MASTER

Detecting change in behaviour in walking, using the accelerometer of a smartphone

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Award date:
2016

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Detecting change in behaviour in walking, using the accelerometer of a smartphone

Master Thesis

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29-07-2016
Executive Summary

This study was conducted with the aim to explore the usage of smartphone sensors in the walking behaviour. The problem owner Gociety asked the University of Eindhoven to study a more advanced method to assess fall risk using smartphones. Based upon literature a method was proposed, which was subjected to two different experiments to test the ability to detect a gradual change over time. The model was found to be able to detect gradual change in step frequency and coefficient of variance. The model was not able to detect change in RMS as expected.

Problem definition

When a person ages his or her fall risk increases. If it increases above a certain level interventions can reduce the fall risk and thus prevent falls. By tracking community dwelling elderly people with a smartphone based fall risk assessment users can be alarmed when an intervention is necessary. Gociety currently develops the GoLivePhone which incorporates such a fall risk assessment, however, a more accurate version is needed. Data provided by Gociety lacked accurate sensor data for this research, thus new data had to be gathered. The research question answered in this research is as follows: How to detect change of behaviour in walking, using data from a smartphone? To answer this question it was studied what an anomaly is in walking behaviour, what features of walking behaviour can be captured by a smartphone, what model can detect gradual change in these features and how this method can be tested.

Background

Walking behaviour can be analysed based upon several features. Of those features step frequency, gait variability and gait instability were found to be important in the fall risk assessment. Research showed that it is possible to detect these features with the build-in accelerometers of smartphones. The step frequency can be calculated by detecting the peaks in the data and measuring the distance between the peaks. The gait variability is represented as the coefficient of variance of distance between the detected peaks. The gait instability can be calculated as the root mean square of the left-right movement.

Model

A new model was created by combining relevant previous studies. The data was gathered with an smartphone running Android and the analysis was performed using Python. The proposed model consisted of the following steps:

1. Data cleaning
   The data gathering was manually started and ended and thus contained irrelevant information. By cleaning the data only the valuable data on walking behaviour was separated.

2. Sampling analysis
   As the saving rate of sensor values is influenced by the availability of the CPU the delay between samples can be of varying length. Sampling analysis was used to make sure the data was valid for further analysis.

3. Filtering
   The smartphone captures noise next to the movements of the user which needs to be filtered out.
4. Data segmentation
   Even after filtering noise might be present. To increase the accuracy the data can be segmented into overlapping segments.

5. Peak frequency
   The peak frequency (PF) indicates the gait cycle, which is the time taken for one step. With the detected peaks the step frequency can be calculated.

6. Coefficient of variance
   The coefficient of variance as calculated as the variation in time between the peaks. This represents the gait variance.

7. Root mean square
   The root mean square is calculated for the left-right movement and represents the gait instability.

The model was designed in a way only short data samples are needed for the analysis, keeping the computational power as low as possible. In the implementation phase the model was coded and the settings for the different features were determined.

Test setting
Two experiments were used to test the model, one for abrupt change and one for gradual change. The first experiment was merely to set up the model. Test subjects walked a distance of 30 meters with different tasks: walk normal, walk with changing frequency, walk with normal steps and walk with wide steps. The second experiment was to prove the abilities of the smartphone accelerometer detecting gradual change. Test subjects walked different with different weights first on both ankles and second only on one ankle.

Evaluation
The results of the first experiment have proven the model is capable of detecting abrupt change, although the results depended heavily on the interpretation of the task by the test person. The results were used to determine the values for the different features to be simulated in experiment 2. The evaluation of second experiment was done by determining the value to which the gradual linguistic summaries 'Step frequency is decreasing', 'CV is increasing' and 'RMS is increasing' were true. True Values for both Step frequency and CV were high, above 0.7. For RMS only in one case a high True Value was found.

Business value
The most recent numbers available for the Netherlands show that in 2011 84,000 treatments on the ER were necessary because of falls. The treatments combined with hospitalisation and deaths caused €820M of healthcare costs. For instance, a fall which causes a hip fracture leads to costs of €12,000,- for surgery and revalidation. As this research indirectly helps decreasing these falls it has a business value both for Gociety and other companies. By implementing the features discussed a more advanced fall risk assessment can be made. Gociety can increase the value of the GolivePhone by implementing the proposed method. On the other hand, an implementation of the method has a high value to insurance companies as well, as it can help reduce falls and thus decrease corresponding costs. Even for society the model has value. By reducing falls it can help people can have a higher quality of life. It is obviously that preventing
falls is pleasant for elderly people. However, as the goal is to intervene when the abilities decline below a certain level, users can stay more active and enjoy life at a higher age.

**Conclusion**

The proposed method was capable of detecting both abrupt and gradual change for the values of step frequency and correlation of variability. A first experiment showed that when simulating an abrupt change in walking behaviour the method was capable of detecting the difference. These results were used as a guideline in the second experiment. This second experiment consisted of test with weights on both legs and on only one leg to simulate different anomalies. By adding weights gradually the gradual decline was imitated. It was shown that the proposed method is also capable of detecting this gradual change for the step frequency and the gait variability.
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1 Introduction

As the number of elderly people living worldwide and the average life expectancy increases, older adults’ safety assurance has become increasingly important [1]. The World Health Organization (WHO) is aware of the challenges of the aging society and operates in multiple projects to create both awareness and actions to guide this aging. As a part of one of the projects WHO wrote a report on Fall Prevention in Older Age [2]. The WHO defines falls as follows:

\[
\text{Falls are commonly defined as "inadvertently coming to rest on the ground, floor or other lower level, excluding intentional change in position to rest in furniture, wall or other objects".}
\]

Due to the increasing number of elderly people it becomes harder to find enough (qualified) caretakers. Working hours are becoming more and more flexible and that combined with female emancipation caused that it is less likely that people are able to take care of the elderly people within there family. Elderly people living in nursing homes are more often checked on and tested by professionals than are community-dwelling people. In the Netherlands only people in need of daily care, which can not be provided in their private home, are allowed to live in nursing homes. These people have a so called ‘indication’ that they can’t live by themselves anymore. Community-dwelling elderly are thus dependent on other forms of monitoring. In order to cope with this problem much research is being done on how to make healthcare more efficient. One of those ways for example is point-of-care testing [3]. Point of care testing facilitates evidence-based medical decisions at or near the place were the patient receives care. However, a professional still needs to be present to perform the tests. Patients can be monitored from a distance in order to alarm when intervention by a professional is indeed necessary. This increases efficiency by preventing redundant checks and it also prevents waiting too long before taking action. [1], [4], [5] and [6] are among others trying to use electronic devices for monitoring patients so that they can alarm caretakers when necessary.

1.1 Context

Several companies have created healthcare hubs and frameworks for people to be more conscious about their well being. A wide range of activity trackers and step counters are available nowadays. This shows that companies see a future market in these devices, but also that people are more aware of the fact that their health is important. Apple created an open source framework to help developers and researchers create apps for medical research [7]. According to Apple doctors are using smartphones more often, changing the perspective of health. Apple already created the HealthKit, a framework around apps which let you as user get a better insight in your own health. The ResearchKit and HealthKit work seamlessly together, resulting in that researchers can access even more relevant data. On the other hand, researchers will have a better way to create useful apps for smartphone users. Microsofts answer to Apples HealthKit is Microsoft Health. Health is a
combination of both apps, devices and storage. The Health platform gives insight in your activity and works together with Microsoft Band. Band is a smart band which can track the users’ activity among other things. Developers can use this data for multiple purposes. All the information is stored in Microsoft HealthVault, which is proposed to become a storage of medical information accessible to doctors as well [8].

In addition to the traditional optical analysis numerous devices are available for walk analysis and more specifically fall risk analysis. It ranges from supervised settings using pressure sensitive walkways [9], fully automated lab settings with Ardunio boards [10] to less invasive ways in the form of wearable accelerometers. Such accelerometers can be found in a variety of versions [11] of which full-body-mounted and wrist-, trunk- or ankle-worn are some examples. Smartphones are a relatively new way to detect behaviour. Nowadays smartphones are equipped with accelerometers which have the accuracy comparable to separate multi-axis versions commonly used in scientific studies [12]. There are many advantages to the use of smartphones in comparison to the earlier mentioned options. They are widely available, relatively cheap and easy to implement. As most of them have more sensors build in they can be used for more than only the monitoring. The fact that they are associated with a young and fashionable spirit make them more appealing to elderly people at the same time.

Gociety is a company in The Netherlands that has multiple products on the market to help elderly people live independently as long and as active as possible. According to their statement, they believe in independence through technology. One of the products Gociety develops is the GoLivePhone to target risk factors from the WHO report. It helps elderly people to easily connect with the world around them, tackling socio-economic problems. But it also operates as a health care device, as it monitors the user. It motivates the user to exercise when the user has been inactive for a long period, and in case of an anomaly it will alarm caretakers. Gociety asked Eindhoven University of Technology to help explore the possibilities of using the data gathered with a smartphone in an even more advanced way in order to predict fall risk and help prevent falls of the user. This should increase the quality of life of the users and decrease the overall costs of falling [13].

A literature study [14] showed that fall risk is influenced by multiple factors. Several studies were found which focus on the prediction and prevention of falling, but most of them make use of (extensive) external hardware or are only applicable in laboratory settings. As different studies were found which prove the usefulness of smartphones, this study will explore the possibilities of using smartphones in the assessment of fall risk.
1.2 Data GoLivePhone

To study the possible ways a smartphone can be used in the assessment of fall risk data from smartphone sensors is necessary. Society is already gathering data using their current GoLivePhone and provided data from their database for this research. Every document was the output of one GoLivePhone and the amount of time covered (and thus the size of the file) differed for all the documents. The smaller files showed only system settings. As the files got bigger they contained a wider variety of events/logs. However, most of the data is categorised or binned already. The smallest time unit of 'raw' data is found to be the log entries HourlyRecord. An example of an HourlyRecord, combined with the JSON scheme can be found in Appendix 7.2.

From the 493 files, 35 had a size of at least 10mb. As bigger files would assume a higher amount of logfiles these were explored to see how many HourlyRecords they contained. The amount of HourlyRecords were extracted per file and plotted against the file size of the corresponding file, as shown in Figure: 1. The mean number of HourlyRecords is 5358.29 with a standard deviation of 3197.42. In the best case scenario this would mean that these 35 files covered on average 244 days each.

![Figure 1: Amount of HourlyRecords against file size](image-url)
The fact that HourlyRecords are present does not always mean that steps are counted. The activity walking is only briefly covered. In Figure 3 an example is presented of the walking data in an hourly record. This is the most raw form of data present in the data sets. Further investigation of the data showed that a lot of phones have been in stand-by mode for most of the time. They reported HourlyRecords, but haven’t been carried around thus have not recorded steps. As can be seen in the example HourlyRecord, the number of steps is recorded for different activities. As walking is the topic of this research only the steps in the subsection ‘walking’ in the MoverADLStats are considered important. (It turned out that most of the others are zero anyway). Only 7 files have both a mean and median amount of steps above 400. Which means, roughly and only in the best case scenario, that the user has walked 6.5 minutes per hour on average.

```
"MoverADLStats" : {
    "walking" : {
        "distanceTraveled" : 518.8407,
        "energy" : 35.157467,
        "steps" : 708,
        "time" : 550000
    }
}
```

Figure 3: An HourlyRecord covers limited information on walking

The amount of steps is highly skewed to a low amount of steps per day. This results in the conclusion that the data set is not useful as an input for anomaly detection. The data is also too much concentrated on certain dates. Society confirmed they are working on anomaly detection on steps counted, however results were not available at the start of this research. Thus, new data is necessary to provide a sophisticated analysis of the walking behaviour.
1.3 Problem definition

The GoLivePhone gathers data from several sensors in the smartphone. With this data periodical reports are generated to show the activity of the user. Taking into account the accelerometer the smartphone is also able to detect falls and alarm in case of such a fall. Gociety would like to use the data in a more advanced way in order to predict a higher fall risk of falls earlier than currently possible. To enable this the walking behaviour of the user could be tracked and analysed as this is one of the factors influencing fall risk [14]. This research is conducted with the following aim:

To explore the possibility to use the smartphone in detecting walking behaviour and preferably the decline of capabilities.

As Gociety is targeting elderly people the following scope was used:
Community-dwelling elderly people who are using a smartphone or are willing to use one in order to track their behaviour.

1.3.1 Research question

If one combines the research problem with the goal and scope it leads to the following research question:

How to detect change of behaviour in walking, using data from a smartphone?

To answer the research question four subquestions are determined. By answering these one by one an answer to the main question will be found.

1. What is an anomaly in walking behaviour?
   There are two types of anomalies. The first is gradual change, over a longer period of time. The second is abrupt change, for example in an instance, or within a day. It is also crucial to decide what is not an anomaly and thus should be ignored. By understanding what walking behaviour is and how it can be measured one can decide what features are important for further analysis.

2. What features of the walk can be captured using the smartphone?
   How can the smartphone be used to gather useful information. Are there previous studies which can be used?

3. What method to use to detect the change?
   By combining the features available in the data set and the knowledge of which anomalies are valuable to detect a method should be created to detect the anomalies. This method will be the most relevant result of this study, as this actually helps the problem owner Gociety.

4. How can the method be validated?
   An experiment will be designed to test and validate the proposed method.
1.3.2 Methodology

The method used in this research is the regulative cycle by Van Aken. This is a practice-oriented method which focuses on making decisions for the best solution. Instead of the empirical cycle the goal is to provide a specific solution. The steps of this cycle including the description of what will be executed during this research is explained below.

1. Problem definition
   The introduction of this research defines the problem including the questions that have to be answered in order to provide a solution to Society.

2. Diagnose/Analysis
   To discuss the as-is state a brief overview is given on what can be seen as anomalies in walking behaviour, in order to get a feeling of what features should be available or measured. By doing so subquestions 1 and 2 are answered.

3. Plan/Design
   Based upon the decisions made in and results from the diagnose phase a method is designed to detect walking behaviour and corresponding anomalies. The method itself is a practical answer to subquestion 3.

4. Implementation
   The proposed model is implemented and trained. Important decisions on thresholds and settings are explained here.

5. Evaluation
   The trained model will be validated by experiments with testpersons.

1.3.3 Contribution to science

Multiple studies have been conducted on predicting and preventing falls. However, no study has been conducted on how a smartphone by itself can be used to determine the fall risk over a longer period of time. This research will provide a method to do so. By recognising an increase in fall risk interventions can be organised to prevent the patient actual falling, which will in return lead to an increase of quality of life and a decrease of costs.
2 Background

To discuss the as-is state first risk factors of falling are explained by discussing various studies on predicting and preventing falls. Second a brief overview is given on what can be seen as anomalies in walking behaviour, in order to get a feeling of what features should be available or measured. By doing so subquestion 1 is answered. As new data has to be gathered a short explanation of the state-of-art in gait analysis using smartphone sensors is given next, answering subquestion 2. This chapter is heavily based on the literature study [14] which was conducted before this research.

2.1 Predicting and preventing falls

It is commonly known that elderly people have a relative high risk of falling. Also widely spread is the drive to prevent incidents from happening and thus both save lives, and resources. To be able to help lowering the amount of incidents the factors which lead to a higher risk are explored.

The American and British Geriatrics Societies [15] classified earlier researches on identified risk factors in the categories intrinsic, extrinsic and environmental. Examples of intrinsic factors are a reduced balance and visually impairment. For extrinsic factors one can think of the use of multiple medications. Environmental factors can be for instance loose carpets and door sills. They also state the importance of appreciating the interaction between the multiple factors. It is shown that as the number of factors increase the risk of falling also increases dramatically.

Preventing falling starts by being able to predict when a person is about to fall. There are several studies explaining how an assessment can be made of the functional abilities of a person, which results in a degree of fall risk.

Swanenburg et al [16] studied whether force plate variables could be used to predict fall risk. Participants were tested under single- and dual-task testing situations, with and without vision. As opposed to earlier research only the single-task conditions provided added value to the prediction. The amplitude of medial-lateral movements was found a significant independent predictor; along with gender, history of multiple falls and the use of medications.

Bongue et al.[17] conducted a literature study and found that there was no single functional mobility tool which alone could predict falls. As there where no simple tests for community-dwelling elderly people, they did research on whether one could be created. Five factors were chosen which influence the fall risk (gender, living alone, psychoactive drug use, osteoarthritis, and previous falls) and combined with the one-leg balance (OLB) test to test whether this could be an simple clinical screening tool. Data of 1,759 participants was analyzed to test the tool. All participants performed both the Timed-Up-and-Go (TUG) test and the OLB test as baseline assessment. The researched showed that combining the risk factors together with an assessment of balance can predict falls.
<table>
<thead>
<tr>
<th>Category</th>
<th>Seconds for TUG Mean</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>60-99 years</td>
<td>9.4</td>
<td>8.9-9.9</td>
</tr>
<tr>
<td>60-69</td>
<td>8.1</td>
<td>7.1-9.0</td>
</tr>
<tr>
<td>70-79</td>
<td>9.2</td>
<td>8.2-10.2</td>
</tr>
<tr>
<td>80-99</td>
<td>11.3</td>
<td>10.0-12.7</td>
</tr>
</tbody>
</table>

Table 1: Simplified table of results Bohannon[18]

At the time of the study Bongue was not confident about the validation of the TUG, thus advises to use the OLB. Another important reason why they chose for the OLB test instead of the TUG test is that one does not need anything to perform the test and that limited space is needed.

Bohannon created normative reference values for the Timed Up and Go test in 2006. [18]. Before the TUG test was already used for the examination of elders, but examiners had to subjectively judge the performance based on reference values from earlier researches. Bohannon combined these reference values in a meta-analysis to obtain a better sense of normal performance on the TUG. In line with the research goal of this literature study Bohannon focused only on apparently normal individuals. The most important results from the study are shown in table 1. Individuals who exceed the upper limit of the 95% confidence interval are considered to have a lower performance, resulting in a higher risk on falling.

The probability of falls can be reduced if the history of falls and fall-related assessments are combined with interventions. This is the fundamental tenet of the Guideline for prevention of falls by the American and British Geriatrics Societies [15]. The Societies recommend multifactorial interventions for community-dwelling elderly people. In terms of physical exercise the interventions should include gait and balance training.

The European Network for Safety among Elderly (EUNESE) splits the multi-factorial intervention in three parts [19]:

- Awareness raising and attitude modification measures such as mass media campaigns, leaflets and video
- Behaviour modification measures such as training and exercise, rewards and incentives.
- Structural modification measures such as environmental changes and regulations.

Again, exercise is highly recommended. Both in their advise for elderly they mention that people have to take care of their fitness as it will increase strength and improves balance and coordination. Three of their six screening questions focus on physical fitness/ability: balance, walking abilities and transitions from sitting to standing up.
Gudlaugsson et al. performed a study on the effects of training over a period of six months.\cite{20} The multimodal training intervention consisted of daily endurance and twice-a-week strength training. The intervention group was tested against an control group and scored better among others on both the Short Physical Performance Battery (mean diff = 0.6, 95 % CI: 0.1, 1.0) and the Timed-Up-and-Go-test (mean diff = 1.0 s, 95 % CI: -1.5, -0.6). This showed that using regular exercise can improve and prevent decline in functional fitness in elderly people.

Karlsson et al. goes even further than showing that intervention is effective. They show that ‘physical exercise that includes several training modalities, especially balance and strength training, is the only intervention program that reduces both the number of fallers and the number of falls in community dwellers.’ \cite{21}

### 2.2 Walking features

As mentioned earlier, the factors of fall risk can be divided in the categories intrinsic and extrinsic. While extrinsic factors can be adjusted quite easily, this is harder for intrinsic factors. For some it is not possible at all. It is thus important to detect anomalies as early as possible. Most of the early signs of a higher fall risk can be seen in the walking behaviour.

Ambrose \cite{22} performed a literature study on risk factors for fall among older adults which showed gait balance as important risk factor. One of the researches concerning gait analysis show that 57% people of the elderly people who fell in the previous six months were unable to walk the fastest speed and had shorter stride lengths. They also has an increased variability for several variables. Pizzigalli \cite{23} mentions the relevance of muscular strength and symmetry of lower limbs in postural stability. As people get older and their walking speed decreases. This is influenced by several risk factors. Pizzigalli mentions that walking speed is one of the most common factors which decreases, thus it can be seen as a general indicator for a higher risk.

Shany \cite{5} mentions possibility of measuring gait variability to check for fall risk. This however is based on supervised fall risk assessments on which Hausdorff showed several potential applications as well \cite{24}. In line with several other researches Shany mentions that walking has high potential application for a unsupervised fall risk assessment. Another study on gait variability was performed by Hausdorff. A 1–year prospective study was conducted and showed that among others stride time variability was more than twice as high in subjects who fell during compared to those who did not experience falls \cite{24}. In line with another research \cite{25} proof was found that gait variability is reflecting underlying disease processes, rather than age–related changes. As these are treatable with interventions, gait variability can be seen as an identifier for elderly people who have a increased risk of falling.
Majumder proposed a fall risk prediction model [6]. By combining a self developed smartshoe with a smartphone it was tried to increase the accuracy. To test the anomaly detection test persons simulated two common abnormalities which lead to a large amount of falls [6], namely peg leg (by straining the knee) and leg length discrepancy (by wearing shoes with different soles. Both abnormalities cause the person to swing left-right while walking.

2.3 Gait analysis using smartphone sensors

Kwapisz [26] explain the plots of accelerometer from different activities. With this knowledge it is possible to interpret newly gathered information. This research was also used by Cola [27]. Cola build a algorithm which analyses the plots/data to recognise walking patterns. The algorithm detects the group of peaks which represent a gait cycle [27] [28]. This method then was used in an on-node unsupervised approach for anomaly detection in gait [29]. An anomaly was defined as an instance with a Euclian distance above a threshold from what was defined as normal. In this latest research [29] the power consumption was studied and it was found that sample streaming only during gait and performing all step (from sampling to anomaly detection) on-node were most energy efficient on average.

[30] used an iPod Touch to measure gait parameters and test the ability to identify age-related changes. Gait speed was calculated as the distance covered during the measurement. Other variables were based on the accelerometer data and included stride, amplitude and frequency. The study emphasises to incorporate more dynamic gait variables instead of focussing on walking speed. Variables highly associated with age were among others mean stride time, Root Mean Square of the medio-lateral acceleration and Sample Entropy of the Anterior-posterior acceleration

[12] validated the use of smartphones for gait analysis by comparing the results with a separate tri-axial accelerometer. The results show a degree of accuracy that is comparable and they thus conclude smartphones are the capacity of quantifying gait parameters. In contrast to several other studies Nishiguichi analysed the gait parameters in such a way data transformation to the frequency domain was not necessary. This decreases the necessary energy and computational power.

One of the important pre-processing steps in activity recognition is data segmentation. According to [31] the fixed-size no-data-overlapping window segmentation method is commonly used in most activity recognition systems. This method is used because of the reduced computational complexity which is preferred in real time analytics. However, [32] found that increasing sample lengths resulted in decreasing accuracy. Using a large window size thus might have a big impact on the recognition accuracy. Using short, overlapping data segments increases the final result.

Anomalies to detect thus are step frequency, the gait variation (variability of the step frequency) and the gait instability (left-right swing). Earlier studies have proven that the smartphone can be
used for gait analysis. Nevertheless, the research such as necessary for Society has not been performed.
3 Model

Based upon the decisions made in and results from the diagnose phase a method will be designed to detect walking behaviour and corresponding anomalies. The method itself will be a practical answer to subquestion 3.

In Gociety’s dataset hours are the smallest time units in which the data is binned. Unfortunately this is not accurate enough for this research, as it is not able to extract the stride frequency from summarised data. Several comparable researches made their data sets with raw sensor data available to the public, among others [33] and [34]. These however turned out to be not useful for different reasons. For some the data, again, was summarised. Others used separate accelerometers instead of smartphone-accelerometers. Also some datasets lacked description of test persons or relevant data on activities measured. This resulted in unreliable or inaccurate data. Therefore the decision was made to gather new sensor data.

3.1 Analysis environment

The analysis part will be conducted offline and external. It is chosen to do so as this suits the aim of this research, to be able to explore the possibilities. Python is chosen as main programming language as it is an open source language for which interpreters are available in both free and paid versions. The reason not to work with the (in scientific researches) more standard Matlab is to provide Gociety with a solution for which no extra investments have to be made.

3.2 Data gathering

Several apps are available to read out the accelerometer for both Android and iOS. There are a lot of differences: paid versus free, ability to save the data, ability to share the data. Some apps perform data transformations in order to increase the readability and understandability. Both data coverages in m/s² and G-force are available. Most of the apps provide the option to choose the accuracy settings.

Gociety chose to use Android as the platform for the GoLivePhone. To increase the usability of this research for Gociety it was chosen to use Android as well, more specifically the Huawei Y360-U61 with Android version 4.4.2. Most of the accelerometer applications available for Android are free. Several apps were selected on the rating received in the Google Play Store for testing. After testing both the accuracy and saving possibilities the Accelerometer Analyzer (version 16.2.9, available in the Play Store) was chosen to be used for analysis. The Accelerometer Analyzer only reports the amount of time elapsed since the last sensor change.
The sensor accuracy in Android can be set in four different options: Normal, UI, Game and Fastest. Table 2 presents the numeric values that belong to the different options. This are not fixed sample rates, but rather a delay after which the sensor is allowed to update the sensor value. The consequence of this is that the intervals between the measurements can be different, as the processor of the smartphone is not always available to update the sensor value immediately on request. This should be taken into consideration for the analysis, as not all methods can handle unevenly distributed signals. It is chosen to use the fastest option to increase accuracy.

The axis of both the device and the human body should be known in order to chose the corresponding axis while performing the analysis. During the data gathering the smartphone will be carried in the subject’s pants, in the right front pocket. Thus, the x-axis represents medio-lateral movement, the y-axis the cranial-caudal movement and the z-axis the anterior-posterior movement. The axis are also visible in Figure 4.

<table>
<thead>
<tr>
<th>SENSOR_DELAY_NORMAL</th>
<th>SENSOR_DELAY_UI</th>
<th>SENSOR_DELAY_GAME</th>
<th>SENSOR_DELAY_FASTEST</th>
</tr>
</thead>
<tbody>
<tr>
<td>200,000</td>
<td>60,000</td>
<td>20,000</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 2: Sensor delays in Android (milliseconds)
(a) The axis of a smartphone

(b) Anatomical Directional References [35].

Figure 4: Orientation of the device in comparison to the human body
3.3 Proposed model

The proposed method to analyse the data is a combination of several articles which all try to do the same: analyse data from a tri-axial accelerometer to detect walking (sometimes also other activities, including walking). Not all the articles follow the same steps or use the same accelerometer, therefore a combination has been made. These steps focus on obtaining values for the step frequency, the gait variability and the gait instability in such a way a gradual change can be detected.

1. **Data cleaning**
   The data gathering is started manually every time the test person performs an experiment to make sure the data sets are separated per person and per experiment. This results in a data set which also covers time in which the person is standing still or is accelerating or slowing down. In this study the analysis is performed offline and the data while the test person is actually walking will be extracted from the data sets manually by removing the start and end sections. In an future implementation of the method it would be possible to code it in a way the analysis will be performed only when a person is walking.

2. **Sampling analysis**
   Due to capacity problems of the CPU the data might not be stored with the same intervals. Therefore analysis of the sampling rate will be conducted. As some mathematical operations need data with equally-spaced samples the delay between the samples will be analysed. If the sampling rate is not constant, interpolation of the data is necessary.

3. **Filtering**
   The smartphone is picking up a lot of noise while measuring the gait which has to be filtered out so only the data of the gait remains. Filters from the class of Butterworth Filters are commonly used for activity recognition using sensors. A Butterworth filter is specified by the cutoff frequency and the order. Most of the articles (among others [30] and [36]) which were found using a Butterworth filter, used a 4th order version. The cutoff frequency differed from 2-20HZ depending on the purpose of the data in a later stadium of the analysis. In the Implementation phase it will be decided which settings will be used based on the frequency response and testing the filter on the gathered data.

4. **Data segmentation**
   Even after filtering noise might be present. To increase the accuracy the data can be segmented into overlapping segments. The data segmentation method with overlapping segments by [31] as explained in the previous chapter was used. Afterwards an algorithm will perform the analysis per smaller segmentation. The size of the segments will be roughly four stride cycles, thus 8 steps.

5. **Peak frequency**
   The peak frequency (PF) indicates the gait cycle, which is the time taken for one step [12].
The PF will be extracted from the cranial-caudal movement, thus the y-axis. The literature shows different methods to extract the frequency. Some studies only use the filtered data, others argue this is not accurate enough and use the filtered data to make an assumption on where the peak is and detect the peak in the raw data.

6. **Coefficient of variance**

Gait variability is the variability in the forward movement while walking. Stopping and continuing walking can be seen as an extreme example of gait variability. The Coefficient of variance (CV) of the cranial-caudal movement can be seen as the gait variability. The CV is calculated as the amount of variance between the acceleration peak intervals. The formula consists of the standard deviation of the peak interval and the mean peak interval.

\[
\frac{t_{SD}}{t_{MEAN}}
\]  

(1)

7. **Root mean square**

[12] found that the Root Mean Square (RMS) indicates the degree of gait instability, thus that a higher RMS would indicate a lower degree of stability. The RMS can be calculated for all the axis of the accelerometer, however, [30] considered the RMS for medio-lateral acceleration to be highly associated with age. For this exploratory research only the data from the x-axis will be used for the stability analysis.

\[
RMS = \left( \frac{\int_{t_1}^{t_n} a(t)^2 dt}{t_n - t_1} \right)^{\frac{1}{2}}
\]

(2)

### 3.4 Experiments

Both in the diagnose and the implementation phase informal interviews were held with physiotherapists. During these interviews information on falling, fall risk and the use of smartphones for risk assessment were discussed. A brief summary is given in the appendix. In an interview the physiotherapists explained that several features are used to detect the fall risk in the clinic. As the goal is to detect change in behaviour before the fall risk is too high, using people with a high fall risk as test persons was in this stage not advised. However, the behaviour of concern can be acted by test persons. Using both the advise from the physiotherapist and the literature study two experiments were designed. Experiment 1 focusses on detecting abrupt change to setup the initial model. Experiment 2 is designed to detect gradual change, the goal of this research.

- **Experiment 1**

  Test persons walked 5 times a distance and every time they had to perform another task from Table 3. The different step lengths were determined per person, as leg length differs. Changing
Walking tasks
1 Walk at preferred speed and preferred step length
2 Walk with fixed step length
3 Walk with changing frequency
4 Walk with narrow step width
5 Walk with wide step width

Table 3: Walking behaviour to test the model

frequency was simulated by walking and stopping every now and then. The physiotherapist mentioned this is a very common sign of high fall risk.

• Experiment 2
Test persons walked a fixed distance several times. The first time they could walk freely. From then on every time weight was added to their ankles in order to simulate the aging process. The method has to be able to detect the gradual increase of weights as it will decrease the walking abilities. This experiment consisted of two types, one with weights on both ankles and one with weights on only one ankle.

3.5 Evaluation
To evaluate whether the model is able to detect gradual change the method of Wilbik and Kaymak [37] was used. As it is an small data set all neighbours were considered during the calculations.

In the case of step frequency it was assumed that it would decrease during the experiments. For every data point was calculated whether all preceding data points were bigger and whether all following point were smaller. This value, if normalised, is then used to calculate the True Value for the gradual linguistic summary 'The step frequency is decreasing'. As it is normalised the True Values can be between 0 and 1. A higher True Value indicates that the step frequency is indeed declining. To calculate the True Value membership functions for both the linguistic quantifier most and the notion value a is bigger than b and value b is smaller than a are necessary.

For CV and RMS the same calculations can be performed, although it is assumed that these values will increase. The preceding numbers will have to be lower and the following higher in order to result in a high True Value. The True Value were calculated for the gradual linguistic summaries 'the CV is increasing' and 'the RMS is increasing'. In the next chapter the implementation is presented.
4 Implementation

In this chapter the results of the implementation of the proposed methods are discussed. The results were used to setup the analysis environment be able to detect the gradual change.

4.1 Experimental setup

Experiment 1 was conducted outdoors, as no accessories were necessary. The phone was worn in the right front pocket with the screen facing towards the leg and in upright position. Experiment 2 was conducted in an exercise room in which ankle weights were available. Test users first walked the distance without weights at their preferred walking speed to form a baseline. Then the researcher mounted extra weights to the ankles of the test person for every consecutive test. As the space was limited inside, the test subjects walked in large circles, preventing to walk in corners which could influence the data. In both experiments the data was gathered over a length of approximately 30 meters.

Figure 5: Exercise room used for the tests
In total 9 test subjects participated in the experiments. Due to availability of both the participants and the test accessories only 2 of them performed all tests. Every test is performed by at least 4 participants. In total 81 different data sets were gathered which were analysed.

4.2 Sampling analysis

The writing of sensor data to CSV is started before the person is actually walking to obtain the necessary accuracy the data before and after the walking is deleted.

A data file was plotted to see whether the walking pattern was measured for the complete duration. As shown in Figure 7 the beginning and end of the data reflects the starting and stopping of the recording, thus can be deleted from the data for the analysis. Delay only occurred in the beginning and end of the data sample, as can be seen in the lowest plot of Figure 7. For the complete measurement the mean delay between samples was 10.74 milliseconds. After extracting the sample in which the actual walking was measured the mean time between samples was only 10.0 milliseconds. This means the data was gathered in a constant manner, the CPU was able to handle the data processing. Therefore, no further interpolation was necessary. However, it was decided to check the mean time between samples for all the data files in order to prevent the analysis of incorrect samples.
4.3 Filterering

The Butterworth filter is advised in several related researches, however with different settings. Most commonly used are the 2nd and 4th orders. 20Hz was used as the standard output. The Python package SciPy contains a Butterworth filter and the ability to plot the frequency response. The filter response was plotted for different settings to understand how it operates. A higher order creates a steeper cutoff slope. The cutoff frequency determines where the middle of the cutoff slope will be. Figure 8 presents the influence of the filter on data from a healthy test person who was walking at preferred walking speed. It is proposed to use a 4th order filter, with 100Hz as input and 5Hz as output frequencies. The filter response of this filter is presented in Figure 9. The filter responses of other settings and the influence on the same data set is presented in Appendix 7.3.
Figure 8: The influence of the 4th order filter with cut-off frequency of 5Hz on a data sample of 6 strides.

Figure 9: The filter response for a 4th order lowpass filters with cut-off frequency of 5Hz.
4.4 Data segmentation

A function was written to segment the data in smaller samples with overlap of 50% of the chosen sample length. For example: if an step frequency of 2Hz is assumed, samples must be 2 seconds long to include 4 separate steps. For a sample of two seconds a sample of 200 frames is necessary. Figure 14 presents the implementation of segmentation in a function for returning the peaks in a data segment. A complete measured walking sample is fed into the function, complete with the size of the segmentation samples. The function resamples, calculates the peaks for every sample and appends new peaks to the list which will be returned.

Pseudocode:

```python
def detect_peaks_segmented_data(data_set, sampleLength):
    peaks = []
    xin = 0
    xuit = len(data_set)
    while xin < xuit:
        data = data_set[xin:(xin + sampleLength)]
        peak = detect_peaks(data)
        xin += sampleLength / 2
        if peak not in peaks:
            peaks.append(peak)
    return peaks
```

Figure 10: Data is segmented into overlapping segments to increase accuracy

4.5 Peak frequency

For the detection an algorithm from Marcos Duarte [38] was used, which is provided under the MIT-license [39]. The algorithm is coded in a way that it has different features based on which the peaks can be detected. Of these features the minimum peak hight and the minimum peak distance are considered to be the most important. The duration $t$ of a gait cycle will be calculated for every gait cycle in the sample.
As can be seen in Figure 11 the correct peaks are detected with the data filtered at 2Hz and a minimum peak distance (MPD) of 30 samples. However, the accuracy of the peaks detected is higher if a higher cutoff frequency is used. In Figure 13 plots are shown for different settings of the peak detection. First is shown the detection for data filtered at 2Hz and with a MPD of 50 samples. The second and third plot show detections in data filtered at a cut-off frequency of 5Hz but with different values for MPD. It is clearly shown that a MPD of 30 samples results in a detection of too many peaks. A MPD of 50 samples detects all the correct peaks. Barak measured the gait speed and stride frequency for elderly people, the result is shown in Figure 12. From this can be taken that the maximum stride frequency will be 1.4Hz, thus the minimum peak distance should at least be 35 milliseconds.

Figure 12: Stride frequency at each walking speed for elderly subjects who experienced at least one fall in the previous 6 months (FE) and elderly subjects with no history of falls (HE). Picture taken from Barak [40]
Figure 13: Peak detection tested for different settings
4.6 Coefficient of variance

The Coefficient of Variance will be calculated using formula 1. The implementation of this formula is represented in Figure 14.

Pseudocode:

```python
def Coefficient_of_Variability(data):
    peaks = detect_peaks(data)
    Sample_Time = 1/sampleFrequency
    difference = difference(peaks)
    Mean_Step_Duration = SampleTime * difference.mean()
    std_Samples_Steps = std_(difference)
    std_Steps = std_Samples_Steps * Sample_Time
    variabilityCoefficient = std_Steps / Mean_Step_Duration
    return variabilityCoefficient
```

Figure 14: Data is segmented into overlapping segments to increase accuracy

4.7 Root mean square

The root mean square will be calculated using Formula 2. The implementation of this can be found in Figure 15.

Pseudocode:

```python
def calculateRMS(data_set):
    dataRMS = (data_set)**2
    integratedData = integrate.trapz(dataRMS)
    RMS = (integratedData/len(dataRMS))**0.5
    return RMS
```

Figure 15: Calculation of RMS

4.8 Evaluation: True Value

In Figure 16 the True Value for a decreasing trend is calculated. This code is used to call the True Value for the gradual linguistic summary 'the step frequency is decreasing'. For the gradual linguistic summaries for CV and RMS a slightly altered code is used. This code calculated the True Values for an increasing trend.

The membership function for the linguistic quantifier value $b$ is smaller than $a$ was defined as \( Trap[0.0075,0.03,1,1] \), as a decline of 0.03Hz was assumed per added ankle weight. The membership
function *Most* then was defined as *Trap*[0.2,0.7,1,1]*

---

**Pseudocode:**

```python
def MostTrueValue(data):
    MembershipValues = []
    for i in range(0, len(data)):
        membership = []
        for j in range(0, i):
            difference = data[j] - data[i]
            difInt = round(difference, 4)
            MV = membershipValue(difInt)
            membership.append(MV)
        for l in range(i+1, len(data)):
            difference = data[i] - data[l]
            difInt = round(difference, 3)
            MV = membershipValue(difInt)
            membership.append(MV)
        MembershipValues.append(sum(membership)/len(membership))
    MostTrue = TrueValueMostMembership(MembershipValues)
    return MostTrue

def membershipValue(value):
    msValue = max(min(((value +0.0075)/(0.03+0.0075)),1),0)
    return msValue

def TrueValueMostMembership(data):
    MostMembership = []
    for i in range(0, len(data)):
        MMS = max(min(((data[i]-0.2)/(0.7-0.3)),1),0)
        MostMembership.append(MMS)
    TV = sum(MostMembership)/len(MostMembership)
    return TV
```

*Figure 16: Calculation of True Value*
5 Evaluation

In this chapter the results of the experiments are represented. With the experiments was tried to prove the abilities to detect the change in step frequency, gait variability and gait instability. All test persons gave written consent and agreed that their data would be used anonymously. Therefore, every test person is represented with a different color or number without name. First the results of the abrupt change are discussed, which can be used to determine the validity of the results for the gradual change.

5.1 Results abrupt change

In experiment 1 the model was used to detect abrupt change. Two different tests were used to gather data, the first test focussed on simulating a changing speed, the second test focussed on simulating walking with a wider track.

5.1.1 Change in step frequency

Test persons created a baseline by walking 30 meters outdoors on their preferred walking speed. Afterwards they were asked to walk the same distance, but this time with a changing frequency. During this second walk the researches talked to the test person and asked to stop every now and then. Figure 17 illustrates the difference in step frequency when test persons first walked their preferred speed and second when they were interrupted by the researcher.

It is clearly visible that in all cases the step frequency decreases. However, when people decrease their constant walking speed the step frequency decreases as well. It is thus important to additionally look at the coefficient of variation. Figure 18 presents these values for both the normal walk and the walk with changing frequency. As every person has a different way of moving, the levels of CV during preferred walking speeds are unique for every person. The test shows that the model is capable of sensing the change in frequency as the CV increases for every test person during the experiment. On average the step frequency decreased with 0,36Hz and the CV increased with 0,19.

Test person 5 showed a deviating result compared to the others. This is due to the interpretation of the exercise by the test person. The test person accelerated much after stopping in an attempt to create a highly variable test run. As the model calculates the average step frequency the high step frequency during accelerating compensates for the low frequency in other data segments. The CV for test person 5 reveals that the person walked with a higher gait variability, proving the importance of the combination of step frequency and the CV.
5.1.2 Change in track width

To detect abrupt change from narrow to wide steps test subjects were asked to first walk in small steps and then with the same frequency in wider steps. A simplified representation is given in Figure 19. The corresponding RMS values are represented in Figure 20. It can be clearly seen that with wider steps the RMS increases. Not all test persons showed an equal change, this is the result of how the test person interpreted the experiment. Especially test persons 2 and 4 focussed on swinging their hips from left to right, while test persons 3 and 5 tried to keep their hips in one line.
while spreading their feet. A consult with two physiotherapists confirmed that as people get older they are either swinging more and more, or their natural swing decreases as they start to walk in a more rigid manner.

Figure 19: The difference in step width in a simplified visual representation

![Figure 19: The difference in step width in a simplified visual representation](image)

Experiment 1 proofs that the model is able to detect abrupt change, however that the results are very depending on how the test person interpreted the test. As the test persons simulated a

Figure 20: RMS in test to prove change in track width

![Figure 20: RMS in test to prove change in track width](image)
very big change the results for the second experiment are assumed to be lower. With the idea of
detecting an anomaly in an early stage in mind, half of the change from experiment 1 would be
sufficient for experiment 2. If so, this means a decline of 0.18Hz for the step frequency, an increase
of 0.9 in CV and an increase of about 0.30 in RMS.

5.2 Results gradual change

Experiment 2 focussed on detecting the gradual decline which happens over time. Two different
tests were performed to simulate a decline in step frequency and to simulate a change in variability.

5.2.1 Gradual change in step frequency

As people get older their muscle strength decreases, making it more difficult to walk. This can be
simulated by carrying weights while walking. Test persons first walked a fixed distance without
weights to create a baseline. To simulate the gradual change test persons had to walk the same
distance several times after the baseline was set, but every time with extra weights attached to
both ankles as explained and showed in the previous chapter. The figures in this section show the
weight which they had to carry in total, which was distributed evenly over both ankles. Due to
restrictions on the weights that were available to the research only the following weights could be
mounted per ankle: 1kg, 2kg, 3kg, 4kg, 5kg, 6kg, 8kg.

While performing the first test runs some test persons tried to keep the same step frequency,
which resulted in abnormal data. The researcher then decided to ask to use approximately the
same amount of energy while walking, instead of focussing on the step frequency. The results of the
these test runs are used for the analysis as this comes closer to the actual decline of walking abilities.

Figure 21 illustrates that when adding weight to both ankles the step frequency decreases. This
is in line with the expectation, as people tend to walk slower when they get older. The True Values
confirm the decreasing frequency, as the values for the different test subjects are 0.862, 0.676, 1.0
and 0.930. Apart from an outlier in the data from one test person carrying no weights all the test
persons show on average the same level for the CV and RMS, represented in Figure 22. For RMS
two test persons had a relatively high True Value for a increasing RMS, namely 0.829 and 0.8152,
two others had only 0.236 and 0.188. The True Values for the CV were showing no significant
increase: 0.235, 0.506, 0.669 and 0.454.

The average decline of steps is 0.204Hz, which is even higher than the change that was deemed
necessary in Section 5.1. Although for two test persons the True Values for increasing RMS were
high, in general can be said the RMS remain constant as the average change is very limited. The
fact that the CV remains the same is plausible as well, as the weight is evenly distributed among
the ankles. The test persons are healthy and without known physical abnormalities, thus capable
of walking with a regular pattern while carrying the different weights, even when it is 8kg.
5.2.2 Gradual change in variability

During experiment 2.2 the weights were attached to only one ankle to create an irregular walking pattern. Again, the test persons were asked to try and focus on using approximately the same amount of energy while walking with the different weights.

Adding weight to only one ankle showed an increase in variability between steps, as can be seen in Figure 23. True values for increasing are 0.990, 1, 1, 0.97 and 1. The average increase in CV is 0.08, although it is 0.01 less then what was planned in Section 5.1, it is still enough to assume the model is capable to detect the gradual change. On average the step frequency declined by 0.05Hz.
The True Values for decreasing step frequency are 0.824, 0.778, 0.981, 1 and 1. As test persons had to carry weight a small decline in step frequency was expected. The average decline of 0.05Hz is less than in experiment 2.2 as it is only mounted on one leg, therefore the other leg was able to compensate.

An change in RMS such as in experiment 1 was not found in experiment 2. Before the tests were performed it was assumed that the test persons would start ‘limping’ as the weight increased and therefore would start swinging with their hips in a left-right manner. However it turned out that two participants walked almost in a straight line, which resulted in the True Values for an increasing RMS of 0 and 0.08. The other three test persons showed True Values for increasing RMS of 1, 0.667 and 0.75. The increase in RMS was for only one of those in line with the expectations of experiment 1, namely 0.27, while the others were only 0.08 and 0.02. Instructions to try swinging more resulted in unnatural and irregular walking behaviour which was not corresponding to what was described as elderly walking behaviour by the physiotherapists. The model was thus not able to detect left-right movement in the tests on gradual decline. As the results from experiment 1 were promising it is assumed the cause lies in the tests which has been conducted.

![CV in experiment 2.2 against the weight on one ankle](image)

Figure 23: CV in experiment 2.2 against the weight on one ankle
Figure 24: Step Frequency and RMS in experiment 2.2 against the weight on one ankle
6 Conclusion

Of the two types of anomalies, abrupt and gradual, this study focussed on the gradual type of anomalies. Gradual change is harder to detect by the human eye as the decline can be very slow. It is possible that gradual decline has no other side effects, where abrupt change often comes after for instance a fall or a flu.

Step frequency, gait variability and gait instability were chosen to measured, as these were found to be the most important features of walking behaviour in the assessment of fall risk. It should be mentioned that the combination of step frequency and gait variability is highly important. As step frequency tend to decrease at higher age, it does not have to mean that the user has a higher fall risk.

A model was proposed to prepare and analyse data gathered with an Android Smartphone. The model was build from different previous studies which focussed on the validation of smartphones in recognition of walking behaviour.

The proposed method was capable of detecting both abrupt and gradual change for the values of step frequency and correlation of variability. A first experiment showed that when simulating an abrupt change in walking behaviour the method was capable of detecting the difference. These results were used as a guideline in the second experiment. This second experiment consisted of test with weights on both legs and on only one leg to simulate different anomalies. By adding weights gradually the gradual decline was imitated. It was shown that the proposed method is also capable of detecting this gradual change for the step frequency and the gait variability.

Experiment 1 showed promising results for the detecting of gait instability. Nevertheless the detection of RMS was not as expected while designing experiment 2.

6.1 Limitations and recommendations

The smartphone available for this research was not equipped with a gyroscoop. Without this sensor it is difficult to extract the gravity from the sensor readings, resulting in a less accurate analysis. Further research should be done using a phone with both an accelerometer and a gyroscoop. This way also the position of the smartphone can be taken into account, allowing the user to be monitored without paying attention to the orientation of the device.

As the model is tested with simulated behaviour it is recommended to test it over a longer time span involving elderly people to validate the results. A larger sample for the experiments can be used as well to further increase the accuracy of the model.
The analysis of the data is done offline. However, it can be performed on the smartphone as well. Instead of manually selecting the data sample the analysis can be started if the smartphone recognises when the user is walking, using the android’s `DetectedActivity` from the `ActivityRecognitionApi`.

The model proposed is supposed to be a helpful tool in order to detect fall risk in an earlier stage. In no case it can be seen as a substitute for the fall risk assessment of a health care professional. However, future research should be done to investigate how this, on long term, could be the case.

### 6.2 Business and Society value

The most recent numbers available for the Netherlands [41] show that in 2011 84,000 treatments on the ER were necessary because of falls. The treatments combined with hospitalisation and deaths caused €820M of healthcare costs. For instance, a fall which causes a hip fracture leads to costs of €12,000,- for surgery and revalidation. As this research indirectly helps decreasing these falls it has a business value both for Society and other companies. By implementing the features discussed a more advanced fall risk assessment can be made. Society can increase the value of the GolivePhone by implementing the proposed method. On the other hand, an implementation of the method has a high value to insurance companies as well, as it can help reduce falls and thus decrease corresponding costs. Even for society the model has value. By reducing falls it can help people have a higher quality of life. It is obviously that preventing falls is pleasant for elderly people. However, as the goal is to intervene when the abilities decline below a certain level, users can stay more active and enjoy life at a higher age.
References


[38] Marcos Duarte. Peak detection algorithm, 06 2016.


7 Appendices

7.1 Example HourlyRecord

{
    "AndroidId": "cb59e4fa9ee39548",
    "Day": 4,
    "Hour": 1,
    "LogID": "Hourly_Record_cb59e4fa9ee39548_1407110400000",
    "Month": 7,
    "MoverADLStats": {
        "cycling": {
            "distanceTraveled": 0.0,
            "energy": 0.0,
            "steps": 0,
            "time": 0
        },
        "laying": {
            "distanceTraveled": 0.0,
            "energy": 19.599983,
            "steps": 0,
            "time": 960000
        },
        "lookingAtPhone": {
            "distanceTraveled": 0.0,
            "energy": 4.2466664,
            "steps": 0,
            "time": 160000
        },
        "moderateActivityTime": 0,
        "notUsingPhone": {
            "distanceTraveled": 0.0,
            "energy": 16.24761,
            "steps": 0,
            "time": 865000
        },
        "running": {
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            "energy": 0.0,
            "steps": 0,
            "time": 0
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            "energy": 0.0,
            "steps": 0,
            "time": 0
        },
        "standing": {
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            "energy": 0.0,
            "steps": 0,
            "time": 0
        },
        "tilting": {
            "distanceTraveled": 0.0,
            "energy": 15.097856,
        }
    }
}
7.2 JSON Scheme HourlyRecord

{  
  "$schema": "http://json-schema.org/draft-04/schema#",  
  "type": "object",  
  "properties": {  
    "LogID": {  
      "type": "string"  
    },  
    "rev": {  
      "type": "string"  
    },  
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      "type": "string"  
    },  
    "type": {  
      "type": "string"  
    },  
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    },  
    "Month": {  
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    },  
    "Year": {  
      "type": "integer"  
    },  
    "Hour": {  
      "type": "integer"  
    },  
    "subtype": {  
      "type": "string"  
    },  
    "AndroidId": {  
      "type": "string"  
    },  
    "ShareActivity": {  
      "type": "boolean"  
    },  
    "MoverADLStats": {  
      "type": "object",  
      "properties": {  
        "tilting": {  
          "type": "object",  
          "properties": {  
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              "type": "number"  
            },  
            "distanceTraveled": {  
              "type": "integer"  
            },  
            "steps": {  
              "type": "integer"  
            }  
          }  
        }  
      }  
    }  
  }  
}
"required": [ 
  "time",
  "energy",
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7.3 Filter response
7.4 Summary interview physiotherapists

It is proposed to use the smartphone as a fall risk assessment
The idea of using a smartphone in fall risk assessment received a very enthusiastic, although the technical implementation seemed very difficult.

How would it benefit the healthcare?
It would be possible to detect anomalies before falls would occur. If so interventions could prevent falls from happening by increase the abilities of the patient. We could give people instructions on how to coop with the declining abilities, how to walk in a way they have a higher balance and how to exercise to maintain or even increase muscle strength.

What kind of tests do you deem important?
User friendliness is very important. People should not have to do anything themselves with the phone to analyse their walking behaviour. Also the position of the phone should be unimportant. Especially for women the current position (thus in the right front pocket) can be a problem. Users should be thought that the phone should always be carried with them. People in the age of 80 and above are currently the ones which would benefit the most from a fall assessment tool as they have the highest fall risk. However, they are used to see the phone as an emergency device or a device which is only used every now and then. If you take people in the age of 60 and above they are more used to have their phone nearby, or even constantly wearing them on them. On the long run they will benefit as well as you can detect decline in an early stage.

And if you consider test in terms of features of walking behaviour? What should be measured?
Try to measure the difference in step length and the sideways movement. And of course speed.

What should then be considered as anomaly? At what level or difference an alarm should be given?
If people start walking with small steps or even go from walking to shuffling it is a clear sign of a higher fall risk. Also walking with a wide track or with a high variability is a bad sign. A fixed value what is an anomaly can not be given as it is different from person to person. A person having the flu will walk differently, but this can be only temporary and can for instance be over in a week or two. The clinical eye of a therapist is always necessary to determine whether there is an actual increases risk or that is is influenced by other factors.

But then, is the smartphone necessary as an extra device when the clinical eye of a therapist is still necessary?
Yes absolutely! Using it on a large scale makes it possible to detect anomalies as early as possible without the need of intervening everybody. Persons who show a high fall risk in the smartphone analysis can be intervened one time by a therapist and afterwards exercise by themselves without the need of healthcare professionals. If necessary digital followups using for instance Skype on how the exercises are working out are much easier to do if a person is intervened in an early stage. Don’t forget that the current value of a hip replacement including revalidation afterwards is about €12.000,–. If you can prevent that from happening it will save a lot of money and also increase the quality of life.