Finnish Journal of eHealth and eWelfare

SCIENTIFIC PAPERS

VERTAISARVIOITU
KOLLEGIALT GRANSKAD
PEER-REVIEWED
www.tsv.fi/tunnus

Technologies for fall risk assessment and conceptual design in personal health record system

Milla Immonen[1,3], Heidi Similä[1], Mikko Lindholm[1], Raija Korpelainen[2,3,4], Timo Jämsä[2,5,6]

[1] VTT Technical Research Centre of Finland Ltd., Finland; [2] Medical Research Centre Oulu (MRC), Oulu University Hospital and University of Oulu, Finland; [3] Center for Life Course Health Research, University of Oulu, Finland; [4] Department of Sports and Exercise Medicine, Oulu Deaconess Institute Foundation, Finland; [5] Research Unit of Medical Imaging, Physics and Technology, University of Oulu, Finland; [6] Diagnostic Radiology, Oulu University Hospital, Finland

Milla Immonen, VTT Technical Research Centre of Finland Ltd., Kaitoväylä 1, P.O. Box 1100, FI-90571 Oulu, FINLAND. Email: milla.immonen@vtt.fi

Abstract

Falls among older people are a major economic and public health problem. Due to the demographic change and aging of populations, there is an urgent need for accurate screening tools to identify those at risk to target effective falls prevention strategies. Clinical fall risk assessments are costly and time-consuming and thus cannot be performed frequently. Technologies provide means for assessing fall risk during daily living, making self-evaluations and fast methods for fall risk assessment for professional use.

This study collects and evaluates existing technological solutions for fall risk assessment including various different sensor technologies. The study also presents one easy to use solution for assessing fall risk and suggests a concept-design for integrating sensor-based solutions into the Finnish national Kanta Personal Health Record.

The optimal solution for technological fall risk assessment is still unclear. A wide implementation still requires extensive validation studies, adoption to health care processes and novel IoT -solutions for collecting large amounts of sensor data. Thorough methods should be utilised in designing the privacy and security aspects of fall risk assessment solutions, as well as different user profiles, to allow suitable interfaces and visualisations to users. It should always be clear what kind of data are collected from users and how the data are utilised. The consent of the users should also always be collected.

Keywords: falls, risk assessment, primary prevention, wearable technology, health technology, patient generated health data

Introduction

One third of people over 65 years old fall at least once each year [1] and the number of falls per year increases with age and frailty level [2]. Falls have serious consequences, since they are related with increased mortality, morbidity, reduced functioning, and premature nursing home admissions [3]. Hip fracture with consequent impaired functional ability and quality of life and financial burden for the society is one of the most serious fall injuries. The total costs of hip fracture treatment are very high and in addition, the quality of life of hip fracture patients decrease dramatically. The cost of care during the first year after a hip fracture was 30258€ during years 2011-2013 € in Finland [4].

The world's population is ageing rapidly; the number of people aged 65 or older is expected to grow from 524 million in 2010 to nearly 1.5 billion in 2050 [5]. One consequence of population's ageing is that the resources for care will be limited. At the same time costs produced by falls increase rapidly, and prevention becomes crucial. Large-scale assessment of the older population by clinicians consumes resources and public funding and novel, less consuming methods are needed.

Comprehensive assessment of individual fall risk factors includes the assessment of balance, muscle strength, dizziness, posture, gait, drugs, environmental factors and cognitive impairment, as well as various medical factors [1]. Recently developed technologies provide possibilities to assess some of these risk factors and thus detect high fall risk by automatic and continuous screening. Automatic and continuous monitoring of fall risk has potential in decreasing the required healthcare costs and resources.

The aims of this paper are to describe and evaluate existing technological solutions, present one possible easy to use solution for assessing fall risk, and suggest a concept-design for integrating a sensor-based solution into a Finnish national Kanta Personal Health Record. Dealhoz and Labrador surveyed fall detection and fall prevention technologies, and propose 3-level taxonomy associated with the risk factors of a fall; physical, psychological and environmental. They also review and compare twenty four fall prevention systems in relation to design issues [6]. More recently, a state-of-the-art in fall prediction and prevention systems was collected by Rajagopalan et al. [7]. The review concludes that the existing fall detection and prediction systems are not tested in real life settings and concentrate only on single risk factors and not on multifactorial fall risk. Rajagopalan et al. also list the main challenges in designing effective fall prediction systems; evaluating performance among frequent fallers and aging adults, user-centric design, security and privacy in data transmission and storage, and energy optimization. Their recommendations for future research include constant measurement of blood pressure; data fusion from wearable and ambient sensors, user interface design, assessment of external fall risk factors, and comparisons to clinical fall risk assessments.

Methods

We used Boolean searches to obtain relevant articles from Google Scholar and IEEE Explorer as well as online platforms ResearchGate and Mendeley. We checked the state-of-the-art literature review papers related to fall risk, fall risk assessment, and technologies and sensors for fall risk assessment. The fall risk assessment literature was narrowed by selecting the most extensive and cited reviews. Background information about falls and fall risk assessment is from 1975-2018. The literature search was further complemented using the references of publications. We made an additional search for specific technologies separately, e.g., "ultra wide band radar and fall risk assessment". The selection of articles for technologies for fall risk assessment was made by selecting those articles, which presented results of utilising a technology for fall risk assessment. The time period for the review of technologies was limited to articles published between 2003 and 2018, since the novel sensor technologies as well as movement analysis has advanced particularly during this time-frame. We reviewed the articles published in journals, conferences, and as books or book chapters. Mendeley Desktop software was used as a tool in organising the literature and composing the bibliography. A few commercial products are additionally described.

Fall risk assessment state of the art

Factors contributing to an individual's fall risk have been widely studied and several classifications exist [3,8,9]. One typical grouping is to divide fall risk factors into intrinsic and extrinsic risk factors [1,3,10,11]. Intrinsic risk factors are, for example, age, gait and balance impairment, muscle weakness and medical illnesses, whereas, e.g., poor footwear is considered as an extrinsic risk factor. Together with precipitating causes, such as dizziness, fall prevention is a complex multifactorial challenge [3]. Sometimes a third risk factor category is included, exposure to risk, including factors that are caused by the situation or activity [12,13]. Examples of intrinsic risk factors, extrinsic risk factors, and exposure to risk are listed in Table 1. WHO represents fall risk factors in four dimensions: biological, behavioural, environmental and socioeconomic factors [2], whereas Lord et al. group the risk factors into six categories; psychosocial and demographic factors, postural stability factors, sensory and neuromuscular factors, medical factors, medication factors and environmental factors [1]. Most of the fall risk factors can be modified by preventive means [12,14].

Clinical fall risk assessment protocols

Health professionals use several different fall risk assessment scales. Some of the assessment scales estimate overall fall risk and probability of future falls. An example of such a scale is Downton fall risk index [8], which covers several different aspects of fall risk, for example, history of falls, medication, sensory deficits, mental state and gait. Some assessment scales focus on specific fall risk factors, e.g., Berg balance scale [15] evaluates postural control, and FES-I [16] fear of falling and confidence for performing different daily activities. Timed Up and Go test (TUG) assesses functional ability [17,18], and the Short Physical Performance Battery (SPPB) physical performance [19]. FRAT-up is a recently proposed predictive tool which issues the probability of falling at least once within the time span of one year [20].

The set of used assessment scales is not uniform between different nations, health care units and organizations, who can independently decide which assessment scales to use. In Finland, National Institute of Health and Wellbeing has made recommendations for fall risk assessment and fall prevention [12]. Regardless of the used protocol, full-scale fall risk assessment is time consuming and needs plenty of health care resources.

Table 1. Fall risk factors.

Intrinsic risk factors	Extrinsic risk factors	Exposure to risk
History of falls Age Gender Living alone Ethnicity Medical conditions Impaired mobility and gait Sedentary behaviour Psychological status Nutritional deficiencies Impaired cognition Sensory disorders or visual impairments Foot and ankle problems Impaired balance and muscle strength Fear of falls Incontinence	Environmental hazards inside and outside home Footwear or clothing Inappropriate walking aids or assistive devices Medicines Polypharmacy	Situation and behavioural factors Rush Carelessness Tiredness Energy level Dehydration Taking unnecessary risks

Technical solutions for assessing fall risk

Sensors provide means for an objective fall risk assessment. They can be seen as an addition or extension to the fall risk assessment scales. Wearable movement monitors can broaden the fall risk screening beyond the clinical arena to the unsupervised environment, although entailing the challenges of design considerations, implementation protocols and signal analysis [21]. Typical sensors used for balance and gait assessment are force plates, optical motion capture systems, gait walkways, gait mats, insoles and wearable sensors, such as accelerometers, gyroscopes and magnetometers [22]. Also smart phone -based fall risk assessment architectures have been developed and tested [23]. In addition, depth cameras and radars can be used for assessing balance and gait [24,25] . Following chapters describe how different ambient and wearable sensors can assess various factors of fall risk.

Wearable sensors

Current technologies enable production of cheap, small-sized and wearable sensors, such as accelerometers and gyroscopes, which are used for measuring movement of the human body. Accelerometers consist of a mass reacting to the movement or gravitation proportionally to the acceleration. By placing three accelerometers orthogonally, the movement can be monitored in three dimensions. Gravitational component of the acceleration can be used for defining the postural orientation of the sensor. The output voltage given by the accelerometer can be converted into m/s2 values based on calibration. Gyroscopes on the other hand have a vibrating mass within the sensor. The displacement of the mass during the rotation of the sensor is proportional to the angle of the rotation. The rotation over time gives angular velocity of the sensor [21].

Accelerometer data can be used, for example, to assess physical activity, sleep, exercise, step count and energy expenditure [26]. Different daily activities are also recognizable from the data [27]. Detecting daily behaviour patterns and especially changes in behaviour might provide valuable information about functional status of a person. Accelerometry is also widely used in gait and movement analysis, e.g. [28,29]. It is possible to detect timing of gait events, such as initial contact and final contact, from the acceleration signals [30]. Many of the existing mobile phones have embedded accelerometers, which opens a possibility to utilize the data they provide for fall risk assessment and additional sensors are not necessarily required. A systematic review by Roeing et al. [31] reviewed mobile applications that evaluate dynamic and static balance. The review included studies that had measured static balance or a clinical measure of balance with a mobile phone . The studies varied in sample size as well as the validity and reliability evaluation of the solutions. Most applications were intended to be used by the clinicians and not by the people at risk. The authors state that the ability of these applications to predict fall risk still remains unproven and that applications should be designed with special consideration for the user’s level of function and test for usability in those populations [31]. The challenge in using the embedded accelerometers of mobile phones is that the phone should be adjusted to certain location to get accurate measurements of gait or sway [32,33].

Besides prevailing heart rate, heart rate monitoring can be used to estimate, to a certain accuracy, oxygen uptake and energy expenditure [34], which are related to intensity of physical activity. In addition, heart rate variability (HRV) provides information about sleep and sleep quality [35]. Studies suggest that HRV can also be used for detecting orthostatic hypotension [36], which has been shown to be related to fall risk [37]. Blood pressure monitors are commonly used in general practice and also self-monitoring at home is increasing in many countries [38].

Wireless systems integrated into shoes provide possibilities for assessing fall risk factors from gait and assessing the critical weather conditions affecting the fall risk [39-43]. Shoe-sensors can detect gait speed, stride-to-stride fluctuations and walking style of the user. Gait features analysed from smart insoles have been shown to correlate with fall risk, and smart insoles are feasible for long term monitoring of fall risk in the home [39] [41]. Smart insoles have been also suggested to be able to distinguish between normal and abnormal walking patterns [42].

Ambient sensors

Ambient sensors are attached to the environmental objects indoors or outdoors and are mostly unobtrusive. Ambient sensors allow detection of human presence, movement and actions, and physiological measures, such as heart rate.

Floor sensors or smart floors can detect similar features from gait [44,45] than wearable sensors presented in the previous chapter. Daily activities and number of steps can be recognized from the data, as well as daily physical behaviour patterns of the resident and changes in it. Previously, it was shown, that gait velocity and functional ambulation profile (FAP) measured with floor sensor were significantly correlated with clinical fall risk measures [46]. The FAP is a summary score (range 0-100) that quantifies the gait based on specific temporal and spatial gait parameters [47].

Sleep quality is an important indicator of health status and it is possible to recognize different stages of sleep with signals from a bed sensor [48]. Sensor mattress is placed under a regular bed mattress and it is composed of multiple pressure-sensitive electrodes that can detect, e.g., body position, respiration and heart rate. Bed sensor information can be used to recognize instances of awakenings, which might indicate a need for getting into bathroom several times during night due to incontinence, which in turn can increase the fall risk [12].

Depth cameras can be used continuously and unobtrusively inside homes for gait analysis. They can also be used for obtaining stride parameters from walk of habitants using assistive walking device [24]. However, depth-cameras have some limitations, such as decreasing precision with distance [49].

Ultra-wideband (UWB) radio technology can use a very low energy level for short-range, high-bandwidth communications over a large portion of the radio spectrum. UWB also has the capability to pass through physical objects that tend to reflect signals with narrow bandwidth. The narrow pulse allows building a radar with good spatial resolution and very short-range capability. The large bandwidth allows the UWB radar to get more information about the possible surrounding targets and detect, identify, and locate only the most desired target among others [50]. UWB radar uses transmitting antennas and receiving antennas for the reflected signal. Humans cause changes in frequency, phase and time of arrival in the reflected signal and thus, movements can also be detected. The UWB technology provides possibilities as a tool for monitoring patients in their home environment and it has been studied for measuring sway of quiet standing [51]. Doppler Radars has also been used in unobtrusive health measurements and quantitative gait measurements [25].

Digital questionnaires

Digital or web-based questionnaires can be used for fall risk assessment at home, assessing subjective fall-risk, fear of falling, fall history or daily health situation [52]. However, only a few studies so far have been published on the effectiveness or applicability of digital questionnaires. A web-based Frat-UP questionnaire was evaluated by Cattelani et al. The performance of the questionnaire has been suggested to be comparable to externally validated state-of-the-art tools [20]. Another study tested an online questionnaire to assess fall risk with 134 older adults and found out that the online survey was feasible and the questions were understood well. However, the response rate to the monthly questionnaire was low, and the discrimination between fallers and non-fallers was moderate [53]. The combination of a questionnaire with another assessment tool may better discriminate fallers and non-fallers, as showed by Ibrahim et al. with a combination of a TUG-assessment and a questionnaire [54].

Falls Efficacy Scale (FES-I) [16] and fall risk for older people in the community assessment (FROP-COM) [55] are examples of questionnaires that could be adjusted to online use or digital questionnaires.

Questionnaire-based assessment scales filled by health care professionals often give a total score that is saved to the electronic health record (EHR) of the person. The score may represent some specific risk factor, such as depression [56] or memory and cognition [57], which together with complementary assessment scales give an overall picture of the person's fall risk.

Patient health records

Utilising background information collected from patient health records can give additional insight on the overall fall risk. Several intrinsic and extrinsic factors can be found from the patient health records; age, gender, familial diseases, previous falls, medical condition, impaired memory or cognition, sensory deficiencies, and drug prescriptions.

Storing PHRs in the cloud makes it necessary to pay attention to privacy and security of the patient data. All the data transferred between the users has to be encrypted and the identity of the users has to be verified with a strong identification method. The users have to have a possibility to decide, who they allow to see or use their personal data. In Europe, the new regulation gives the control to individuals over their personal data. The General Data Protection Regulation (EU) 2016/679 ("GDPR") is a regulation in EU law on data protection and privacy for all individuals within the European Union (EU) and the European Economic Area (EEA). It also addresses the export of personal data outside the EU and EEA areas [58].

Other information sources

Recently, increasing interest has emerged in applying game consoles to fall risk assessment. Game console manufacturers have integrated various sensors; Microsoft Kinect uses a depth camera and Nintendo Wii Fit uses a sensor board. Game-based fall risk assessment has several advantages; the user does not feel as being monitored, the movements are natural and the games can be persuasive towards better performance. Nintendo Wii Fit has been found to be able to recognize dual tasking problems, which have been suggested to be associated with fall risk [59].

Intelligent gym equipment and interlinked smart cards allow easy follow-up of gym exercises. Planned exercises and number of repetitions are saved on a smart card by, e.g., personal trainer. By inserting the card into each of the gym device when beginning the exercise, the plan is shown to the user on a screen. After completing the exercise, the performed repetitions and workloads are automatically saved on a personal account or memory stick [60,61]. Monitoring of performed exercises and workloads enables detection of long term trends, progress or possible deterioration in muscle strength.

Smartphones have significantly penetrated into society and with powerful computing capability, large memory capacity, large screens and open operating systems they have spurred the development of health related applications [62]. Smartphone embedded sensors can be utilized for retrieving health related data from its user. GPS -sensor can give the current location of the smartphone and it can also be used to track paths and distances, e.g., from outdoor exercises. Accelerometer can be used to assess activity levels at different times of day or activity recognition methods can be applied to the data [27,63].

Conceptual framework for a cloud service for monitoring and assessing fall risk

Collecting a large amount of data from different sensors brings challenges to computers and mobile phones. Cloud computing gives a possibility to store the data and use the extended computing capabilities. The data stored in the cloud is available on-demand for the user, and doctors and researchers can use the data in the cloud [64].

If all the data are stored and documented in a way they are available and useful for new services, data eventually accumulates into an extensive data repository, where big data analysis methods can be applied for producing more advanced and meaningful information of a persons' health and health status [65]. These data analysis services can then feed refined information into other services, for example, visualizing the knowledge for the person in an understandable way.

Different types of services can be built upon the data repository, i.e. the same data can be used for many different purposes. For example, physical activity data may be used to track activity behaviour of a person, adherence of prescribed physical exercises, and use that information in an application service that keeps activity diary and motivates person to exercise. Such a service would be important in preventing falls [66]. Moreover, by tracking activity behaviour and more importantly noticing periods of inactivity, it allows development of alarm services, e.g., for detecting potential falls [67].

Fall risk assessment with several sensors needs a lot of computing and data storage resources. Cloud systems provide resources for making population-wide fall risk assessments. We propose a system for fall risk assessments with sensors in Figure 1. The different sensors collect information from gait, activity, sleep, environment and health factors to Personal Health Record (PHR) My Kanta [68], whis is a national data repository in which citizens may enter personal information on their health and wellbeing. The actual data from connected devices or applications are stored to third party i.e. the application providers' storages and the data are accessed via Fast Healthcare Interoperable Resource interface (FHIR) [69]. The data is pre-processed and stored into a database with appropriate context information, such as time of day or location. Pre-processing can also reduce the amount of data stored and save storage space. Actual fall risk assessment applies data mining, fall risk calculation logic and data interpretation. The system provides recommendations for the user or appropriate body responsible or interested of the fall prevention. The advantages of making fall risk assessment in cloud are various. Possibility to store history data enables noticing rapid or incremental changes in behaviour, movements or health.

The stored data can be raw data, or results analysed utilising the data. Economically it may be more feasibly to store only pre-analysed data from pre-defined periods, instead of raw data collected day and night. The user can be guided to make a certain test and the system only collects the data measured during the test. Another possibility is that the system can automatically detect certain activity and context (for example walking or sit to stand) and utilise the data from that activity in the analysis. These methods would save the storage space and the amount of data sent to cloud via the communication networks.

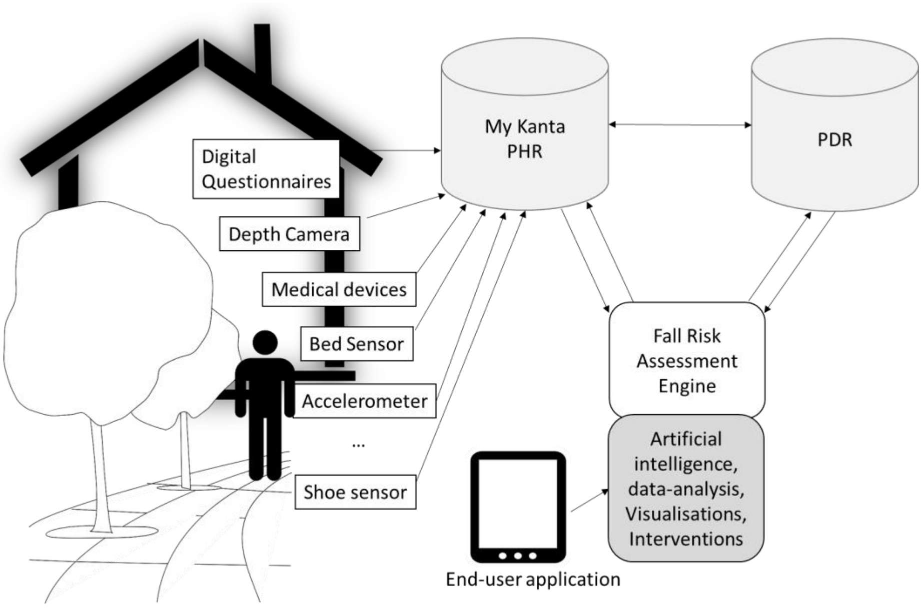

Figure 1. Fall risk assessment system utilising Finnish Personal Health Record (PHR) system My Kanta and Patient Data Repository (PDR).

In the future, citizens of Finland will have the option of sharing their My Kanta PHR data with social welfare and healthcare professionals. This is not yet possible, because the current regulation does not support this (October 2018) [69]. A Client Data Act is currently under review in Parliament of Finland [70]. Health researchers and decision makers also benefit from the collected data. If the users allow use of their anonymised data, the health researchers can find new methods for assessing fall risk with a large amount of data collected in daily living. Decision makers can use the data for predicting how the inhabitants will cope with their daily lives at home in near future. The same data can be used for many different purposes and the purpose of collecting the data can vary while the person ages. At an earlier age, the person can follow health information and later on the same sensors could be used for assessing fall risk, and also the historical stored data could be used as a baseline for assessing fall risk and finding out how the person's capabilities have changed during the years.

The health data stored in Kanta service is secure and trustworthy. Identification of users is done by electronic identification methods. All the information is encrypted and the professionals log in to the system using their professional cards, which means strong electronic identification. All organisations also have a named person responsible for information security, who can be contacted if an unauthorized use of data is suspected. The patient is also able to see, which health care units or pharmacies have handled his/her prescriptions or health information. In addition, the patient can request information who has viewed or handled the data. Viewing the data requires a care or client relationship and a consent from the patient [68].

The proposed system includes several possible user profiles; doctors, nurses, physical therapists, older adults, relatives and decision makers, and each of them have also differences in wishes from the services and understanding the data and results. Careful design methods should be utilised when creating the end-user interfaces and visualisations to make sure effective utilisation of the services and correct interpretation of the results. The services should be clear in telling the users what kind of information is collected from them and how the data are utilised. The consent of the users should always be collected. We also found out, that the physical frailty status of older adults is associated with ICT use independent of age, education, and opinions on ICT use [71]. The risk groups' experience and ability to use mobile technologies, should also be taken into account in designing the fall risk assessment solution.

Sensor fusion for fall risk assessment

Sensor fusion can be grouped in three groups; competitive, complementary, and cooperative [72]. In competitive fusion, multiple equivalent sources of information are used. In complementary fusion, each sensor captures different aspects of the fall risk and complementary fusion can be used to improve the accuracy and reliability of assessing the fall risk. Cooperative fusion provides information that cannot be achieved by using independent sensor signals alone. In the concept of fall risk assessment, multiple equivalent sensors are placed in different locations on the human body and each sensor can provide complementary information.

Data processing in sensor fusion can also be grouped into three different groups; direct data fusion, feature-level fusion and decision-level fusion. Combining raw data (direct data fusion) can be used, if the sensors are measuring the same physical parameter. On feature-level fusion, feature vectors are first extracted from the sensor data to form multi-dimensional feature vectors, which are then used for analysis. In decision-level fusion, the information has already been processed to a certain level for a high-level decision making [72].

From the literature, only a few studies about sensor fusion for fall risk assessment can be found. A recent study combined clinical fall risk factors with body-worn sensor data [73]. The authors applied a classifier combination theory and averaged the posterior probabilities produced for a given subject by the sensor-based fall risk estimation and the clinical fall risk estimation to produce a combined fall risk estimation. They stated that combination of the sensor-based fall risk assessment classifier and clinical fall risk factor classifier led to better accuracy compared to either clinical or sensor data alone. One approach for fusing inertial sensor data with a pressure sensor platform for fall risk assessment has been patented in [74]. Another study compared the ability of several wearable sensors to predict falls of older adults with clinical assessments [75]. In that study, multi-sensor gait assessments provided the best input data for fall-risk prediction, using a combination of posterior pelvis, head, and left shank accelerometers. The study also found that sensor-based models outperformed clinical assessment-based models and wearable sensors have advantages over commonly used clinical assessments when assessing fall risk.

A state-of-the-art survey of sensor fusion using body sensor networks has been written by Gravina et al. [76]. The authors conclude that new research is required to adapt current state-of-the-art approaches and techniques of multi-sensor fusion.

Decision making and defining thresholds for actions

A large data repository allows application of different data mining methods to discover patterns and rules that relate to increased fall risk, for example, combining several data sources to analyze person's daily behavior and detect possible anomalies in normal patterns [72,77]. From the professional point of view, data mining and population-wide visualizations may even provide new insight to the fall risk assessment and fall prevention [78,79]. Furthermore, application of descriptive modelling to the data may reveal clusters of fall risk factors that incorporate new knowledge [80]. Using technology for assessing fall risk and for preventing falls in daily living setting requires also automatic decision making protocols and defining thresholds for alarming, recommending further actions or interventions to prevent falls. These thresholds can be defined either using clinical assessment tools as a reference [75,81], or by collecting a large dataset from daily living of real persons to detect, which persons actually fall and analyse the sensor signals to find correlations.

End-user application for fall risk assessment

Several technologies enable automatic or semi-automatic assessment of fall risk, but most of them are not utilized as a solution or product that could be used by end-users. A prototype application for fall risk assessment was developed to demonstrate a solution for end-users. The implementation is a mobile software; an Android application using acceleration data received from a Movesense device over Bluetooth® LE connection. The application interface is designed to guide the user to make self-evaluation of fall risk or to perform fall-risk assessment for a client for example in home care. The actual test is a simple walking test. After the test is performed by the user, the collected acceleration data are analyzed by the application. Predetermined features are calculated from the data and a fall risk index (FRI) is determined as a weighted sum of the features. The user instruction and result visualization is shown in Figure 2. The gait analysis is based on our recent study [82]. The application implementation has been presented in more detail previously [83].

Although, the current prototype application stores the data only in the mobile phone it can be enhanced to support the conceptual design presented in this paper. The analyzed data, i.e. FRI values, can be sent to PHR where it can be combined with other personal data and used as a complementary information in holistic assessment of an individual fall risk.

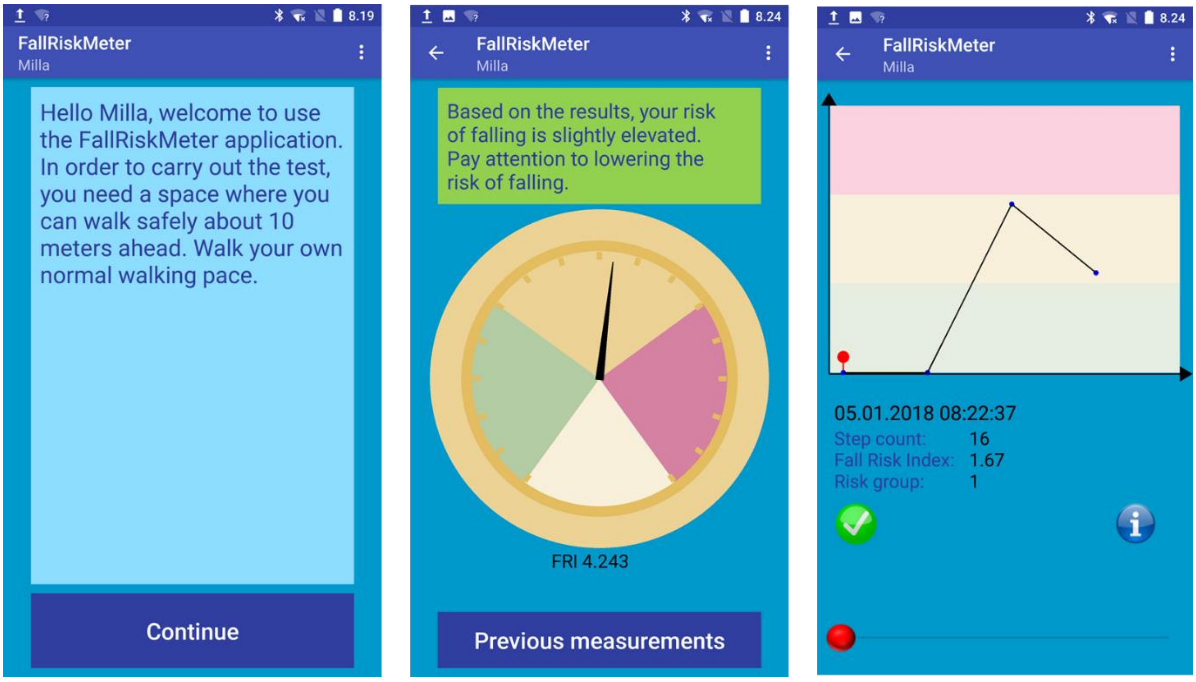

Figure 2. Screen shots from end-user application for assessing fall risk.

Conclusion

This article reviews various technological solutions for detecting fall risk. The paper also describes a solution developed for self-assessment of fall risk and how this example solution could be part of a multi-source fall risk assessment framework and integrated into a national Kanta Personal Health Record and patient data repository and how the collected data could be utilised. The proposed conceptual design collects data from various wearable and ambient sensors and devices, and utilises also the data collected to patient health record. The data analysis includes data mining, fall risk calculation logic and interpretation. When increased fall risk is detected, the user or responsible bodies get recommendations for making preventive actions for falls.

Fall risk assessment as a part of a larger eHealth system allows the same data to be used for many different purposes and the purpose of collecting data can change in time. Younger people can follow health information, and later on, the same sensors or collected data can be used for assessing fall risk and finding out how the person's functional capabilities have changed over time.

The current EU regulation requires the service developers to pay attention how they utilise the data collected from users and what kind of permissions are needed from the users to utilise their data. The regulation gives control of the personal data to individuals, requires encryption in data transfer, and authorised persons can only access data. The current legislation in most countries do not allow the data collected with personal devices to be accessed by healthcare professionals, but the legislation is constantly evolving and this may be possible in the near future.

Making the automatic fall prevention system possible has some important steps ahead. Many sensor-based solutions have already been found to predict falls, but the optimal solution or combination of information is still unclear. The integration to health care paths and processes and interventions has to be defined. The design of the solutions should also take into account the different profiles of users; their profession and way of interpreting the data and the ethical issues of the solutions. The data collected from users should only be utilised with the consent given by the users. The usage of the different ICT technologies may also differ between user groups and the most suitable method for each group should be found.

Acknowledgements

This work was partly funded by research grants from University of Oulu Fund and Tauno Tönningin säätiö. The authors would like to thank Timo Niemirepo for developing the mobile software for fall risk assessment.

References

[1] Lord SR, Sherrington C, Menz HB. Falls in older people. Risk factors and strategies for prevention. Australia, Port Melbourne: Cambridge University Press; 2001. 249 p.

[2] WHO. WHO Global report on falls Prevention in older Age. World Health Organization; 2007. Available from: https://www.who.int/ageing/publications/Falls_prevention7March.pdf?ua=1

[3] Rubenstein LZ, Josephson KR. Falls and their prevention in elderly people: what does the evidence show? Med Clin North Am. 2006 Sep;90(5):807–24. https://doi.org/10.1016/j.mcna.2006.05.013

[4] Perfect project website [Internet]. National Institute for Health and Welfare; updated 2017. Available from: https://thl.fi/fi/tutkimus-ja-asiantuntijatyo/hankkeet-ja-ohjelmat/perfect

[5] WHO. WHO Global health and ageing. NIH Publication no. 11-7737. Available from: https://www.who.int/ageing/publications/global_health.pdf?ua=1.

[6] Delahoz Y, Labrador M. Survey on Fall Detection and Fall Prevention Using Wearable and External Sensors. Sensors. 2014 Oct 22;14(10):19806–42. https://doi.org/10.3390/s141019806

[7] Rajagopalan R, Litvan I, Jung TP. Fall Prediction and Prevention Systems: Recent Trends, Challenges, and Future Research Directions. Sensors. 2017 Nov 1;17(11):2509. https://doi.org/10.3390/s17112509

[8] Downton JH. Falls in the elderly. Sevenoaks: E. Arnold; 1993. 158 p.

[9] Ambrose AF, Paul G, Hausdorff JM. Risk factors for falls among older adults: A review of the literature. Maturitas. 2013 May;75(1):51–61. https://doi.org/10.1016/j.maturitas.2013.02.009

[10] Bueno-Cavanillas A, Padilla-Ruiz F, Jiménez-Moleón JJ, Peinado-Alonso CA, Gálvez-Vargas R. Risk factors in falls among the elderly according to extrinsic and intrinsic precipitating causes. Eur J Epidemiol. 2000;16(9):849–59. https://doi.org/10.1023/A:1007636531965

[11] Perell KL, Nelson A, Goldman RL, Luther SL, Prieto-Lewis N, Rubenstein LZ. Fall Risk Assessment Measures: An Analytic Review. Journals Gerontol Ser A Biol Sci Med Sci. 2001 Dec 1;56(12):M761–6.

[12] Pajala S. Iäkkäiden kaatumisten ehkäisy. Terveyden ja hyvinvoinnin laitos (THL); 2012. Available from: http://urn.fi/URN:NBN:fi-fe201205085108

[13] Health Evidence Network - Evidence for decision makers. What are the main risk factors for falls amongst older people and what are the most effective interventions to prevent these falls? World Health Organization; 2004. 28 p.

[14] Gillespie LD, Robertson MC, Gillespie WJ, Lamb SE, Gates S, Cumming RG, et al. Interventions for preventing falls in older people living in the community. Cochrane database Syst Rev. 2009;(2):CD007146. https://doi.org/10.1002/14651858.CD007146.pub2

[15] Berg KO, Wood-Dauphinee SL, Williams JI, Gayton D. Measuring balance in the elderly: preliminary development of an instrument. Physiother Canada. 1989;41(6):303–11. https://doi.org/10.3138/ptc.41.6.304

[16] Yardley L, Beyer N, Hauer K, Kempen G, Piot-Ziegler C, Todd C. Development and initial validation of the Falls Efficacy Scale-International (FES-I). Age Ageing. 2005 Nov 1;34(6):614–9. https://doi.org/10.1093/ageing/afi196

[17] Podsiadlo D, Richardson S. The timed "Up & Go": a test of basic functional mobility for frail elderly persons. J Am Geriatr Soc. 1991;39(2):142–8. https://doi.org/10.1111/j.1532-5415.1991.tb01616.x

[18] Barry E, Galvin R, Keogh C, Horgan F, Fahey T, Tinetti M, et al. Is the Timed Up and Go test a useful predictor of risk of falls in community dwelling older adults: a systematic review and meta- analysis. BMC Geriatr. 2014;14(1). https://doi.org/10.1186/1471-2318-14-14

[19] Guralnik JM, Simonsick EM, Ferrucci L, Glynn RJ, Berkman LF, Blazer DG, et al. A Short Physical Performance Battery Assessing Lower Extremity Function: Association With Self-Reported Disability and Prediction of Mortality and Nursing Home Admission. J Gerontol. 1994 Mar 1;49(2):M85–94. https://doi.org/10.1093/geronj/49.2.M85

[20] Cattelani L, Palumbo P, Palmerini L, Bandinelli S, Becker C, Chesani F, et al. FRAT-up, a web-based fall-risk assessment tool for elderly people living in the community. J Med Internet Res. 2015 Feb 18;17(2):e41. https://doi.org/10.2196/jmir.4064

[21] Shany T, Redmond SJ, Narayanan MR, Lovell NH. Sensors-Based Wearable Systems for Monitoring of Human Movement and Falls. IEEE Sens J. 2012 Mar;12(3):658–70. https://doi.org/10.1109/JSEN.2011.2146246

[22] Ni Scanaill C, Garattini C, Greene BR, McGrath MJ. Technology Innovation Enabling Falls Risk Assessment in a Community Setting. Ageing Int. 2011 Jun;36(2):217–31. https://doi.org/10.1007/s12126-010-9087-7

[23] Habib M, Mohktar M, Kamaruzzaman S, Lim K, Pin T, Ibrahim F. Smartphone-Based Solutions for Fall Detection and Prevention: Challenges and Open Issues. Sensors. 2014 Apr 22;14(4):7181–208. https://doi.org/10.3390/s140407181

[24] Stone EE, Skubic M. Unobtrusive, Continuous, In-Home Gait Measurement Using the Microsoft Kinect. IEEE Trans Biomed Eng. 2013 Oct;60(10):2925–32. https://doi.org/10.1109/TBME.2013.2266341

[25] Wang F, Skubic M, Rantz M, Cuddihy PE. Quantitative gait measurement with pulse-Doppler radar for passive in-home gait assessment. IEEE Trans Biomed Eng. 2014 Sep;61(9):2434–43. https://doi.org/10.1109/TBME.2014.2319333

[26] Murphy SL. Review of physical activity measurement using accelerometers in older adults: Considerations for research design and conduct. Prev Med. 2009 Feb;48(2):108-14. https://doi.org/10.1016/j.ypmed.2008.12.001

[27] Parkka J, Ermes M, Korpipaa P, Mantyjarvi J, Peltola J, Korhonen I. Activity Classification Using Realistic Data From Wearable Sensors. IEEE Trans Inf Technol Biomed. 2006 Jan;10(1):119–28. https://doi.org/10.1109/TITB.2005.856863

[28] Moe-Nilssen R, Helbostad JL. Estimation of gait cycle characteristics by trunk accelerometry. J Biomech. 2004 Jan;37(1):121–6. https://doi.org/10.1016/S0021-9290(03)00233-1

[29] Bautmans I, Jansen B, Van Keymolen B, Mets T. Reliability and clinical correlates of 3D-accelerometry based gait analysis outcomes according to age and fall-risk. Gait Posture. 2011;33:366–72. https://doi.org/10.1016/j.gaitpost.2010.12.003

[30] González RC, López AM, Rodriguez-Uría J, Álvarez D, Alvarez JC. Real-time gait event detection for normal subjects from lower trunk accelerations. Gait Posture. 2010 Mar;31(3):322–5. https://doi.org/10.1016/j.gaitpost.2009.11.014

[31] Roeing KL, Hsieh KL, Sosnoff JJ. A systematic review of balance and fall risk assessments with mobile phone technology. Arch Gerontol Geriatr. 2017 Nov 1;73:222–226. https://doi.org/10.1016/j.archger.2017.08.002

[32] Tacconi C, Mellone S, Chiari L. Smartphone-Based Applications for Investigating Falls and Mobility. In: Proceedings of the 5th International ICST Conference on Pervasive Computing Technologies for Healthcare. IEEE; 2011. https://doi.org/10.4108/icst.pervasivehealth.2011.246060

[33] Chan H, Zheng H, Wang H, Gawley R, Yang M, Sterritt R. Feasibility Study on iPhone Accelerometer for Gait Detection. In: Proceedings of the 5th International

ICST Conference on Pervasive Computing Technologies for Healthcare. IEEE; 2011. https://doi.org/10.4108/icst.pervasivehealth.2011.245995

[34] Montgomery PG, Green DJ, Etxebarria N, Pyne DB, Saunders PU, Minahan CL. Validation of Heart Rate Monitor-Based Predictions of Oxygen Uptake and Energy Expenditure. J Strength Cond Res. 2009 Aug;23(5):1489–95. https://doi.org/10.1519/JSC.0b013e3181a39277

[35] Stein PK, Pu Y. Heart rate variability, sleep and sleep disorders. Sleep Med Rev. 2012 Feb;16(1):47–66. https://doi.org/10.1016/j.smrv.2011.02.005

[36] Sannino G, Melillo P, Stranges S, Pietro G De, Pecchia L. Blood Pressure Drop Prediction by using HRV Measurements in Orthostatic Hypotension. J Med Syst. 2015 Nov 7;39(11):143. https://doi.org/10.1007/s10916-015-0292-5

[37] Heitterachi E, Lord SR, Meyerkort P, McCloskey I, Fitzpatrick R. Blood pressure changes on upright tilting predict falls in older people. Age Ageing. 2002 May;31(3):181–6. https://doi.org/10.1093/ageing/31.3.181

[38] Parati G, Stergiou GS, Asmar R, Bilo G, de Leeuw P, Imai Y, et al. European Society of Hypertension Practice Guidelines for home blood pressure monitoring. J Hum Hypertens. 2010 Dec 3;24(12):779–85. https://doi.org/10.1038/jhh.2010.54

[39] Hausdorff JM, Rios DA, Edelberg HK. Gait variability and fall risk in community-living older adults: A 1-year prospective study. Arch Phys Med Rehabil. 2001 Aug;82(8):1050–6. https://doi.org/10.1053/apmr.2001.24893

[40] Bamberg S, Benbasat AY, Scarborough DM, Krebs DE, Paradiso JA. Gait Analysis Using a Shoe-Integrated Wireless Sensor System. IEEE Trans Inf Technol Biomed. 2008 Jul;12(4):413–23. https://doi.org/10.1109/TITB.2007.899493

[41] Talavera G, Garcia J, Rösevall J, Rusu C, Carenas C, Breuil F, et al. Fully-Wireless Sensor Insole as Non-invasive Tool for Collecting Gait Data and Analyzing Fall Risk. In: Bravo J, Hervás R, Villarreal V (eds). Ambient Intelligence for Health. AmIHEALTH 2015. Lecture Notes in Computer Science, vol 9456. Springer, Cham; 2015. p. 15–25. https://doi.org/10.1007/978-3-319-26508-7_2

[42] Majumder AJA, Zerin I, Ahamed SI, Smith RO. A multi-sensor approach for fall risk prediction and prevention in elderly. ACM SIGAPP Appl Comput Rev. 2014 Mar 1;14(1):41–52. https://doi.org/10.1145/2600617.2600621

[43] Nakajima K, Saito M, Kodama M, Iwakami Y, Ino S, Ifukube T, et al. Evaluation of Ambulatory Function by Using the Shoe Device. In: Jobbágy Á (eds). 5th European Conference of the International Federation for Medical and Biological Engineering. IFMBE Proceedings, vol 37. Springer, Berlin, Heidelberg; 2011. p. 868–71. https://doi.org/10.1007/978-3-642-23508-5_226

[44] GaitRite. GaitRite [Internet]. Available from: http://www.gaitrite.com

[45] ELSI. Elsi smart floor [Internet]. Available from: http://www.maricare.com/en/how-it-works/elsi-smart-floor

[46] Rantz M, Skubic M, Abbott C, Pak Y, Stone EE, Miller SJ. Automated Fall Risk Assessment and Detection in the Home: A Preliminary Investigation. In: AAAI Fall Symposium Series; 2012 AAAI Fall Symposium Series. 2012. p. 22–5.

[47] Nelson AJ. Functional Ambulation Profile. Phys Ther. 1974 Oct 1;54(10):1059–65. https://doi.org/10.1093/ptj/54.10.1059

[48] Kortelainen JM, Mendez MO, Bianchi AM, Matteucci M, Cerutti S. Sleep Staging Based on Signals Acquired Through Bed Sensor. IEEE Trans Inf Technol Biomed. 2010 May;14(3):776–85. https://doi.org/10.1109/TITB.2010.2044797

[49] Stone E, Skubic M. Evaluation of an Inexpensive Depth Camera for Passive In-Home Fall Risk Assessment. In: Proceedings of the 5th International ICST Conference on Pervasive Computing Technologies for Healthcare. IEEE; 2011. https://doi.org/10.4108/icst.pervasivehealth.2011.246034

[50] Wang X, Dinh A, Teng D. Radar Sensing Using Ultra Wideband – Design and Implementation. In: Ultra

Wideband - Current Status and Future Trends. IntechOpen; 2012. https://doi.org/10.5772/48587

[51] Joshi V, Knoefel F, Goubran R, El-Tanany M. Measurement of spontaneous body sway during quiet stand using UWB sensor. In: 2017 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI). IEEE; 2017. p. 281–284. https://doi.org/10.1109/BHI.2017.7897260

[52] Rubenstein LZ, Vivrette R, Harker JO, Stevens JA, Kramer BJ. Validating an evidence-based, self-rated fall risk questionnaire (FRQ) for older adults. J Safety Res. 2011 Dec 1;42(6):493–9. https://doi.org/10.1016/j.jsr.2011.08.006

[53] Obrist S, Rogan S, Hilfiker R. Development and Evaluation of an Online Fall-Risk Questionnaire for Nonfrail Community-Dwelling Elderly Persons: A Pilot Study. Curr Gerontol Geriatr Res. 2016;2016:1520932. https://doi.org/10.1155/2016/1520932

[54] Ibrahim A, Singh DKA, Shahar S, Omar MA. Timed up and go test combined with self-rated multifactorial questionnaire on falls risk and sociodemographic factors predicts falls among community-dwelling older adults better than the timed up and go test on its own. J Multidiscip Healthc. 2017 Oct 26;10:409-416. https://doi.org/10.2147/JMDH.S142520

[55] Russell MA, Hill KD, Blackberry I, Day LM, Dharmage SC. The reliability and predictive accuracy of the falls risk for older people in the community assessment (FROP-Com) tool. Age Ageing. 2008 Nov 1;37(6):634–9. https://doi.org/10.1093/ageing/afn129

[56] Yesavage JA, Brink TL, Rose TL, Lum O, Huang V, Adey M, et al. Development and validation of a geriatric depression screening scale: a preliminary report. J Psychiatr Res. 17(1):37–49. https://doi.org/10.1016/0022-3956(82)90033-4

[57] Folstein MF, Folstein SE, McHugh PR, Ingles J. “Mini-mental state”. A practical method for grading the cognitive state of patients for the clinician. J Psychiatr Res. 1975 Nov;12(3):189–98. https://doi.org/10.1016/0022-3956(75)90026-6

[58] General Data Protection Rule: EUR-Lex - 32016R0679 - EN - EUR-Lex [Internet]. [cited 2018 Nov 10]. Available from: https://eur-lex.europa.eu/eli/reg/2016/679/oj/eng

[59] Yamada M, Aoyama T, Nakamura M, Tanaka B, Nagai K, Tatematsu N, et al. The Reliability and Preliminary Validity of Game-Based Fall Risk Assessment in Community-Dwelling Older Adults. Geriatr Nurs (Minneap). 2011 May;32(3):188–94.

[60] HUR Labs OY. HUR Smarttouch [Internet]. Available from: http://www.hur.fi/en/products/hur-smarttouch

[61] Technogym. Technogym [Internet]. Available from: https://www.technogym.com

[62] Boulos M, Wheeler S, Tavares C, Jones R. How smartphones are changing the face of mobile and participatory healthcare: an overview, with example from eCAALYX. Biomed Eng Online. 2011 Apr 5;10(1):24. https://doi.org/10.1186/1475-925X-10-24

[63] He Y, Li Y. Physical Activity Recognition Utilizing the Built-In Kinematic Sensors of a Smartphone. Int J Distrib Sens Networks. 2013 Apr 3;9(4):481580. https://doi.org/10.1155/2013/481580

[64] AbuKhousa E, Mohamed N, Al-Jaroodi J. e-Health Cloud: Opportunities and Challenges. Futur Internet. 2012 Jul 4;4(4):621–45. https://doi.org/10.3390/fi4030621

[65] Raghupathi W, Raghupathi V. Big data analytics in healthcare: promise and potential. Heal Inf Sci Syst. 2014;2:3. https://doi.org/10.1186/2047-2501-2-3

[66] Howe TE, Rochester L, Neil F, Skelton DA, Ballinger C. Exercise for improving balance in older people. In: Howe TE, editor. Cochrane Database of Systematic Reviews. Chichester, UK: John Wiley & Sons, Ltd; 2011.

[67] Becker C, Schwickert L, Mellone S, Bagalà F, Chiari L, Helbostad JL, Zijlstra W, Aminian K, Bourke A, Todd C, Bandinelli S, Kerse N, Klenk J. Proposal for a multiphase fall model based on real-world fall recordings with body-fixed sensors. Z Gerontol Geriatr. 2012 Dec;45(8):707-15. https://doi.org/10.1007/s00391-012-0403-6

[68] My Kanta pages - Kanta.fi [Internet]. Kanta-palvelut, Kansaneläkelaitos [cited 2018 Oct 24]. Availa-

ble from: https://www.kanta.fi/en/web/guest/my-kanta-pages

[69] My Kanta Pages Personal Health Record - Kanta.fi [Internet]. Kanta-palvelut, Kansaneläkelaitos [cited 2018 Oct 24]. Available from: https://www.kanta.fi/en/professionals/kanta-phr

[70] Proposal for a Data Protection Act and related legislation [Internet; in Finnish]. Eduskunta; 2018 [cited 2018 Oct 24]. Available from: https://www.eduskunta.fi/FI/vaski/HallituksenEsitys/Sivut/HE_9+2018.aspx

[71] Keränen NS, Kangas M, Immonen M, Similä H, Enwald H, Korpelainen R, et al. Use of Information and Communication Technologies Among Older People With and Without Frailty: A Population-Based Survey. J Med Internet Res. 2017;19(2). https://doi.org/10.2196/jmir.5507

[72] Yang G-Z, Hu X. Multi-Sensor Fusion. In: Body Sensor Networks. London: Springer London; 2006. p. 239–85. https://doi.org/10.1007/1-84628-484-8_8

[73] Greene BR, Redmond SJ, Caulfield B. Fall Risk Assessment Through Automatic Combination of Clinical Fall Risk Factors and Body-Worn Sensor Data. IEEE J Biomed Heal Informatics. 2017 May;21(3):725–31. https://doi.org/10.1109/JBHI.2016.2539098

[74] Greene B, inventor. Care Innovations LLC, assignee. Quantitative falls risk assessment through inertial sensors and pressure sensitive platform. United States patent US20140024972A1. 2012-07-20.

[75] Howcroft J, Kofman J, Lemaire ED. Prospective Fall-Risk Prediction Models for Older Adults Based on Wearable Sensors. IEEE Trans Neural Syst Rehabil Eng. 2017 Oct;25(10):1812–20. https://doi.org/10.1109/TNSRE.2017.2687100

[76] Gravina R, Alinia P, Ghasemzadeh H, Fortino G. Multi-sensor fusion in body sensor networks: State-of-the-art and research challenges. Inf Fusion. 2017 May 1;35:68–80. https://doi.org/10.1016/j.inffus.2016.09.005

[77] Danielsen A, Olofsen H, Bremdal BA. Increasing fall risk awareness using wearables: A fall risk awareness protocol. J Biomed Inform. 2016;63:184–94. https://doi.org/10.1016/j.jbi.2016.08.016

[78] Witten IH, Fran E. Data Mining: Practical Machine Learning Tools and Techniques. Second Edition. San Francisco, USA: Elsevier; 2005. 525 p.

[79] Marschollek M, Gövercin M, Rust S, Gietzelt M, Schulze M, Wolf K-H, et al. Mining geriatric assessment data for in-patient fall prediction models and high-risk subgroups. BMC Med Inform Decis Mak. 2012 Dec 14;12(1):19. https://doi.org/10.1186/1472-6947-12-19

[80] Helgadottir B, Moller J, Laflamme L. Patterns in health-related behaviours and fall injuries among older people: a population-based study in Stockholm County, Sweden. Age Ageing. 2015 Jul 1;44(4):604–10. https://doi.org/10.1093/ageing/afv051

[81] Howcroft J, Kofman J, Lemaire ED. Review of fall risk assessment in geriatric populations using inertial sensors. J Neuroeng Rehabil. 2013;10(1). https://doi.org/10.1186/1743-0003-10-91

[82] Similä H, Immonen M, Ermes M. Accelerometry-based Assessment and Detection of Early Signs of Balance Deficits. Comput Biol Med. 2017 Jun 1;85:25-32. https://doi.org/10.1016/j.compbiomed.2017.04.009

[83] Similä H, Immonen M, Niemirepo T. Mobile Fall Risk Assessment Solution for Daily-Life Settings. Conf Proc IEEE Eng Med Biol Soc. 2018 Jul;2018:1530-1533. https://doi.org/10.1109/EMBC.2018.8512589