Mobile Assisted Living: Smartwatch-based Fall Risk Assessment for Elderly People

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ABSTRACT

We present a novel Smartwatch-based approach, to enable Mobile Assisted Living (MAL) for users with special needs. A major focus group for this approach are elderly people. We developed a tool for caregivers applicable in home environments, nursing care, and hospitals, to assess the vitality of their patients. Hereby, we particularly focus on the prediction of falls, because falls are a major reason for serious injuries and premature death among elderly. Therefore, we propose a multi parametric score based on standardized fall risk assessment tests, as well as on sleep quality, medication, patient history, motor skills, and environmental factors. The resulting total fall risk score reflects individual changes in behavior and vitality, which consequently enables for fall preventing interventions. Our system has been deployed and evaluated in a pilot study among 30 elderly patients over a period of four weeks.

CCS CONCEPTS

• **Human-centered computing** → **Accessibility technologies**; • Human-centered computing. → Ubiquitous and mobile computing systems and tools.

KEYWORDS

Mobile Assisted Living; Fall Risk; Assistance; Elderly People; Smartwatch; Health Care; Health Technology; Pulse Detection; Vital Signs; Pattern Recognition.

1 INTRODUCTION

Many facilities, such as nursing homes or geriatric wards experience high costs due to follow-up treatments related to injuries caused by falls. According to Luukinen et al. [35] and Rubenstein et al. [38] nursing homes experience around 1.5 falls per bed per year, whereas Nurmi et al. [36] state 1.4 falls per person per year. Factors that contribute to the risk of falling include injuries or pathologic conditions (e.g., hip fracture, stroke) or even unfamiliar environments. According to Dromerick et al. [13] and Forster et al. [15], from 25% to 46% of all patients in stroke rehabilitation wards have been reported to fall at least once during their admission. According to Rubinstein et al. [39], 75% of deaths in the age group of 65+ in the Unites States are due to fall. This concern 13% of the population. Heinrich et al. [25] reviewed 32 studies with regard to costs of falls in old age. The review investigated study data of different regions including the UK, the US, Europe, and Australia. According to the authors' results, between 0.85 % and 1.5% of the total health care expenditures of each region are related to falls. In the United States, about 0.2% of the gross domestic product (547 USD PPP) is paid per inhabitant per year (age group 65+; ~13% of US population). Figure 2 shows the cumulative costs of fractures due to fall among women in the age of 50+ years according to Bleibler et al. [5], [6].

Usual interventions aim to avoid falls include exercise, medication optimization, vitamin D supplementation, education, and environmental modifications [10]. However, many therapies

Figure 1. **We present a Mobile Assisted Living Smartwatch-app, which runs on a No.1 D5+ Android watch. Implemented features include the detection of: Respiratory Parameters, Cardiac Parameters, an explicit Help Gesture, Fall Detection, Sleep Parameters, Posture Parameters, as well as Gait and Activity Parameters. These parameters are used to calculate a fall risk level for the elderly.**

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and fall intervention methods are expensive while they commonly require prescription in order to be reimbursed by health insurance companies. In fact, most prescriptions that qualify as fall preventing interventions (e.g., supervised exercises, physiotherapy, or quality vitamin supplementation) are just prescribed after a fall occurred that resulted in significant injuries for the elderly person. Even if fall intervention therapies are prescribed prior to fall events, a reliable method of evaluating the possible success of these preventive measures is either missing, or insufficient [10].

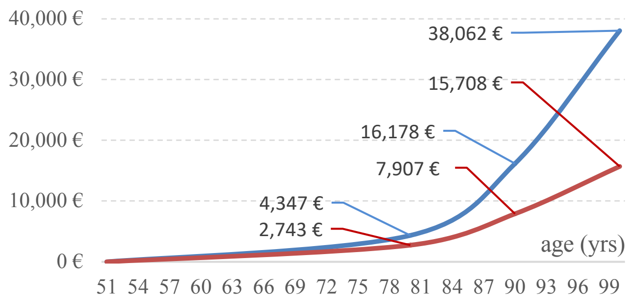

Figure 2. Cumulative average costs of fractures among women in the age of 50+ years. The blue graph shows expenditure for patients with osteoporosis and red graph without [5], [6].

In this paper, we introduce a system for evaluating the individuals' fall risk with a customary Smartwatch. Our approach relies on a number of standard tests with regard to balance, lower body strength, general fitness, sleep quality, environmental factors, as well as the patients' history. We calculate a total fall risk score that provides a measure for caregivers, to identify patients with a special need for a close-meshed fall prevention monitoring. Furthermore, individual needs for exercises and physiotherapies can be identified, which enables individually tailored assistance in order to prevent falls. Our assistive approach is mobile and not tied to a specific environment, in contrast to most Ambient Assisted Living (AAL) solutions.

We introduce a Mobile Assisted Living (MAL), which is demonstrated with a Smartwatch-based prototype. To evaluate the feasibility of a MAL system, we developed a proof-of-concept Smartwatch application (*see Figure 1*), which enables for the assessment of the user's vitality and fall risk level, which are both based on a variety of medical parameters. Particularly the assessment of fall risk enables a prevention of falls, which is estimated on a multi-parametric fall risk scale. In summary, we contribute:

- a proof-of-concept Smartwatch-based Mobile Assisted Living system, which assists elderly, people with special needs, and their caregivers,
- a novel fall risk assessment based on a multifold set of medical state-of-the-art tests, vital and environmental parameters, which now allows for tailoring individual fall prevention intervention to the patient's need.

2 MOBILE ASSISTED LIVING

Assisted Living (AL) or better known as Ambient Assisted Living (AAL) comprises technical systems to support user groups with special needs in their daily routines. Typically, these user groups consist of elderly, ill, or people with disabilities. Especially in case of elderly people, the goal is to retain independency and a safe lifestyle for as long as possible [14]. Due to the rapid development of smart sensor technology and the internet of things (IoT), AAL technologies proliferate. While the level of application is still at a moderate stage, it may just be a matter of time until intelligent assistive technologies fully pervade our daily lives [48]. A frequently used example in AAL is the smart kitchen [3], [33], in which an ambient intelligence senses the user's activity in order to provide instructions or assistance respectively. While we can utilize camera tracking [11], which is affected by occlusion or generally challenging lighting conditions, we can embed any other type of sensor at any suitable position (e.g., into a shelf). Instrumenting everyday objects (e.g., a bed, sofa, chair, or a table) with proximity sensors also enables a rudimentary activity tracking [9]. In contrast to dense sensing approaches, Laput et el. [33], demonstrate how a future smart home could only rely on a single sensor-board that is capable of sensing state changes of a great variety of machines and objects without instrumenting them. Exemplary demonstrated activities, include operating a faucet, soap dispenser, paper towel dispenser, dishwasher, kettle, microwave, and refrigerator. When dealing with noisy sensor data, one can also utilize context information [41], such as the user's location, and determine the most probable activity (e.g., when being in the bathroom, it is very likely that the detected event has been an operated faucet and not the dishwasher). Apart from tracking the operation of an object, solely knowing about the user's location can be particularly interesting with patients suffering from dementia, since they suffer of disorientation and may often randomly wander around during the night [28].

Since the human is an agile subject being always on the move, it can quickly occur that the user might be out of defined sensing ranges. Therefore, an event tracking, such as tracking the user's location, would be prone to error (e.g., when going for a walk). As a result of this, we envision a Mobile Assisted Living (MAL) system in order to extend or even replace traditional AAL technology. Here, a wearable sensing of activities [1], [32] comes in handy. While we can sense standard activities [19], such as walking, running, cycling, etc., we can also train specific motion sequences in order to find out about the dish that is being cooked [32]. However, supporting elderly people would require different types of information such as data about their physical and mental well-being. In 2013, Bieber et al. [4] and in 2015, Hernandez et al. [26] proposed approaches applying the accelerometer of a commercial Smartwatch for extracting vital data. This motion data can be used to determine the user's heart rate and respiration rate. When combining mobile activity tracking and health monitoring, as recently demonstrated [7], [45], [46] we can pave the way for MAL. Since Smartwatches already incorporate a rich density of sensor types and actuators, they yield a great potential to be used as a MAL hardware. For instance, Smartwatches allow to sense bio signals such as using an ECG wristband or an embedded Photoplethysmography sensor that enables to the sense heart rate. Inertial sensors (e.g., accelerometers, gyroscopes, or magnetometers) can be considered as very powerful, while they enable to detect a variety of motions and thus allow for classifying a great range of human activities. In addition to that, many Smartwatches provide GPS localization and wireless connectivity (e.g., WiFi or Bluetooth). Even GSM modules for a mobile internet connection and phone calls can be found in certain autarkic models. In combination with a multi-touch display and other actuators, such as audio or vibrotactile feedback, these watches can serve as a powerful assistive system for MAL.

Since many people of an advanced age are still very active, static and locally tied assistance cannot fulfill basic requirements. Thus, common AAL technologies should be mobile. Besides our presented concept of a Mobile Assisted Living for the purpose of fall risk estimation, a broad variety of other application scenarios can be named. Exemplary scenarios include assisting disoriented dementia patients in outdoor navigation tasks, calling an autonomous walking aid in an outdoor environment, or automatically notifying a means of public transportation that a person with special needs will be boarding at the next station.

3 FALL RISK ASSESSMENT

In this section, we introduce our fall risk assessment for elderly people, which is based on a variety of parameters that are being explained in detail.

3.1 Motivation

In Sweden, but also in any other European country, there is an elderly fall accident every two minutes, causing pain, fear, and misery for the involved person and concerned relatives. While the moment of a fall often significantly harms the elderly, also the after-treatment in hospitals yields great danger, since elderly people are already weakened. Following statistical data, falls often lead to an earlier death, while it takes more lives than traffic accidents. In Swedish hospitals, fall emergencies as well as resulting treatments create 24 Billon SEK ($5 Billion) in costs every year [16]. Moreover, there are as long as 6 months waiting time to obtain a room in elderly homes and fall accidents are a major reason for this. These are not just local, but global problems of our continuously aging society in Europe and the entire World. Therefore, it is reasonable to develop a solution that predicts fall risks and prevents falls amongst the elderly people. Such system would be able to estimate by continuously analyzing the user's vital parameters, such as gait, balance, strength of step impact, posture transition times, stride, cardiac, and sleep parameters. With this focus in mind, we researched and developed a MAL system monitoring elderly people and estimating their fall risk.

3.2 Hardware

In fact, the hardware configuration used plays a substantial role for recognition capabilities. In research, we usually make use of various types of sensor. Quality parameters such as sensing quantization, noise level, and range play a significant role in choosing a suitable sensor. However, sticking to consumer hardware is more challenging, because we underlie many sensor limitations in terms of variety and precision, as well as limited battery life time.

Our initial goal is to use a commercially available Android Smartwatches, such as the G99 and D5+, which offers us to access the accelerometer with a sampling rate of only 50Hz. Considering the Nyquist-Shannon sampling theorem, the provided rate is sufficient for human motions and locomotion as performed in activities of daily living as pointed out by Bouten et al. [8]. Nevertheless, faster motions, such as certain types of tremor or body vibrations such as seismocardiac motions require higher sampling rates. The aforementioned devices do not support higher sampling rates, as the Android SDK and manufacturers firmware does not allow it. Also, the maximum sensing range is limited to +/- 19.6133m/s^2. The resolution of the accelerometer sensor is 0.039226603m/s^2, which is a quantization of 8bit per g and thus comparably low. Although the Smartwatches provides a sensor hub, the acceleration sensor does not support the Batch-Mode or FiFo-Buffering, which is another constraint at the expense of the battery life time. With the mentioned restrictions, a battery life of two days was achieved.

3.3 Implementation of Fall Risk Assessment Parameters

In order to calculate the fall risk level, we rely on a variety of tests, context information and user history parameters. We categorized the parameters into three groups, which sum up to the total fall risk score:

- Basal Fall Risk Score (BFRS)
- Environmental Fall Risk Score (EFRS)
- Variable Fall Risk Score (VFRS).

Activity Level and Gait Parameters (VFRS)

Analyzing the user's gait can provide essential information to assess the risk of fall. Something similar has also been found in literature; knowing about the user's walking activity can be particularly essential for elderlies to assess their wellbeing [2]. Apparently, gait parameters from elderly people are different to younger people due to the much slower body movements. Therefore, standard recognition algorithms demonstrate great deviations and would require an adjustment. For detecting gait parameters from an elderly person, we extended the walking algorithm proposed by Neil Zhao [50]. The basic algorithm adapts to varying offsets and intensities and counts maxima as steps, that meet certain step criteria (e.g., min and max time between consecutive steps). In contrast to Zhao [50], we applied a 3D vector norm instead of choosing a particular axis for the detection algorithm. By doing this, we avoid choosing the wrong axis and leaving out valid parts of the 3-dimensional walking motion. Besides a basic step count, we also detect the impact of each individual step by calculating the acceleration intensity on all axes combined. By applying the algorithm of Scarlett [40], we can estimate the step length and thus the distance traveled. Since the algorithm is affected by the individual walking style, we also added the possibility to compute the step length based-on height and gender as shown by Pratama et al. [37], or even setting a fixed step length based on precise measurements. The aforementioned parameters rely on improved accelerometer-based step counting algorithms [44],[49]. In addition to the previously mentioned parameters, we compute a 6-minute walking test in the background. The test runs on the fly, every time the user continuously walks for at least 6 minutes. We also apply a trained classifier for identifying simple daily activities. In summary, our classifier [19] is able to distinguish between the activities walking, running and sleeping. All types of data are stored on a web-server within a daily basis.

In order to evaluate the influence of gait related parameters, we applied two standard tests: 1) *a standardized 6-minutes walking threshold test* (*see Table 1*); and 2) the *number of steps walked throughout the day threshold test* (*see Table 2*).

6-minute Walking Threshold Test:
In this standardized test, a subject has to walk for 6 minutes in a row. Depending on the subject's age and physical state, average step thresholds have to be crossed in order to pass the test.

Table 1. Showing the threshold performances of the six-minute walk test for three age groups (see also Chetta et al. [12] and Steffen et al. [42]).

	I	*II*	*III*
Age in yrs.	60-69	70-79	80-89
Distance in m (male)	572	527	417
Distance in m (female)	538	471	392

Once the calculated distance cannot be reached within six minutes, we add a risk point to the total fall risk level of the user. This risk point is valid for the day it is scored. After a successfully passed 6-Minute walking test, the risk point is reset, which leads to a reduction of the total fall risk score.

No. of Steps Walked throughout the Day Threshold Test:
In this test, a subject has to achieve the recommended daily number of steps depending on the subjects age group. In case the threshold for the recommended number of daily steps is exceeded or met, the test is passed.

Table 2. Showing the threshold performances of the number of steps taken per day for five typical age groups (see also Tudor-Locke et al. [47]).

	I	*II*	*III*	*IV*	*V*
Age in yrs.	8-10	10-20	20-50	50-70	> 70
#steps/ day	12000-16000	11000-12000	7000-13000	6000-8500	3500-5500

In case the daily step performance in one of the tests falls below the given threshold of the user's age group, we add a risk point to the total fall risk score because motor-memory is negatively affected and thus the risk of fall is potentially increased, in particular for higher age groups. This risk point is valid for the following day, since the daily step peak is achieved before going to bed. In case the daily steps walked test is passed, the risk point is reset for the following day.

Postures and Transitions (VFRS)
Postures and their transitions can provide valuable information on the user's physical fitness. Based on this information we determine the vitality of a person, which directly impacts the fall risk level. Moreover, the duration of changing postures (e.g., time needed to get up) gives an insight on the lower body strength of a user. In comparison to younger people, posture changes performed by elderly people are differing in terms of execution style. This affects almost every accelerometer-based posture detection algorithm [18]. Our algorithms can distinguish between standing, sitting, and laying down, while additionally information on the transition times and the created peak impact during execution yield important information.

In order to detect changes in posture via a wrist-worn accelerometer, we detect distinctive arm positions and orientations with respect to limitations in motion due to a biological human model. In addition, we included contextual knowledge about the positions sitting and standing and the related arm postures. Thus, our standing algorithm is triggered by arm postures that are mainly vertical in a direction pointing to the ground, whereas the sitting algorithm is triggered by arm postures that are mainly horizontal or in an upward pointed vertical position. Hence, we use the sign-based axes orientation of the acceleration sensor (*see Figure 3*). Since the axis orientation changes with respect to the wrist the device is worn at, the preferred wrist has to be selected in the initial setup.

Figure 3. Our C4.5 DT classifier distinguishes between these three common postures: sitting, standing, and walking, while we calculate according transition parameters.

In order to determine a possible risk level, we utilize a standardized *timed up & go (TUG) threshold test - see Table 3.*

Timed Up & Go (TUG) Threshold Test:
Hereby, we measure the time, it takes the user to change from a sitting to an upright position and walk for three meters. We only add a risk point to the total fall risk score, once the age dependent average threshold is exceeded. The risk point is valid for the day it was scored. The risk point resets every day.

Table 3. Showing threshold performance for the timed up & go test (TUG) for 3 typical risk groups (see also Steffen et al. [42]).

	I	*II*	*III*
Age in yrs.	60-69	70-79	80-89
Time in s (male)	8	9	10
Time in s (female)	8	9	11

Detected Falls (VFRS)

People who have a prehistory of falling are apparently at greater risk of falling again - see also Gaßmann et al. [17]. The major reasons for this can be found in an increased fear of tripping and injuries resulting from previous falls. The detection of falls itself is a complex issue, because there are many different ways of falling. Still, current state-of-the-art fall detections [30] are rather inaccurate. Especially detecting falling with elderly people is challenging, since very different forces are being created, which are mostly lower and thus a huge challenge for current algorithms. Therefore, we needed to develop an improved fall detection that also works with lower impacts. Our proposed fall detection is based on four stages, which is demonstrated in Figure 4

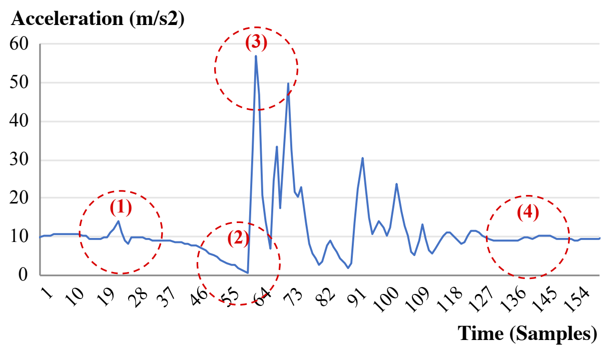

Figure 4. Acceleration data recorded by a wrist-worn Smartwatch showing a typical (real) fall. In this case, we can ideally identify a fall based on the characterization of four distinct stages.

In the first stage, the loss of equilibrium is sensed as a quick and strong change in motion.

$$1)\quad x[n] = \alpha \cdot x[n] + (1-\alpha) \cdot xn + 1$$

This is followed by a detection of free fall in the second step. The detection of the free fall is based on the fact, that all acceleration axes show almost zero g during this phase.

$$2)\quad \vec{a} = \begin{pmatrix} x \\ y \\ z \end{pmatrix};\ |\vec{a}| = \sqrt{a_x^2 + a_y^2 + a_z^2}$$

Subsequently, we detect the impact generated by hitting the ground or an object.

$$3)\quad \delta(n) = \begin{cases} \delta(n)\ if\ \delta(n-1) < \delta(n) \wedge \delta(n+1) < \delta(n) \\ 0\ otherwise \end{cases}$$

This is followed by the fourth stage; in which we can sense a longer period of no motion.

$$4)\quad N_{Steps} = \sum_0^N \delta(n)$$

In case all stages occurred within a pre-defined timespan, our algorithm checks whether the device is worn or doffed.

$$if: (n_{x+1} - n_x) > lower_{freq\_thresh} \wedge (n_{x+1} - n_x) < upper_{freq\_thresh}$$

$$if: (\delta_{x+1} - \delta_x) > lower_{ampl\_thresh} \wedge (\delta_{x+1} - \delta_x) < upper_{ampl\_thresh}$$

Basically, the acceleration signal is scanned for Microvibrations, while additionally a PPG-based heart rate measurement is conducted.

Besides utilizing the fall detection to increase the total fall risk score, we also implemented an automated emergency notification, which is send out via a call, SMS, or web-message. Our system allows to set an emergency contact in the initial setup. This contact is usually a caregiver but can also be a relative or a person of trust. Part of the emergency message is the description of the incident (e.g., "I just fell and may need help") as well as the detected parameters of the fall history (current heart rate, motion intensity computed over all acceleration axes, number of falls today).

The total fall risk score is increased by adding a risk point right after a fall. This risk point will be set for 6 months. In case no fall happened within the last 6 months, the risk point will be reset.

Emergency Communication (VFRS)

As an additional emergency function, our system also features an explicitly triggered emergency call by a distinct arm-waving gesture [34] or taping a software button, which establishes a phone call, sends an SMS, or a digital message to a web-server, as configured on the watch. In case a user indicates the need of help, the fall risk may also increase. Exemplary, this situation could be illustrated by a resident with special needs in an elderly care that urgently needs help, such as to go to the toilet. In case a caregiver cannot get to the patient in time, the total fall risk score is increased by one risk point. The aforementioned increase of the total fall risk score happens because the resident might try to get there on its own, which contains an increased risk of fall and injury. In other circumstances, the emergency notification could also mean that the elderly person is not feeling well (e.g., feeling dizzy or sick), which also indicates a higher risk of falling.

The temporary added risk point is reset 24h after an emergency message was triggered.

Sleep Parameters (VFRS)

Bad sleep can result in risk factors, such as headache, increased blood pressure, dizziness, fatigue, or a lack of concentration, which contribute to a higher risk of fall. Certain sleep related disease patterns, such as apneas and epileptic seizures can lead to a reduction in blood oxygen and therefore result in brain damage. These anomalies are also detectable with Smartwatches during sleep [24]. By simply calculating standard sleep related parameters, our system can infer on the quality of sleep, and reveal important information on the user's mental and physical state. We implemented a set of standard tests for evaluating the quality of sleep.

The computed parameters include the sleep efficiency (SE), total sleep time (TST), wake-time after sleep onset (WASO), time in bed (TIB), sleep onset latency (SOL), number of position changes, as well as the wake-up and fall asleep time based on low-motion body amplitudes [20].

For the purpose of fall risk assessment, we chose 4 tests that combine the meaningfulness of all sleep parameters computed. The selected tests include 1) *a sleep efficiency threshold test;* 2) *a total sleep time threshold test;* 3) *a bedtime schedule threshold test;* 4) *a number of position shifts threshold test.* Each test that is failed (threshold exceeded), increments the total fall risk score.

<u>*Sleep Efficiency (SE) Threshold Test:*</u>

An important sleep parameter is the so-called sleep efficiency (SE), it is defined as the quotient of total sleep time (TST) divided by time in bed (TIB). Usually, a SE of > 85% is defined as healthy or normal. According to Stone et al. [43] who conducted a large study of older women, a TST of <7 hours and SE <65% was associated with an 30-40% increased risk of subsequent falls. Therefore, we defined a SE of <70% as a failed test and therefore increase the total fall risk score by one risk point. The risk point counts for the daytime following the night it was scored. With the end of each night a reevaluation is done.

<u>*Bedtime Schedule Threshold Test:*</u>

Figure 5 shows the variation in going to bed and standing up in the morning.

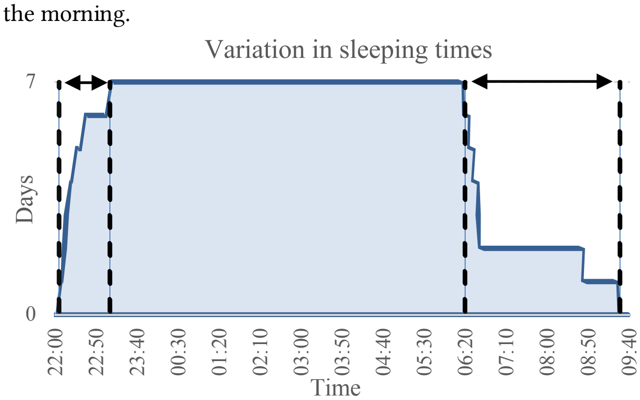

Figure 5. Variations in go to sleep and get up times.

The example in the figure shows a regular go to bed time, but a varying get up time (e.g., as normally seen during the weekend). Irregular bedtime schedules throughout the week disturb the circadian rhythm, and therefore may lead to a poor quality of sleep [29]. In case of an irregular bedtime frequency (shift of >1h for 1 or more days throughout the week) we add a risk point to the total fall risk score. The added risk point counts for the whole week. The risk point is being reset at the beginning of the next week.

<u>*Number of Position Changes Threshold Test:*</u>

The number of position changes during sleep can provide crucial information on the elderly person's sleep quality and on his mental and physical state on following day. Because too many position changes (*see Table 4*) indicate light and uncomfortable sleep, the user is very likely to feel tired next day, which we credit with a risk point that is added to the total fall risk score. The risk point counts for the daytime following the night it was scored. With the end of each night a reevaluation is done.

Table 4. Number of position shifts during sleep according to De Koninck et al. [31].

	I	*II*	*III*	*IV*	*V*
Age in yrs.	3-5	8-12	18-24	35-45	65-80
$\#pos_{shifts}$	42.3	44.5	27.1	19.6	16.4

<u>*Total Sleep Time (TST) Threshold Test:*</u>

Another important parameter is the accumulated sleep duration within one night. Reduced sleep obviously results in tiredness but can also result in dizziness particularly in elderly people. When the suggested [27] total sleep time is being undershot, we add a risk point to the total fall risk score. The risk point counts for the daytime following the night it was set. With the end of each night a reevaluation is performed.

Table 5. Sleep duration categorized in age groups (I-V). The table shows the recommended total sleep time (TST)1 as well as to short and therefore not recommended total sleep times2 (See also Hirshkowitz et al. [27]).

	I	*II*	*III*	*IV*	*V*
Age in yrs.	6-13	14-17	18-25	26-64	> 64
[1]TST in h	9-11	8-10	7-9	7-9	7-8
[2]TST in h	<7	<7	<6	<6	<5

Cardiac & Respiratory Parameters (VFRS)

Parameters of the cardiovascular system are good indicators for evaluating the physical constitution. Simple parameters, such as the resting heart rate, heart rate variability, or the recovery time after exertion give insights with regard to the stamina or general fitness level. A user with a bad fitness level is more likely to trip due to exhaustion or a lack of concentration. In addition to this, a bad stamina can lead to high pulse rates, as well as heavy breathing, which can lead to dizziness and therefore an increased fall risk.

In order to evaluate the current level of fitness, we sense the heart rate throughout the day. Therefore, we apply two sensing techniques. The first technique, reads the built-in Photoplethysmography (PPG) sensor of our Smartwatch (No.1 D5+). In case of a resting state, such as laying down or sitting the sensor is read every 15 minutes. This interval allows to safe battery and therefore extend the runtime of the device. In case of motion, such as walking or exercising we constantly read the heart rate with the PPG sensor.

The second technique is based on the watches built in acceleration sensor. This sensor allows the implementation of Ballistocardiography (BCG) algorithms. Our developed algorithms [22] enable a detection of heart rate in states of rest, whereby the best results can be achieved during sleep. This technique also enables the detection of heart rate, heart rate variability, as well as the respiration rate [21] during the night. The major advantage in comparison to optical PPG sensors is the very low energy consumption of such micro-electromechanical systems (MEMS). Moreover, a BCG approach allows to sense more heart rate parameters that can also be used to discover cardiac diseases.

While the resting heart rate as well as the breathing rate can provide information on the user's stress level, which has an impact on the elderly person's fall risk, we can adjust the individual's total fall risk score when the heart rate exceeds the age dependent average (*see Table 6*). In this case, a risk point will be added. This risk point is valid for the day it was scored and will be reset the next day.

Table 6. Average resting heart rate in bpm* depending sorted by age group (I-VI).

	I	*II*	*III*	*IV*	*V*	*VI*
Age in yrs.	18-25	26-35	36-45	46-55	56-65	> 65
****HR in bpm***	70-73	71-74	71-75	72-76	72-75	70-73

Environmental Change (EFRS)

Unfamiliar environments bare great challenges for elderly people, while they tend to feel insecure and thus pose in a different way. In contrast, a familiar environment, which is either a flat, house, or facility such as an elderly care or hospital ward, is by definition a well-known place. Therefore, in our model, we added another parameter concerning unfamiliar environments. Therefore, we are checking the current SSID of the WiFi network connection. Once the WiFi connects to a known network, we assume that surrounding areas are well known by the elderly, and therefore bare a small risk of unknown obstacles or tripping hazards. In addition to the known WiFi network, we track the current GPS position of the user. Moreover, the weather forecast is being checked, in case the user is recognized as outside (no familiar WiFi in range and GPS indicates position outside of a building, mainly walking activity). For the purpose of fall risk assessment, we apply two tests: 1) a *familiar environment test;* and 2) a *challenging outdoor conditions test.*

Familiar Environment Test:

In case the user is outside of a familiar environment, the risk of tripping, distraction, or disorientation and thus falling increases. By tracking the SSID of a known WiFi network, this condition can be recognized. Therefore, a risk point will be added to the total fall risk score. This risk point is valid for as long as the user is outside of the familiar surroundings.

Challenging Outdoor Conditions test:

In case of challenging weather conditions, such as snowfall, icy streets, or rainfall the total risk level of falling increases. Therefore, a risk point is added to the total fall risk score. This environmental risk factor is only considered, if the user leaves the familiar environment (GPS location) and weather forecast reports rain, snow, or icy roads. When being located inside the risk point is reset.

User History (BFRS)

Many elderly people have a patient history of diseases or pre-existing conditions, which also result in an increased risk of falling. These co-morbidities need to be considered in order to compute a more precise total fall risk score. Influencing factors include diseases such as diabetes, that can lead to sensory disorders or numbness. In addition, blood pressure medication, such as beta-blockers can lead to dizziness, especially in case of a false or less-than-ideal dosage. Also, artificial joints that can negatively influence the degree of freedom in walking can increase the risk of falling. Besides the aforementioned factors, visual or cognitive impairments could also be identified as risk factors with regard to falling.

Therefore, our system initially determines individual factors that determine the basal fall risk score (BFRS). To achieve this score, a caregiver has to fill out a set of questions during the initial setup of the application. This set includes the following question that have to be answered with either yes or no. Each question that is answered with a yes increments the basal fall risk factor.

- Does the user have artificial joints?
- Does the user have amputated extremities?
- Does the user have to use a walking aid?
- Does the user have to wear a hearing aid?
- Does the user have diabetes?
- Does the user have dementia?
- Does the user have visual impairments (e.g., cataract)?
- Does the user have had a stroke?
- Does the user have to take blood pressure medication?
- Does the user have to take multiple medication (n>5)?

The resulting basal BFRS is considered in the total fall risk score.

3.4 Total Fall Risk Score Calculation

Our total fall risk score calculation is based-on an overall evaluation of all afore introduced tests with regard to balance, lower body strength, general fitness, sleep quality, and environmental factors. In addition, we apply patient data, such as age, sex, medication, and pre-exiting conditions like prior history (e.g., falls, stroke, Parkinson, etc.) in order to adapt the total fall risk score.

The total score consists of 22 individual risk points, which can either be set to "1" or "0". These risk points are categorized into 1) basal fall risk; 2) variable fall risk; as well as 3) environmental fall risk. The sum of all risk points is referred to as the total fall risk score.

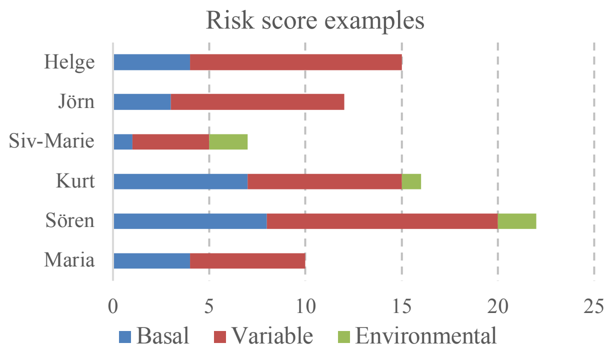

Figure 6. Examples of different total fall risk scores (sum of blue, red, and green bar) for 6 patients. The blue bar indicates the basal fall risk score, the red bar indicates the variable fall risk score, whereas the green bar indicates the environmental fall risk score.

In order to ensure valid recognition, we implemented a detection for recognizing a watch that is not worn (doffed detection). We implemented a doffed detection since it becomes crucial to validate the gathered data before processing it, when connecting the data to important health services. An example for an artifact is given by shaking a Smartwatch without wearing it on the body, which can be misinterpreted as steps. Also "ghost heart rates" may be detected, although the device is solely lying on the table [21]. Therefore, we implemented a doffed detection based-on changes in Microvibrations [23] emitted by the body and distinctive PPG outputs. A doffed watch will lead to an *unknown* total fall risk score. During sleep, we reset the total fall risk score to the basal risk.

3.5 Evaluation

All aforementioned parameters have been evaluated in dedicated user studies with 13 subjects, with multiple trials and sessions. These studies helped us to tweak the accuracy of our algorithms up to a level of recognition that lies between ~80% and ~94%.

Finally, we evaluated our MAL system in a rather broad pilot field study with 30 elderly people over four weeks. Among these 30 elderlies, the following prehistories were given: 16 had a stroke, 24 had a prior history of fall, and 22 had low blood pressure. Our fall risk model triggered preventive care in six cases by predicting a fall risk well ahead of classical approaches. This has been determined involving a physician that is especially trained on fall risk assessment, who was permanently observing the data and the elderly people in their environment. According to the physician, in one case the prediction was done as early as almost four weeks ahead of time following information about the patient's balance and strength parameter deviations.

One of the major conclusions from the pilot is that, of the 23 instances where the fall risk was high, a strong indicator was the degradation in the lower body strength parameters primarily the posture transition time taken to stand from a sitting position. About 60% of those cases had low blood pressure. While a relation of these parameters is not ultimately conclusive, we determined a correlation and future tests are planned in order to analyze this in detail. Also, there are ongoing plans to start another trial with a larger group of elderly spreads across seven municipalities in Northern Skåne, Sweden.

6 CONCLUSION & FUTURE WORK

In this paper, we introduced the concept of a Mobile Assisted Living (MAL) in the context of fall risk assessment. Therefore, we developed a Smartwatch application that allows the computation of multiple fall risk related parameters. We evaluated our approach by conducting a pilot study in the field with 30 elderly people in an elderly care for the duration of four weeks, while a physician evaluated the data and prescribed interventions. Our proof-of-concept allows for a tailored fall prevention therapy for an individual's need. Therefore, we expect a reduction of health costs related to fall, by rolling out the proposed MAL approach in future. We see our MAL solution in the role to complement already implemented AAL solutions (e.g., by improving the recognition of activities performed or determining the users' state).

Since we could not weigh each individual risk point because of a lack of ground truth data, we weighed each risk point with the factor "1". The investigation of individual weights is part of future research. As a result of this, we envision a better approximation of the total fall risk score. Moreover, we envision MAL systems to significantly improve lifestyle of especially elderly people. This trend is supported by the growing popularity of Smartwatches with several new start-up companies, which use Smartwatches and wristbands as an assistive technology to support users with special needs such as elderly people[1,2,3,4,5,6]. While our Smartwatch-based MAL system may still have the status of being a proof-of-concept, we already developed a web

[1] NextStepDynamics: http://www.nextstepdynamics.com

[2] &gesund: https://und-gesund.de/en/

[3] b-cared: https://b-cared.com

[4] Living Safely: http://www.livingsafely.com

[5] Safe Link: http://safelinkgps.com

[6] Revolutionary Tracker: http://revolutionarytracker.com

database service capturing all user data in a digitalized form, which allows us to apply data mining for pattern recognition in order to discover anomalies throughout the day, week, and months. This can be in particular interesting for physicians and caregivers helping to discover and monitor disease progressions besides a fall risk estimation. Based on the opinion of the fall risk expert evaluating our system, if rolling out such a proposed system, we may reduce fall accidents by more than 70%. In future, we also imagine such health monitoring systems to be connected to a digital medical record and third-party services, such as emergency assistance for elderlies. Since the collected and processed data is very sensitive, technologies for ensuring user privacy will also be a part of the future research.

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