iStoppFalls intervention participants as part of the larger iStoppFalls trial. The inclusion and exclusion criteria are described in Chapter 3.

4.2.2 Kinect-Based 5STS

The Kinect-based 5STS relies on motion capture technology to assess performance on the 5STS. When conducting the test, participants saw themselves represented as an avatar in a virtual test environment on a television screen, and their movements were

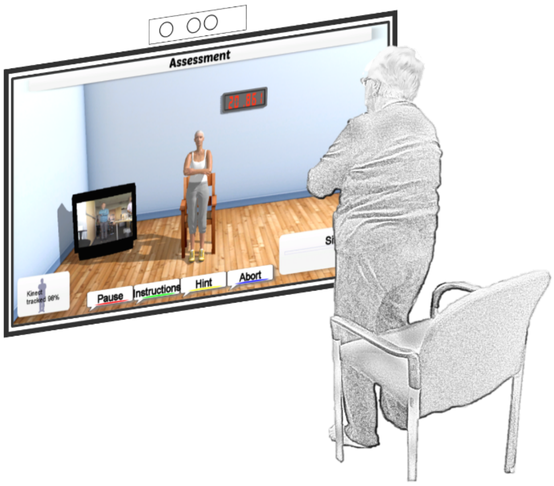


Figure 4.1: The Kinect-based five-times-sit-to-stand test.

synchronously reflected by the avatar movements (Figure 4.1). The system consists of a personal computer, the Microsoft Kinect sensor for Windows and the assessment software. The software program supports the test procedure by providing visual test instructions and a test start countdown. Furthermore, it displays the avatar in the virtual test environment during the test and stores the Kinect data to the personal computer.

4.2.3 Laboratory Assessment

Participants were asked to stand up and sit down from a standard height chair (45 cm) five times as quickly as possible with their arms folded across their chest. Movements during the 5STS were recorded with the Microsoft Kinect sensor; the total stop-watch measured 5STS time was documented for comparison. The assessments were video recorded with two standard video cameras (i.e. front and side view) to assist with the interpretation of any unusual patterns in the data during the data analysis process. The Physiological Profile Assessment (PPA) was used to estimate the overall fall risk based on tests which assess sensorimotor abilities: balance (sway when standing on medium-density foam with eyes open), lower extremity muscle strength (knee extension), hand reaction time, contrast sensitivity (Melbourne edge test (MET) and peripheral sensation (proprioception) [35]. A medical history was recorded during a face-to-face interview, including medications, the presence of medical conditions and number of self-reported falls in the past 12 months. Participants were followed-up for six months and asked to report their falls with monthly falls calendars. Telephone interviews were conducted if participants failed to return their calendars. A fall was defined as ‘an unexpected event in which the person comes to rest on the ground, floor, or lower level’ [13].

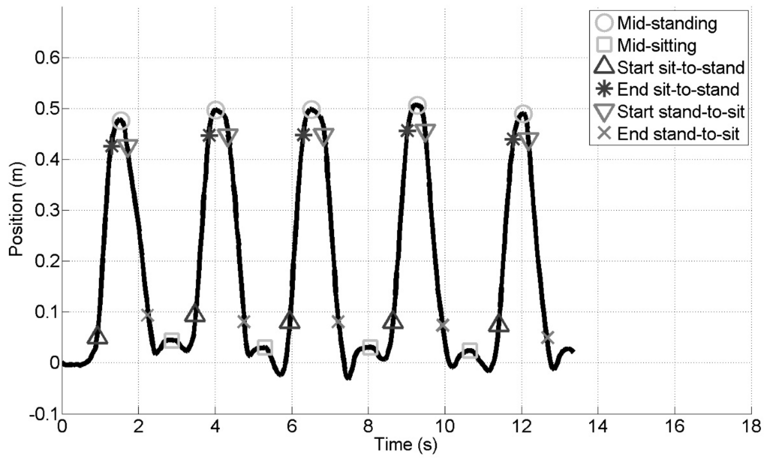


Figure 4.2: Detailed analysis of the 5STS phases (head tracking point) recorded with the Microsoft Kinect.

4.2.4 In-Home Assessment

The Kinect-based 5STS was conducted in the homes of a subsample of 20 participants (eight fallers, 12 non-fallers) by a trained researcher (i.e. supervised assessment). The time between baseline (laboratory) testing and the in-home supervised assessment was on average 40 (± 20) days. Participants were asked to perform the 5STS unsupervised within the first 30 days after installing the system. For this study, the correlations between 1) the laboratory and supervised in-home assessment and 2) the laboratory and first unsupervised in-home assessment were analysed.

4.2.5 Data Acquisition and Analysis

Skeleton data of anatomical landmarks in world coordinates were recorded using the Kinect Software Development Kit for Windows with a frequency of 30 Hz and a resolution of 640 x 480 pixels. Microsoft Kinect data from the vertical displacement of the head movement were used to quantify sit-to-stand performance (Figure 4.2). The offset of the data was corrected by using the coordinates of the head tracking point during the start of the test as the initial position. The global start and end point of the 5STS was detected as the first vertical increase above the empirically found threshold 5 cm, respectively last decrease below 5 cm. A sit-to-stand cycle was split up into four phases: sitting, sit-to-stand transition, standing and stand-to-sit transition phase. A similar threshold-based method to that described by Doheny et al. [152] for accelerometer signals was used to detect the phases of the linear displacement data of the 5STS.

The developed algorithm used three steps to automatically quantify 5STS performance (Figure 4.2):

1. *Identification of the mid-standing and mid-sitting points:* The signal (head position) was low-pass filtered using a 4^{th} order Butterworth filter with a cut-off frequency of 2 Hz. Mid-standing and mid-sitting positions were defined by the peak and trough respectively.

2. *Identification of the start and end points of sitting and standing phases:* The standing phase started when the signal amplitude first crossed a threshold 5 cm below the mid-standing point and ended with the second crossing. The sitting phase was similarly defined by a head position within 5 cm of the mid-sitting point.

3. *Feature extraction:* A set of timing and speed related measurements were derived from the sensor signal. Total time of the Kinect-based 5STS, mean duration of the sitting and standing phases and the mean vertical velocity of the sit-to-stand and stand-to-sit transitions were calculated.

4.2.6 Statistical Analysis

Analysis of covariance (ANCOVA) was used to evaluate differences between the faller and non-faller groups adjusted for participants' height. Cohen's d values were calculated to obtain measures of effect size. Pearson's correlation coefficients were calculated to quantify the association between the supervised laboratory, supervised and unsupervised in-home assessments, and between the 5STS and clinical fall risk measures. Correlation results were categorized as weak (0.1 – 0.3), moderate (0.4 – 0.6), and strong (0.7 – 0.9) after the schema from Dancey and Reidy [153]. The paired t-test was used to test for significant differences between the laboratory and in-home assessments. P-values less of 0.05 (*) were considered to be statistically significant. Signal processing and statistical data analysis were performed in MATLAB 8.2 (R2013b).

4.3 Results

Participants (n=94) aged 79.7 ± 6.4 years old; 66 (70%) women participated in this study. 29 (31%) people were classified as fallers with one or more falls in the past 12 months. There were no significant differences in age, weight and Body-Mass-Index (BMI) between the fallers and non-fallers. The differences in height were close to significance (Table 4.1).

Table 4.1: Characteristics of fallers and non-fallers.

Parameter	**Fallers (n=29)**	**Non-fallers (n=65)**	**P-value**
Age (years)	80.6 ± 6.7	79.3 ± 6.3	0.369
Height (cm)	159.2 ± 8.1	163.1 ± 9.1	0.055
Weight (kg)	67.2 ± 10.8	71.6 ± 13.7	0.135
BMI (kg/m^2)	26.5 ± 3.2	26.9 ± 4.6	0.680

4.3.1 Laboratory Assessment

Fallers were significantly slower than non-fallers on Kinect-based measures and the total stop-watch measured 5STS time (Table 4.2). The mean velocity of the sit-to-stand transitions was the best discriminator between the fallers and non-fallers with an effect (d) of 0.67. This effect size was comparable to the one of the PPA ($d = 0.65$); a multi-component clinical fall risk assessment.

The correlations between the Kinect-based measures and the strength (i.e. knee extension), balance (i.e. sway when standing on medium-density foam with eyes open) and reaction time (i.e. hand reaction time) components of the PPA were weak to moderate (Table 4.3). The mean velocity of the sit-to-stand transitions was the only measure that was significantly correlated to all three PPA-measures, with a stronger correlation to the knee extension strength compared to the other performance indicators of the 5STS.

4.3.2 Association with Future Falls

Further analyses confirmed similar associations with future falls. Fourteen participants reported one or more falls during the six-month follow-up period. Participants who fell were significantly slower than non-fallers on the Kinect-based total time ($p = 0.042$) and sit-to-stand velocity ($p = 0.021$) measurements. Furthermore, the mean sit time was longer compared to the group of non-fallers ($p = 0.02$).

Table 4.2: Test scores for the clinical and Kinect-based 5STS assessments for the fallers and non-fallers.

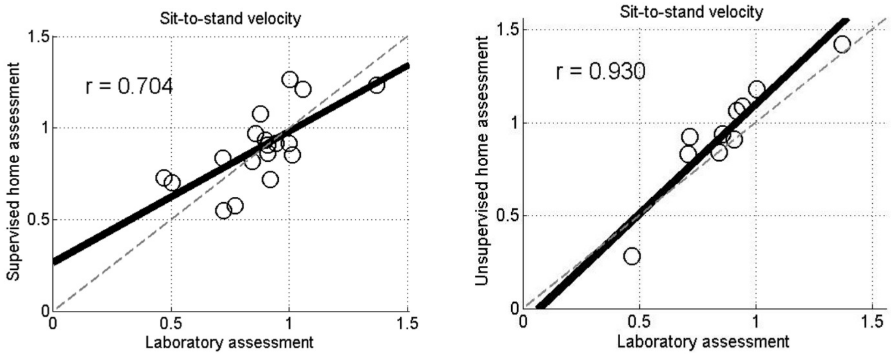
Measurement	Fallers (n=29)	Non-fallers (n=65)	P-value	|d|
Clinical fall risk measures				
Stop-watch measured 5STS time (s)	16.80 ± 5.68	14.33 ± 4.53	0.028*	0.50
PPA (score)	1.73 ± 0.87	1.18 ± 0.83	0.014*	0.65
Kinect-based 5STS measures				
Total time (s)	15.33 ± 5.45	13.12 ± 4.06	0.034*	0.49
Mean sit time (s)	1.75 ± 0.88	1.46 ± 0.59	0.071	0.42
Mean stand time (s)	1.02 ± 0.38	0.85 ± 0.31	0.063	0.51
Mean sit-to-stand velocity (m/s)	0.78 ± 0.20	0.94 ± 0.24	0.019*	0.67
Mean stand-to-sit velocity (m/s)	0.65 ± 0.20	0.76 ± 0.22	0.151	0.48

* $P < 0.05$; 5STS, Five-times-sit-to-stand; PPA, Physiological Profile Assessment

Table 4.3: Correlations between the Kinect-based 5STS measures and the strength, balance and reaction time components of the Physiological Profile Assessment.

Measurement	Stop-watch 5STS	Strength	Balance	Reaction time
Clinical fall risk measures				
Stop-watch measured 5STS time (s)	-	-0.317**	0.255*	0.188
Kinect-based 5STS measures				
Total time (s)	0.994**	-0.316**	0.234*	0.167
Mean sit time (s)	0.904**	-0.304**	0.252*	0.055
Mean stand time (s)	0.874**	-0.326**	0.161	0.285**
Mean sit-to-stand velocity (m/s)	-0.586**	0.533**	-0.246*	-0.321**
Mean stand-to-sit velocity (m/s)	-0.517**	0.432**	-0.078	-0.274**

* $P < 0.05$, ** $P < 0.01$; 5STS, Five-times-sit-to-stand



(a) (b)

Figure 4.3: Correlations between the (a) laboratory and supervised respectively (b) laboratory and unsupervised home assessments for the mean sit-to-stand velocity.

4.3.3 In-Home Assessment

The supervised in-home assessment (i.e. Kinect-based 5STS) was conducted by 20 participants. One person was not able to perform the 5STS with arms folded and one recording had to be excluded because of technical issues. On average, the 18 participants completed the test in 11.01s ± 2.79s in their homes compared with 13.42s ± 5.30s in the laboratory ($p = 0.008$). The correlations between the Kinect-based 5STS assessments in the laboratory and the supervised in-home assessments for the total time ($r = 0.832$, $p < 0.001$), sit time ($r = 0.824$, $p < 0.001$), stand time ($r = 0.758$, $p < 0.001$), sit-to-stand velocity ($r = 0.704$, $p = 0.001$), and stand-to-sit velocity ($r = 0.777$, $p < 0.001$) were strong. Figure 4.3a illustrates the comparison of the mean sit-to-stand velocity for the two assessments.

Thirteen participants (six fallers, seven non-fallers) performed the unsupervised 5STS on their own. Three participants had to be excluded from further data analysis because of data recording issues. Two participants performed four instead of five repetitions and therefore only their mean sit-to-stand velocity measurements were included into the analysis. Participants completed the 5STS in 11.82 s ± 2.04 s in the laboratory and in 9.70 s ± 1.39 s independently in their homes ($p < 0.001$). The correlations between the laboratory and the unsupervised in-home assessments for the total time ($r = 0.922$, $p = 0.001$), sit time ($r = 0.845$, $p = 0.008$), stand time ($r = 0.775$, $p = 0.024$), sit-to-stand velocity ($r = 0.931$, $p = 0.002$), and stand-to-sit velocity ($r = 0.820$, $p = 0.013$) were strong. Figure 4.3b shows this relationship for the mean sit-to-stand velocity. Participants reported no falls or other adverse events in relation to undertaking the Kinect-based 5STS test.

4.4 Discussion

In this study, the feasibility of the Kinect-based 5STS for fall risk assessment in community-living older people was examined. For the first time, the Kinect sensor has been used to assess 5STS performance in the laboratory and home setting in older people.

The present findings showed that an automated and more detailed analysis of the 5STS is feasible. The presented algorithm was able to correctly identify each phase and to extract time and speed related measures from the sensor signals of all successfully completed tests. The mean sit-to-stand velocity classified fallers and non-fallers well based on 12 months retrospective fall data. Further, it had stronger associations to clinical tests for balance, strength and reaction time than the stop-watch measured 5STS time. Noteworthy, the correlation between the sit-to-stand velocity and the stop-watch measured 5STS time itself was only moderate which supports the hypothesis that the sit-to-stand velocity, as a performance indicator for muscle power, is more than just an alternate measurement of total STS time. The findings are in accordance with the study from Doheny et al. [152] who used accelerometers and concluded that a more detailed analysis of the 5STS phases provides an improved discrimination of fallers from non-fallers compared to the stop-watch measured 5STS time. In addition, the findings demonstrate good criterion validity indicated by good correlations between the in-home and laboratory Kinect-based 5STS measures.

The study had certain limitations most of which relate to the pioneering use of a new technology. First, the assessments were not standardized for time of day or attire. Second, the avatar-based approach might have influenced participants' timing of the 5STS. In the supervised settings, participants were instructed to focus on the task rather than on the movements of the avatar. While it was feasible to administer the Kinect-based 5STS in a supervised home setting, only 56% of the participants performed the Kinect-based 5STS unsupervised within 30 days. Participants reported technical issues with the system, especially at the beginning of the study which might have prevented them from turning the Kinect-based 5STS on. The Microsoft Kinect is also sensitive to different light conditions and sometimes fails to locate and isolate the participant if objects (e.g. a chair) are in close proximity. Further studies are warranted to assess the feasibility of the unsupervised Kinect-based 5STS. Based on informal user feedback it appears that unsupervised assessments would be improved by 1) less complex system designs, 2) clearer test instructions, 3) more reliable equipment and 4) more engaging test assessments (e.g. gamification). Lastly, it has to be acknowledged that an unsupervised Kinect-based assessment might not be feasible in people with higher levels of frailty.

In future, the Kinect-based 5STS could be used in clinical settings as an objective, inexpensive and quick test to identify older people at increased risk of falls. With further development in-home assessments could be conducted by the following means 1) test administered in regularly home visits by trained personnel or 2) test performed independently and unsupervised as a self-assessment. Both in-home methods would provide measurements of fall risk over time and could be used to provide feedback regarding physical benefits (e.g. of a fall prevention exercise program). This feedback could be in written or visual form and accessible through the television for older people. Further, the Kinect-based 5STS system could be connected to the internet. This would enable clinicians to access the results remotely and the system could automatically generate alerts regarding significant improvements or declines.

In summary, the findings indicate that the Kinect-based 5STS discriminated well between fallers and non-fallers and was feasible to administer in clinical and supervised in-home settings. This study represents an important step towards the development of home-based fall risk assessments. With further research, especially under unsupervised conditions, the assessments may prove useful as a fall risk screen and home-based assessment measure of functional mobility for monitoring changes over time as well as the effects of fall prevention interventions.

CHAPTER 5

Kinect-Based Reaction Time Assessments

Summary

Background. Quick protective reactions such as reaching or stepping are important to avoid a fall or minimize injuries. Two Kinect-based reaction time tests, a stepping reaction time and a reaching reaction time test were developed in this regard.

Objective. The main objectives of this study were to 1) develop algorithms to quantify performance on the new Kinect-based choice reaching and stepping reaction time tests (Kinect-based CRTs) and 2) investigate their ability to differentiate between people who are at risk for falls from people who are not at risk. Further, it has been preliminary explored whether these tests can be used for in-home fall risk assessments.

Methods. A total of 94 community-dwelling older people were assessed on the Kinect-based CRTs in a clinical setting and were followed-up for falls for six months. Additionally, a subgroup (n=20) conducted the Kinect-based CRTs at home. Signal processing algorithms were developed to extract features for reaction, movement and the total time from the Microsoft Kinect skeleton data.

Results. Nineteen participants (20.2%) reported a fall in the six months following the assessment. The reaction time (fallers: 797 $\pm$ 136 ms, non-fallers: 714 $\pm$ 89 ms), movement time (fallers: 392 $\pm$ 50 ms, non-fallers: 358 $\pm$ 51 ms) and total time (fallers: 1189 $\pm$ 170 ms, non-fallers: 1072 $\pm$ 109 ms) of the reaching reaction time test discriminated well between the fallers and non-fallers. The stepping reaction time test did not significantly differentiate between the groups in the prospective study. The correlations between the clinical and in-home assessments were 0.689 for the reaching reaction time and 0.860 for the stepping reaction time.

Conclusion. The developed algorithms successfully measured performance on the Kinect-based CRT tests. The findings indicate that the tests are feasible to administer in clinical and in-home settings, and thus represents an important step towards the development of sensor-based in-home fall risk assessments.

5.1 Introduction

Quick protective reactions that involve reaching or stepping movements are important to avoid falls [46] or to reduce the risk of injuries [47, 48]. Tests that reveal deficits in upper- or lower-limb responses may help identify older people at risk of falls or increased risk of fall injury because of poor protective responses after a loss of balance has occurred [46, 154].

Previously, simple and choice reaction times with finger- or foot-press responses have been measured with electronic timers and switches in the laboratory [34, 35]. However, to date, only a few studies have focussed on the development of a home-based reaction time test for fall risk assessment. In one study a choice reaction time test using an infrared laser in combination with a plus-shaped mat was developed to measure stepping responses to optical cues [70]. Another stepping study evaluated a mat-based system with pressure sensors to assess and improve stepping responses [71, 84]. No research exists on home-based upper-limb reaction time tests.

The aim of this study was to examine the potential of Kinect-based, portable and low-cost assessment tests of choice reaching and stepping reaction time (referred as Kinect-based CRTs) to assess fall risk. The aims of the study were to: 1) develop algorithms to quantify performance on the Kinect-based CRTs, 2) determine whether these tests could identify people at increased risk of falls and 3) examine the feasibility of conducting the CRT tests in a home setting.

5.2 Methods

5.2.1 Participants

A total of 94 community-dwelling older people living in retirement villages in Sydney, Australia participated in this study. The sample was drawn from two trials: 1) iStoppFalls trial [9] and 2) SureStep trial. The inclusion and exclusion criteria are described in Chapter 3.

5.2.2 Kinect-Based Choice Reaction Time Tests

The Kinect-based CRTs are tests which rely on video-based motion capture technology (i.e. Microsoft Kinect). They comprise 1) a choice reaching reaction time test (Figure 5.1a) and 2) a choice stepping reaction time test (Figure 5.1b). When conducting the Kinect-based CRT tests participants saw themselves represented as an avatar in a virtual environment on a TV screen. The participants saw two lights, one to the left and one to the right side of the avatar, which flashed in random order. In the reaching reaction time test, participants were asked to lift their corresponding arm to the flashing light as fast as possible. In the stepping reaction time test, participants were instructed to take a step onto the flashing light, using the left foot when the left light flashed and the right foot when the right light flashed, as quickly as possible.

(a) (b)

Figure 5.1: Schematic representations of Kinect-based CRT tests: (a) reaching reaction time test and (b) stepping reaction time test.

5.2.3 Protocol

The study protocol included the following parts:

1. *Laboratory assessment:* All participants were assessed on the Kinect-based CRTs and on clinical tests for reaction time and fall risk.
2. *Association with future falls:* Participants were followed up for falls for six months and the ability of the Kinect-based CRT tests to discriminate between the fallers and non-fallers was determined.
3. *In-home assessment:* Following the laboratory assessment the Kinect-based CRTs were conducted with a subgroup of participants at home and the relationships between the laboratory and in-home assessments were analysed.

5.2.4 Laboratory Assessment

All participants were initially assessed with the Kinect-based CRT tests in the laboratory. For each participant 40 reaching and stepping responses were recorded with a short break of less than a minute after 20 responses. The first 5 trials were practice trials and excluded from data analysis. The assessments were video recorded with two video cameras (i.e. front and side view) to support the researchers during the data analysis process. The Physiological Profile Assessment (PPA) was conducted as an estimate of the overall fall risk of the participants. The PPA is based on tests which assess sensorimotor abilities: balance (sway when standing on medium-density foam with eyes open), lower extremity muscle strength (knee extension), contrast sensitivity (Melbourne edge test (MET), peripheral sensation (proprioception) and single hand (i.e. finger-press) reaction time [35].

The convergent validity of the Kinect-based CRT tests in relation to the simple reaction time of the PPA and choice reaction time of the Attention Network Test (ANT) were examined. The ANT is a computer-based test where participants had to determine whether a central arrow points to the left or right and to press the corresponding button on a PC-keyboard as quickly as possible [149].

5.2.5 Association with Future Falls

Participants were followed-up for six months and asked to report their falls with monthly falls calendars. Follow-up telephone interviews were conducted if participants failed to return their calendars. Participants were classified as fallers if they experienced at least one fall in the six months follow-up period. A fall was defined as 'an unexpected event in which the person comes to rest on the ground, floor, or lower level' [13].

5.2.6 In-Home Assessment

The feasibility to administer the Kinect-based CRTs at home was examined in a subsample of 20 participants. The system was installed in the participants' homes and the CRT tests were conducted under supervision of a trained researcher. The time gap between the laboratory assessment and the in-home assessment was on average 40 ($\pm$ 20) days.

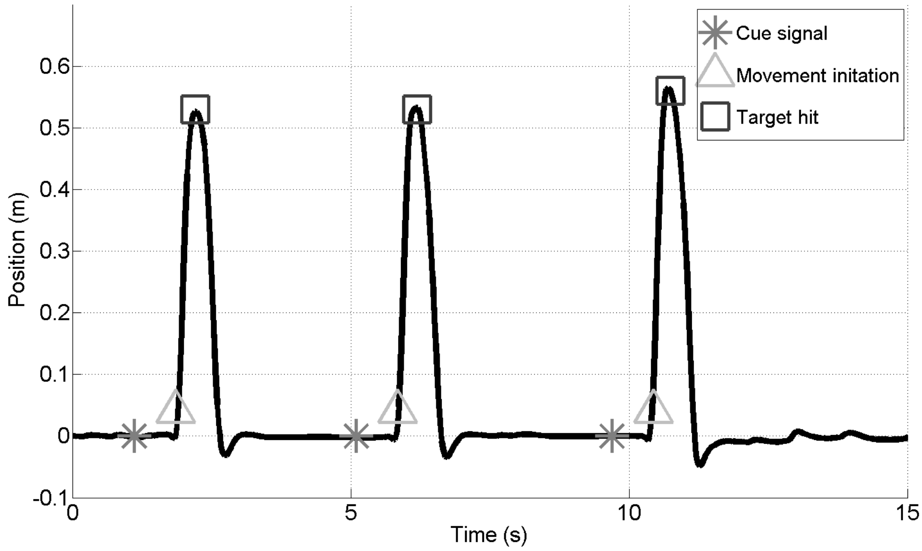
5.2.7 Data Acquisition and Analysis

For the Kinect-based CRTs the horizontal displacement data (i.e. coordinates in the x-axis) of the Microsoft Kinect sensor were used for the algorithms. In detail, the skeleton data of the left and right hand tracking were obtained for the reaching reaction time test and the tracking data of the feet for the stepping reaction time test. The signals were low-pass filtered using a 4^{th} order Butterworth filter with a cut-off frequency of 2 Hz to reduce noise. The following features were automatically extracted from each recording (Figure 5.2):

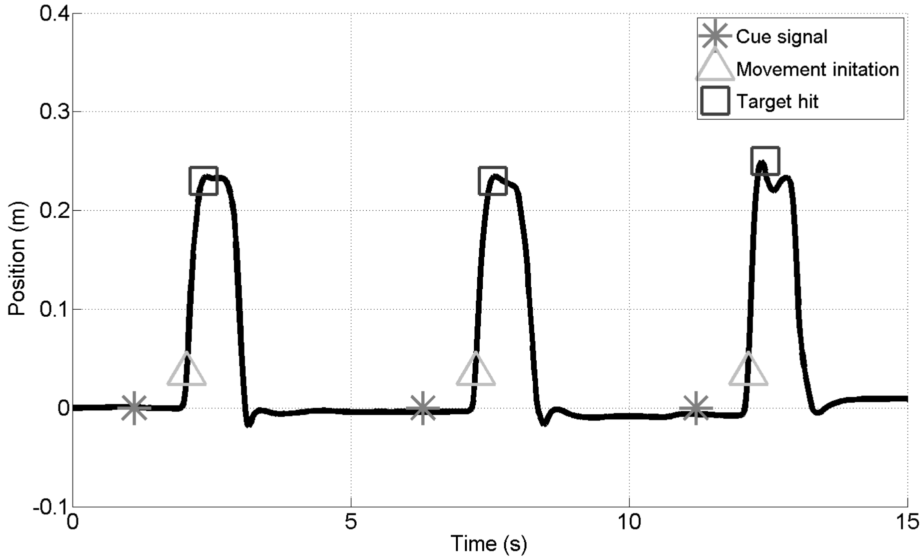
1. *Reaction time:* The reaction time was defined as the time from the cue signal until the first movement of the hand or foot. The movement initiation was detected as a change in position of at least 5 cm (i.e. to the left or right) compared to the rest position. The mean across all reaction times was calculated.

2. *Movement time:* The movement time was defined as the time from the movement initiation until the corresponding target was hit by the hand or foot. Incorrect movements for example in the opposite direction of the cue signal were excluded. The mean across all movement times was calculated.

3. *Total time:* The total time was defined as the sum of the reaction and movement time.



(a)



(b)

Figure 5.2: Skeleton data of (a) hand tracking (reaching reaction time test) and (b) foot tracking (stepping reaction time test) of the Microsoft Kinect. The figures illustrate three responses of the hand (a) and foot (b) to cue signals.

5.2.8 Statistical Analysis

One-way ANOVA was used to evaluate mean differences in the test measures between the fallers and non-fallers. Pearson's correlation coefficients were calculated to quantify convergent validity and the relationship between the laboratory and in-home assessments. Correlation results were categorized as weak (0.1 – 0.3), moderate (0.4 – 0.6), and strong (0.7 – 0.9) [153]. P-values less of 0.05 were considered to be statistically significant. Signal processing, data analysis and statistical analysis were performed in MATLAB 8.2 (R2013b).

5.3 Results

Ninety-four (62 women) aged 80.6 $\pm$ 6.9 years participated in the study. On average, participants were 163.7 $\pm$ 9.8 cm tall, weighed 72 $\pm$ 15.2 kg, had a Body-Mass-Index (BMI) of 26.8 $\pm$ 4.7 and PPA fall risk score of 1.48 $\pm$ 0.88 indicating a moderate risk of falls [35].

5.3.1 Convergent Validity

The Kinect-based reaching reaction time was significantly correlated with the simple reaction time of the PPA ($r = 0.338$, $p < 0.001$) and choice reaction time of the ANT ($r = 0.593$, $p < 0.001$). Similarly, the Kinect-based stepping reaction time measurement was significantly correlated to the PPA reaction time ($r = 0.403$, $p < 0.001$) and ANT reaction time ($r = 0.576$, $p < 0.001$) tests.

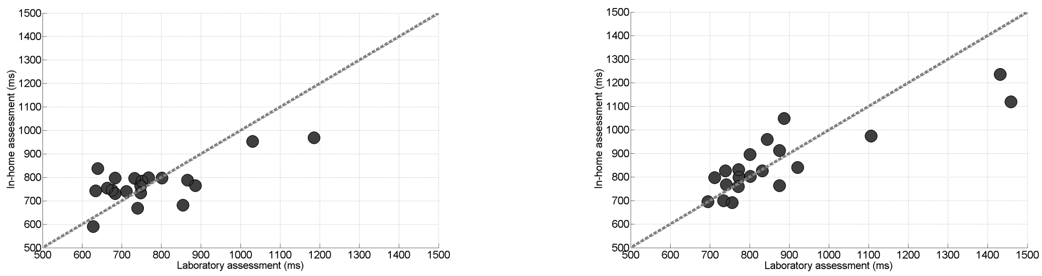
5.3.2 Association with Future Falls

Nineteen participants reported one or more falls in the six months following the assessment. There was no significant difference in age, height, weight or BMI between the fallers and non-fallers. Fallers were significantly slower than non-fallers on the reaching reaction time test measurements (Table 5.1). The stepping reaction time test, the simple reaction time of the PPA assessment and ANT choice reaction time did not significantly discriminate between the groups.

Table 5.1: Test scores of the Kinect-based CRT tests and clinical reaction time measurements for the fallers and non-fallers.

Measurement	Fallers (n=19)	Non-fallers (n=75)	P-value
Choice Reaching reaction time test			
Reaction time (ms)	797 ± 136	714 ± 89	0.002**
Movement time (ms)	392 ± 50	358 ± 51	0.010*
Total time (ms)	1189 ± 170	1072 ± 109	< 0.001**
Choice Stepping reaction time test			
Reaction time (ms)	894 ± 168	849 ± 150	0.257
Movement time (ms)	360 ± 55	342 ± 44	0.125
Total time (ms)	1254 ± 189	1190 ± 158	0.132
Clinical measurements			
ANT choice reaction time (ms)	827 ± 118	785 ± 141	0.232
PPA simple reaction time (ms)	243 ± 32	235 ± 42	0.398

* $P < 0.05$, ** $P < 0.01$; ANT, Attention Network Test; PPA, Physiological Profile Assessment



(a)

(b)

Figure 5.3: Correlations between the results from the laboratory and in-home assessments of the (a) reaching reaction time test (r = 0.689) and (b) stepping reaction time test (r = 0.860).

5.3.3 In-Home Assessment

The in-home assessments were conducted with 20 participants. Figure 5.3 illustrates the linear relationships between the laboratory and in-home assessments. On average, the Kinect-based reaching reaction time was 772 ms ± 85 ms at home compared with 771 ms ± 139 ms in the laboratory ($p = 0.987$). The correlations were moderate to strong for the reaction time ($r = 0.689$, $p < 0.001$), movement time ($r = 0.505$, $p = 0.023$) and total time ($r = 0.737$, $p < 0.001$). Similarly, there was no significant difference between the Kinect-based stepping reaction time at home with 862 ms ± 144 ms and in the laboratory with 876 ms ± 215 ms ($p = 0.594$). The correlations were strong for the reaction time ($r = 0.860$, $p < 0.001$) and total time ($r = 0.814$, $p < 0.001$). Movement time was moderately correlated ($r = 0.609$, $p = 0.004$).

5.4 Discussion

In this study, the feasibility of Kinect-based reaching and stepping reaction time tests were examined and in relation to falls evaluated. For the first time, a Kinect-based approach was used to assess upper- and lower-limb reaction time conducted in both the laboratory and home in community-dwelling older people.

It has been found that fallers were slower than non-fallers on the reaching reaction time test measurements. The finding is consistent with the results of previous studies showing that slow reactions are associated with an increased risk of falling [46, 155]. Use of the upper-limbs is a common response to prevent a fall and to reduce risk of injuries [46, 47]. It has recently been reported that in frail older people the protective responses are often ineffective because of lack of strength and movement speed [154]. The Kinect-based CRT may help to reveal deficits in upper-limb responses for targeted improvement.

In a previous study, a test of stepping reaction time was shown to discriminate well between older fallers and non-fallers based on 12 month fall history [4], but this could not be verified in this prospective study, possibly because of the short follow-up period. I believe the Kinect-based stepping reaction time test has some benefits when compared to other approaches. Other systems require a step mat placed on the floor. This could be seen as an advantage as it provides physical targets during stepping. However, step mats also pose a potential trip hazard, require more time to set up and limit movements to the pre-defined fields.

The advantages of a Kinect-based system are 1) easy to set up - no further physical equipment is needed, 2) safe - no additional trip hazards, 3) inexpensive - the Microsoft Kinect is a widely available consumer device and 4) fairly accurate [92, 93] - enables whole body tracking of participants' movements. These characteristics enable its use in a clinical setting or even in the homes of the older people as an assessment or training tool. Currently, regular repeated assessments are not feasible in clinical practice and, therefore, the assessments are often only weakly associated with falls. The correlations between the Kinect-based CRT laboratory and in-home assessments were moderate to strong which suggests the conduct of the Kinect-based CRT tests at home are feasible.

This study had certain study limitations. The in-home assessment was conducted with a relatively small subgroup of participants and that might limits the generalizability of the results. The sample size was only moderate for a fall risk study and the prospective follow-up period relatively short for capturing sufficient fall events. Larger-scale studies are therefore necessary to confirm the presented results. However, the findings suggest the Kinect-based CRTs could be conducted by the following means 1) tests performed in a clinical setting, 2) tests administered in regular home visits by trained personnel or 3) tests performed independently and unsupervised as a self-assessment.

In summary, the findings indicate the Kinect-based CRT tests are feasible to administer in clinical and in-home settings, and thus represents an important step towards the development of sensor-based fall risk self-assessments. With further validation, the assessments may prove useful as a fall risk screen and home-based assessment measures of upper- and lower-limb movements for monitoring changes over time as well as the effects of fall prevention interventions.

CHAPTER 6

Sensor Fusion (Kinect and Inertial Sensor)

Summary

Background. In a previous study (Chapter 5), the Kinect-based choice stepping reaction time test could not differentiate between people who are at risk for falls from people who are not at risk.

Objective. The main objectives of this study were to 1) develop a new algorithm to quantify performance on the stepping reaction time test using both Kinect and inertial sensor data and 2) examine if the new measurements can successfully discriminate older fallers from non-fallers.

Methods. The stepping test was conducted in a cohort of 104 community-dwelling older people (mean age: 80.7 ± 7.0 years). Spatial and temporal measurements of the lower body were extracted from the Kinect skeleton data and measurements of the upper body were derived from the data of an accelerometer (i.e. wearable pendant device).

Results. Fallers had a slower stepping reaction time (970 ± 228 ms vs. 858 ± 123 ms, $P = 0.001$) and a slower reaction of their upper body (719 ± 289 ms vs. 631 ± 166 ms, $P = 0.052$) compared to non-fallers. It took fallers significantly longer than non-fallers to recover their balance after initiating the step (2147 ± 800 ms vs. 1841 ± 591 ms, $P = 0.029$).

Conclusion. This study demonstrated that sensor-based measurements derived from two low-cost sensors were able to identify significant differences between performances by fallers and non-fallers. The findings indicate that an inertial sensor provides complementary information regarding the quality of movements to that provided by the Kinect.

6.1 Introduction

In real-life situations stepping is the most effective way to avoid a fall [43]. The selection of an appropriate response and its execution are important to maintain balance [34]. Studies have demonstrated that impaired stepping is prevalent in older people, especially in people with a higher risk of falls and balance impairments [34, 43, 71].

The Kinect has demonstrated to be accurate in measuring temporal and gross spatial movements, but less accurate in measuring fine motor movements [92]. Recent research investigated the fusion of the Microsoft Kinect sensor with inertial sensors for human body tracking [156] and its application in rehabilitation tasks [157]

In this study, the feasibility of the Microsoft Kinect in combination with an accelerometer (i.e. wearable pendant device) to measure temporal and spatial stepping parameters in a choice stepping reaction time test was examined. The test was conducted with 104 community-dwelling older people. With the long-term goal to use this stepping test in an unsupervised home assessment and to predict falls more accurate the performance differences in fallers and non-fallers has been analysed.

6.2 Methods

6.2.1 Participants

In total, 104 community-dwelling older adults (mean age: 80.7 ± 7.0 years, 67% women) living in retirement villages in Sydney, Australia participated in this study. The people were recruited from two randomized controlled trials, 71 people took part in the SureStep interactive step training trial and 33 took part in the iStoppFalls [9] trial. Participants in the SureStep trial undertook the assessments at the four-month retest, while participants in the iStoppFalls trial underwent the assessments at baseline. The inclusion and exclusion criteria are described in Chapter 3.

A medical history was recorded during a face-to-face interview, including the presence of medical conditions and self-reported history of falls in the past 12 months. A fall was defined as ‘an unexpected event in which the person comes to rest on the ground, floor, or lower level’ [13].

6.2.2 Protocol

Participants were asked to perform the choice stepping reaction test (Figure 6.1). In the test, the left or right light flashed up in random order using the same time interval. Participants were instructed to take a step “on the light” to turn it off as fast as possible using the left foot when the left light flashed and the right foot when the right light flashed. Participants were also instructed to transfer weight while taking a step. In total 40 steps were assessed in two trials with a short break of less than a minute after 20 repetitions. The first five repetitions were classified as practice steps and excluded from further data analysis. The complete test took about 15 minutes including instructions.

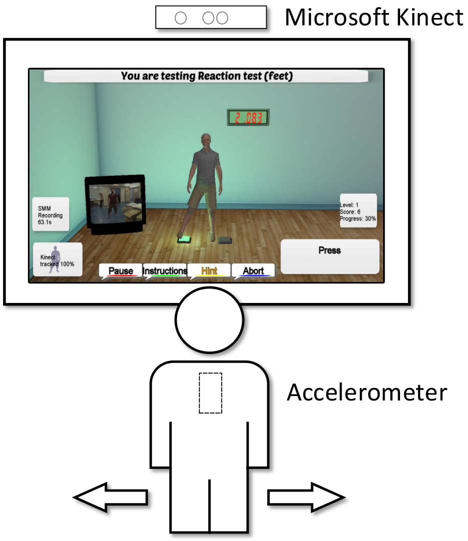


Figure 6.1: Schematic representation of the sensor-based Choice Stepping Reaction Time Test. Participants were asked to step laterally as quickly as possible after a light stimulus, indicated by the system, appeared on the TV screen.

6.2.3 Data Acquisition

Skeleton data of anatomical landmarks were recorded using the Microsoft Kinect Software Development Kit with a sampling rate of 30 Hz. In addition, three-dimensional accelerometer (ADXL362, $\pm$ 8 g) data were acquired in 50 Hz with a custom-made and wearable device. Participants were asked to wear the sensor attached to a cord around their neck. The sensor was placed at the height of the sternum. Participants were asked to wear the device beneath their clothes touching the skin.

6.2.4 Data Analysis

Temporal and spatial parameters were examined to quantify performance differences in fallers and non-fallers. Parameters from the lower and upper body were measured with the Microsoft Kinect and the body-worn accelerometer.

From the Microsoft Kinect signals the medial-lateral skeleton data of the left and right feet were analysed. A step task was divided into two parts: response and execution. All parameters are representing the average value of all steps across all trials. The reaction time, defined as the time from the cue signal to the movement initiation has been calculated (Figure 6.2). The movement time was defined as the time from the initiation to the first foot-contact. The overall time from the cue signal to the first foot-contact was defined as the total step time. In addition, the step length and the variability of the step length were examined.

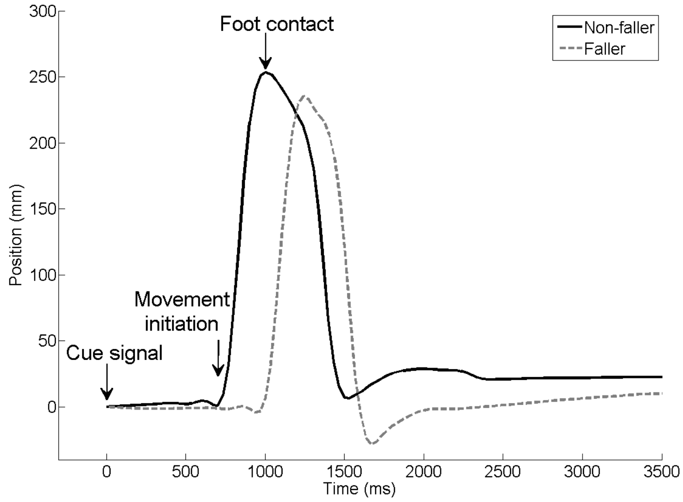


Figure 6.2: Leg movement of a step to the side recorded with the Microsoft Kinect from an example faller and non-faller. Fallers showed a slower reaction time compared to non-fallers.

From the accelerometer signal the vector sum (SVM) of all three directions was calculated as shown in (6.1). Reaction time was defined as the time from the cue signal to the first movement of the trunk. The movement initiation was detected as a significant increase in the acceleration measure compared to the mean value. During the test participants were asked to step sideways and back to the initial position. The stability time was determined as the time from the movement initiation until the participants regained their balance, i.e. reached a similar level of acceleration prior to the step, compared to the mean value. In addition the RMS acceleration was analysed for the SVM, media-lateral (ML) and anterior-posterior (AP) signals.

$$SVM = \sqrt{x^2 + y^2 + z^2} \tag{6.1}$$

6.2.5 Statistical Analysis

A two-sided Student's t-test for independent measures was used to evaluate differences between the faller and non-faller groups. P-values less of 0.05 (*) were considered to be statistically significant. Data and statistical analysis were performed in MATLAB 8.2 (R2013b).

Table 6.1: Characteristics of fallers and non-fallers.

Parameter	**Fallers (n=36)**	**Non-fallers (n=68)**	**P-value**
Age (years)	81.7 ± 8.3	80.1 ± 6.2	0.271
Female, n (%)	27 (75.0)	43 (63.2)	0.319
Height (cm)	161.3 ± 9.3	164. ± 4 9	0.102

Table 6.2: Group differences fallers vs. non-fallers.

Measurement	**Fallers (n=36)**	**Non-fallers (n=68)**	**P-value**
Kinect (Lower Limb)			
Reaction time (ms)	970 ± 228	858 ± 123	0.001**
Movement time (ms)	261 ± 67	255 ± 76	0.678
Total step time (ms)	1231 ± 242	1113 ± 151	0.003**
Step length (mm)	270 ± 46	276 ± 62	0.612
Step length variability (mm)	32 ± 12	31 ± 11	0.864
Accelerometer (Trunk)			
Reaction time (ms)	719 ± 289	631 ± 166	0.052ˆ
Stability time (ms)	2147 ± 800	1841 ± 591	0.029*
Total stability time (ms)	2866 ± 888	2472 ± 636	0.010*
RMS Acc VS (m/s^2)	0.644 ± 0.356	0.696 ± 0.334	0.465
RMS Acc ML (m/s^2)	0.940 ± 0.237	0.921 ± 0.203	0.675
RMS Acc AP (m/s^2)	0.566 ± 0.221	0.562 ± 0.201	0.927

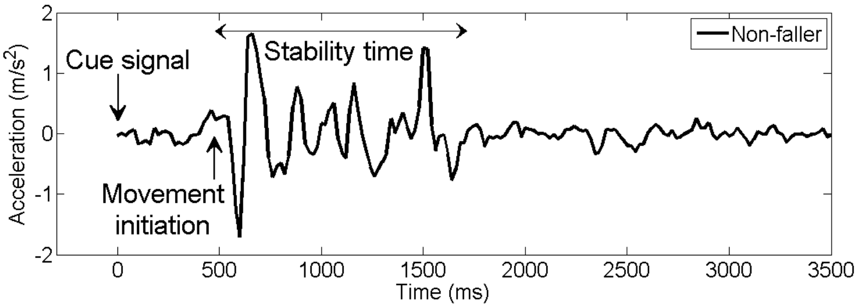
ˆ $P < 0.10$, * $P < 0.05$, ** $P < 0.01$

6.3 Results

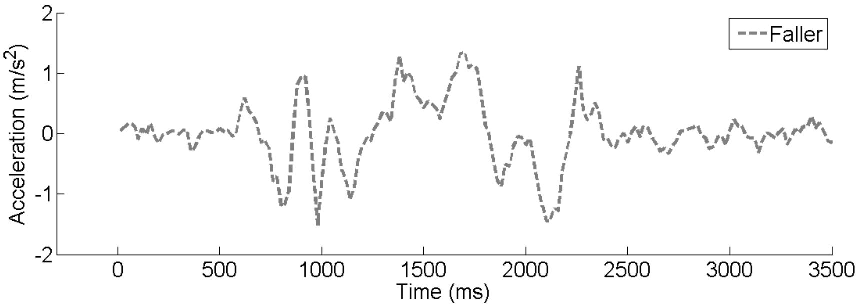
Participants were classified as 36 fallers, who had one or more falls within the past 12 months, and 68 non-fallers. There was no significant difference in age, gender and height between fallers and non-fallers in this study (Table 6.1).

Figure 6.2 illustrates the lower body movement of an example faller and non-faller. From the Kinect measurements it has been observed that the mean stepping reaction time and total step time in the fallers group was significantly slower than in the non-fallers group (Table 6.2). There was no difference in the step length, step length variability or the movement time of the lower limbs.

Figure 6.3 shows the upper body acceleration of a typical faller and non-faller. Fallers needed longer to regain their balance after movement initiation compared to non-fallers. There was a trend for longer trunk reaction time for fallers ($P = 0.052$). In addition, the total stability time was longer for fallers. There was no group difference for the RMS acceleration.



(a)



(b)

Figure 6.3: Acceleration trace (SVM) of the upper body movement (mean amplitude of the signal subtracted) for an example (a) non-faller and (b) faller. Fallers showed a slower reaction time and needed longer to stabilize after movement initiation.

6.4 Discussion

In this study, the feasibility of a sensor-based, low-cost and portable choice stepping reaction time test to identify people at high risk of falls by analysing the group differences between older fallers and non-fallers has been examined.

Recent technological studies have used an infrared laser sensor in a four square choice stepping test and a custom dance-mat with pressure sensors in a test with a high attention component [70, 71]. In the present study, the Microsoft Kinect a commercially available consumer device and a three-dimensional accelerometer have been used. With this combination steps and large scale movements, using the Kinect, and smaller postural adjustments, using the accelerometer were detectable. This work focused on lateral stepping as it has been reported that fallers step more frequent laterally than non-fallers and that the lateral falls are most likely to result in hip fractures [46].

A choice stepping reaction test is a composite measurement of cognitive function, reaction time, strength and balance [34]. The results confirm previous study findings in that fallers performed this test more slowly. In addition, trunk movements with a body-worn sensor have been analysed and a significant trend for a longer upper body reaction time has been observed. A large body of literature exists, that demonstrates that the reaction time increases with age [43, 61, 158] and that a longer reaction time is related to a higher risk of falling [34, 36].

Furthermore, the results suggested that fallers needed significant longer to recover their balance after taking a step compared to non-fallers. In the literature, several studies associated falls with poor balance [38, 159]. In addition, it has been shown that the time to regain a stable posture after executing a step increases with age [160]. These findings are in accordance with the results.

This study had certain study limitations. The Microsoft Kinect has been used in research settings before and was applied for fall risk assessments in older people [161]. However, the device was primarily developed for consumer purposes, which means a low price but with limitations in accuracy compared to other more expensive three-dimensional motion capture systems [139]. The resolution of the accelerometer was 4 mg with a range of ± 8 g, which was sufficient to detect reaction and stability time but might not be sufficient to detect very small differences in the accelerations between fallers and non-fallers. The recall of falls history might have underestimated the real number of falls. However, a reported history of falls has been shown to be a good predictor of future falls [162]. It is also acknowledged that as the fall surveillance period coincided with the intervention in the SureStep trial, stepping performance in the assessments may have been influenced by the exercises in those allocated to the intervention group. Nevertheless, this study presents an important first step towards establishing the validity of combining Kinect technology with inertial sensors to assess choice stepping reaction time in older people.

In summary, this study demonstrated the feasibility of a choice stepping reaction time test. The inertial sensor provided complementary information regarding the quality of movements to that provided by the Kinect. Using these data the test was able to differentiate between fallers and non-fallers. Therefore, it has potential to be used in clinical practice or regular unsupervised home assessments in future.

CHAPTER 7

Wearable Sensor-Based Sit-To-Stand Assessment

Summary

Background. There has been recent interest in replacing or complementing clinical fall risk assessments with assessments undertaken at home. The sit-to-stand movement is a common activity in daily life and advances in wearable devices may provide new ways to continuously monitor the ability of older people to perform this important postural transition.

Objective. The aims of this study were to 1) develop a new wavelet-based algorithm to automatically detect and quantify sit-to-stand movements using a pendant-style wearable sensor and 2) investigate the ability of this algorithm to differentiate between older fallers and non-fallers.

Methods. The developed algorithm used wavelet transformations of the accelerometer and barometric air pressure sensor data. Detection accuracy was tested in 25 older people performing 30 minutes of typical daily activities and 94 older people performing sit-to-stand movements as part of a clinical study. The ability to differentiate between people who are at risk of falls from people who are not at risk was investigated by assessing group differences of sensor-based sit-to-stand measurements in 34 fallers and 60 non-fallers.

Results. Sit-to-stand movements were detected with 93.1% sensitivity and a false positive rate of 2.9% during activities of daily living. In the clinical study, 98.9% of the sit-to-stand movements were detected with no false positives. The fallers had significantly slower maximum acceleration and velocity during the sit-to-stand movement compared to non-fallers.

Conclusion. The wearable sensor based on the new algorithm accurately detected sit-to-stand movements in older people and differed significantly between older fallers and non-fallers.

7.1 Introduction

Recent studies have used inertial sensors to automatically detect [163–171] and quantify sit-to-stand movements [85,172–174]. The majority of these studies used one or more body fixed sensors (i.e. accelerometers and/ or gyroscopes), and only a few have investigated the value of barometric air pressure sensors [168,169,175].

Several detection algorithms have been proposed. For example, Najafi et al. [163,164] developed an algorithm based on trunk tilt estimation to detect sit-to-stand movements, and reported sensitivity and specificity of 93% and 82% respectively in 11 older people [164]. Similarly, Godfrey et al. demonstrated 83% sensitivity and 89% specificity in 10 older people using trunk tilt and vertical velocity estimations [166]. Pattern matching methods using cross-correlation analysis [168] or dynamic time warping [167] have also been proposed. Zhang et al. [168] reported 61% sensitivity and 89% precision in detecting sit-to-stand movements during activities of daily living in 30 older people, while Ganea et al. [167] reported 25-60% sensitivity and 80-98% specificity in a group of 10 healthy people and 30 people with chronic pain.

In brief, an algorithm to detect sit-to-stand movements based on wavelet transformations of the data of 25 older people performing 30 minutes of free-living activities and 94 older people performing a standardized clinical assessment using a pendant-style inertial monitoring device was developed. The wavelet transform [176] is a powerful technique which provides excellent time and frequency localization and therefore may be well-suited for the multiresolution analysis of non-stationary sit-to-stand signals. The pendant device is worn around the neck on a lanyard and comprises a tri-axial accelerometer and a barometric air pressure sensor (Chapter 3). A neck-worn pendant may be good for maximizing sensor use by older people in their daily life, as it is easy to put on, self-adjustable and all sensors are incorporated into a single device [166,167,177]. Further, the discriminant ability of the algorithm by exploring group differences of sensor-based sit-to-stand measurements in relation to fall history in the larger sample was investigated.

7.2 Methods

7.2.1 Participants

A total of 119 community-dwelling older people living in Sydney, Australia, participated in this study. Participants took part in a free-living (n=25) or clinical assessment (n=94) and were drawn from the Sydney Memory and Ageing [178], iStoppFalls [9] and SureStep [12] studies. The inclusion and exclusion criteria are described in Chapter 3.

7.2.2 Study Protocol

The protocol comprised two studies to investigate the accuracy and discriminant validity of the developed sit-to-stand detection algorithm.

Free-Living Study

The free-living study comprised 30 minutes of daily activities that people might perform in their home environment while wearing the pendant device around their necks without further restrictions. Free-living activities were semi-structured; participants performed several tasks (including eight sit-to-stand movements) in a given order, but were not given specific instructions about how to complete each task. The tasks are described in detail in Chapter 3.

Clinical Study

In the clinical study, participants were asked to follow a standardized protocol while wearing the pendant device at the height of their chest and under their clothes. Participants performed the following routine in which they had to stand up from a chair (height: 45 cm), walk 10 m and sit down again at their normal comfortable speed.

7.2.3 Detection of Sit-To-Stand Movements Using Wavelet Transformations

Detection of Sit-To-Stand Candidates

The continuous wavelet transform (CWT) was used to detect sit-to-stand patterns in the acceleration and barometric air pressure sensor signals. The main advantage of the wavelet transform is that it can be used to detect shapes, which are similar to the shape of a mother wavelet, by constructing a representation of a signal that offers excellent time and frequency localization. Therefore, the CWT divided the sensor signals into dilated (i.e. scaled) and translated (i.e. shifted) versions of a wavelet function (called the mother wavelet). The scale and position of a sit-to-stand pattern in the data was estimated by analysing the CWT coefficients. If a match was found in the acceleration and barometric air pressure recordings a sit-to-stand candidate was identified.

First, for the detection of the sit-to-stand pattern in the acceleration signal a custom wavelet was generated, using the MATLAB 'pat2cwav' function, from a representative sample sit-to-stand movement (Fig. 7.1). For comfort reasons, the pendant device was attached to a lanyard and not directly fixed to the body. Therefore, the acceleration signal's vector magnitude (SVM) was calculated (7.1) which is independent of the orientation of the device (Fig. 7.2a).

$$SVM = \sqrt{x^2 + y^2 + z^2} \tag{7.1}$$

Second, the CWT over the durations (scales) of 0.5-5s was obtained using the custom wavelet to decompose the SVM into an array of coefficients representing the energy distribution (Fig. 7.2b). Third, a match was identified by computing the energy distribution over the scales. If a value exceeded the empirically found (i.e. by perusing all of the data) threshold of 0.3 m/s^2 its temporal position was considered a match (Fig. 7.2c).

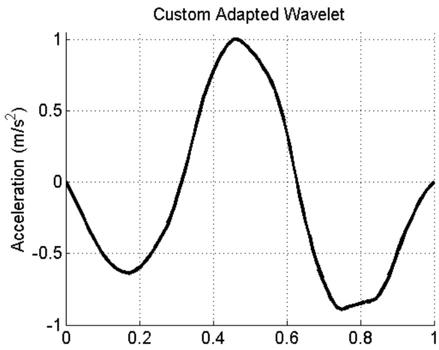
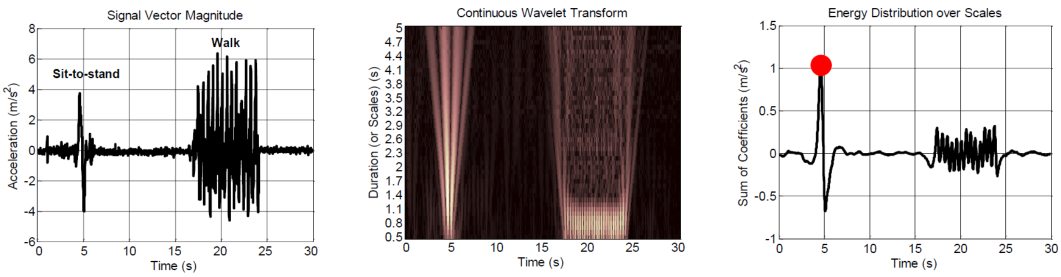


Figure 7.1: Custom wavelet used for the continuous wavelet transform representing a sit-to-stand pattern in the vector magnitude of the acceleration signal.



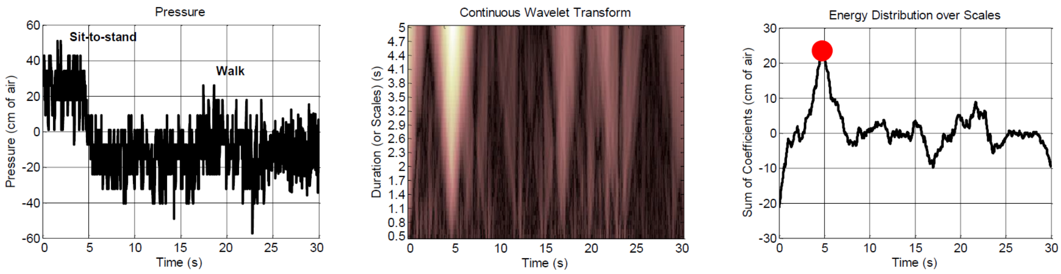
(a) (b) (c)

Figure 7.2: Wavelet-based analysis of a sit-to-stand movement and short walk using the accelerometer data. (a) Vector magnitude of the acceleration signal. (b) Wavelet decomposition using the custom wavelet. (c) Energy distribution computed from the coefficients of the wavelet transform. Sit-to-stand movement identified by a peak greater than 0.3 m/s^2.

A sit-to-stand pattern is represented as a step in the barometric air pressure signal (Fig. 7.3a). The signal was pre-processed by applying linear interpolation to up-sample the signal to 50 Hz and converted to centimetres (of air). In the CWT, the Haar wavelet was used as the mother wavelet, which is well-suited for step detection problems. After obtaining the CWT (Fig. 7.3b) and computing the energy distribution a match was considered if the value exceeded the empirically identified threshold of 10 cm similar to the method applied for the acceleration signal (Fig. 7.3c).

Analysis of Pre- and Post-Transfer Phases

The pre-and post-transfer phases were analysed by the algorithm to eliminate candidates that were not sit-to-stand movements. The usual pre-transfer activity is sitting and the usual post-transfer activities are standing or walking. Therefore, features were computed from the pre- and post-transfer phases, defined by a three second interval before and after



(a) (b) (c)

Figure 7.3: Wavelet-based analysis of a sit-to-stand movement and short walk using the barometric air pressure data. (a) Barometric air pressure signal. (b) Wavelet decomposition using the Haar wavelet. (c) Energy distribution computed from the coefficients of the wavelet transform. Sit-to-stand movement identified by a peak greater than 10 cm.

the sit-to-stand candidate respectively, to identify the sit-to-stand movements fulfilling all of the following requirements:

- *Signal intensity*

  Sitting may be characterized as a low intensity activity. Activity intensity was estimated by applying a low-pass 2$^{\text{nd}}$ order Butterworth filter with a cut-off frequency of 3 Hz to the SVM and calculating the standard deviation. Sitting required a signal intensity below 0.8 m/s^2 during the pre-transfer phase.

- *Device orientation*

  Sitting may be characterized by an upright trunk position. The trunk inclination θ (i.e. angle of the z-axis relative to gravity, where the z-axis is vertical) was estimated from the low-pass filtered acceleration data (7.2). Upper and lower limits of the trunk inclination during the pre-transfer phase were -70° and 70°.

$$\theta = \arctan \frac{\sqrt{x^2 + y^2}}{z} \cdot \frac{180°}{\pi} \tag{7.2}$$

- *Positive height change*

  A sit-to-stand movement may be characterized by a positive change in height that corresponds to a drop in air pressure (Fig. 7.3a). Positive height change was estimated by subtracting the mean pressure of the post-transfer phase from the mean pressure of pre-transfer phase.

- *Maximum height change*

  To prevent height changes related to stair climbing or elevator use erroneously being confused with sit-to-stand movements, the maximum height change, either during pre- or post-transfer phase, was limited to 40 cm. Height change was estimated by applying a low-pass 2^{nd} order Butterworth filter with a cut-off frequency of 1 Hz to the barometric pressure signal and calculating the range of the signal's amplitude.

7.2.4 Accuracy of the Sit-To-Stand Detection Algorithm

First, the performance of the algorithm was evaluated on the free-living data to demonstrate the detection ability under conditions similar to real-life. For validation, the free-living activities were recorded with a hand-held video camera. Second, the performance was evaluated on the data from the clinical study. All sit-to-stand movements were annotated manually by an experienced researcher.

Agreement between the sit-to-stand movements detected by the algorithm and the real transfers was measured using sensitivity (defined as the percentage of correctly identified sit-to-stand movements) and false positive rate (defined as the percentage of incorrectly identified sit-to-stand movements among all other activities, including stand-to-sit, recline-to-sit, sit-to-recline, bending movements as well as walks and stair climbs).

7.2.5 Sit-To-Stand Performance Measurements (Discriminant Validity Analysis)

Sit-to-stand performance was compared between the fallers and non-fallers in the clinical study. During a face-to-face interview the number of self-reported falls in the past 12 months was recorded. A fall was defined as an "unexpected event in which the person comes to rest on the ground, floor, or lower level" [13]. For the discriminant validity analysis, the following sensor-based measurements were extracted:

- *Duration*

  In the CWT, the scales can be defined in terms of the dilation factor or duration of the pattern to be detected. By incorporating the sampling period the position and scale were translated into temporal notions of instant and duration. The sit-to-stand duration was detected by identifying the maximum of the absolute value of the coefficients (Fig. 7.4).

- *Maximum acceleration*

  The maximum acceleration of the low-pass filtered (cut-off frequency 3 Hz) SVM during the interval of the sit-to-stand movement was calculated. The start and stop of the sit-to-stand interval were computed based on the instant and duration detected above.

- *Maximum velocity*

  The maximum velocity was estimated by numerical integration of the low-pass filtered SVM. It was assumed that velocity was 0 m/s at the start of the sit-to-stand movement.

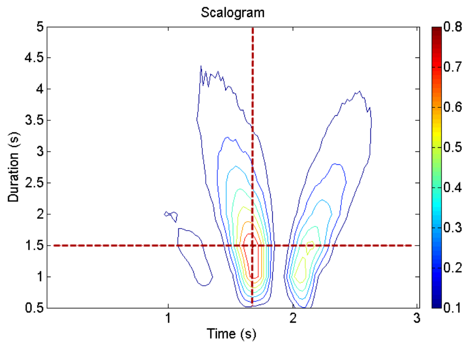


Figure 7.4: Percentage of energy for each wavelet coefficient. Sit-to-stand duration estimated by the maximum of the absolute value of the coefficients.

- *Forward trunk tilt*

  The forward trunk tilt θ was estimated from the device orientation of the sensor.

7.2.6 Statistical Analysis

Measurements were tested for normality with the Lilliefors test. For normally distributed variables, two-sided Student's t-test was applied to evaluate differences between the faller and non-faller groups. For measurements which were not normally distributed, the Mann-Whitney test was used. P-values less of 0.05 (*) were considered to be statistically significant. Data analysis and algorithm development were performed using MATLAB 8.2 (R2013b).

7.3 Results

Participants in the free-living study (n=25) and participants in the clinical study (n=94) were 82.8 $\pm$ 3.3 years and 79.9 $\pm$ 6.5 years old. Thirty-four participants (36%) in the clinical study reported one or more falls in the year before assessment. Body height, weight and body mass index of the participants are presented in Table 7.1.

7.3.1 Accuracy of the Sit-To-Stand Detection Algorithm

In the free-living study, 202 sit-to-stand movements were performed and 188 were detected successfully (93.1% sensitivity) by the algorithm. Nineteen out of a total of 650 other activities were misclassified as sit-to-stand movements (2.9% false positive rate). The video recordings revealed that false positives occurred during standing up after bending down to switch power outlets, slow stair ascents and when participants attempted to stand up but sat back down again before standing upright.

In the clinical study, 93 out of 94 sit-to-stand movements were detected correctly (98.9% sensitivity). No other activities were misclassified as sit-to-stand movements. Table 7.2 summarizes the performance of the detection algorithm.

7.3.2 Discriminant Validity Analysis

Fallers (n=34) performed the sit-to-stand movement with less power than non-fallers (n=60) in the clinical study (Table 7.3). The maximum acceleration and velocity measurements showed good discriminant validity between the two groups.

Table 7.1: Characteristics of participants in the free-Living and clinical studies.

Characteristic	**Free-living**	**Clinical**
Participants	25	94
Gender (F / M)	9 / 16	64 / 30
Age (years)	82.8 ± 3.3	79.9 ± 6.5
Height (cm)	167.6 ± 9.2	162.3 ± 8.9
Weight (kg)	70.7 ± 11.4	70.2 ± 12.7
BMI (kg/m^2)	25.1 ± 3.3	26.6 ± 4.1

Table 7.2: Sensitivity and false positive rate for sit-to-stand movements detected in the free-living and clinical studies.

Parameter	**Free-living**	**Clinical**
STS movements	202	94
STS movements detected	188	93
Other activities	650	188
False positives	19	0
Sensitivity	93.1%	98.9%
False positive rate	2.9%	0%

Table 7.3: Test scores for the sensor-based sit-to-stand assessment for the fallers and non-fallers in the clinical study.

Measurement	**Fallers (n=34)**	**Non-fallers (n=60)**	**P-value**
Duration (s)	1.6 ± 0.46	1.55 ± 0.35	0.59
Max acceleration (m/s^2)	2.41 ± 1.02	2.9 ± 1.12	0.04*
Max velocity (m/s)	0.61 ± 0.25	0.73 ± 0.26	0.03*
Forward trunk tilt (°)	15.84 ± 8.81	12.24 ± 10.17	0.09

7.4 Discussion

A new algorithm that could accurately detect sit-to-stand movements by applying wavelet transformations to sensor data from a wearable pendant device was developed. The method proved feasible in both free-living and clinical settings. Clinical relevance was demonstrated in that sit-to-stand velocity and acceleration measures discriminated significantly between older fallers and non-fallers.

Previous studies have also reported good detection of sit-to-stand transitions based on characteristic trunk tilt movements [163, 164, 166]. These algorithm could not be used, as the pendant-style sensor was worn on a lanyard around the neck and not directly fixed to the body, motivated by a desire to make the device more comfortable and easier to use in daily life in older people.

In lieu, an algorithm incorporating acceleration and barometric air pressure data was developed. In accordance with Masse et al. [169], the results demonstrate that a barometric air pressure sensor provides complementary information to that provided by an accelerometer and is sensitive to the height changes that occur during sit-to-stand movements.

Similar to others [167, 168], the presented approach used pattern matching to detect sit-to-stand movements. However, the dynamics of sit-to-stand transitions are diverse in older people. Therefore, the continuous wavelet transform which scales and shifts the template to find the best match for the sit-to-stand movement in the signal data has been selected; an approach that enabled more vigorous movements in more athletic participants and slower movements in frailer participants to be detected [179].

The accuracy of the detection algorithm was tested in both the free-living and clinical assessment studies. In the free-living study, participants completed sit-to-stand transitions from soft and hard chairs of various heights as well as miscellaneous activities of daily living to reduce the likelihood of overfitting the algorithm. Compared with previous studies [164, 166–168], the proposed method showed excellent sensitivity (93.1%) and had a low false positive rate (2.9%); demonstrating potential for long-term monitoring in older people.

In addition, good results for the detection of sit-to-stand movements (sensitivity 98.9%, false positive rate 0%) in the clinical study have been achieved. The results of the discriminant validity analysis suggest the feasibility of using this approach to identify fallers in older cohorts. In accordance with previous work [2], sit-to-stand velocity (a performance indicator for muscle power) discriminated significantly between fallers and non-fallers and did so better than sit-to-stand duration, which is commonly used in clinical evaluation.

Certain study limitations have to be acknowledged. First, although the free-living study was designed to include miscellaneous activities of daily living, it may not have captured the complete range of activities older people perform throughout the day. Second, without accurate information about the pendant's change of orientation during the sit-to-stand movement (e.g. by combining accelerometer and gyroscope data) it is likely that the measurements overestimate true velocity and trunk tilt. Third, the continuous wavelet transform has been selected due to its ability to use custom wavelets in MATLAB; an algorithm that is more computationally expensive than a discrete wavelet transform.

Future studies could determine if the presented algorithm can detect sit-to-stand movements and identify fallers in long-term monitoring of everyday life. Such an assessment in a person's natural environment could have advantages over a clinical assessment. It provides scope for convenient and continuous monitoring that is more representative of a person's real-life performance, and also provides an easy solution for people living in rural areas with limited access to such clinical services.

In summary, a new wavelet-based algorithm accurately detected sit-to-stand movements during activities of daily living in older people and discriminated significantly between fallers and non-fallers. In future, this algorithm and wearable pendant device may be used to capture sit-to-stand movements in home settings (over days or weeks) to assess fall risk and to monitor the success of exercise-based fall prevention interventions.

CHAPTER 8

Home Study

Summary

Background. The Kinect-based system and the wearable sensor, based on the presented algorithms, differentiated accurately between people who are at risk for falls and people who are not at risk in the clinical setting. The derived sensor-based measurements demonstrated good convergent validity to traditional fall risk assessments and preliminary results suggest the validity of these measurements in the home setting.

Objective. The aims of this study were to 1) empirically examine the feasibility of the Kinect-based system and the wearable sensor to be utilized at private homes, 2) investigate the experience of older people with these new assessment methods and 3) make recommendations for future home-based assessments.

Methods. The Kinect-based system and the pendant device were deployed into the homes of 62 community-living older people in Australia, Germany and Spain for the duration of four months. Participants were asked to perform the Kinect-based tests at least every month and to wear the pendant device during the day as often as possible. At the end of the study, semi-structured interviews were conducted to investigate user experience.

Results. In total, 241 assessments (one session included the static balance, five-times-sit-to-stand, choice stepping and reaching reaction time tests) were independently performed by the participants. The pendant device was worn for a total of 39,803 hours; on average 642 hours per participant. Through the interviews the design, usability (wearability) and reliability of the applied technology as well as motivational aspects, user feedback and safety and support arrangements were identified as important characteristics of a home-based fall risk assessment method. Most participants felt positive about their experiences with these new technologies and could see themselves continuing with the Kinect-based tests or to wear the pendant device on a regular basis.

Conclusion. The findings demonstrate the feasibility of the Kinect-based system and the wearable sensor in the unsupervised home setting with older people. Future research should consider the design requirements identified by this study.

8.1 Introduction

Fall risk assessments help to determine and monitor the individual's likelihood of falling. However, clinical fall risk assessments have been criticized as one-time snapshots, overly subjective, and only moderately predictive of falls. There has been recent interest replacing or complementing clinical fall risk assessments with assessments undertaken at home. Therefore, the iStoppFalls assessment, including a set of Kinect-based tests for unsupervised and regular repeated fall risk assessments, and a wearable pendant device for continuous monitoring of daily life activities have been developed.

It has been demonstrated that the Kinect-based tests and daily life activities measured with the wearable pendant device could discriminate well between older fallers and non-fallers in the clinical setting. In brief, the present study complements these findings and addresses the following research aims: 1) to examine the feasibility of the iStoppFalls assessment and the wearable sensor at private homes, 2) to investigate user experience and 3) to make recommendations for improved sensor-based home assessments.

8.2 Methods

8.2.1 Home-Based Study

The feasibility of the iStoppFalls assessment and the pendant device in the homes of older people were examined for a period of four months. This study was part of the iStoppFalls randomized control trial (RCT). The study protocol of the RCT is described in detail elsewhere [9]. In the RCT, participants were asked to perform strength and balance exercises delivered through the iStoppFalls system with the same technical equipment used for the iStoppFalls assessment. For the present study, participants were asked to conduct the iStoppFalls assessment additionally to the exercises at least once per month and to wear the pendant during the day.

Participants

The sample was drawn from the iStoppFalls RCT intervention group with participants in Cologne (n=22), Valencia (n=21) and Sydney (n=19). Only people who completed the four months trial have been included. The inclusion and exclusion criteria are described in Chapter 3.

Protocol

The participants were instructed on how to perform the assessment and completed an assessment during the initial installation of the iStoppFalls system in their homes. Participants were asked to perform the iStoppFalls assessment (i.e. standing balance, sit-to-stand and reaction time tests) at least once per month and were reminded via monthly phone calls to perform the assessment. In addition, participants were asked to wear the pendant device during the day.

Data Analysis

The feasibility of the iStoppFalls assessment was investigated by analysing the number of assessments performed during the four month period. The iStoppFalls system automatically recorded the start time of each session. From these recordings, the total number of assessments and the mean number of assessments per participant for each study site were calculated. Participants were asked to conduct the assessment at least once per month on their own and adherence was measured for each month. The first month was defined as the initial 30 days after the installation of the system, the second month between 30 days and 60 days, the third month between 60 days and 90 days and the fourth month between 90 and 120 days after installation. Assessment tests that were started but not completed (e.g. aborted), or lasted excessive longer than the usual duration, and assessments with insufficient data captured were excluded from the analysis.

The feasibility of the wearable pendant was investigated by analysing the sensor data stored on the devices. Based on the recordings the wearing time was estimated. Exceeded the standard deviation of the accelerometer signal a certain threshold (within one hour) activity and therefore wearing time were assumed.

8.2.2 Qualitative User Study

A qualitative study was carried out to examine the acceptability of the iStoppFalls assessment and the wearable pendant device. Face-to-face semi-structured interviews were conducted in the participant's homes at the end of the four-month study period. A semi-structured interview technique was chosen in order to allow the interviewer to tailor the questions to different participants and contexts and to allow for exploration of themes. Interview topics were chosen to enhance the understanding of the participant's reasons for using the iStoppFalls assessment and the wearing the pendant device; perceived benefits and barriers to utilize them at home; their experience while using these new technologies; and whether they thought they would like to continue using them in the future (Table 8.1).

Each interview lasted approximately 30 minutes. To ensure correct representation of participants' responses, member checking was performed at the end of each interview. A summary of the interview findings was verbally presented to the interviewee at the end of the interview and changes were made when necessary. Participants were also encouraged to add further information.

Table 8.1: Interview guide, questions covered in the semi-structured interviews.

Assessment of Fall Risk	
"Please try to answer the following questions independent from your experience as participant in the study."	
"Did you ever fall in the past?"	• (Yes) *"How do you feel about it?"* • (No) *"How do you think a fall would have impacted your life?"*
"Can you describe me what you think about tests which assess your risk of falling in general?"	• *"Did you ever get your fall risk tested before?"* • *"Are you interested in monitoring/knowing your fall risk?"* • *"How much time would you be willing to spend on testing your fall risk?"* • *"What would be your expected benefit?"* • *"How would an ideal test look like for you?"*
Kinect-Based System	
"I would like you to think about your experience with the Kinect-based assessment tests. You performed the tests [#] times in the four months." »Show pictures of the Kinect-based tests«	
"Try to remember a day when you did the fall risk assessment on your own. Can you describe me your experience with the tests?"	• *"Can you tell me more about your motivation to perform the tests?"* • *"What were reasons that might have prevented you from performing the tests more often?"* • *"Which test did you like the most and why?"* • *"Did you feel safe?"*
"Would you see yourself continuing to perform the Kinect-based assessment tests (let's say once per month)? Can you tell me more about it?"	
"Can you think of any suggestion to improve the fall risk assessment system?"	
Wearable Pendant Device	
"I would like you to think about your experience with the pendant." »Show pendant device«	
"Try to remember a day when you used the pendant. Can you describe me your experience?"	• *"Can you tell me more about your motivation to use the pendant?"* • *"What were reasons that might have prevented you from wearing it more often?"*
"Would you see yourself continuing to wear the pendant device? Can you tell me more about it?"	
"Can you think of any suggestion to improve the pendant?"	
End of Interview	
"Is there anything else you would like to tell me? I will try to summarize the main points I gathered from your answers. I would like you to tell me if they reflect what you told me?"	

Participants

A purposive sampling strategy was used to ensure maximum variability within participants in regards to the number of assessments conducted, wearing time of the pendant, and their history of falls. Ten participants from Sydney were invited to participate in the qualitative study. All agreed to be interviewed. The participants were in average 78.1 ± 6.1 years old, seven (70%) were female. Half of the interviewees performed the iStoppFalls assessment at least twice or more on their own and half reported a fall in the past 12 months prior to the study. The computer literacy was high; eight (80%) participants owned a computer and used it in average 3.0 ± 0.8 hours per week. Informed consent was attained prior to the interview.

Data Analysis

All interviews were digitally recorded and transcribed verbatim. A thematic context analysis was conducted. Interviews were coded using NVivo (Version 10) for Windows and major themes were developed.

8.3 Results

Sixty-two participants aged 74.3 ± 6.7 years participated in the study; of these 33 (53%) were women (Table 8.2). Twenty-one participants (34%) experienced one or more falls in the past 12 months. The participants from Cologne had a lower risk of falling compared to participants from Valencia and Sydney, indicated by good performances in the Physiological Profile Assessment and Short Physical Performance Battery.

Table 8.2: Characteristics of the participants and information about the use of the iStoppFalls assessment in Cologne, Valencia and Sydney.

Parameter	Cologne (n=22)	Valencia (n=21)	Sydney (n=19)
Medical			
Age (years)	73.5 ± 5.5	70.1 ± 3.8	79.9 ± 6.7
Female, n (%)	10 (45)	12 (57)	11 (58)
BMI	25.1 ± 3.6	25.9 ± 3.4	27.6 ± 3.4
Fall Risk			
Previous falls, n (%)	8 (36)	5 (24)	8 (42)
Physiological Profile Assessment	0.19 ± 0.77	0.96 ± 1.04	1.12 ± 0.76
Short Physical Performance Battery	11.4 ± 1.1	9.3 ± 1.8	9.5 ± 2.9
iStoppFalls Assessment			
Number of assessments (n)	125	82	34
Mean per participant (n)	5.7 ± 8.7	3.9 ± 8.5	1.8 ± 1.3
Winsorized mean (n)	4.5 ± 5.3	3.0 ± 5.1	1.8 ± 1.3
Adherence (%)	48	33	36
Wearable Sensor			
Wearing time (hours)	19098	14701	6004

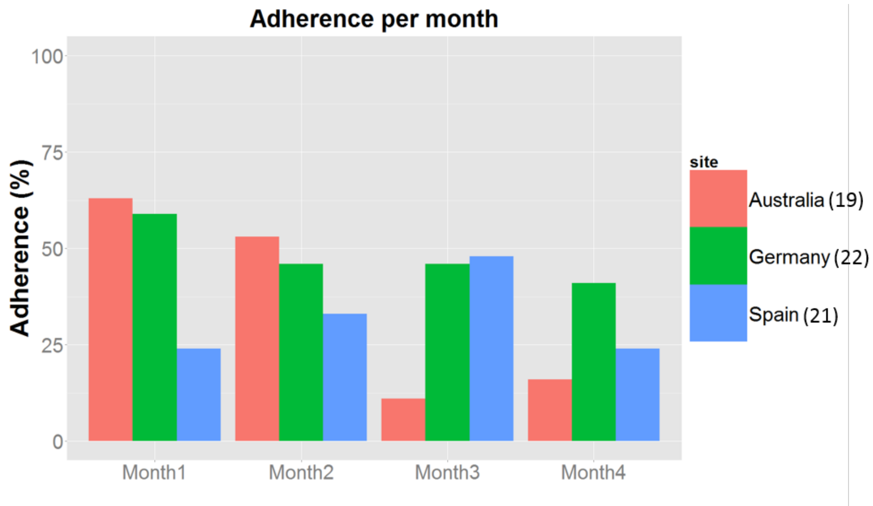


Figure 8.1: Adherence to the iStoppFalls assessment for each month and study site.

8.3.1 Feasibility of iStoppFalls Assessment

In total 241 assessments were performed by 62 participants over four months (Table 8.2). The large spread in the Cologne and Valencia group was because of two participants in each study site performing the assessment very frequently. On average 3.2 ± 4.5 assessments were performed per participant after accounting for the spread with the Winsorizing method [180]. There was no significant difference between participants with a high risk of falling and low risk falling or between previous fallers and non-fallers in the number of performed assessments.

The participants were asked to perform at least one assessment per month. The adherence was 39% for each month across all sites (Figure 8.1). In detail, 48% performed the assessment in Cologne, 33% in Valencia and 36% in Sydney every month.

8.3.2 Feasibility of Wearable Sensor

In total, more than 300 GB of sensor data were recorded with the pendant devices. Participants have worn the devices for 39,803 hours; on average 642 hours per participant. In detail, the devices were worn for 19098 hours in Cologne, 14701 hours in Valencia and 6004 hours in Sydney (Figure 8.2).

8.3.3 Motivation to Use Home-Based Health Technology

Motivation is a complex phenomenon and to motivate older people to use home-based health technology can be a challenge. In this study, two main sources of motivation have been observed. First, participants had a general interest in their health and fall risk. In daily life, the individual fall risk is not always obvious and visible. *“To know my fall risk makes me feel a bit more secure”*(Female, faller), commented one of the participants.

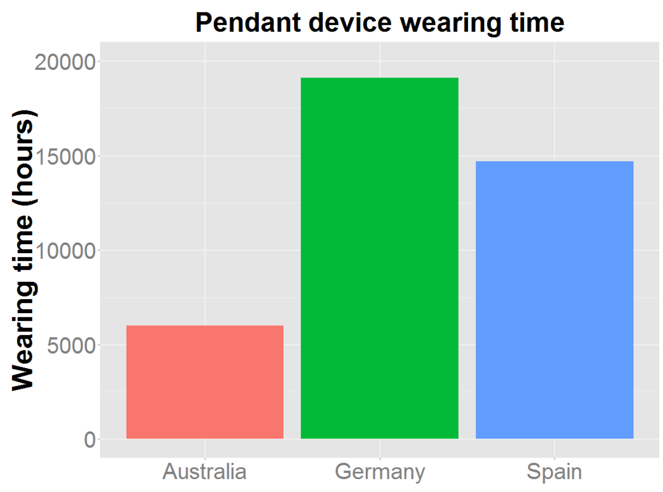


Figure 8.2: Pendant device wearing time for each study site.

Others mentioned that they were interested in their health and fall risk to improve on the deficits. Second, participants wanted to help and please the researchers. When they were questioned about their motivation to use the iStoppFalls assessment and pendant device their answer was as simple as *"because we were asked to"*.

Normally, fall risk assessments are conducted in a clinical environment supervised by a health professional. The home-based assessments were perceived as more natural, less time consuming and more convenient. One man summarized, *"I don't think normal [clinical] assessments can give you a true result because you can have a bad day... when you go there and you know it's going to be a long period... and you need a lot of concentration and whether you say to yourself, well, it doesn't matter what the results are, you are still nervous because you want to do as well as you can"* (Man, non-faller).

8.3.4 Experience with iStoppFalls Assessment

Most of the participants considered the experience with the iStoppFalls assessment as positive. This is shown in the comments from the open-ended questions on their experience with the fall risk assessment (Table 8.3).

The participants who did not perform the iStoppFalls assessment explained that they were already aware of their risk of falling and therefore careful. Further, they mentioned that technical issues, personal reasons (i.e. health problems or home situations) or that they did not know about that functionality of the system as the main reasons that prevented them from performing the assessment.

Table 8.3: Comments about the experience with the iStoppFalls assessment.

Participant	Comment
Woman, non-faller	*"I found it [the fall risk assessment] good because it made me remain alert and I didn't have any problem with it."*
Woman, faller	*"I liked doing the fall risk tests. I think they helped me."*
Woman, faller	*"I felt quite happy with it [the fall risk assessment]. Yeah. I think I was able to do it reasonably well."*
Man, non-faller	*"I thought it [the fall risk assessment] was quite good. It made me to concentrate."*

Technology

When deploying health technology in private homes the available space has to be considered. For the Microsoft Kinect a space of about 2m by 2m free of obstacles in front of the TV is recommended. In this study, those numbers were the absolute minimum and it has been found that a space of 3m by 3m was comfortable and safe for physical movement. It has been observed that the Microsoft Kinect was sensitive to different light conditions which had to be considered when installing the equipment in the private homes close to windows and doors. In the majority of households, participants preferred the system to be placed in the living room. The participants had favorite places to sit or work in the living room which had made furniture arrangements sometimes difficult.

The iStoppFalls assessment system used the participant's existing TV as the central communication device. This has been accepted and appreciated by the participants. However, at the beginning of the study some people raised concerns that the system could interfere with their daily TV program.

In general, when participants were asked about their experience with the iStoppFalls assessment they mentioned technical issues, especially at the beginning of the study. It has to be emphasized that the iStoppFalls assessment was conducted as part of an RCT where participants were asked to exercise two to three times per week with the same equipment and that might have influenced their experience. However, the comments can be categorized in usability and hardware issues. One participant who experienced hardware issues emphasized the need for reliable equipment, *"It [the system] has to be reliable because it's frustrating to get up and be ready and... it doesn't work"* (Woman, non-faller). Another participant was more vocal and said, *"I felt it was sort of fruitless doing it when it did not work properly... it was annoying... not all the time, I mean it was really good when it worked"* (Woman, faller). Participants developed their own strategies to overcome technical issues as one male participant explained, *"Sometimes the program did not work... a log in problem or something that came up... we turned the PC off, had a look at it the next day and started it up again and it was all right"* (Man, non-faller).

Design of Tests

The iStoppFalls assessment comprised of a reaching reaction time test, stepping reaction time test, a set of static balance tests and a five-time-sit-to-stand test. The majority of the interviewed participants mentioned that they liked the reaction time tests most. They attributed this to the facts that they were fun, challenging and *"not too difficult"*. This was the case with a female participant who argued, *"The reaction time tests are better from a game point of view"* (Woman, faller). Another participant commented on the challenging aspect, *"That [the stepping reaction time test] is a challenge... one day I wanted to get through this without a mistake... I tried it about four times and I finally did it, and I felt good"* (Woman, non-faller). A third participant mentioned, *"The stepping reaction time test seemed like a really good test of not only reaction time but also of my balance"* (Woman, faller).

In this study, balance testing and in consequence balance training were perceived as very useful to prevent falls. Participants used phrases like *"the balance part was beneficial"* and *"balance is very important to prevent a fall"*. For example one participant said, *"Even though I don't particularly like it [the balance test] that much I think it would be beneficial"* (Woman, faller). The static balance tests were remembered as useful but also as challenging and uncomfortable. One participant explained the difficulty, *"When I did the balance tests with the one foot in front of the other, I found it very hard to keep my balance"* (Man, non-faller). Another participant mentioned, *"I did not like the balance tests where you had your one foot in front of the other... the position felt uncomfortable"* (Woman, faller).

In general, participants reported no issues with the five-time-sit-to-stand test. Only one participant explained that she had knee problems and did not like to perform the test. She said, *"Your sit to stand [test] doesn't worry me greatly, but I can't afford to damage my knees"* (Woman, non-faller). Strength was perceived as an important factor to prevent a fall. This was evident from the comment of a participant who said, *"If you are strong enough you can save yourself from a fall"* (Man, non-faller).

The exergame approach with full-body interaction was considered as very interesting. No participants had a problem in understanding the concept of controlling the avatar. However, sometimes the avatar irritated participants with unusual poses which resulted from problems in detecting the correct movements of participants. One woman explained her experience, *"The tests are good, they are easy to understand with the avatar... as long as the avatar does what I'm doing and not decides to do its own thing"* (Woman, faller).

Frequency and Duration

The participants were asked to perform the iStoppFalls assessment at least once every month. The technology had to fit the individual schedule and routines to be accepted by the participants. In the case of a female participant this integration was not achievable. She explained, *"It was just a pain with my husband and the television... he watches it* *all day... it was a nuisance for him if I was doing it [the assessment] and so I tended to do it very early in the morning, five o'clock in the morning or late at night after he had gone to bed, which wasn't really very convenient for me"* (Woman, faller).

One session which included the balance, strength and reaction time tests took about 15 to 20 minutes. When participants were asked about their preferred frequency for a home-based assessment the answers varied from once a week to once every three months. One woman argued for longer intervals and said, *"It just gives you a longer period to judge how you're going"* (Woman, faller). When asked about how much time they would be willing to spend performing the fall risk assessment their answers varied from five minutes to 60 minutes, but most participants agreed that 30 minutes would be acceptable.

Safety and Support

No adverse events have been reported in this study. Participants were asked if they felt safe when they performed the iStoppFalls assessment and all participants answered yes. At the beginning of the iStoppFalls assessment study and in the instructions of each test participants were instructed to place a chair in close proximity and to hold on the chair if required. However, four participants admitted that they did not always use a chair. As one man said, *"When I first started yes [I used a chair], but then after a while I didn't need the chair"* (Man, non-faller). Another man put it this way, *"Not always... I had no fear of falling"* (Man, non-faller). One woman talked about using the chair and said, *"That was the worst thing about it... these chairs are heavy [to carry]"* (Woman, faller). Most participants reported using a chair at least for the balance tests.

In this study, participants were asked to perform the iStoppFalls assessment independently on their own instead of a supervised assessment performed by a trained person. The majority of participants said that they preferred to do the iStoppFalls assessment on their own. One woman stated, *"I think it's better to do it [iStoppFalls assessment] on your own, because you're not being judged by anybody else... I would get embarrassed especially if I did things wrong"* (Woman, non-faller). She also told us that she might make more mistakes if someone was watching her. Another participant told us that he would prefer to perform the fall risk tests together with a trained person or his wife, because it would encourage him to perform the tests better.

8.3.5 Experience with Wearable Sensor

The participants were asked about their experience with the pendant device. Most of the participants considered their experience as positive which is evident from the comments in the interview study (Table 8.4).

Technology

Similar to the iStoppFalls assessment, some people reported technical issues with the pendant device especially at the beginning of the study and emphasized the need for

Table 8.4: Comments about the experience with the wearable pendant device.

Participant	Comment
Woman, faller	*"It was quite comfortable. You forgot that it was around your neck."*
Man, non-faller	*"I really had no problem with the pendant."*

reliable equipment. One participant commented, *"There was no point wearing the device while it was not working"* (Woman, non-faller). Another participant argued for reliable and unobtrusive wearable devices in general, *"It should be something you just put on in the morning and forget about it"* (Woman, non-faller).

The pendant device had a LED light to signal its operating status. When the device was turned on and ready for recording the green light flashed up every 40 seconds. The participants did not like the flashing LED because although the device was worn under clothing the light was sometimes visible to others. One woman said, *"I didn't like the flashing light because people kept asking me about it"* (Woman, faller). Another woman explained, *"People asked me if something is wrong with me because I'm flashing"* (Woman, faller). One man joked about the light, *"It was very bright, I looked like a terrorist"* (Man, non-faller). However, participants developed their own strategies to cope with this issue, *"I put the pendant on back to front with the light towards my body"* (Man, non-faller). Other participants reported that they used tape to cover the LED light.

Design

Interviewees were asked about their opinion on the form factor of the device. It has to be mentioned that the pendant was a research prototype and not a final product. In general, participants argued for small, lightweight and thin wearable devices. This was evident from the comments, *"The pendant needs to be lightweight that you don't feel a drag"* (Woman, non-faller), *"The pendant would be probably nicer if it would be a bit smaller and flatter, but that's not the end of the world"* (Man, non-faller) and *"Wearables should be not too heavy, because you want to forget that you are wearing something extra"* (Man, non-faller).

Overall, participants were satisfied with the position and attachment of the pendant device. *"The position around the neck didn't worry me"*, said one woman (faller). Another interviewee mentioned, *"It was easy to put on and off"* (Woman, non-faller). One participant explained in detail, *"Wearing wasn't any problem. I guess we were lucky that it was mainly winter all the time and therefore you could just put the pendant under your shirt or jumper. I'm not too sure how it would be in the middle of summer when you are just wearing a sleeveless shirt with no collar. Then it might be much more visible. You might think sometimes, I'm not going to wear it today because I'm going out to a party and I don't want people to ask about it"* (Woman, faller).

Especially women were worried about the look of the pendant. One woman argued, *"I* *didn't like the pendant around my neck. A lot of times I'm attending meetings and things like that. I have to look reasonably nice"* (Woman, faller). Similar the comments from other participants, *"I prefer to wear the pendant underneath clothing. Because at our age you don't want to have things hanging around your neck. If I went out and dressed up, I wanted to look my best and didn't wear the pendant"* (Woman, non-faller) and *"If you want to go out looking really lovely and have your gold chains hanging around your neck and then you have the pendant to put on you maybe don't think it looks too good"* (Woman, faller).

Compliance

When asked participants about the reasons which prevented them from wearing the pedant they mentioned that they sometimes just forgot to put it on or that they did not like to wear the device outside of their homes. One woman explained, *"It was probably forgetfulness in a lot of cases. . . I forgot that I should have been wearing it all the time"* (Woman, non-faller). Another participant described, *"I had to remember every morning to put the pendant on after charging. A couple of mornings I didn't remember to put it on for the first hour or so and then I remembered it"* (Woman, faller). One female participant explained that it was highly context dependent if she used the device or not, *"It depends where I was going whether I would wear it or not. I didn't wear it when I was going shopping or visiting someone"* (Woman, faller). Another interviewee explained in this context, *"I didn't wear it when I was going out shopping or anything like that, but other than that I wore it"* (Woman, faller).

8.3.6 User Feedback

With the iStoppFalls assessment participants received instant feedback on their performance after each test and were able to monitor how their performance and fall risk changed over the four months. From the wearable pendant device participants received feedback regarding their daily and weekly physical activity levels. When asked about their thoughts on knowing their own fall risk the majority of participants stated they were interested in that information, especially the participants who had already experienced a fall. Participants discussed the importance of the accuracy and reliability of the information given in the feedback and how the information had an impact on their motivation to be more active. *"I think everybody likes to see that what they are doing is worthwhile and therefore you are more enthusiastic to continue if you see that you are improving"* (Woman, faller), explained a participant. They were satisfied with the combination of numbers, text and graphs in the feedback. One woman commented, *"Well, the result that I got from test with the graph showing lines this way and that way, that was helpful"* (Woman, non-faller). In general, the participants preferred simple visualizations and written text. When asked about their ideas on how to improve the feedback they used phrases like *"just written information is fine"*, *"it should be fairly simple"* and *"as long as you can see a number or a word that you know you are improving it is fine"*.

8.3.7 Continuing with Home-based Assessments

The participants were asked if they could see themselves to continue with the iStoppFalls assessments on a regularly basis or to wear the pendant device. Two participants answered that they could not imagine doing so. One woman explained that at 86 years of age she just felt too old for the program. The other participant believed that it would not be of great benefit for her because she was already aware of her risk of falling. The other eight interviewees said that they would like to continue.

8.4 Design Considerations for Future Fall Risk Assessments

In order to develop an individualized care plan for preventing falls, the factors contributing to a person's increased risk of falling need to be systematically and comprehensively identified. Based on the findings from the home study and interviews important aspects for the future design of sensor-based home assessments, by means of directed routine assessments or monitoring of daily activities, will be discussed and highlighted hereafter.

8.4.1 Directed Routine Assessments (e.g. Using the Microsoft Kinect)

Technology

Sensors used for directed routine assessments should be accurate, low-cost and reliable. The Microsoft Kinect is a low-cost computer vision sensor which does not require any additional equipment (e.g. sensors on the floor) which could be a potential tripping hazard. The Kinect has been shown to be accurate in measuring temporal and gross spatial movements. However, it showed less accuracy for smaller movements, especially in the anterior-posterior direction [92]. Therefore, it is recommend to focus on the measurement of larger rather than small movements when designing virtual tests for assessments or to complement the Kinect measurements with a body-worn sensor (as investigated in Chapter 6).

The Kinect was sensitive to different light conditions and sometimes failed to locate and isolate the participant if objects (e.g. a chair for safety reasons) were in close proximity. The successor model Kinect One looks promising and might be a big step forward in reliability. If proven, this would make it an ideal device for future sensor-based home assessments.

Aligned with Axelrod et al. [113], the findings suggest that when deploying health technology in private homes, the available space, purpose of rooms (e.g. living vs. bed room) and use of existing technology (e.g. TV) should be considered. In a recent study, higher user acceptance has been observed if the health technology was not bulky and could be freely positioned within the homes [104]. In addition, the complexity of the technology has to be taken into account. For the iStoppFalls assessment a TV, PC, set-top-box and

Kinect were required. Connection issues - especially between the set-top-box and PC - were common causes for system failures. The main advantage of the set-top-box was that participants could start the assessment directly via the TV. However, less complex system designs for example by combining the functionality of the PC and set-top-box would be recommended.

Design of Virtual Tests

It is recommended that assessments should be based on clinical tests which already have proven evidence in discriminating between fallers and non-fallers and in predicting fall risk; preferably based on data from prospective studies. However, such tests cannot be implemented in a virtual environment without modifications. For home-based self-assessments tests should be engaging, safe and challenging, but not too difficult for older people. The reaction time tests (i.e. choice stepping and reaching reaction time test) were favored by the participants. This may be because they were more similar to a "real" video game compared to the other tests in the iStoppFalls assessment. In order to design future directed routine assessment tests, the concept of gamification might play an important role to improve user experience and user engagement [181].

For example, the game aspects of the five-times-sit-to-stand test of the iStoppFalls assessment could be improved by having participants virtually collect items by standing up and sitting down five times as fast as possible. The Pigeon Express Game [144] is an example of a sit-to-stand exergame which could be adapted for the assessment of fall risk. Interviewees described the balance testing as difficult, but useful because in their mind a fall was directly associated with losing the balance. This is consistent with the health belief model, in that people are more likely to adhere to regular assessments if they believe that it is associated with their risk of falling [182]. In order to make the balance test more engaging, it could be redesigned along the following lines: Participants see a target (e.g. dartboard) on the TV screen while they have to hold the position of a moving object, controlled with their body movements, in the bull's-eye of the target. The score increases as long the participants keep their balance and the position of the moving object in the bull's eye.

Safety and Support

Safety is an important aspect for the design of home-based self-assessment tests. From the home study and interviews it has been learned that some participants did not use a chair during the tests although they were advised to do so several times. This might be explained by the overestimation of one's own capabilities or underestimation of the risk of falling. This is in line with the results of a recent study investigating the use of exergames for balance training in older people [119]. As a possible solution, assessment tests in which a chair or support forms an integral part of the test (e.g. the five-times-sit-to-stand test) are recommended.

Home-based assessments like the iStoppFalls assessment can be conducted in regular home visits by trained personnel or independently by older people as a self-assessment. The majority of interviewees said that they would prefer to perform the assessment tests on their own. Therefore, the level of support has to be considered for the future setting of home-based assessments. Tests assessed by an evaluator ensure the correctness and safety. However, an observer could have a negative influence (e.g. social anxiety) on the test performance [183].

Frequency and Duration

In general, home-based health technology has to fit the individual routines of daily life to be accepted by older people. Therefore, the interval, duration and rules required for a directed routine assessment should be considered.

Regularly repeated fall risk assessments could help identify and target those people at an increased risk of falls and predict falls with more accuracy in future. Incorporating technology-based self-assessments provides an opportunity to gradually increase the frequency of risk assessments. To my knowledge, there is no evidence available yet about the optimal time interval to capture changing health conditions in old age. From the interviewed healthy community-dwelling older volunteers w various answers regarding the preferred frequency of a home-based directed routine assessment were received. There was no tendency towards a specific interval, but answers varied from once a week to once every three months. However, when using short intervals (e.g. weekly) a possible training effect would need to be taken into account and with long intervals a prompting system to remind participants to perform the assessments would be necessary. It is recommended to use automatic reminders for example delivered through a smart phone or television. It would be also recommended that an assessment lasts for 30 minutes or less.

8.4.2 Monitoring of Daily Activities (e.g. Using Wearable Sensors)

Technology

Wearable sensors should be accurate, reliable, low-cost and unobtrusive to be accepted by their users. When designing wearable technology there is always a tradeoff between accuracy, size, weight and power consumption. The pendant device used within this thesis included a three-dimensional accelerometer and a barometric air pressure sensor and was accurate in detecting sit-to-stand movements in older people. Therefore, a multi-sensory approach using different types of sensors is recommended as it may improve accuracy, reliability and lead to more complete information [184].

Interviewees mentioned that they stopped wearing the pendant device if they had the impression it did not work properly. Therefore, a wearable device used for day-to-day measurements should be reliable and operate maintenance-free for long periods [185]. A LED light signalled the user that the pendant device was active and working. Participants mentioned that they did not like the flashing light because it was sometimes visible through clothes and also visible to other people. Based on these findings, it is recommended that wearable devices provide feedback regarding the operational status, but the feedback should be unobtrusive and not disruptive.

User feedback on fall risk monitoring should be accessible, reliable, simple, understandable and should include comments on possible improvements. With an appropriate feedback people can reflect on their results and its correlation to their routines and daily activities [112].

Interviewees mentioned that regular feedback about their physical performance was helpful for their motivation. A wearable device used for long-term monitoring should provide a method to unobtrusively access the data for regular evaluations. Smart algorithms could automatically generate performance indicators from the sensor data as demonstrated in this thesis. These algorithms could be implemented directly on the wearable devices, on a separate device (e.g. PC or smartphone) or in the cloud depending on the required computational resources.

Battery lifetime and power consumption are great challenges when it comes to wearable technology [185]. In the home-based study, participants wore the device during the day and charged it overnight. It has been decided not to integrate a gyroscope (in addition to the accelerometer and barometric air pressure sensor) due to high power consumption. However, in general, it is recommended that a wearable device should be designed to be useable for at least one day without recharging.

Design of Wearable Technology

For any wearable technology it is important to consider the size, weight and shape of the device. In agreement with previous studies, it has been found that the devices need to be kept small, lightweight, thin and should not hinder people in their daily movements [177, 185]. The position and form of attachment have to be considered too [177, 186]. Figure 8.3 illustrates unobtrusive areas characterized by large surfaces and low movement when the body is in motion to position wearable devices. Current wearables require to be attached directly to the skin or use a form of indirect attachment with straps or belts to provide reliable measurements. In the home study, participants were asked to wear the pendant device attached to a self-adjustable lanyard around the neck. Overall, participants were satisfied with this approach as it was perceived as easy and more comfortable than attaching the device to the skin. Some participants mentioned that they were worried about stigmatizing and preferred to hide the pendant below clothing. Therefore, when designing future wearable technology it is recommended to offer an alternative way of wearing the device to achieve maximum compliance.

8.5 Discussion

8.5.1 Feasibility of iStoppFalls Assessment

In previous studies the iStoppFalls assessment, including Kinect-based tests for fall risk assessment, has been shown to discriminate well between fallers and non-fallers in the clinical setting. In this study, the feasibility of the iStoppFalls assessment at home was examined. This is the first study where older adults were asked to assess their fall risk, with a sensor-based self-assessment delivered through their television, on their own at home.

Sixty-two older people from Australia, Germany and Spain performed 241 assessments over a period of four months. The iStoppFalls assessment was conducted by participants with a high or low risk of falling. There was no significant difference in the number of assessments performed regarding the fall risk measures. The present findings suggest that the Kinect-based assessment tests are feasible to administer in the home setting, but also that further research is necessary to refine it.

8.5.2 Feasibility of Wearable Sensor

In a previous study the wearable pendant based on a proposed algorithm accurately detected sit-to-stand movements during activities of daily living and successfully differentiated between people who were at risk for falls from people who were not at risk. In this study, the long-term use of the pendant device was investigated. The participants wore the pendant for a total of 39,803 hours over a period of four months. The findings of this study suggest the feasibility and preliminary acceptance of the pendant in daily life, but also highlight that further work (e.g. on the design) is necessary to improve user acceptance.

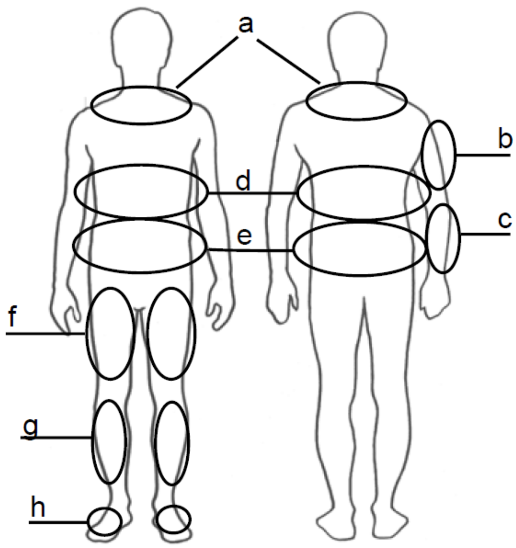


Figure 8.3: Unobtrusive areas for wearable technology: (a) collar area, (b) rear of the upper arm, (c) forearm, (d) rear, side, and front ribcage, (e) waist and hips, (f) thigh, (g) shin, and (h) top of the foot [177].

8.5.3 Study Limitations

The adherence to the monthly assessments was moderate across all sites (39%). In a recent systematic review the adherence to home-based exercise programs to prevent falls was estimated with 21% [187]. However, an assessment is different to an exercise. This study had certain limitations that might have prevented us from achieving a higher adherence: 1) this study was conducted as part of an RCT and participants might have focused on the exercises rather than on the assessments and 2) a mid-term assessment between month two and three was conducted by a trained researcher as part of the RCT and might have been mistaken for the monthly assessment. Participants were assessed on the iStoppFalls assessment in the laboratory prior to the study and this might have influenced their skill level with the technology. However, the laboratory assessment were supervised and the system operated by a trained researcher.

8.5.4 Conclusion

In summary, this study described the feasibility of a Kinect-based system and a wearable pendant device to be utilized at private homes. The user experience and acceptance was investigated and considerations for future home-based assessments were elaborated. The findings constitute an important first step towards the development of accurate, objective and low-cost methods to assess fall risk at home.

CHAPTER 9

Summary, Conclusions and Future Work

9.1 Summary

Accurate fall risk assessments may assist by identifying individuals at increased risk to enable appropriate intervention before a fall occurs. To date, the methods used to assess fall risk often lack objectivity or require expensive equipment and specialized knowledge. Clinical tests are often only moderately predictive of falls because such assessments are a one-time snapshot performed under ideal circumstances dissimilar to those experienced by older people in everyday life.

As outlined in the literature review (Chapter 2) new sensor-based methods may provide inexpensive ways to objectively assess fall risk. Two approaches were identified as suitable: 1) directed routine assessments (e.g. using the Microsoft Kinect) and 2) monitoring of daily activities (e.g. using wearable sensors). This thesis investigated the feasibility of these two approaches to accurately assess fall risk of older people in both clinical and home settings.

The main research questions were:

1. Can physical tests of balance, strength and reaction time measured using a Kinect-based system assess fall risk in older people?
2. Can the monitoring of activities of daily life using a wearable sensor assess fall risk in older people?
3. Can assessments of fall risk be undertaken with the Kinect-based system and wearable sensor by older people unsupervised at home?

Can physical tests of balance, strength and reaction time measured using a Kinect-based system assess fall risk in older people?

To address this question, a Kinect-based system including physical tests of several domains was developed (Chapter 3) and evaluated in community-living older people (Chapter 4 and 6). This included the development of algorithms to quantify performance on these tests based on the sensor signals.

In Chapter 4, a signal processing algorithm was proposed to quantify performance on a new Kinect-based five-times-sit-to-stand test. Timing and speed related measurements were successfully extracted from the skeleton data of the Kinect. The measurements differentiated well between the fallers and non-fallers in 94 community-dwelling older people and showed good convergent validity to clinical fall risk measurements. The findings demonstrated it is feasible to use the Kinect-based five-times-sit-to-stand test to assess fall risk in older people.

In Chapter 5, algorithms were presented to quantify performance on new Kinect-based choice reaching and stepping reaction time tests. Measurements were derived from the skeleton data of the hand and feet movements in response to cue signals. The sensor-based measurements discriminated well between the fallers and non-fallers and demonstrated good convergent validity to traditional reaction time measurements in 94 older people. The findings demonstrated it is feasible to use the Kinect-based reaction time tests to measure upper and lower limb movements, which are important to avoid a fall or minimize injuries if a fall occurs.

The Kinect has demonstrated to be accurate in measuring temporal and gross spatial movements, but less accurate in measuring fine motor movements. Therefore, in Chapter 6, the feasibility of complementing the Kinect measurements with data from a wearable inertial sensor was investigated. The findings indicate that the inertial sensor provides complementary information regarding the quality of movements (e.g. stability-related data) to that provided by the Kinect.

Can the monitoring of activities of daily life using a wearable sensor assess fall risk in older people?

In Chapter 7, the ability of a wearable sensor to monitor fall risk during activities of daily life was investigated. A signal processing algorithm based on wavelet transformations of accelerometer and barometric air pressure sensor data was developed to detect sit-to-stand movements (i.e. an indicator of fall risk). The algorithm accurately detected sit-to-stand transitions in 25 older people performing typical daily activities and 94 older people performing sit-to-stand movements as part of a clinical assessment. Further, the algorithm differentiated well between the people at risk of falls from the people not at risk, which indicates the feasibility of the wearable sensor to assess fall risk during activities of daily life.

Can assessments of fall risk be undertaken with the Kinect-based system and wearable sensor by older people unsupervised at home?

Over a four month study period, the long-term use of the Kinect-based system and pendant-style wearable sensor was investigated in the homes of 62 older people (Chapter 8). Participants were asked to independently perform at least one assessment session each month and to wear the pendant during the day. At the end of the study, interviews were conducted to investigate user experience. Most participants used the Kinect-based system and wearable sensor on a regular basis, felt positive about their experience and could see themselves continuing using such assessment methods. Therefore, the findings suggest that both fall risk assessment approaches can be undertaken by older people in an unsupervised home setting.

9.2 General Discussion

There is a strong interest in new methods for fall risk assessments. Recent research has focussed on accurate and objective technologies to enhance clinical fall risk tests and has provided preliminary evidence that these methods can differentiate between people at risk of falls from people not at risk (Chapter 2). However, the sample sizes of the majority of studies have been too small to provide any definitive conclusion regarding the accuracy of classifying fallers from non-fallers. Most of the studies have been conducted in a laboratory setting and therefore, do not provide any information regarding the feasibility of using these new technologies outside of this setting.

For the first time, physical tests using the Microsoft Kinect were developed and evaluated to assess fall risk in a large sample of community-living older people. Further, in contrast to other studies, the long-term use of this system to assess fall risk unsupervised at home was investigated. A Kinect-based approach has several advantages compared to other sensor-based methods in clinical and home settings and they can be summarized as: 1) easy to set up and administer - no further physical equipment is needed, 2) safe - no additional trip hazards, 3) inexpensive - the Kinect is a widely available consumer device and 4) fairly accurate - enables whole body tracking of participants' movements.

There is an emerging interest in the use of wearable sensors for continuous monitoring of daily activities (Chapter 2). This thesis extends the findings of previous work by: 1) providing a new method to accurately detect and assess sit-to-stand movements in daily life using a new pendant-style inertial sensor and 2) investigating the long-term use of such a device in older fallers and non-fallers. The proposed algorithm demonstrated excellent detection accuracy and allowed more vigorous movements in more athletic participants and slower movements in frailer participants to be detected. In contrast to other wearable sensors, the pendant could be freely worn on a lanyard around the neck. This approach presented a new challenge for developing an accurate detection algorithm, but was motivated by a desire to make the device more comfortable and easier to use in daily life.

9.3 Applications

In the clinical setting, these new methods could lead to accurate, objective, low-cost and easy to administer tests to identify older people at increased risk of falls. An accurate and objective diagnosis could assist in the selection of participants who would benefit most from intervention programs or for tailoring interventions to the individual needs of older people. Accurate and objective assessment systems (e.g. electronic walkways, force plates or camera-based systems) exist, but they have not found their way into clinical practice as they are expensive and require special expertise to administer. The Kinect-based system and wearable sensors have the potential to overcome these barriers and may therefore enter mainstream clinical practice.

These new methods could be also used to prevent falls in hospitals and nursing homes. Older people who are living in such facilities fall more often than those who are living in the community [18]. The presented approaches could be used to regularly assess and monitor the fall risk in these residents and therefore would enable timely interventions.

In addition, such sensor-based tests could complement or replace clinical tests to provide older people's health care providers and caregivers more information about the performance of their patients at home. This would allow older people to stay in their familiar environment for as long as possible and in consequence reduce health care costs.

For example, the Kinect-based tests could be conducted at private homes by the following means: 1) test administered in monthly visits by trained personnel or 2) test performed independently and unsupervised as a self-assessment or self-management program to empower older people. The pendant device could be worn during the day to provide an unobtrusive method to quantify the quality and duration of daily activities. Both methods would provide measurements of fall risk over time which could be used to provide feedback regarding physical benefits (e.g. of a fall prevention exercise program) and to alert older people or their caregivers if fall risk increases significantly.

The sensor-based methods presented in this thesis may not be limited to fall prevention in older people. For example, home-based assessments of motor and non-motor functions could enhance the treatment of diseases (e.g. Parkinson disease) which are traditionally based on periodic clinical evaluations or self-reporting of symptoms [188]. In addition, home-based assessments could guide rehabilitation strategies (e.g. after stroke) by providing feedback regarding the success of training programs. Another application could be the early detection of diseases (e.g. dementia) by monitoring risk factors before symptoms appear.

9.4 Limitations and Future Work

Guidelines for the future design of sensor-based home assessments were described in detail in Chapter 8. Based on these recommendations and the results of this thesis important topics of future research have emerged and are summarized below.

The algorithms introduced for the Kinect-based system and wearable sensor accurately differentiated between the people who were at risk for falls from those who were not in the clinical setting. The home-based study confirmed the feasibility of both approaches to be undertaken at older people's private homes. However, future longitudinal studies are required to investigate the sensitivity of the Kinect-based tests and the pendant device to track long-term changes of fall risk in daily life.

The Kinect-based system included physical tests of balance, strength and reaction time. Within this thesis, the tests were examined separately. Future studies could investigate the ability of the whole system to quantify fall risk. In this regard, machine learning algorithms could be applied for decision support using the most discriminant features identified by this thesis.

The Kinect was accurate in measuring gross spatial movements, but sensitive to different light conditions and sometimes failed to locate and isolate the participant if objects were in close proximity. The successor model Kinect One looks promising with regard to significantly improved reliability.

Another means for providing more reliable results would be to complement the measurements from the Kinect with a wearable sensor as preliminary investigated in Chapter 6. These initial results look promising, but future studies are warranted to evaluate the advantages of this approach to quantify fall risk.

The wearable pendant device containing an accelerometer and barometric air pressure sensor was accurate in assessing sit-to-stand movements and feasible to utilize in both clinical and home settings. In younger people, wearable devices (e.g. smartwatches [189]) are gaining popularity and are slowly becoming mainstream. Future studies should investigate the ability of smartwatches or other next-generation wearable devices (e.g. e-textile sensors [190]) to assess fall risk in daily life.

In this thesis, the sit-to-stand movement was chosen because it is a common activity in daily life and provides a salient measure of mobility status of an older person. However, future wearable sensor-based algorithms could be developed to detect and assess different daily activities and may provide insights into the daily habits of older people by summarizing the time per day spent undertaking motor and non-motor tasks.

Another method to unobtrusively assess fall risk during the day could be to use smart home technologies (e.g. environmental sensors attached to house furnishings). For example, pressure sensors installed under chair legs [191] could be used to quantify sit-to-stand movements, smart scales could be used to unobtrusively measure day-to-day balance abilities and motion detectors could be used to passively measure gait velocity [192]. Future studies are warranted to investigate the potential of these technologies and their associations with fall risk in older people.

9.5 Conclusion

In summary, the findings of this thesis suggest that sensor-based methods to assess fall risk using the Microsoft Kinect or wearable sensors are accurate, objective, low-cost and easy to administer as well as feasible to be undertaken in both clinical and home settings. This thesis constitutes an important step towards the development of new methods to assess fall risk and in consequence to prevent falls in older people.

List of Figures

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Curriculum Vitae

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Personal Information

Nationality: Austrian
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Education

Higher Education

Vienna University of Technology, from February 2012 to January 2016
Doctoral Program in Computer Science (Medical Informatics),
focused on novel and innovative solutions in the field of health technologies

Vienna University of Technology, from May 2010 to November 2011
Master of Science in Computer Science (Medical Informatics),
graduated with honors, awarded degree *Diplom Ingenieur (MSc)*

Vienna University of Technology, from October 2006 to March 2010
Bachelor of Science in Computer Science (Business Informatics),
awarded degree *Bachelor of Science (BSc)*

WWEDU, Worldwide Education, from July 2010 to November 2012
MBA in General Management,
graduated with honors, awarded degree *Master of Business Administration (MBA)*

WWEDU, Worldwide Education, from April 2007 to June 2010
Academic Certificate Program in Finance Coaching,
graduated with honors, awarded degree *akad. FVB*

Secondary Education

HTL Rennweg (Higher technical secondary school), Vienna, from 2001 to 2006
Main focus on Information Technologies (Networking Technologies)
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Work Experience

Austrian Institute of Technology, Vienna, from February 2012 to September 2015
Researcher at the Safety and Security Department,
Assistive Healthcare Information Technology group

Neuroscience Research Australia, University of New South Wales, Sydney, from October 2013 to September 2014
Visiting PhD-student at the Falls & Balance group
(Prof. Stephen Lord and Dr. Kim Delbaere)

Hewlett Packard, part-time, Vienna, from July 2008 to February 2012
HP Education Service department

Central European Institute of Technology, Schwechat, from May 2011 to October 2011
Master student project (diploma thesis)

University of Applied Arts Vienna, project-based, from 2005 to 2008
Second Level support at the Central Computing Service (ZID) department

Highlights of Qualifications and Accomplishments

Honors and Awards

Awarded for the "Most Innovative Solution" at the Health and Wellness Innovation Hackathon 2013, Media Lab, Massachusetts Institute of Technology (MIT), Boston

1st place - Young Researcher and PhD competition, Ambient Assisted Living (AAL) Forum 2012, Netherlands

Personal Interests

- Crossfit
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- Surfing
- Mountain-biking
- Snowboarding
- Skiing