# Sensor technologies and fall prevention

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# CHAPTER 7

## Summary & General discussion

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The objectives of this thesis were to investigate the potential for using technology-based risk assessments for (1) fall risk identification in long-term care residents with dementia; and (2) to determine the changes in gait dynamics due to natural aging. ´Fall prevention´ is the overarching theme linking these two aims to identify situations that can lead to falls for highly vulnerable psychogeriatric patients, and detect deterioration in gait and balance of healthy old adults who might fall later in life. This final chapter summarizes the main findings, discusses the current state of knowledge and clinical implications, and proposes future directions per aim.

## Technology-based fall risk assessment in long-term care residents with dementia

### *Main findings*

Fall prevention is a critical issue in old adults in nursing homes and hospitals. Those adults fall more often than their healthy peers in the community because of physical and cognitive impairments. Fall prevention methods, including mobility training or behavior change interventions, have demonstrated limited success in reducing nursing home falls. Due to recent developments in sensor technology, it seems that monitoring long-term care residents would be a suitable alternative method of fall prevention. **Chapter 2** presents an overview of the effectiveness of wearable and non-wearable sensor technologies to prevent geriatric long-term care residents from falling. Fall rates, fall-related injuries, false alarms, and user experience were examined in twelve studies. Three randomized controlled trials showed no reductions in fall numbers, whereas three before-after studies reported a reduction of 2.4 to 37 falls per 1000 patient days. Although reductions in fall-related injuries up to 77% were reported, the current data are inconsistent and give no convincing evidence that sensors reduce the number of falls or fall-related injuries. Moreover, the number of false alarms (16%) is too high. The percentage of correct alarms should be greater than 90% to maintain full nursing staff attention. The following recommendations were made in Chapter 2 to improve clinical applications of sensor systems: 1) an effective fall prevention sensor system should cover multiple locations 24 h per day and monitor the circumstances in which falls occur; 2) such a system should map individual fall risks and underlying processes and lead to a decision-making model that can predict falls; and 3) sensor manufacturers should involve designers and users in sensor development and fabrication. Chapters 3 and 4 discuss the second and third recommendations.

**Chapter 3** described the fall incidence, fall-related injuries, and fall circumstances for twenty long-term care residents living at a geriatric ward. Eighty-five percent of the long-term care residents fell at least once during the 19 months in which falls were recorded.

A total of 115 falls (5.1 ± 6.7 falls/person/year) occurred, with 28% of falls witnessed by staff or a family member. Nearly one-third of all falls were associated with serious consequences. Two residents died prematurely as a result of hip fractures due to falls; these outcomes underscore the need for effective fall prevention in this population. Using existing data reported by nursing home staff, the relationship between patient characteristics and fall rate in long-term care residents with dementia was assessed to develop a fall risk decision-making model. Sixty-six patient characteristics were extracted from the electronic patient records and classified into seven domains: demographics, activities of daily living, mobility, cognition and behavior, vision and hearing, medical conditions, and medication use. A model was developed to identify the relationships between the sixty-six patient characteristics and fall rate. The results showed that cognitive impairment related to disinhibited behavior, in combination with mobility disability and fall-risk-increasing-drugs (FRIDs), was associated with a high fall rate. In contrast, immobility, heart failure, and the inability to communicate were associated with lower fall rates.

In **Chapter 4** the attitude of health care staff toward fall prevention technologies was examined. Participating staff members came from four closed wards housing long-term care residents with dementia. One of the wards was involved in the development of a new fall prevention system. The available sensor systems in the nursing home were bed-exit alarms and shoe chips. Questionnaire results showed that caregivers considered fall prevention very important. Caregivers were content with available sensor systems because a notification was given when a high (fall) risk situation occurred, but shortcomings were identified in the notification, activation, and availability of sensors. Proposed requirements for a new fall prevention system were: event notification without delay, an automatically activated sensor system, and availability for all residents. Interviews revealed that time, education, and management support were considered as very important factors by health care workers for the successful implementation of a new fall prevention sensor system technology. User involvement appeared crucial for nursing home staff to take part in research and generate willingness to invest in a new fall prevention sensor system.

### ***Sensor requirements in long-term care residents with dementia***

*Sensor type*

Chapters 2 and 4 presented data concerning the effectiveness and the pros and cons of fall prevention sensors currently used in intramural care facilities. It seems that long-term care residents with dementia prefer non-wearable sensors to wearable sensors because cables and patches of wearable sensors might cause obstructive situations which lead to resident agitation and attempts to remove sensors. Although many wearable sensors are applied and hidden within clothes, it is not uncommon that residents with dementia undress themselves several times per day in their confusion, making the sensors useless. Even non-wearable sensors must operate unseen by residents, as residents are often unable to cope with visible devices in their rooms [1,2]. For example, residents can feel threatened by a small active indicator light in their room. Residents will try to turn the light off, thereby making the device non-operational. Furthermore, automatic sensor activation is necessary in long-term care facilities because residents with dementia will be unable to activate a sensor independently [3]. However, sensor activation by staff is not the solution; health care staff often includes temporary employees who are unfamiliar with the available sensors and individual alarm settings. Automatic sensor activation can reduce human errors and false alarms. Thus, non-wearable, invisible and automatically activated sensors should be used for fall prevention in long-term care residents with dementia.

*Sensor network*

Multiple non-wearable sensors could be integrated into an interlinked sensor network. A coupled multi-sensor network provides the opportunity to examine resident characteristics and monitor residents at different locations in the facility. Various sensors and algorithms have been developed to recognize specific human activities and determine deviations from expected patterns [4,5]. Those technologies, among others, are used for fall detection, sleep monitoring, physiological parameter tracking (e.g., heart rate, breathing rate, and gait) and activity estimation [4]. Integrating multiple existing sensors and algorithms makes it possible to detect, classify, and monitor daily activities. The recorded data can be used as input for a fall risk decision-making algorithm to more effectively prevent falls. This will be further discussed in paragraph 7.1.3.

Their small spatial scope limits the operational range of the sensors currently used for fall prevention. Such sensors can 'see' only a small area (Chapter 2). Multiple sensors, interlinked within a network, could cover a larger area and monitor residents in multiple rooms. The broader spatial permits increased resident freedom of movement and assists health care staff in monitoring residents. However, one difficulty in processing data from (multiple) non-wearable sensors is monitoring multiple persons in the same room or residents moving between rooms. If the software is designed to capture only one individual, the presence of multiple people in the same room might cause false alarms or miss situations with risks for a fall [3]. In long-term care facilities, multiple residents will require monitoring and health care staff and visitors will be present in those monitoring areas. Therefore, the software processing the sensor data should distinguish residents from one another, from visitors, and from health care staff by means of a resident recognition algorithm. Sensor systems might lose track of a resident when one person blocks the line of sight to another person or when residents change rooms [3]. Programming an algorithm to recognize residents is a great challenge for future software development.

*Privacy Issues*

Monitoring residents and storage of sensor data entails addressing privacy issues, especially when a camera is integrated in the sensor system. Data of residents, health care staff, and visitors are stored and might identify individuals. Therefore, laws and regulations concerning the storage and accessibility of the gathered data need to be strictly applied. In The Netherlands, data management should comply with the privacy law ('Wet bescherming persoonsgegevens'). Additionally, the European Commission intends to strengthen and unify data protection for individuals with the General Data Protection Regulation (GDPR), which will be introduced in 2016. Finally, when data is used for research purposes, the Declaration of Helsinki is applicable.

Regulations about data storage and accessibly are strictly formulated. All data needs to be made anonymous prior to storage. The key to identifying individual residents from the coded data must be stored separately, only accessible to select personnel. Collected data should only be used for the goals set prior to data recording to protect the privacy of all people involved. Thus, even those with authorization to access data shall not use the data without a pre-determined purpose [6]. Storing data anonymously and controlling access helps ensure a safe environment for residents, visitors, and staff.

### ***A fall risk model in long-term care residents with dementia***

A fall risk profile is the basis for the decision-making algorithm. A decision-making algorithm is the software in a fall prevention sensor system that identifies high fall risk situations. A profile, the 'ground-truth,' based on the normal activity patterns and health status of the resident, is necessary to distinguish deviations from normal situations. By determining fall risk factors and underlying causes for falls, residents with an increased fall risk can be identified. A threshold must be set to sufficiently discriminate between a high fall risk situation and a not-at-fall-risk situation. By comparing the 'ground-truth' with the current state of the resident, unusual behavior and high fall risk situations can be identified.

*A static versus dynamic fall risk model*

Chapter 3 presents a model that determined the association between fall rate and patient characteristics. The results showed that the combination of impaired mobility, indicators of disinhibited behavior, diabetes, and use of analgesics, beta blockers, and psycholeptics were associated with falls. Those results already give some useful guidelines for health care staff in clinical practice. Health care staff can specifically address the need for firm and safe footwear for residents. In addition to footwear, regular foot care is important to minimize mobility problems. Furthermore, careful medication prescriptions and frequent updates to medication use and doses can further minimize loss of balance and falls [7–9]. By reviewing medication use regularly, prescriptions can be adjusted to avoid unnecessary and excessive medication use.

Chapter 3 presents a static fall risk model, as the model considers residents' fall risk at one given moment in time. However, given the nature of dementia, with progression of mental state and changes in physical well-being, one might expect residents' 'normal' situation to change over time. Therefore, a dynamic fall risk model is required for a technology-based fall prevention system. The model could be updated and adapted to the medical and physical state of each resident. Adding regular health care measures (e.g., blood pressure and weight) and lab test results (e.g., hydration status, glucose level, and cholesterol) and including up-to-date information about diagnoses, behavioral problems, and actual medication use might improve fall risk model accuracy.

*Adding sensor data to the fall risk model*

Monitoring residents with sensors 24 h per day allows more real-time information about residents' health status and activities. Information about activities, walking abilities, restlessness, and location can be derived from various sensors. When using a camera-based system, silhouettes can be generated to anonymize the visual data, as presented in Figure 7.1 [10]. However, those silhouettes have another purpose: they are useful to determine resident gait abilities. With shape analysis, one can obtain spatiotemporal gait parameters such as stride time, step length, and step width [10–12]. In addition to camera-based systems, sleep mattress sensors are introduced into health care facilities to measure large body movements, heart activity, and respiration efforts [13,14]. Data derived from various sensors should be added to the personalized profiles to determine the current health state of the resident and update the level of fall risk.

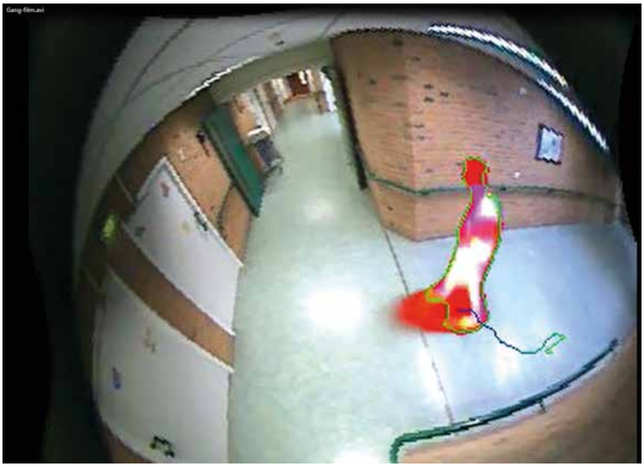

**Figure 7.1** Video monitoring with silhouette generation.

*Personalized and self-learning fall prevention model*

Residents with dementia in long-term care facilities exhibit highly heterogeneous physical and cognitive characteristics. Therefore, an individual approach is mandatory in the development of a smart fall prevention system. The fall risk decision-making model needs

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to be personalized so that fall risk alarms are accurate and reliable. Personalized models that identify fall risks are highly data intensive: models must collect a large amount of individual data over extended periods of time and perform on-line self-updates. The model would incorporate new event information detected automatically or entered by an operator and would re-train itself using self-learning strategies to aid in current and individual fall risk decision-making [3].

### *User requirements for a fall prevention system*

Developing and implementing technologies successfully into practice requires involvement of both designers and users. A recent review addressed the underrepresentation of user acceptance, ease of use, business models, and privacy in technology development [5]. These factors are strong indicators of how well the technology will eventually be accepted by users and the market [5,15]. However, with the introduction of more and more technology into clinical settings, awareness of the importance of user involvement is increasing. Depending on the setting and the device that is developed, users might be residents, family members, or health care staff. In our fall prevention project, the users were the health care staff of the long-term care facility, as described in Chapter 4.

The International Organization for Standardization (ISO) presented an overview of the activities that are recommended in user-centered designs, in the ISO 9241-210. The standard includes the following six principles of a user-centered design: (1) understanding the context of use (e.g., users, tasks, environment); (2) active involvement of users in design and development; (3) user-centered evaluation of the design; (4) iterative process; (5) evaluation of user experience (e.g., perceptual and emotional aspects); and (6) the design team includes multidisciplinary skills and perspectives [16]. Applying those principles in designing new sensor technologies is expected to reduce the risk for developing systems that will not be used, or used less than intended. Additionally, a user-centered design might enhance the work quality, reduce support and training costs, and improve user satisfaction because the technologies are based largely on wishes and demands of the users. Ultimately, users determine whether or not a sensor system will be successfully used; thus, user involvement in technology development is crucial.

### *Development of a fall prevention system*

*Sensor introduction in long-term care facilities*

The first recommendation of Chapter 2 was to use non-wearable sensors that monitor residents' activities 24 h per day under a variety of living conditions and at multiple locations. We introduced two cameras and a sensor mattress into our psychogeriatric intervention ward, monitoring one bedroom and the hallway with the bedroom door. The videos protected privacy by silhouetting the images (Figure 7.1) and allowed us to characterize walking ability afterwards. The bed in the monitored room was equipped with the sensor mattress (Emfit bed sensor mat, Emfit Ltd, Finland)), measuring movements, respiration, and heart activity. We were mainly interested in the events and resident status prior to the fall. In total, four falls were captured, including two falls due to unbalanced standing in the hallway, one due to a wet floor near the bed, and one due to unbalanced rocking in bed (presented in Figure 7.2). Although the number of falls recorded was not large enough to allow any statements about the situation prior to a fall, the data do indicate that a variety of circumstances is associated with fall incidents.

**Figure 7.2** Fall due to unbalanced rocking in bed.

*Spin-off monitoring system*

The smart fall prevention system proposed by the INTERREG IV A project (Chapter 1, Page 13), is not yet available. However, by combining multiple existing sensors with decision-making algorithms recognizing a pre-fall situation, a smart fall prevention system might be realized in the near future. As a spin-off of the project, two involved companies (AVICS and DYSI) have developed the smart optical sensor (SOS; http://www.avics.nl/domotica/slimme-optische-sensor-sos). This device is able to detect restlessness in bed, movement outside the bed, residents leaving the room to visit the bathroom, inactivity (fall detection), and the presence of other persons in the room (to avoid false alarms). The sensor is placed at the ceiling and the alarm threshold is adjusted to the personal needs of the resident. Although the SOS does not prevent residents from falling, a quick detection of a fall incident might prevent the consequences of a prolonged lie after a fall. Those consequences include: hospitalization, dehydration, hypothermia, pneumonia, and death [5,17]. When, in the future, an algorithm is developed to detect high fall risk situations, such an algorithm could be integrated into the SOS software to extend the device features.

### *Future directions in the development of a smart fall prevention system*

Based on the information presented in this thesis, we surmise that a smart fall prevention system should have the following properties, to prevent residents with dementia in a long-term care facility from falling:

- Multiple, non-wearable, invisible, and automatically activated sensors, integrated into an interlinked network. The system operates by an algorithm that can identify activities and recognize individuals. Privacy laws and regulations about data storage and accessibility preserve privacy of residents, visitors, and health care staff.

- The data in this thesis suggest that a dynamic fall risk decision-making model is necessary to identify risk factors for an (impending) fall. The model requires data collected over 24h, supplemented by resident information retrieved from electronic patient files. A self-learning strategy optimizes and personalizes the model.
- Users (health care staff) need to be involved in the development and implementation of any such smart fall prevention system.

In conclusion, using a combination of existing sensors within a coupled sensor network and a personalized fall risk profile might lead to the realization of a smart fall prevention system in the future. Users must be involved during the design and implementation phases of the system and their opinions and needs should be carefully considered. A smart fall prevention system will assist health care staff 24 h per day to prevent resident falls and reduce the number of serious fall-related injuries, thus improving quality of life for this vulnerable group.

## Technology-based gait assessment in healthy adults

### *Main findings*

Gait and balance control change over the life span due to natural aging but also because of neurologic and non-neurologic disorders. Monitoring gait changes over time might enable early identification of balance and mobility impairments. This monitoring offers the possibility to provide timely and personalized interventions to reverse or slow disease progression and health deterioration. Objective assessments using technological devices, such as tri-axial accelerometers, play an important role in quantifying gait and balance abilities. Recently, smart devices such as smart phones and iPods have come equipped with tri-axial accelerometers. This feature provides the opportunity to assess gait and balance in clinical practice with a user-friendly and low-cost device. In **Chapter 5** the validity and reliability of the built-in, tri-axial accelerometer in the iPod Touch was investigated. The iPod Touch was validated in a group of 60 healthy adults aged 18 to 75 years, under different standing and walking conditions. Participant trunk characteristics during gait and balance were measured using an iPod Touch and stand-alone accelerometer while they walked under single- and dual-task conditions, and while standing in parallel and semi-tandem stances with eyes open, eyes closed or while performing a dual task. The anterior-posterior (AP) and medio-lateral (ML) accelerometer signals of the iPod Touch and stand-alone accelerometer were highly correlated. Three different characteristics (time, amplitude, and frequency-related variables) of the accelerometer signal were assessed to determine the validity and reliability of the iPod Touch during walking and standing. The gait variables derived from the signal were the foot contact moments, the amplitude variability, and the index of harmonicity. Standing variables included the sway area, the root mean square of the acceleration signal, and the median power frequency. Overall, the iPod Touch obtained valid and reliable measures of gait and postural control in healthy

young, middle-aged, and older adults under different conditions. This finding highlights the potential of smart devices to be used for clinical gait and posture assessments.
Pursuing a frame of reference for gait changes due to natural aging, various gait variables were derived from the trunk acceleration signal recorded with the iPod Touch during the single walking task in Chapter 5. The gait variables included stride, amplitude, frequency, and trajectory-related variables based on the AP and ML acceleration signals. Furthermore, gait speed was supplemented. **Chapter 6** described the relationship between gait variables and their relation to age. The gait variables associated with age included mean stride time, phase variability index, root mean square, stride variability, AP sample entropy, and ML maximal Lyaponov exponent. More specifically, younger adults walked with a higher mean stride time and with more variability but less stability than older adults, whereas older adults walked with a less symmetrical gait pattern compared to younger adults. Additionally, the discriminative ability of the gait variables associated with age was examined. This combination of gait variables associated with age accurately classified younger (ages 18 to 45) and older (ages 46 to 75) adults. Normative data of how natural aging affects gait can serve as a frame of reference for gait dynamics changes due to pathological aging.

### *Validity and reliability of smart devices*

Objective assessments using technological devices play an important role in gait and balance quantification. The advent of smart devices with built-in, tri-axial accelerometers allows for an easy and accurate way to assess gait and balance abilities in clinical and community settings. Several studies have validated the built-in, tri-axial accelerometer in smart devices during walking and standing; results have been reported as reliable and accurate [18–20]. The data presented in Chapter 5 underscored those results and provided new insights about the use of smart devices for adults aged 18 to 75 years under different standing and walking conditions. Using the iPod Touch, reliable and valid results were obtained for the different aspects of the accelerometer signal (e.g., time, amplitude, and frequency domains).

Smart devices are increasingly used for research purposes (e.g., gait ability assessment in patients with rheumatoid arthritis and Parkinson’s disease) [19,21,22]. In addition to using smart devices in research, it is important to introduce smart devices in clinical settings to assess balance and gait. Smart devices are low-cost and user-friendly compared to standard assessment devices (e.g., Optotrak systems, stand-alone accelerometers); thus, objective gait and balance assessments are more accessible for clinicians.

### *Gait variables associated with age*

*Gait variables sensitive to aging*

Multiple gait variables can be derived from trunk acceleration signals, representing different gait pattern characteristics. Step and stride variables, based on foot contacts (peaks) identified in the AP trunk acceleration signal, for example, are frequently used in gait assessments [23–27]. Although acceleration signals provide a wealth of information, including information about variability, smoothness, predictability, and stability of gait, only a small set of variables representing those characteristics is included in studies [28,29]. Additionally, the sophisticated analyses needed to obtain gait variables and interpret the trunk acceleration signal present a major barrier for clinicians to use accelerometers in clinical settings. However, to determine specific gait changes due to aging, different gait characteristics should be considered. A combination of multiple gait variables sensitive to age-related changes provides more insight into age-related gait changes than a single variable. Age-related changes in individual gait variables appear small, as presented in Chapter 6. However, a combination of gait variables based on different accelerometer signal characteristics was sensitive to age-related changes. Specifically, younger adults walked with a higher mean stride time and with more variability but less stability compared to older adults, whereas older adults walked with a less symmetrical gait pattern compared to younger adults.

Interestingly, the published literature frequently reports higher gait variability in old adults and frail elderly persons compared with young adults [30,31,28], and more locally unstable gait in old adults and fallers [32,33]. It is well known that gait variability is higher in children compared with healthy adults [31,34]. Children use variability to explore and optimize their walking ability; gait variability decreases steeply during the first period of life [31]. It has been suggested that healthy and adaptable gait relies on the achievement of optimal variability, stability, and predictability. Non-optimal gait patterns can be characterized by too much or too little variability, stability, or predictability. Abnormal gait may be characterized by rigidity, inflexibility, and high predictability (as with Parkinson's disease [35]) or random, unfocused, and unpredictable (as with Huntington's disease [36]). However, there is a range between those two extremes that determines optimal gait. Thus, both low and high variability can characterize a safe gait pattern in healthy adults [25]. Variability of movement patterns has been linked to stability, flexibility, and predictability of movements and is related to task requirements [37]. Variability is necessary to maintain balance; adapting movements while walking leads to greater stability [25]. Healthy gait is characterized by 'organized' variability, whereas disease is defined by loss of complexity, increased regularity, decreased stability, and either increased or decreased variability, depending on the patient group and the task to be performed [38]. Although we proposed in Chapter 6 that a graph of gait variability over time creates U-shape, this has not yet been modeled over the adult life span. Most studies include distinct groups, such as healthy older adults vs. frail or cognitively impaired elderly, or fallers vs. non-fallers. Hardly any reference data exist with respect to variability, stability, and predictability of gait patterns over the adult lifespan. Further research should investigate the pattern of gait variability over the lifespan to more specifically define healthy variability and unhealthy variability in relationship to stability, flexibility and predictability.

*Classification algorithms*

Aging and health-related problems affect multiple gait variables; therefore, a reference frame based on multiple variables is necessary. The gait variables sensitive for age presented in Chapter 6 had good discriminatory ability to classify younger and older adults. The next step is to create a frame of reference, including normative values for natural aging, to recognize subtle changes which indicate unusual gait and balance characteristics. However, to further improve the classification model and obtain a reference model for gait ability, the number of participants over all ages should be expanded. Furthermore, reference data should be obtained for healthy adults older than 75, for less healthy old adults (e.g., frail elderly, fallers), and patients with various disease states (e.g., Parkinson's disease, diabetes, multiple sclerosis). Algorithms can be developed based on reference data to distinguish healthy adults from fallers, frail elderly, adults with cognitive impairments, and patients with particular diseases.

### *Gait and balance assessment applications in clinical settings*

Smart devices are increasingly used for research purposes, especially to gather and store data [18–20,39]. However, data processing and data analysis are still performed on laptops or computers with sophisticated software; this software requirement is a major barrier for clinicians to perform gait and balance assessments in clinical settings. Therefore, prior to the implementation of smart devices as gait and balance assessment instruments in clinical settings, applications (apps) are required to collect data, process data, and identify gait and balance characteristics [40]. An app is a piece of software that can be installed on a smart device. Apps are designed for a specific task or contain a certain set of information. Apps to assess gait and balance can be developed for diagnostic, monitoring, or intervention purposes.

*Diagnostics*

A quick, objective, and easy-to-use gait and balance assessment device could provide disease identification prior to symptom revelation. Interventions could start early to slow or reverse disease consequences. The gait variable most often associated with aging, falling, diseases, and even mortality, is reduced gait speed [41]. In distinct groups (younger vs. older adults, healthy adults vs. adults with medical conditions), gait speed seems to be a discriminating variable [30,42,43]. However, our analysis in Chapter 6 did not mark gait speed as a sensitive measure for natural aging. Gait speed might be sensitive for disease-related changes, but it is not specific in determining the underlying cause of the reduced speed. Accelerometer-based assessments are sensitive and specific for measuring gait and balance ability [44–46]. Detecting deviations from the natural gait pattern by assessing multiple gait variables might identify the underlying disease state cause of gait changes such as a preliminary stage of Parkinson's disease or Alzheimer's disease. Normative data are required about natural, age-related changes, but also about changes in gait and balance due to deteriorating health and diseases. Smart devices could be used for diagnostic purposes when a reference frame with normative gait and balance performance values is available. Gait and balance assessments with a smart device are easy and quick to perform: only a few minutes are needed to set up and complete the task.

*Monitoring*

The effectiveness of an intervention or the progression of a disease can be (home-) monitored with smart devices. Almost 80% of the Dutch population owns a smartphone, and this number is increasing, especially among those aged 65 years and older [47]. Due to the wide availability of smart devices in the general population, these devices can be used as self-assessment tools. Gait and balance characteristics can be monitored over a longer time period to detect subtle changes, with data collection occurring every week or for a certain period of time. The monitored person does not have to visit a physician for routine check-ups because the apps are accurately monitoring the patient's situation. A patient may receive a warning to visit a physician for a medical check or the physician would receive a notification when changes occur.

*Intervention*

Gait and balance intervention programs can be provided with smart devices [23]. Facilitating long-term gait and balance training at home could reduce hospitalizations and physiotherapist visits. Based on patient trunk movements, real-time feedback on motor performance can be provided to help improve gait or balance performance. Casamassima et al. (2014) used a smartphone and an inertial sensor to improve gait in patients with Parkinson's disease using real-time feedback [23]. Instructions were sent to patients to execute the most effective gait pattern, based on real-time computation of gait characteristics. For example, one of the gait characteristics monitored was gait symmetry. When asymmetry was detected, the instruction content included 'increase right/left step length'. Providing real-time feedback during walking or standing will help to improve or maintain mobility in old adults.

*Additional smart device measures*

The gait and balance information can be combined with other patient monitoring applications such as diabetes management and medication adherence apps [48]. Information about sleep rhythm, activity patterns, and heart rate can be added. Integrating multiple health-related outcomes provides the opportunity to monitor people more closely without frequent physician visits. Changes preceding events or disease evolution can be detected early and intervention can occur at an early stage.

There are a few commercial apps currently available to collect the measured acceleration signals from smart devices. However, these applications do not yet process the data to provide comprehensible information to the user about gait and balance performance. The introduction of such an app will probably only be a matter of time with the fast evolving developments in the field of technology and application use. App developers will have to take into account the required input data, the algorithms to process the data, and the presentation of results to the user.

### *Future directions in technology-based gait and balance assessment*

In view of the results of the present thesis, we consider the following aspects necessary to realize a low-cost, user-friendly, and objective gait and balance assessment in clinical settings:

- The combination of gait variables that is sensitive to age-related changes, as identified in Chapter 5, needs to be examined in a larger study, including more healthy adults and adults older than 75. To make a better distinction between healthy and unhealthy variability in relationship to stability, flexibility, and predictability, the pattern of gait variability over the entire lifespan should be investigated.
- Normative data are required for natural, age-related changes, but also for the changes in gait and balance due to deteriorating health and disease states. Classification algorithms can be based on those reference frames to distinguish healthy adults from adults with physical or cognitive impairments.
- Applications (apps) are necessary to implement gait and balance assessments into clinical settings. An app is needed to collect and process the data, identify gait and balance characteristics and present the results in a way the user (physician or patient) understands. Apps can be developed for diagnostic, monitoring, or intervention purposes.

In conclusion, smart devices can be used as objective gait and balance assessment instruments. Normative data of how natural aging affects gait can serve as a frame of reference for changes produced by aging coupled with disease. The next step is to develop (commercial) applications that collect and process gait and balance data to distinguish normal from abnormal gait characteristics. In the near future, old adults might be able to monitor their gait and balance ability by self-assessment at home. Physicians are then informed about the health status of patients without regular visits. Personalized training targeting gait and balance capacities can then be provided to maintain or improve the mobility of this population.

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# Nederlandse samenvatting

# Dankwoord

# Curriculum vitae

# Publications