Research Proposal

Gait Analysis for Elderly

Using Wearable Sensors to Detect Gait Abnormalities

Connected Healthcare
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Abstract. Conspicuities in gait can have several reasons and are most common with elderly people as they occur as part of the aging process. However, there can be various musculoskeletal and neurological causes that affect a persons quality of life. Gait Analysis is a widespread method for observing a user's walking behaviour to diagnose issues that could be connected to undiscovered health risks or to help to cure discovered walking problems.

Existing classical solutions often either require an observing doctor himself or are expensive setups in clinical surroundings. Different research is developing promising approaches as in-sole solutions or attachments to the user's shoes that can be worn continuously during normal life activities to not bias the collected data and provide a longer observation time.[16][21]

On the other hand these solutions only offer a restricted view on gait analysis, which can lead to less accurate data and false conclusions. We propose *GaitSet*, a setup of an inconspicuous in-sole solution supported by various sensing devices on different body parts, that observes the whole body movement. The collected data should be aggregated and conspicuous patterns evaluated by a machine learning algorithm. The analyzed data should then be displayed in an application that can provide recommendations for further actions to ease the gait issues.

1 Introduction

The ability of walking is a key to life satisfaction and significantly impacts the living quality. While growing up as a child, it requires a lot of exercise to learn to walk. When getting older, it can be hard seeing how the ability to walk decreases.

In the next sections, we are going to get a theoretical understanding of how the gait can be analyzed and how a gait cycle is defined. We will then take a look at what kind of tests exist to test physical mobility. This information can be used to make a hypothesis about whether somebody has a gait disorder. We classify the most common diseases by their root causes. After that, we will also investigate gait abnormalities of elderly people more closely since they are predestined for an alternated gait. A gait disorder increases the chance of falling, which can have a big impact on the ongoing life of aged people. One section will investigate the correlation between widespread Parkinson's disease and gait disorders.

1.1 The Gait

The ability to walk is dependent on more areas than only the lower body. Besides the lower extremities, such as legs and feet, also the upper extremities, the trunk, and pelvis are required for the act of walking since the human needs to balance all the time.[14]

Some key metrics to rate the gait of a person are the ability to balance and the stability, the walking speed as well as the rate of motion of the limb and trunk as part of the weight transfer. The placement of the foot and the foot form can also have an impact on the gait of a person. In the next section, we will examine the role of each metric in the gait cycle.

1.2 The Gait Cycle

The walking movement of a person can be separated into a repeating series of steps. Therefore, you always focus on a single leg only. We will name it the monitored leg. You can either monitor the left or the right leg. To describe the different steps, we need to declare a small set of terminology first:

A *step* starts with the initial contact of the monitored foot and ends with the initial step of the other foot. The *stride* describes the whole gait cycle and is made out of two steps. It starts with the initial contact of the monitored foot and ends with the next touch of the same foot. The *step time* describes the duration of one step in seconds. The *step width* describes the maximum distance between the two feet while they are touching the ground. The *stride length* describes the distance between the two initial contacts of the same foot. These metrics are used to rate the gait in an objective way.

As shown in Figure 1 the gait cycle splits into two phases: the stance phase and the swing phase. The *stance phase* takes roughly the first 60% of a full gait cycle and describes the time were the monitored foot is in contact with the floor. In more detail, the phase is about the time between the heel strike and the toe off. The second phase, which takes the remaining 40% of the gait cycle, is the *swing phase*. As the name already indicates, this stage is about the time between the toe-off and the next heel strike – the swing. Both phases consist of multiple steps.

The stance phase has four steps. The first step is summarized as the loading response and takes the first 10% of the cycle. It includes the initial contact (the heel strike) of the monitored foot where the heel begins to touch the ground. At that time the toe remains still in the air. It ends as soon as the other foot lifts of the ground. The mid-stance is the second step of the stance phase. It usually goes from 10-30% of the cycle. As soon as the monitored foot heels off, the end of the mid-stance is reached. The main phase is the terminal stance, which happens at 30-50%. It starts when the other foot has initial contact/heel strike and the monitored foot heels off at the same time, which is also called the propulsive phase. The first phase gets completed with the pre-swing, which happens at 50-60% of the cycle and lasts while the other foot reaches full contact with the ground.

The swing phase can be separated into three steps before the gait cycle starts over again. The initial swing covers the time where the toe of the monitored side goes off and lasts until the feet are next to each other (60-73%). This step is for the acceleration of the body, which brings the body forward. The mid-swing (73-87% of the cycle) and the terminal-swing are part of the deceleration phase. This last step slows down the body movement to gain back enough stability and balance to put the foot of the swinging leg down. The terminal-swing completes the swinging phase as well as the gait cycle. [44]

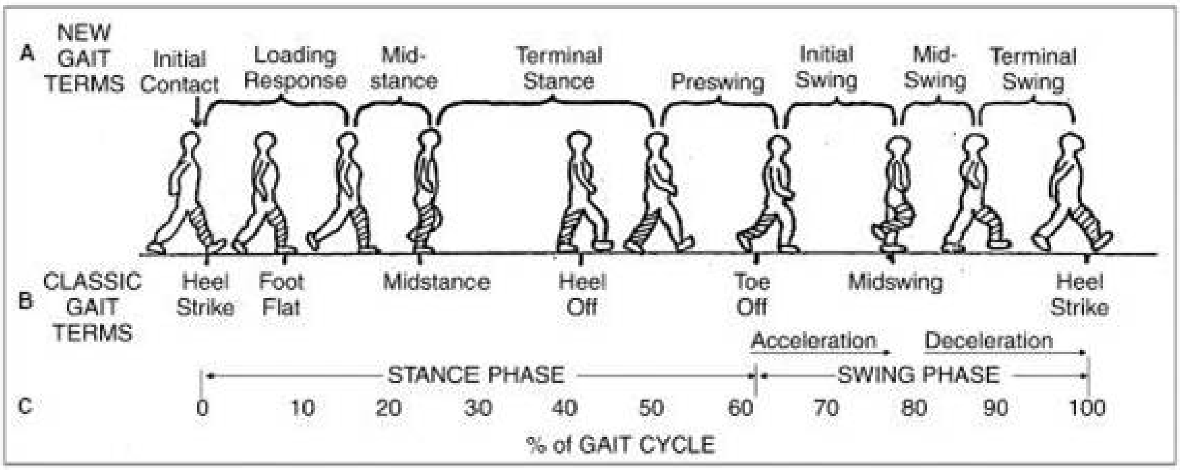

Figure 1: A visualization of the phases and steps of the gait cycle [42]

1.3 Physical Mobility Tests

There are several common clinical tests to characterize the physical mobility and the risk of falling of a person. We will briefly describe the Six-Minute Walk Test, the Berg Balance Scale, and the Timed Up & Go Test. Other mobility tests are for example the Comfortable Gait Speed Test and the Fast Gait Speed Test. All tests are easy to execute and could be theoretically performed at home.

The *Six-Minute Walk Test (6MW)* is a modification of the 12-Minute Walk Test and is very simple. The patient needs to rest for ten minutes and then walks as fast as possible (without running or jogging) between two cones which are placed 30 meters apart. During the test the participant is allowed to rest, however, the person should continue to walk as soon as possible. Despite the recording of additional measurements such as the oxygen level, the final walking distance serves as a metric to estimate the level of physical mobility. In case somebody uses walking aids, it is allowed to use them in this test.[45]

In a study of subjects that had been between the age of 40 and 80, the median distance for men was 576 meters (117 subjects, median age of 59.5) and 494 meters for women (173 subjects, median age of 62).[55]

The *Berg Balance Scale Test (BBS)* is a series of exercises in order to estimate the ability to keep balance. The test consists of 14 exercises, starting with the ability to transition from the sitting position into a standing position without any support such as the armrest of the chair. Further steps include studying the balance while standing. Therefore the subject has to stand unsupported for two minutes, stand with both feet together for one minute, stand using one leg only and has to stand with both feet several seconds with closed eyes. Further tests contain the ability to balance using the trunk to stabilize. The subject is asked to pick up an item from the floor and the distance gets measured, on how far the patient can lean forwards while maintaining overall stability. While until now the test is to be executed in front of an educated medical person which has to judge the ability of the patient, the current developments in technologies as machine learning and artificial intelligence indicate that defined metrics, such as the amount of waving or the overall variety of movements, will help to automatically supervise this test in the future.[43]

Another very simple test which measures both, the balance and the agility of a patient is the *Timed Up & Go Test (TUG)*. The test is also used to estimate the likeliness of a person falling at some time in the future. The patient starts in a sitting position and is asked to stand up and walk in a comfortable speed to a marker which is located three meters away from the chair. Then the patient turns around in order to walk back to the chair and sit down. The time of the overall procedure and possible balancing issues can be used as a metric. In case a patient needs more than 14 seconds this could be an indicator for higher risk of falling.[46]

All presented tests should be repeated on several days at the same time of the day, without workout performed prior to the test. The recorded metrics of each individual test might serve as an indicator for the overall walking performance of a patient.

1.4 Causes for Gait Abnormalities

Abnormalities in the gait pattern of a patient can have several reasons. Some changes are normal and occur as part of the aging process. However, there are also several causes and diseases which affect motor control or create pain. They can be grouped into musculoskeletal causes and neurological causes.

The musculoskeletal causes can be further divided by the body part, that is causing problems, including the hip, knees, foot, ankle, and leg. Arthritis is well known to reduce the range of movements of the hip, while the Ankle Dorsiflexion Weakness results in increased step height and a prolonged swing phase. When it comes to the legs, it is natural that both legs do not share the same length. However, if the difference is too big (leg length discrepancy) the body tries to overcome this problem by modifying the way of walking. This changed pattern of walking can also be a result of pain, which is summarized under the group of Antalgic Gait. Antalgic Gait due to ankle pain increases the stride length for example. If the hip is affected, a reduced stance phase on one side can be detected. As Pirker W, Katzenschlager R. state in their article, "Hip and knee osteoarthritis are common non-neurological causes of gait disorders."[47]

When it comes to common neurological causes, the most common disorders are associated with dementia and parkinsonism. Typical gait patterns are Hemiplegic Gait, Diplegic Gait or Parkinsonian Gait. If a patient has a Hemiplegic Gait, he/she will drag the toe of the affected leg, since the paralyzed leg is hyperextended. This can also be detected by the flexion of the hip. The Spastic Diplegic Gait is described as "a walk in which the legs are held together and move in a stiff manner, the toes seeming to drag and catch." [11]

Is a patient suffering from Parkinsonian Gait, it might be noticeable by abnormally small steps and a small overall movement. The stride length is reduced. Most of the problems occur while the patient starts or stops walking.[64] [47]

1.5 Altered Gait of Elderly People

As already mentioned in the previous chapter, most elderly people are undergoing a change of their gait pattern while aging. Elderly people have a slower movement in general, which also affects the gait. This also comes with a reduced overall activity which results in faster physical and psychological exhaustion. Some patients might also experience an overall feeling of weakness. All these factors can influence the gait with reduced walking speed, shortened step width, a wider gait or a shamble foot movement. Furthermore, a reduced rate when swinging arms is possible.[38]

An investigation with 488 community-residing people (age ranged from 60 to 97) analyzed how many elderly people are suffering from gait problems. Nearly a third of all participants were experiencing an impaired gait. A quarter had neurological gait disorders and 17.4% had non-neurological gait problems. 9.2% of the participants had a combination of neurological and non-neurological gait disorders. Interestingly, 38.2% of all participants that were 80 or older, did not show any abnormalities.

Elderly persons with gait problems also tend to fall, which can cause a serious change in life quality. A fall is defined as "An event, which results in a person coming to rest inadvertently on the ground or other lower level"[8]

The study with the 488 participants also found out, that only neurological gait disorders might lead to recurrent falls - 33.2% of elderly people are vulnerable to falling. Furthermore, the study was able to proof, that gait disorders which result in falls abet a depressed mood, cognitive dysfunction and therefore results in a reduced quality of life. [32]

1.6 Influence of Falls in Old Age

The danger of falling exists for a third of people in older age. This is a huge number which is also reflected in a statistic about emergency transports which found out that every tenth transport is because of an elderly person who fell down. Most of the fallen people just take this as 'fateful' as if they could not have prevented this. Further statistics show, that a third of people being over 65 falls 1 time per year. This number increases with age, people that are 80 or older are 10% more likely to fall. Furthermore, there is a correlation of people who already fell once: 60% of the people who already fell once, will fall again within the next year after falling.[59]

Another study investigated what kind of injuries occur from falling. While most of them are just superficial wounds the fall can also be responsible for brain injuries and cause death. Regardless of what kind of injuries the fallen persons suffer, they also face

superficial wounds	16-27%
femoral neck fracture	25%
traumatic brain injury	10%
death	5%

Table 1: The likeliness of injuries that occur from falling

consequential damages in life quality. First of all, after the event of falling, 50% of the fallen cannot get up without help. Additionally, 80% are restricting their activities and express a need for additional help and care in daily life. Every fifth of those affected even moves into a care home.[59]

To conclude, you can say that elderly people tend to fall more often since they become less active in their daily life. Their feeling for balance decreases and the amount of movements is reduced. The gait gets influenced by several factors and the changes in the gait are one common reason for falling. Other possible reasons for falling are over-medication (polypharmacy) and a decrease in visual skills.

1.7 Altered Gait of Elderly People with Fall History

This section is about the mentioned changes in the gait that occur after a person has fallen. A study was investing this under the assumption that the kinematic is different. Therefore they compared a group of elderly people who had fallen before and another group with no prior history of falling. 57% of the subjects who already fell could not reach the fastest speed which was still comfortable to walk for the non-fallers in the test. The fallers had a significantly greater preferred stride frequency combined with a smaller stride length. They concluded that the walking patterns of fallen elderly people have an increased variability of kinetic measures.[17]

A second study was doing research with a similar objective: they wanted to measure the gait unsteadiness in community-dwelling elderly fallers. They monitored the stride time, the stride-to-stride variability, the absolute stance time and the percentage stance time. Except for the walking speed, all measured values showed a significantly higher variability. [29]

1.8 Parkinson's Disease

Abnormalities in the gait and Parkinson's are highly related. Parkinson's which is also known as the "disease of the elderly" occurs more often the higher the age. Only 4% of all Parkinson's patients are under 50. This rapidly increases for people who are older than 60. One percent of all people who are 60 have Parkinson's. The number is higher for people who are above the 85 years – every 20th person is diagnosed with Parkinson's. The disease itself affects the body as well as the brain via motor symptoms. The changed gait is one of its symptoms – the movement speed may be lower, impaired balance, lack of coordination, tremor of legs and rigidity of limbs or trunks are possible: "Gait impairments are among the most common and disabling symptoms of Parkinson's disease"[34]

All in all, 93% of the patients develop a gait disorder. Nearly two-third of those who have developed the disease have fallen already.[56][60]

2 State of the Art

Following the already outlined medical implications of gait problems and their value as indicators for more severe diseases and psychological issues, analysing the human gait became a growing field of interest in research. However it is not only of importance for discovering physical and mental health conditions of patients, but also in other fields like sport or rehabilitation. Consequently there are multiple current practices used in medical and professional settings with new evolving applications the patient and consumer can use independently. In the following chapter we will introduce the history and development of gait analysis and the resulting state-of-the-art approaches to monitor and measure the human gait. We will furthermore set our focus on emerging new technologies that use wearable sensors for gait analysis.

2.1 Development and Common Applications of Gait Analysis

Ghoussayni et al. defined gait analysis as the systematic study of human locomotion including the measurement, description and assessment of its quantities.[27]

Gait analysis therefore enables the discovery of gait phases and gait events and the analysis of factors influencing the gait of individuals, covering intrinsic aspects like muscular functions, skeletal displacements or mental health problems as well as extrinsic factors like badly accessible environment or weather conditions. Gait analysis can be applied in prevention of orthopaedic issues and health issues, in health diagnostics or after incidences in rehabilitation, but also in application areas outside of the health care context.[58] One example for this is the optimization of athletes' performance and avoidance of injuries through analysis of their running style and correction of identified false or inefficient movement.[52, 54] In the healthcare context however, gait analysis can not only be used to prevent or treat gait problems, but also to identify gait problems as symptoms for other health issues like Parkinson's or dementia.[34, 61]

Gait analysis is thus amongst others used as a method to monitor the patient healing progress in rehabilitation, to discriminate different forms of osteoarthritis, for ambulatory monitoring of Parkinson's disease and to characterize the human locomotion in general.[58]

These applications are only possible due to the research performed in the field of gait analysis since the late 19th century and due to its broad application based on the availability of video camera systems.[26, 35] Building on multi-camera systems, gait laboratories established a standard to analyze the human gait combining visual analysis using said cameras and force analysis using force platforms in the ground for the patients to walk on. The common clinical gait analysis consists of 5 elements: measurement of general gait parameters, video recording and examination, kinematic analysis, kinetic measurement and electromyography (EMG).[63] This technology was widely adopted in a lot of locomotive laboratories. Nevertheless it has the caveats of being relatively expensive and time consuming, being immobile and restricting the movement area of the patient to the force platform, thereby also restricting the scenarios that can be analyzed. Gait analysis with these classic installations can only be performed in equipped gait laboratories and with the help of trained medical professionals.

2.2 Sensor Equipped Insoles

To overcome the limitations of gait laboratories, new alternatives for gait analysis using wearable sensors gained traction in research during the recent two decades. While the sensors being used differ for each experiment or study, the set of most common sensors that are being used includes accelerometers and pressure sensors, as well as gyroscopes, magnetometers and rotation sensors.[25] A large focus of the research on wearable technology for gait analysis are insoles for shoes which are equipped with sensors, often referred to as smart insoles or connected insoles. The development of smart insoles has advanced rapidly leading to several suppliers already being on the market. One can separate the sensor-equipped insoles on the market into two categories: health-centered and lifestyle-centered.

2.2.1 Sensor Equipped Insoles for Lifestyle

Lifestyle insoles are mainly targeting runners and offer analysis of the gait in the context of running or jogging to optimize the training and prevent fatigue and injuries.[33] With 10 million people being active runners in Germany alone in the year 2013 and with a rising trend, the target group is large enough for a profitable market, leading to many evolving commercial solutions.[20] While lifestyle insoles are marketed directly at the end user as a customer, the health-centered insoles are mainly targeting practitioners as customers who can in turn offer the solution to their patients. An example to see that strategy by one single supplier is the French start-up *Digitsole*, which offers lifestyle insoles for runners and cyclists under the *Digitsole* brand.[23] On the other hand they offer a similar insole under a different brand named *PodoSmart* for podiatrists or physiotherapists to connect to their clinical system and analyze the patient's gait by transferring the data to the practitioners system.[24]

The professionally marketed insole by *Digitsole* offers 13 measures including support asymmetry, propulsion speed, dynamic pronation, cadence and more which might be too abstract or complex for a private user. Compared to this, the lifestyle running sole of dutch start-up *Arion* offers 9 measures plus pace, duration and distance of the run.[19] The lifestyle insoles by *Digitsole* and other suppliers like *Arion*, *Runvi* and many more offer more running specific and customer focused measures like running distances, fatigue and stride information. The lifestyle insoles are connected to a smartphone via Bluetooth and give feedback directly to the user, the retail prices range from 50€ to 250€. While *Digitsole* does not offer information on the used sensors, *Runvi* is using 30 pressure sensors and 2 accelerometers in its prototypes and *Arion* is using 8 pressure sensors and extra pods outside the shoe containing multi-axis accelerometers, gyroscopes and GPS.[19, 28]

Apart from private companies with commercial interest, projects like *Runsafer* by the Fraunhofer Institute together with European research institutes like the IBV or the EII performed research in providing a complete smart shoe instead of only an insole.[20] The project was founded and funded by the European Commission, indicating that there is a political interest in supporting the field of gait analysis and thereby the health of the people. It had two years of active development and finished in October of 2014. We can conclude that most lifestyle-centered insoles are targeted at runners and the running context and offer fitting information which can be enriched by GPS data to track running routes etc. and present less complex but more amateur-friendly measures to the user.

2.2.2 Sensor Equipped Insoles for Healthcare

For the insoles we classify as more health-centered than lifestyle-centered, different focuses have been set. A large focus area is the detection of plantar pressure with pressure sensors not only in insoles but also in complete shoes.[40, 50] There are already numerous commercial plantar pressure measurement systems on the market, with some of the most popular ones being the *Emed sensor platform*, the *Pedar insole system* or the *F-Scan system*.[13, 48, 49] These solutions offer clinicians a high degree of mobility, permitting utilization at multiple sites or clinics instead of having to got to a gait laboratory.

Another research topic of large traction are smart insoles for diabetics to monitor their feet for the risk of foot ulcer.[18] A foot ulcer is an open sore at the foot of which the wound healing process is hindered by diabetes mellitus. Due to poor blood circulation and a tendency of decreased sensitivity in their extremities, foot ulcers affect 25% of all diabetics and can in the worst case lead to the amputation of the foot or a part of the lower leg. Rescio et al. proposed a monitoring system based on identification of foot pressure loads and temperature distribution across the plantar surface.[51]

Adding to the standard sensor equipment for insole like pressure sensors, accelerometers and gyroscopes, and increasing number of researchers combine the disease detection function of the insoles with approaches to treatment. Pappas et al combine a gyroscope-based gait detection and the identification of dropped-foot walking dysfunction with a programmable functional electrical stimulation (FES) system to induce electrical stimulation in paralyzed muscles which are the cause for the gait abnormality.[41] As with the lifestyle or sport centered insoles, also for health issues of elderly people there was the European project *Wireless Insole for Independent and Safe Elderly Living (WIISEL)* that built a fully wireless insole that analyzes collected gait data for fall risk of elderly people to enable earlier detection and counter measurements and treatments. The *WIISEL* project has introduced the self-claimed first fully wireless insole and in the same time investigated and brought to more light the long term monitoring to guarantee more autonomy and safety for elderly people.[57]

2.3 Other Approaches to Wearable Gait Analysis

Adding to the trend of measuring movement and forces at the feet via insoles, different parts of the body have been investigated on their role in the human gait and the information one can measure with sensors being placed at said body-parts.

The health and location of the waist and pelvic were found to be relevant factors for human gait, as according to Stagni et. al. the misplacement of the waist joint centre has to be determined to avoid measurement errors during gait analysis due to the dislocation.[53] Since patients after resurfacing total waist arthroplasties were found to be comparable to normal test subjects during gait analysis, including the waist into the gait analysis might not only help to reduce errors and improve accuracy but also to discover side effects of waist arthroplasties or malfunctioning waist implants.[37] Using a single waist-mounted tri-axial accelerometer, Kobsar et al. could detect age-related changes in gait and proof differences in gait variability, regularity and symmetry correlating with the age of the subjects.[31] This undermines the value of gait analysis for detection of mental diseases, like Parkinson's disease, and their consequences like raised risk of falling. Zach et al. used a single waist-mounted accelerometer to detect freezing of gait, an effect of Parkinson's disease where patients are not able to start stepping forward and are forced to tremble, shuffle or are completely unable to move their feet. While the Parkinson's patients performed freezing provoking tasks like rapid turns the accelerometer achieved a reasonable sensitivity and accuracy.[66]

Other popular measure points for gait analysis are the knee and ankle joints as to be seen for example in the fuzzy model for gait event classification by Ng and Chizeck, who combined measurements at the waist, ankle and knee joints to identify five gait phases.[39]

3 Proposal

We propose *GaitSet*, a setup of various sensing devices on different body parts, that observes the whole body movement to provide an as extensive and detailed gait analysis as possible. The main focus lies on the shoe sole which utilizes pressure sensors and a flexible bend sensor to provide data on how the user distributes his body weight one his feet. Additional gyroscopes and acceleration sensors are implemented in the sole as well as in separate devices that can be placed on the legs, the hip and the shoulders. The different devices can be attached to the user separately to provide isolated data but also together to return a complete walking habit image. Through that we want acquire better and more accurate data than just with only the connected shoe soles. The collected data is synchronized, aggregated and can be evaluated in the proposed *GaitApp* described in section 3.3.

The vision is to detect issues as described in this report especially in section 1.4, section 1.5 and section 2.2.2 in your own walking habits before they either directly cause problems to your health or to discover other diseases that can be indicated by certain conspicuous gait features. The narrower target group is in elderly people because they have the highest tendency to show problems in their walking habits and have a high risk in falling as described in section 1.6 that could be avoided by predicting issues early.

The sensors used in the *GaitSet* were selected with the goal of creating a highly instrumented system capable of sensing many parameters that characterize gait. The goal is to place them on various human body parts as sketched in Figure 2.

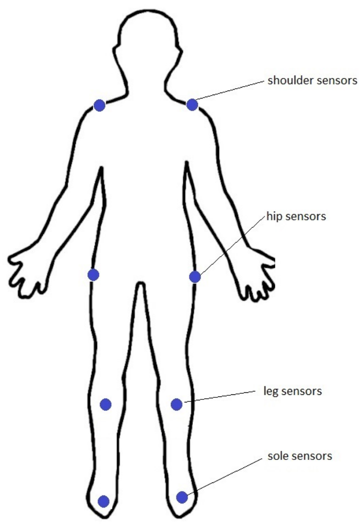

Figure 2: Sketch of where sensors are applied on the human body

In Table 2 we describe the used sensor types, their output and what parameters are analyzed:

Sensor Type	Sensor Output	Analyzed Parameters
Accelerometers	Voltage change corresponding to acceleration; single integration of acceleration yields velocity, double integration yields distance	Stride velocity, stride length, other displacements
Bend Sensors	Resistance change corresponding to dynamic pressure across the sensor	Force distribution under foot, heel-strike timing and toe-off timing
Force sensitive resistors	Resistance change corresponding to dynamic pressure across the sensor	Force distribution under foot, heel-strike timing and toe-off timing
Gyroscopes	Voltage change corresponding to angular velocity; single integration yields angle of rotation	Orientation of the foot or body part

Table 2: Sensor Types, their output and the to analyzed parameters

3.1 GaitSole

At first we present *GaitSole*, a product designed for the general public that can be weared continuously as common inlay soles to take countermeasures against foot misalignments. The goal is an inlay shoe sole, that allows a user to monitor their gate habits in an easy way.

For the design of the for gait analysis developed insole we have to address various essential functional requirements: Even though we would like to offer a perfect observation of walking habits to provide an as good issue detection accuracy as possible, we have to keep in mind the trade off between material price, provided wearing comfort and gait analysis accuracy. *GaitSole* should come in all usual shoe sizes and it shouldn't be thicker than usual soles to be applicable in all of the users shoes. Furthermore it should be as lightweight as possible to not aggravate walking and through that distort the gait analysis output. One key aspect is that we don't need any changes or attachments on the shoe itself but only insert the sole which provides all the needed sensor technique. The measurement system should be a self-standing wearable system, which is able to transmit all relevant data wirelessly to a remote data storing/computing unit, strictly speaking a mobile phone or similar app supporting device that synchronizes the collected data (see *GaitApp* in section 3.3).

All the measuring instruments should be operated by a thin lithium polymer battery to be as space efficient as possible and guarantee an autonomy of at least eight hours:

This is desirable in order to provide enough power to use the system for longer recording sessions and to monitor walking habits during daily life activities. Through that the device is hidden in the shoe and completely inconspicuous to others.

To provide a comfortable wearing experience which prevents that the user actually feels the sensors under his feet the to connected sole needs to be manufactured of stable but also comfortable material that also is easily editable to be able to enhance it with our sensor techniques. The hardware compromised in this system is chosen on the basis of the review of various literature which suggests aspects such as sensor selection, suitable locations for the sensor positioning and signal conversion for reliable and optimal results [15][16][21][36]. *GaitSets* devices consist of two main parts: The different sensor systems to collect data and the on-board electronics for power supply and data transmission. A conceptual description of the system architecture is given in Figure 3.

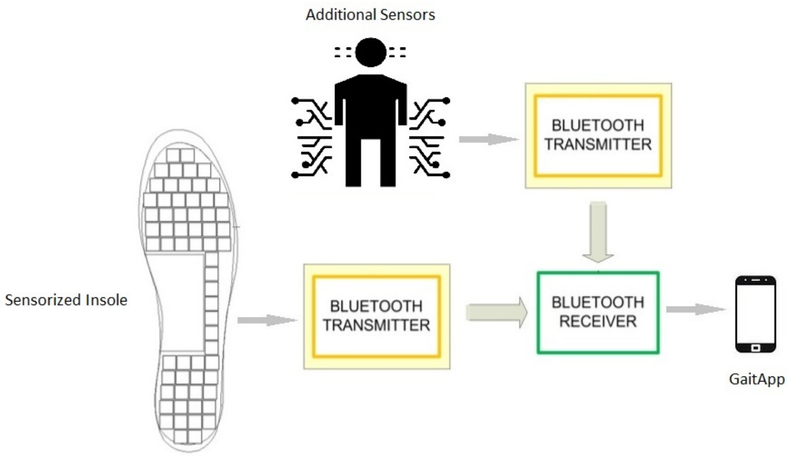

Figure 3: Overview of the system architecture

For the examination of the kinematic movement as well as pitch, yaw and roll of the foot, we want to utilize a device known as an inertial measurement unit (IMU) as seen in Figure 4. In detail this means two dual-axis accelerometers and three gyroscopes are placed in the sole, arranged with the goal that the individual sensing axes are aligned along the three perpendicular axes.

As recommended in the literature [16] we suggest dual-axis accelerometers which are microelectromechanical system (MEMS)-based ADXL202E [1] from Analog Devices. Additionally we propose two different types of gyroscopes: The MEMS-based ADXRS150 [5] from Analog Devices, and the vibrating-reed-based ENC-03 J [6] from Murata which are both sensing in orthogonal planes that allow the construction of a flat IMU device.

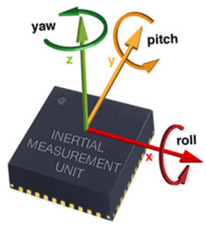

Figure 4: Inertial Measurement Unit [12]

For the planar pressure monitoring we propose Force Sensing Sensors (FSR) model 402 [10] from Interlink electronic and Flexible Bend Sensors (FBS) model FLX-01 [9] from Spectra Symbol for this prototype as recommended by Anas [36]. Both are resistive based so that the electrical resistance changes under tension or compression of those sensors. The active area of the FSR sensors are 12.7mm diameters in size. On the other hand the FBS sensor has an active length of 95.25mm. Those two sensors are made of polymer thick film (PTF) material. When the applied force on the FSR sensors surface increases, it resistance decreases and when the bending angle of the FBS sensor is increased, it resistance increases as well. Both sensor's accuracy determining force and bend angle ranges from 5 percent to +/-25 percent in 10K ohms to 100K ohms for FSR and +/-30 percent from 60K ohms to 110K ohms for FBS sensor. Furthermore those Force Sensing Sensors and Flexible Bend Sensors are very popular due to their cost efficiency and suitability for measuring foot force and flexion. *GaitSoles* sensors are powered by a thin lithium polymer battery integrated in the shoe sole.

Furthermore the smart sole is equipped with a bluetooth module as the SESUB-PAN-T2541 [2] from TDK that convinces with its extremely small size of just 4.6 x 5.6 x 1.0mm and allows to transmit the data to an external device on which *GaitApp* is installed. Figure 5 sketches the placement of the different sensors and electronic devices under the human foot sole. Four FSRs are build into the sole placed on the spots where most pressure of the foot is applied. The other devices are placed under or in the lower part the sole to provide maximum walking comfort. Gyroscope and accelerometer are centered under the foot while batterie and bluetooth module are attached under the sole arch, where least pressure is applied.

3.2 Additional GaitSet Devices

Related to section 2.3 we additionally propose the other *GaitSet* devices *GaitLeg*, *GaitBelt* and *GaitShoulder* which are providing further information for gait analysis from the other corresponding body parts so that we hope to achieve better over all results by that. The devices are similary set up as described in section 3.1 and also contain accelerometers and a gyroscopes each in form of IMUs, powered by thin lithium polymer batteries. *GaitApp* synchronization works over a bluetooth module. The various *GaitSet* devices can be attached to the user with straps which sizes are adjustable to

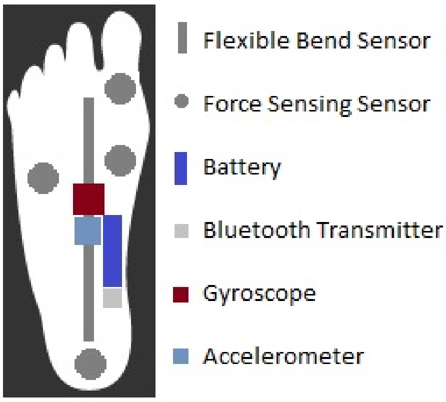

Figure 5: Sketch of different sensors on the human shoe sole

the respective person.

GaitLeg which is placed around the knees delivers supportive information on the leg movement to discover foot misalignments like knock-knees or bow legs.

GaitBelt is a belt supported with two sensoring devices on each side, that help to observe the hip position while walking. This separate device offers additional data and prohibits larger miscalculations in the gait analysis results [53].

GaitShoulder is a setup of two sensoring devices placed on the users shoulders which detect problems in the upper body posture. We expect that by this approach we can draw a better image of the whole walking habit that allows to detect and explain issues in more detail.

3.3 GaitApp

GaitApp is a taken further idea for how a future application to evaluate the collected data by the user could look like. *GaitSets* devices could be connected via a bluetooth module to a provided complementary mobile phone application and synchronized through their output. The mobile phone applications main task would be to evaluate the different sensor measurements and warn the user when conspicuous patterns in movement are detected. If a problem indicating pattern is detected over a longer amount of time it should provide background knowledge of the issue but mainly it could recommend the user to visit a doctor or other specialist that can offer a professional observation in a clinical environment. There the gait analysis results can be confirmed or negated.

Furthermore it should be possible to display the collected data in a more detailed version that should allow the application to explain the user but also at a later point the professional how its decisions where calculated.

4 Feasibility Study

To evaluate the feasibility of the proposed measurement system we are performing a feasibility study in form of a measurement experiment with simulated gait abnormalities. The goal of this measurement experiment is to evaluate whether different styles of gait abnormalities are distinguishable and identifiable by patterns in the results of the measurements. Furthermore we would like to evaluate the importance of the different sensors as well as their placement positions for achieving an as good as possible result.

4.1 Experimental Measurement Setup for the Feasibility Study

Due to budget and consequently hardware restrictions, we could only use the six wireless IMU devices that were accessible to us for the measurements of this feasibility study. To analyze the walking behaviour of the test persons, we equipped them with those devices as described below:

Four Bonsai's smart system for motion capturing IMU devices by QuantiMotion [4] are used to measure the acceleration and rotation of the experimentees hip and knees. Two of those are mounted on a flexible stripe to be worn as a belt so the sensors are positioned on the person's right and left pelvic bones. The other two are attached slightly above the knees, one on each leg, also by stripes. Additionally two EXLs3 IMU devices by EXEL [7] are mounted on top of each test persons foot. It is important to position each pair of the six devices in the same axis rotation to get a matching and interpretable output.

Both sensor types provide acceleration and angular velocity for each of the three axes X, Y and Z at a set rate of 100 Hz. The Bonsai devices can be accessed via bluetooth using the manufacturer's provided application [3] that only works on iOS devices though and logs the collected data in the CSV format. The logs can be send to a computer afterwards. Furthermore the app displays the sensor data live, which helps us to time the exercises in a way that a later algorithm can classify those as described in section 4.3.3. The EXLs3 sensors have to be connected to a Linux machine via bluetooth and also log their data in the CSV format. We run a Linux Ubuntu system in the emulation software Virtual Box to make use of those.

4.2 Walking Routines for Data Measurement

We attached the described setup onto three subjects of different body sizes and consequently different step lengths to provide some variability for our algorithm described in section 4.4. They performed a standardized walking routine each with their normal gait followed by different gait abnormalities to be simulated between marked stations. To be able to synchronize the collected data of the six different sensors, every routine starts with three jumps. These will show three strong peaks in the data, by which the various measured time series can be aligned later. The chosen forms of gait abnormalities were pelvic obliquity, limping, small steps, shuffling and insecure walking.

Pelvic obliquity simulates issues with the right hip that we expect to be detectable in the hip sensors' data. The limping performance simulates a stiff right leg that is dragged behind by the test person. We expect differences in the sensor data of the right and left sensors especially the ones attached to the feet and knees. Small steps should imitate the typical walking behaviour of elderly people having an insecure movement habit and only moving forward in small steps. While shuffling the subject imitates problems in lifting their legs from the ground and thus shambles along. Especially the feet sensors could show conspicuities in the leg lifting acceleration data. The abnormality insecure walking is performed by inducing force by another person pushing or pulling the test subject from behind. We expect a large factor of randomness in this behaviour, so the data is assumed to be quite irregular which could lead to bad results in the classification algorithm. The complete walking procedure can be seen in Figure 6.

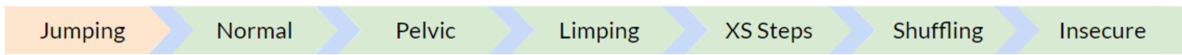

Figure 6: Procedure of the measurement experiment for the feasibility study

All specified types of walking were performed between marked stations and separated by two waiting phases of about 200 ms and a turning movement to allow to distinguish the different types of walking performances. Later only the individual strides will be extracted out of the exercises as described in section 4.3.4. To provide a bigger variability in these steps and to avoid fatigue in the individual exercises, the routine lengths and thereby the exercise lengths were chosen differently between 10 and 200 meters for each run. In total we did 12 runs of variable lengths so that each test subject provides about the same amount of strides. The calculated strides for each exercise can be seen in Table 3. Logically performing the different exercises over similar distances leads to a diverse number of strides per exercise.

Exercise	Calculated Strides
Normal	191
Pelvic Obliquity	412
Limping	360
Small Steps	342
Shuffling	506
Insecure Walking	321
Total	2132

Table 3: An Overview of Our Collected Stride Data

4.3 Preparing the Measured Data for Further Processing

The goal of the feasibility study is to detect gait abnormalities in sensor data. As described in the previous section, we now created a big amount of sensor data saved in CSV format. However that would be too much to process manually. We therefore want to use a machine learning approach to detect possible patterns of people who suffer from gait problems. Before we can apply a classification algorithm the gathered sensor data needs to be preprocessed. To do so, we developed a preprocessing pipeline for the imported data consisting of four steps: The calibration of each sensor, the synchronization of the different sensors, the exercise detection, as well as the stride extraction and normalization. For the implementation, we have decided to use a jupyter[1] notebook running on python3. In this chapter we will briefly explain the algorithms we developed for each of these steps. Our implementation and measurements data can be found on GitHub[2].

4.3.1 The Calibration

At that step we assume that the data has been already read and brought into a uniform format. Since there was no option to calibrate the sensors before executing the experiments, we have decided to do that on the software side. This also has the advantage that we eliminate the gravity which is added to each measurement point. The code for the calibration is given in Algorithm 1 and is fairly simple. The calibration method takes any Series object from the Pandas library and translates each value to its absolute first. In the next step, a rolling window function on the whole series is applied. A rolling window has a specific length and is like a restricted view that shifts over the whole series from left to right. In this case, the rolling window has a size of 200 time points because our measurements were taken with a sample rate of 100 Hz resulting in an absolute window size of two seconds[3]. The algorithm then finds the window were the least activity is happening by choosing the one with the lowest median. In the last step, this median is subtracted.

The left chart of figure 7 shows the raw measurement data of the beginning of a measurement that is used as input for the calibration. The right chart shows the result of the calibration algorithm. As you can see the beginning of the result is still not precisely neutral, probably due to small variations that occur even when no movements are happening.

4.3.2 The Alignment of Multiple Sensors

We now have calibrated all series for each dimension of each sensor. Since it is obviously not possible to manually start all measurements at the exact same time, we need to align the timelines of the different sensors. As already stated, we are using a sequence of three

[1] `https://jupyter.org/`
[2] `https://github.com/dkipping/gait-analysis`
[3] 2 s * 100 Hz = 200

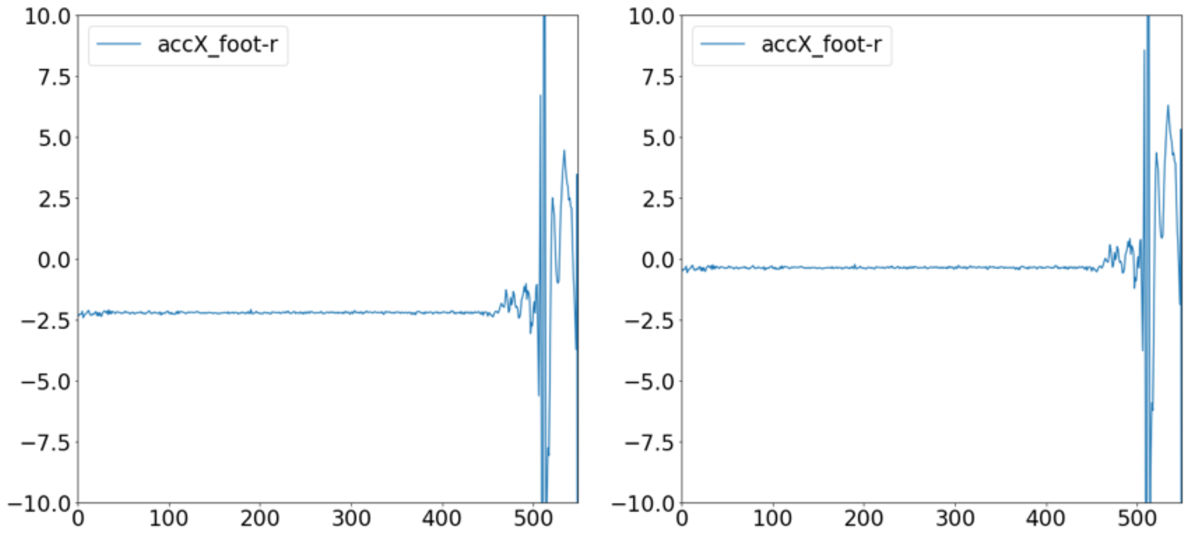

Figure 7: Comparing the raw and calibrated measurement for the x-axis of the right foot.

subsequent jumps at the beginning of each measurement to synchronize the series. We assume that (ideally) while jumping, both feet are lifting off at the same time and that the maximum acceleration values occur conjunct with the jumping sequences.

The algorithm for aligning the series consists of three steps. The first step is a threshold function applied to every single value. If the value is below a specific threshold it is set to 0. The specific threshold is determined relative to the overall maximum value of the measurement. We empirically found 7/12 to be a good threshold.

In the second step adjacent values are combined into bins. We do this since we want to count the number of possible jumps per time window in the next step. Sometimes the sensors measure two values during a single jump. This results in two maximum values which are very close to each other. However, they belong to the same jump and should only be counted as one. One jump takes roughly half a second, therefore every 50 subsequent values get merged into one bin by using the maximum.

In the last step, we use a rolling window function similar to the calibration algorithm and find the window including all three jumps. We have measured the time that is required for three jumps including the pauses and set the window size to 8 seconds. The stronger the jumps and the more jumps occur, the more likely this window is chosen as the jumping window. The alignment algorithm then finds the time point of the first jump for both measurements and shifts the measurements for each dimension of the sensors accordingly. For the alignment, we use the y-axis of each sensor since we jump vertically. The result of aligning the left and the right foot is shown in figure 8.

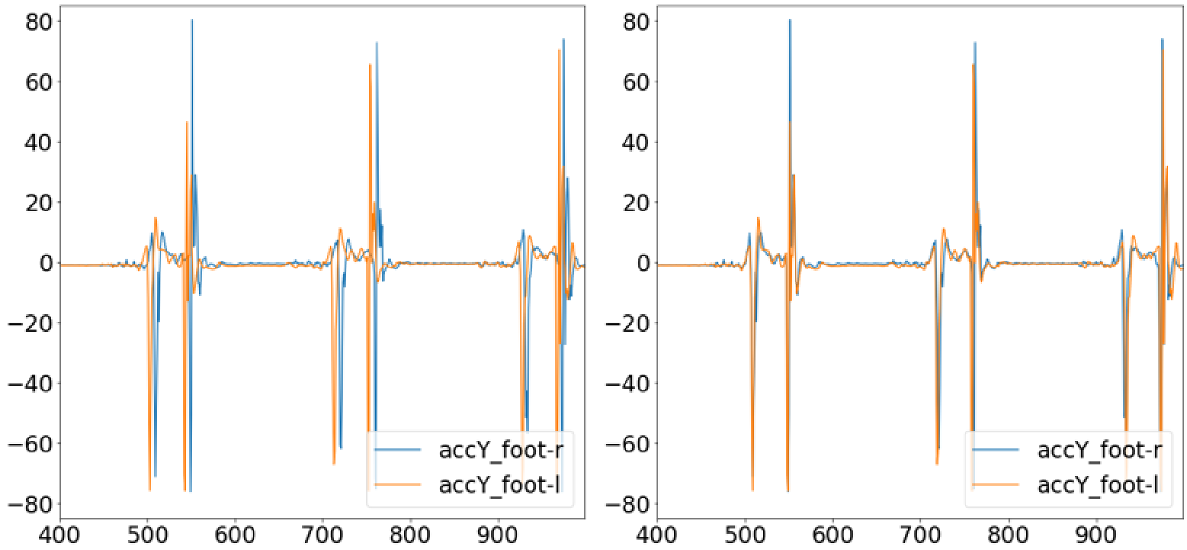

Figure 8: The alignment of sensor timelines

4.3.3 The Exercise Detection

The calibration and alignment of the series result in a plot as displayed in figure 9.

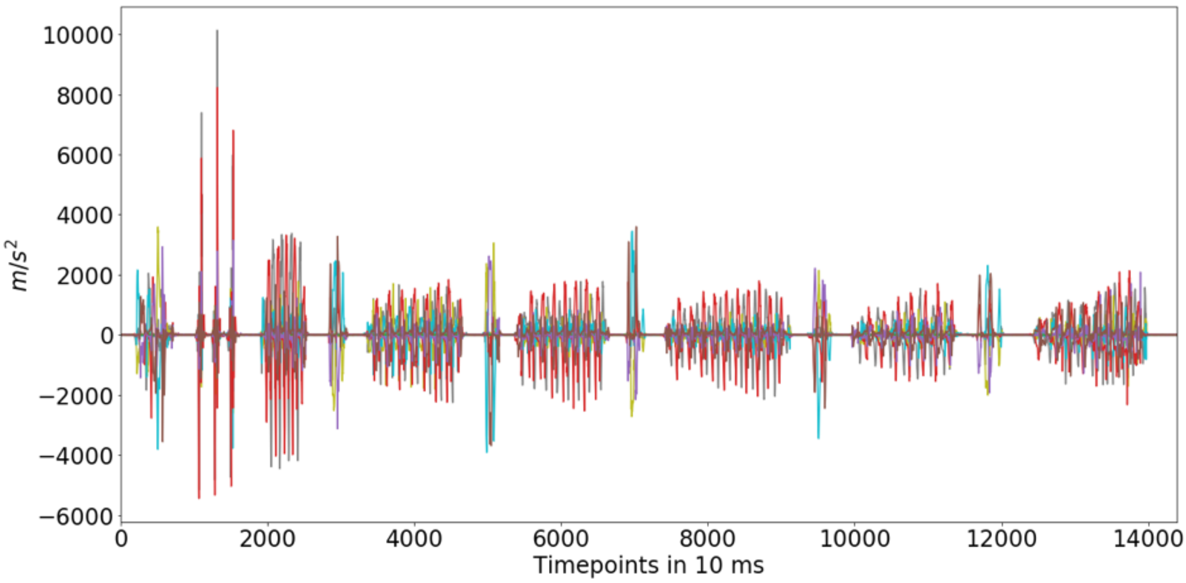

Figure 9: A complete measurement including all sensor dimensions

As a human, we can clearly distinguish the different exercises, the turns and the breaks between them. Firstly we have some arbitrary movement, followed by three jumps that are being used for synchronization, ending in a series of exercises, breaks and turns.

The algorithm should be able to extract the exercises and turns by recognizing the pauses. It then distinguishes between the exercises and turns by using a threshold for the minimum duration of an exercise.

In more detail, the algorithm first uses the end of the jumping sequence as a starting point. It then applies a threshold function on the series for the y-acceleration of the right foot, which has proven to be very suitable for separating the different phases. The threshold function transforms all values below a specific threshold into a zero, otherwise into a one. That threshold is chosen in a way that it cancels the no-movement noise. We have empirically found $1.5m/s^2$ to be a good threshold to remove most of the noise. Figure 10 shows the original measurement compared to the result after the threshold is applied.

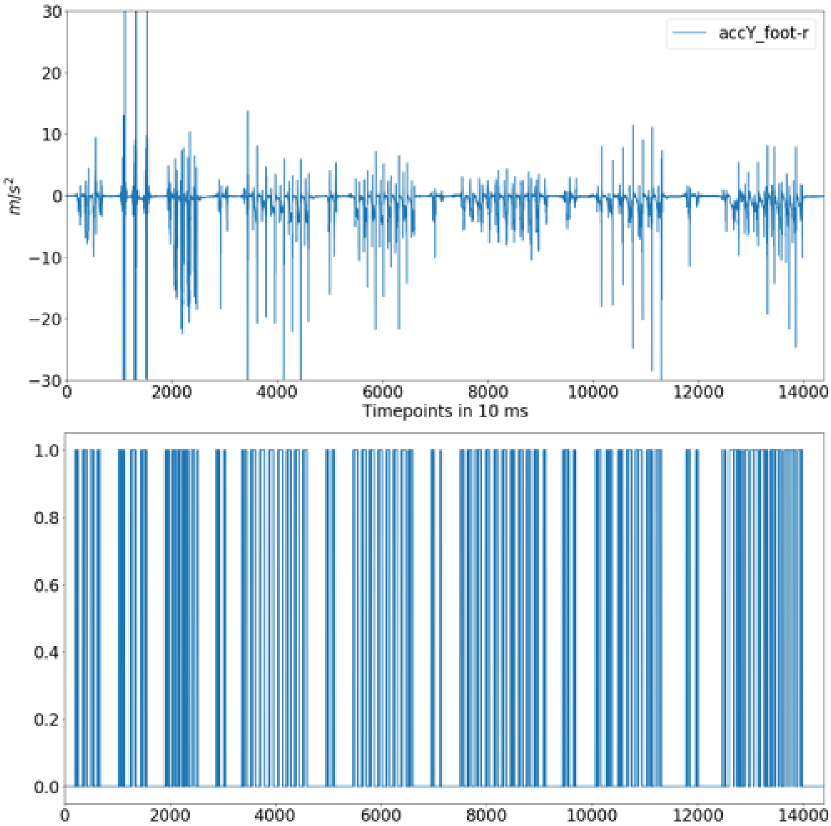

Figure 10: The threshold that gets applied on the y-acceleration of the right foot for the exercise detection.

The algorithm now can search for the longest subsequent blocks of zeroes that are above a certain length. Everything between two such blocks can be considered as an exercise or turn. The indices can now be used to split the original data. The split measurement is shown in figure 11.

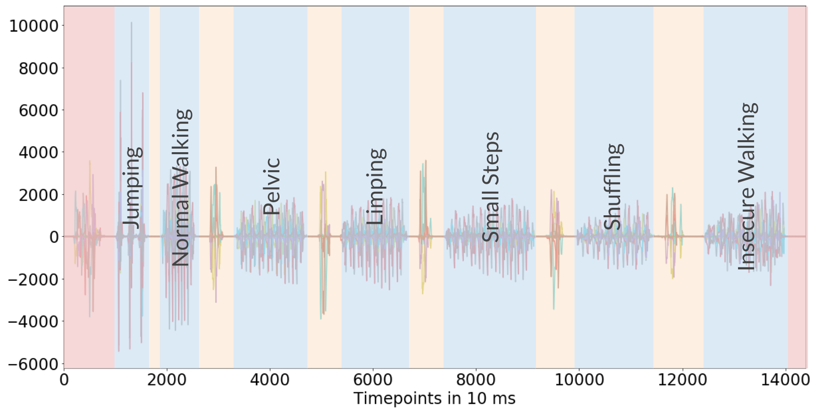

Figure 11: The measurement, split into its exercises

4.3.4 The Stride Extraction

The machine learning algorithm only works with feature spaces of the same size. Since a subject can do a different number of steps on the same walking distance, the algorithm should split each exercise into individual strides. Since the stride time can be different too, the algorithm also normalizes the extracted strides by bringing them to the same length. Furthermore, the values get mapped to the normalized range of zero to one. The algorithm uses the y-acceleration of the left and right foot to detect the different strides. A stride consists of one step per leg. As introduced with the gait cycle, while the monitored foot is moving, the other foot is resting most of the time. In figure 12 the resting phases for the normal walking exercise are highlighted. Consequently the algorithm can now exploit this feature.

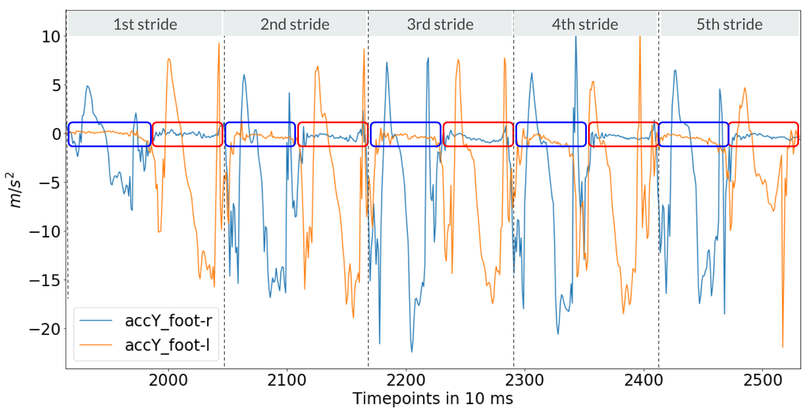

Figure 12: The strides highlighted in the *normal-walking* exercise

The algorithm works similar to our exercise extraction. Firstly, the threshold function to distinguish between movement and resting is applied. The algorithm then seeks for the resting intervals of the left and right foot and calculates the stride range. Additionally, we make sure that all measurements are starting with the movement of the right foot, by discarding an incomplete first step if required. After extracting the individual strides, they are normalized to the same length. This happens either by down-sampling the stride or by padding it. We decided to pad the stride in order to keep the information about the stride length. However, you could also save the stride length as an additional feature and stretch the measurement afterwards.

The final result that gets passed into the machine learning algorithm can be seen in figure 13. For the normalization that is shown in the plot, we have chosen a stride length of 150. This value has to be evaluated in order to optimize the precision and recall of machine learning.

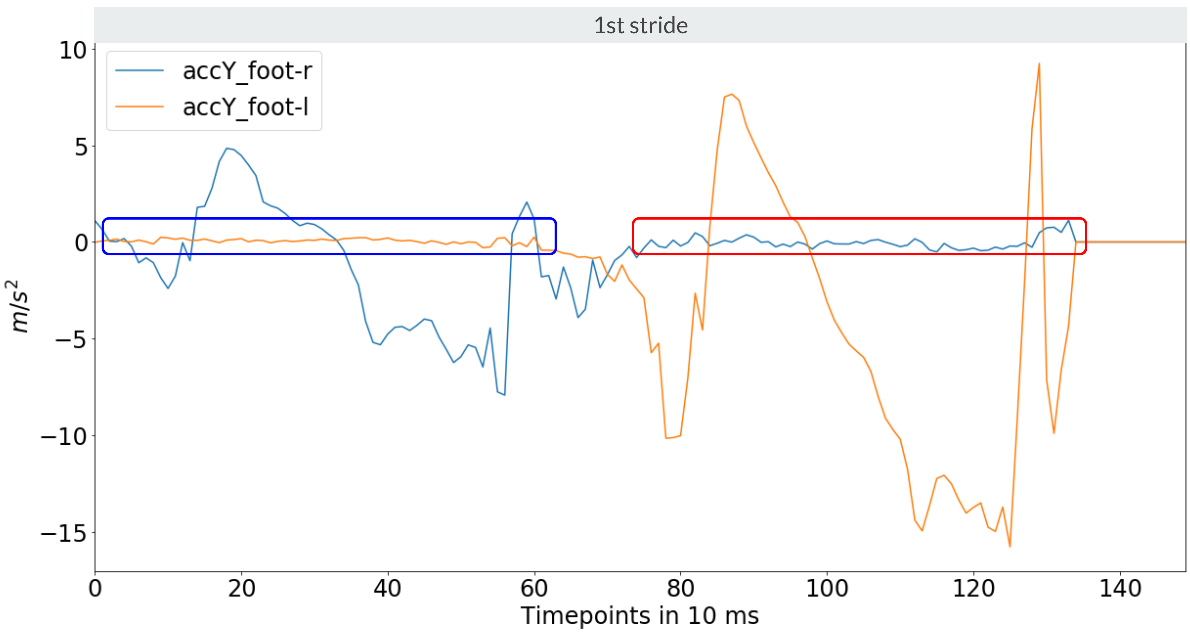

Figure 13: A normalized stride that now is ready to get passed to the ML algorithm

4.4 Detecting Gait Problems Using Machine Learning

After having generated gait data with our experiment and being able to pre-process it into the form of separated, normalized and labelled strides, we want to complete our pipeline with an automated classification of the strides to detect gait abnormalities. Together with the machine learning powered classification and the automated stride extraction, our pipeline would enable autonomous monitoring of the patients and users of our proposed solution. For the classification of the strides, we decided to use the k-nearest neighbors algorithm (*k-nn*) together with dynamic time warping based on the work of Dr. Eamonn Keogh, University of California Riverside, where this combination has proven to deliver state-of-the-art performance in time series classification [62, 65] We will now give an overview of the general *k-nn* algorithm, dynamic time warping and the application of both in our study.

4.4.1 The K-Nearest Neighbor Classifier

The k-nearest-neighbors algorithm is a non-parametric method that can also be used for regression or classification, for our use-case only the latter is of interest.

The basic functionality of the *k-nn* algorithm for classification can be described like the following:

Labelled example data, also called training data, is provided to the classifier, which then stores said example data in its model as feature vectors with the attached class label.

The classifier compares the input with all of the examples that are stored in the model and finds the k nearest neighbors, or in other words the k examples with the highest similarity. The similarity is computed via a distance metric, which we will discuss in the following section. Within these examples, the classifier does a majority vote of the class labels and thus assigns the most frequent class label to the input. Every input therefore gets the class label that is the most frequent one of the k most similar examples, as can be seen in figure 14[30].

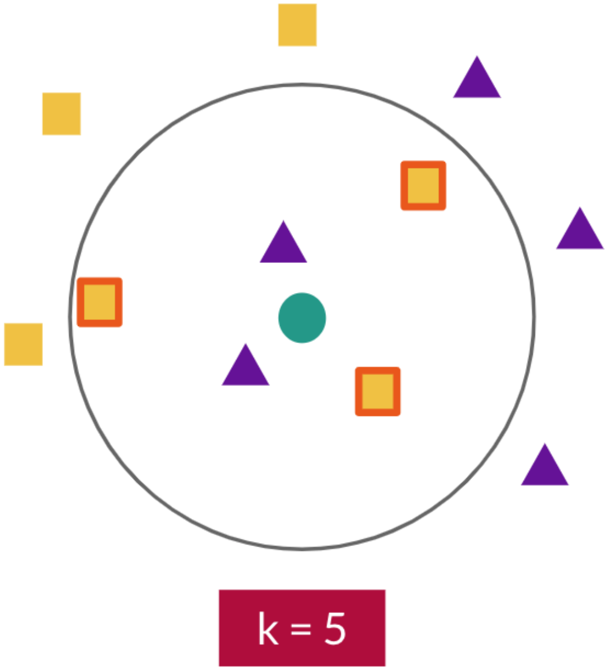

Figure 14: A visualization of the class label assignment by the *k-nn* classifier. The green circle represents input data, while the other objects are training data.

4.4.2 Dynamic Time Warping as a Distance Metric

As described in the last section, *k-nn* compares input data with stored example data in its model to determine the most similar examples. The similarity between input data and an example is computed with a so called distance metric.

This distance metric tries to map the input data to the data from the example and gives back the distance between the two samples. The smaller the distance between two samples is, the more similar they are regarded. A common distance metric for *k-nn* is the Euclidean distance, which for time series can be described as the straight-line distance between two points and yields a linear alignment of the two samples. This means that the direct distance between one point in time of the input series and the point at the same position in the example series is calculated, resulting in an aggregated distance. For time series, this works sufficiently to detect differences between the y-axes, but fails if similar series are shifted or distorted along the x-axes, since this results in similar points being not aligned any longer. They are therefore compared against other points[22].

This is were the usage of Dynamic Time Warping (DTW) as a distance metric can improve the comparison of time series. DTW scans both series for the optimal non-linear alignment. This means that within restrictions, points in the time series can be aligned to multiple points in the other time series and more importantly to points which are not directly aligned. The comparison using DTW therefore shows a remarkably higher robustness against time stretching, as can be seen in figure 15. In this example, the euclidean distance between time series 1 and time series 3 is 23.19 and thereby lower than the distance between time series 1 and time series 2 of 26.96. This would mean that the sine curve (series 1) would be closer to a straight line (series 3) than to another sine curve (series 2). This is not what we want to achieve for time series comparison. The DTW distances yield the correct result, that the DTW distance between series 1 and series 2 of 17.93 is smaller than the distance between series 1 and series 3 of 21.55. It thus handles the stretching and resulting shift between the sine curves better due to its non-linear nature.[65]

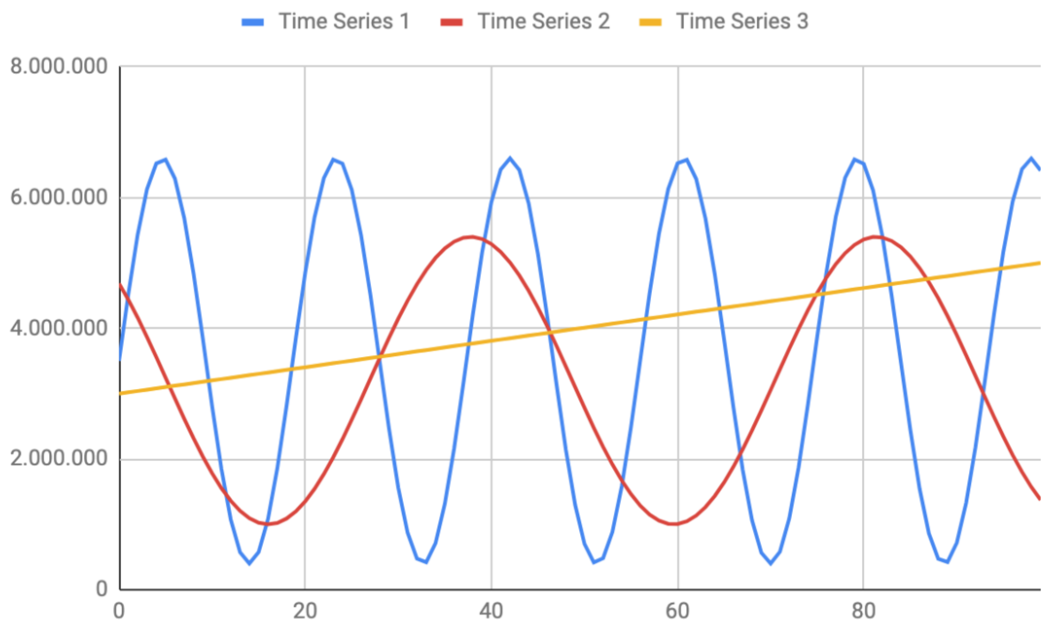

Figure 15: An example use case with time series, where DTW performs better than the euclidean distance

This flexibility is achieved via dynamic programming and comes with the cost of quadratic performance. One approach to optimize the performance is by setting a fixed window size that limits the positions before and after the currently compared point in the time series which are considered for the comparison in the other time series. A window size of n would therefore make the DTW algorithm only compare each point with the aligned point in the other sample and *n-1* positions before and after it.

4.4.3 Application of the Algorithm to our Study

We applied the *k-nn* classification algorithm in combination with dynamic time warping as the distance metric of choice in our study with the following considerations: According to our experiment setup we have six classes of strides, which consist of normal walking, pelvic obliquity, limping, small steps, shuffling and insecure walking. For convenience, we labelled them with the numbers from one to six in the given order in our data. To implement our classifier, we use the *KNeighborsClassifier* implementation from the *scikit learn* python library[4]. We also sticked with the default amount of neighbors, setting *k=5*.

To classify strides with our classifier, we first have to provide training data, which will be used as examples. We therefore split our data into training and testing data, with the latter one being the actual input that should be classified. Of our complete set of extracted strides, we chose a split of 70% for the training data and 30% for the testing data. Before the actual split we shuffle the data to ensure a fair distribution of subject data in the training and testing data and store the resulting split for later re-use.

As we did not include feature extraction in our feasibility study, the classifier learns the raw time series in the training step as its model and stores it for later experiments. The model therefore consists of already labelled strides as extracted from our experiment.

Having stored the model, we can use it in a separate testing step. We therefor load the model and the testing data which were both stored. The testing data is cleaned from the class labels, which we store for later performance assessment. Afterwards, we let the classifier compare every input element from the testing data to all of the examples in the training data by using Dynamic Time Warping to provide us with the most frequent class label in the nearest neighbors. The code we used for Dynamic Time Warping can be seen below in algorithm 2 and is build upon an example use case from Alex Minnaar[5]. For optimization of the run time, we set a window size of 4 for the DTW.

With these steps we already get the class labels for a list of unlabelled time series from the testing data. Since the classification requires the comparison of an input sample to a training sample, the both samples actually have to be comparable. This is only the case with the exact same sensor metrics. With us having used six sensors and recorded three dimensions for both an accelerometer and a gyroscope from each sensor, this results in 36 different metrics. To consider all of them, we have to run the already outlined steps for each metric and store the results in sub-models. This also results in 36 separated comparisons during the testing.

To get the final class label, we perform a majority voting on the class labels yielded by the separate metrics with their respective measured precision as a weight. After aggregating these weighted votes, we take the most frequent class label as the final classification result for the stride and return it together with the other final labels as the result.

[4] `https://scikit-learn.org/stable/modules/generated/sklearn.neighbors.KNeighborsClassifier.html`

[5] `https://github.com/alexminnaar/time-series-classification-and-clustering`

4.5 Evaluation of the Gait Abnormality Detection Algorithm

In the following section we will evaluate the performance of our previously described pipeline including the pre-processing and the classification on the already introduced data set. In addition we compare multiple settings of normalization parameters of the strides to assess their influence on the results and thereby the robustness of our approach. The settings we investigate are the target-length of the normalized strides the normalization of the value range of the strides. The performance is measured with common performance metrics including: precision, recall and f1-score. We evaluate these metrics for the final classification results after the voting to judge the overall performance and include the separate performances of the sensor metrics to rate the importance of the sensors for our proposed solution of the *GaitSet*. We have to take into account, that we have to normalize the data again for each setting. Since this step happens before the split of training and testing data in our pipeline and contains shuffling, we also have inconsistencies between the data sets for the different settings. We therefore only take into account reasonably large changes in the performance metrics as an indicator for actual change in the performance. For the generation of the following performance reports, we used *scikit learn's* functionality for classification performance reports[6].

4.5.1 Performance

The performance of our algorithm is assessed with the originally set parameters for the normalization. These are a normalization length of 500 ms and no normalization of the value range. The normalization length was found as a reasonable length as it was close to the minimal lengths and slightly below the median, thus offering a good balance of padding and down-sampling. This results in the final results after sensor voting that can be seen in table 4

Class	**Precision**	**Recall**	**F1-Score**
Normal	1.00	0.98	0.99
Pelvic Obliquity	0.99	1.00	1.00
Limping	1.00	0.96	0.98
Small Steps	0.88	1.00	0.93
Shuffling	0.95	0.92	0.94
Insecure Walking	1.00	0.85	0.92
Weighted Average	0.96	0.96	0.96

Table 4: The performance report of our classification with stride lengths normalized to 500 ms

We can directly see that the classifier scored *perfect* results for the precision in three

[6]`https://scikit-learn.org/stable/modules/generated/sklearn.metrics.classification_report.html`

classes, which is half of the assessed classes. The recall on the other hand only reached 1.00 for the classification of pelvic obliquity and small steps. In combination of those results, the classifier only reached one perfect f1-score of 1.00 for the pelvic obliquity. Nevertheless the rest of the metrics, apart from two exceptions, always reaches a score above 0.92. With a weighted average of 0.96 for precision, recall and f1-score we could be contented with the performance of the classifier. We want to refer again to our study setup at this point and to the generation of the data. Since we only had three unique subjects which enacted gait abnormalities in multiple runs, there is still a high chance that the performance is influenced by over-fitting.

To set the metrics more into relation to our use case, we can say that a higher precision is more important than a higher recall, since the setting of an ongoing monitoring of patients and users with wearable sensors does not require the detection of every stride that shows an abnormality. The precision is then more important to ensure that the patient or the clinician do not get worried and irritated by false positives but can trust in the system and get reliable alarms. When optimizing our algorithm we therefore target mainly an improvement of the precision.

4.5.2 Influence of Normalization Length

Since the compute time of the classification is of high interest for a real time monitoring, we try to identify if down-sampling the data would be a reasonable off-trade of performance for better run time. To evaluate the influence of different lengths for the normalization of the strides, we compare the performance from the last section with a normalized length of 500 ms to the performance of shorter normalized strides with a length of 200 ms, which can be seen in table 5, and the performance of strides with a length of 100 ms, which can be seen in table 6.

Class	**Precision**	**Recall**	**F1-Score**
Normal	1.00	1.00	1.00
Pelvic Obliquity	1.00	0.99	1.00
Limping	0.99	0.99	0.99
Small Steps	0.96	1.00	0.98
Shuffling	0.93	0.94	0.94
Insecure Walking	1.00	0.93	0.96
Weighted Average	0.98	0.98	0.98

Table 5: The performance report of our classification with stride lengths normalized to 20 ms

The performance metrics in table 5 compared to the performance metrics in table 4 show that the overall performance did slightly increase. We now have two f1-scores with a value of 1.00 and have lifted all metrics above 0.93. Most of the changes are too small

Class	**Precision**	**Recall**	**F1-Score**
Normal	1.00	0.98	0.99
Pelvic Obliquity	0.99	1.00	1.00
Limping	1.00	1.00	1.00
Small Steps	1.00	1.00	1.00
Shuffling	1.00	1.00	1.00
Insecure Walking	1.00	1.00	1.00
Weighted Average	1.00	1.00	1.00

Table 6: The performance report of our classification with stride lengths normalized to 10 ms

to be based on the change of the normalization length with certainty, since we also need to take into account the influence of the shuffling in the splitting of training and testing data. we therefore have to conclude that we do not see a significant overall change in performance. Two values that stand out though are the precision of small steps having risen from 0.88 to 0.96 and the recall of insecure walking having improved from 0.85 to 0.93. This could be related to the elimination of padding, which might therewith eliminate wrong classifications based on stride length.

The performance of the even shorter normalized strides of 10 ms again improved slightly. As can be seen when comparing the metrics for 200 ms in table 5 with the metrics for 100 ms in table 6, nearly all values, except for precision for pelvic obliquity with 0.99 and recall and f1-score for normal strides with 0.98 and 0.99 respectively, have risen to the perfect score of 1.00. We now also reached a weighted average of 1.00.

While this seems like a (nearly) perfect classification result, we need to again refer to the shuffling in the data set that makes the certainty of this trend questionable. That taken aside, the metrics show a slight trend for better performance with more strongly normalized strides by higher down-sampling ratios. This could be based on not only the elimination of padding, but also on the overall elimination of large differences in the distance from original to down-sampled sampling rates of the strides.

With the overall weighted average having risen only by 0.02 in both normalization shortenings for all metrics however, we see a small trend for improvement without enough certainty for consistent results regarding the normalization length of strides and have to conclude that it does not seem to have an impact of large significance.

4.5.3 Influence of Value Range Normalization

Another approach of normalizing the data is the normalization of the value range. To rate this approach, we simultaneously tested the classification algorithm with a normalized stride length of 100 ms for both the raw value range and a normalized value range from 0 to 1. When we compare the performance results of the classification on strides normalized to 100 ms of the non-normalized value range with the performance results of the normalized value range, we come to the conclusion that this parameter does not seem to have any momentous influence on the performance of the classification. We would therefore not focus on this in further investigation for improvement.

4.5.4 Impact of the Sensor Combination

The goal of combining multiple sensors on different measure points on the test subjects body was to improve the overall performance and detect more gait abnormalities with higher precision. Evaluating the performance results of our experiment with strides normalized to 500 ms makes it clear that the combination did indeed improve the performance. The weighted average f1-scores of the single sensor metrics range mostly from 0.59 to 0.70, with the exception of the feet which score higher weighted averages of f1-scores at least in the acceleration measures with ranging from 0.75 to 0.86. This agrees with our assumption that the feet would be the most important measurement points, which would justify the use of smart insoles. The knee sensors on the other hand have the lowest overall performance. But only the combination of all sensors could reach the weighted average f1-score of 0.96, especially by incorporating strengths of sensors like the influence of the hip sensors in detecting hip-related abnormalities like pelvic obliquity or limping but still balancing out weaknesses like the lower performance of the hip sensors with feet-focused abnormalities like shuffling.

4.5.5 Evaluation of the Run Time

Apart from comparing the test results, we also monitored the run time of our classification approach and had side findings regarding the impact of the different normalization settings.

Despite the comparison of the performance results, we can make clear statements about the difference in run time. With DTW having quadratic run time, our algorithm took 30 minutes to test all input values for one sensor metric with strides normalized to a length of 500 ms. For all 36 sensor metrics together, this aggregates to 18 hours of total run time for the testing, in other words the actual classification step. With the stride length sampled down to our smallest example, 100 ms, the run time for testing per sensor metric was around 3 minutes, which resulted in 108 minutes (1.8 hours) of total run time. We could therefore reduce the total run time to 10% of the original assessment. The value range normalization did not have a noticeable impact on the run time.

Even with the strides being highly down-sampled to 100 ms, we came to the conclusion that *k-nn* as a classifier was sufficient for this feasibility study but not the optimal choice for real-time monitoring of patients. A consideration for optimizing the run time of *k-nn* would be to abstract the data via feature extraction. Our suggestion for ongoing, autonomous, and real-time monitoring as described in our proposal would be to choose another classifier that shifts more of the computation effort to the training step and less to the testing step.

4.6 Conclusion of the Feasibility Study

After the successful execution of the feasibility study we can conclude, that it is possible to apply machine learning on sensor data in order to detect gait abnormalities. To pass the recordings to the machine learning algorithm, it first needs to get pre-processed. We described such a pre-processing pipeline that is independent from the walking distance and returns strides in a normalized form. Furthermore we have been able to show that additional sensors indeed improve the overall accuracy of such an algorithm. The most important sensor locations are however the feet.

For the data collection three subjects have simulated several gait problems based on YouTube videos. However, that also indicates that the results are potentially biased, since the amount of test subjects is rather low and nobody really suffered from a gait problem. The accuracy therefor might be higher due to over-fitting.

On the other hand we could verify, that jumping indeed works for synchronizing the different sensors. We suggest to have a dedicated phase, were the subject is not moving, at the beginning. That could improve the calibration even further. Other than that it is important, to comply with the waiting time in order to get the best results. Another approach could be to separate the exercises into several measurements instead of doing all exercises in a single measurement.

Last but not least, we would advise to do some test measurements first to get familiar with the sensor equipment. We learned for example that the Bluetooth connection, that is being used for transferring the data between the sensors and a storage device, can be very poor and interfere with the measurements.

5 Discussion and Conclusion

In this research proposal we described an approach to improve the Gait Analysis of elderly people. In section 1 we introduced the procedure of the human gait cycle itself and described typical problems and abnormalities as well as causes for those in the walking behaviour of elderlies.

In section 2 we gave an overview of different existing techniques to analyse the human gait with a focus on wearable devices, especially sensor equipped insoles.

Finally we proposed *GaitSet* in section 3, a setup of various sensor-equipped devices that can be attached to the user's body to collect long term data in daily life activities. Therewith it should be possible to draw a full picture of a persons walking behaviour by considering the test subject's whole body. The collected data should be evaluated by an algorithm and analyzed conspicuities recognized so further steps to improve the issues can be recommended.

The feasibility study in section 4 gave an overview of a possibility to use data of sensorized devices attached to an experimentee to recognize patterns in human gait. Additionally it helped to define the importance of the different sensors. The feasibility study described a setup of six IMU sensors placed on various test persons to gather sensor data of different walking abnormalities. The measured time series sequences were preprocessed into normalized strides and later classified by a machine learning K-Nearest Neighbors approach. Using this procedure we were able to recognize and classify conspicuious walking issues as respective gait abnormalities automatically.

6 Appendix

Algorithm 1 The calibration algorithm

```
zeroMovementWindowSize = 200 # 10ms * zeroMovement

def calibrate(series):
    zeroWindowIndex = series
                        .abs()
                        .rolling(zeroMovementWindowSize)
                        .median()
                        .sort_values()
                        .index[0]
    zero = series
            .rolling(zeroMovementWindowSize)
            .median()
            .iloc[zeroWindowIndex]
    series -= zero
```

Algorithm 2 The Dynamic Time Warping algorithm

```
def DTWDistance(series1, series2):
    windowSize = 4
    DTW = {}

    windowSize = max(windowSize, abs(len(series1) - len(series2)))

    for i in range(-1, len(series1)):
        for j in range(-1, len(series2)):
            DTW[(i, j)] = float('inf')
    DTW[(-1, -1)] = 0

    for i in range(len(series1)):
        for j in range(
            max(0, i - windowSize),
            min(len(series2), i + windowSize)):
                dist = (series1[i] - series2[j])**2
                DTW[(i, j)] = dist + min(
                    DTW[(i - 1, j)],
                    DTW[(i, j - 1)],
                    DTW[(i - 1, j - 1)])

    return math.sqrt(DTW[len(series1) - 1, len(series2) - 1])
```

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