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Gait analysis of older adults: Gait characteristics calculation and environmental factors

GEO 511 Master's Thesis

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Abstract

Background: Gait characteristics are good indicators for physical health. Early detection improves clinical outcomes. The main influences on gait characteristics come from health factors, individual factors and environmental factors. While health and individual factors are widely researched, the environmental factors have been largely disregarded. This thesis aims to support the health monitoring research with a smartphone-based gait characteristics calculation and shine some light on environmental factors.

Methods: GPS and inertial measurement unit (IMU) data is pre-processed with GPS noise filters, step detection and bout detection. This allows for the calculation of the gait characteristics gait speed, step length, step time and cadence. These characteristics are put in context with more intermediate characteristics and external data.

Results: The GPS data was already filtered, so additional filtering did not yield better results. A high accuracy for step detection was found, with consistent undercounting. The calculated gait characteristics were higher than in other literature, but within a reasonable range. Few correlations were significant. The stop characteristics could be linked directly to most gait characteristics. The surface of asphalt could be linked to a reduced number of stops and stop time.

Conclusion: The correlation between stops and gait characteristics is potentially great news. If stops can be directly linked to health, then a simple IMU would be sufficient for health monitoring. This would improve health monitoring in areas with degraded GPS signals, like inside buildings. However, many limitations were found that may be reduced with future research.

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1 Introduction

1.1 Motivation

We live in a world where many countries have increasing life spans combined with reduced birth rates, especially in first world countries (Taylor et al., 2019). Switzerland is no exception to this rule. In 1970, only 11.5% of the population was aged 65 and older. In 2020 this value has almost doubled to 18.8% and the trend is only going into one direction. Half of the baby boomer generation (1946-1964) is already older than 65 and the other half is following in the next decade (Bundesamt für Statistik, 2020). With the increased number of older adults and less of the younger generation to take care of them, the healthcare system must find new solutions for the already increasing demand in health services.

Gait characteristics, such as gait speed, are good predictors for physical health in older adults (Studenski et al., 2003). Additionally, gait speed is also an early predictor for health decline. An important factor in improving clinical outcomes is the early detection of health deficiencies. Mobility limitation correlates with mortality rates and poor clinical outcomes (Kawai et al., 2020). Therefore, it is important to find reduction in mobility as early as possible. Early detection can often reverse the clinical outcome (Münch et al., 2019).

In this context, monitoring the physical mobility of older adults plays an important role for this early detection (Bischoff & Weiss, 2019). This is called health monitoring. One example of health monitoring is gait speed testing in a clinical setting (Bischoff & Weiss, 2019). In this regard, there is a potential to use gait characteristics for health monitoring. However, this potential is rarely used by general practitioners (Studenski et al., 2003). To increase the use of these methods, they must be easily accessible and cheaper than the alternatives. With the rise in popularity of smartphones, most people are already carrying sensors capable of recording the necessary data for monitoring physical health.

Gait characteristics are measured with two main devices: GPS logger and an Inertial Measurement Unit (IMU). Both are contained in most smartphones. With the correct pre-processing and the data derived from these two devices, gait characteristics can be calculated (Ishikawa et al., 2019).

However, the physical health of a person is not the only influence on gait characteristics (Sprager & Zazula, 2011). Individual factors and environmental factors are also important. With all these different factors to consider, the goal of this thesis is to calculate good gait characteristics with data provided by the *Mobility Assessment with Modern Technology in Older Patients' Real-life by the General Practitioner* (MOBITEC-GP) project. The calculated characteristics and environmental factors can be put in context with each other. The data will be more closely examined in section 3.2. The experiment consisted of measurements taken, while they participants walked as instructed, in the Merian Gärten in Basel. The participants were aged 65 and older.

1.2 Overview

First, a brief introduction to the most important terms is given in Section 3.1, followed by the state of the art (3.2). From there, the three main research subsections are described (3.2.1, 3.2.2 and 3.2.3) and a research gap is identified. In 3.4 and 3.5, research necessary for the calculation of the gait characteristics is identified and the pre-processing steps are introduced. Next, research questions are formulated and hypotheses are presented, connected to literature where possible (3.6).

In chapter 3 material and methods are introduced and discussed in detail. Chapter 4 displays the results of the calculations in figures and tables and chapter 5 discusses the results and the connected hypotheses. In chapter 6 a conclusion is drawn, limitations discussed and an outlook is given.

2 Background

2.1 Introduction of Terms

Gait is how a person walks. In literature, gait can also be used as the description of the repetitive movement or in some cases even as a single cycle (Kuo & Donelan, 2010). However, in this thesis it will only be used as the term for the description of human movement. Each foot lifting of gait movement will be referred to as a step. The different values to describe gait are called gait characteristics and gait parameters (Pepa et al., 2017). This thesis will refer to them as gait characteristics.

An inertial measurement unit (IMU) is an electronic device measuring local changes with a sensor. These sensors include an accelerometer (ACC), a gyroscope and a magnetometer. The accelerometer (ACC) measures changes in acceleration (gravity and movement). The gyroscope measures changes in the angular orientation. The magnetometer measures changes in the magnetic field.

The Global Navigation Satellite System (GNSS) refers to a satellite system providing location information. The Global Positioning System (GPS) is an example of a GNSS. For the rest of this thesis, GPS will be used instead of GNSS for both, the type of system and the example.

The experiment with the participants consisted of three parts (Münch et al., 2019): walk a 10m, 50m and 400m track in a Stadium, walk around for a certain duration (approx. 30 min) in a park and wear the device in their everyday life for a week. These three parts will be referred to as Stage 1, Stage 2 and Stage 3 in this thesis.

2.2 State of the art

Research on gait can be divided into three subsections. The first subsection derives gait measures so that they can be used to monitor the health of their subjects (Lin et al., 2014). This subsection of gait research will be called health monitoring. A second subsection aims to better understand differences in individual gait. Biometric identification is an example of this research domain (Kwapisz et al., 2010). Research in this subsection focuses on finding applications for the differences in individual gait measurements. This subsection of gait research will be called personalized gait research. Health monitoring focuses on the commonalities of gait characteristics and their use as health predictors. The last subsection focuses on improving measurement of gait. This subsection aims to improve the accuracy of measurement (Pham et al., 2018), their availability (Khademsohi et al., 2017) and their ease of use (Sun & Metaxas, 2001). This subsection of gait research will be called general gait research. While these are the three subsection covering most of gait research, they are not mutually exclusive. Münch et al. (2019) for example tries to create health monitoring that is easy to use for general practitioners. This would place it in the subsection of general gait research as well as health monitoring.

2.2.1 Gait measures for health monitoring

The connection between mobility and physical health has been widely researched in the literature, especially for older adults (Section 1.1). Measures of mobility are a great predictor for health (Studenski et al., 2003).Walking speed has been connected to health in older adults (Kawai et al., 2020). Studenski et al. (2003) tested multiple measures of mobility and most are good predictors for health. The most important among those predictors is gait speed. This predictor serves as an early warning sign. Often, the change in gait speed is early enough to prevent a severe impact on health with the correct therapy (Pahor et al., 2014). However, this is only the case if the predictor is found early enough. It necessitates a regular assessment of measures of mobility (Cesari, 2011).

There are two ways to test measures of mobility. They can either be tested in a laboratory setting (LWS) or in their daily lives (DWS) (Chan et al., 2011). Historically, measures of mobility have been tested in LWS, however this has multiple downsides. The testing of measures of mobility in a laboratory requires a trained staff and often general practitioners to test the subjects. The amount of required equipment and the staff salary causes high costs. Despite the advantages of early detection older adults are not regularly checked by general practitioners (Calkins et al., 1991). There is a difference between the gait speed measured in

LWS and DWS as values gained in LWS are higher than in DWS (Carcreff et al., 2020). However, the LWS and DWS values are highly correlated, so both can be used to predict health with a different reference frame. Another disadvantage of LWS is the necessity to regularly measure the gait speed.

In order to regularly measure gait speed and reduce the costs of health monitoring, a smartphone based approach is considered (Chan et al., 2011). Most people carry a smartphone around with them every day. Automatically recording the measures of mobility and making it possible to be examined by a general practitioner would substantially decrease the costs associated with health monitoring (Pham et al., 2018). However, so far, no automated and easy to use approach for health monitoring has been developed. This is the goal of Münch et al. (2019) that provided the data for this thesis analysis.

2.2.2 Gait measures for personalization and authentication

Personalized gait research is newer than health monitoring. The reduction of IMU cost and their common use in smartphones is important to allow for this possibility at a reasonable price (Sprager & Juric, 2015). This research considered more measures of gait to find connections useful for authentication such as step length, cadence and gait symmetry (Scapellato et al., 2005). While the main goal of this research area is to create an authentication system similar to a fingerprint based on measures of gait (Zou et al., 2020), their insights also have a positive impact for health monitoring. One such insight is that the location of the gyroscope has a larger impact on the performance than it has for the accelerometer (Ngo et al., 2014).

2.2.3 General gait research

General gait research improves both other research subsections. Any improvement to measurement accuracy or measure of gait calculation, can be applied in both of these areas. In this area, the calculation of the measures of gait are an important research topic. The collected raw data cannot be directly used but has to be processed first. With regards to this thesis, there are three pre-processing steps of major interest: GPS noise reduction, Step detection and Bout detection.

In recent years, the use of GPS has become widespread. The technology has become inexpensive and is widely available in devices such as smartphones. This can be used to get a track with high accuracy of a few meters, which can be used for health monitoring.

GPS is used to calculate the speed of a person in their everyday setting. Unlike measurement in LWS, this measurement is available nonstop. This would reduce the need of repeated trips to the hospital for measurements. Additionally, it is increasing the convenience and reducing the cost for health monitoring. This can be used to calculate measures of gait in everyday settings.

Widely used sensors are contained in the IMU. This can be used for detection of the walking pattern, which in turn is used to calculate the start and stops of steps. This process is called step detection (Rajagopal, 2008). Because of GPS measurement errors and their influence on calculated measures of gait, stops are important to detect. This can be achieved with stop detection. The automation of these processing steps is one of the difficulties in general gait research (Sun & Metaxas, 2001).

2.3 Research gap and focus of this thesis

Measures of gait are used to predict health in health monitoring and personalized gait research allows identification based on measures of gait. However, Sprager & Zazula (2011) found that measures of gait are influenced by two types of factors: Physiological and environmental factors. The physiological factors are divided into health factors, used in health monitoring, and individual factors, used in identification. The impact of slope condition of measures of gait has been research by Ngo et al. (2014) and the impact of carrying weight by Sprager & Zazula (2011). The impact of the environment can have an impact on the measures of gait, but there has not been sufficient research in that area yet (Bayat et al., 2020).

Because of this gap in research, this thesis focuses on the calculation of solid gait characteristics and then tries to put these gait characteristics into the context of the environment. This will include path surface types, path sinuosity, weather, and locations of stops. If the impact of the environment on the gait characteristics can be found, this would reduce the uncertainty for health monitoring and personalized gait research. For example, if people stop because they arrive at the fork in the road, then, this could be considered for gait monitoring and would less likely be misinterpreted as an indicator for bad health.

In order to achieve this goal, first, the GPS and IMU data are combined and pre-processed to calculate the gait characteristics. These pre-processing steps should be validated where possible. The calculated gait characteristics can be set in context with environmental data from OSM and weather data.

2.4 Gait characteristics

This thesis choses relevant gait characteristics for health monitoring. Gait speed is chosen because it is a good predictor for health (Kawai et al., 2020). In addition, cadence, step length and step time are chosen, because these are necessary for calculation of stop and stroll characteristics. These are also widespread enough in literature to have good comparison values.

2.5 Pre-processing

Before the measures of gait can be calculated, the raw data has to first be pre-processed and brought into a more useful form. This thesis will take a closer look at three pre-processing steps, GPS filters, step and bout detection, before applying them.

2.5.1 GPS noise filters

GPS provides the location and time of a moving object. From the combination of these two measurements the speed can be calculated. The location of the GPS device is calculated with connection to the satellites. Places with poor connectivity severely reduce the accuracy of the measurement (Godha et al., 2006). One example of this is very poor GPS measurements indoors. The GPS has a significant amount of noise, even under normal condition. In order to counteract this and improve the measurements, a method called noise filtering is used (Hide et al., 2003; Mahony et al., 2008).

There are multiple types of noise reduction filters, such as adaptive estimations and innovation-based adaptive estimations (Hide et al., 2003; Mohamed & Schwarz, 1999). For this thesis three of the simpler approaches for noise filtering were chosen: outlier filters, mean filters and Kalman filters.

The outlier filter used is based on speed. For each point the speed can be calculated and if the speed is an impossible value, the point can be removed from the dataset. This approach was used by Yuan et al. (2010). This reduces the number of outliers, which can significantly improve the data. This is also a filter that can be used in addition of another filter, with this filter being used first.

The mean/ median filter recalculates any point as the mean or median of the temporally adjacent points. This is a good approach to outliers and smooths trajectories (Zheng, 2015). The median filter is more robust than the mean filter. Both perform badly with a low sampling rate (Zheng, 2015).

Kalman filters are widely used for most filtering application. They are often easy to set up and the initial conditions are quickly corrected. They rely on a priori knowledge of the behaviour to function best (Zheng, 2015). While the details of Kalman filtering are very interesting, they are beyond the scope of this thesis. We will simply use the same approach used by Zheng (2011) for a basic Kalman filter.

2.5.2 Step detection

There are multiple approaches to gait detection, frame based approaches and cycle based approaches (Sprager & Juric, 2015). Frame based approaches assume that a certain amount of time passes for each step. This would eliminate all possible analysis based on changing gait cycles. A cycle based approach allows for accurate step detection, while still allowing analysis of change in the gait cycle (Nishiguchi et al., 2012). There are multiple types of cycle gait detection. The two most notable approaches are ACC peak detection (Pham et al., 2018) and gyroscope based zero crossing (Hundza et al., 2014). For peak detection the data is smooth with a low pass filter and the peaks are defined by the local maxima (Sprager & Zazula, 2011). With every step the foot is lifted, the y angular rate suddenly increases and then decreases again. Because of gravity, the y axis of the gyroscope is aligned horizontally, which results in the value being below zero when the foot is on the ground. Due to the foot rise, the y axis angular rate increases into the positive and then falls back into the negative. This results in the y axis gyroscope measurement crossing 0 (degree/s) twice for each step. So every second 0 cross can be counted as one step (Hundza et al., 2014).

The wearing location of the gyroscope has a large impact on the performance, unlike the ACC (Ngo et al., 2014). Since we have different wearing locations for the gyroscope (smartphone), the ACC should be more reliable and is chosen for step detection.

The best way to validate step detection is to manually count the steps and compare the results.

2.5.3 Stop/ Bout detection

When estimating speed with GPS data, it can be difficult differentiate between stops and movement. But multiple stops have an impact on the average gait speed and if not removed they will reduce the gait speed measurement. This makes detecting stops important. In the literature, multiple different definitions of stops exist: A pause longer than 5s (Shah et al., 2021), 4s (Carcreff et al., 2020) or based on a bout definition. A bout is a number of continues steps without a pause in between. Defining stops based on a bout, would mean that any time not spent in a bout is considered a stop. Orendurff et al. (2008) examined the human walking behaviour with a focus on bout length and bout duration. 60% of all bouts last 30s or less. Only 1% off all bouts last 2min or longer. 40 % of all bouts had only 12 steps and 75% of all bouts had less than 40 steps. Shah et al. (2021) tested different bout definitions based on the pause regarding the end of the last bout: 1.25s, 2.5s and 5s. A bout has to consist of at least three consecutive steps. Despite the three different definitions, they could not find a difference in the bout definition between the different healthy and unhealthy subjects. This suggest that measures of gait between healthy and unhealthy subjects are not influenced by the bout definitions.

2.6 Research Questions and Hypotheses

2.6.1 Research Questions

Based on the gait characteristics and calculation steps, the following research questions are chosen:

Research Question 1: Which GPS noise reduction filter performs best?

Research Question 2: How well does step detection with accelerometer perform?

Research Question 3: Are the calculated gait characteristics reasonable? How do they compare with the values in literature?

Research Question 4: Where do stops occur? Is there a different distribution for shorter or longer stops?

Research Question 5: What impact does the path have on the gait characteristics and stops, both for ground surfaces and sinuosity?

Research Question 6: How do gait characteristics correlate with themselves, with stroll characteristics and stop characteristics?

Research Question 7: What impact does weather have on the gait characteristics and stroll characteristics?

2.6.2 Hypotheses: Expected outcomes

In this section, a brief overview of expected outcomes will be given and wherever possible connected and compared to values in the literature.

Research Question 1: Which GPS noise reduction filter performs best?

In the literature, the Kalman filter is most used. It can be applied to a number of different situations, if the matrices are adjusted appropriately (Zheng, 2011), while the outlier filter and mean filter have more limitations (Zheng, 2015). However, the ease of implementing and lower computational requirement of the mean and outlier filter might be more important if the results are comparable (Khademsohi et al., 2017).

Research Question 2: How well does step detection with accelerometer perform?

The step detection algorithm by Pham et al. (2018) performs well. It is expected that the accuracy is on the same level between 95% and 99%. The algorithm used will usually have an undercount, since the same method is used, the same result is expected.

Research Question 3: Are the calculated gait characteristics reasonable? How do they compare with the values in literature?

The measured values are expected to be in the same range as those for people aged 65+ in literature. The gait speed is estimated between 0.58m/s in a normal setting (Peel et al., 2013) and 0.88m/s in a clinical setting (Studenski et al., 2003). For the step length there is a measurement for belt at 0.55m with a standard deviation of 0.1m and pocket at 0.58m with a standard deviation of 0.14 (Nishiguchi et al., 2012). The cadence for older people in literature is 1.69 steps/s (Taylor et al., 2019). For younger adults the cadence in literature has been measured at 1.92 steps/s (Silsupadol et al., 2017). A result in between these two is expected.

Research Question 4: Where do stops occur? Is there a different distribution for shorter or longer stops?

The impact of resting period between bouts has been research for older adults with resting periods between 1-6s and up to 30s (Barry et al., 2015). However, their main goal was to detect the impact on bout definition. Participants with bout pauses between 1-6s did not change their resulting maximum speed and bout length much. For the differences in stops length two hypotheses shall be tested. It would make sense if smaller stops <5s are more due to changes in the environment. For example, when approaching a fork in the road, the participants would stand still for a few seconds to decide where to go. This would result in more short stops close to street forks. On the other hand, longer stops are unlikely to be due to exhaustion in the park setting, but rather the finding of a location of interest. This would mean that longer stops >5s are more likely to be close to interesting areas. Also, this would make longer stops a bad indicator for health if the stops are voluntary, so an increase in long stops does not have an impact on the gait speed.

Research Question 5: What impact does the path have on the gait characteristics and stops, both for ground surfaces and sinuosity?

Paths with higher sinuosity are more likely to be footpaths than paths street. This would most likely change the walking behaviour on these paths. The hypothesis is that on paths with higher sinuosity there will be more participants choosing that path during their stroll and the average gait speed on these paths would be lower. Ground surfaces with asphalt, that are paved or compacted, make worse resting places than paths that are not. There is also a possibility that the ground surface impacts the gait characteristics. The paths with these surfaces are less likely to distract participants from walking than the other paths in the rest of the park. Therefore, the gait speed on these surfaces should be higher. This thesis assumes long stops (>5s) are at least partially a distraction, these are less likely to happen on paths with these surfaces.

Research Question 6: How do gait characteristics correlate with themselves, with stroll characteristics and stop characteristics?

For almost every combination of gait characteristics and stroll/ stop characteristics, a hypothesis can be formed. Participants with longer bouts are more likely to be healthy, because they do not need a break. This suggests an increase in bout length increases the gait speed. With similar argumentation, step length and cadence should also increase since an increase in gait speed would have a direct impact on these two. For the distance travelled, one can once again assume a positive correlation with gait speed. Healthier participants are more likely to walk farther before getting tired. For time that has passed since the start of the stroll, a correlation is hard to predict. If the participants become tired, they are more likely to take breaks. This would decrease the gait speed. However, if they are far away from the starting point, they might speed up and hurry back to get there in time. This would increase the gait speed with time. For the total stop time a negative correlation with gait speed is assumed. People spending more time on breaks in total are probably less fit than their counterparts. For time spent walking, a reduction in gait speed would be obvious. Spending more time walking should slow down the participant.

Most participants participated in the test twice. It will be interesting to see if the knowledge of the procedure and the experience has a measurable impact on the gait characteristics. Maybe, if they have already explored the park the first time around, they will simply enjoy their time some more and spend less time traveling around. Also, if they know the park from the first time already, they may need less orientation (short) stops than the first time, increasing bout length.

For correlations between gait characteristics and stroll characteristics, a hypothesis would be negative. Participants who are required to stop because of their health will stop more often. And adults with worse health have worse gait characteristics. Therefore, a negative correlation is expected across the board. The assumption is that short stops are involuntary because of health and long stops are voluntary and because of the distractions in the environment. If this assumption holds true, the correlation coefficient for short stops is expected to be smaller than for long stops

Research Question 7: What impact does weather have on the gait characteristics and stroll characteristics?

While much of the weather correlations are not obvious, it is expected that participants spend less time on the stroll and go back to the endpoint in less time than when it is raining.

3 Material and Methods

3.1 Workflow

In Figure 1 is the workflow of the analysis displayed. The individual steps will be explained in detail in further chapters. The goal is to create gait characteristics good enough to use them as predictors for the environment and vice versa. For this GPS and IMU data will be combined with multiple pre-processing steps that allow the calculation of gait characteristics and stops. This data can then be combined with external OSM data. This data after some pre-processing of their own can be combined with the gait characteristics to analyse for correlations.

Figure 1: Workflow diagram

3.2 Data Collection

The data used in this thesis were collected by "*MOBIlity assessment with modern TEChnology in older patients' real-life by the General Practitioner"* (MOBITEC-GP) project. The MOBITEC-GP project is run by the Division of Sports and Exercise Medicine from the University of Basel (Münch et al., 2019). The study consists of three stages and has been conducted with older adults aged 65 and more. In the first stage, the participants carried a high-end GPS device, a medium-accuracy GPS/IMU logger, and three different smartphone models: Xiaomi, Samsung, and iPhone for walking tests. The first stage consisted of 10m, 50m and 400m walking tests on a prearranged 400m round stadium track. The participants were also videotaped for a whole walking test and timed with laser barriers upon passing the start and end points. The second stage consisted of a 30-min stroll with the same equipment right after the first stage. This stage was conducted without the laser barrier and videotaping. The third stage collected data during the participants' daily lives at home and is not used in this thesis. Stage 1 and Stage 2 are repeated after one week.

The sample of participants used in this thesis consisted of 60 participants. They are all anonymized and identified with a number. All participants of this sample are used. Any exclusion criteria are outlined in Section 4.4.

During the data collection, participants wore the phones at different locations on their body. The locations are waist belt, sling bag, and neck pouch (Münch et al., 2019). The longitude and latitude were collected relying on GPS. In addition to recording the longitude and latitude, it also recorded the time, altitude, speed, error data, and the number of satellites used. The average sampling rate of the GPS is 1 Hz.

The phones also collected IMU data from a tri-axis-accelerometer (ACC) data and gyroscope. The ACC collected the acceleration in the direction of each axis, as well as the time and date. The gyroscope recorded the angle change on the same three axes, time and date. The average sampling rate of ACC and the gyroscope is 50 Hz.

Additionally, the time difference between the GPS and the ACC data is recorded and allows for synchronization of the data from GPS and ACC.

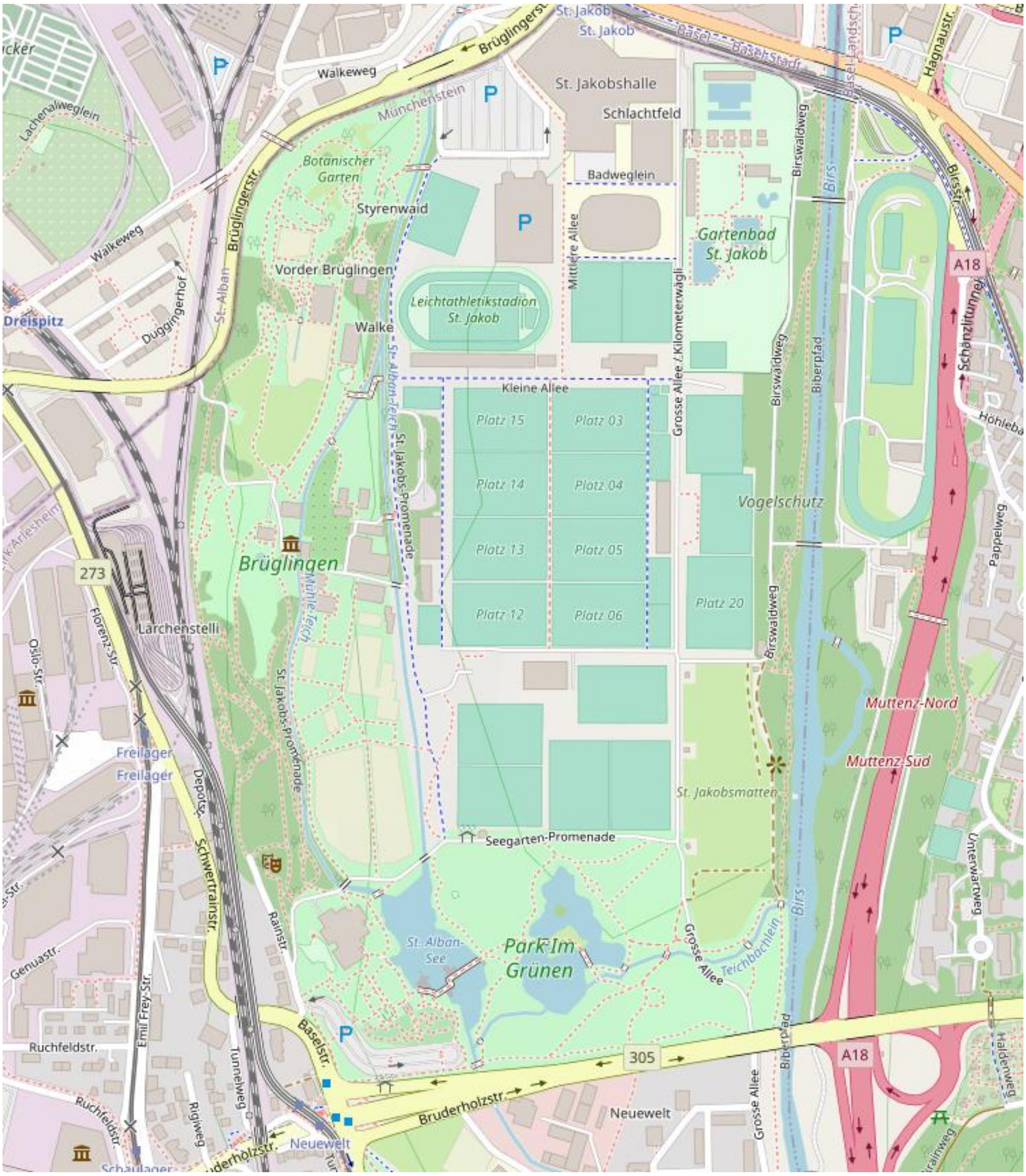

Figure 2: OSM map Merian Gärten

The first measurement of the subsample was conducted in July 2019 and the last measurement was conducted in February 2020. Stage 1 was conducted in the *Leichtathletik-Stadion St. Jakob* and Stage 2 in the adjacent *Merian Gärten* in Basel. During Stage 1, participants could not roam freely but instead conducted the walking tests in an order: 10m, 50m, and 400m. In Stage 2, they were instructed to roam freely within the Merian Gärten for 30 min, after which they were to return to the *Eissporthalle St. Jackob-Arena* that is also adjacent to the *Leichtathletik-Stadion*

Figure 3: Leichtathletik-Stadion St. Jakob used for the 10m, 50m and 400m test

3.3 Data

The data used in this thesis are the GPS and IMU data collected by the Xiaomi and Samsung smartphones during Stage 1 and Stage 2.

The GPS data of Xiaomi shows some irregularities. Longitude and latitude values were rounded. However, the average rounding is 0.4m, which is insignificant in comparison with an average location error of more than 3m with both Xiaomi and Samsung.

The ACC data has a very high sampling rate average of 50Hz. While this sampling rate is irregular, this irregularity does not have a large impact, because the sampling rate is 50 times higher than the GPS counterpart. Another reason is that it is low-pass filtered to create a smooth regular curves, where the maxima are easy to calculate. The gyroscope data have the same sampling rate.

Videos of Stage 1 were used for the validation of the step detection. While these videos are timestamped, the raw timestamps have two hours off, most likely due to a time zone difference. In addition to the different hours, minutes and seconds of the video are not the same as in the GPS/IMU data, with differences of up to 5 minutes.

For weather and wind, data from Meteoblue Basel (*Weather History Download Basel - Meteoblue*, n.d.) are being used. It provides hourly values for *temperature*, *precipitation*, and *sunshine duration*.

Geographical data are exported from OSM with overpass turbo, by selecting all *highways* within a bounding box around the entire park. The resulting dataset is cleaned so it only contains lines and no more points and polygons. Then the lines are further pre-processed with the process described in Section 4.9.2.

The information provided on OSM is inconsistent and incomplete, but there is much interesting information to use. For example, some paths are classified as *footpath* or as different levels of *streets*. For some paths, it is recorded whether it is a bicycle path and whether the ground is gravel or paved.

3.4 Data Exclusion criteria

Considering the subsample contains data of only 60 participants, the goal is to use all data. However, some parts of the data had to be excluded.

The GPS data of the iPhone was inaccurate. While the distance of the correct location during the test of the track with Xiaomi and Samsung rarely exceeded 10m, in the iPhone data this showed a distance of more than 15 meters off the track. After testing some preliminary examples, it was decided to only use Xiaomi and Samsung data for the analysis.

Files of some participants are structured incorrectly, with additional lines and wrong ending symbols. Some files are also completely or partially missing. For example, with some participants it shows the GPS data but not the ACC data. Consequently, these participants are also excluded from the combined dataset, but included for the GPS noise reduction analysis.

Many files are named incorrectly. If possible, these naming errors are corrected and respective data still used.

In some cases, the session information file, which records the time difference between the GPS data and the IMU data, is missing. If this information was completely missing for Stage 1 and Stage 2, the data were only used for the GPS and IMU separate analysis and dropped for the combined analysis (section 4.3 – 4.6). However, in most cases this information is only missing for either the first Stage or the second Stage. Since both Stages are recorded without a break between Stage one and Stage two, the session information file of the other Stage is used.

While these different exclusion criteria accumulated during the workflow, eventually only 29 out of 480 datasets were excluded.

3.5 GPS noise reduction

To accurately calculate gait characteristics, it is important to have good location information. However, unfiltered GPS data is often noisy. This noise can be reduced with noise reduction filters. There are many different noise reduction filters such as model-based adaptive estimations (MMAE) and innovation-based adaptive estimation (IAE)(Mohamed & Schwarz, 1999) and Hide et al., 2003). For location data, there are three main types of noise reduction filters: Mean/median filters, Kalman filters, and outlier filters (Zheng, 2015).

3.5.1 Mean/median filters

Based on temporally adjacent points, mean/median filters recalculate the location of every point. Each point is recalculated as the mean or median location of a certain number of temporally adjacent points. As the only parameter, the number of previous and following points is the moving window size. A larger moving window results in a more robust noise reduction but with the cost of increased data loss. For example, with a large moving window, small movements might no longer be visible. Median filters are more robust towards extreme outliers, but otherwise perform similarly to mean filters. Mean and Median filters perform better with higher temporal resolution and few consecutive errors(Zheng, 2015).

This thesis created a mean filter with adjustable moving window size X, the new point is recalculated with the previous X points and the following X points as well as the current point. The pseudocode is defined as follows:

$$New\ point\ =\ Prev1 + \ldots + prevX + point + next1 + \ldots + nextX\ /(2X+1)$$

3.5.2 Outlier filter

The outlier filter is helpful to get rid of extreme outliers. By constraining impossible points, the quality of the dataset can be improved dramatically. This filter can be used by itself or in combination with other filters, such as the mean filter. The outlier filter for this thesis is based on speed. If a point is impossibly far away, it means that the speed between that point and the previous one is too high. As a consequence, there must have been a measurement error and the faulty point is deleted (Zheng, 2015). The outlier filter created by this project is tested for multiple speed thresholds and evaluates their impact. The chosen threshold was Z =2, since 2m/s is faster than any normal human walks:

The pseudecode is defined as follows:

$$If\ distance\ (pre;\ next)\ >\ Zm/s:$$

$$remove\ point\ from\ set$$

3.5.3 Kalman filter

The Kalman filter is very commonly used and is often considered the gold standard. The Kalman filter assumes a priori knowledge. In the case of the Kalman filter used in this thesis, it is assumed that a moving person will continue to move into the same direction and the same speed (Zheng, 2015).

The Kalman filter used, is the default Kalman filter of the Pykalman library (*Pykalman — Pykalman 0.9.2 Documentation*, n.d.).

The Kalman filter uses the following matrices, which were also used by Zheng (2011). The observation matrix determines the which incoming values are observed, in this case the x-coordinate and the y-coordinate. The Transition matrix predicts the location of the next point and the velocity. It assumes that the velocity the same as the current velocity:

$$new\ location = current\ location + velocity * timedif$$

This results in the following matrixes:

Transition matrix:

$$\begin{matrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{matrix}$$

Observation Matrix:

$$\begin{matrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{matrix}$$

3.6 Step detection

In order to calculate good gait characteristics, a good step detection is necessary, since all calculated gait characteristics, apart from the gait speed, depend on the correct detection of a step. The chosen step detection is based on the correct identification of peaks in the ACC data, which models the moment a foot threads on the ground (Pham et al., 2018).

Step detection occurs in multiple phases. In the first phase the three directional amplitudes (x-, y- and z-direction) are combined into one single amplitude.

$$AMP = \sqrt{x^2 + y^2 + z^2}$$

Then, in order to reduce the noise of the amplitude, a low pass filter is used. The cut-off frequency is 3 Hz (Pham et al., 2018). Normally, in the second Phase, there would be a dynamic classification of walking speed. However, as the population consisted of older people only, it was decided to use the parameters of slow walking speed of the original paper for all situations.

In order to find a step, in phase Three peaks are being detected. There is a minimum time between steps, the minimal peak distance. This defines the minimum time between two possible peaks that has to pass to be considered a real peak. Due to our choice of the slow walking parameters, the minimal peak distance used is 14 (measurement steps, with the sampling rate of 50hz this is 0.28s). This ensures that not every peak found in the accelerometer data is considered a new step. There is also a minimal peak prominence threshold making sure real peaks must be at least a certain amount bigger than any false peak. The minimal peak prominence value used is 0,2g (g=9.81m/s^2).

With these methods and parameters the step detection presented can be conducted based on Pham et al. (2018) algorithm. This results in a dataset with all real peaks and their timestamps, which can now be classified as individual steps.

3.7 Bout detection

3.7.1 Bout definition

In order to calculate gait characteristics, it is important to detect stops. A stop could be considered any step with duration 2.5 second or more or any step with 0.5m change in distance or less. However, with this definition severe negative impact on the calculated average gait characteristics could be expected. There are two main approaches to detect stops. The simple approach just assumes a time threshold. If more than 4 seconds pass between two steps, it is considered a stop (Carcreff et al., 2020).

A more precise approach can define so-called bouts. A bout is defined by a certain number of consecutive steps. Then, anything not part of a bout can be defined to be a stop. Normally, the definitions of a bout have fairly little impact on the calculated gait characteristics. Therefore, as proposed by Shah et al. (2021)the bout definition used in this thesis is with at least three steps and with less than 1.25 sec between each individual step.

3.7.2 Step Validation

With the individual step detection, the steps counted within the bout are comparable to the steps counted manually on the video. Given the time difference between the video and the IMU timestamp, it can be a little tricky to find the correct bout in the data. Since these bouts are easy to spot within the IMU data, the time difference can be reconstructed starting with the bouts in the 400m tests.

3.8 Combination: IMU and GPS dataset

Based on their timestamp IMU and GPS data can be combined. With the help of the session information, the time conversion can be calculated. The location data provided by the GPS is used to assign each step found by the step detection within a physical location. Since the time of the steps does not coincide with the time of the GPS measurements, the position of a step was linearly interpolated using the GPS points that are temporally adjacent.

3.9 Enrichment by external data

In order to compare the gait characteristics with some external data, the external data is set in relation with the GPS and IMU combined step data. This can be done by finding a value, that both data frames possess and then combine the data frames based on that. For the weather this value is the time. For OSM data this is the location.

3.9.1 Weather

The temporal resolution of the weather data is 1 hour. The timestamp of the combined dataset was rounded to 1 hour and then merged with a left join to the weather data. This means for every row in the data that the matching weather time is searched and the corresponding weather data is looked up.

3.9.2 OSM Data

In order to find some information about the path participants are walking on, the OSM data (OpenStreetMap contributors, 2017) were matched with the combined data of GPS and IMU. This combination is achieved through map matching. Most map matching algorithms focus on real-time applications with either GPS data or with IMU data known as pedestrian dead reckoning (PDR) (Perttula et al., 2014). Many of these map matching algorithms are used for matching a car onto the correct street. However, their methods cannot easily be transferred to pedestrian-based map matching (Brakatsoulas et al., 2005). Because our data are already Kalman-filtered by the GPS module in the smartphone and pedestrians have low speed and high temporal resolution, a naive approach was taken that the trajectory points are matched to their closest OSM street.

Another point of interest is not simply the attributes of the paths but also their geometric layout. Strongly winded paths could affect the speed of participants walking on them. To measure how direct a path is, sinuosity can be calculated with the following formula:

$$Sinuosity = \frac{path\ length}{beeline\ length}$$

This would provide a value that could be compared between the different participants to find out if it affects the gait characteristics.

However, because the data was taken from OSM, it provided an additional challenge. Because not all paths share the same level of detail and accuracy, the sinuosity would become a modifiable area unit problem (MAUP). A MAUP means the value (sinuosity) is dependant on the recording accuracy of the path. In order to counteract this problem, two steps were taken. Firstly, to prevent certain problematic paths, all paths were dissolved. For example, for a path that loops around and end close to the start has a very high sinuosity, since the beeline is very low. However, if the path intersects other paths, a participant may only walk on this path to go straight to a destination. So, the path doesn't really have a circle shape, but connects other paths directly. A high sinuosity value would misrepresent that path. In a second step all paths were recalculated with the Douglas Peucker algorithm (Visvalingam & Whyatt, 1990). To find the right tolerance for the Douglas Peucker algorithm a knee plot is used. As seen in figure 4 the knee is around 5m for an average point reduction of 0.5. So, a tolerance of 5m is used. This should reduce the MAUP for the sinuosity calculation. It also gives us an alternative value for sinuosity. The reduction of points can be an effective estimator of sinuosity (García Balboa & Ariza López, 2009). The reduction of the number of points and the sinuosity can both be used as a measure of path directness.

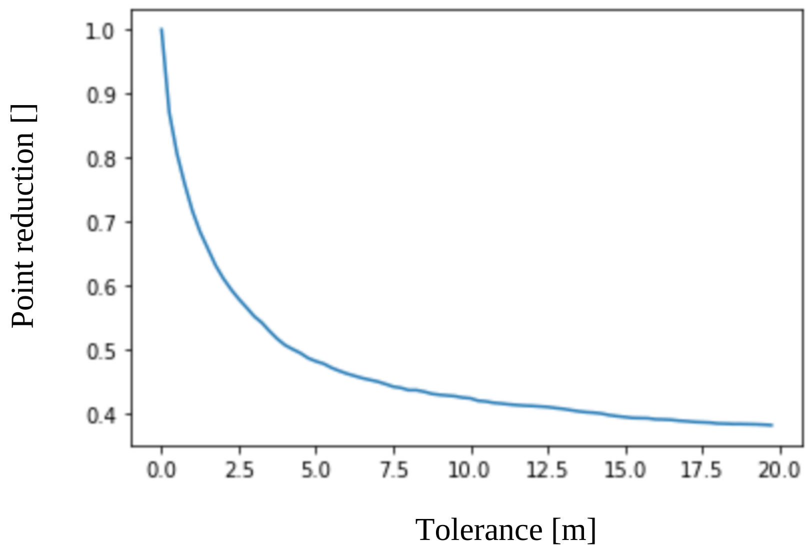

Figure 4: tolerance knee plot: line point reduction with increasing tolerance

3.10 Calculation of Gait characteristics

For the calculated gait characteristics, the following were chosen: step length, step time, gait speed and cadence. Step length is the distance travelled with a single step. Step time is the time taken to complete a step. Gait speed is the speed in m/s. Cadence is the number of steps taken in a time interval.

3.10.1 Step length

Step length refers to the distance travelled within a single step. Step length is a good estimator for health. Each entry in the combined data defines a step. The step length is calculated as the distance from the previous point to the current point.

The step length is calculated with the trajectory $\vec{k}$ between two points. Each point is defined with time, x-coordinate and y-coordinate:

$$\vec{k} = \overrightarrow{p_\iota p_{\iota-1}}$$

The step length l_k of trajectory $\vec{k}$ is calculated as the distance between the point:

$$Step\ length\ l_k = \ d(p_i, p_{i-1})$$

3.10.2 Step time

Step time is defined by the time taken to complete a step. Step time t of the trajectory $\vec{k}$ is calculated with the time difference between two points.

$$Step\ time\ t_k = \ t_{p_i} - t_{p_{i-1}}$$

3.10.3 Gait speed

Gait speed v_k is the speed in m/s of trajectory $\vec{k}$. The gait speed is calculated on a per step basis.

$$gait\ sped\ v_k \ = \ l_k/t_k$$

3.10.4 Cadence

Cadence c refers to the number of steps within a certain time interval. It is calculated for each trajectory $\vec{k}$, which represents a single step. Cadence c is calculated as the inverse of step time. In this thesis, cadence c is defined as the steps per second (hz).

$$Cadence\ c_k = 1 / t_k$$

To reduce the impact of the extreme values, outliers that do not reside within a 97% confidence interval were removed. This was applied only to gait speed and step length. Large outliers of step time do not exist, because the stop detection and bout detection had already removed them.

3.11 Calculation of stroll characteristics

From the calculated trajectories and gait characteristics stroll characteristics can be calculated. These are characteristics calculated based on the stroll (Stage 2).

3.11.1 Bout length

The bout length is defined by number of steps in a bout.

3.11.2 Distance travelled

The distance travelled during the stroll so far. The distance is only counted during bouts so GPS error while standing still does not have an impact.

3.11.3 Active walk time

The time spent walking (in a bout) during the stroll so far.

3.11.4 Time on walk

The time spent on the stroll so far since the start of Stage 2.

3.12 Stop characteristics

These characteristics are calculated based on the stops on the stroll (Stage 2). A stop is defined as a trajectory not part of a bout.

3.12.1 Stop count

The number of stops during the Stage 2.

3.12.2 Stop time

Time spent of stops since the beginning of Stage 2.

3.12.3 Stop frequency

Stop frequency measures how often stops occur. Calculated by dividing the stop count by the stop time. It is only calculated for the entire stroll:

$$stop\ frequency\ = \sum stop\ count\ \ / \sum stop\ time$$

3.13 Correlation Analysis

With the gait characteristics calculated and external geographical data selected and enriched, the data were explored for finding correlations. Because gait characteristics are inherently individual, in most cases of correlations within a participant (intraindividual correlations) a normal correlation is not appropriate. Instead, the repeated measurement correlation (rmcorr) has to be used. Rmcorr is used to determine the intra-individual association of paired measures (Bakdash & Marusich, 2017). Simple regression/ correlation assumes the independence of observations, which of course is not given with our participants differing from person to person. Rmcorr evaluates the common regression of the tested correlation intraindividually. For example, if walking speed decreased with time for the walk, the normal correlation would compare time to walking speed and try to find a connection across all data points. Rmcorr compares the time with the gait speed for each person and summarizes the individual correlations into a combined correlation.

For some aggregated data or unpaired data, rmcorr cannot be used. Instead, an ordinary least squares (OLS) regression analysis is conducted. In one case an independent t test is conducted, to test if there is a connection:

Table 1: Statistical methods used

	Test Used
Table 7: Gait characteristics vs stroll characteristics	rmcorr
Table 8: Correlations between sessions	Independent t-test
Table 9: stop correlations	OLS
Table 10: Impact weather data on gait speed with OLS	OLS
Table 11: Sinuosity correlations	rmcorr
Table 12: correlation surface and gait characteristics	rmcorr
Table 13: correlation surface and stops	OLS

4 Results

At first, the results of the intermediary products such as GPS noise reduction and step detection are presented. This is followed by the explorative analysis of the gait characteristics, stop characteristics and environmental factors correlations are presented with the use of maps. In section 4.5 correlations presented in bulk with tables to find correlations. In section 4.6 some chosen correlations with hypotheses are presented. In Chapter 5 (discussion), a critical evaluation of these results will be provided.

4.1 GPS noise reduction

For the mean filter different window sizes are tested. An increase in window size leads to a reduction in the measured travel distance during the 400m test (Stage 1).

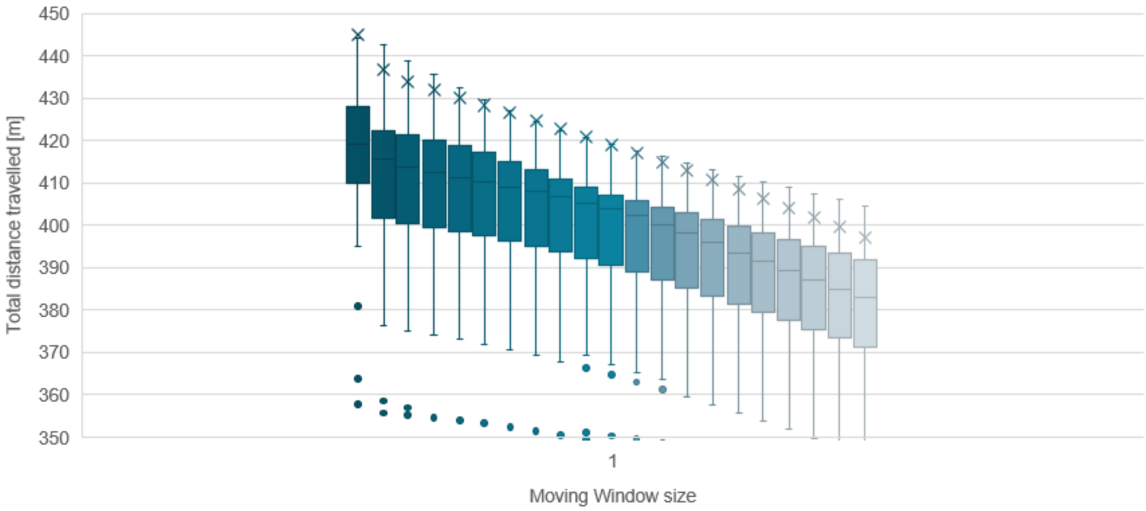

Figure 5: Distance travel during 400m test calculated with mean filter. Increasing window sizes from left to right. Starting with base data, window sizes: 3, 5, 7, ...,41

The impact of the different GPS noise reduction algorithms is displayed in table 2. The deviation from the ground truth track is small. In case of the mean algorithm, it even worsens the results. In the same time, changing the parameters of the different algorithm has also shown little impact. For the Kalman algorithm the difference doesn't even exceed 0.01m, beyond the first few points during which the algorithm is calibrating. The outlier filter doesn't even affect less than 2 points on average per dataset. Continually reducing the travel distance with increasing window size (figure 5), the rolling window size of the mean filter shows the largest impact. Therefore, it increases the distance to the ground truth (GT).

Table 2: Results comparison filters and ground truth

Algorithm	Mean distance GT [m]	Sd [m]	min distance GT [m]	max distance GT [m]
Base data	4.00	1.89	0.00	7.64
Kalman	4.00	1.89	0.00	7.63
Outlier (2m/s)	3.93	1.85	0.00	7.63
Mean (roll 5)	4.01	1.88	0.10	7.60

4.2 Step detection

Counting the steps, the validation of the step detection is done manually. The following tables contain the results of the step counting for the 10m, 50m and 400m test. For the step detection three participants were selected for evaluation. Since visual step validation is a manual process, only a few individuals could be chosen. The participants were chosen, because of their different characteristics, which might influence the step detection. 01_03 was chosen because she used a walking aid. 01_08 is an example for a participant with high gait speed. 08_01 is an example for a participant with a low gait speed.

Table 3: Step validation 10m test

ID	Hand count	Samsung step detection	Accuracy Samsung	Xiaomi step detection	Accuracy Xiaomi
01_03	21	16	76.19%	17	80.95%
01_08	20	19	95.00%	17	85.00%
08_01_try1	24	15	62.50%	Nan	Nan
08_01_try2	20	16	80.00%	23	115.00%

For the 10m test there was a complication. The participant 08_01 started walking too early for the laser measurement, so the 10m test had to be repeated. These data were not included in the Xiaomi data but in the Samsung data. Therefore, only data for the Samsung step detection is available for the first 08_01 10m test. Participant 08_01 walked very slowly during the test, even stopping at the start of try 1. Participant 08_01 seemed unsure if she could walk already. Because of this the test was repeated. On try2 participant 08_01 walked slowly in after completing the 10m test. Upon closer inspection of the step detection revealed the overcount in 08_01_try2 Xiaomi, the individual steps that were overcounted were during the slow walk after the 10m test. The participant was half walking or standing still during that period, while also talking to the instructors.

Results

Table 4: Step validation 50m test

ID	Hand count	Samsung step detection	Accuracy Samsung	Xiaomi step detection	Accuracy Xiaomi
01_03	81	77	95.06%	77	95.06%
01_08	73	72	98.63%	71	97.26%
08_01	86	83	96.51%	82	95.35%

The results for the 50m test are displayed in table 4. There are no anomalies. Compared to the 10m test, the results improve to at least 95% accuracy.

Table 5: Step validation 400m test

ID	Hand count	Samsung step detection	Accuracy Samsung	Xiaomi step detection	Accuracy Xiaomi
01_03_bout1	425	416	97.88%	418	98.35%
01_03_bout2	222	216	97.30%	217	97.75%
01_08	543	539	99.26%	537	98.90%
08_01	628	621	98.89%	620	98.73%

The results for the 400m test are displayed in table 5. The participant 01_03 took a small break after step 425 for multiple seconds. The participant 01_03 was the only participant who‘s step in the middle of walking was not registered, evident in the data by doubled the step time for this step. Upon comparison with the time of the video, two steps were clearly not registered; step 308 and step 114 in the second bout, however this was for the Samsung data only.

4.3 Gait Characteristics

The following boxplot figure displays the distribution of the calculated gait characteristics inside the 97% confidence interval. Since step time and cadence are a function of each other, only one of them is included. The median is displayed as a green line within the box.

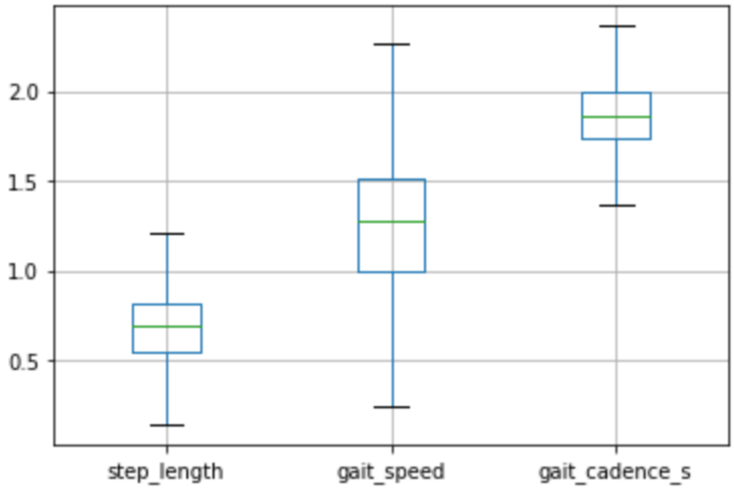

Figure 6: Gait characteristics Xiaomi Session 2, step length [m], gait speed [m/s] and cadence [hz]

Figure 6 shows the boxplot of Xiaomi session 2 gait characteristics. The values of the gait characteristics are all similar between the different phones, respective boxplots can be found in the appendix (Chapter 8). Table 6 shows the statistical values of the gait characteristics. All gait characteristics are calculated during bouts only and stop trajectories are ignored for the calculation.

Table 6: Gait characteristics Xiaomi Session 2

Gait characteristics	mean	Sd	min	max
Gait speed [m/s]	1.24	0.43	0.05	2.34
Step length [m]	0.66	0.23	0.04	1.27
Cadence [hz]	1.87	0.20	0.80	2.81

4.4 Explorative Results with maps

This chapter presents explorative results. These results are made of point maps, heat maps and path maps. The goal of this chapter is to both provide some evidence of impacts on gait characteristics and to put them into a geographical context. Moreover, it also visualizes the testing area and provides an overview of the testing area. In the first part stop behaviour will be presented followed by a path map to visualize the routes taken.

4.4.1 Stop behaviour

Stops are classified according to two types, short stops (< 5s) and long stops (>= 5s). These stops are further classified to see if a pattern emerges. In figure 7 the long stops are displayed. Around the Leichtatlethikstation St. Jakob and Brüglingen two main clusters can be observed. The area around the Stadion has many stops over 30s, while Brüglingen shows mostly stops between 5s and 30s. The Leichtatlethikstadion is the starting location of the stroll, since the gait measurement was taken inside the Stadion. In the Brüglingen area there are many different animals in show cages, many benches to rest and information tables to read. This location can easily be considered as one of the main attractions of the Merian Gärten.

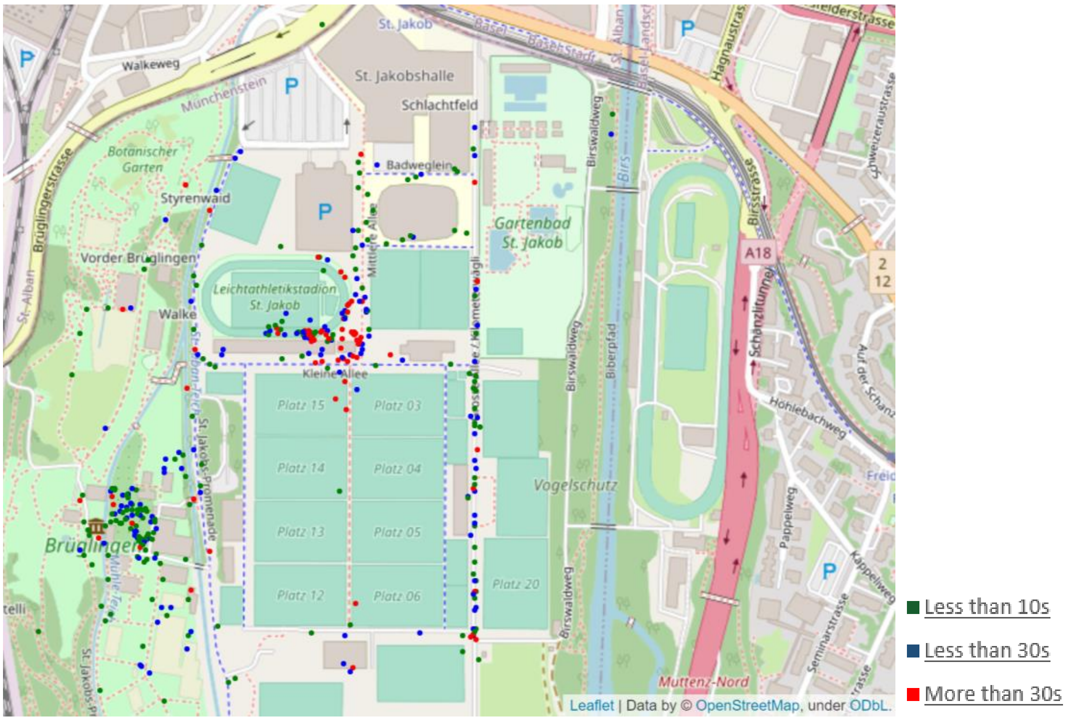

Figure 7: Samsung measurements, stop longer than 5s, less than 10s is green, less than 30s is blue, more than 30s is red

In figure 8 stops shorter than 5s are displayed. Here once again a cluster can be observed around the Stadion. There are, however, also more points along the paths from one location to another. The cluster around Brüglingen is less pronounced.

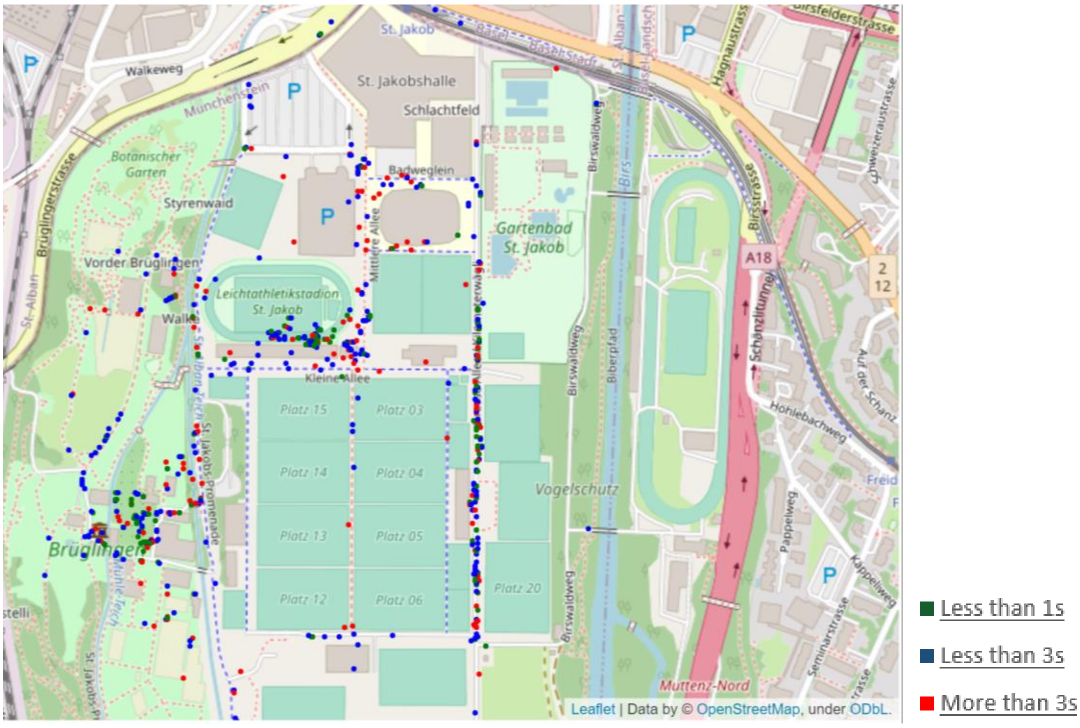

Figure 8: Samsung measurements, stop less than 5s, less than 1s is green, less than 3s is blue, more than 3s is red

Figure 9 shows a heatmap for the stop distribution around the Stadion for stops less than 5s, while figure 10 shows the same for stops more than 5 seconds. There is hotspot at the exit to the southeast of the Stadion. In the short stop heat map the areas along the roads show higher values than they show in their longer stops equivalent. More heatmaps can be found in the appendix (Chapter 8).

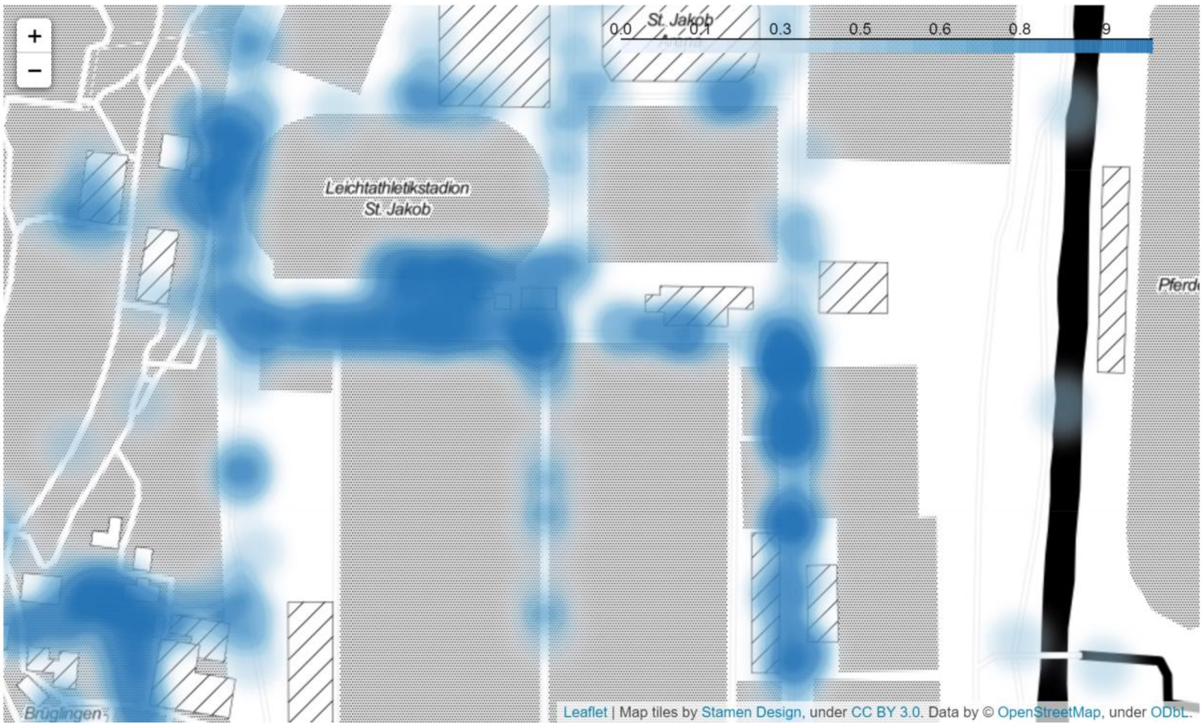

Figure 9: Xiaomi stop heatmap less than 5s

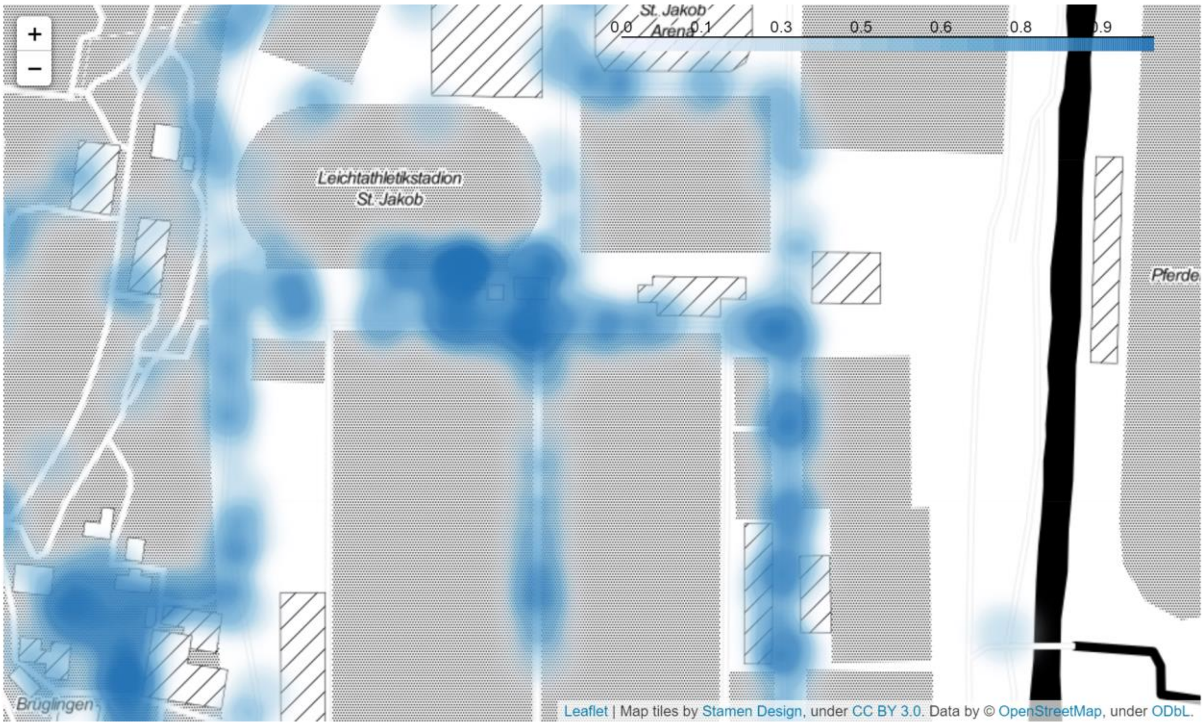

Figure 10: Xiaomi stop heatmap more than 5s

4.4.2 Path characteristics

Figure 11 displays the path network of the stroll area. This shows all possible routes that could have been taken by the participants. The next figures visualize both, paths that actually have been taken by the participants (figure 12) and the average gait speed of a person walking on the path (figure 13).

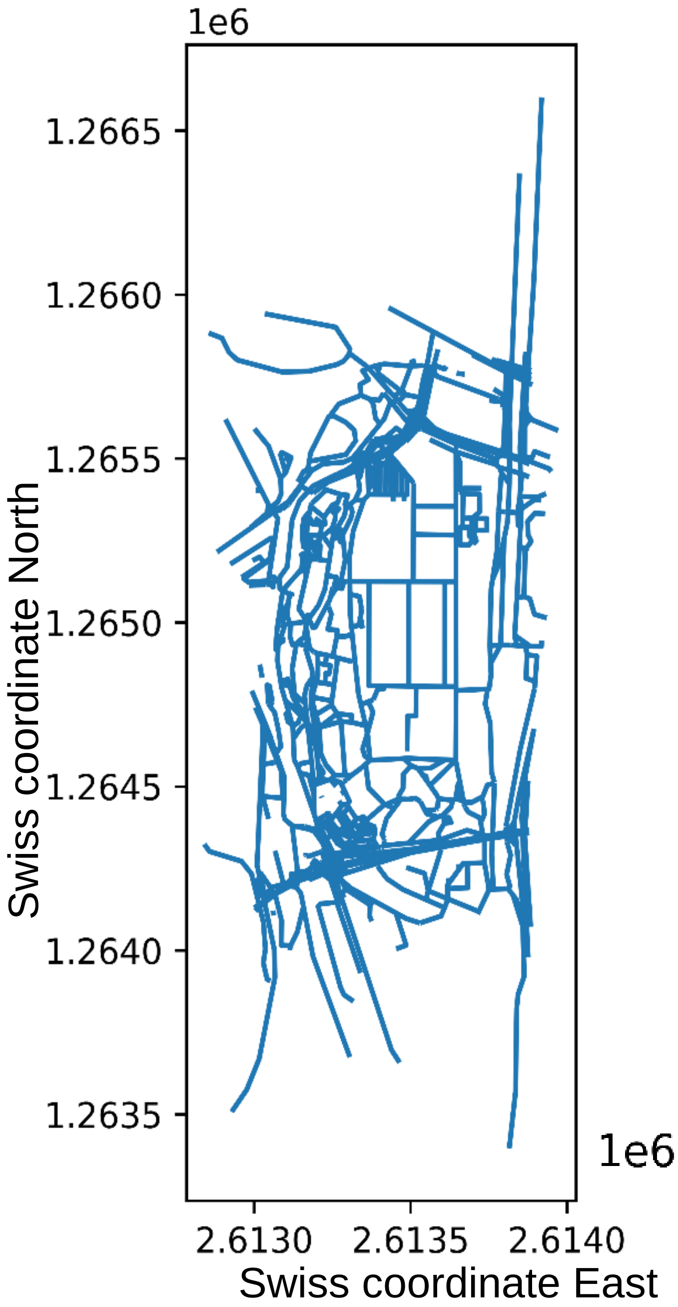

Figure 11: Path network

To improve readability of the map, in figure 12 the number of participants displayed is capped at 20. The same was done for the gait speed figure (13), which was capped at 2m/s. Paths not visited at all, are assigned the value 0.

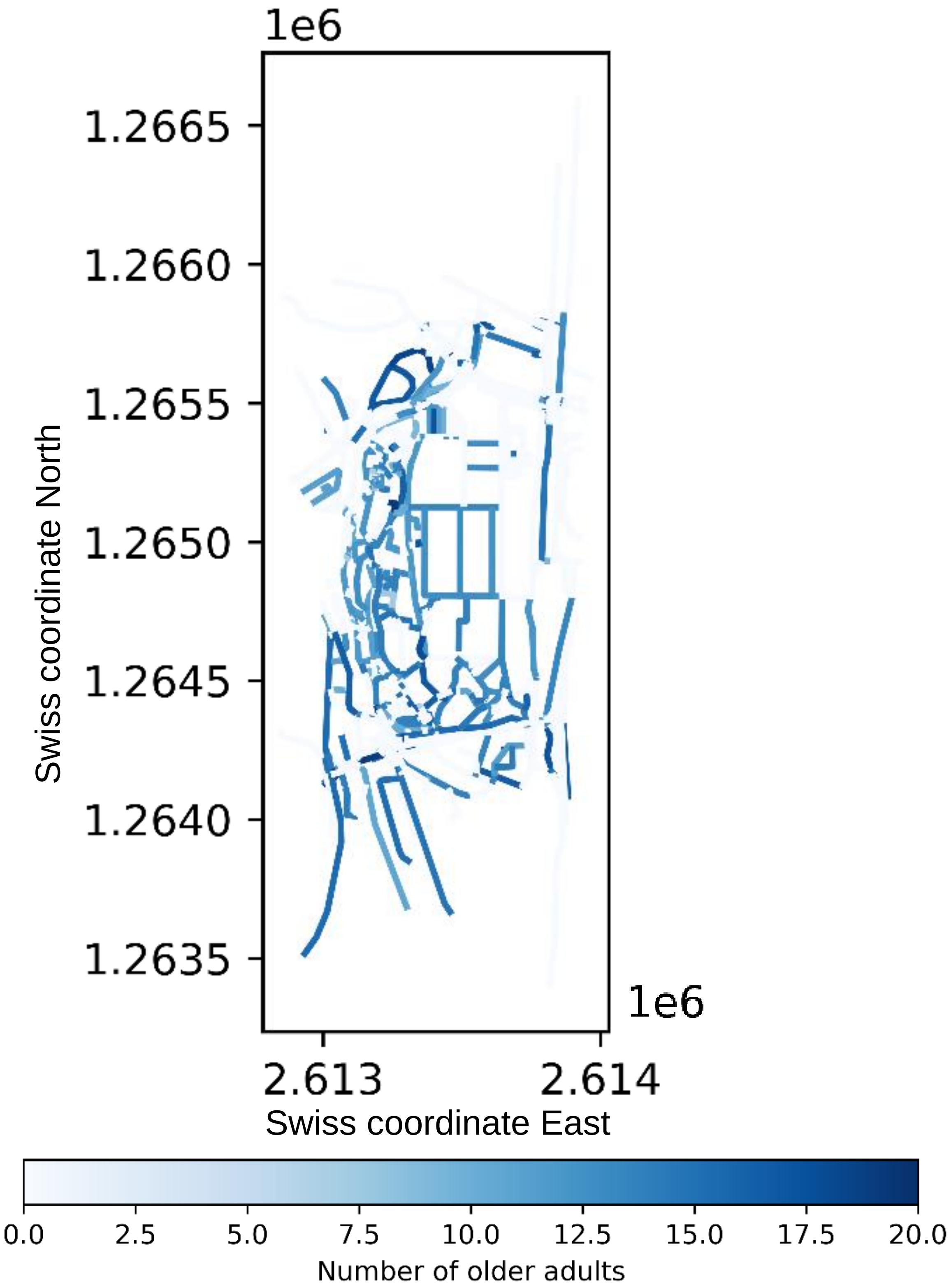

Figure 12:Path plot from OSM, coloured based on number visiting that path.

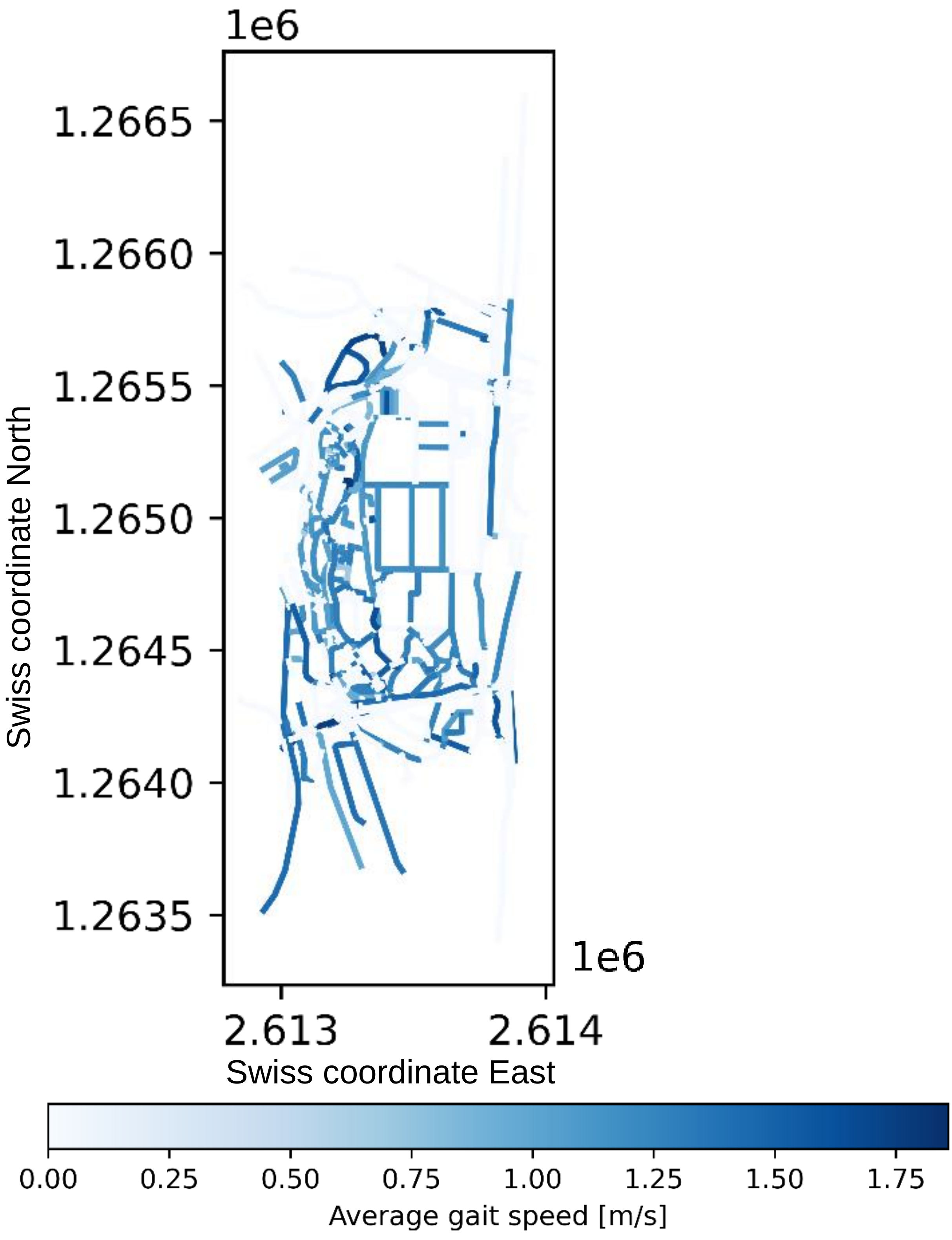

Figure 13: Path plot from OSM, coloured based on speed of participants walking on that path.

4.5 Gait Characteristics correlation

The gait characteristics correlations are presented in two steps. First, correlations between different characteristics will be examined. In the second part chosen correlations are examined, each to test hypothesis.

4.5.1 Intraindividual correlations

The first results are intraindividual correlations calculated with rmcorr (Bakdash & Marusich, 2017). Rmcorr easily provides significant results, however, despite most results being significant in theory, the r values are low. Since each correlation is tested four times, the r and p values of all four tests should be comparable to make a more educated conclusion. Results are coded with the r value followed by the p value. Instead of the normal p value, the negative exponent to the power of 10 is recorded. As an example, a result with r value of 0.2 and p value of 2.4e-20 is recorded as 0.2 (20).

Table 7: Intraindividual correlations of gait characteristics by phone and session: r value (p value negative exponent) with rmcorr

Intraindividual correlations		Gait speed		Step length		Cadence		Step time	
		Session 1	Session 2	Session 1	Session 2	Session 1	Session 2	Session 1	Session 2
Bout length []	Samsung	0.07(151)	0.09(239)	0.05(91)	0.06(122)	0.02(10)	0.03(31)	-0.03(27)	-0.05(62)
	Xiaomi	0.05(76)	0.08(145)	0.03(26)	0.03(31)	0.07(149)	0.15(0)	-0.08(179)	-0.15(0)
Distance travelled [m]	Samsung	-0.02(10)	-0.02(19)	-0.01(2)	-0.01(5)	-0.01(8)	-0.02(11)	0.02(16)	0.02(12)
	Xiaomi	0.09(233)	0.07(123)	0.08(185)	0.07(114)	0.02(12)	0(1)	-0.02(8)	0.00(1)
Time on walk [s]	Samsung	-0.01(8)	-0.02(14)	-0.00(1)	-0.01(2)	-0.01(8)	-0.02(11)	0.03(22)	0.03(15)
	Xiaomi	0.08(196)	0.06(94)	0.07(145)	0.06(81)	0.02(22)	0.00(1)	-0.02(17)	0.00(1)
Active walk time [s]	Samsung	-0.02(14)	-0.03(20)	-0.01(3)	-0.01(5)	-0.02(9)	-0.02(11)	0.03(23)	0.02(14)
	Xiaomi	0.10(257)	0.07(126)	0.09(201)	0.07(112)	0.02(16)	0.00(1)	-0.02(12)	0.00(1)
Total stop time [s]	Samsung	0.02(21)	0.02(15)	0.03(27)	0.03(24)	0.00(1)	0.01(4)	0.00(3)	0.02(13)
	Xiaomi	-0.02(18)	-0.03(18)	-0.03(33)	-0.03(23)	-0.03(30)	-0.02(10)	-0.03(29)	-0.03(22)

As shown in table 7, almost all intraindividual correlations are statistically significant. However, the r values are often low. Their results can be compared right away, since each group of 4 measures the same effect, but simply with different data. Considering that the r value for repeated measures correlation (rmcorr) refers to the slope for the intraindividual regression line, this would lead to negative and positive r values cancelling each other out within a data group. So, for a group to be considered significant all parts of the group should have a similar r value.

4.5.2 Correlations between sessions

Gait characteristics and stroll data between the sessions are compared and searched for correlations. Because of this the independent t-test of the Scipy Library (Jones et al., n.d.) is used. All correlations are tested for both Xiaomi data and Samsung data. Not a single independent t-test was significant.

Table 8: Correlations between sessions 1 and 2 with independent t-test

Intersession correlation		Session1 / Session 2	
		Statistic value	P value
Avg gait speed [m/s]	Xiaomi	0.57	0.57
	Samsung	0.43	0.67
Total stop time[s]	Xiaomi	-0.46	0.64
	Samsung	1.15	0.25
Number of stops []	Xiaomi	-0.14	0.88
	Samsung	0.45	0.66
Stop frequency [hz]	Xiaomi	-0.73	0.47
	Samsung	0.02	0.98
Distance travelled [m]	Xiaomi	-0.13	0.89
	Samsung	0.70	0.49
Avg step length [m]	Xiaomi	0.52	0.60
	Samsung	0.70	0.48
Avg bout length []	Xiaomi	-0.28	0.77
	Samsung	1.80	0.07

4.5.3 Stop correlations

The correlations between stop characteristics and gait characteristics are calculated with an ordinary least square regression (OLS). Without exception for both Samsung measurements and Xiaomi measurements, there is a significant correlation between every stop characteristic and gait characteristic. Instead of writing down the exact p-values, all p-value below 0.001 are written as 0.001. The coefficients are all negative, indicating a negative correlation between stops and these gait characteristics. The coefficients for the long stop frequency are at average twice as negative as the short stop frequencies.

Table 9: Correlation between stops characteristics and gait characteristics calculated with ordinary least square regression

		Avg gait speed [m/s]		Avg step length [m]		Avg cadence [hz]		Avg bout length []		Distance travelled [m]	
		R^2	p	R^2	p	R^2	p	R^2	p	R^2	p
Stop time [s]	Samsung	0.58	0.001	0.43	0.001	0.33	0.001	0.23	0.001	0.35	0.001
	Xiaomi	0.581	0.001	0.340	0.001	0.508	0.001	0.272	0.001	0.490	0.001
Stop count []	Samsung	0.365	0.001	0.163	0.01	0.339	0.001	0.28	0.001	0.22	0.001
	Xiaomi	0.43	0.001	0.183	0.001	0.505	0.001	0.325	0.001	0.34	0.001
Stop Frequency [hz]	Samsung	0.419	0.001	0.20	0.001	0.365	0.001	0.306	0.001	0.368	0.001
	Xiaomi	0.45	0.001	0.20	0.001	0.51	0.001	0.34	0.001	0.419	0.001
Short stop frequency [hz]	Samsung	0.306	0.001	0.132	0.001	0.301	0.001	0.245	0.001	0.289	0.001
	Xiaomi	0.30	0.001	0.11	0.001	0.386	0.001	0.260	0.001	0.26	0.001
Long stop frequency [hz]	Samsung	0.56	0.001	0.364	0.001	0.40	0.001	0.354	0.001	0.58	0.001
	Xiaomi	0.650	0.001	0.38	0.001	0.61	0.001	0.39	0.001	0.61	0.001

4.5.4 Weather correlations

While the combination of weather data worked smoothly, there were only 2 participants with more than 0.1mm of rainfall. Because of this it could not be used for correlations analysis. table 10 shows the correlations for both the impact of the sunshine duration and the elevation corrected temperature. The sunshine duration does not have a significant impact on the gait speed. The temperature however has a small negative correlation with the gait speed.

Table 10: Impact weather data on gait speed with OLS

Impact Weather data	Avg gait speed [m/s]	
	R^2	p
Sunshine duration [m/h]	0.017	0.33
Temperature 2m [C]	0.075	0.041

4.6 Chosen Correlations

This chapter focuses on correlations relevant to the research questions. Three subsections are presented: impact of sinuosity, impact of ground surface and impact of distance to endpoint.

4.6.1 Sinuosity impact

Since it is an intraindividual correlation, Sinuosity and the reduction by the Douglas algorithm are used as an independent variable to predict gait speed with rmcorr. The results are displayed in table 11. P values lower than 0.001 are displayed as 0.001. While the results are statistically significant, the r values are low.

Table 11: Intraindividual impact of path directness on gait speed with rmcorr

		Gait speed [m/s]	
		r	p
Sinuosity []	Samsung	-0.017	0.001
	Xiaomi	0	0.008
Douglas Reduction []	Samsung	0.03	0.001
	Xiaomi	-0.015	0.001

4.6.2 Impact of ground surface

In order to answer the research questions, the impact of the ground surface is calculated in two steps. In table 12 the results of the intraindividual correlations are displayed. This was measured by rmcorr. P values lower than 0.001 are displayed as 0.001.

Table 12: Intraindividual correlation of surface and gait characteristics with rmcorr

Ground surface type	Phone	Gait speed [m/s]		Step length [m]	
		r	p	r	p
compacted	Samsung	-0.007	0.001	-0.002	0.14
	Xiaomi	-0.01	0.001	-0.01	0.04
asphalt	Samsung	-0.00	0.68	0.01	0.001
	Xiaomi	0.015	0.001	0.015	0.001
paved	Samsung	-0.001	0.46	-0.002	0.13
	Xiaomi	0.013	0.001	0.011	0.001

The correlations between surface and stops are displayed in table 13. These are analysed with OLS. P values lower than 0.001 are displayed as 0.001. Some of the results are statistically significant, which indicates that the ground surface has an impact on gait speed and step length.

Table 13: Ordinary least squares regression between Ground surface type and long stops

Ground surface type	Phone	Long stop count []		Long stop duration []	
		R^2	p	R^2	p
compacted	Samsung	0.025	0.24	0.043	0.12
	Xiaomi	0.02	0.91	0.01	0.53
asphalt	Samsung	0.14	0.004	0.174	0.001
	Xiaomi	0.13	0.006	0.163	0.001
paved	Samsung	0.08	0.03	0.038	0.146
	Xiaomi	0.01	0.40	0.015	0.36

In correlation with stop characteristics only one surface type shows a significant result. Asphalt has a negative slope coefficient of -0.37 for duration and -9.6 for stop count. This would indicate that on asphalt participants both stopped fewer times and if they stopped the stopped for a shorter duration.

5 Discussion

5.1 GPS Noise reduction

Research question 1: Which GPS Noise reduction filter performs the best?

GPS measurements can be very noisy (Hide et al., 2003), because of this it is important to have a good noise reduction filter. Of the three types of filters, mean filter, Kalman filter and Outlier filter, that were tested, none performed well. The changes of the Kalman filter basically did not change the positions of the points at all. The outlier filter affected less than 2 points in most datasets, which did have a tiny impact, but not enough to justify even running a filter in the first place. On first glance the reduction of the distance travelled during the 400m gait test seems like a good impact. Increasing the moving window size to reduce the total distance travelled, brings the distance closer to 400m. However, this is not due to the filter smoothing the path, but rather because the test track is a circle. Increasing the filter window size reduced the circle radius, thus reducing the distance travelled. This method is compared to the ground truth which results in the only filter that worsens the result, making it even more inaccurate than the base data.

There is barely any change of the distance to the chosen ground truth for any filter: less than 1 cm for the mean filter, 7 cm for the outlier filter and none to the second decimal for the Kalman filter. This seems to directly contradict the literature claiming that noise filters are important in the first place.

However, after researching the literature on smartphone GPS measurements in particular, it was found that there are two GPS measurements that can be extracted from the phone: the Raw GPS measurement, but also GPS measurements that are already Kalman filtered (Manual, 2018). It turned out that the GPS data used for this project was already Kalman filtered. Consequently, research question one cannot be answered.

5.2 Step detection validation

Research question 2: How well does step detection with accelerometer preform?

The step detection does not perform very well during the 10m test. Since every single missed step will have a large impact, this is not exactly surprising. However, there is one outstanding measurement: the 08_01_try2 Xiaomi measurement. Looking at the entire validation range, this is the only overcount by the step detection. Since this overcounting can be traced back to the slow walking and the stopping at the end, this indicates a disturbance of the step detection in special walking conditions. This is not surprising, since the step detection (Pham et al., 2018) assumes a certain walking behaviour and parameters, that are not given in this instance.

The 50m walking test already showed an accuracy of 95% across all participants. Compared to the value of the literature (Pham et al., 2018) this is considered to be a decent result.

During the 400m walking test, accuracy increased again to at least 97%, with some instances even reaching 99% accuracy. This indicates the error in step detection does not increase with distance travelled. In combination with the data examination for the 08_01_try2 10m test this leads to the conclusion that the majority of errors in the step validation comes from the start and stop periods. This makes sense because the algorithm is designed to work under conditions of regular walking. While speeding up and slowing down the impact on the accelerometer measurement in different, which in turn lead to a reduced likelihood that a step is detected. This is further supported by the result that, with one exception, all algorithm step counts are undercounts, not overcounts. This indicates that the step detection does not recognize the irregular steps. This would make the step detection robust against overcounting.

To improve that algorithm, special cases could be introduced, that would view the different accelerometer measurements during starts and stops, other measurements like gyroscope could be used in addition (Formento et al., 2014).

This problem, however, will most likely not impact most applications for step detection. Stops and starts can still be pinpointed and since the error is predictable. The error in counting can be accounted for during the evaluation of the step detection. The error mostly likely can be reduced further by using methods to personalize gait detection such as by Soltani (et al., 2020).

5.3 Gait characteristics

Research Question 3: Are the calculated gait characteristics reasonable? How do they compare with the values in literature?

In order to critically evaluate our calculated gait characteristics, they will be compared to values from the literature. Peel et al. (2013) measured the gait speed of patients 70 or older. The gait speed median was estimated at 0.58m/s, whereas the measurements in the 95% confidence interval are between 0.49-0.67. Studenski et al. (2003) performed a similar test in a clinical setting with patients age 65 and older. Their gait speed is measured at 0.88m/s with a standard deviation of 0.22m/s. The measurement of this thesis shows an average gait speed of 1.24m/s with a standard deviation of 0.43. This measurement compares better to the value measured in subjects aged less than 65 as pointed out by Obuchi et al. (2020). They measured 1.3m/s with a standard deviation of 0.1m/s. This means, while our measurements are in a reasonable range, they are rather too high for older adults. There are multiple reasons why this could be the case: All stops/ non-bouts have been excluded from the measurements. Starts and stop steps are not well detected, which, if not measured, will also increase the gait speed. But there is also the possibility that the combination of GPS and accelerometer for gait speed calculation introduces an error to the gait speed calculation.

For both, cadence and step length, there is a large individual impact for measurements (Soltani et al., 2020). With regards to this measurement, the data can be compared to Nishiguchi et al. (2012), which measured the impact of step length with smartphones based on different locations on the body. The locations on the body can have a fairly large impact that has not been considered in this study. Their data for smartphone measurement on the belt shows 0.55m with a standard deviation of 0.1m. For the pocket the measurement is 0.58m with a standard deviation of 0.14. The measured step length was 0.66m with a standard deviation of 0.23. This is, once again, a little higher but in a reasonable range.

Cadence measured by Taylor (et al., 2019) for older people with dementia is 1.69 steps/s. For younger healthy adults 1.92 steps/s were measured (Silsupadol et al., 2017). Our value is once higher than expected with 1.87. However, the participants would be expected to be healthier than dementia patients. This gait characteristic is once again in a reasonable range.

5.4 Explorative Results

This chapter will examine the more geographical oriented questions and tries to confirm some hypotheses, in a research area mostly untouched by literature. It will make this chapter more explorative with dismissing some of the hypotheses by visual argumentation rather than statistical evidence.

5.4.1 Stop behaviour

Research Question 4: Where do stops occur? Is there a different distribution for shorter or longer stops?

In figure 7 two main clusters were identified. One cluster at the exit of the Stadion, the second cluster in Brüglingen. The first cluster is easy to explain. When the participants finish with the initial measurement on the 400m track end, they continue immediately with the stroll measurement (Stage 2). However, the participant most likely has a few words with the organizers and some questions about how everything works and how long they should walk around for or where they are allowed to go and were not. This will cause them to stand around for some time, which will be registered by the phone as a stop. Since this will likely take a minute or two, it also explains why most of these stops are longer than 30s. In between some questions the participants are likely to make a step or two, enough for the step detection, but not enough to classify as bout (Definition Chapter 4). This also explains many of the smaller stops in the Stadion and right at the exit.

The second cluster is more interesting, when also not very surprising. The area of Brüglingen is, as mentioned in the Results chapter, one of the nicest places in the Merian Gärten to visit. There is a collection of different farm animals like chicken and cows to look at. Almost half of all benches in the park in that area are next to various nice plant life and trees for shade. In addition, this is also the place with many information tables with interesting facts about animal life cycles and nature in general. The hypothesis, that stops of more than 5s are probably voluntary and not due to fatigue seems to be supported by the locations of these two clusters. When exploring this area starting at the Stadion, this is also the area that was immediately found, even without memorizing all the paths. It seems, that the path to Brüglingen is the most natural path to take.

When inspecting the distribution of stops of less than 5s (figure 8), there is still a cluster at the Stadion exit, although much smaller than in Brüglingen. The stops are more spread out along paths, for example at the east side of the park. The hypothesis that many of the small stops occur on street corner, where the participants have to decide where to go, does not seem to hold true.

When taking a closer look at the heat maps (figure 9 and 10), we get a direct comparison between short stops and longer stops. While they both in general follow a similar distribution, the longer stops have their biggest hotspot right at the exit of the Stadion and right outside of it. On the other hand, the short stops are much more concentrated along the road outside the Stadion. This seems to support the hypothesis that the short stops are for unexpected occurrences on the path or small fatigue break, while the longer breaks are for looking at interesting things or talking to people.

5.4.2 Path characteristics

Research question 5: What impact does the path have on gait characteristics and stops, both for ground surfaces and sinuosity?

The hypothesis in regard to sinuosity, is that more natural path, so paths in the woods, not in a straight line and made for humans rather than cars, would reduce the average walking speed on those paths. However, the display in figure 13 does not seem to support this theory. It would have been expected that the walking speed on the nature paths is noticeably lower than on the normal streets. This does not seem to be the case. The one thing that can be observed in figure 13 is that the average gait speed increases in places farther away from the starting position. This does make sense since only the fittest participants would venture that far. Healthier participants will have a higher average gait speed. This research question will be picked up again in later section 5.5 and 5.6. The distribution of older adults on the paths shows a similar distribution to the overall distribution of stops overall. This does also make sense, areas with more participants will have more stops.

5.5 Gait characteristics correlation

Research questions 6: How do gait characteristics correlate with themselves, stroll and stop characteristics?

In this chapter multiple correlations will be analysed and based on their statistical performance the hypotheses are examined. First, with the use of rmcorr the intraindividual correlations will be examined. The correlations between sessions will be checked with independent t tests. The impact of stops on gait characteristics is tested with OLS regression.

5.5.1 Intraindividual correlations

While almost all the results are statistically significant (table 7), very few have an r value above 0.05. Since each of the 4-part clusters are the same calculation with different data, it would be expected, that they all share the same result. However, this is rarely the case. A hypothesis states an increase to bout length will also increases the gait speed. The rmcorr is below 0.001 across the whole cluster. The r-value, which in case of rmcorr is the slope, is between 0.05 and 0.09.

Another hypothesis is that participants who walk farther and longer have an increase in walking speed. While this does seem to hold true for the Xiaomi measurement with a positive r value between 0.6 and 0.9, the Samsung counterpart for the same cluster has a negative r value.

Although all p-values are significant, no more hypotheses could be confirmed with such a low r-value. The hypothesis that people who have already spent more time walking slowly become tired cannot be confirmed. It is likely that the time spent on the stroll is not enough for most participant to impact their fatigue.

5.5.2 Correlations between sessions

This section takes a closer look at the connection between sessions. One hypothesis is that those who have explored the park the first time will take more time in the second session to pause and enjoy nature. This would increase the number of stops. The second hypothesis considers that because the participants know the part better the second time around, they will have less stops and go to their destination without an orientation stop. This would increase the bout length.

Of all the measured characteristics, not a single one has a significant change between the two sessions. The independent t test used reaches a p value of 0.07 at the lowest point. However, with these many measurements, this might be coincidentally. This means the null hypothesis of the t-test, that the measurements are independent, cannot be rejected.

5.5.3 Stop correlations

This section discusses the connection between the stop characteristics and the gait characteristics. Because they are exhausted, older adults sometimes need to make pauses while walking (Münch et al., 2019). The hypothesis states that different stop characteristics can be used as predictors for gait characteristics. The stop characteristics total stop time, number of stops, stop frequency as well as short and long stop frequency were tested as predictors for average gait speed, average step length, average cadence, average bout length and total distance travelled. These were conducted with OLS regression for both Samsung and Xiaomi data. The p value is lower than 0.001 in every single test. Between the measurements of Xiaomi and Samsung for the same correlation the R^2 values are similar for most measurements. Also, for every single measure the slope of the found regression was negative, indicating a negative correlation. This does seem to confirm the hypothesis that the more stops a participant makes the slower their walking speed is.

A second hypothesis is that longer stops are often voluntary and shorter stops are involuntary. This would mean long stops are a worse predictor for gait speed than short stops for gait speed. However, this is not the case. The coefficient for the regression slope between long stops and gait speed is twice as a large as it is for short stops. This means long stops are a twice as strong predictor of gait speed than short stops. This might come from less healthy participants spending more time on their stroll, taking more breaks than they are walking around. For a closer examination of this effect and impact further research is necessary.

5.5.4 Weather correlations

There was not sufficient data with rainfall to do a regression analysis. After an inquiry it was determined that the measurement day were chosen in a manner to avoid rainfall. While this makes the experiment easier to conduct, it limits the conclusion drawn. The negative correlation with temperature makes sense. However, it is hard to determine if this negative correlation is really due to reduced temperature or other effects that might occur because of temperature, such as snow and ice.

5.6 Chosen Correlations

Research question 5: What impact on gait characteristics and stops does the path have, both for ground surfaces and sinuosity?

This chapter aims to examine research question 5. The impact of the environment on a person's gait is a major research gap. If a connection could be drawn between the environment, this could be used to make more accurate predictions with gait.

5.6.1 Sinuosity impact

Sinuosity is a measure of how direct a path leads to the destination. Footpaths for pedestrian are most of the time less direct (Stangl, 2012). If the goal of a participants is to arrive at their destination as quickly as possible, they will take a path that is more direct. The combination of this leads to the hypothesis, that a more indirect path would likely cause a pedestrian to walk slower, than a more direct path. Both, the reduction of points by the Douglas Peucker algorithm and the calculated sinuosity are used as a measure of directness. This is once again a measure with rmcorr. This means for each person individually it is checked, if there is a linear regression between the sinuosity of the path they are on and their gait speed. The p values are once again below 0.05. This means there is a statistical significance. However, with the r value being so low with -0.017 and 0 for sinuosity and 0.03 and -0.015 for Douglas reduction, the connection seems to have a minor impact.

5.6.2 Impact of ground surface

In this section the connection between the ground surface and gait characteristics as well as stop characteristics are discussed. The three types of ground surfaces are used as a predictor for gait speed and step length, compacted surface, asphalt surface and paved surface. The intraindividual correlation between the surface and the gait characteristics is tested. Do participants change their gait speed or step length, when they are walking on these surfaces? The hypothesis states that their gait speed increases on these surfaces. Because it easier to get distracted on a nice side path and take a stop looking around and be distracted than on a paved road. However, this does not seem to be the case. While the test shows a significant result, the slope coefficient is with two expectations less than 1 % change in gait speed/ step length. And even for the exceptions, the equivalent test with the other phone data does not yield the same result. Because of this we are unable to reject the null hypothesis, that the ground surface is not related to the gait speed. However, it can be assumed that with more complete data of the ground surfaces, at least some changes in gait characteristics should be visible.

The connection between the ground surfaces and the number of long stops and long stop duration is increased. This is once again tested for three surface types, compacted, asphalt and paved, conducted with OLS regression. Of the three surface types, only asphalt has a significant correlation. The coefficient between asphalt and the number of long stops is negative. This indicates that a participant is less likely to stop for a long stop on asphalt. This seems to confirm the hypothesis that surfaces impact a person’s chance to stop. The correlation between asphalt and the duration of long stops is also significant. If the number of stops is lower on asphalt, this automatically means that the time spent during long stops on asphalt is also lower. However, more research is needed to better predict the exact nature of these correlations. The increase in stop numbers could be due to asphalt or there is also the possibility that the reduced number of stops is due to people stopping at information tables, all of which just happen to not be on asphalt.

6 Conclusion

In this study simple measurement data collected with smartphones are used to estimate the location with GPS. The individual steps are derived from the accelerometer data. This allows the calculation of simple gait characteristics. By combining the steps with a definition of bout, the steps could be detected and brought into correlation. And also, with the location data derived from the GPS, this data could be combined with external data like OSM to provide information about surface and sinuosity information on the current path. In order to establish a relation between the environmental factors and individual gait and stop factors many different hypotheses could be tested. However, most of these formulated hypotheses could not be confirmed, some even seem to show the exact opposite of what was expected.

This combination of GPS and IMU data for position and gait calculation is not often used in literature. The measurements either are often done relying on accelerometer data for gait detection in clinical settings, while on the other side GPS data is used for gait estimation in real world setting. Because of this most of the hypotheses are formulated based on logical thinking, rather than hypotheses already formulated in literature.

The GPS filter tests were not necessary since the data was already filtered. On one side this makes GPS data easier to use, since it doesn’t have to be filtered. However, it could introduce difficulties since the filter is not controlled by the user. There might be applications where the filtered data is missing crucial information.

The step detection confirms a high level of accuracy for longer bouts. There is a reliable undercounting, which this thesis connected to the start and stops. If this effect could be accounted for, the step detection would be even better.

The gait characteristics were reasonable. This thesis concludes that while the process probably could be improved to better calculate the gait characteristics, it works to a reasonable degree. One main advantage this kind of procedure brings to health monitoring, is that the stops can be accounted for, even short stops. These would normally be harder to detect with a GPS only approach und therefore impact the calculated gait speed.

Some initial explorative visual results showed a different spatial distribution for long and short stops. The increased number of large stops in Brüglingen suggest that area of interest increase the likelihood of long stop. The hypothesis that short stops are more voluntary, than long stops however could not be confirmed. This leads this thesis to the conclusion that there are more factors impacting the number of stops and their duration. The differences in the statistical tests and the different distributions of the short/long stops on the map suggest that there is an effect there. However, to find out which ones these are exactly further research is necessary.

The impact of sinuosity could not be confirmed. The impact of asphalt on long stops could be confirmed. The correlations suggest a negative impact of asphalt on the number and duration of long stops.

6.1 Limitations

Multiple limitations became apparent during the course of this thesis. The sample size and number of individuals is not very large and the differences between individuals are large due to the high variance in gait. A difficulty in evaluating gait in comparison to the environment is that it requires an uncontrolled or at least only partially controlled variable. This makes it more difficult to figure out the causes of certain behaviour and evaluating how well the data actually reflects the reality of movement in Stage 2. Another difficulty is that the data were checked in the controlled environment of Stage 1, all the accuracy measures are from that environment. This thesis simply assumed that the measurements and accuracy evaluated from Stage 1 can be translated to Stage 2, but that is not necessarily a given. While the measurement items are not turned off it can be assumed, that at least they should work for the entire stroll in a similar manner, but other effects, such as connection loss of GPS due to tree cover, cannot be accounted for.

Another limitation is the selection of testing dates. This thesis tried to assess the impact of rainfall on the participants, however the measurement days were set in a way to avoid rainfall. In a similar fashion no adults were chosen with a physical health level so poor, they could not walk for even a short period of time. This shows that selection methods can limit the evaluations and conclusions that can be drawn from this data.

While OSM has almost every path in the Merian Gärten, not all aspects, such as ground surface, are consistently recorded. The reason attributes are recorded might impact the results. For example, if the ground surface of asphalt is only recorded for car road, but pedestrian footpaths with asphalt are not recorded, this would skew the results. Also, the resolution of paths recorded on OSM is not given. Different levels of resolutions have a direct impact on the calculated sinuosity.

6.2 Outlook

The negative correlations of stops with all gait characteristics, suggest that stops could be used as an indicator of health. The number, duration and frequency of stops all reduce the gait speed. If the stop characteristics can be linked to health directly and used as an indicator, that would be very useful. Stops can be detected purely based on IMU data, this would allow the health monitoring to continue even in areas with degraded GPS environment such as buildings.

This type of gait characteristic calculated seems to achieve reasonable results. If the methods used could be improved and automated, this might make the future job of general practitioners easier and allow our aging population to still get the good healthcare they deserve. Being able to remove the influence of stops on the gait speed measurements, should help get more accurate measurements from a daily life setting.

One of the goals of this thesis was to put gait characteristics in the context of the environment. This goal has mostly failed, while the explorative maps indicate that there is in fact an impact of the environment on the gait and stop characteristics, the only connection that could be confirmed was for ground surface of asphalt. And considering the possible inaccuracy of OSM even that should be taken with a grain of salt.

Despite the lack of found correlation, this thesis still believes that the impact of the environment has measurable impact on the gait characteristics and is worthy of being further researched. For future projects, a study with more participants and in different conditions would be interesting. Also, the lack of a ground truth for the semi-controlled environment should be addressed. One possibility is to set up Wi-Fi access-points across an area like the Merian Gärten to map the Phone locations with the Wi-Fi. Depending on the number of Wi-Fi access-points this could be a very accurate approach to get ground truth data for comparison. Further research is necessary to work out the difficulties of this approach.

7 Literature

Bakdash, J. Z., & Marusich, L. R. (2017). Repeated measures correlation. *Frontiers in Psychology*, *8*(MAR), 1–13. https://doi.org/10.3389/fpsyg.2017.00456

Barry, G., Galna, B., Lord, S., Rochester, L., & Godfrey, A. (2015). Defining ambulatory bouts in free-living activity: Impact of brief stationary periods on bout metrics. *Gait and Posture*, *42*(4), 594–597. https://doi.org/10.1016/j.gaitpost.2015.07.062

Bayat, S., Naglie, G., Rapoport, M. J., Stasiulis, E., Chikhaoui, B., & Mihailidis, A. (2020). Inferring Destinations and Activity Types of Older Adults From GPS Data: Algorithm Development and Validation. *JMIR Aging*, *3*(2), e18008. https://doi.org/10.2196/18008

Bischoff, B., & Weiss, E. (2019). *Optimal Distance for Normal Gait Speed Testing*.

Brakatsoulas, S., Pfoser, D., Salas, R., & Wenk, C. (2005). On map-matching vehicle tracking data. *VLDB 2005 - Proceedings of 31st International Conference on Very Large Data Bases*, *2*, 853–864.

Bundesamt für Statistik. (2020). *Szenarien zur Bevölkerungsentwicklung der Schweiz und der Kantone*.

Calkins, D. R., Rubenstein, L. V., Cleary, P. D., Davies, A. R., Jette, A. M., Fink, A., Kosecoff, J., Young, R. T., Brook, R. H., & Delbanco, T. L. (1991). Failure of physicians to recognize functional disability in ambulatory patients. *Annals of Internal Medicine*, *114*(6), 451–454. https://doi.org/10.7326/0003-4819-114-6-451

Carcreff, L., Gerber, C. N., Paraschiv-Ionescu, A., De Coulon, G., Newman, C. J., Aminian, K., & Armand, S. (2020). Comparison of gait characteristics between clinical and daily life settings in children with cerebral palsy. *Scientific Reports*, *10*(1), 1–11. https://doi.org/10.1038/s41598-020-59002-6

Cesari, M. (2011). Role of gait speed in the assessment of older patients. *JAMA - Journal of the American Medical Association*, *305*(1), 93–94. https://doi.org/10.1001/jama.2010.1970

Chan, H. K. Y., Zheng, H., Wang, H., Gawley, R., Yang, M., & Sterritt, R. (2011). Feasibility study on iPhone accelerometer for gait detection. *2011 5th International Conference on Pervasive Computing Technologies for Healthcare and Workshops, PervasiveHealth 2011*, 184–187. https://doi.org/10.4108/icst.pervasivehealth.2011.245995

Formento, P. C., Acevedo, R., Ghoussayni, S., & Ewins, D. (2014). Gait event detection during stair walking using a rate gyroscope. *Sensors (Switzerland)*, *14*(3), 5470–5485. https://doi.org/10.3390/s140305470

García Balboa, J. L., & Ariza López, F. J. (2009). Sinuosity pattern recognition of road features for segmentation purposes in cartographic generalization. *Pattern Recognition*, *42*(9), 2150–2159. https://doi.org/10.1016/j.patcog.2009.02.004

Godha, S., Lachapelle, G., & Cannon, M. E. (2006). Integrated GPS/INS system for pedestrian navigation in a signal degraded environment. *Proceedings of the Institute of Navigation - 19th International Technical Meeting of the Satellite Division, ION GNSS 2006*, *4*(September), 2151–2164.

Hide, C., Moore, T., & Smith, M. (2003). Adaptive Kalman filtering for low-cost INS/GPS. *Journal of Navigation*, *56*(1), 143–152. https://doi.org/10.1017/S0373463302002151

Hundza, S. R., Hook, W. R., Harris, C. R., Mahajan, S. V., Leslie, P. A., Spani, C. A., Spalteholz, L. G., Birch, B. J., Commandeur, D. T., & Livingston, N. J. (2014). Accurate and reliable gait cycle detection in parkinson's disease. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *22*(1), 127–137. https://doi.org/10.1109/TNSRE.2013.2282080

Ishikawa, M., Yamada, S., Yamamoto, K., & Aoyagi, Y. (2019). Gait analysis in a component timed-up-and-go test using a smartphone application. *Journal of the Neurological Sciences, 398*(October 2018), 45–49. https://doi.org/10.1016/j.jns.2019.01.023

Jones, E., Oliphant, T., Peterson, P., & others. (n.d.). *SciPy: Open source scientific tools for Python*. http://www.scipy.org/

Kawai, H., Obuchi, S., Watanabe, Y., Hirano, H., Fujiwara, Y., Ihara, K., Kim, H., Kobayashi, Y., Mochimaru, M., Tsushima, E., & Nakamura, K. (2020). Association between daily living walking speed and walking speed in laboratory settings in healthy older adults. *International Journal of Environmental Research and Public Health*, *17*(8), 1–11. https://doi.org/10.3390/ijerph17082707

Khademsohi, H., Sharifian, S., & Faez, K. (2017). Accuracy-energy optimized location estimation method for mobile smartphones by GPS/INS data fusion. *Proceedings - 2016 2nd International Conference of Signal Processing and Intelligent Systems, ICSPIS 2016*, 14–15. https://doi.org/10.1109/ICSPIS.2016.7869888

Kuo, A. D., & Donelan, J. M. (2010). Dynamic principles of gait and their clinical implications. *Physical Therapy*, *90*(2), 157–174. https://doi.org/10.2522/ptj.20090125

Kwapisz, J. R., Weiss, G. M., & Moore, S. A. (2010). *Cell phone-based biometric identification*.

Lin, B. S., Liu, Y. T., Yu, C., Jan, G. E., & Hsiao, B. T. (2014). Gait recognition and walking exercise intensity estimation. *International Journal of Environmental Research and*

Public Health, *11*(4), 3822–3844. https://doi.org/10.3390/ijerph110403822

Mahony, R., Hamel, T., & Pflimlin, J. M. (2008). Nonlinear complementary filters on the special orthogonal group. *IEEE Transactions on Automatic Control*, *53*(5), 1203–1218. https://doi.org/10.1109/TAC.2008.923738

Manual, U. (2018). *Raw GNSS Measurements | Android Developers*. https://developer.android.com/guide/topics/sensors/gnss.html#release%0Ahttp://files/3543/gnss.html

Mohamed, A. H., & Schwarz, K. P. (1999). Adaptive Kalman filtering for INS/GPS. *Journal of Geodesy*, *73*(4), 193–203. https://doi.org/10.1007/s001900050236

Münch, M., Weibel, R., Sofios, A., Huang, H., Infanger, D., Portegijs, E., Giannouli, E., Mundwiler, J., Conrow, L., Rantanen, T., Schmidt-Trucksäss, A., Zeller, A., & Hinrichs, T. (2019). MOBIlity assessment with modern TEChnology in older patients' real-life by the General Practitioner: The MOBITEC-GP study protocol. *BMC Public Health*, *19*(1), 1703. https://doi.org/10.1186/s12889-019-8069-2

Ngo, T. T., Makihara, Y., Nagahara, H., Mukaigawa, Y., & Yagi, Y. (2014). The largest inertial sensor-based gait database and performance evaluation of gait-based personal authentication. *Pattern Recognition*, *47*(1), 228–237. https://doi.org/10.1016/j.patcog.2013.06.028

Nishiguchi, S., Yamada, M., Nagai, K., Mori, S., Kajiwara, Y., Sonoda, T., Yoshimura, K., Yoshitomi, H., Ito, H., Okamoto, K., Ito, T., Muto, S., Ishihara, T., & Aoyama, T. (2012). Reliability and validity of gait analysis by android-based smartphone. *Telemedicine and E-Health*, *18*(4), 292–296. https://doi.org/10.1089/tmj.2011.0132

Obuchi, S. P., Kawai, H., & Murakawa, K. (2020). Reference value on daily living walking parameters among Japanese adults. *Geriatrics and Gerontology International*, *20*(7), 664–669. https://doi.org/10.1111/ggi.13931

OpenStreetMap contributors. (2017). *Planet dump retrieved from https://planet.osm.org* .

Orendurff, M. S., Schoen, J. A., Bernatz, G. C., Segal, A. D., & Klute, G. K. (2008). How humans walk: Bout duration, steps per bout, and rest duration. *Journal of Rehabilitation Research and Development*, *45*(7), 1077–1090. https://doi.org/10.1682/JRRD.2007.11.0197

Pahor, M., Guralnik, J. M., Ambrosius, W. T., Blair, S., Bonds, D. E., Church, T. S., Espeland, M. A., Fielding, R. A., Gill, T. M., Groessl, E. J., King, A. C., Kritchevsky, S. B., Manini, T. M., McDermott, M. M., Miller, M. E., Newman, A. B., Rejeski, W. J., Sink, K. M., & Williamson, J. D. (2014). Effect of structured physical activity on prevention of major mobility disability in older adults: The LIFE study randomized clinical trial. *JAMA - Journal of the American Medical Association*, *311*(23), 2387–2396. https://doi.org/10.1001/jama.2014.5616

Peel, N. M., Kuys, S. S., & Klein, K. (2013). Gait speed as a measure in geriatric assessment in clinical settings: A systematic review. *Journals of Gerontology - Series A Biological Sciences and Medical Sciences*, *68*(1), 39–46. https://doi.org/10.1093/gerona/gls174

Pepa, L., Verdini, F., & Spalazzi, L. (2017). Gait parameter and event estimation using smartphones. *Gait and Posture*, *57*(September 2016), 217–223. https://doi.org/10.1016/j.gaitpost.2017.06.011

Perttula, A., Leppäkoski, H., Kirkko-jaakkola, M., Davidson, P., Collin, J., Takala, J., & Member, S. (2014). Inertial Measurements and Map Matching. *IEEE Transactions on Instrumentation and Measurement*, *63*(11), 1–14.

Pham, V. T., Nguyen, D. A., Dang, N. D., Pham, H. H., Tran, V. A., Sandrasegaran, K., & Tran, D. T. (2018). Highly accurate step counting at variouswalking states using low-cost inertial measurement unit support indoor positioning system. *Sensors (Switzerland)*, *18*(10). https://doi.org/10.3390/s18103186

pykalman — pykalman 0.9.2 documentation. (n.d.). Retrieved October 7, 2021, from https://pykalman.github.io/

Rajagopal, S. (2008). Personal dead reckoning system with shoe mounted inertial sensors. *Signal Processing*, *C*, 1–47. http://www.ee.kth.se/php/modules/publications/reports/2008/XR-EE-SB_2008_013.pdf

Scapellato, S., Cavallo, F., Martelloni, C., & Sabatini, A. M. (2005). Assessment of Walking Features From Foot Inertial Sensing. *Sensors and Actuators, A: Physical*, *123–124*(3), 418–422. https://doi.org/10.1016/j.sna.2005.03.052

Shah, V. V., McNames, J., Harker, G., Curtze, C., Carlson-Kuhta, P., Spain, R. I., El-Gohary, M., Mancini, M., & Horak, F. B. (2021). Does gait bout definition influence the ability to discriminate gait quality between people with and without multiple sclerosis during daily life? *Gait and Posture*, *84*, 108–113. https://doi.org/10.1016/J.GAITPOST.2020.11.024

Silsupadol, P., Teja, K., & Lugade, V. (2017). Reliability and validity of a smartphone-based assessment of gait parameters across walking speed and smartphone locations: Body, bag, belt, hand, and pocket. *Gait and Posture*, *58*(May), 516–522. https://doi.org/10.1016/j.gaitpost.2017.09.030

Soltani, A., Dejnabadi, H., Savary, M., & Aminian, K. (2020). Real-World Gait Speed Estimation Using Wrist Sensor: A Personalized Approach. *IEEE Journal of Biomedical* *and Health Informatics*, *24*(3), 658–668. https://doi.org/10.1109/JBHI.2019.2914940

Sprager, S., & Juric, M. B. (2015). Inertial sensor-based gait recognition: A review. In *Sensors (Switzerland)* (Vol. 15, Issue 9). https://doi.org/10.3390/s150922089

Sprager, S., & Zazula, D. (2011). Impact of different walking surfaces on gait identification based on higher-order statistics of accelerometer data. *2011 IEEE International Conference on Signal and Image Processing Applications, ICSIPA 2011*, 360–365. https://doi.org/10.1109/ICSIPA.2011.6144100

Stangl, P. (2012). The pedestrian route directness test: A new level-of-service model. *Urban Design International*, *17*(3), 228–238. https://doi.org/10.1057/udi.2012.14

Studenski, S., Perera, S., Wallace, D., Chandler, J. M., Duncan, P. W., Rooney, E., Fox, M., Guralnik, J. M., S., S., S., P., D., W., J.M., C., P.W., D., E., R., M., F., & J.M., G. (2003). Physical performance measures in the clinical setting. *Journal of the American Geriatrics Society*, *51*(3), 314–322. https://doi.org/10.1046/j.1532-5415.2003.51104.x

Sun, H. C., & Metaxas, D. N. (2001). Automating gait generation. *Proceedings of the 28th Annual Conference on Computer Graphics and Interactive Techniques, SIGGRAPH 2001*, *August*, 261–269. https://doi.org/10.1145/383259.383288

Taylor, M. E., Brodie, M. A., Van Schooten, K. S., Delbaere, K., Close, J. C. T., Payne, N., Webster, L., Chow, J., McInerney, G., Kurrle, S. E., & Lord, S. R. (2019). Older People with Dementia Have Reduced Daily-Life Activity and Impaired Daily-Life Gait When Compared to Age-Sex Matched Controls. *Journal of Alzheimer's Disease*, *71*(s1), S125–S135. https://doi.org/10.3233/JAD-181174

Visvalingam, M., & Whyatt, J. D. (1990). The Douglas-Peucker Algorithm for Line Simplification: Re-evaluation through Visualization. *Computer Graphics Forum*, *9*(3), 213–225. https://doi.org/10.1111/j.1467-8659.1990.tb00398.x

Weather History Download Basel - meteoblue. (n.d.). Retrieved October 7, 2021, from https://www.meteoblue.com/en/weather/archive/export/basel_switzerland_2661604

Yuan, J., Zheng, Y., Zhang, C., Xie, W., Xie, X., Sun, G., & Huang, Y. (2010). *T-Drive: Driving Directions Based on Taxi Trajectories*. 99. https://doi.org/10.1145/1869790.1869807

Zheng, Y. (2011). *Compute with spatial trajectories*.

Zheng, Y. (2015). Trajectory data mining: An overview. *ACM Transactions on Intelligent Systems and Technology*, *6*(3), 1–41. https://doi.org/10.1145/2743025

Zou, Q., Wang, Y., Wang, Q., Zhao, Y., & Li, Q. (2020). Deep Learning-Based Gait Recognition Using Smartphones in the Wild. *IEEE Transactions on Information*

Forensics and Security, *15*, 3197–3212. https://doi.org/10.1109/TIFS.2020.2985628

8 Appendix

8.1 Additional figures

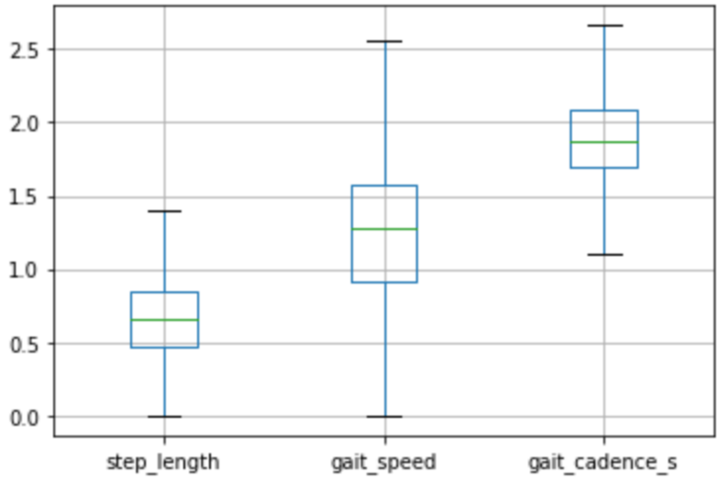

Figure 14: Gait characteristics Samsung Session 1

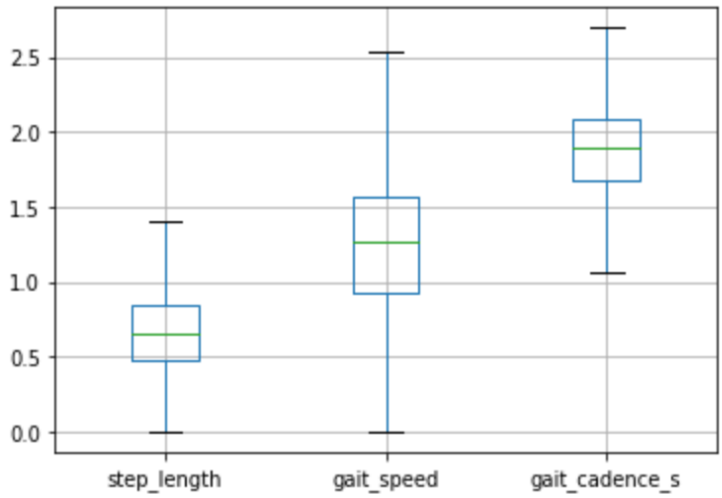

Figure 15: Gait characteristics Samsung Session 2

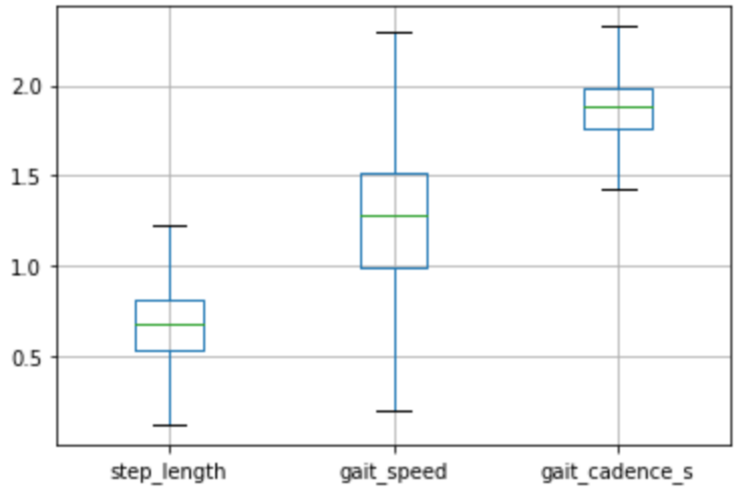

Figure 16: Gait characteristics Xiaomi Session 2

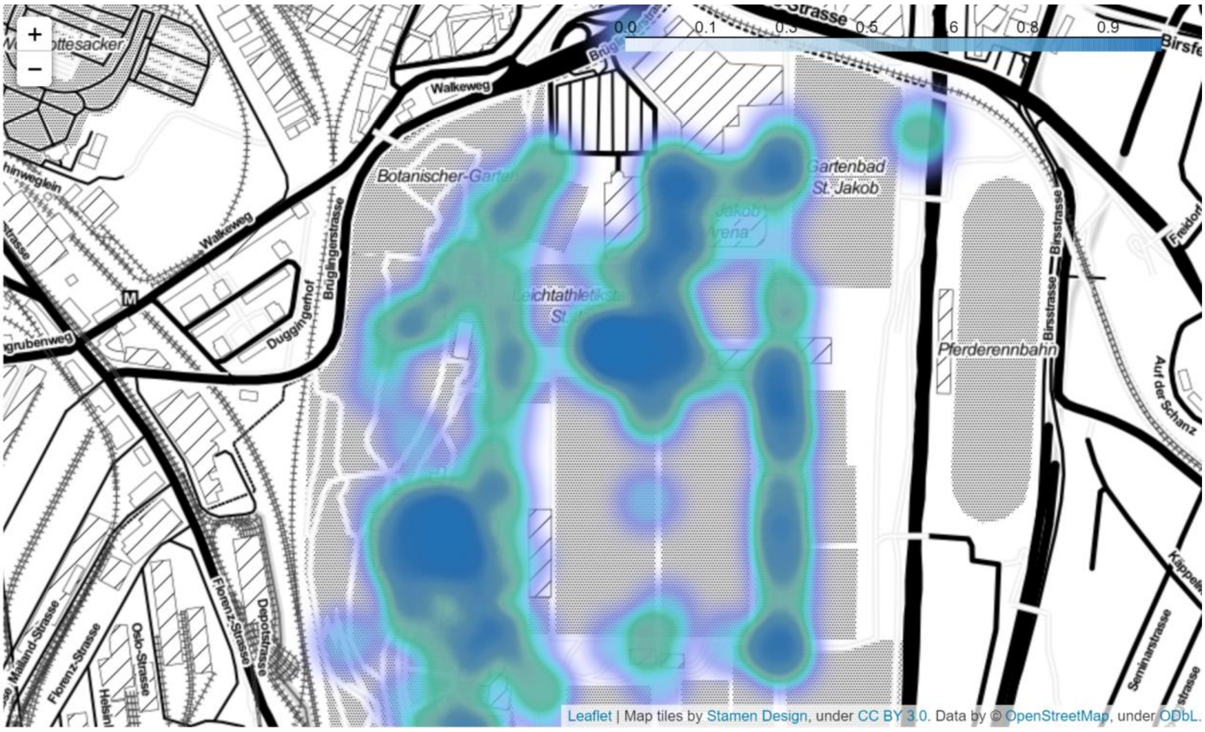

Figure 17: Samsung stops longer than 5s; heatmap

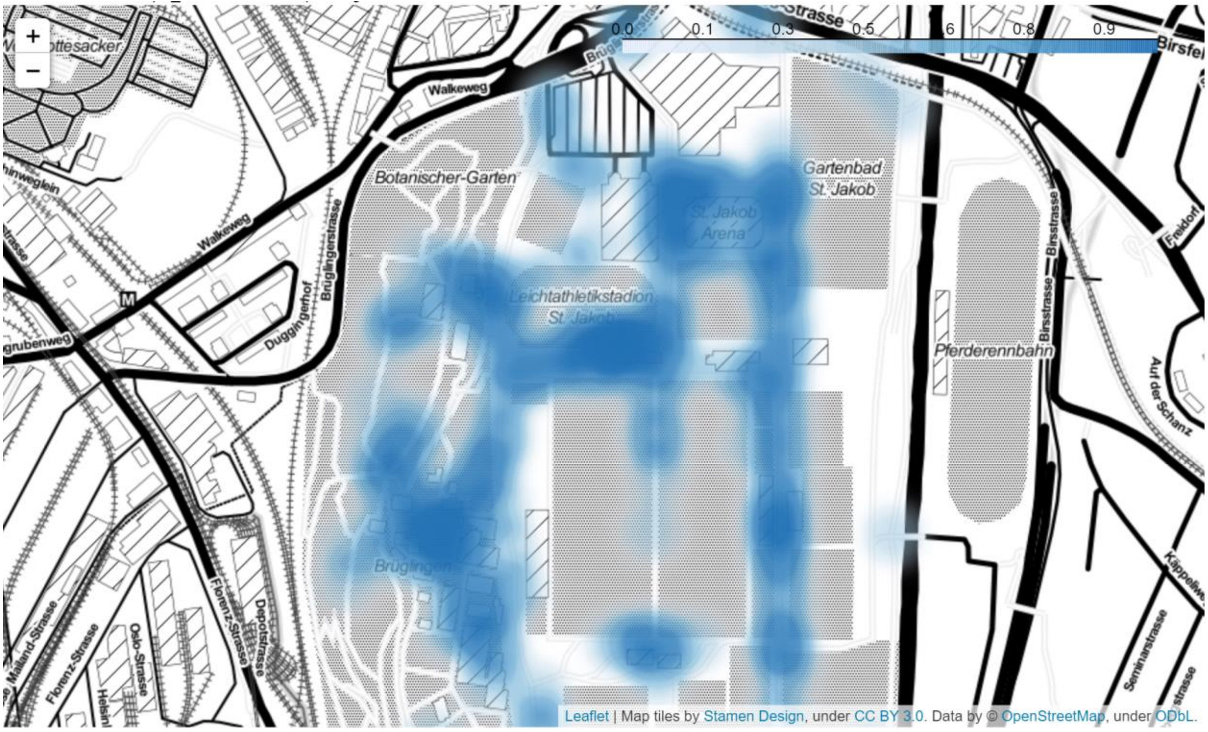

Figure 18: Samsung stops less than 5s; heatmap

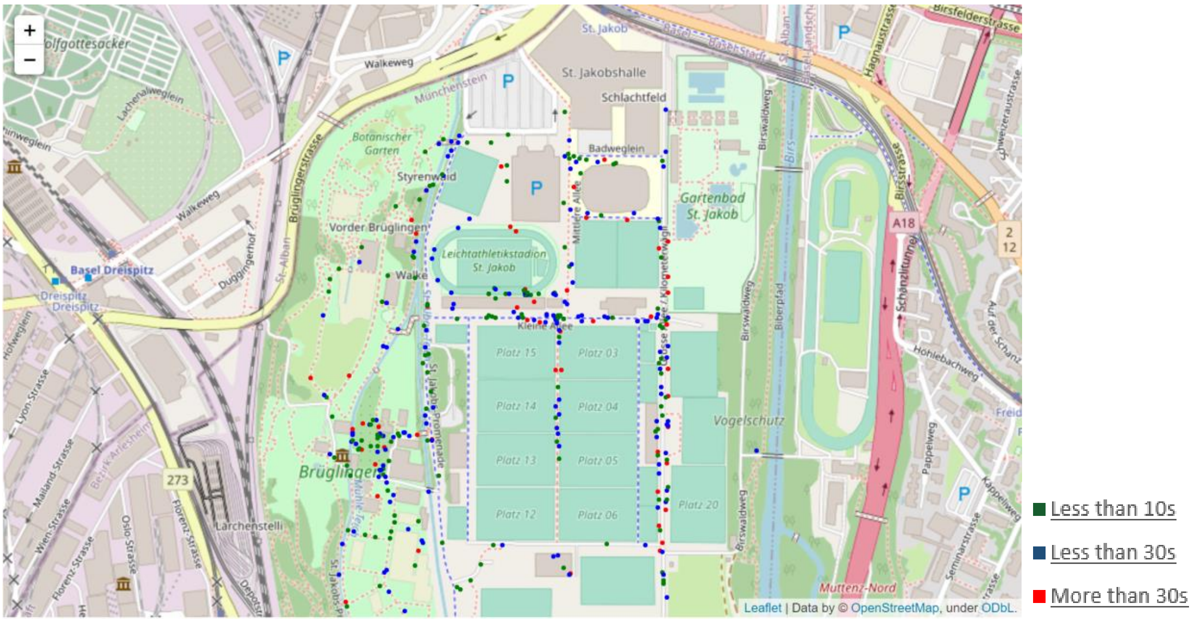

Figure 19: Xiaomi stops longer than 5s

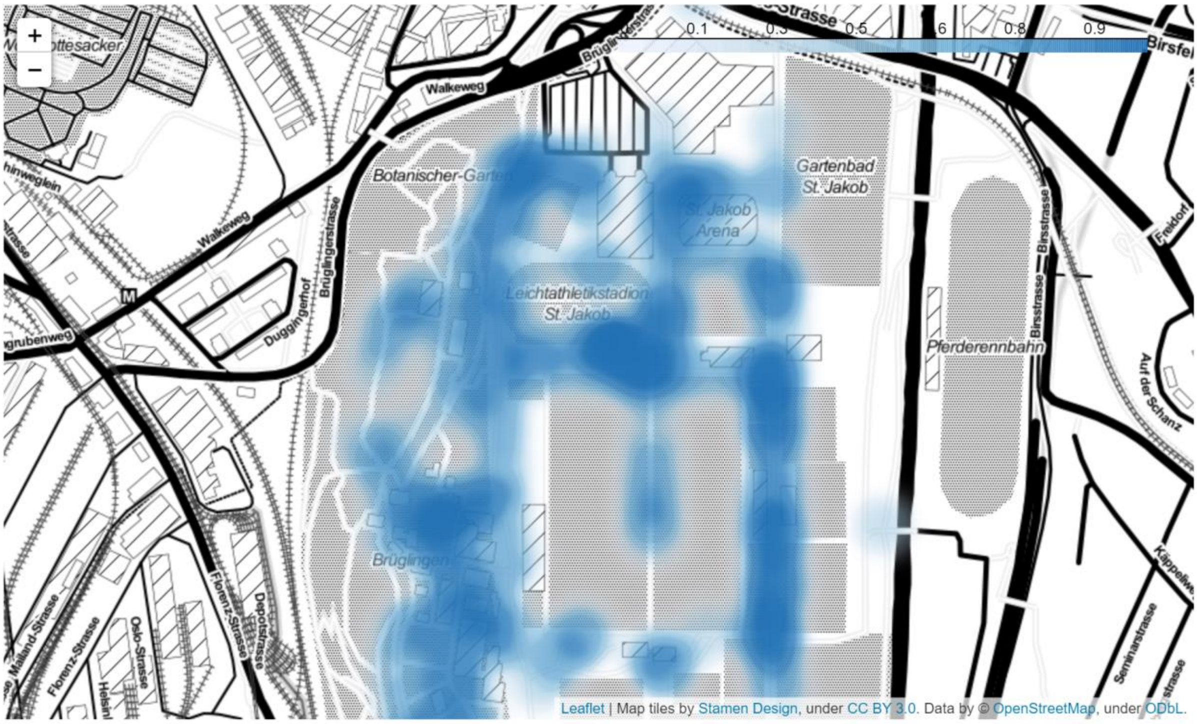

Figure 20: Xiaomi stops longer than 5s; heatmap

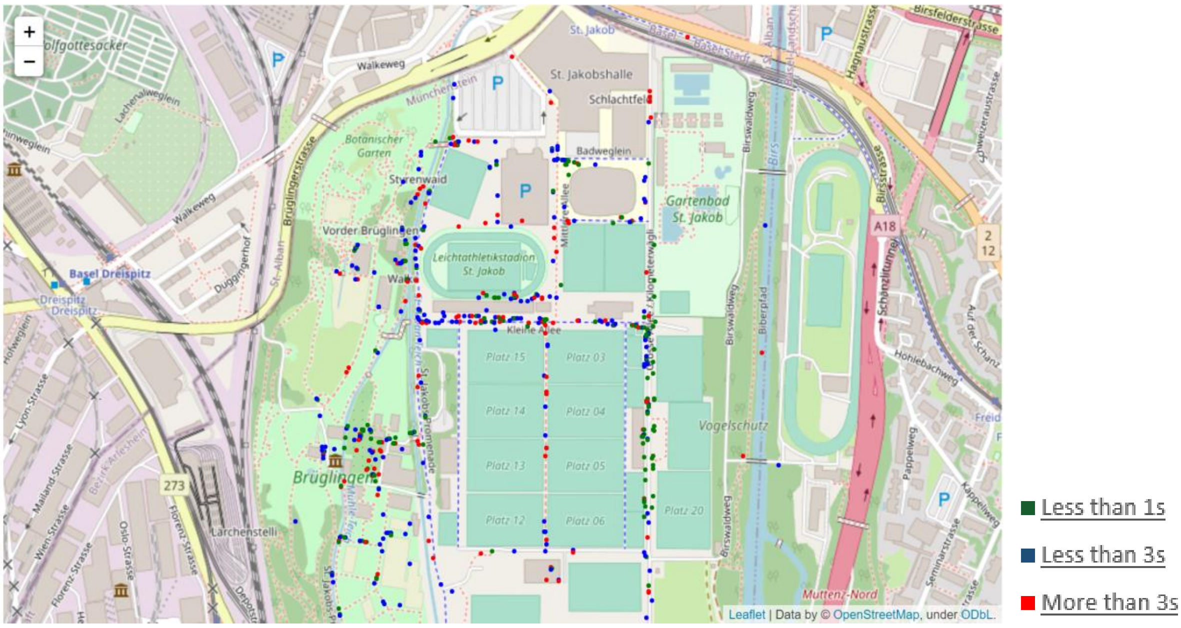

Figure 21: Xiaomi stops less than 5s

Figure 22: Xiaomi stops less than 5s; heatmap

8.3 Personal Declaration

I hereby declare that the submitted Thesis is the result of my own, independent work. All external sources are explicitly acknowledged in the Thesis.

Martin Specker, 2 December 2021