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Radar-based gait analysis for medical applications using a millimeter wave FMCW radar

A Feasability Study

Master's thesis in Biomedical Engineering

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Abstract

When it comes to gait analysis in clinical settings, constant monitoring of patients is something that has not yet been fully realized. Current methods often involve added sensors or discrete equipment that is generally limited by the monitoring environment or the patient's ability to interact with on a daily basis. Recent developments in millimetre wave technology has given us radar sensors with high operating frequencies which allows for a significantly higher resolution when compared to conventional microwave radar sensors. In this thesis we present a potential solution that utilizes a millimetre wave sensor for a non-contact, privacy preserving method of gait analysis that yields relatively accurate data as a result.

The primary focus of this thesis is to explore the feasibility of using this millimetre wave radar sensor for gait analysis and to extract clinically relevant parameters from radar data. The data was acquired from human subject measurements that we performed in front of the radar sensor. The parameters are extracted from the data using signal and image processing methods in Matlab which are then compared with parameters acquired from video footage of the same tests in order to gauge the relative accuracy of our methods.

In the end we find that the millimetre wave radar sensor is indeed a good candidate for non-contact gait analysis, as it shows a relatively accurate measure of relevant gait parameters ranging from temporal to kinematic. The findings presented here are a significant foundation for further research and development of constant, non-contact gait monitoring methods.

Keywords: Radar, Gait, Analysis, FMCW, Continuous, Wave, Non-Contact, micro-Doppler.

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This thesis is dedicated to my late grandfather, Halldór Stefán Pétursson, whose support inspired me to pursue the field of engineering.

Halldór Stefán Laxdal Báruson, Gothenburg, June 2022.

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1

Introduction

With a steadily increasing world population, which is estimated to surpass 8 billion in the year 2022, the population of elderly grows steadily along with it as modern medicine and new technologies continue to improve the quality and capability of life [1]. According to the World Health Organization, the global proportion of elderly individuals over the age of 60 is estimated to double from around 11% to 22% between 2000 and 2050 [2]. The normal process of aging does come with a decrease in body functionality which has been linked with a decrease in quality of life, sometimes even an increase in the risk of falling and mobility impairments as the person grows older [3]. The fact that the population that is at a greater risk of developing and su ering from cognitive diseases would still remain proportional to the population of elderly has brought the question forward whether it is possible to predetermine or detect ahead of time if a patient is at risk of developing severe cognitive disabilities.

Diseases that a ect a person's cognition and cognitive abilities most commonly begin the onset in senior or elderly persons, with Parkinson's patients usually developing their rst symptoms around the age of 60 and Alzheimer's patients aged 65 and older [4] [5]. The prevalence of new Alzheimer's patients in the United States was found to be increasing with age, ranging from 4 out of 1000 individuals aged 65 to 74 and up to 76 per 1000 for individuals older than 80 [5].

Numerous studies have shown that a link exists between early cognitive degeneration and an increased abnormality in a person's gait, which can manifest in variations on the person's gait parameters based on where the cognitive degeneration originates [6] [7]. For patients with early onset Dementia, this can be observed as insecure, short steps, widened stances and an overall decrease in the patient's ability to regulate their own movement speed [8]. Patients with early onset Parkinson's exhibit similar gait abnormalities with an added di culty of performing key gait related events such as starting, stopping and turning while walking [9].

The gait changes are usually incredibly minuscule as the disease begins to manifest, but they grow more and more apparent as the disease progresses, which makes it di cult to detect early on so that preventative or mitigative measures can be taken. The current clinical evaluation of gait parameters is carried out by a specialist of the eld, but tends to give highly subjective results as the tests can be both time consuming and costly and also lacking reproducibility as they are based on a controlled observation of the patient.

In order for a more objective analysis, the patient must be passively observed for longer periods of time over many days. This would result in a baseline estimation of the patient's gait and their gait parameters which can be monitored over time for signs of changes. This means that patients that are at risk of developing gait abnormalities could be observed earlier and for longer periods of time in order to detect any gait abnormalities early, and therefore be able to take preventative or mitigative measures against cognitive degeneration.

1.1 Existing Methods

There have been developments in technology that have enabled the possibility of constant gait monitoring, but a lot of the solutions are not feasible for long term monitoring of the elderly. Some solutions include wearable sensors that monitor inertia of limbs which is not feasible to expect elderly patients and users to apply to themselves every time monitoring is to take place [10].

Other directions to solve this problem have been explored, with one company developing oor sensors that can detect if patients have fallen or are at the risk of falling. This is mainly to be used in elderly homes, but the company is exploring private use [11]. This can be quite expensive to set up, as every square meter of walkable oor space will have to be covered in these sensors as it is quite di cult to predetermine where the patient is at risk of falling.

Camera monitoring in both visible and infrared (IR) light have been explored extensively for gait monitoring purposes, as depth based systems that utilize IR light can calculate time of ight [6], which can be used to determine distances traveled to a very precise degree. Infrared light is also the primary tool behind infrared thermography, which is able to create visual images based on thermal intensity of the target, which can be recorded and classi ed to extract relevant gait parameters.

These systems have shown decent performances in most environments, though as with all camera systems, the environmental lighting levels have to be considered as it can a ect the output signi cantly, change based on clothing re ectivity levels or even thermal levels during days or hours where the radiation of the sun can a ect indoor surface temperatures. Camera systems that are installed in the patient's home are also perceived to be rather intrusive for their sense of privacy, regardless of the system's purpose.

For this reason radar technology seems to be the most optimal candidate for gait monitoring. Microwave radar sensors have been widely examined and researched for the purposes of gait monitoring [12] [13] [14] as they o er a non-contact solution due to the ability to be set up virtually anywhere and with a good eld of view and delivers continuous monitoring of a person within that eld. It is also cost e ective, simple to use and set up and preserves the person's privacy if it is being used at home.

1.2 Using Radar Devices for Gait Analysis

Recent developments in the eld of radar technology has brought forth millimeter wave sensors, which can operate at a signi cantly higher frequency than the conventional microwave radar sensors. The available bandwidth that they operate on gives a signi cantly higher spatial resolution than conventional radar sensors. The higher frequency range means that the antenna array is signi cantly smaller as well, so the form factor of a millimeter wave system is smaller, cheaper and more compact than a microwave system, which makes it optimal for in-home deployment. The smaller antenna array has the bene t of a narrower radar beamwidth, which can help reduce interference and to focus the EM energy that is radiated towards the subject in front of it. These sensors have already been researched for the purpose of human body measurements in the automotive industry as a vital sign monitoring system [15], but they are a promising candidate for gait monitoring as well.

1.3 Thesis Structure

The papers cited in this thesis were obtained via the Chalmers digital library and Google by using simple search terms such as gait analysis, gait in elderly, radar based gait analysis, and more. The data processing in this thesis was performed using Matlab on the student's computer, which was also used for communicating with and recording tests with the radar system used in this thesis.
In chapter 2 - Theory, we outline the physiological process of the human gait; what parameters make up the gait, where it originates from and how it is affected by cognitive diseases. We then introduce the radar system chosen for this thesis, how it works and what signal processing methods are used for processing the data from it. In chapter 3 - Methodology, we delve deeper into the test set-ups using the radar device, the methods we use for processing the acquired data and how we will be able to perform gait monitoring and parameter extraction using them. In chapter 4 - Results we present the different tests we performed, all from simple target tracking, to analyzing gait variation and parameter extraction. We briefly cover a simultaneous experiment performed side by side with a Continuous Wave (CW) microwave sensor which was done in order to visualize the differences between the two systems. In the end we perform a comparison analysis of the extracted parameters from the radar system and the measured parameters from a video recording of the same tests. The results from this chapter are then further discussed and elaborated on in chapter 5.
The thesis is then concluded in chapter 6 - Conclusion, where we summarize our experiments and the results from it and come to a conclusion regarding the thesis question posed here at the start. We also discuss how the presented methods could be improved as well as potential future work related to this topic.

1.3.1 Aims

Currently there exists no non-contact product on the market that performs gait analysis continuously, while also fulfilling the patient's requirements of personal privacy and being cost-efficient enough for the private market. In this thesis we aim to show how feasible it is to use a millimeter wave, frequency modulated continuous wave (FMCW) radar sensor for the purpose of continuous gait monitoring and to examine how it can be used to extract medically relevant gait parameters.

2

Theory

In this chapter we cover the necessary theoretical concepts required for this thesis. We discuss how Frequency-Modulated Continuous Wave sensors operate and the basics of data analysis. We also discuss the origin of gait in the brain and how cognitive diseases can a ect the gait process.

2.1 Frequency-Modulated Continuous Wave Radar Sensors

A FMCW (Frequency Modulated Continuous Wave) radar sends out a series of chirps, which are an oscillating sine wave with an increasing frequency over time for some de ned bandwidth [16].
As shown in gure 2.1, the chirp signal is characterized by a starting frequency fc, a bandwidth B representing the frequency interval and a chirp duration time Tc. The slope S of this frequency-time curve determines how fast the chirps increase in frequency, and is a function of its bandwidth and the chirp duration, which is represented in equation 2.1 [16].

$$S = \frac{B}{T_c} \tag{2.1}$$

The main method of generating, transmitting, receiving and processing these chirps is demonstrated in the block diagram in gure 2.2 [17].
The signal transmitted from the radar can also be described mathematically as T(t) in equation 2.2, with an amplitude $A_t(t)$, starting frequency f_c, bandwidth B and a chirp duration Tc as shown in equation[18].

$$T(t) = A_t(t)\sin\left(2\left(f_c t + \frac{B}{2T_c}t^2\right)\right) \tag{2.2}$$

Since the emitted signal is electromagnetic in nature and propagates from the antenna to an object and re ects back towards the receiving antenna with the speed of light c, there will be a slight time di erence between transmitting and receiving as the wave propagates from the radar sensor towards a target positioned D_0 meters away from the sensor and back again. This time di erence can be calculated using equation 2.3.

$$t_d = \frac{2D_0}{c} \tag{2.3}$$

To describe the re ected signal reaching the receiving antenna, the delay de ned in equation (t_d) must be taken into account. If the object is assumed to be still when it is hit by the radar signal, the re ected signal can be described according to equation 2.4 [18], where $A_r(t)$ is the amplitude of the received signal.
However this is not really realistic as the body does not remain still. People breathe, dget and the body sways and moves slightly as the person tries their best to remain still. This

(a) Amplitude-Time

(b) Frequency-Time

Figure 2.1: Illustration of a chirp: (a) Time-Domain waveform (b) Frequency versus time

can be addressed by making T_c as small as possible, making it so that the measured range (D_0) between consecutive chirps separated by T_c, can be seen as constant as the signal is re ected from the target.

$$R(t) = A_r(t)\sin\left[2\pi f_c(t - t_d) + \frac{B}{2T_c}(t - t_d)^2\right] \tag{2.4}$$

The process of demodulating is inherently similar to how regular FM signals are demodulated: The received signal, $R(t)$ (2.4), is mixed with a copy of the transmitted signal $T(t)$ (2.2), low pass ltered, and the e ects of the transmitted signal are thereby removed, forming a signal referred to as the intermediate frequency (IF) signal. This IF signal can now be sampled using the onboard A/D converter, allowing us to sample the signal at a signi cantly lower frequency as we now have just the information acquired from the radar, not the 77 GHz carrier wave. This IF signal is described as $S(t)$ in equation 2.5 [18]

$$S(t) = A_{IF}(t)\cos\left[2\pi\left(\frac{2BD_0}{cT_c}t + \frac{2f_cD_0}{c} - \frac{B}{2T_c}\frac{2D_0}{c}^2\right)\right] \tag{2.5}$$

Where $A_{IF}(t)$ is the amplitude of the IF signal. For very small distances D_0, we can approximate the last part of that equation to zero, which results in the following approximation:

Figure 2.2: A Typical FMCW Radar System Block Diagram[17]

$$S(t) \quad A_{IF}(t)\cos\ 2\quad \frac{2BD_0}{cT_c}t + \frac{2f_cD_0}{c} \tag{2.6}$$

As demonstrated by equation 2.6, the IF signal contains the information of a single reflected object with a fixed, constant distance D_0 from the sensor with one frequency, f_{object}. This frequency is inherently proportional to the range of this object, which we can estimate by using equations 2.6 and 2.1:

$$f_{object} = \frac{2BD_0}{cT_c} = \frac{2SD_0}{c} \tag{2.7}$$

However in reality, the radar produces an IF signal that contains responses from several different reflections, which range from static to dynamic objects within the radar sensor's field of view. These frequencies are proportional to the distances to the targets as stated in equation 2.7.
The radar's ability to distinguish between two objects close to each other is determined by the range resolution, which means if two objects are closer to each other than the range resolution allows, they will be indistinguishable from each other in the IF signal. For an FMCW radar, this resolution is described according to equation 2.8 [16].

$$D_{res} = \frac{c}{2B} \tag{2.8}$$

The maximum range that can be acquired is described in equation 2.9 and is determined by the sampling rate, F_s.

$$D_{max} = \frac{F_sc}{2S} \tag{2.9}$$

Note how the phase of the IF signal in equation 2.6 is also proportional to the range D_0. Because of this we can utilize the phase of the IF signal to detect smaller movements over time.

2.1.1 Fast time and slow time in FMCW radar

As we capture each chirp, the resulting IF signal is sampled by an A/D converter before being collected in a matrix as shown in figure 2.3(b). This figure shows how data from each chirp is placed in its own row in the matrix.

This matrix is inherently de ned by two time dimensions, fast and slow time. Fast-time corresponds to minuscule time measurement of the radar data that is acquired with each chirp and slow-time is a typically much larger time scale, which corresponds to the dimension of when each chirp was sent out [18].

In order to measure instantaneous velocity using this system, the radar must transmit at least two chirp frames. The high transmission rate of these frames would show that while two consecutive frames might have peaks in the same place in the range data, their respective phase information will di er. This is because the phase of each frame is a ected by velocity, not the range so in order to measure the velocity of a target, we need to observe the phase di erence between frames. This transmission is referred to as a chirp frame, which is illustrated in gure 2.3(a) [16]. For our project, the radar was con gured so that the system would transmit one chirp per chirp frame for convenience.

In gure 2.3(a), the time di erence between two chirps is labeled as T_s, and the frequency with which these chirps are transmitted can be calculated simply as $f_s = \frac{1}{T_s}$, which we can de ne as our sampling frequency.

(a) The chirp train

(b) The matrix that is formed by recorded chirps.

Figure 2.3: Illustration of (a) the chirp train and (b) the resulting matrix that is formed from the data acquired from the FMCW radar. Each subsequent chirp is recorded in each row of the matrix depicted in (b)

The data obtained from the radar that is sampled and collected into the rows of the matrix described in gure 2.3(b) is complex valued and also referred to as I/Q data [15].
The I/Q data is separated into two components; in-phase (I) and quadrature (Q) phase, which are phase shifted 90 to each other [15]. In order to obtain microscopic velocity movements of the target as it moves in front of the radar sensor, we need to extract this phase information from the complex I/Q data [15]. In this section we describe the process used to obtain the necessary information from the complex radar signal.

If an object travels within the radar's de ned maximum range then it is possible to detect this speci c object's precise movement by studying the phase di erence in the resulting IF signal. The accuracy of these movements is determined by the range resolution that is described with equation 2.8.
For this project, we heuristically decided upon a frequency bandwidth of 3.6 GHz, which

with equation 2.8 results in a range resolution of 4.16 centimeters. This allows us to detect each leg as a separate object in front of the radar and to distinguish between the foot and the knee joints. However, the phase of the IF signal is very sensitive to small movements from di erent objects. This can be various microscopic movements of clothes, arms, even just torso movement. The phase can be mathematically described with equation 2.10, where $= cf_c$ is the chirp's starting wavelength [19] [20].

$$= \frac{4 f_c D_0}{c} = \frac{4 D_0}{} \tag{2.10}$$

Even if the phase information contains D_0, it is not possible to determine the absolute range between the radar sensor and the object by only observing the phase when it is 2 - periodic [19]. Instead the phase can only be used on its own to detect the target's relative range displacement [15]. For each transmitted chirp, a phase value is obtained and therefore the phase sampling frequency will be equivalent to the chirp transmission rate. By observing the phase di erence, between IF-signals from two consecutive chirps, the relative range displacement D_0 can be used to describe the phase di erence with equation 2.11 [20].

$$= \frac{4 f_c D_0}{c} = \frac{4 D_0}{} \tag{2.11}$$

This phase di erence can then be used to nally calculate the instantaneous velocity of an object at distance D_0 between those consecutive chirps with equation 2.12 [20] where T_c is the observation interval of the current chirp frame.

$$v = \frac{}{4 T_c} \tag{2.12}$$

2.1.2 Preprocessing of radar signals

In section 2.1.1 we showed how the IF signal is acquired from each chirp frame of the data, resulting in the slow and fast time matrix described in gure 2.3. If we apply the fast Fourier transform (FFT) to the I/Q data of each chirp, for every row in gure 2.3(b), the di erent frequency components of the IF signals can be distinguished by observing the amplitude spectrum as a function of its frequency. If the signals contain re ections from some range away from the sensor, it will contain the frequency corresponding to the current distance that target was re ected from, as determined by equation 2.7. At that frequency we can obtain a peak in the amplitude spectrum. This is referred to as range-FFT [15]. In gure 2.4, we can see the steps required to extract the fast-time and slow-time data from the radar sensor's I/Q data.

Figure 2.4: Flow diagram of the preprocessing of raw data.

Figure 2.5: An example of the amplitude spectrum as a function of range from one I/Q data row.

Figure 2.5 demonstrates what the amplitude spectrum as a function of range looks like from the I/Q data of a chirp. For this gure, we've chosen an arbitrary minimum value so that the peaks in the spectrum can be considered re ected objects.
The resolution of the horizontal axis in gure 2.5 is limited by the range resolution of the range-FFT in equation 2.8. This scale is divided into range bins. To nd information regarding a speci c target within the range-FFT, we can look at the range bin that corresponds to the distance to the target [15].
For each chirp, the phase of the current range bin is then obtained by calculating the phase of the complex signal obtained after the FFT has been applied to the I/Q data [15], [20]. This obtained phase value ranges between and radians, which is therefore said to be wrapped.
In this wrapped phase there can be discontinuities in the data when the phase value is close to either or . In order to eliminate this issue, we can perform phase unwrapping. One way to unwrap the phase is to add or subtract 2 when the phase di erence between two consecutive chirps is greater than or less than radians [21].
We can use this unwrapped phase to observe the relative displacement of the detected object at the range bin selected by using equation (2.10).

2.2 Gait Analysis

The human gait is for the most part periodic and we can de ne it with a set of spatial, spatio-temporal and kinematic parameters. Spatial parameters refer to distances that the limbs travel. These can be divided further into stride width, which is the width between feet in a successful stride,stride length and step length, which is the length between consecutive, alternating steps [12]. Spatio-temporal parameters refer to both space and time and in the case of gait analysis it refers to the time duration of various gait events. Namely stance time, step time and stride time. Finally, kinematic parameters describe the gait velocity. That is the stride velocity which is usually tracked at the foot level. Stride velocity is also de ned as the product of step length and cadence, or walking rate.

In gure 2.6 the spatial gait is illustrated, along with a few of its most notable parameters [22].

Figure 2.6: Spatial Gait and the most notable parameters [22]

These parameters tend to be vary slightly between individuals, which makes gait analysis ideal for person identi cation and classi cation [23] For the purposes of video surveillance, the stride length was found to be the most signi cant spatio-temporal parameter for identifying di erent persons [24].

The periodic motion of the human gait cycle can be classi ed and separated by the speed of which it is performed, and can be separated into walks, jogs or runs. The speed we are most interested in for this project however is the regular human walking gait, which is what most are capable of performing, and nd most comfortable to perform. The preferred walking speed for adults ranges between 1 and 1.4 m/s and tends to decrease signi cantly as the person ages, where studies have shown that gait velocity in community dwelling elderly trends down between 0.7 and 1.1 m/s [25] [26]. This variation in speed can generally be linked to various physiological parameters, such as physical tness, height and limb length but this sudden decrease in speed is mostly linked to some of the myriad of factors that come with aging, such as a general decrease in cognitive function and physical capability [27]. However gait disturbances can also occur much earlier than anticipated due to further cognitive decline caused by the onset of brain disorders such as Parkinson's, Alzheimer's or dementia.

This dramatic change of walking speed as the person ages has also been linked to an increased risk of adverse e ects, with gait velocities going below 0.7 m/s being a strong indicator of fall risk among community dwelling elderly aged 75 and over [26].

2.2.1 The origin and control of gait in the brain

The gait process is a ected by many internal and external factors, though the regulation of gait is performed by the central nervous system (CNS) as a combination of both autonomous and voluntary commands which are generated within the Central Pattern Generators (CPG) [28]. The CPG are a cluster of neurons within the spinal cord which control the rhythmic pattern of human gait.
As mentioned, the regulation of the human gait can be divided up into voluntary and automatic commands and processes. The automatic process which is de ned as the periodic limb movements that are performed during walking is regulated within the cerebellum and the midbrain which respond directly to the CPG [28]. The automatic process is dependent on a lot of sensory inputs, such as direct visual input, somatosensory information originating from joints and muscles, cutaneous sensory information for identifying surface characteristics and gravity information from the graviceptors in the stomach and brain.
The complexes that provide the goal and purpose during walking are located in the forebrain and which are then regulated within the cerebellum, spinal cord and brainstem. Together these parts form the processing section of the gait pathway [28]. -
The voluntary process of gait is primarily derived from the cerebral cortex in the forebrain, which is in direct communication with the brainstem and spinal cord for gait regulation. There, the sensory inputs from the visual, vestibular and primary sensory cortices are combined and regulated for ne locomotive execution. The information generated here is transmitted to the supplementary motor area (SMA) which handles postural control and the premotor area. These processes are still dependent on automatic processes for the execution of gait and maintaining posture and regulating balance and muscle tone [28]. The voluntary processes that exhibit emotional references can also be a ected by sympathetic nervous system responses, such as ght or ight events [29], which are further regulated within the brainstem and spinal cord.

2.2.2 How does cognitive decline a ect gait?

As previously established, the gait process is primarily controlled in the CPG and regulated by the cerebellum, brainstem and spinal cord. The forebrain also contains many complexes that a ect the gait process. Among them are the basal ganglia, frontal subcortex and motor cortex, which provide the purpose and goal for walking and are very sensitive to perturbations. As these complexes are within the gait pathway, it is only natural that gait disturbances occur due to some form of disturbance in these complexes [27].
Gait disturbances can be expressed in multiple di erent ways, both very minute and subtle changes to very exaggerated or reduced movement. The most common patterns of gait disturbances can range between hypo- and dyskinetic (meaning slowed and staggered movement), ataxic (unsteady and staggered) and psychogenic (excessive slowness and hesitation).
These disturbances are most often observed in patients who su er from various cognitive diseases. An example that can be seen in patients su ering from Parkinson's disease is how their gait freezes between steps. This is expressed as arrested movements during kick-o of the foot [27].
In the elderly population, the pattern of gait disturbances are increasingly common as sensory de cits and cognitive decline are the leading ailments that a ect this population, especially as the years go on. The prevalence of Parkinson's disease in Europe alone is 108 to 257 persons per 100,000 and the incidence rate is 11 to 19 per 100,000, making Parkinson's the most common neurodegenerative condition, with the most common age

of development being around 60 [30].
Research of Parkinson's disease has so far mostly been focused on the e ect on the basal ganglia, but recent investigations have shown that the cerebellum plays a certain role in how the disease manifests from the beginning of onset [31]. The cause of Parkinson's disease is still unknown, but research has shown that it a ects the basal ganglia signi cantly, causing a degeneration of dopamine secreting neurons. This hormonal imbalance has been shown to cause morphological changes in the cerebellum, which are related to a variety of gait related symptoms; such as rigidity, tremors, dyskinesia and other non-motor related symptoms [31]. As both the cerebellum and the basal ganglia are a part of the gait pathway, it is no surprise to discover a reciprocal connection between the two, especially when it comes to expressing gait disturbances.

A patient su ering from early Parkinson's disease might present with a shortened stride length, increased stride variability and reduced gait velocity [32]. In a control study of early stage Parkinson's disease patients and healthy individuals found that the most signi cant temporal parameters were cadence, stride duration and stance duration [32].

Other highly prevalent neurodegenerative diseases that are worth mentioning are multiple sclerosis (MS) and amyotrophic lateral sclerosis (ALS), which a ect the motor cortex and the spinal cord, causing gait disturbances as the disease manifests. For instance, patients with MS usually exhibit higher cadence and shorter overall walking speed than subjects without MS [6].

Impaired gait can also be observed with increased di culty of performing dual- or multi-task actions. This was further researched in a paper by Lundin-Olsson et al [33], where they observed an increased risk of falling when the patient stopped walking when talking , showing how gait observation can be a good measure for fall risk among the elderly population [33].
In a study by Kenshi Saho et al, a single frequency micro Doppler radar system was used to measure gait features in an elderly group of patients who su ered from cognitive decline. The study was performed alongside cognitive function tests which were used to validate their results and as a statistical basis. Among these tests were the mini-mental state examination (MMSE), which is a common test used to screen for dementia. The results revealed that the foot and leg velocities were statistically e ective as a means of classi cation of elderly participants with cognitive decline[12]. In particular was the leg velocity in the swing phase very signi cant in their results.

3
Methods

In this section we cover the various methods we used to perform gait analysis using the FMCW radar sensor. We describe how the data collection took place and which hardware was used to process the data received from the sensor. Finally we cover the data processing methods and how micro Doppler signatures and the respective envelopes were extracted.

3.1 Project Hardware

For this thesis we used an AWR1642BOOST radar board along with a DCA1000EVM data capture board, both from Texas Instruments for performing radar measurements and capturing the resulting raw data.

(a) AWR1642BOOST Sensor (b) DCA1000EVM Capture Board

Figure 3.1: Figure (a) shows the AWR1642BOOST Radar Sensor Board and (b) shows the DCA1000EVM Data Capture Board

The radar system modules are depicted in gures 3.1(a) and (b) and in gure 3.2 the assembled device is pictured as it was set up in its operating mode. The AWR1642BOOST module is an automotive FMCW radar sensor with an operating frequency of 77 GHz and a possible bandwidth of 4 GHz. In order to capture and process the data, the software mmWave Studio was provided by Texas Instruments. As of the release of this thesis, it is only available for Microsoft Windows computers [34]. For data processing and analysis,

the most recent version of Matlab was used, along with various signal and image processing packages that Matlab o ers.

Figure 3.2: Assembled Radar Sensor Module and the Data Capture Board

There were several di culties with the set-up of the radar user software due to various software and hardware incompatibilities. After a long back-and-forth between the student and Texas Instruments support, a full reset of the student's personal computer, the software was up and running and we were able to perform the data capture, processing and analysis for this project.

3.1.1 Radar Con guration

As mentioned in chapter 2, the bandwidth of our transmitted signal was chosen heuristically to be 3.6 GHz as it yielded a 4.16 cm range resolution. There are several more parameters that we are able to con gure within the operating software mmWave Studio. These parameters control the direct shape of the chirp frame, as well as how many frames the radar sends out. These parameters a ect the depth of penetration of the transmitted radar waves, the range of transmission and reception, as well as resolution of the re ected data. We can select the frequency that we start transmitting at, the bandwidth that we wish to modulate our chirps across, the time duration of each frame as well as the time duration of the chirps within and the number of chirps per chirp frame.
As our tests are kinematic for the most part, we decided on having only one chirp per frame and instead to increase the number of frames to correspond with the recording time. The frame duration was set to 0.5 milliseconds with a chirp ramp up time set to 0.45 microseconds. The number of frames varied between 30000 and 60000 depending on the type of tests we performed, which gave us a recording time of 15 to 30 seconds total.

Since our purpose is only to measure and observe the human gait cycle, we do not need a deep penetrating radar signal which is why we select the default starting frequency to be 77 GHz. In order to penetrate the target, we would choose a signi cantly lower frequency, something that the chosen radar system is not designed for. The received radar signal was sampled with a rate of 6.25 MHz which gave us 250 samples per frame.
The radar sensor's radiation pattern is depicted in gure 3.3 as it will become important for the analysis of our results [35]. As the sensor is designed primarily for automotive purposes, we can see that the sensor's horizontal plane is attenuated evenly as its eld of view is expanded, but its elevation plane is rather non-linear in its attenuation. Therefore the positioning of the radar system could seriously a ect the test results as anything directly outside of the 20 degrees eld of view could be attenuated signi cantly, making it di cult to extract any meaningful information.

Figure 3.3: AWR1642BOOST mmWave Radar Sensor Radiation Pattern[35]

3.2 Design of tests

We designed a basic test format for this thesis in order to capture the pattern of gait as accurately as possible for each occasion and situation that we decided to capture.
Due to availability and accessibility issues at the start of the thesis, we decided to rather utilize overground walking instead of walking on treadmills to base our results around[1].
Past research has shown that most gait analysis methods have utilized treadmills rather than overground walking, but according to Kenshi Saho's research that was mentioned in chapter 2, using controlled methods like treadmills only really produces more consistent results than overground walking and that the numerical di erences between the two di er only slightly [12].
We also estimated that by using only overground walking for our data analysis, that we would get more realistic data which could further support our question on whether the radar system is a feasible method for gait analysis.

[1] At the time of releasing this thesis, Chalmers University has opened a biomechanical laboratory on campus that o ers a wide treadmill along with plenty of motion capturing equipment for gait analysis.

Data was recorded and collected in three di erent environments, all within the Chalmers university campus at Johanneberg.
Some of these locations included various environmental clutter that was not too dissimilar to the ones found in a typical home environment.
This clutter consisted of o ce chairs, tables, desks and even a large metallic locker, which proved to be a challenge to work around.
The last location was a large and open gym hall, which for the most part was free of clutter. Most of the tests recorded for this thesis were collected in the gym environment. These environments can be seen in gure 3.4.

For each of these tests, a single subject is tasked with moving in front of the radar system and asked to perform di erent actions and activities while the system recorded them. In order to mitigate active re ections generated from excessive movements in the data, the subject was asked to keep their arms behind their back and to remain as still as possible while walking. These tests varied from the subject walking at di erent speeds, with a constant or varying pace and either towards or away from the radar sensor where it was set up. In the gym environment, a track was marked on the oor with half meter steps that the subject was encouraged to walk along with in order to keep the step length as xed as possible for data analysis.

The radar system itself was also addressed during the beginning stages of testing in order to fully resolve what the best positioning and orientation of it was in order to get the highest quality data possible. The quality of the recorded gait data was evaluated at di erent sensor elevations which takes into account the sensor's radiation pattern, seen in gure 3.3. In an attempt to resolve the range attenuation e ect of the radiation pattern on the data, the orientation of the sensor was also evaluated. The results of these experiments can be seen in section 4.1. In order to validate the results from our data analysis, a phone camera was set up to record a few tests to validate accuracy. In Seifert [14], they state that their radar system was able to produce parameters with a result di erence close to zero for all of their means of validation which was motion capture.
It was di cult to acquire tools to aid us in validating the results generated by this thesis, as velocity sensors were hard to come by during the time of this project.

A brief statistical analysis on the parameter estimation was therefore performed to estimate the accuracy of our methods with respect to video recordings of the tests. The student's phone was used to record a few tests and the parameters were visually estimated from there. The camera was limited to 30 frames per second, which for a frame by frame estimate had at least a 0.033 second error, which made accurate comparisons di cult. This analysis is covered in section 4.3.6 and compared with the visually estimated step times extracted from camera recordings of the same tests as the target traveled across 5 meters with a duration of 15 seconds.

The tests and the results of this thesis were produced and processed in Matlab, and the data was captured through the data capture board that was coupled with the radar sensor. This data was processed in the Texas Instruments mmWave Studio program which was run through a virtual machine on the student's MacBook Pro, as currently the only operating system which this software has been released for is Microsoft Windows.