Presence Detectors and Remote Heartbeat Sensing Using Radar Technology

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Abstract

Presence detectors based on different technologies have been around for many years now, with a constant expansion of situation implementations. In this thesis, an overview of the capabilities of different types of presence detectors has been done and the radar technology have been further investigated. A 60 GHz pulsed coherent radar has been used to measure the limits of the radar sensor's distance and movement capabilities to extract motions originating from the heartbeat. With the radar set to a constant distance measurements of different aspects of the heartbeat characteristics as well as breathing pattern and its influence on the heart rate were performed.

Measurements of the authors' chest movement from breathing and heartbeats have been performed to yield information about the morphology of the chest movement based on the characteristics of the heartbeats. A neural network was set up and trained by data sets from heartbeat movements while holding the breath to identify the small changes of heart beats from different persons and to classify and predict who the heartbeat belongs to. An average success rate of 90 % was achieved when predicting which person the heartbeat sequence belong to.

The heart rate variability (HRV) has also been a subject to investigation where the breathing pattern is taken into account for changes in the heart rate throughout the breathing cycle. The results indicate a promising method of measuring breathing pattern, heart rate and corresponding heart rate variability needing no physical contact.

Popular Science Summary

Detektering och igenkänning av hjärtslag med radar och maskininlärning

Att använda sitt egna hjärtslag för att kunna identifiera sig med kommer helt och hållet förändra sättet vi ser på biometrisk identifiering. Med hjälp av en radar med millimeter-stora vågor kan vi idag mäta otroligt små avståndsförändringar, och tillsammans med maskininlärning kan vi använda detta för att mäta hjärtslagets unika rörelser för att skilja på personer med upp till 97% säkerhet. Detta utförs dessutom av en väldigt energisnål och billig radarsensor som man kan implementera i många olika typer av produkter.

Man har nyligen börjat använda kontaktlösa metoder för att känna igen personer och ha möjligheten att logga in på en telefon med till exempel ansiktsigenkänning. Med radarteknik kan man dock göra detta på ett mycket längre avstånd då man inte behöver vara nära själva kameran. Detta gör så att man kan utöka detta system till större områden och därmed till nya användningsområden samtidigt som det ger ett alternativ för igenkänning på kortare avstånd.

Radar är en relativt gammal teknik som använts framför allt av militären för att detektera objekt som man annars inte kunnat se. Efter närmare 100 år av utveckling har man idag möjligheten att detektera extremt små rörelser då vi idag använder oss av frekvenser på upp till hundratals GHz (hundratals miljarder svängningar per sekund), allt detta gjort möjligt på en yta som är mindre än nageln på ett lillfinger. Då radar använder sig av elektromagnetiska vågor krävs heller inget synligt ljus för att använda systemet, som många kameror för ansiktsigenkänning idag använder sig av. Att använda sig av hur hjärtats slag ser ut gör det även extremt svårt att göra en förfalskning av då det är något som är mycket svårt att alternera eller återskapa.

För att kunna skilja på de olika hjärtslagen användes maskininlärning som genom klassificering av hjärtslagets form kan spara en matematisk representation av hjärtslaget som man senare kan jämföra med. Man börjar först med att bygga upp en databas av hjärtslag för att få en bra klassificering. Detta är inte något en människa kan göra genom att bara titta på datan utan det krävs artificiell intelligens (AI) för att hitta mönstren i datan. Vi lyckades här med att klassificera rätt hjärtslag till rätt person med upp till 97% säkerhet, med ett snitt på cirka 90%. Skillnaden beror mest på vilka hjärtslag som används för att bygga upp databasen och vilka som användes för att jämföra med databasen. Genom att utveckla maskininlärningen och använda lite mer sofistikerade metoder kan man troligen få ännu högre träffsäkerhet.

Även andra användningsområden som Heart Rate Variability testades där vi kan se hur andningen påverkar hjärtats frekvens och rytm. Vi kunde se hur hjärtfrekvensen går ner vid utandning och går upp med inandning vilket gör att denna teknik även kan användas till olika hälsoundersökningar. Detta utan att vara i kontakt med personen vilket ökar bekvämligheten under en undersökning, något som kan uppskattas av många.

Acknowledgments

We would like to express our gratitude for all the people that have been involved in helping and supporting us during the work of this thesis:

Our supervisor, Professor Daniel Sjöberg at the Faculty of Engineering, Lund University, for his valuable reflections and acceleration of work flow.

Our industrial supervisor Simon Preutz at Axis Communications for the exchange of ideas which inspired us to differentiate our investigation and measurements and to further develop the possibilities of the technology used.

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Acronyms

BCG Ballistocardiography.

BiLSTM Bidirectional LSTM.

BRNN Bidirectional RNN.

CMOS Complementary Metal-Oxide-Semiconductor.

CW Continuous Wave.

ECG Electrocardiogram.

EMW Electromagnetic Wave.

FFT Fast Fourier Transform.

FMCW Frequency-Modulated Continuous Wave.

HRV Heart Rate Variability.

I/O Input/Output.

IEEE Institute of Electrical and Electronics Engineers.

IoT Internet of Things.

IQ In-phase and Quadrature.

IR Infrared (radiation).

LSTM Long Short-Term Memory.

PCR Pulsed Coherent Radar.

PIR Passive Infrared Radiation.

PPG Photoplethysmograph.

RADAR RAdio Detection And Ranging.

RNN Recurrent Neural Network.

SDK Software Development Kit.

SNR Signal-to-Noise Ratio.

SPI Serial Peripheral Interface.

USB Universal Serial Bus.

Chapter 1

Introduction

Different types of presence and motion detection systems have been used for a while now[1]. Many of them have had a military beginning in its use [2]. Nowadays many types of these technologies play an important role in daily life, from navigation and traffic control, automatic doors and lights to security and health uses[1] These technologies have been in constant development for several decades and some of them for more than a century [2]. To further this development we investigate the possibilities that these technologies can be used to, primarily in the security scene.

The different technologies we set out to investigate are as follows:

- Passive Infrared Radiation (PIR)
- Active infrared radiation
- RAdio Detection And Ranging (RADAR)
- Ultra sonic
- Other viable technologies

1.1 Thesis Goal

The goal of this thesis is to investigate if and how current technologies used for proximity detection could be improved or used in a new way to detect other data. These types of movements could for example be heart beat and heart rate variability or even identification through heart beat analysis from a distance, and also use simple and cheap sensors to detect movement paths, distances and presence which usually requires more expensive system solutions. In this thesis we try to determine what the possibilities of the different technologies are and what their potential could be. After identifying the opportunities for the different technologies one technology was put to test.

1.2 Thesis Work Division

This thesis is written by Mikael Thorström and Gustaf Anderson for the Department of Electrical and Information Technology at the Faculty of Engineering, Lund University.

The division of work during this project report has been divided evenly throughout with certain portions divided as follows:

Mikael Thorström has written most of the background text as well as most of the tools being used, he also wrote a significant portion of the radar section.

Gustaf Anderson did most of the work on the chapters regarding machine learning and the Theory of data classification, Gustaf also put much effort into the machine learning programming.

1.3 Outline

In the second chapter an overview of the different technologies researched and considered have been explained with a short description of the physical principle and historic use together with identified plausible applications.

The third chapter contains a descriptive section of the main detector used, the radar, and the theory behind this technology.

In the forthcoming chapters is a description of our work trying to achieve a successful “proof of concept” on one of the identified applications in chapter two. These chapters contain a more extensive description of the sensor used. They also contain a part on tools used as well as the results acquired.

In chapter 8 a discussion of what our results from chapter 7 tell us and what could be improved upon. The thesis is finished with a conclusion of our work and what future work could focus on when investigating further as well as the references used.

Chapter 2

Presence detectors

Presence detector technologies have been around for a long time now, initially used mostly by the military, beginning in the second world war where radar technology started to be widely used [2]. From being mostly used by military in different applications and technologies to being used in everyday security system today, these technologies play a very important role in today's society.

2.1 Passive IR

2.1.1 Background

The applications that are based on passive infrared radiation detection can be divided into two categories, mainly in infrared cameras/thermal imaging or temperature changes which is used for motion detection. The simpler of the two is the detection of temperature changes in order to detect motion. The principle build upon detection of changes in radiated heat to trigger on either motion or large changes in temperature, as shown in 2.1. This could detect explosions due to large temperature changes or simply someone moving in front of the sensor.

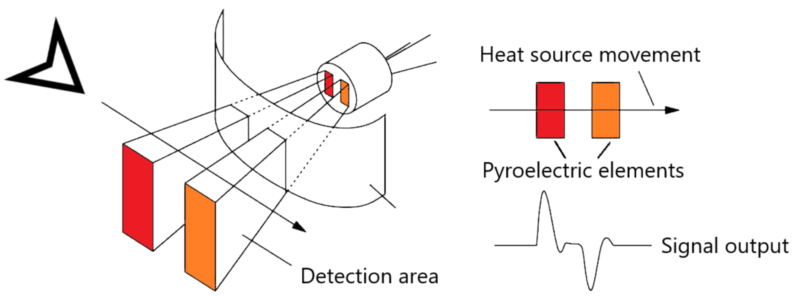


Figure 2.1: Principle of the PIR sensor function [3].

Passive infrared detectors (PIR) are usually based upon a pyroelectric effect when implemented in low powered motion detection applications. When the sensor is subject to a change in temperature a small current will be induced in the pyroelectric material. The pyroelectric sensors can detect very small temperature changes and the heat radiated from a body will be well enough to induce a current in the sensor (the average human adult radiate roughly 100W of heat with peak intensity at 9.3 μm, according to Wien's law equation 2.1).

$$\lambda_{max} = \frac{b}{T} \tag{2.1}$$

Where the peak intensity wavelength λ_{max} is given by the temperature T and the constant $b = 0.2898$ cm·K. To selectively use humans as the main detection object, PIR sensors usually have a filter which passes radiation in the 8-14 μm range. However the PIR is not a presence detector as much as it is a movement detector, if a person is stationary the temperature of the sensor will reach a steady state and the induced current will disappear. The use of passive IR built upon pyroelectric sensors is considered a non intrusive technology which makes it useful where high privacy is considered paramount to security level and is mostly used in low security situations. This technology does not give very much information about the situation and usually only has an on or off state. Pyroelectric sensors are also a cheap technology where a sensor element can be bought for a few dollars making it widely used in simpler applications.

Thermal imaging on the other hand is also a type of passive infrared radiation detection technology which functions as a camera, i.e. it will detect electromagnetic waves in the same way as a Complementary Metal-Oxide-Semiconductor (CMOS) camera [4]. The difference is that the sensor element is chosen to be sensitive to wavelengths in the medium to long wavelengths in the infrared spectrum, which are in the 3-8μm and 8-15μm range respectively. This gives a much more informative look on the situation and is useful for various applications, for example to detect heat leaks, detect movement and even being able to see through mists/dust/smoke and in darkness. It is considered less intrusive compared to visible light cameras since it is not a valid method of identification by law [5]. However it is used for detection, orientation, recognition and identification according to the Johnson criteria, which determine the resolution required to make a reasonable prediction of a target from the respective criteria [6].

2.1.2 Identified opportunities

The recently successful studies by [7] and [8], showing that an array of PIR-sensors could be used to measure relative speed, height and movement pattern to distinguish between several people. This could be used to identify a small number of people as well as being able to replace some simpler forms of radar presence detectors and tracking. By using an array of PIR-sensors it would be possible to determine the speed, direction, and to some degree the distance to a moving object [9]. This would allow useful tracking in office buildings, and smaller spaces to a much cheaper price compared to radar since these sensors are very cheap in production. These two opportunities rely on an array of multiple sensors placed separately from each other with a central data processing device, this makes it relatively complicated to install and setup.

2.2 Active IR

2.2.1 Background

The use for active infrared radiation can be used to create an image of an object by illuminating the object with short wavelength infrared light to get reflections of the object in order to create an image of it[10][11].

A more simple type of active IR, but with the same principle is the IR emitter and detector, which emits IR light and if the reflected lights amplitude is large enough, will trigger the sensor.

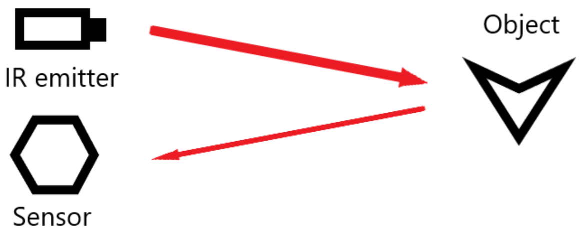


Figure 2.2: Schematic of a reflective active IR

Another frequently used type of active IR-sensors are beam break sensors. Where the IR light is emitted either towards the sensor directly or towards a reflector which reflects the light back towards the sensor located near the emitter. When the beam is disrupted by something or someone the sensor is activated as seen in figure 2.3.

2.2.2 Identified opportunities

By illuminating the object with infrared lights in a dot pattern it is possible to map the topography of the object, a widely used method for face identification used in many smartphones [12][13]. This method would also be useful to other areas where the detail and topography information available from regular thermal cameras is not sufficient. The simpler types of active IR sensors, the beam breakers, are widely used in several applications today, from door opening mechanisms to industrial application in production lines etc. Other types of active IR, such as automatic door opening and automatic taps could probably be used in more future applications since they do not rely on breaking a fixed beam and thus can be used in longer ranges.

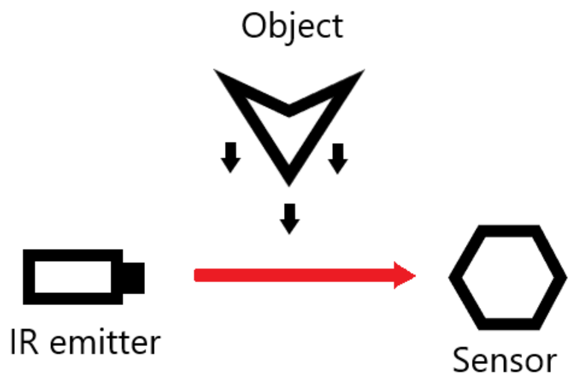


Figure 2.3: Schematic of a beam break sensor.

2.3 Radar

2.3.1 Background

RADAR (**RA**dio **D**etection **A**nd **R**anging) uses radio frequency electromagnetic waves, as shown in 2.4, which propagates to and reflect off the target [2]. The returning waves can be used to detect either the distance of the target, the velocity of the target or both depending on the wave modulation used.

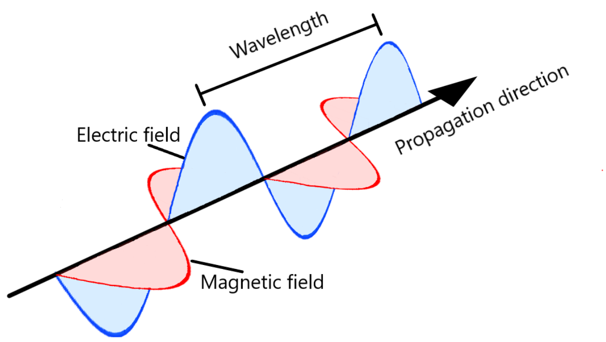


Figure 2.4: Illustration of an electromagnetic wave and its propagation.

As earlier mentioned, radar technology have been widely used since the second world war, with extensive research and development given to it in the 1930's and during the war [2]. Although being mostly used by military in the beginning of the technology, it is now widely used in many different applications. From applications such as regular range object tracking to speedometers, self-driving car systems as well as gesture detection and recognition and radar imaging in different scenarios. This is a technology with many possible applications due to the amount of information it is able to collect. In today's security applications it is mostly used as a tracking device, but since this technology is capable of giving much more information when using different implementation methods it could probably do a lot more in everyday security applications. It has also been proven to be sensitive enough to detect small movements originating from biometrical events such as the chest movement of breathing or even the heart beating [14].

2.3.2 Identified opportunities

As shown several times a radar is capable of detecting the movement of the chest deriving from a heartbeat[15]. There are also studies linking the chest movement with the Electrocardiogram (ECG) [16][17]. Further there have been studies showing that it is plausible to identify persons from features in their ECG [18] [19]. Taking this into account it could be possible to use radar to measure a persons chest movement and use the signal for identification or authentication.

Viable places for such applications would be stationary or in confined spaces such as an elevator for granting access to certain floors, in a car to identify the person behind the wheel, or at a desk to unlock the workstation.

There have also been studies linking the change of heart rate linked to the breathing, or Heart Rate Variability (HRV) to the stress level of the test subject [20][21]. Other studies have shown successful attempts to use the HRV to identify people [22].

2.4 Ultra sonic

2.4.1 Background

The use and development of ultra sonic based technologies have also been made by the military industry, where it serves a big role in under water detection and navigation [23]. This system, also called sonar, has been used in regular civilian marine systems as well and has been developed to the use in sonograms which play a major role as a health condition diagnostic tool. The basic principle of the technology is much like radar, where a pulse, in this case ultra sonic, is sent out and later receiving the echo of the pulse.

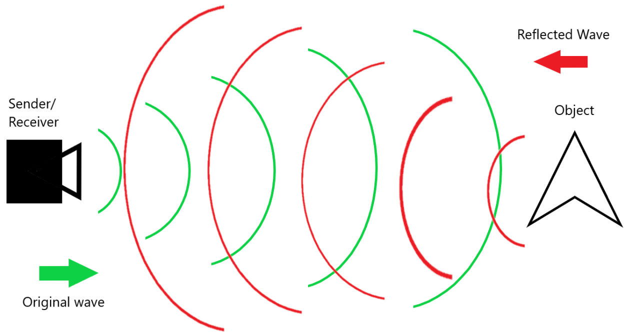


Figure 2.5: Basic principle of ultrasonic detection.

2.4.2 Identified opportunities

Much like radar this technology can determine distance through time of flight measurements and can thereby be implemented in similar applications. The technology also support high accuracy measurements just as the radar but are generally cheaper to produce and makes use of a simpler user interface. These sensors are however not as versatile as their radar counterpart, but will perform well in places with low temperature fluctuations, smaller ranges and where the object is generally flat and will be able to reflect back the transmitted energy. This makes the radar technology more viable for the applications used in this thesis since the intended use of this technology would require larger ranges covered as well as possible outdoor use where temperature can harm the performance of ultrasonic. The implementation of radar for these applications are intended for longer ranges as the attenuation in the air is far greater for ultrasonic waves. However larger distances will not be measured in this thesis due to set limitations.

2.5 Microwave

Other microwave techniques besides radar could also be used in presence detection. For example the microwaves used to transmit information through the Wi-Fi protocol [24]. Technology using Wi-Fi has been shown to be able to detect the presence of a person even through walls when analysing the Wi-Fi-signal's propagation compared to the same space without a person in it [25]. This type of presence detector could be possible to implement in office spaces with existing Wi-Fi access points due to the vast availability of access points in such spaces. As the system would use an existing signal the system would be "passive" and consequently relatively energy efficient. Implementing this will however be solely software based and not in the scope of this thesis.

2.6 Other

Many other techniques for presence detection also exist, these types use a rather specific type of detection method based on for example capacitive carpets, [26] and piezoelectric film used for detecting a person sitting on a seat through vibrations [27]. Since the opportunities based on these methods are already well established and no further application area have been found to make use of them these methods will not be further investigated.

2.7 Summary

To continue with this thesis, the radar technology was chosen for further investigation. The radar technology is a very interesting technology overall since it has so many applications and can be useful in so many situations. We consider it more capable compared to ultrasonic because it does not have the same limitations when it comes to certain circumstances such as temperature fluctuations, maximum usable range and potential dampening of the ultrasonic wave from clothing. It would also have been interesting to investigate further on the PIR-sensors since there are several promising opportunities to pursue.

Chapter 3

Theory of Radar

3.1 Introduction

Radar systems are used in many kinds of applications and use several types of radar methods to achieve the desirable results. For measuring distance and speed, two different types of signals are being sent out by the radar [2]. A few different configurations of radar can be used, specializing in their own type of application, the most common are continuous-wave radar, frequency modulated continuous-wave radar, Doppler-radar and a few types of pulsed radar. For high accuracy distance measurements, both the time of flight pulsed radar and modulated continuous wave can be used, but will behave different in different applications or circumstances [2]. The time of flight of a pulsed radar method is the simplest method since it measures only the time it takes for the transmitted pulse to be received again, with no demodulation of the returning signal needed. Although for both methods the pulse repetition (or modeling repetition) frequency needs to be taken into consideration in order to avoid any ambiguities of the distance. For velocity measurements, a frequency modulated continuous wave is usually used since it makes it possible to measure the Doppler-shift in a very accurate way, it also has the advantage of being able to measure both distance and velocity of measured object at the same time.

As shown in figure 3.1, the time of flight is a measurement of the time it takes for the radar wave to reach the target and reflect back to the radar. The distance is given by

$$D = \frac{c_0 t}{2}, \tag{3.1}$$

where the speed of light, c_0, and the time of flight, t, is divided by two (since the distance the pulse travels is double of the distance).

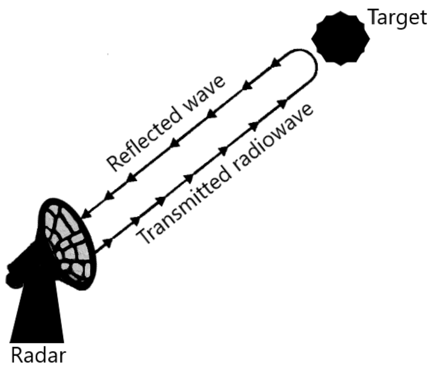


Figure 3.1: Principle of the radar system function.[28]

3.1.1 Radar frequency bands

Radar is a wide concept with frequencies ranging from few MHz to hundreds of GHz. Different frequencies have different applications depending on requirements in range, resolution, interference with objects and systems [2]. The used frequencies have been divided into several "bands". Several standards to classify the frequencies depending on application have been made by organisations as International Telecommunication Union (ITU) and NATO. However the most used in scientific applications is the standard set by Institute of Electrical and Electronics Engineers (IEEE) in table 3.1

Band	Frequency [GHz]	Wavelength [cm]
L	1-2	30 - 15
S	2-4	15 - 7.5
C	4-8	7.5 - 3.75
X	8-12.5	3.75 - 2.4
K_u	12.5-18	2.4 - 1.7
K	18-27	1.7 - 1.11
K_a	27-40	1.11 - 0.75
V	40-75	0.75 - 0.40
W	75-110	0.40 - 0.27
mm/G	110-300	0.27 - 0.1

Table 3.1: IEEE standard radar frequency bands, mm wave band can also be considered from 30-300 GHz since this is where wavelengths range between 10 mm and 1 mm [29].

3.2 Continuous Wave Radar

Continuous Wave (CW) radar is a type of radar which uses a continuous transmission, as the name implies. This type transmits a fixed frequency wave and typically uses a minimum of two antennas, one for transmitting and one for receiving.

The echo signal which is received will either have the same frequency which implies that the object is at a constant distance or have a relative velocity of 0. If the object is moving away of towards to radar, the frequency will change due to the Doppler effect, this makes it possible to extract the relative velocity. The received frequency,f_r, is function of the transmitted frequency, f_t and the relative velocity of the object described by (3.2)

$$f_r = f_t\left(\frac{1+v/c}{1-v/c}\right) \tag{3.2}$$

where c is the speed of light, and v is the relative velocity of the object. The velocity can thereby be calculated, using the simplified equation (3.3) (assuming $c \gg v$)

$$f_r \approx 2v\frac{f_t}{c} \tag{3.3}$$

which makes it easy to determine the object velocity. However, using the simple continuous wave will not be able to determine the distance since the Doppler effect will not be present and will not cause a change in the received signal. To solve this a transmission with changing frequency can be used to being able to pinpoint when the same known frequency is received again. This type of radar is called Frequency-Modulated Continuous Wave (FMCW), which will be able to determine both the velocity and distance [2]. These frequency-modulated waves could be done in several ways, for example triangle wave, sine wave and sawtooth wave as shown in figure 3.2.

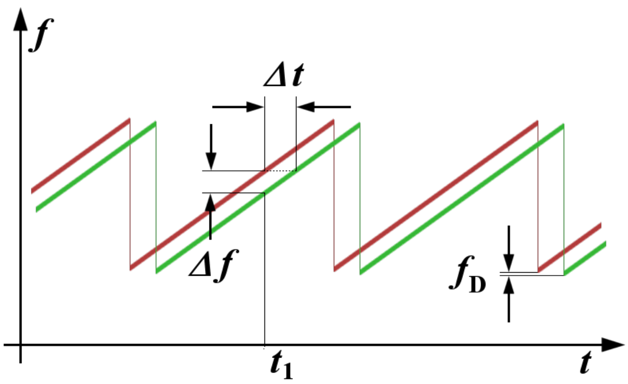


Figure 3.2: Principle of sawtooth frequency-modulation, 🅭🅯🄎[30]

By measuring the time from when a particular frequency is transmitted to when the same frequency is received can be compared to also measure the Doppler effect and thus the objects velocity. Interpreting the change in frequency or the time for the particular frequency to be received is not trivial since the relative velocity of the object can change the frequency which can wrongfully be interpreted as time of flight. To counter this some processing is done to the signal, Fast Fourier Transform (FFT) for example, to extract useful information by removing noise from the higher frequencies from the transform. The continuous-wave radar will also use the most amount of power since it is always sending and receiving signal, making it suitable for larger radar facilities but not very useful for small mobile use or Internet of Things (IoT) applications where low power consumption is a priority.

3.3 Pulsed Radar

Pulsed radar is a radar technique where a pulse is transmitted, reflected and then received. The time between transmitted and received signal is measured which gives a high accuracy distance measurement. Instead of a continuous wave, this technique has frequent pulses transmitted that will reflect on a target and be received by the radar to determine distance, figure 3.3. The velocity can also be measured using this method, although it depends on the pulse repetition frequency how accurate the velocity will be, as the velocity will be the change in distance between two measurement points and not an absolute shift in frequency as used in Doppler-radars. To function properly, the pulse transmitted will need to be received again before sending another pulse which can decrease the accuracy for long range applications.

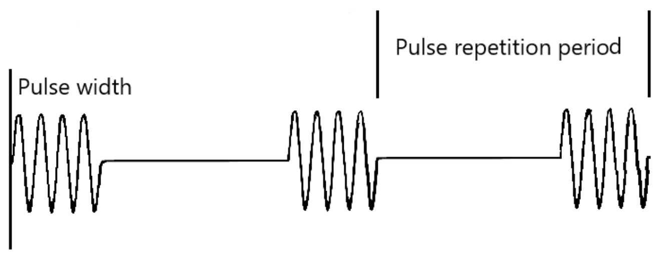


Figure 3.3: Principle of pulsed radar pulses.

Since this technique is using pulses instead of a continuous signal output, these pulses can be tuned for either high accuracy or for power saving. In very simple applications such as detecting if a car is present or not in a parking space the pulse repetition frequency can be set very low which makes it very power efficient, which bodes well for mobile and IoT applications.

3.3.1 Pulsed Coherent Radar

Pulsed Coherent Radar (PCR) is a type of pulsed radar but uses a more sophisticated integration. This technique uses a reference signal which makes it possible to have a coherent signal output, i.e. the signal phase and amplitude will be the same for each pulse making it easier to extract valuable information. The implementation of this would offer higher resolution compared to the regular pulsed radar and at the same time holding the power requirements down. This type of radar would not only perform very well but also be a viable option for mobile use of technologies discussed in the thesis.

Chapter 4

Theory of heartbeats as biometrics

Biometrics or biometric recognition are techniques used to identify persons using physiological characteristics [31]. Common currently used biometric recognition methods are fingerprints, face recognition, retinal recognition, and voice recognition. However, while the voice is alterable and forgeable and the widely used fingerprint can be forged as well whereas the specific characteristics of the heartbeat used as biometrics can not easily be altered and almost impossible to be forged, which makes it a good addition to other biometrics but also a strong candidate for standalone use [18].

4.1 Electrocardiogram

Electrocardiogram (ECG) is the recording of the electrical activity in the heart. The electric pulse recorded originates in the depolarization and re-polarization of the cardiac muscle. The ECG of one pulse is shown in figure 4.1. Numerous recent studies have shown that the specifics in the ECG i.e the relative heights, duration and distances of the P, Q, R, S and T features can be used in order to identify persons with a high accuracy of 94.95% [18]. These features are based on the polarization and re-polarization of the hearts nerves which governs which portions and when the heart muscles contracts.

4.2 Ballistocardiography

The Ballistocardiography (BCG) is similar to the electrocardiogram, but is, instead of electrical, a measurement of the mechanical aspect of the heart beat. This technique is not as common as the ECG since the ECG will give much more information of the overall heart health [33]. The advantage with BCG is that there is no need to use electrical contact pads to do a measurement, and can also be done with no contact at all [34].

The ballistocardiography is a measurement of the ballistic ejection of blood from the heart which leads to prominent surface motion close to the heart muscle and at major blood vessels. To execute a BCG an accelerometer or a force measuring device is often used. A comparison between the ECG and the BCG is shown below in figure 4.2, where the R-J interval is the time between the electrical impulse of the isovolumetric contraction and its corresponding surface motion.

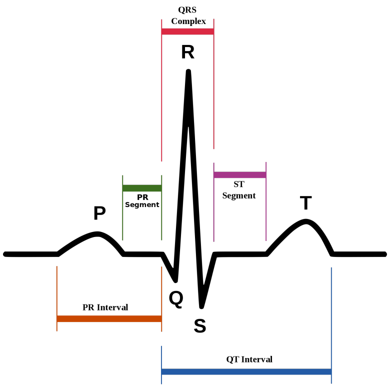


Figure 4.1: Representation of the different electrical components of an electrocardiogram, Ⓟ[32].

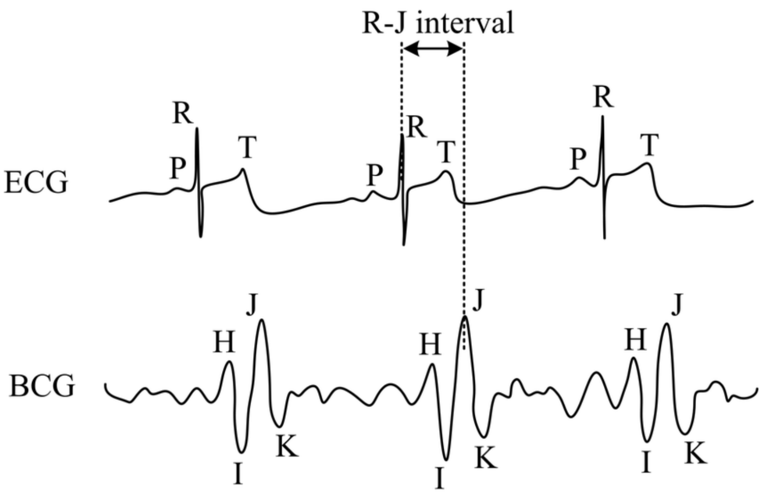


Figure 4.2: Visual representation of the difference between a ECG and BCG measurements, ⓒⓘ[16].

4.3 Heart rate variability

Heart Rate Variability (HRV) is the variability of the heart rate which usually occurs during the breathing cycle. Another reason of the phenomenon of the variability is the Mayer waves, which is a low frequency oscillation originating in the blood pressure homeostasis reflex control system. A sinus-shaped heart rate variability following the breathing pattern is an indication of normal heart rhythm and is a sign of ideal heart function. Having an irregular shape of the heart beat variability could be an indication of poor health or a stressful state of mind, where normal is age dependent but usually is in the range of 50 ms difference in the heartbeat pulse [35].

To measure the heart rate variability the time between each pulse is measured to measure the change in time between the pulses. There are several ways of measuring the heart rate variability as there are several ways to measure the heart beat, however the heart rate variability-measurement is highly sensitive to artifacts and other measurement errors since the exact time between pulses is being measured and compared to the previous. This makes the ECG the best option to accurately measure the HRV. Other methods includes blood pressure measurements, BCG and Photoplethysmograph (PPG). Radar will be a method of remote BCG monitoring in this case since it will measure the movement of the chest.

Chapter 5

Theory of data classification

5.1 Pre-processing

5.1.1 Band-pass filtering

The output signal from the radar module consisted of the phase and amplitude of the returning radar pulses. By comparing the phase shift between succeeding measurements the velocity of the measured object can be determined. The output signal from the radar module contained a lot of high frequency noise as seen in figure 7.1. To deal with the noise an exponential smoothing was applied to act as a low-pass filter with the result seen in figure 7.2.

5.1.2 Sequence Treatment

To train the network the sequences in the training set were divided into pulses with one heartbeat cycle in each pulse, with the pulses keeping the same classification as the sequence. These pulses and labels were then used as input to train the neural network as shown in figure 5.1. The test sequences were then also divided into their pulses, while still keeping track of sequence inheritance. The pulses were then classified individually, without taking sequence inheritance into account. The predictions in all sequences were then put together and the sequence was classified as the most recurrent pulse classification, see figure 5.2. The original idea behind this was that if the classification of each individual pulse was made with relatively high accuracy the statistical probability of enough pulses to get an incorrect classification for the sequence would quickly vanish as the number of pulses increased. However in order for this to be true the probabilities of the pulses within a sequence to get an incorrect classification have to be statistically independent from each other.

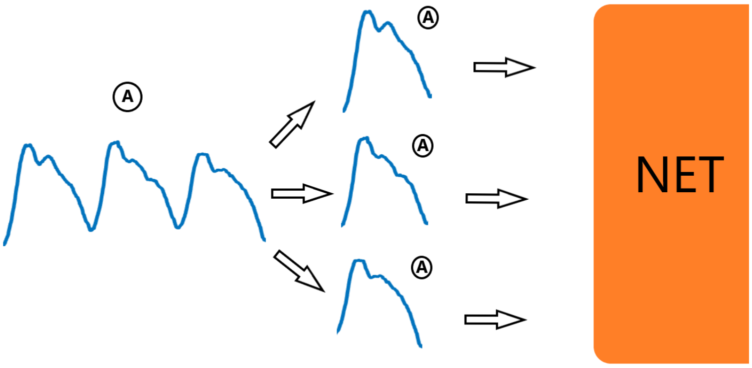


Figure 5.1: The Sequence is divided into its pulses. Which then individually are used to train the neural network

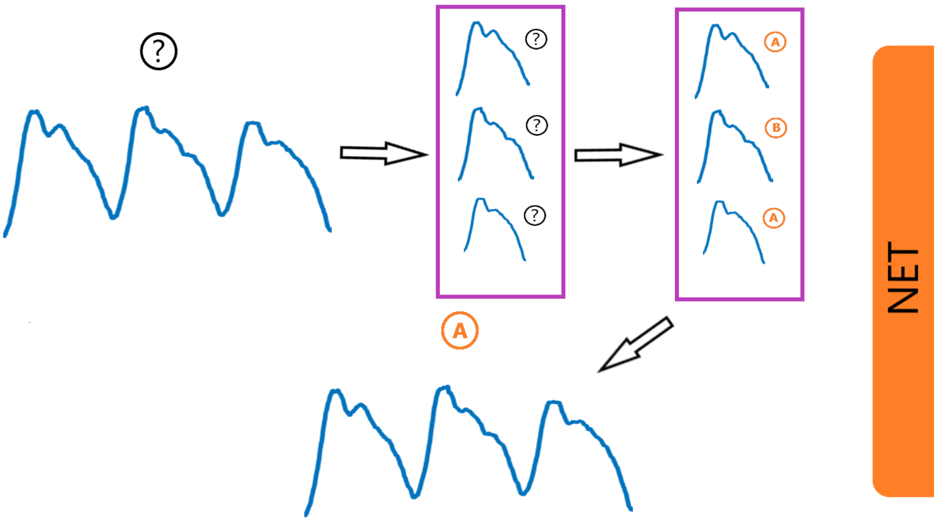


Figure 5.2: To classify a sequence it is first divided into its pulses. The pulses are then classified by the neural network individually. The classification of all the pulses within a sequence are then weight together to classify the sequence.

5.2 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is an architecture of a Recurrent Neural Network (RNN) primarily used to classify sequences of data. A RNN has a connection from a node in the previous time step as well as the connections from a previous node as seen in figure 5.3. This architecture makes it possible to make connections within the sequence. One of the drawbacks of the RNN architecture is that it can only make correlations of data points nearby in the sequence. However if the desired connections are too far spaced in the sequence the connections will either explode or vanish, this phenomenon is called “the vanishing gradient problem” [36]. The LSTM architecture is also based upon the idea of having connections from a previous time step but is much more complicated as seen in figure 5.4. Instead of the simple architecture of RNN the connection from the previous time step is complemented by an input gate, output gate and a forget gate which regulates the ingoing and outgoing connections. The fact that the LSTM has these gates makes it possible for the cell to just pass a value forward to the next cell, which solves the vanishing gradient problem. During training of the LSTM the weights' connections into the gates need to be trained as well as the weights making it more computational demanding than a RNN but often also grants better results [37].

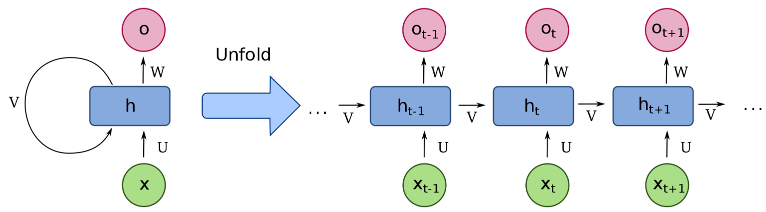


Figure 5.3: A basic RNN unfolded in time. 🅭🅯🄎[38]

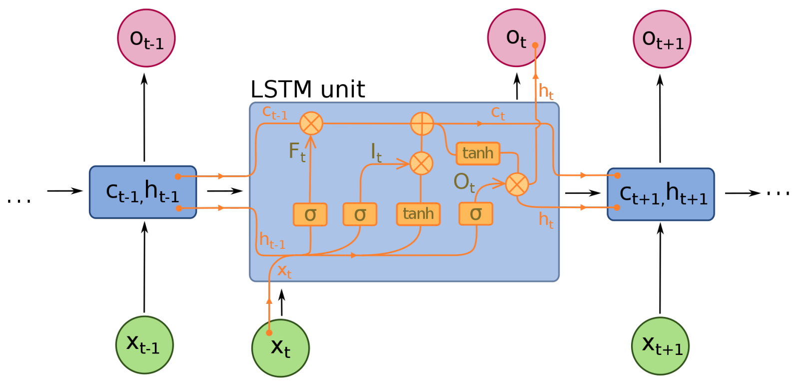
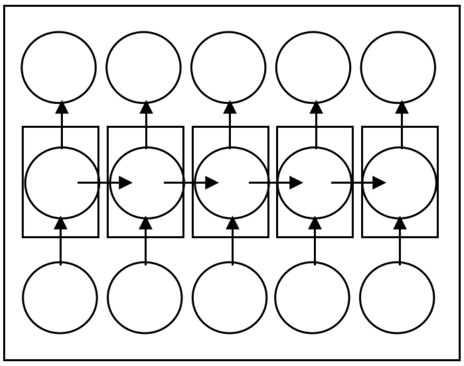


Figure 5.4: A LSTM network unfolded in time. 🅭🅯🄎[39]

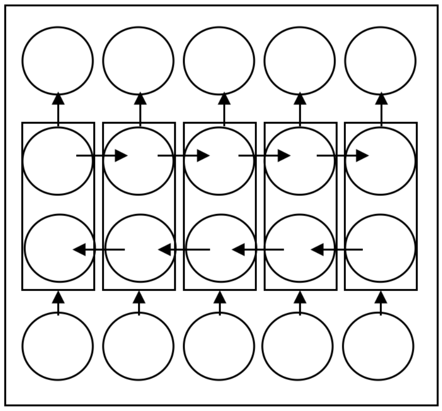
For a more in depth explanation of RNN and LSTM see [37].

5.2.1 Bidirectional Long Short-Term Memory (BiLSTM)

A Bidirectional LSTM (BiLSTM) is a type of Bidirectional RNN (BRNN). While an ordinary RNN only has the information flowing in the forward direction of the sequence, figure 5.5a. Therefore only the data from previous time steps are used to predict the current data point. The idea with a BRNN is to combine a RNN going forward in time with a RNN going backwards in time. The result being that data both from previous time steps and future time steps are used to produce the output [40], figure 5.5b.



(a) A unidirectional RNN ©ⓘⓢ[41].



(b) A bidirectional RNN ©ⓘⓢ[41].

Figure 5.5: Basic principles of unidirectional RNN (a), and bidirectional RNN (b)

5.3 The Neural Network

To classify the data a trained neural network containing multiple stacked LSTM was used. To prevent overfitting dropout layers were added in between the LSTM layers. Numerous different architectures and layer sizes were tried and evaluated on the same division of training and validation data before reaching a conclusion of the best performing network. Bayesian optimization was also used in order to achieve this, and also to decide on the global parameters. The architecture of the neural network used is shown in table 5.1. Other parameters used can be found in table 5.2

Neural Network Layers (size)
Sequence Input (2)
LSTM (20)
LSTM (36)
Dropout (50%)
LSTM (25)
Dropout (50%)
BiLSTM (12)
Dropout (50%)
Fully Connected Layer (2)
Softmax

Table 5.1: The architecture used in the neural network.

Training Options	
Solver	Adam
Mac epochs	15
Mini Batch Size	32
Gradient Threshold	7.5
Gradient decay factor	0.9
Momentum	0.9
L_2 regularization factor	0.0001

Table 5.2: Parameters used in training of the neural network.

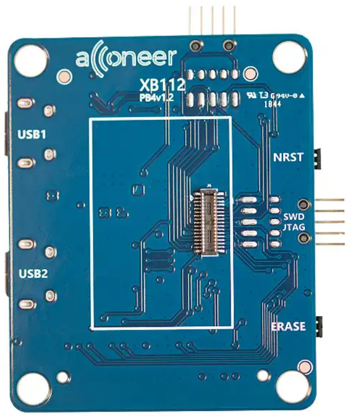
Chapter 6

Software and hardware tools

6.1 Acconeer Radar modules XB112/XM112

The setup used for the heart beat measurements consisted of a radar module from Acconeer with matching breakout board with built in microprocessor and Input/Output (I/O) (XB112/XM112), a matching mounting module and lenses for the sensor and board, together with a computer for controlling the sensor output and perform measurements with the sensor. A small box was also constructed using cardboard to mount the sensor in place which made it possible for reliable measurements without being affected by nearby objects on the side of the measurement spot and a constant measurement distance, shown in 6.1. The lens mostly used in the setup was a hyperbolic lens, which is aimed to have the best gain and a narrow beam in both the E- and the H-plane, having a half power beam width of 17 and 15 degrees in the E-plane and the H-plane respectively according to the data sheet for the lens kit [42]. This can be compared to the 55 degree and the 80 degree half power beam width for the E-plane and the H-plane respectively without the lens, resulting in a 10 dB radar loop gain increase. Other lenses tested includes a Fresnel lens and a flat cover lens, shown in figure 6.3.

Figure 6.1: The setup used while conducting measurements.



(a) XB112 module, connector in white rectangle connects to the XM112 module.

(b) XM112 module, front view of the A111 radar sensor.

Figure 6.2: Picture of hardware used in tests.

The radar module uses a technique known as Pulsed Coherent Radar (PCR) as covered in section 3.3.1. The function of PCR is to send out bursts of radar pulses instead of a continuous wave. The timing and phase of the returning pulses can then be used to determine both distance and velocity of the object being measured. It also has the advantage of being less energy consuming than a continuous wave technique as the radar only transmits Electromagnetic Waves (EMWs) a fraction of the total time. This type of radar is very versatile since it can range from small measurements with high sweep rates to large distances with low sweep rates and provides a very modular approach to fit the specific type of measurements required. However there are also some drawbacks, one is that the power consumption will increase drastically with increasing increasing sweep rates and distance intervals.

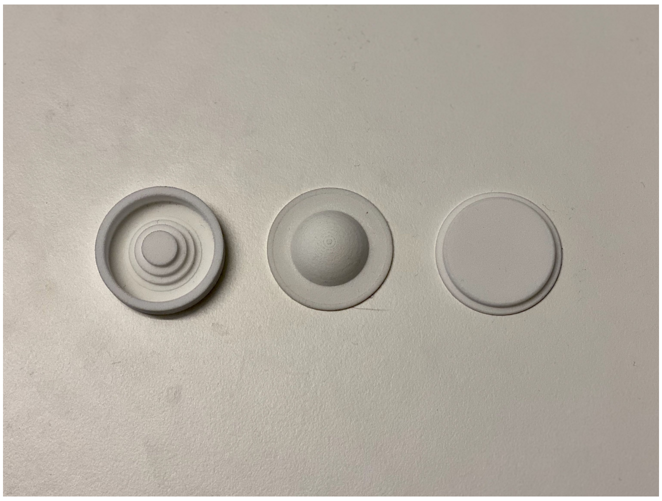


Figure 6.3: The lenses tested, where A is the Fresnel lens (back view), B i the hyperbolic lens (front view) which was used during the final measurements and C is the flat cover lens (front view).

The software for the radar module assembly was firmware installed on the radar hardware and a software development kit acquired from Acconeer's product developer page. The module was setup to the computer via Universal Serial Bus (USB) with either both power and data in one port or separate power by USB and data by Serial Peripheral Interface (SPI). The latter appeared to show a higher data throughput without dropping sweeps. The software environment for the Software Development Kit (SDK) was developed in Python which was used in all data gathering processes, using a modified version of Acconeer's prebuilt program.

The Acconeer XB112 sensor data collection functions by dividing the preset distance interval, dividing it up by increments of about 0.5mm. For each increment (i.e the time of flight interval) 9 pulses of 60 GHz EMWs are sent out in a frequency of 15 MHz, the amplitude and phase of the returning 9 pulses are averaged and the value of the increment is set. This is done for each increment, so for example a 20 cm depth interval is using 400 depth increments and each increment is based on the average of 9 pulses. This is done for each sweep, which is the number of readings of the interval each second. In this thesis 250 Hz is the most used sweep rate, which adds up to the radar sampling data 900 000 times per second. Although, this only results in 100 000 data points, with the resulting averaged, weighted, somewhat smoothed and graphed data points to be the sweep rate of 250 Hz.

Each sweep will be weighted based on the intensity of each depth increment, which yields the distance to the object in question. To avoid large fluctuations and jumps caused by misreadings or other anomalies, the next sweep can not jump between too many depth increments, an exponential function to the next sweep is thereby applied. This causes a rather big smoothing which is both positive and negative, with negative being in the sense of potential loss of information.

To achieve a depth interval a filter is applied to be used as a boundary where the depth is being used. This could cause some problems close to the edges hence a recommendation to not have the objective too close to the interval boundaries. As can be seen in figure 6.4, the filter applied will make the signal go to zero where the interval ends, which could cause measurement errors when close to the interval boundary.

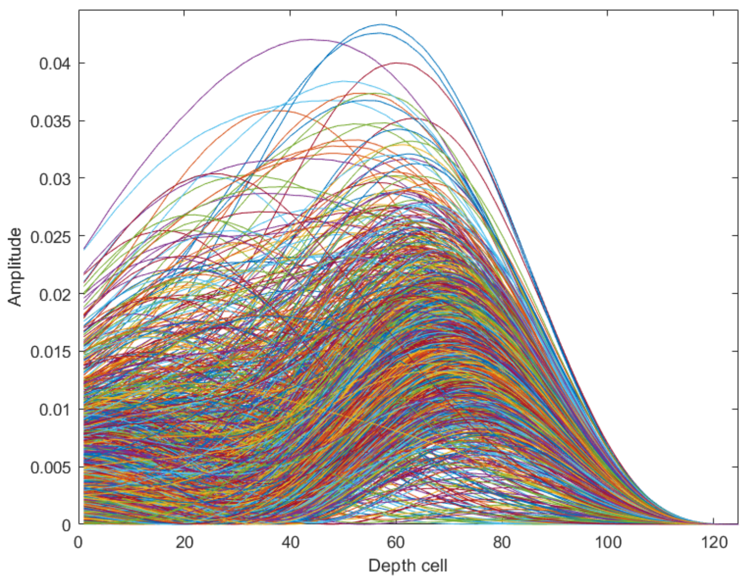


Figure 6.4: Filter effect on signal close to boundaries, showing that the signal is weakened when approaching the boundaries. Each depth cell corresponds to 0.5 mm. Each line is a reading on one time step.

The data was exported from python to MATLAB for further processing. The choice of MATLAB is mostly due to the fact that we are more skilled and comfortable in MATLAB than python. To extract the heart beat shape, form, rate and heart rate variability an algorithm was scripted to remove noise, excess data from the underlying signal shape and to boost the actual heart beat signal. The algorithm then detected where a heart beat was present, making it possible to extract single heart beat shapes to later be analyzed and categorized using deep learning.

6.1.1 Data acquisition

6.1.2 Data Services and processing

The exploration tool provided in the SDK makes use of a few different processing techniques to achieve the desired results, be it the maximum depth resolution, Signal-to-Noise Ratio (SNR), power reflectivity or other desirable data. Two common methods are In-phase and Quadrature (IQ) components and envelope which both are good for detecting fine movements, however they have different approaches to do this.

In-phase and Quadrature (IQ) and Envelope

The IQ service is used to produce phase-stable measurements which gives the ability to measure small movements in the sub mm range. This processing is based on decomposing a phase-modulated sinus wave into two amplitude-modulated sinus waves with an phase offset of $\pi/2$. The relation between the before and after decomposition can be described as

$$\sin(2\pi ft + \phi(t)) = \sin(2\pi ft)\cos(\phi(t)) + \cos(2\pi f)\sin(\phi(t)). \tag{6.1}$$

The equation can be visually represented as in figure 6.5.

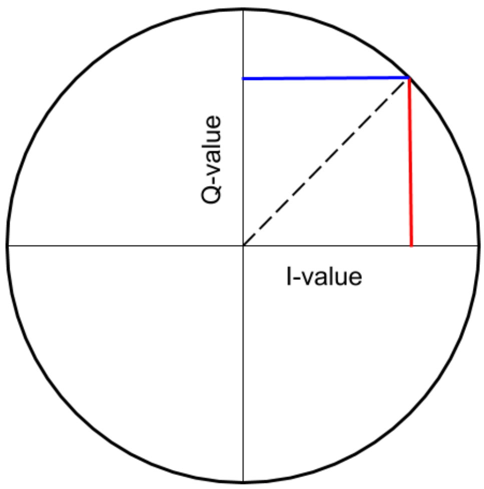


Figure 6.5: Visual representation of in-phase and quadrature components decomposed from the original signal.

The envelope service is focused on getting the best envelope estimate as possible, whereas the IQ service is optimised to getting the best phase-stable measurement as possible [2]. Both of the methods work in similar ways but with a different focus. Both methods achieve this by sending a set of pulses to measure the energy content of the returning echo for a set of time delays from the time the pulses are transmitted. Together with a decent depth resolution this will generate a good set of data for the reflectivity from different distances from the radar. The envelope service will thereby be more concerned with the amplitude of the wave whereas the IQ service will be focused on the phase-content and by that have a superior distance accuracy.

6.2 Matlab Deep Learning Toolbox

For the heart beat analysis and attempt to distinguish between different persons' heartbeats MATLAB's deep learning toolbox was used. This tool is a deep learning program which lets the user create and train a neural network in order to analyze or categorize data. It is here used to learn the heart beat signature from sequences of multiple heart beats and then make predictions of an unknown sequence of heart beats to determine who it belongs to based on what the learning phase of the program was able to achieve.

Chapter 7

Measurement results

The results of this thesis include the different types of measurements performed, where all measurements were performed with the same setup as shown in chapter 6. All measurements were performed by sitting on a chair in front to the sensor with our chest lightly in touch with the box, to ensure a constant distance to minimize sources of errors. The different types of measurements include breathing pattern, heartbeat, heart rate and heart rate variability as well as results from identification using machine learning. A depth interval of 0.22 cm to 0.36 cm was used in the final result measurements.

7.1 Limitations and data acquisition

To simplify the signal processing of the radar signal it was decided to measure in as controlled environment as possible. All measurements were therefore made at a fixed distance with no movement. While doing the measurements for the identification tests the measurements were even made while the test subject holding its breath to minimize the need for removal any movements by the test subject. This was done to maximize the potential of the sensors to be able to get as much information as possible, as a first step to using radar for identification alternative.

The raw data acquired can be seen in figure 7.1. After applying an exponential smoothing to low-pass filter the signal the result in figure 7.2 was acquired. The signal in the frequency domain can be seen in figure 7.3 and figure 7.4

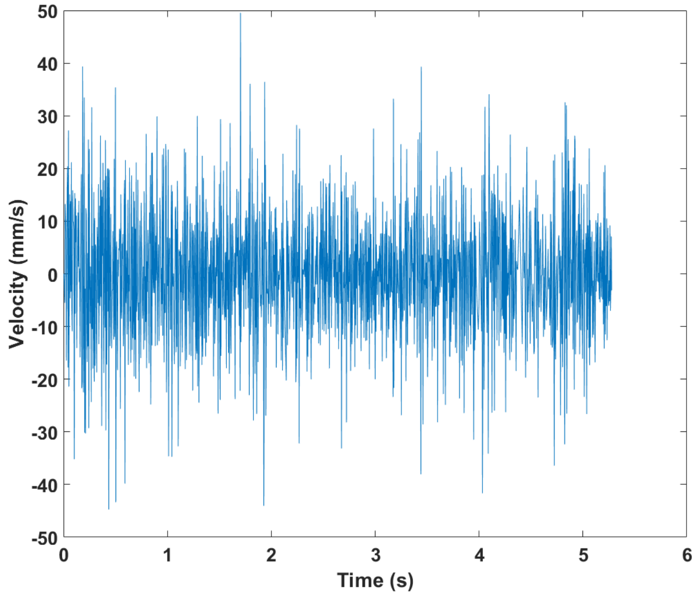


Figure 7.1: The signal without the exponential low-pass filter.

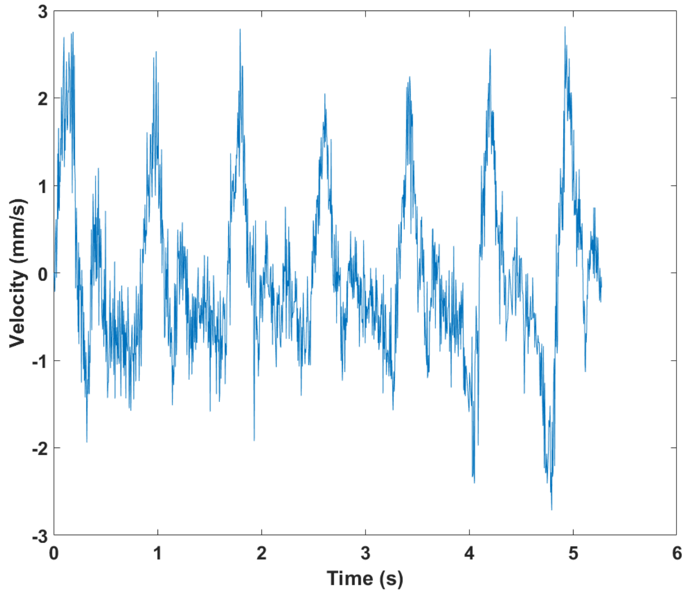


Figure 7.2: The signal after the exponential low-pass filter was applied.

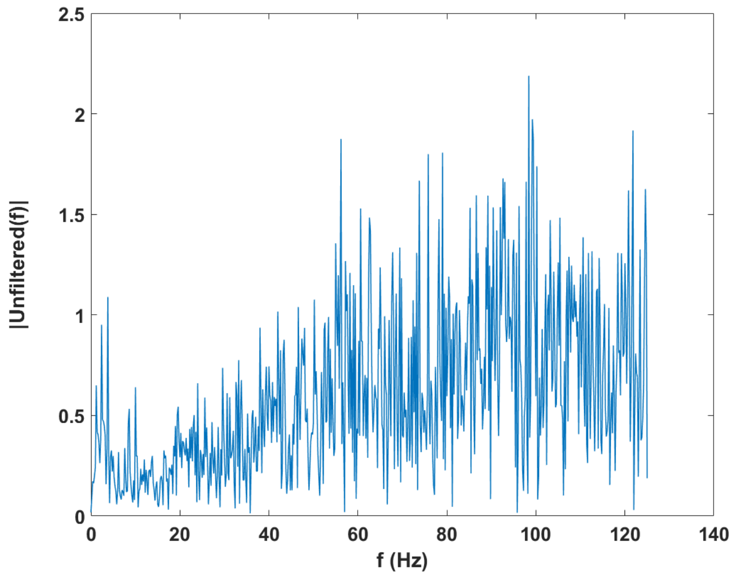


Figure 7.3: FFT of the unfiltered signal shown in figure 7.1

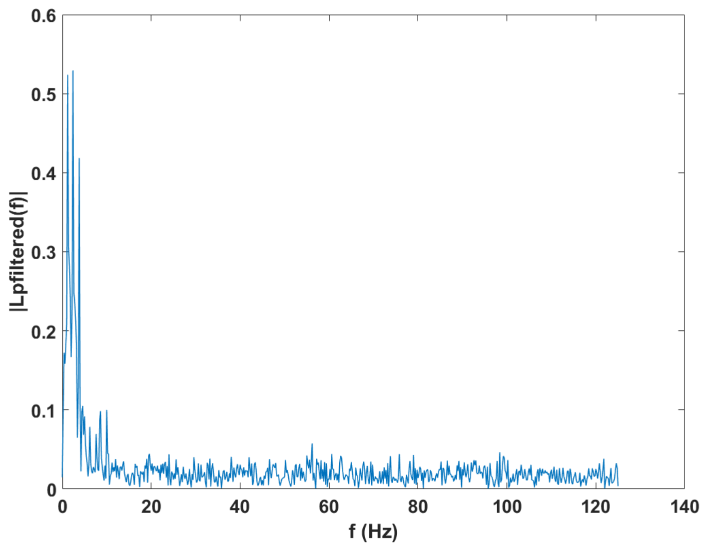


Figure 7.4: FFT of the filtered signal shown in figure 7.2

7.2 Detection of breathing pattern

To get familiarized with the radar and the SDK a few pre-programmed services for breath tracking were used. This measurement was performed by simply sitting in front of the sensor and breathing normally. In the main GUI of the exploration tool for radar sensor, as can be seen in 7.5 a few different services can be used as well as settings for the range interval, sweep rate and recording can be dialed. The breathing tracking acts as a very smoothed tracking of a person's breathing pattern, with very few spikes and jumps in the output data, as can be seen in 7.6. This is useful when the fine details of the signal are not needed which also reduces power consumption. As seen in 7.5 a few plots are used in this mode, IQ at peak, envelope and delta, breathing movement and relative movement. The IQ at peak shows the IQ where the signal is the strongest, presumably where the chest is located. The envelope and delta graph shows the echo signal and the relative change from previous received signals. The breathing movement graph shows the smoothed output and the relative movement shows the small movements before the smoothing occurs.

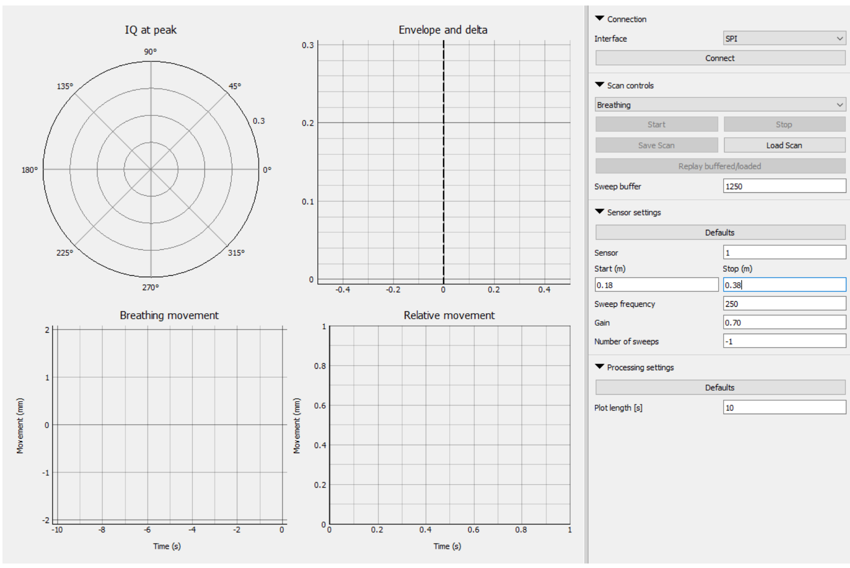


Figure 7.5: User interface of the Acconeer exploration tool.

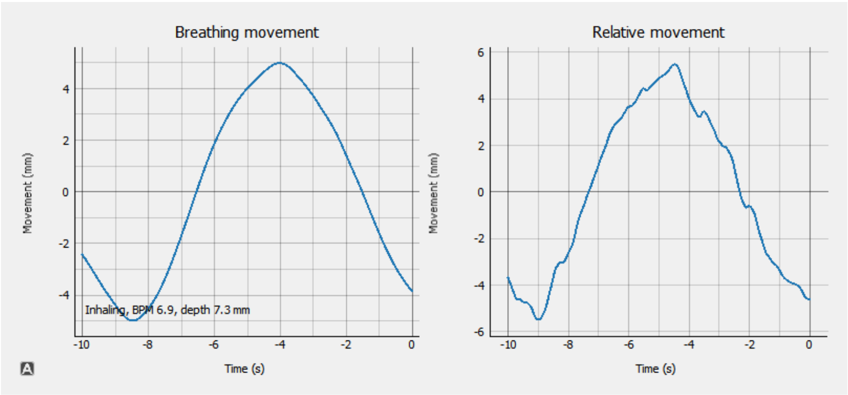


Figure 7.6: Measurement of breathing pattern, showing smoothed capture to the left and raw capture to the right.

7.3 Detection of heartbeat

Continuing with the detection of heartbeat, a modified version of Acconeer's software was used together with algorithms and processing signal to extract the heartbeat, heart rate and its morphology. These measurements were performed while holding the breath to get the best possible signal from just the heartbeat and to minimize the sources of errors. In these measurements phase tracking was used which utilizes the IQ service to achieve the best resolution of small movements. The user interface of this setup is shown in figure 7.7, where a single graph of amplitude and distance was monitored during the measurements. As can be seen in the start of the measurement in figure 7.8, some artifacts can be seen due to the start up of the sensor, since small measurements are performed these could be hard to disregard without losing some valuable data. These artifacts also continue on the detrended data shown in figure 7.9.

The heartbeat causes a relative distance offset of about 0.3 mm which is a reasonable amount for the type of movement being measured. When looking even closer to the heartbeat morphology some other distinct features can be seen. However, these even smaller movements are even more prone to be affected by noise and artifacts which becomes challenging when trying to quantify these features to be able to use these for identification purposes.

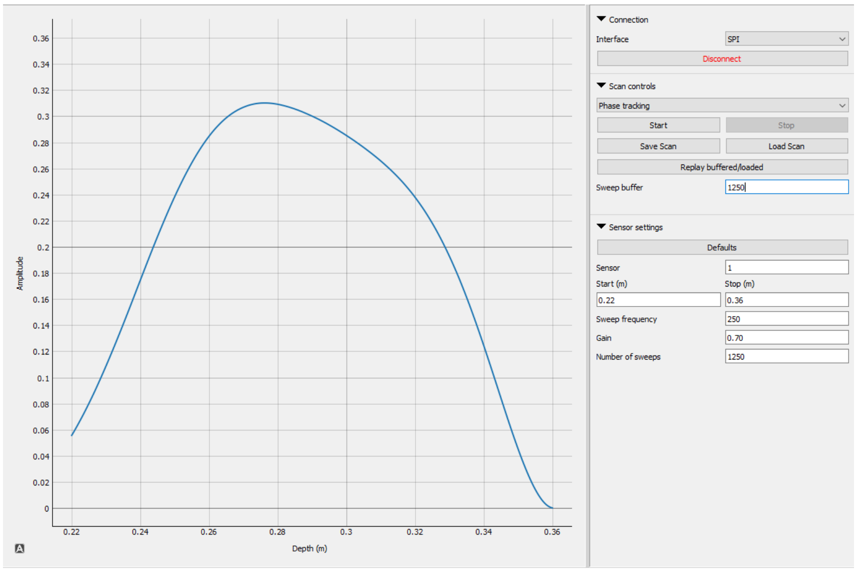


Figure 7.7: User interface of heartbeat measurement program.

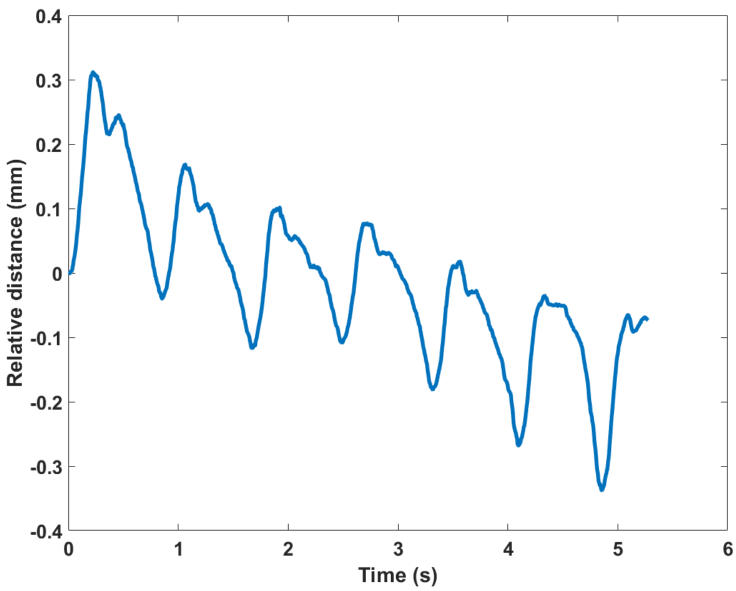


Figure 7.8: Somewhat preprocessed data from measurement of heartbeat when holding breath, showing clear and prominent heartbeats with few artifacts.

The heart rate extracted from this measurement can be calculated to be 70

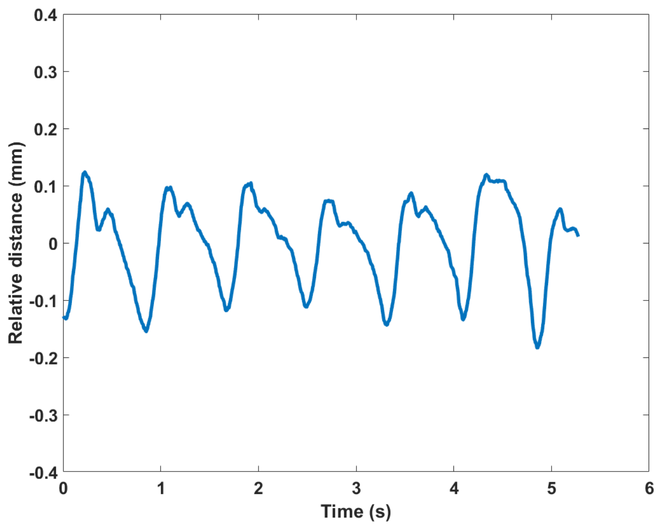


Figure 7.9: Detrended data from heart beat measurement, showing significantly more prominent heartbeats but some artifacts introduced.

beats per minute, from 7 beats in a period of 6 seconds. This is a normal heart rate and also confirmed by manual heart rate measurements corresponding to this measurement, showing 72 BPM. Manual measurements were taken during some of the measurements to ensure that the heartbeats detected actually are from heartbeats and not noise or other artifacts. The manual measurements were taken with a PPG heart beat monitor enabled smartwatch with a mean error percentage of 5.86% [43].

A program in MATLAB was written to detect and mark peaks and valleys to be able to isolate each heartbeat for later analysis as well as calculate heart rate and heart rate variability.

7.4 Heart Rate Variability

Detecting heart rate variety when breathing was also performed, as can be seen in figure 7.11 the heart rate is linked to the breathing cycle. The heart rate in the figure is calculated by measuring the time between heartbeats, making it very sensitive to small deviations from the measurement itself. Some artifacts and inconsistencies can be seen here since it is difficult to detrend the breathing pattern without losing some information about the heartbeat. Heartbeats can also be buried in the peaks and valleys of the breathing cycle making it even more difficult to extract the exact heartbeats, however it is possible to see some of the heart beats directly from the graph. The measurement is showing that the heart rate decreases when exhaling.

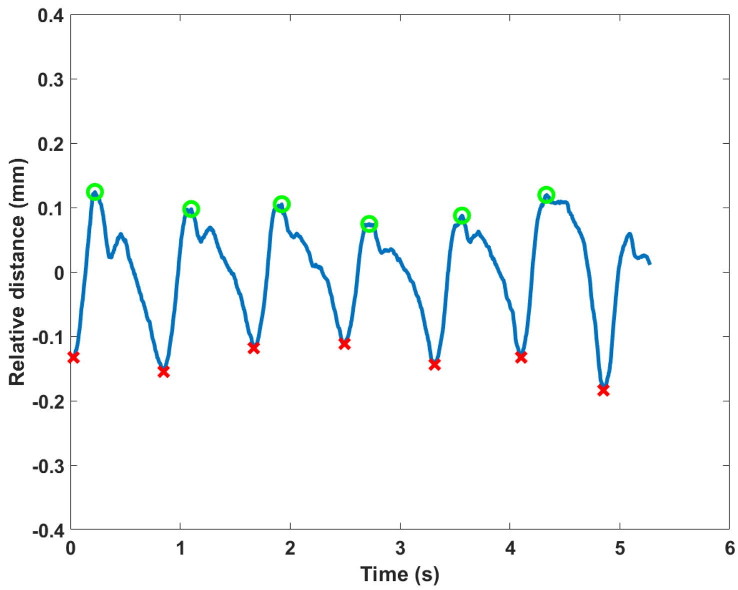


Figure 7.10: Detrended data with peaks and valleys identified.

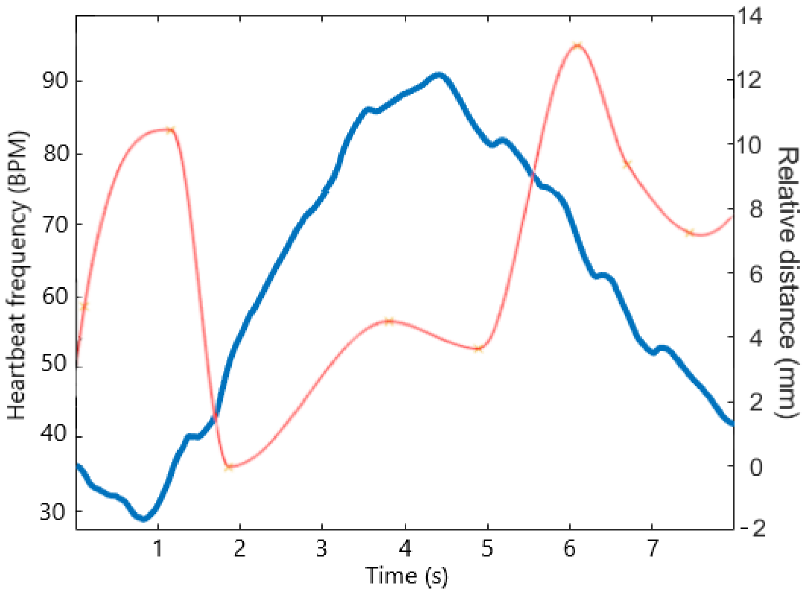


Figure 7.11: Heart rate linked to breathing pattern, with the blue line showing the relative chest distance from the sensor and orange line showing the heart rate.

7.5 Identification of heartbeat using machine learning

A data set of 320 sequences 5 seconds long each was gathered with limitations stated in section 7.1. Subsequently the sequences were pre-processed as described in section 5.1 and shown in figure 7.12. All sequences with less than 4 pulses identified were deemed to be faulty measurements and automatically removed from the data set. The remaining 200 sequences were randomized and divided with $\frac{2}{3}$ into the training set, $\frac{1}{6}$ into a validation set and $\frac{1}{6}$ into a test set. The training and validation sets were used to train the net described in section 5.3.

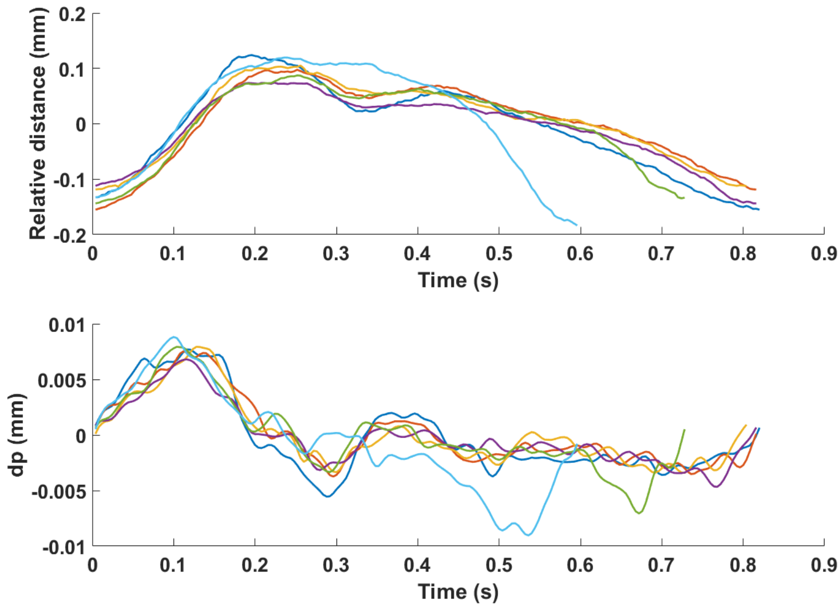


Figure 7.12: The pre-processed data as put in to the net, where the upper showing the relative distance of the heartbeat for different heartbets and the lower showing the velocity of the movement for the respective heartbeat.

The net was then used to classify the test set to evaluate its performance. As the result would be dependent on the randomized division of the data set into training, validation and test sets the procedure was repeated 20 times to get an average value of the performance. The performance for predicting correct classification on individual pulses was only at 80%, however when putting the pulses back into their sequences and classifying the sequences as the majority of the pulses a correct classification was achieved on 90% of the sequences.

In order to examine the reproducibility of the results over time a data set measured 3 months prior to the sampling of the main data set was classified using a network trained by the main data set. During these tests the accuracy of the predictions was decreased to 80% on average while repeated on 10 different nets.

However it should be noted that the main data set which was used to train the net made use of a larger depth window during the sampling which might have decreased the filter effect mentioned in section 6.1.

Chapter 8

Discussion

8.1 Breathing pattern, heartbeat detection and morphology

The breathing pattern was as can be seen in figure 7.6 easily extracted with low rates of error and artifacts. The method for this was straightforward and not prone to errors. Since this measurement is relatively easy due to a large motion compared to what the sensor is capable of detecting, this could also have been measured at a greater distance without losing too much information of the breathing pattern.

When moving on to the detection of heartbeats we opted for the lowest possible amount of errors by minimizing movement and not breathing during the measurements. Together with using a constant distance allowed us to have a consistent measurement method throughout. This was done to have the cleanest possible signals to be able to test the potential of machine learning for identification by heartbeat.

However the measurements were not without problems, many measurements were not consistent regarding to signal strength between measurements as well as within measurements. We set up a threshold where the signal would not go under said threshold to be a valid measurement and used in the machine learning process. This was most likely due to a hardware issue caused by the sensor or the breakout board since it might not have been able to remain consistent processing of the signal which could cause some loss of signal strength in the measurements. A software problem is unlikely since it should not be able to cause a signal strength problem. Measurements with this low signal strength were found to contain many artifacts such as sudden large jumps in phase reading as can be seen in 8.1.

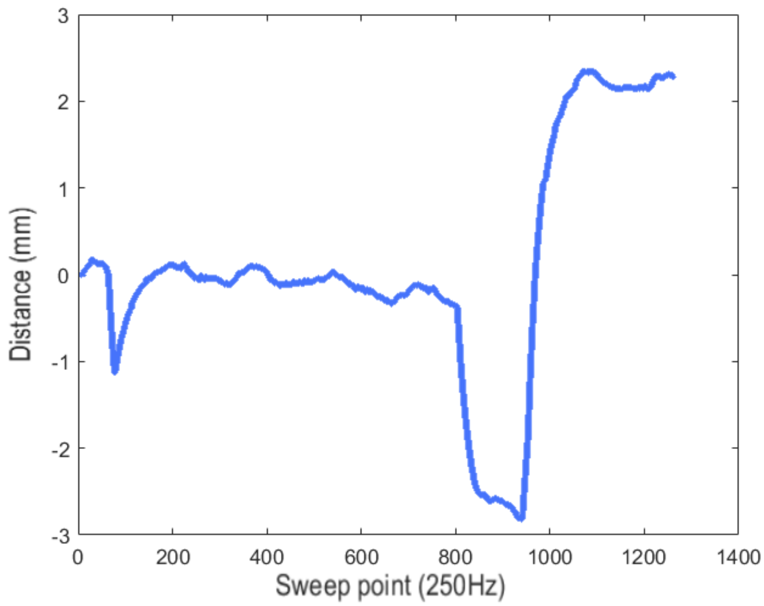


Figure 8.1: Distance measurement errors due to low signal strength.

This issue presented itself not only when changing sitting position but was as much present during the measurements which were performed back to back with the exact same position, distance and clothes. Since the radar used in this thesis i relatively inexpensive, other types of radar sensors and processing could have been used to battle this issue by having a more thoroughly designed circuit. The same sensor could also have been coupled with a Raspberry Pi which allows for up to 4 sensors to be connected at the same time to create an array using Acconeers own Raspberry Pi breakout board. An array would also be beneficial for better depth estimation and further elimination of artifacts and other errors, together with offering more of a three dimensional reading of the environment which would also increase the usability at greater distances.

8.2 Identification of heartbeats using machine learning

The results from identification using machine learning are promising but it remains to be investigated on how it works on a larger set of persons. To have a usable biometric identification method a much higher percentage is required, which makes this method in its current state not ready for security applications. However this could be improved upon by using some other type of neural network together with more information intensive data. In the neural network used here, only the signal from the depth with highest amplitude was used, since there are a lot more information in the files collected from the radar sensor further analysis could be made to obtain a greater success rate. Together with more sensors, or other sensors for that matter a lot more could have been done to extract more unique information about the person's heart beat. As the radar sensor penetrates the body other information about the specific body could also be incorporated into the machine learning algorithms to increase the complexity of the security applications. This would also further increase the difficulties forging such an imprint.

It should also be noted that a large portion (about 1/3) of all the collected data was discarded and not used in the later training and classification. This makes it obvious that the data gathering have a lot of room for improvements. As the methods for discarding faulty data was very simple it is also probable that some data of lesser quality slipped into the used sets of sequences. This would mean that an improved method of sampling and pre-processing the data can be a great opportunity to improve the results. Other types of pre-processing could also have been used and might be able to create even more consistent results, for example the use of FFT in combination with the relative distance measurements could be implemented into the machine learning algorithm.

The fact that the predictions could be made with old data shows that the method could be useful over a period of time as well. This makes the used method of identification a viable option. Although there was a decrease in accuracy that would have to be investigated further. One possible explanation to the decreased performance is that the differences in the settings used might have influenced the signal in different ways. As a result this makes classification of data with one set of settings with the net trained by data with other settings less viable.

However there are things that can affect the rhythm of the heartbeat for example caffeine consumption, stress, and physical activity which have not been investigated here. It remains to be examined whether these things will only have an impact on the heart rate or if they will alter the signature of the heartbeat as well. Other types of signal interfering circumstances such as what types of clothes used could also be something to further investigate.

8.3 Heart beat and heart rate variability

The heart rate variability (HRV) requires the most post processing to achieve reasonable results, which also makes it the most complicated measurement to extract the heartbeats'. Due to the large motion of inhales and exhales relative to the heartbeats' effect on chest movement much of the heartbeats motion will be easily drowned and hard to detect. This is especially true at the peaks and valleys of the breathing motion, as well as other small motions that could make it impossible, or close to, to extract the heartbeat signal. This could likely be helped by analysing other depth cells, as described in chapter 6, to be able to gain additional data which might have a stronger heartbeat signal. As previously mentioned an array of sensors could also be useful to increase the information gathered, and might be especially important for heart rate variability measurements because of the low heartbeat signal to breathing pattern is currently so low. By having improved depth data and resolution the heartbeat could be more easily detectable.

Chapter 9

Conclusions and future work

9.1 Conclusions

While this thesis was originally set out to investigate many different types of presence technologies, radar quickly became the obvious choice to further investigate and researching its potential since possibilities with radar are very interesting and yet not fully explored. We started out with the Acconeer radar setup to begin with, with possibilities of also using other types of radar sensors. The sensor we used seemed to be enough since it gave us solid results with some modification of the developer kit which was provided. Since the sensor was not the main issue to get decent results, software optimization and machine learning programming and testing was the main focus during large portions of the project.

Measurements of breathing pattern were performed as a way of evaluating the radar sensor's developer kit and function. After some initial tests of the system heartbeat was also measured. To obtain an as consistent result as possible the radar sensor was mounted to the back of a box to set a fixed distance which helped with distance consistency. The sweeping frequency was set to 250 Hz to achieve an as detailed reading of the chest movement as possible and to collect all small movements to be able to use even the smallest of motions in the machine learning algorithm. When we could achieve consistent readings of the heartbeat we moved on to measuring several hundreds of sequences each. The sequences were collected in several different occasions and were used to train the neural network.

To use the heartbeat sequences in the neural network, an algorithm to select and individually extract each heartbeat was developed. The process of finding an algorithm to detect almost all of the heartbeats were done with many iterations. When the algorithm was consistent enough we could notice that some of the sequences were of poor quality, most likely due to some errors during the measurement causing the amplitude to be become significantly lower than the average measurement, an example of this can be seen in figure 9.1 where the low amplitude causes a phase shift of about π which causes a distance measurement error of a half wavelength. This caused a very flat distance measurement, i.e. not detecting the heartbeats at all or just causing many artifacts which could not be corrected afterwards. The remaining measured heartbeat sequences were divided in order to train and validate a neural network.

798	799	800	801	802
-0.0247 - 0.0142i	-0.0454 - 0.0845i	0.0444 + 0.1223i	-0.0100 - 0.0532i	-0.0452 - 0.1050i
-0.0249 - 0.0164i	-0.0466 - 0.0864i	0.0432 + 0.1208i	-0.0115 - 0.0559i	-0.0474 - 0.1064i
-0.0251 - 0.0183i	-0.0476 - 0.0884i	0.0420 + 0.1194i	-0.0129 - 0.0583i	-0.0496 - 0.1079i
-0.0254 - 0.0203i	-0.0486 - 0.0901i	0.0408 + 0.1179i	-0.0144 - 0.0608i	-0.0518 - 0.1091i
-0.0256 - 0.0222i	-0.0496 - 0.0918i	0.0396 + 0.1165i	-0.0156 - 0.0630i	-0.0537 - 0.1104i
-0.0256 - 0.0239i	-0.0505 - 0.0933i	0.0383 + 0.1147i	-0.0168 - 0.0652i	-0.0557 - 0.1113i
-0.0256 - 0.0256i	-0.0515 - 0.0947i	0.0371 + 0.1130i	-0.0181 - 0.0671i	-0.0576 - 0.1123i
-0.0256 - 0.0273i	-0.0522 - 0.0959i	0.0359 + 0.1113i	-0.0193 - 0.0691i	-0.0593 - 0.1130i
-0.0256 - 0.0288i	-0.0530 - 0.0972i	0.0347 + 0.1096i	-0.0205 - 0.0708i	-0.0610 - 0.1138i
-0.0256 - 0.0303i	-0.0537 - 0.0981i	0.0334 + 0.1079i	-0.0215 - 0.0725i	-0.0625 - 0.1143i
-0.0256 - 0.0315i	-0.0544 - 0.0991i	0.0322 + 0.1062i	-0.0225 - 0.0740i	-0.0640 - 0.1147i
-0.0256 - 0.0327i	-0.0549 - 0.0999i	0.0310 + 0.1042i	-0.0234 - 0.0754i	-0.0652 - 0.1150i
-0.0256 - 0.0339i	-0.0554 - 0.1003i	0.0298 + 0.1023i	-0.0244 - 0.0767i	-0.0664 - 0.1152i
-0.0256 - 0.0349i	-0.0559 - 0.1008i	0.0286 + 0.1003i	-0.0251 - 0.0779i	-0.0676 - 0.1152i

(a) Weak signal causing one misread (800) resulting in phase jumps between sweeps.

798	799	800	801	802
-0.5581	0.3233	-2.9674	-3.0721	-0.2108

(b) The phase jumps results in an almost full 2Π angle change (800, 801), which later causes and error in distance calculations as seen in figure 8.1

Figure 9.1: Phase jumps caused by low amplitude resulting in distance measurement errors seen in figure 8.1. Figure 9.1a showing the complex amplitude read out and figure 9.1b the angle change between sweeps.

Data from an earlier measurement was also classified using the same neural network to determine if the classification would also be consistent in the longer run. There was a slight difference in result but as the method in sampling the data was slightly different between the sampling occasions, it remains unclear if it the worsen result was a consequence of this or an inconsistent over time.

To further investigate the possibilities of the radar sensors HRV measurements were conducted, these measurements differ themselves from the previous as no breathing occurs during the previous. The HRV-measurements rely on the breathing pattern as the heart rate will be linked to it. This measurement also increased the complexity of the heartbeat extraction since the heartbeat easily get lost in the other more prominent chest movements during breathing.

As the original idea for this thesis was set out to investigate different types of presence detector technologies, only one of the technologies were pursued. This was due to the many opportunities the radar sensor can offer, and a deeper dive into one specific technology would be more interesting both technology-wise and opportunity-wise compared to a more shallow investigation of several technologies.

9.2 Future work

While this thesis only used two persons to differentiate from each other a larger set of participants could be used to evaluate the performance of this technology. The methodology could also be increased to moving objects as well, since this will further increase the relative movements compared to the movements originating from the heartbeat. As mentioned in section 8.2, many different signal and heartbeat altering circumstances could also be further investigated to evaluate if this kind of identification method is viable. Future applications could also be able to detect several heartbeats simultaneously and thus be able to count the people in a room, as well as detect heart defect or heart attacks if the sensors and software would be able to advance to such level. Since this thesis only is a first try of a method as such, many improvements could be done to many different aspects of the technology. As machine learning is advancing in a rapid rate today, the sophistication of these classifications and identifications will most likely be much improved compared to what it is today.

The technology itself does not need to be improved for this to be improved, the aspects of the classification process could be processed differently as well. By not only looking at the strongest signal and instead incorporate several levels of information the radar sensor already gives, many possibilities could be explored further. There is a lot of information in the radar signal received which could be used. Other tweaks in the radar sensor could also be done, for example evaluating the pulse width, use larger depth cells to be able to increase the effective depth for same performance as well as use different sweep frequency which also would allow for larger distance measurements without affecting performance. A higher frequency radar sensor could also be an option for improved distance resolution which could be especially useful for the small chest movements as the ones measured in this thesis.

Even if the methods are improved until perfection the question remains how viable the method can be in identifying persons for an entire population. Even if the ECG is unique the question is if the BCG has the same number of unique features to make each individual distinguish itself from the others. Although it can probably be useful as a part in a multi-step authentication process and might be a viable option for on device authentication where only a single user is active.

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