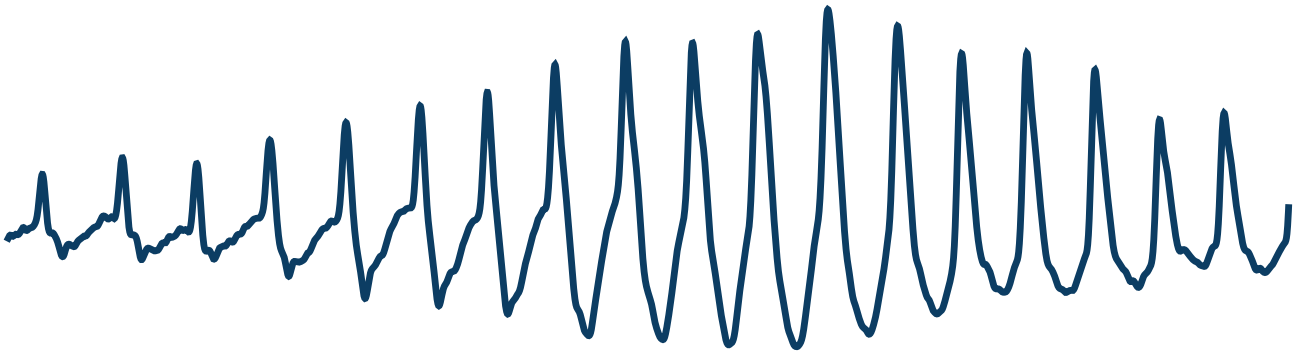
MSc Project: Oscillometric Blood Pressure Measurement



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Abstract

Blood pressure is one of the essential indicators for cardiovascular diseases. Because manually taking blood pressure requires a medical professional, automatic blood pressure monitors have become widespread for home and professional use. Automated methods use a cuff wrapped around the patient's arm or wrist equipped with a pressure sensor and measure the oscillations during the deflation of the cuff to determine blood pressure. Unfortunately, the algorithms implemented in these devices are proprietary and closed-source. This report gives an overview of algorithms for oscillometric blood pressure measurements that are proposed in literature and judges them based on their applicability in a real-time system. The more than 40-year-old fixed-ratio algorithm is deemed the most feasible and implemented in an open-source C++ program. Herein, the user is guided through the process of taking blood pressure using a manual sphygmomanometer with a pressure sensor inserted into the tubing. After a successful measurement, the raw pressure data is stored as a file, which could be used to build a dataset. Because the fixed-ratio algorithm is only reliable for determining mean arterial pressure (MAP), the ratios to calculate systolic and diastolic pressure can be configured in the software.

Keywords: C++, real-time, blood pressure, oscillometric, fixed-ratio, systolic, diastolic, mean arterial pressure

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Nomenclature

$mmHg$	Millimetres of mercury
AAMI	Association for the Advancement of Medical Instrumentation
ADC	Analogue to digital converter
BHS	British Hypertension Society
BP	bandpass
DBP	Diastolic blood pressure
GUI	Graphical user interface
HP	high-pass
ICU	Intensive care units
LP	low-pass
MAA	Maximum amplitude algorithm
MAP	mean arterial pressure
OMW	Oscillometric waveform
OMWE	Oscillometric waveform envelope
PP	Pulse pressure
SBP	Systolic blood pressure
UI	User interface

Chapter 1

Introduction

1.1 Problem Description

Blood pressure is one of the essential indicators for cardiovascular diseases. Because manually taking blood pressure requires a medical professional, automatic blood pressure monitors have become widespread for home and professional use. Automated methods use a cuff wrapped around the patient's arm or wrist equipped with a pressure sensor and measure the oscillations during the deflation of the cuff to determine blood pressure. Unfortunately, the algorithms implemented in these devices are proprietary and closed-source. This report gives an overview of algorithms for oscillometric blood pressure measurements that are proposed in literature and judges them based on their applicability in a real-time system.

Traditional blood pressure measurements require an inflatable cuff that is fixed tightly around the upper arm of the patient. Pressure in the cuff is increased above the value of the expected blood pressure and slowly released while listening to the heart sounds on a stethoscope to determine blood pressure. This process is performed by a medical professional. In recent years, automatic tools have eliminated the dependency on professionals and made taking one's blood pressure at home possible and convenient.

Most automatic devices use small changes in pressure during deflation to detect blood pressure. This is the oscillometric method. It has been around for more than 40 years but has not improved much since its beginnings. Its limitations are known, and many proposed algorithms have tried to address them since. Unfortunately, without notable success. Besides, commercially available devices use proprietary, closed-source algorithms that can not be scientifically challenged.

1.2 Objectives

This project aims to examine existing and proposed algorithms for oscillometric blood pressure measurements. They are judged based on robustness, underlying theory and applicability in real-time

systems.

The most promising identified algorithm is implemented using the provided hardware on a Linux system. The hardware consists of a simple, manual blood pressure cuff equipped with a pressure sensor that is connected to an analogue to digital converter (ADC). The ADC is connected to a Linux computer. The implementation is done in C++ as an open-source project that is available on GitHub (Kneubühler, 2020). The software is designed so the algorithm implementation can easily be adopted in other projects.

The developed application guides the user through taking a measurement and reports the results on the screen. Meanwhile, raw pressure data is recorded and stored in a file. Ideally, the project would have been concluded by performing a small set of experiments and building a database of measurements. Unfortunately, this was not possible in the current environment and the short time frame.

1.3 Outline

This report is split up into three main parts, the theory, discussed in chapter 2 Background, the implementation of the developed application, discussed in chapter 3 Algorithm, 4 Hardware and 5 Software and the discussion of the results in chapter 6 Results and Discussion and 7 Conclusion.

The first part, chapter 2 Background, discusses the theory of oscillometric blood pressure measurements. It focusses on research material and algorithms suitable for real-time processing. It starts by explaining what blood pressure is and how it is can be accurately measured. Next, different algorithms for automatic oscillometric measurements are explained starting with the most popular ones and ending with proposed alternative methods. The chapter is concluded with a summary and the identified algorithm to implement in this project.

The next part, chapter 3 Algorithm, discusses the implemented algorithm in detail. It is a description of the logic and principles upon which the software is built on.

Chapter 4 Hardware defines briefly the used hardware, followed by chapter, 5 Software. The latter discusses the implementation of the application that was developed. It focusses on the implemented architecture and structure of the application. The complete source code of the software is available on GitHub and documented using Doxygen.

The next part, chapter 6 Results and Discussion, highlights what approaches worked well to determine blood pressure from oscillometric data and what caused difficulties.

Finally, the last chapter, 7 Conclusion looks back at what was achieved in the project. Recommendations are given on further steps, how to develop the software and improve the algorithm.

Chapter 2

Background

This chapter discusses the findings of researching existing and proposed algorithms for determining systolic and diastolic blood pressure through the oscillometric method. This report focusses on relatively simple algorithms that can be implemented in a real-time application, which is the goal of this project.

The first part of this chapter defines what blood pressure is and how it is measured manually. Afterwards, different algorithms are explained and examined.

A section at the end of this chapter explores algorithms beyond the scope of the project that have been proposed in recent literature.

2.1 What is Blood Pressure?

Blood pressure is an essential bio-medical measurement and often used for diagnostics in cardiovascular diseases. Most commonly, systolic and diastolic blood pressure are mentioned in pairs, but what do those mean?

The heart is a pump that has two phases. When the ventricle is relaxed, the heart fills up, and the diastolic blood pressure (DBP) is observed. When the heart contracts, it pushes the blood through the arterial system, and the systolic blood pressure (SBP) is observed. A third characteristic is the difference between SBP and DBP, the pulse pressure (PP). Finally, the mean arterial pressure (MAP) is defined as the average pressure in the artery. Figure 2.1 shows how these pressure values are connected in two heartbeats. MAP is the area underneath the blue curve divided by the time of one pulse, indicated by the orange area (Boron and Boulpaep, 2012). Because blood pressure is simplified as a sine wave, the MAP is in the middle between SDP and DBP. Usually, the MAP is closer to DBP.

Blood pressure can be measured with invasive and non-invasive methods. The most accurate technique is invasive and requires professional expertise because a catheter has to be injected into the blood vessel (Boron and Boulpaep, 2012). Subsequently, non-invasive methods are more common

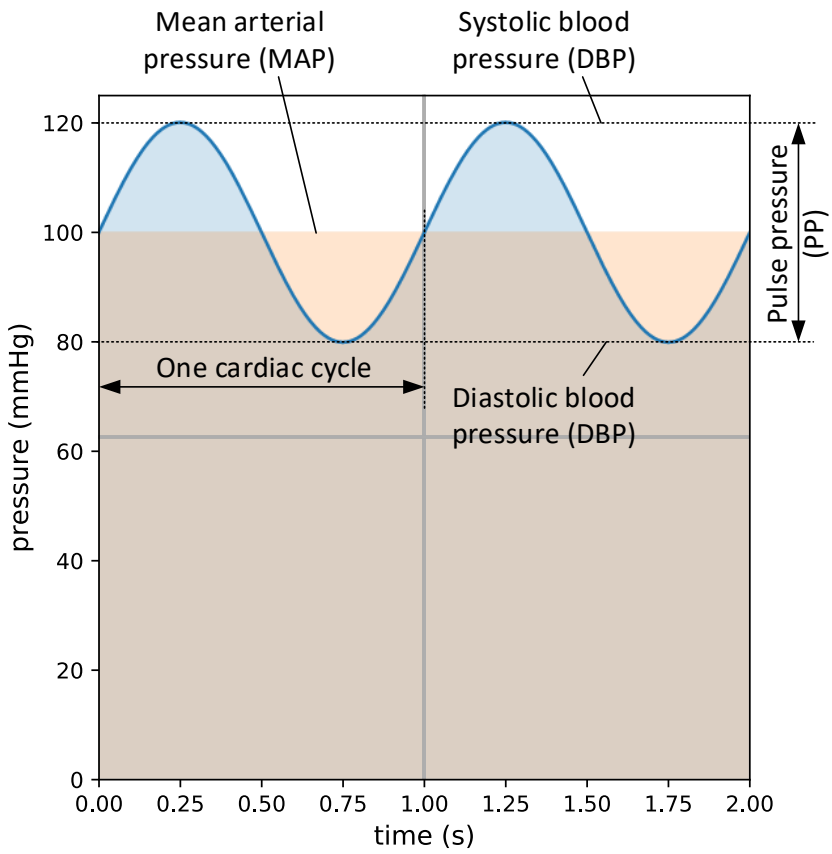

Figure 2.1: Characteristic blood pressure values simplified as a sine wave. The values are: MAP: 100 mmHg, SBP: 120 mmHg, DBP: 80 mmHg, PP: 40 mmHg and heart rate: 60 beats/s.

because they are more convenient to use. With automated means, taking blood pressure at home has become comfortable and straightforward. However, the inaccuracies of these measurements are often ignored or even unknown.

2.2 Manual Blood Pressure Measurement

The manual method of measuring blood pressure relies on a sphygmomanometer and listening to the heart or Korotkoff sounds (named after their discoverer) with a stethoscope. This is called the *auscultatory method*. *Palpation* is another method where the pulse is felt at the wrist. It only allows detection of the SBP (Boron and Boulpaep, 2012). The auscultatory method is described below because it provides recommendations that are true for all blood pressure measurements using a cuff.

A sphygmomanometer is shown in figure 2.2. It consists of an inflatable cuff, connected to a rubber pump and a scale that indicates the pressure in the cuff in Millimetres of mercury (mmHg). The pump is equipped with a valve that can be opened to release air.

Millimetres of mercury is a unit to describe pressure. 1 mmHg is defined as the pressure generated

by a column of mercury of 1 mm height. Millimetres of Mercury is not part of the International System of Units (French: Système international (d'unités) (SI)) but was defined by them before 2019 as 1 mmHg = 133.322 Pa using standard gravity (SI, 2006). Since 2019, mmHg is no longer included in the SI brochure. However, it is still widely used in the medical field (Pražák et al., 2020).

Figure 2.2: Picture of a sphygmomanometer showing the cuff, inflation pump and mercury meter.

Intra-arteria or direct BP measurement is considered the 'gold standard', but most studies compare the developed algorithm with the auscultatory method, which underestimated SBP and overestimates DBP according to Sapinski (1996). Nonetheless, the protocols to test automatic blood pressure monitors given by the British Hypertension Society (BHS) and their American counterpart, the Association for the Advancement of Medical Instrumentation (AAMI), both use the auscultatory method as a reference (Jazbinsek et al., 2010; O'Brien et al., 1993; AAMI, 2013).

2.2.1 Auscultatory Method

The cuff size must be appropriate for the patient's arm. The rubber bladder inside the cuff should cover more than 80 % but less than 100 % of the arm's circumference.

The cuff is completely deflated and tightly fit around the upper arm of the patient. The centre of the bladder should be over the brachial artery and the arm supported at heart level. The stethoscope is to be placed over the artery between the cuff and the patient's elbow and should not touch the cuff. The stethoscope being pressed on the arm could influence the reading because it puts additional pressure on the artery and can interfere with hearing the sounds (Reeves, 1995).

The valve at the pump is completely closed. Then the cuff is inflated to a pressure of about 30 mmHg above the expected systolic pressure. That causes the artery to flatten and not let any

blood through. Next, the valve is slightly opened to slowly deflate the cuff at a rate of approximately 3 mmHg/s. The artery will open and let small amounts of blood through. Systolic pressure is read when a pulse is first heard. Meanwhile, deflation continues. Diastolic pressure is read when the sounds disappear. Ultimately, blood can flow freely through the artery. After making sure that no further sounds can be heard by deflating for at least another 10 mmHg, the valve is opened completely to empty the cuff. (Bos et al., 2007; Lloyd, 2018; Reeves, 1995)

There are some discrepancies in literature on how to define the point of the diastolic blood pressure. Some references define it as when the Korotkoff sounds disappear entirely (Lloyd, 2018; Reeves, 1995). Others describe it as the point where the sounds are muffled (Boron and Boulpaep, 2012). Here, the former is assumed, because most current literature does and some research suggests that the auscultatory method overestimates diastolic blood pressure (Chandrasekhar et al., 2019).

2.2.2 Calculation of MAP

Traditionally, MAP is calculated as an estimate by adding a third of the PP to the DBP. Or, how it is more commonly referred to, adding SBP and twice the DBP and dividing the result by three (equation 2.1). According to calculations by Bos et al. (2007), this underestimates the MAP, and they suggest to add 40% rather than a third of DBP. Furthermore, they propose to use MAP measured by oscillometric devices rather than calculating it from values obtained through the auscultatory method.

$$MAP = \frac{SBP - DBP}{3} + DBP = \frac{SBP + 2 \times DBP}{3} \tag{2.1}$$

As explained by Joe (2019), nurses in intensive care units (ICU) today still use the manual calculation method on the automatically obtained SBP and DBP rather than trusting the measured MAP, which introduces significant errors.

2.3 Automatic Blood Pressure Measurement

Most modern automatic devices use the oscillometric method to determine blood pressure. They are used both at home and in professional environments.

Automatic blood pressure monitors measure pressure in a cuff similar to the one used in the manual method. However, they use the small pressure changes (oscillations) extracted from the deflation curve to estimate blood pressure. Commercially available devices are usually equipped with an electric pump, and the bladder contains a pressure sensor. Otherwise, they look similar to the cuff used for manual measurements. Some devices use wrist cuffs, but those are rarely recommended (BIHS, 2020). The most significant problem using wrist measurements is the influence of gravity on blood pressure and the accompanying risk of systematic errors when the device is not at heart level (Boron and Boulpaep, 2012). This problem is avoided by taking blood pressure at the upper arm.

General Procedure The procedure is likewise similar to the manual method. Pressure in the cuff is increased to a level above the expected systolic pressure, which leads to the artery being pushed close. While releasing the air slowly through the valve, blood starts flowing through the artery, resulting in small increases in pressure relative to the continued deflation of the cuff. As the cuff deflates further, these relative changes increase to a maximal value before they start decreasing again (Forouzanfar et al., 2015; Drzewiecki et al., 1994; Ursino and Cristalli, 1996). The shape, magnitude or envelope of these oscillations are used in various automatic blood pressure algorithms. Methods that do not use oscillations exist, but are not discussed here.

Oscillation Extraction There are two ways the oscillometric waveform (OMW) is extracted from the deflating pressure curve. The first one is filtering. A bandpass filter with a lower cut-off frequency between 0.1 to 0.5 Hz and an upper cut-off frequency between 5 to 20 Hz is recommended (Forouzanfar et al., 2015). Implementations usually use first (Lim et al., 2015) to sixth order (Jazbinsek et al., 2010) Butterworth filters. They are known for their flat pass-band response and good frequency response.

The second approach is to use detrending. It requires to know the beginning of each pulse to be able to fit a line of continuously deflating pressure to the identified points. Its advantage is, it additionally reproduces an estimated deflation curve. However, it requires additional data, for example, ECG for pulse detection (Forouzanfar et al., 2015).

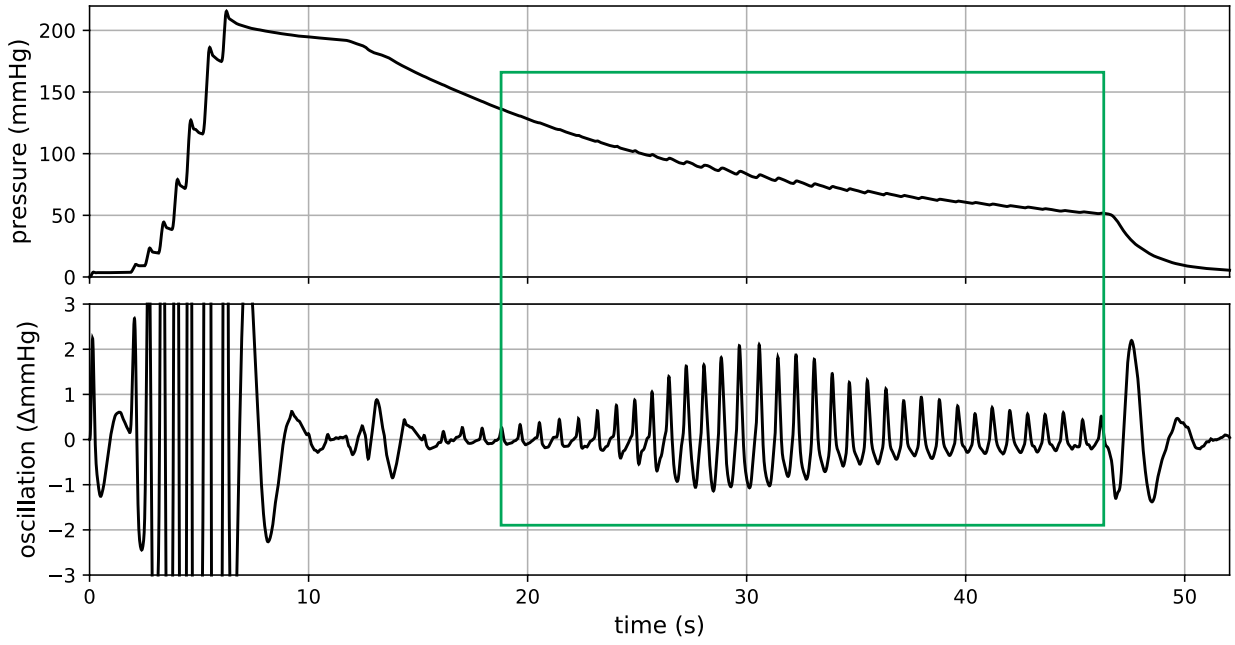

Figure 2.3: The deflating pressure data in the top plot is filtered with a 4^{th} order Butterworth high-pass filter with the cut-off frequency at 0.5 Hz to extract the oscillations. The green rectangle highlights the vital part of the data.

Ultimately, from a deflation curve as in the signal in figure 2.3 on the top, the oscillations are

extracted. The bottom plot in figure 2.3 shows oscillations extracted with a 4^{th} order Butterworth high-pass filter with the cut-off frequency at 0.5 Hz. The rectangle shows the part of the signal that is analysed further.

Envelope Basic automatic algorithms use the oscillometric waveform envelope (OMWE). Formation of the envelope is achieved in different ways. The simplest is to register only local maxima. Most common is the subtraction of the following through from a local peak. Similar is interpolating the curve of local maxima and local minima to subtract them from each other. Some algorithms additionally fit a curve on the obtained OMWE in an attempt to remove artefacts (Forouzanfar, 2014).

2.3.1 Maximum Amplitude Algorithm

The maximum amplitude algorithm (MAA) is based on the assumption that the oscillations are maximal when the pressure in the cuff equals arterial pressure. Accordingly, the recorded pressure at which oscillations are maximal is considered a valid estimate of the MAP (Babbs, 2012; Geddes et al., 1982; Drzewiecki et al., 1994; Ramsey, 1979), as long as the compression chamber is kept small (Mauck et al., 1980). The cuff should always be tightly fit, to avoid introducing errors. Air in the cuff causes maximum oscillations to be above the accurate MAP. Hence, Ursino and Cristalli (1996) suggest using the lowest pressure of the plateau of maximal oscillations as the value to assess MAP.

The publication by Chandrasekhar et al. (2019) employs a more complex model than the one initially introduced by Mauck et al. (1980). They conclude that the MAA results in a weighted average of systolic and diastolic BP. According to their model, MAA underestimates MAP for higher blood pressures.

Fixed-Ratio Algorithm The fixed-ratio algorithm builds on the MAA. It is based on the assumption that the systolic and diastolic blood pressure occur at specific fractions of the maximum oscillation before and after its occurrence. Determining SBP and DBP after applying the MAA was tested by Geddes et al. (1982). They recorded the Korotkoff sounds while measuring oscillations to find a ratio of amplitudes for SBP and DBP. They defined the coefficient for the systolic pressure to be 0.5 and the one for the diastolic pulse as 0.8. These ratios were found empirically, and Geddes acknowledges that the systolic pressure is overestimated and the ratio for the diastolic pulse is not constant for a range of different diastolic pressures.

Later studies tried to find accurate ratios, mostly experimentally with the ratio for SBP usually being determined between 0.45 and 0.73 and the ratio for DBP a bit higher between 0.69 and 0.83 (Drzewiecki et al., 1994; Forouzanfar et al., 2015). Mathematical models confirmed that a generalised ratio can not be found. Parameters like the age of the subject, the arterial stiffness and pulse pressure influence the ratios (Ursino and Cristalli, 1996). A higher PP results in a smaller ratio for SBP and larger ratio for DBP. A stiff arterial wall causes volume changes to happen slower. While this has little

effect on the systolic ratio, the diastolic ratio decreases with the stiffness of the artery (Babbs, 2012).

2.3.2 Derivative Algorithm

The derivative algorithm uses the OMWE and plots it against the deflating pressure. Next, the points of the maximal and minimal slope are determined. The pressure point where the derivative of the OMWE is maximal is assumed to be the diastolic BP and where the derivative is minimal is the systolic BP, respectively (Jazbinsek et al., 2010; Forouzanfar et al., 2015).

Even though mathematical models have confirmed this method to produce valid estimates of both SBP and DBP without the need for empirically obtained ratios, it is exceptionally vulnerable to noise and therefore not used in practical applications (Babbs, 2012; Chandrasekhar et al., 2019).

Jazbinsek et al. (2010) evaluated the fixed-ratio and derivative algorithm. They used a device equipped with an electrocardiogram (ECG) and a microphone to validate their results. Various ways to form the envelope were used, including detrending, filtering and even using the low-frequency part of the audio signal of a microphone that recorded Korotkoff sounds. However, to evaluate the fixed-ratio method, they used a commercial device to find average ratios and used the values from the same tool as a reference for the evaluation. As was to be expected, their implementation of the derivative algorithm showed many local extrema. The algorithm was only able to perform by applying additional constraints that bias the measurements significantly. For example, the extrema have to be distanced from the MAP value more than 15 mmHg (Jazbinsek et al., 2010, 2005).

2.3.3 Other Algorithms

Since the algorithms mentioned above use only the envelope of the oscillations to determine BP, they discard all the information that lies within the shape of every pulse. Naturally, scientists have tried to find ways to use this information to improve BP algorithms.

There are a variety of different ideas that have been tested in small scale experiments, mostly with less than 30 test subjects. While they all claim to improve BP measurements compared to the fixed-ratio algorithm, they often lack significant evidence and mathematical verification.

Non-Fixed Ratio Sapinski (1996) proposed a standard algorithm. The algorithm uses ratios to determine the SBP and DBP from MAP as above but calculates the ratios based on the oscillations. The integral of the maximal oscillation is divided by its time period and results in the amplitude of the pulse wave at systolic pressure. The amplitude at diastolic pressure is defined as the difference between the MAP amplitude and the SBP amplitude. This algorithm is based on theoretical assumptions formed form comparisons to the direct method, i.e. that the added oscillation pulse amplitudes at systolic and diastolic pressures equal the amplitude at mean pressure. Sapinski mentions that the average value of systolic oscillation is 40 % of the MAP amplitude and 60 % for the diastolic oscillation, respectively.

This part is regularly quoted in other literature, without mentioning that this is not a proposed ratio. Sapinski concludes, that the proposed algorithm does not fulfil the criteria of the AAMI standard compared to the auscultatory method, but does compared to the invasive method. No further literature has been found that validate or contradict these findings.

Pulse Morphology Specific characteristics of single pulses can be examined to determine blood pressure. Following are four of the most commonly used indices. The definitions are as presented by Mafi et al. (2011).

- Stiffness index (SI): The height of the subject (h) divided by the time difference between systolic and diastolic peak (ΔT) (equation 2.2) is an indicator for arterial stiffness, but requires to know the person's height.

$$SI = \frac{h}{\Delta T} \tag{2.2}$$

- Augmentation index (AI): The difference of systolic (A_S) and diastolic peak (A_D), divided by the systolic peak, expressed in percentage of pulse pressure is called AI (equation 2.3).

$$AI = \frac{A_S - A_D}{A_S} \times 100\% \tag{2.3}$$

- Reflection index (RI): The amplitude of systolic (A_S) divided by the diastolic peak (A_D), expressed in percentage is the RI (equation 2.4), which is related to the vascular tone.

$$RI = \frac{A_S}{A_S} \times 100\% \tag{2.4}$$

- $\Delta T/T$ Ratio: The time difference between systolic and diastolic peak (ΔT) is divided by the duration of the pulse (T). Both T and ΔT increase with age.

Mafi et al. (2011) plotted the indices in time and used absolute maxima or minima to determine MAP. The plot shows a significant spike where MAP is expected. Using local maxima and minima next to the found MAP to estimate SBP and DBP has less significance. Problematic with this approach is that the reference values were measured by an Omron device which implements an unknown algorithm. Because the device did not display the measured MAP, the MAP reference was calculated using equation 2.1, which is known be wrong using accurate representations of SBP and DBP and likely delivers erratic values when using values from an automatic device.

Another implementation by Mafi et al. (2012) takes the '1st' derivative of each pulse. They take the maximal value of that to form another curve that looks similar to the one used in the MAA. This curve is then processed like the fixed-ratio algorithm to determine MAP, SBP and DBP. The ratios are determined experimentally using reference measurements. Additionally, the MAP is again calculated

using the faulty equation 2.1 and the 18 test subjects aged between 24 and 68 are healthy and have no history of cardiovascular disease. The authors argue that the shape is less sensitive to noise than the amplitude, and therefore, their approach is more robust than the MAA.

Model-Based Algorithms These algorithms use a predicted OMWE and fit it to the observed one to determine the characteristics. While they do consider factors that the standard algorithms discard, such as arterial stiffness and pulse pressure, they are vulnerable to artefacts that are not recognised by the model. They could be used to validate algorithms (Babbs, 2012).

Neural Networks The features extracted from above, and more, are often used in neural networks (NN). However, it has been shown, that the indices can reliably only be used to determine the MAP. Moreover, some of the features are highly dependant on external factors. For example, the exact deflation rate influences the duration of the OMWE (proposed by Lee et al. (2013)) and the constraint of 2 to 3 mmHg/s given by Lim et al. (2015), who implemented a NN using the proposed features, seems hardly enough. Similarly, the used filter by Lee et al. (2013), a first-order bandpass Butterworth filter with cut-off frequencies of 0.5 Hz and 5 Hz, is likely to remove valuable information from the pulses.

2.4 Summary

The decision on which algorithm to implement is difficult because none of the known algorithms have been established. Commercial devices use proprietary closed-source algorithms. Even those that are approved by the British and Irish Hypertension Society (BIHS, 2020).

The MAA is known to give valid estimates of MAP. Although various studies have tried to find an actual connection from the MAP and OMWE to SBP and DBP, none have made significant changes to the method described 40 years ago (Geddes et al., 1982). Jazbinsek et al. (2010) used an automatic device to determine ratios before testing the fixed-ratio algorithm. The results of their algorithm are then compared against values measured by the same device. They acknowledge that it is a drawback, to compare the results to an automatic measurement, but argue that they confirmed its accuracy by measuring Korotkoff sounds. However, this introduces a bias in the ratios. That they produce results that agree with the measurements from the device they are derived from, is likely. Nonetheless, the algorithm performs poorly for estimating SBP and DBP in their study (Jazbinsek et al., 2010).

Similarly, other methods using pulse morphology, only seem to be useful for determining MAP. In the experiments done by Mafi et al. (2011, 2012) even that is questionable. They measure SBP and DBP using an Omron device and calculate MAP from that, which introduces a chain of errors in the reference data.

The promising algorithm for non-fixed ratios proposed by Sapinski (1996) has no real mathematical foundation. It has, to the author's knowledge, not been confirmed in the considerable time since

it was introduced.

The most promising algorithm to determine systolic and diastolic BP is the derivative. It is known to be extremely sensitive to noise. Initially, it was considered as a way to improve the estimation of SBP and DBP but was later discarded, following the experiments explained in 6.1.2 Derivative Algorithm.

Ultimately, a fixed-ratio algorithm is implemented, with a clear emphasis in the results, that the MAP is the trustable value. The ratios can be changed by the user and only provide guidelines for SBP and DBP.

Chapter 3

Algorithm

This chapter explains the general principles behind the algorithm and separates the logic from the implementation, which will be discussed in a separate chapter, 5 Software.

The realised algorithm is a fixed-ratio algorithm. It analyses the oscillations to find MAP form the maximum amplitude as described in 2.3.1 Maximum Amplitude Algorithm. It estimates the position of the systolic and diastolic BP as where the amplitudes are at a specific ratio of the maximum. The systolic BP is evaluated while the oscillation amplitudes increase and the diastolic BP while they decrease, respectively.

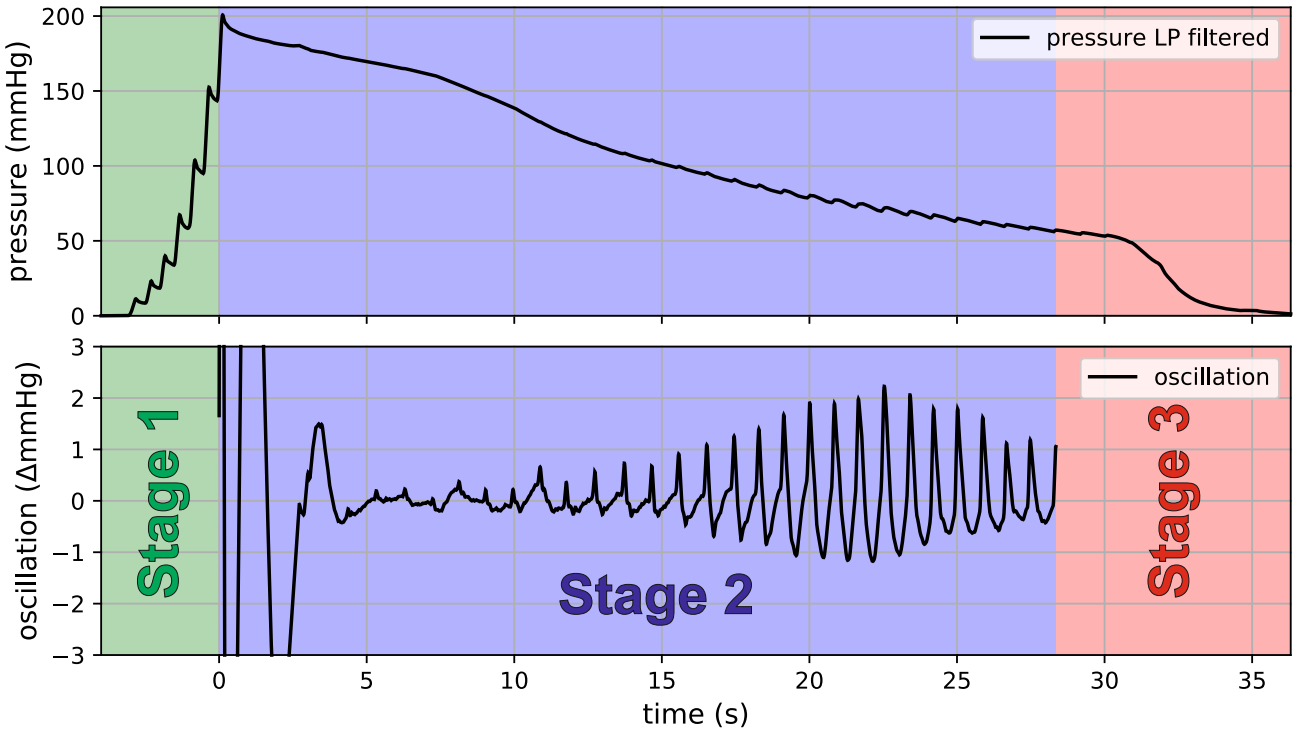

Figure 3.1: A sample dataset is shown in the top plot and divided into three parts. The blue portion is where oscillations are analysed. These are shown in the bottom plot.

The top plot in figure 3.1 shows one data set and how it is divided into different steps for pro-

cessing. The first part (green) is when the user pumps-up the cuff pressure. The second part (blue) is the deflation. Here, the oscillations, shown in the bottom plot, are recorded and analysed. Once these oscillations have increased to a maximum and decreased again to a certain value, the last step (red) is simply the deflation of the cuff. The core part of the algorithm works on the blue part of the data.

3.1 Preprocessing

The data is always filtered. Additionally, preprocessing decides which stage of the dataset is active. Concerning figure 3.1, stage one is green, stage two is blue, and stage three is red. Figure 3.3 shows the basic diagram of data processing. The core algorithm processes only the deflating and filtered data.

3.1.1 Filtering

Unwanted noise is removed from the data by a filter. Oscillations are extracted by a second. Figure 3.3 below shows the simple cascade of a low-pass (LP) and high-pass (HP) filter, resulting in a bandpass (BP) filtered output signal, the oscillogram. The results of both filter outputs are used in the algorithm.

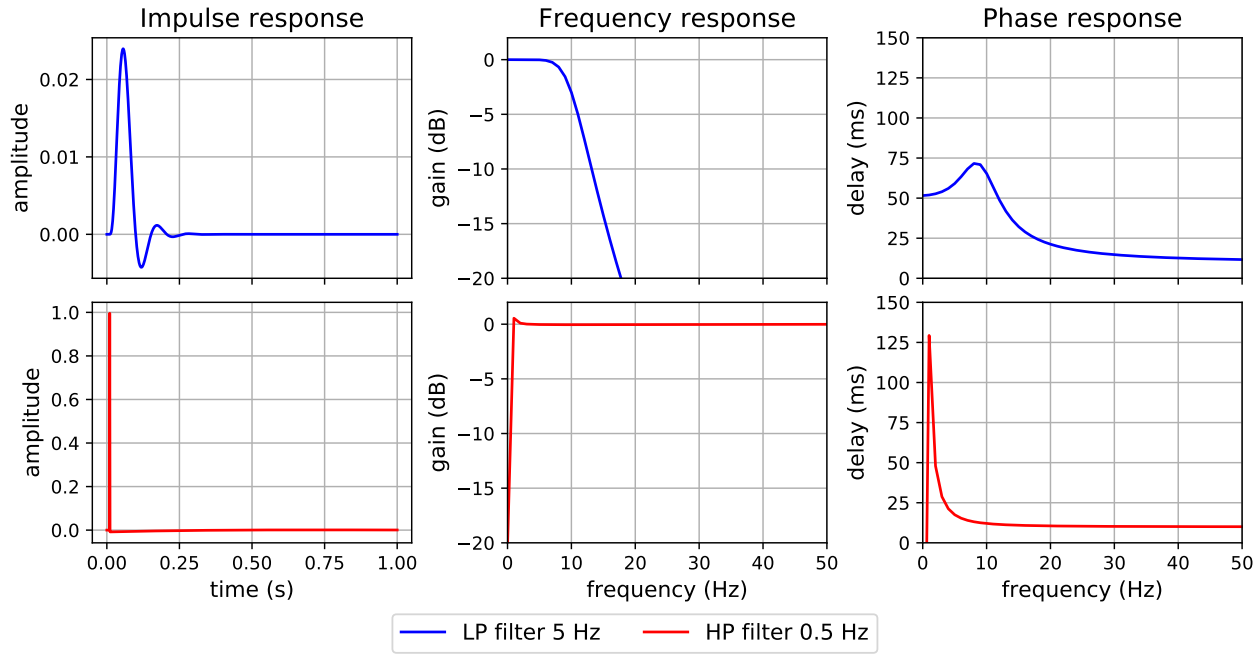

Figure 3.2: The top row shows the analysation of the low-pass filter and the bottom row the high-pass filter.

From the research done in chapter 2 Background, it is known that most algorithms use band pass filters of low orders up to 6^{th} with cut-off frequencies between 0.1 to 0.5 Hz and 5 to 20 Hz (Forouzanfar et al., 2015). The implemented algorithm does not rely on pulse shape and can, therefore, use

relaxed constraints. Best results were achieved with a lower cut-off frequency of 0.5 Hz. The upper cut-off frequency was fixed at 10 Hz. Generally, there is very little activity between 5 to 20 Hz, but because no experiments could be done with test subjects that have higher blood pressure, a mean value was chosen.

The implemented filters are shown in figure 3.2. The low-pass filter has a small delay in the impulse response, and the phase response shows that for very low frequencies, there is a slightly higher delay. The frequency response shows a steep slope after 10 Hz and suppression of more than 20 dB of the spectrum above 20 Hz. The HP filter expectedly lets the impulse pass. In the frequency response, there is a small overshoot but otherwise a good suppression of DC. The bottom right plot in figure 3.2 shows that the HP filter has a significant delay of about 125 ms for frequencies around 1 Hz, which could potentially cause inaccuracies. Section 3.3.2 Implications of Filter Delays will explain why this is not a problem.

3.1.2 Stage Detection

The LP filtered data is analysed by the preprocessing step to detect if the second stage, the deflation, is active. Figure 3.3 shows how the preprocessing step then passes both the LP and BP filtered data to the core algorithm, symbolised by a switch.

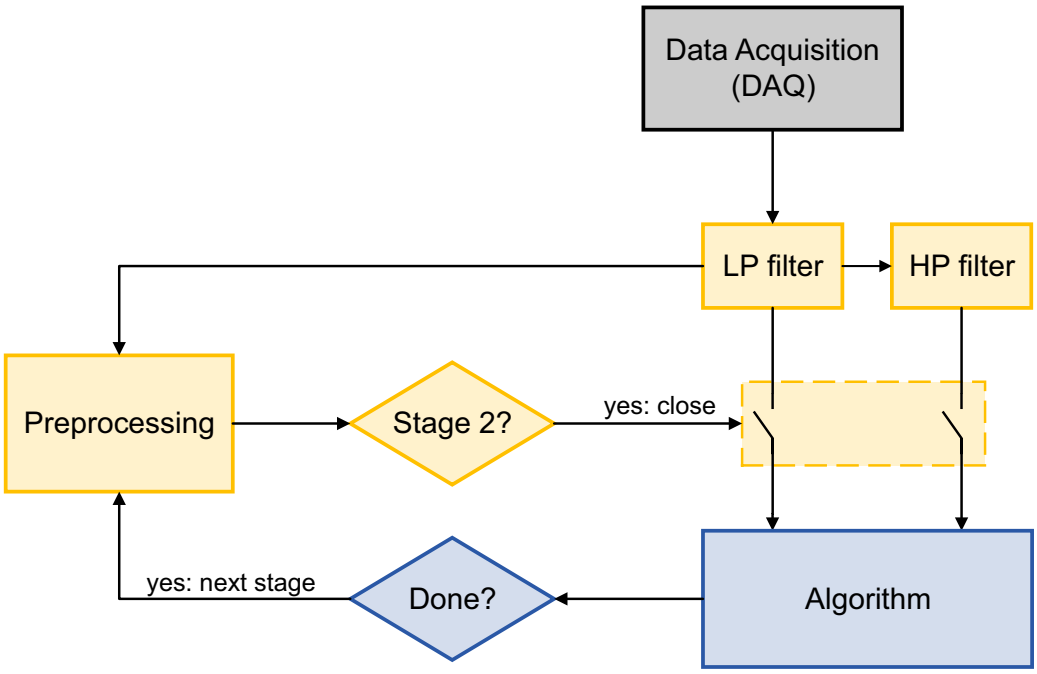

Figure 3.3: The figure shows the simple basic data processing flow. The data is acquired and passed first to a low-pass filter (10 Hz) and then to a high-pass filter (0.5 Hz), resulting in a bandpass output. The preprocessing part of the diagram is marked yellow, the algorithm blue.

In the first stage, the data is checked if the pressure in the cuff is high enough to start deflation. If so, the preprocessing switches to the second stage. This inflation value is configurable. The default value is 180 mmHg. Figure 3.3 shows how the decision is made based on the LP filtered data.

Once the second stage is active, the preprocessing checks the core algorithm if it is done. In figure 3.3, this is indicated by the arrow from the algorithm back to preprocessing. Additionally, the data is checked if it is below a value of 20 mmHg, where taking blood pressure makes no sense, and the measurement is potentially cancelled.

3.2 Deflation

Figure 3.4 shows data recorded during the deflation stage. ① shows the low pass filtered data, which is used in the core algorithm as a reference. ② is the BP filtered data upon which the algorithm is performed.

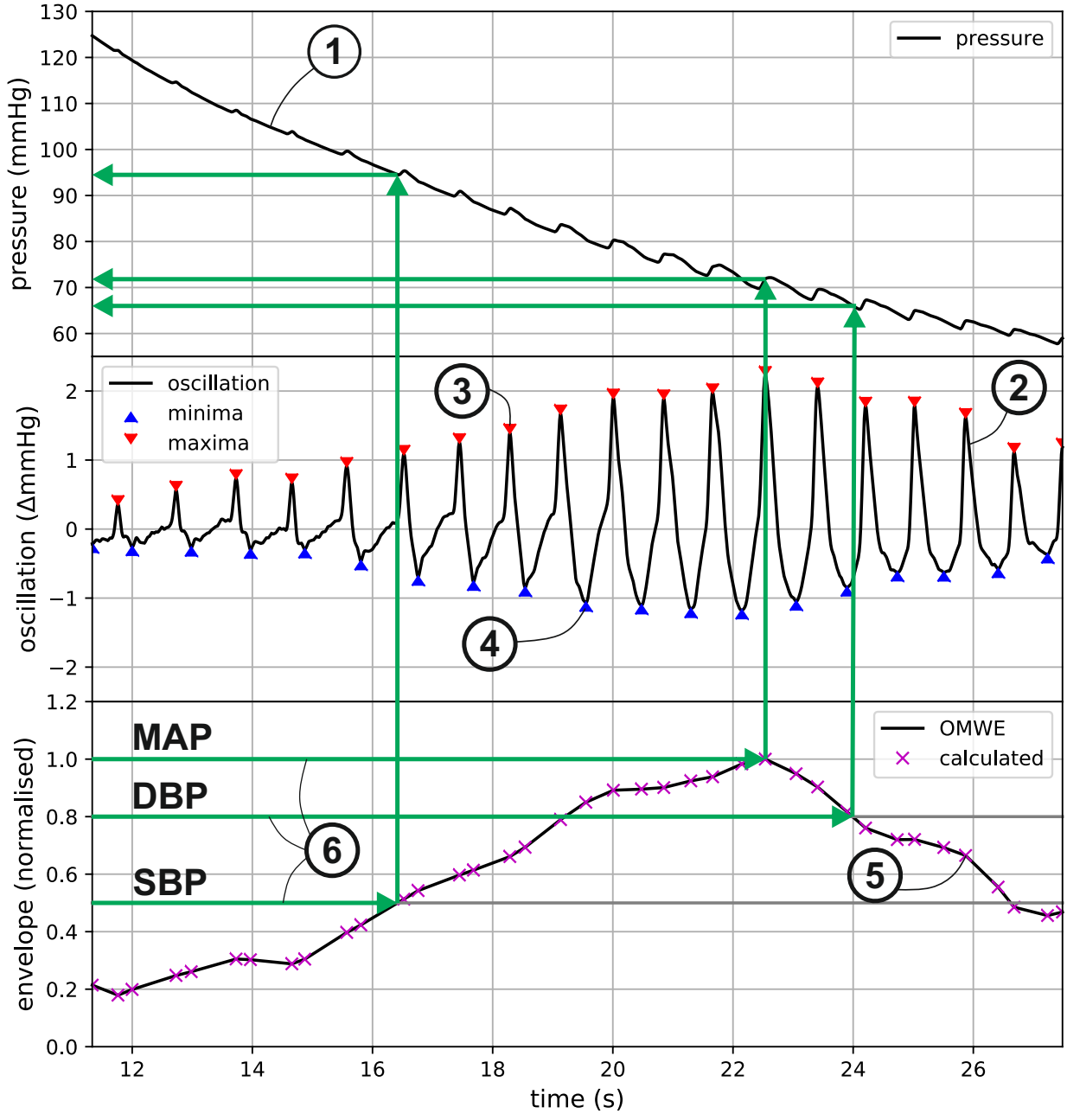

Figure 3.4: The top plot is the deflating pressure, the centre the extracted oscillations and the bottom the calculated OMWE. An explanation of how they are all used in the algorithm is given below.

3.2.1 Extrema Detection

Maxima The next step, indicated with ③, is to detect the maxima. There are local maxima in the troughs between two oscillations. To avoid detecting these, a value needs to have a minimal pronunciation of 0.25 ΔmmHg to be considered as a maximum. This limits how quickly the first oscillations can be recognised but does not influence the algorithm because they are less than 10 % of the expected maximal amplitude.

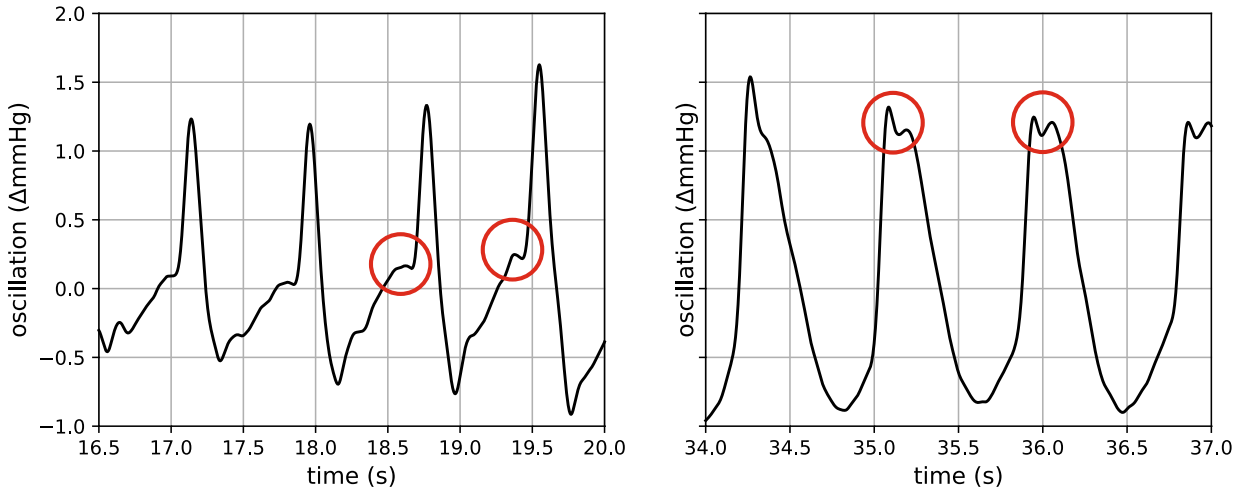

Figure 3.5: The plots show two common problems when detecting maxima. The left-hand side shows how the rising edge can fall slightly before rising to the maximum. The right-hand side shows a typical double maxima.

A sample is identified as a local maximum, due to the previous and following value being lower. Next, it is checked if the current and last detected maxima result in a valid heart rate given by a configurable range. The default range is 50 to 120 beats/min. Also, if the last maximum was less than 300 ms ago, only the larger of the two is kept, and the lower is discarded.

This also solves two concerns that were observed in the data and are shown in figure 3.5. The first, shown on the left-hand side, is if the bump in the rising edge of the oscillations results in a detected maximum. It often happens if the deflation is not steady or the arm is moved. When oscillations are small and rising, these can lead to wrong detections. Either these extrema are irrelevant because they occur before systolic BP, or they will be discarded because they lead to errors.

The second issue is shown in figure 3.5 on the right. It occurs mainly in decreasing oscillations and if the filtering is not optimal. The algorithm successfully handles these double maxima, but it might also influence the detected DBP value.

Minima Minima detection, indicated by ④ in figure 3.4, is considerably more difficult, especially at the beginning of oscillations as shown in figure 3.6. Because there has to be a minimum in between two maxima, minima detection is simplified. After detecting two maxima, the lowest value between them is recorded as the minima.

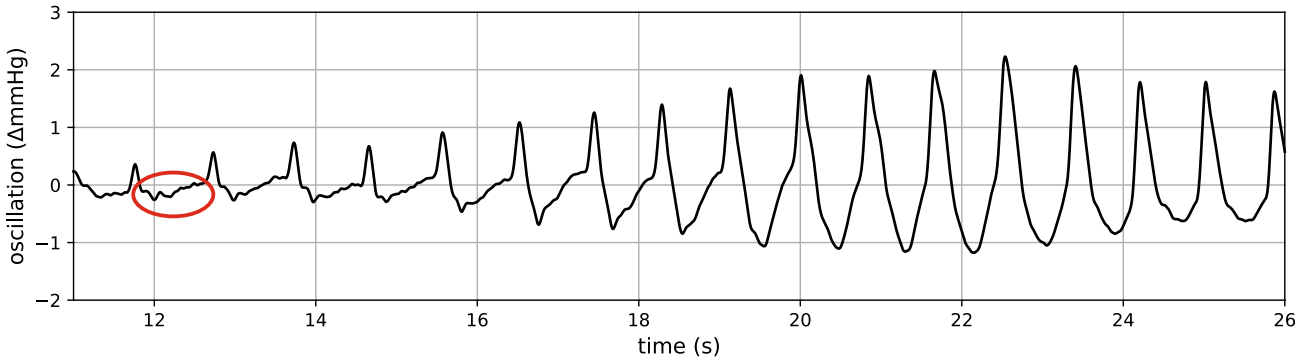

Figure 3.6: Minima are harder to detect than maxima, especially in the beginning, when maxima are still small (marked with a red circle).

3.2.2 Heart Rate Detection

Heart rate is already part of the extrema detection described above. Therefore, the current heart rate is detected after each valid maxima starting from the second one. Because each pulse stems from a heartbeat, each peak represents one. By calculating the time between the last two maxima, a heartbeat is estimated using equation 3.1 below.

$$pulse = \frac{60s}{t_{curMax} - t_{lastMax}} \tag{3.1}$$

After finishing the measurement, the average heart rate is calculated from all validly detected maxima.

3.3 Oscillometric Waveform Envelope

When the detected maxima, marked by the red triangles in 3.4, have reached their highest amplitude and declined again, the OMWE can be calculated.

This condition is estimated by taking the largest recorded maximum and multiplying it with the ratio for the diastolic blood pressure minus a hysteresis of 0.3 (equation 3.2). If the last recorded maxima is below this value, the extrema detection part of the algorithm (③ and ④ in figure 3.4) can be concluded. To avoid wrong detections, the largest maxima needs to be at least 1.5 ΔmmHg and two consecutive pulses have to be decreasing. Otherwise the condition can be detected when oscillations first start occurring and are small with large variations.

$$A_{cutoff} = A_{Max} \times (r_{DBP} - 0.3) \tag{3.2}$$

3.3.1 OMWE Calculation

The following approaches were tested to calculate the OMWE from the determined extrema:

1. Only considering the maxima.
2. Subtracting the following minimum from each maximum.
3. Subtracting the preceding minimum from each maximum.
4. Interpolating between maxima and minima to find the corresponding values and subtracting them.

1. works decently but discards the information in the minima. 2. works well for pressure in the systolic range because minima follow quickly after maxima. Vice versa, 3. works well in the diastolic range. 4. requires the most computations, but is the least sensitive to noise, because it takes the time difference between minima and maxima into consideration.

When referring back to figure 3.4, ⑤ shows how the OMWE was calculated using the 4^{th} approach and calculating a value for each of the maxima and minima.

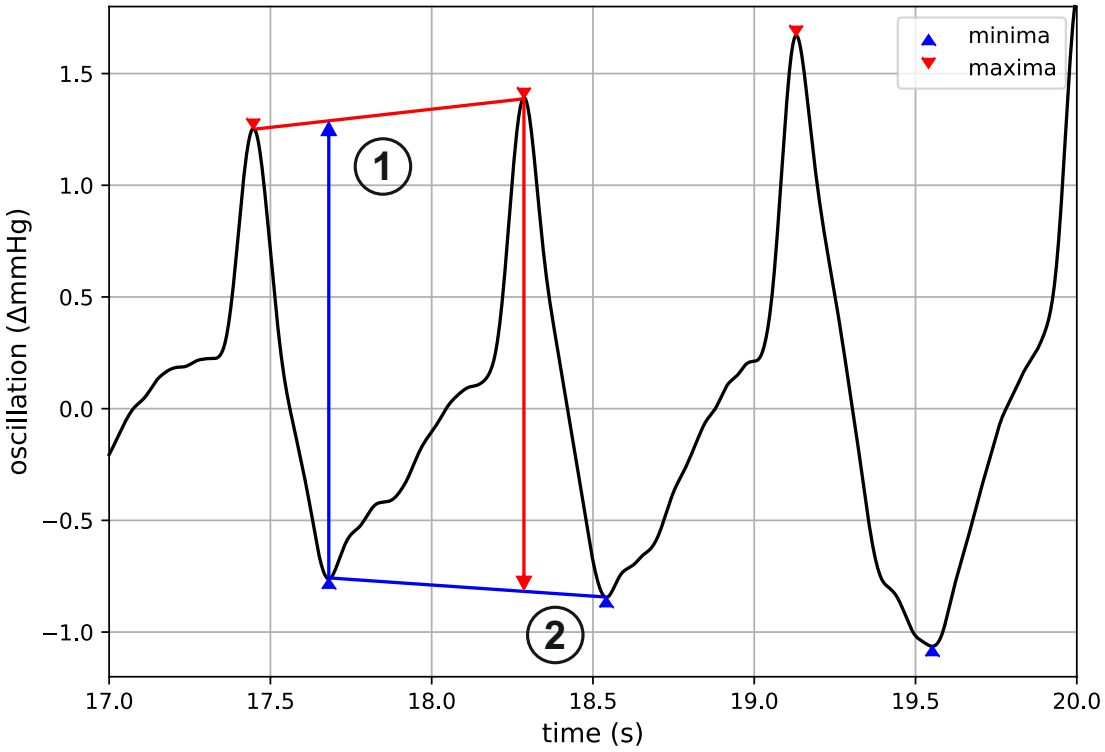

Figure 3.7: Because minima and maxima do not happen at the same time, interpolation is used to calculate a maximum at the time of a minimum (①). Likewise, a minimum is determined at the time of a maximum (②).

Figure 3.7 explains how interpolation is used to calculate an interpolated maximum at the time where a minimum occurs (①) to then be able to subtract the minimum from the maximum. Inversely, A minimum is interpolated between two measured minima where a maximum occurs (②). The resulting plot is displayed in figure 3.4 at the bottom. Note that the values are normalised by the maximal value.

3.3.2 Determination of Blood Pressure Values

After calculating the OMWE, the last step is to determine the BP values from it. As explained in chapter 2 Background, MAP occurs where the OMWE has its maximum. The time, when the maximum is recorded, is compared to the pressure at that time. The green arrows at ⑥ in figure 3.4 indicate this. To account for the oscillations in the deflation curve, the pressure is averaged throughout the average heartbeat centred around the detected time. The average heartbeat is determined from the measurement, as explained in section 3.2.2 Heart Rate Detection. In the example above, this results in a MAP of 71 mmHg.

Likewise, to determine SBP and DBP, the specific ratios of the maximal oscillations are looked for in the OMWE. The example in figure 3.4 uses a ratio of 0.5 for systolic BP and 0.8 for diastolic BP.

The systolic BP is determined by stepping backwards in time from the maximal oscillations and the diastolic BP by stepping forwards in time, respectively. Once the value falls below the specific ratio, interpolation is used to find the time where the exact ratio would have occurred. Using the same approach as for the MAP, the specific values found with ⑥ for the data in figure 3.4 is 95 mmHg for SBP and 67 mmHg for DBP.

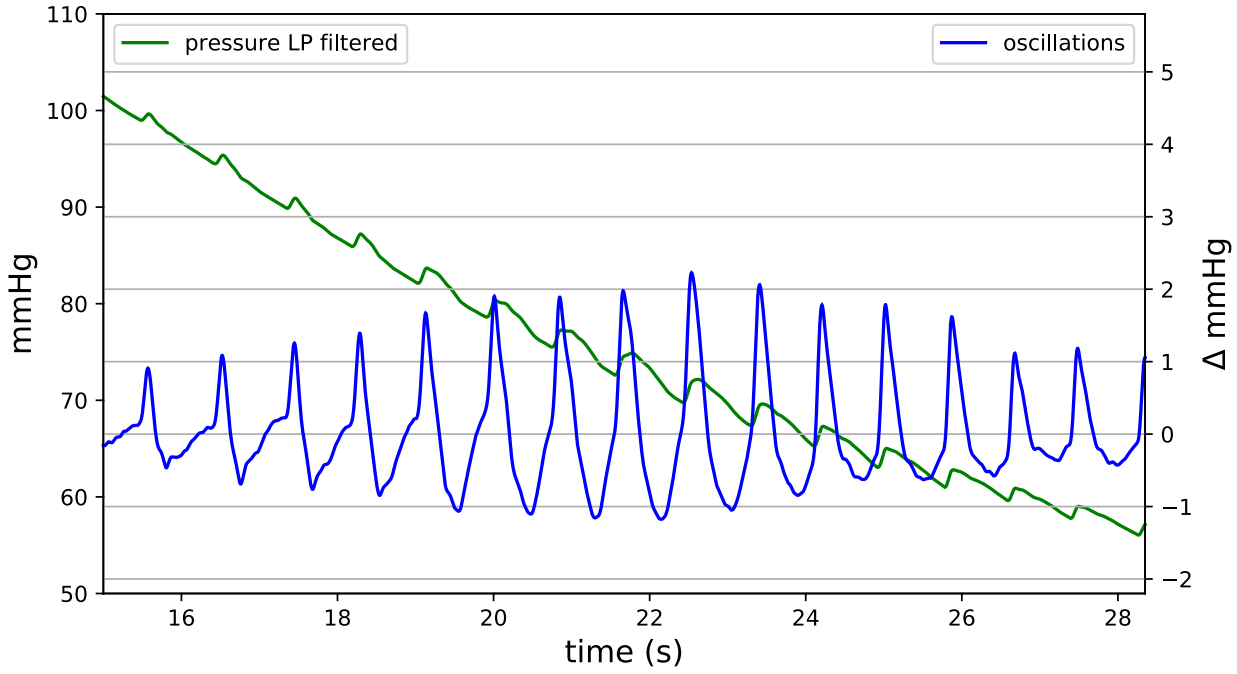

Figure 3.8: The figure shows a plot of the low-pass filtered data with the y-axis on the left. The y-axis on the right is used by the bandpass filtered oscillations.

Implications of Filter Delays

As pointed out in section 3.1.1 Filtering, the original data is delayed first by the LP and then the HP filter. Since the oscillogram is based on the LP filtered data, the delay of the first filter (LP) is

irrelevant. The second filter (HP) has up to 125 ms delay for certain frequencies. Figure 3.8 shows the oscillations superimposed over the deflating data. At a deflation rate of 3 mmHg/s, the error could be 0.375 mmHg. The calculated pressure is averaged throughout an average heart rate to account for the oscillations in the deflating data. Compared to the inaccuracies of the algorithm in general, this is neglectable.

Chapter 4

Hardware

The hardware used in this project was provided. This chapter describes the basic setup upon which the developed application relies.

Overview

Figure 4.1 shows a schematic view of the hardware setup. The computer running the application is connected to the data acquisition device, the USB-DUX Sigma, through an USB-port. On channel 0 of the device, the pressure sensor is connected through a voltage divider with a backup capacitor. The voltage divider distributes the voltage roughly 2:1. The software should be calibrated to account for the actual values.

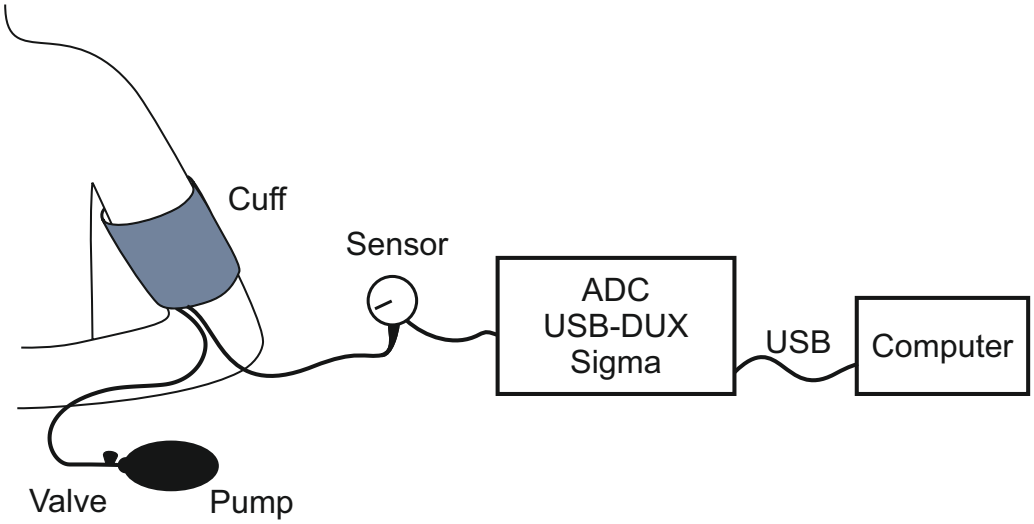

Figure 4.1: A pressure sensor is inserted in the tubing of the cuff and connected to the USB-DUX Sigma for data acquisition. USB connects the device to the computer.

Pressure Sensor

The pressure sensor measures absolute pressure. It operates on 5 V supplied by the USB-DUX Sigma. Figure 4.2 shows a simplified schematic of how the sensor is connected to the analogue to digital converter (ADC) on the USB-DUX device. The sensor outputs 1 V per 50 kPa measured pressure. The output range is from 0.204 to 4.896 V. More information can be found in the datasheet[1].

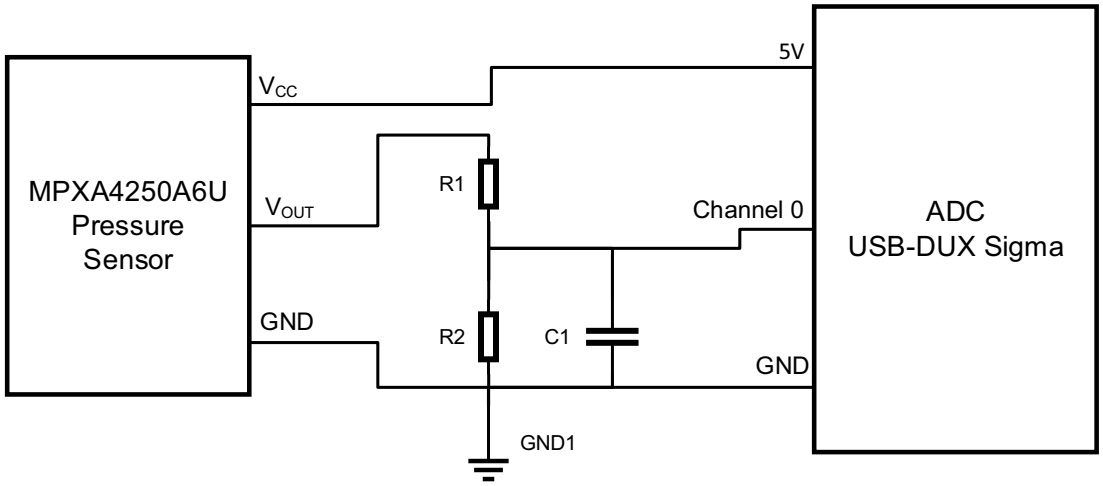

Figure 4.2: A voltage divider is needed to connect the pressure sensor to the ADC.

Analogue to Digital Converter

The provided ADC is part of a USB-DUX Sigma device. The device offers multi-channel input and output. However, only a single ADC channel was used. The used channel provides 24-bit resolution at a sampling rate of 1 kHz. The input range of the device is -1.375 to 1.375 V, which is not large enough for the output of the pressure sensor to be directly connected. Therefore, the voltage divider, as mentioned earlier, is required. A detailed description of the device can be found online[2].

[1] MPX4250A: `https://www.nxp.com/docs/en/data-sheet/MPX4250A.pdf` Accessed: 2020-08-15
[2] USB-DUX Sigma: `http://www.linux-usb-daq.co.uk/tech2_duxsigma/` Accessed: 2020-08-15

Chapter 5

Software

This chapter is a description of the developed software. It provides an overview of the architecture and implementation. The project's GitHub page contains the full source code, setup instructions and Doxygen documentation (Kneubühler, 2020).

The project is licensed under the GNU General Public License v2.0.

5.1 Overview

The application is split into the user interface (UI) and data processing. Each part runs in a thread, and they are kept separated from each other. The data processing class is called Processing, and the user interface class Window.

The user interface is built with Qt, an open-source widget toolkit for creating graphical user interfaces. Additionally, the subset Qt Widgets for Technical Applications (Qwt) is used to display the acquired data.

The Processing class handles data acquisition and processing, and is sending notifications to the UI with instructions on what action to perform or what values to update.

5.1.1 Class Diagram

Figure 5.1 shows a simplified class diagram of the application. It shows the Processing and Window classes in the centre with their most important attributes.

The Processing class has a ComediHandler object to acquire data, the OBPDetection object implements the core algorithm described in 3 Algorithm, and the Datarecord object saves the raw data to a file. The state of the application is stored as a ProcState enum.

The Window class holds all the UI components. The class diagram in figure 5.1 only shows the high-level parts that are not directly from the Qt library. SettingsDialog and InfoDialog can be opened through the menu bar to access the configuration and get further information about the application.

The two Plot objects are always visible, while the rest of the main window depends on the Screen enum.

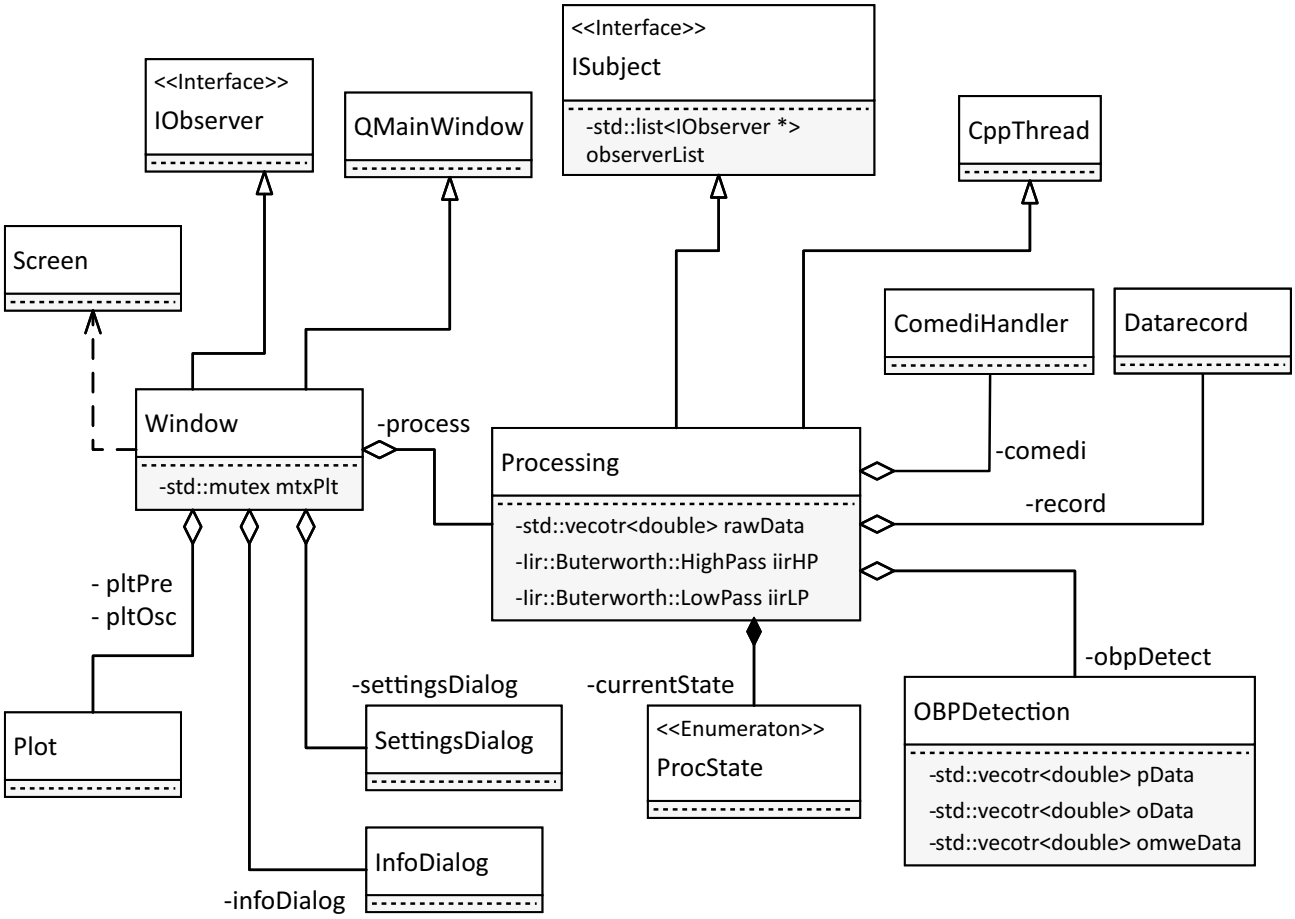

Figure 5.1: The Class Diagram of the application shows the Window and Processing class in the middle. Only the most essential parts of the program are included.

Communication between the two main objects is done with callbacks in an observer pattern from the Processing to the Window class. The Processing class is an observable subject that the Window class can register to because it implements IObserver. The Window has a reference to the Processing class to pass on user input.

Following is a more in-depth discussion of the elements mentioned above.

5.2 Data Processing

In the Processing class, the data is acquired and processed. A ComediHandler object handles the acquisition and separates handling of the underlying hardware. The data is then filtered, and the observers are notified so they can display the new data.

The logic in the Processing object is handled through a state machine. The OBPDetection class needs deflating pressure to extract the blood pressure characteristics from the oscillations. The state

machine identifies this in the state 'Deflate'. The following section discusses the state machine in detail.

5.2.1 State Machine

Figure 5.2 shows the state machine of the processing class. It is made up of an initial state ('Config') that is only accessed at start-up, an 'Idle' state and four states that are consecutively entered in an ideal measurement, called 'Inflate', 'Deflate', 'Empty' and 'Results'.

For every arriving sample, the state machine is executed according to the current state and potentially switched to another one.

In every state, except 'Config', the arriving sample is filtered, and the results are sent to the observing objects. In the 'Inflate', 'Deflate' and 'Empty' states, the raw data is additionally recorded and ultimately saved as a file when exiting the 'Empty' state.

Config After a reset, the state machine starts in the 'Config' state, where the ambient voltage is registered. Doing this is necessary, because the pressure sensor gives an absolute value, but pressure values are needed relative to atmospheric pressure. The raw pressure is read for 250 ms and averaged. If that value has a deviation of less than 1 mV to the maximal value, it is stored as ambient pressure and the state machine switches to the next state.

Idle In the 'Idle' state, the processing class is waiting for the start of a measurement while filtering data and sending it to its observers. The start is externally triggered.

Inflate While the pressure is below the configured pump-up pressure (default of 180 mmHg), in the 'Inflate' state, the raw data is recorded. When the pump-up pressure is surpassed, the state switches to 'Deflate'. In case the maximum data size for the recorded data is reached, the measurement is cancelled, and the state switched to 'Idle'. Reaching the maximum data size takes 5 min and should never happen during regular operation.

Deflate In the 'Deflate' state, the data is fed into the OBPDetection object, which is described below in section 3.2 Deflation. This object decides when enough data is recorded, and the progression to the 'Empty' state is possible. Alternatively, if the pressure falls below 20 mmHg, or the maximum data size is reached for the recorded data, the measurement is cancelled.

Empty This state is only needed to finish recording data until the pressure reaches zero. When this happens, the data is written to a file, and the state is changed to 'Results'.

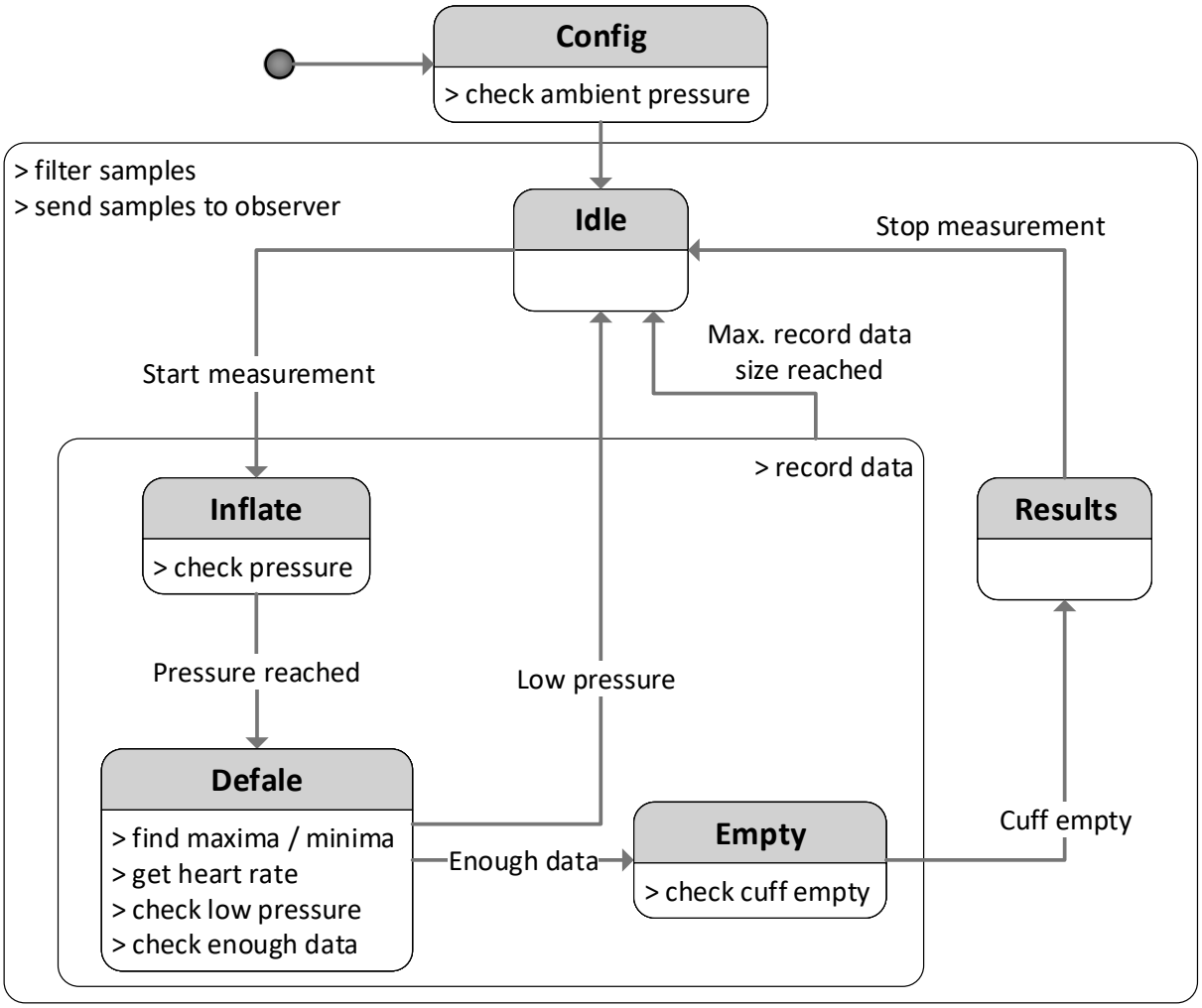

Figure 5.2: The state machine as it is implemented in the Processing class. The 'Deflate' state is where the algorithm is performed.

Results After a successful measurement, the results are valid in this state. Upon leaving this state, all results are reset, and a new measurement can be started. The process can be cancelled externally anytime. If the results state is never reached, the data will not be saved.

5.2.2 Processing Class

The Processing class inherits from the CppThread class and the ISubject class. CppThread is a wrapper to the `std::thread` class that was written by Porr (2020a) to avoid static methods and makes the inheriting class a runnable thread. Processing has an instance of ComediHandler to acquire, and two IIR filter instances to preprocess the data. The raw, unfiltered data is stored in a vector that can be handed to the Datarecord instance to save it as a file. The filtered data is sent to the GUI to display and passed to the OPDetection instance that performs the algorithm. Data acquisition and filtering are

happening whenever the thread is running, the state machine described above decides when data is passed to the OBPDetection or stored to a file.

Thread Safety

The Processing class has public getter and setter methods, that allow objects, with access to it, to read and change configuration variables. These variables are defined as atomic, to make access to them thread-safe. Additionally, the configuration values can only be changed when the thread is not running. This is a design choice, so a restart is necessary to apply changes and avoid modifying the configuration mid-measurement.

Similarly, the booleans set by starting and stopping the measurement and stopping the thread are atomic.

5.2.3 ISubject Class

ISubject is a simple interface defined in a header file that lets the implementing class notify its observers about specific events. Each notification is realised as a protected notify-X method. The public methods are 'attach' and 'detach'. Through these, a class that implements the IObserver (see section 5.3.4) can be attached to the subject. When an observer is attached to the subject, a reference to the object is stored in a list. If one of the notify methods is called, the notification is sent to all the observers in the list. An observer can be removed through the detach method.

The ISubject class can not be instantiated directly. A child class has to inherit from it. A protected constructor ensures this. Likewise, only an implementing class can call the protected notify methods.

5.2.4 Data Acquisition

Access to the hardware is abstracted in the ComediHandler class. The class uses the comedi library (comedilib) (Schleef, 2017) to read data from the hardware device. The ComediHandler is initialised when the Processing object is created. If the initialisation fails, e.g. because there is no device connected, the application terminates, and an error message is printed.

Upon a successful start-up, single samples can be read from the device either as a raw integer value or as a voltage value. Optionally, the entire buffer content can be read as raw values. The application is only reading voltage values.

5.2.5 Filtering

Two filters are used to process the acquired data as described in section 3.1.1 above. The filter implementation was done by Porr (2020b). The objects are initialised when the Processing class is created. They process data sample by sample as needed by a real-time application. Whenever a new sample is

passed to them, a single filtered value is returned. They are casual, so the order in which the samples are given to it influences future outputs.

5.2.6 OBPDetection Class

The OBPDetection class performs the core algorithm. An object is initialised upon creation of the Processing object. The detailed description of what happens inside is provided above in section 3.2 Deflation. Configuration values that are stored in the OBPDetection class work correspondingly to the ones stored in the Processing class. They can be accessed through public getter and setter methods. It could be done anytime, but should only be done when no measurement is happening. If it is done during a measurement, the behaviour can not be guaranteed.

The configuration values can only be set if they are within reasonable boundaries as defined in macros. However, a valid measurement is not guaranteed if the values are changed from the default ones.

The data is passed to the object sample by sample like in the filters. Here, a pair of samples of pressure and oscillation data is always needed. The return value is a boolean, which is true whenever a new maximum was detected in the oscillations. In this case, a new heart rate value can be read through the corresponding public method of the OBPDetection class. Additionally, the method should be checked that indicates when the measurement is finished. When the process is successfully done, the getter functions for the BP values, MAP, SBP and DBP will return valid values. Otherwise, they return 0.0.

5.2.7 Storing the Recorded Data

The class Datarecord is used to store data in a file. There are two options. One is to store it sample by sample, the other by handing it a vector of doubles to store. If the sampling rate is supplied, it will save the values with the corresponding time. Otherwise, data will be numbered with the sample. In this application, the data is stored at the end of a measurement. A vector is handed to the object together with a file name that represents the current date and time.

5.3 User Interface

The user interface is shown in figure 5.3. It is split up into two parts. The left side accepts user input and gives instructions to the user what they have to do to take their blood pressure. The right side shows the data being acquired in real-time. There are two plots. The upper plot shows pressure data filtered with a low-pass filter of 10 Hz. The lower plot shows the data additionally high-pass filtered at 0.5 Hz, which results in a bandpass filter. This is the oscillogram, the primary input for the algorithm to determine the user's blood pressure.

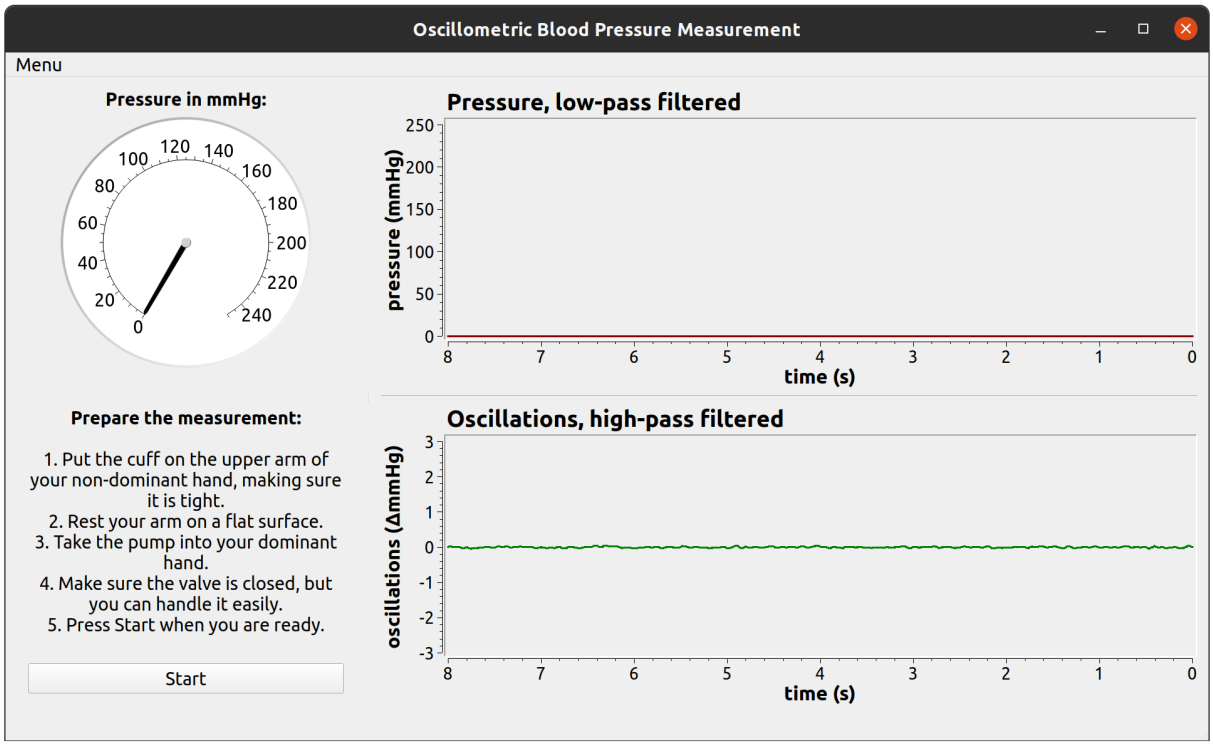

Figure 5.3: The figure shows the GUI, how it presents itself to the user upon start-up. The instructions are given on the left, they change depending on the program state. The plots are always displayed on the right.

As mentioned above, the graphical user interface (GUI) is built with Qt. The QtDesigner was used to design a first draft of the GUI. Because this does not allow integration into applications that are built outside of the Qt development environment, the whole GUI was constructed entirely in C++ code from this draft.

5.3.1 Guided Blood Pressure Measurement

The left side of the GUI guides the user through taking blood pressure. The process is split-up into five pages that are shown in figure 5.4. The pages are numbered in the order they appear. All pages have a dial that shows the current pressure in mmHg. The first page has information on how to prepare for the measurement. Pressing the button at the bottom of the page starts the measurement process. The button is only enabled if the processing part of the application is ready.

The second page instructs the user to pump-up the pressure in the cuff to a specific value. The default value is 180 mmHg. Once that value is reached, the GUI switches to the next page.

This page tells the user to release the pressure in the cuff again. It should be done slowly at a rate of approximately 3 mmHg/s. There is no other feedback than the dial for how fast the pressure is being released. At the bottom of the page, the current heart rate, calculated from the latest oscillation peaks, is shown.

Once enough data is collected, the fourth page is shown. It requires the user to deflate the cuff completely to show the results. If the algorithm fails to collect enough data within a specified time (configured as 5 min), the measurement stops and goes back to the start page.

When the pressure in the cuff reaches nearly zero, the results page is shown. It displays MAP, SBP, DBP and the average heart rate during the measurement. All data is shown as whole numbers without decimals.

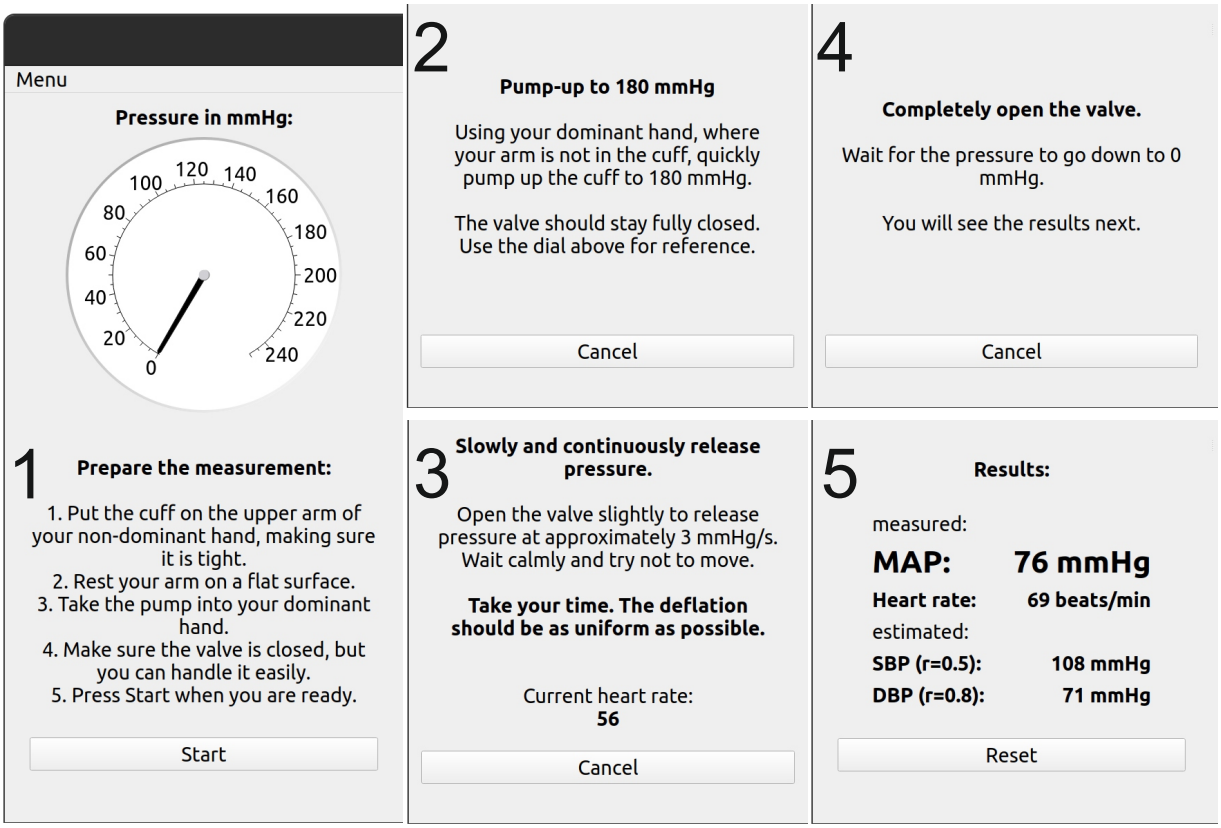

Figure 5.4: The screens that guide the user through taking their blood pressure, numbered in the order that they are shown.

5.3.2 Menu

A menu bar provides access to an information pane as well as a settings pane. Both open up as dialogue windows and disable user input on the main window. Data acquisition is kept running and is displayed in the plots.

Information

The information pane shows the application version number, the licence and provides a link to the project GitHub page. Figure 5.5 shows the dialogue on the left-hand side.

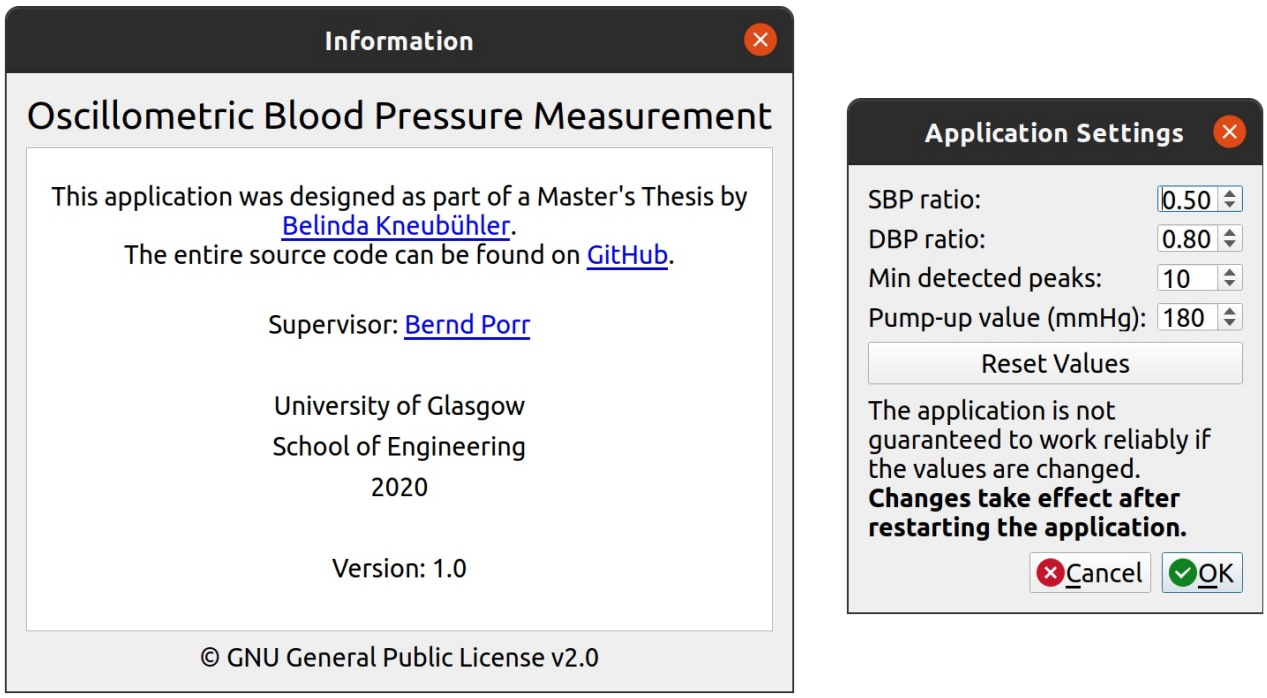

Figure 5.5: The information dialogue on the left and the settings dialogue on the right can be opened through the menu bar.

Settings

The settings dialogue (shown in figure 5.5 on the right-hand side) lets the user change some application configurations. The user is not recommended to change these if they are not aware of the consequences. The settings are stored persistently but only take effect after restarting the application. The range of accepted values is limited to keep the algorithm working. Because not all values have been tested, the user is warned that the program might not perform reliably anymore. The configuration is stored once the user presses the 'OK' button. If the 'Cancel' button is clicked, the settings application is closed without saving the values.

The values can be reset by pushing the corresponding button. These changes take effect immediately.

Handling and storing of these values is done through the QSettings class of the Qt library. It allows to save and load values from a configuration file by specifying a string key. If there is no key found with the provided name, the default value is selected. The default value is what is hard-coded in the Processing class.

5.3.3 Window Class

The Window class inherits from QMainWindow and IObserver. The QMainWindow makes the class an executable Qt window, with Qt taking care of updating the GUI, generating events for button clicks

and so on. The IObserver makes the class able to be registered as an observer for a subject that will send notifications. More on the IObserver below.

All GUI elements are set up in the constructor of Window, including the settings and info plane. However, they will only be shown if necessary. I.e. what page of the user instructions is displayed is defined by the state of the screen enum (currentScreen).

The Window object is instantiated with a reference to a Processing object in the constructor. This is necessary so the user inputs can be relayed and the Processing thread can be stopped when the window is closed, and the application exited.

5.3.4 IObserver Class

The IObserver class defines the functions that the observable class (the subject) uses to notify the observer. All methods are virtual but implemented as empty functions. This way, the observing class can choose to implement, and therefore listen to, the notifications that it wants to and ignore the ones that it does not.

Just like the ISubject class, the IObserver class can not be instantiated directly, but a child class has to inherit from it.

The following methods can be implemented:

- **Ready:** Informs the observer that the subject is ready.
- **New Data:** Sends a new data pair to the observer. Each data pair consists of pressure data and oscillation data.
- **Switch Screen:** Tells the observer which the screen to display.
- **Results:** Sends the results to the observer. The results are three doubles for MAP, SBP and DBP.
- **Heart Rate:** Sends a new heart rate value to the observer.

These methods are called from a class that inherits from ISubject, which is explained in detail in section 5.2.3 above.

Thread safety

The methods from the IObserver class are called from an object, which is likely to be running in another thread than the Window. Therefore, it is essential to implement all functions in a thread-safe manner. Qt offers a decent way to do this by sending queued events.

One example of how to enable the start button, in a not thread-safe way is by accessing it directly, as follows:

```
btnStart->setDisabled(false);
```

Instead, the function `QMetaObject::invokeMethod` is called to send an event to the GUI thread. This is done by specifying the object, which function of the object to call, what arguments to set, and the type of event to send. The `Qt::QueuedConnection` will send an event into a queue that will be handled when the thread is executed. The function to call is given as a string argument. Considering the example above, this results in the following statement:

```
bool bOk = QMetaObject::invokeMethod(btnStart, "setDisabled",
 ↪  Qt::QueuedConnection,  Q_ARG(bool, false));
assert(bOk);
```

The return value confirms if the connection could be made, i.e. the given string is a valid function to call for the given object. It is tested through an assert during development. The assert will fail if the boolean is not 'true'. It is essential not to have the assert around the whole function call, because it will be removed in the release build.

The plots have their underlying data set changed every time a new sample is available because a new sample is always added on the right side, and an old one is discarded on the left side. For this, the underlying data is changed in memory. The Qt process is not informed about that, and the plots must be regularly updated manually. A timer event with an interval of 50 ms does this, which is enough for the human eye to see a continuous movement. The plot objects are accessed after acquiring a mutex so as not to clash with the automatic GUI update handled by Qt.

5.4 Third Party Software

The following third party software is used in the developed application:

- **Qt** 5.12.8 LTS, an open-source widget toolkit for creating graphical user interfaces. (Qt, 2018)
- **CppThread**, a wrapper to the std::thread class written by Bernd Porr to avoid static methods. (Porr, 2020a)
- **iir1** An implementation of the infinite impulse response (IIR) filters for sample-by-sample, real-time processing written in C++ by Bernd Porr, provided as a library. (Porr, 2020b)
- **plog** 1.1.5, a portable, simple and extensible C++ logging library. (Podobry, 2019)
- **comedilib** 0.11.0, a library that provides an interface to Comedi data acquisition devices. (Schleef, 2017)

Chapter 6

Results and Discussion

This chapter highlights the important results of the project. It starts off discussing the outcomes of preliminary tests that were done offline with prerecorded data using python. Next, the implemented software is evaluated against the results from python, Korotkoff sounds and by doing repeated measurements.

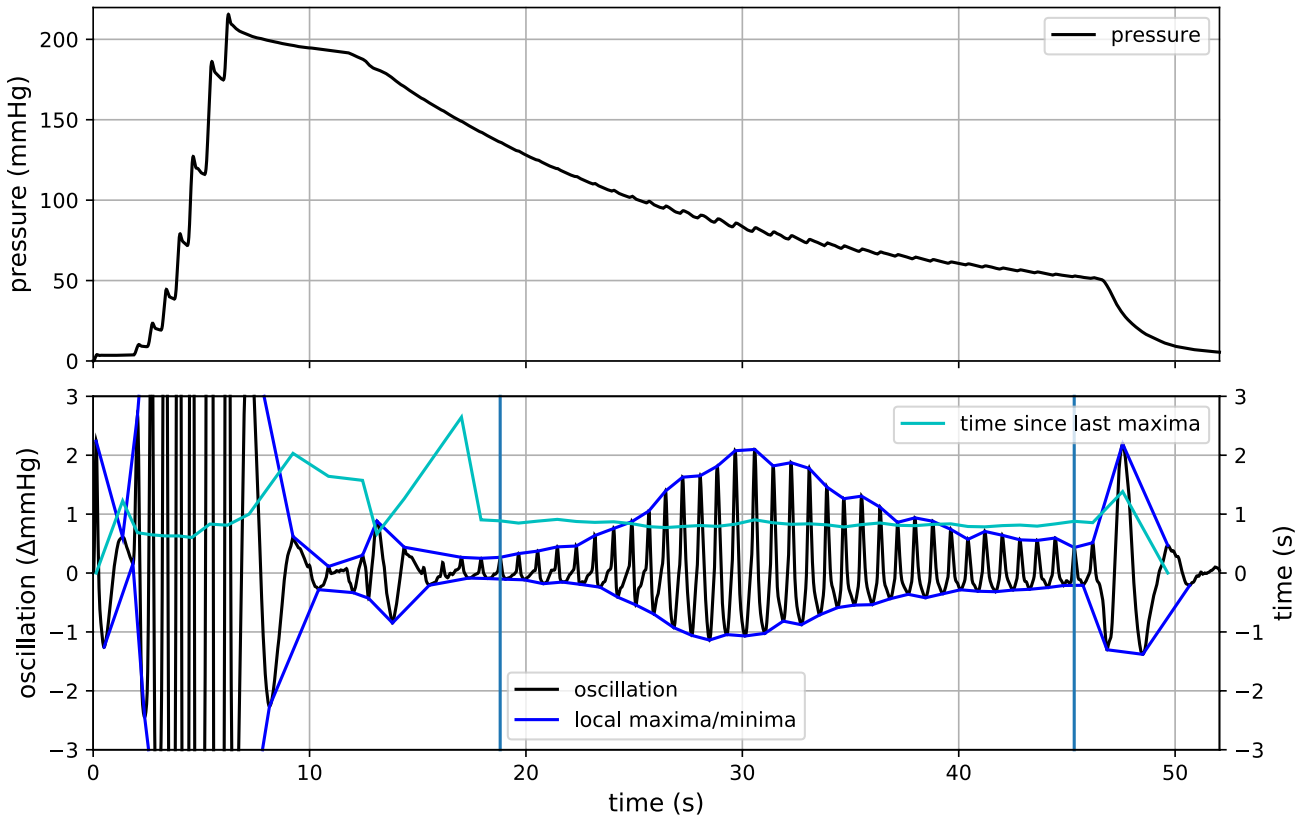

Figure 6.1: Processing of a dataset. The top plot shows a dataset, and the bottom one shows how it is analysed by identifying the extrema and comparing the time between maxima..

6.1 Python Algorithm Tests

Before deciding on an algorithm to implement, some test data was recorded and analysed offline using python. Different approaches of the MAA were implemented as well as the derivative algorithm. All python tests are done on the same dataset. The manually determined blood pressure was 110/70, with a large, expected error because the pressure was taken by an untrained person on themselves.

The top plot in figure 6.1 shows the outline of a BP measurement. The bottom plot illustrates how it was analysed. The oscillations were examined for local extrema and the resulting points connected for the maxima and minima. The result is the blue line that forms the envelope around the oscillations. The cyan line is the time difference between two subsequent maxima. From this, the heart rate can be calculated. It is used to determine when to analyse the oscillations. When the heart rate is stable and changes less than 20 % per detection, the start of the oscillometric envelope is assumed. When it changes suddenly, the end is recognised. These points are identified in the bottom plot in figure 6.1 by the vertical lines.

6.1.1 Fixed-Ratio Algorithm

Figure 6.2 shows the same data as before but analyses only the part between the vertical axes in figure 6.1. The plot shows the different ways the OMWE can be calculated. They have been normalised for comparison. The blue trace is simply the detected maxima connected. Every minimum subtracted from its preceding maximum is the green track. For the red trace, interpolation is done between each of the detected maxima and the equivalent for the minima. The subtraction of the resulting minima from the maxima is the red trace. Finally, the purple curve is a polynomial of 4^{th} order fit to the points calculated in the green track.

MAP is determined where the envelopes have their maximum as explained in chapter 2.3.1 Maximum Amplitude Algorithm. Vertical lines are drawn at $r_S = 0.5$ and $r_D = 0.8$ where SBP and DBP are estimated in this example.

Table 6.1.1 lists the values for MAP, SBP and DBP that were calculated for each of the OMWE formation methods.

	max value	min/max value	interpolation	polynomial fit
MAP (mmHg)	82.64	85.50	82.49	81.53
SBP (mmHg)	97.21	98.83	99.14	105.63
DBP (mmHg)	73.04	72.64	71.83	66.53

Table 6.1: Comparison of different methods to form the OMWE on the calculated BP values for MAA. MAP was estimated at the maximum of the OMWE, SBP at a ratio of 0.5 of the maximum while rising and DBP at a ratio of 0.8 of the maximum while falling.

All methods estimate MAP within a range of 4 mmHg. The furthest off is the min-max OMWE (green). Small shifts in time influence it because minima are happening after maxima. Surprisingly,

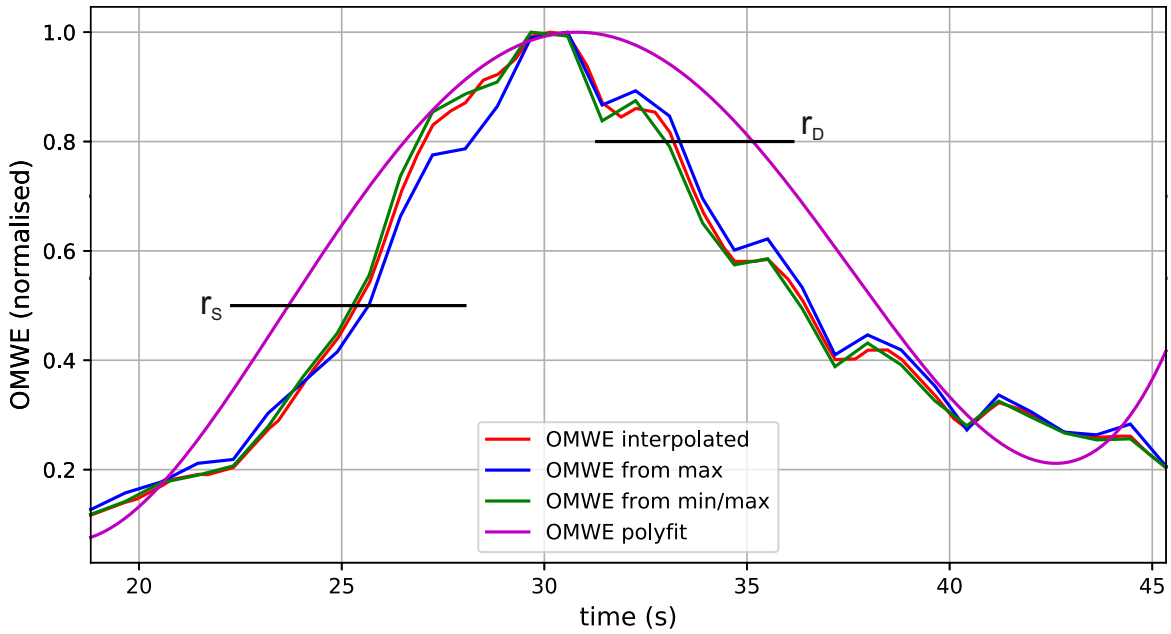

Figure 6.2: Ways to form the OMWE. The plot shows different ways to calculate the OMWE, normalised by their maximal value for comparison. Vertical lines are drawn at $r_S = 0.5$ and $r_D = 0.8$, where SBP and DBP are assumed.

the OMWE using only the maximum values (blue) estimates MAP closer to the other methods. However, while oscillations are increasing and decreasing, the blue trace shown in figure 6.2 seems to lag behind the others in time, and SBP is therefore estimated slightly lower, with 97 mmHg. DBP is not determined lower, with 73 mmHg, although it is happening later. This is due to a pulse peak occurring in the deflating data and a weakness in the python script. It estimates the values at their exact position in the deflating plot without taking into consideration the small pulses that are still occurring there (see figure 6.1, top plot).

The purple polyfit trace does a decent job identifying MAP, but the trail hardly fits the envelope. As is shown in figure 6.2, it is wider than the other methods. Therefore, it estimates SBP sooner and DBP later, resulting in a considerably higher value for SBP with 106 mmHg and a lower value for DBP with 66 mmHg.

The green OMWE that is considering minima and maxima is similar to the red interpolation one from 23 to 27 s. Looking back at figure 6.2, maxima are followed quickly by minima in this period. The way this trace is calculated explains why it is slightly shifted backwards in time compared to the red one: The values are evaluated when the maxima happen, and the following minimum is subtracted from it. During deflation, the time difference between extrema increases and the curves differ increasingly.

Altogether, the red interpolation trace looks the most continuous. Changes in timings of minima and maxima have the least effect on it.

Finally, the determination of the pressure at the identified time should be done by averaging over

the current pulse and not by evaluating the given sample directly from the low-pass filtered deflation curve.

6.1.2 Derivative Algorithm

The same data was used to test the derivative algorithm. The oscillation data plotted in time is shown again in figure 6.3 on the left-hand side. The top is the deflating pressure and the bottom the shows the oscillations.

The right-hand side shows the oscillations plotted in terms of pressure when they were happening. Note that this changes the x-axis and the resulting plot is an inversion in time. The lower pressures occurred later than the higher pressures.

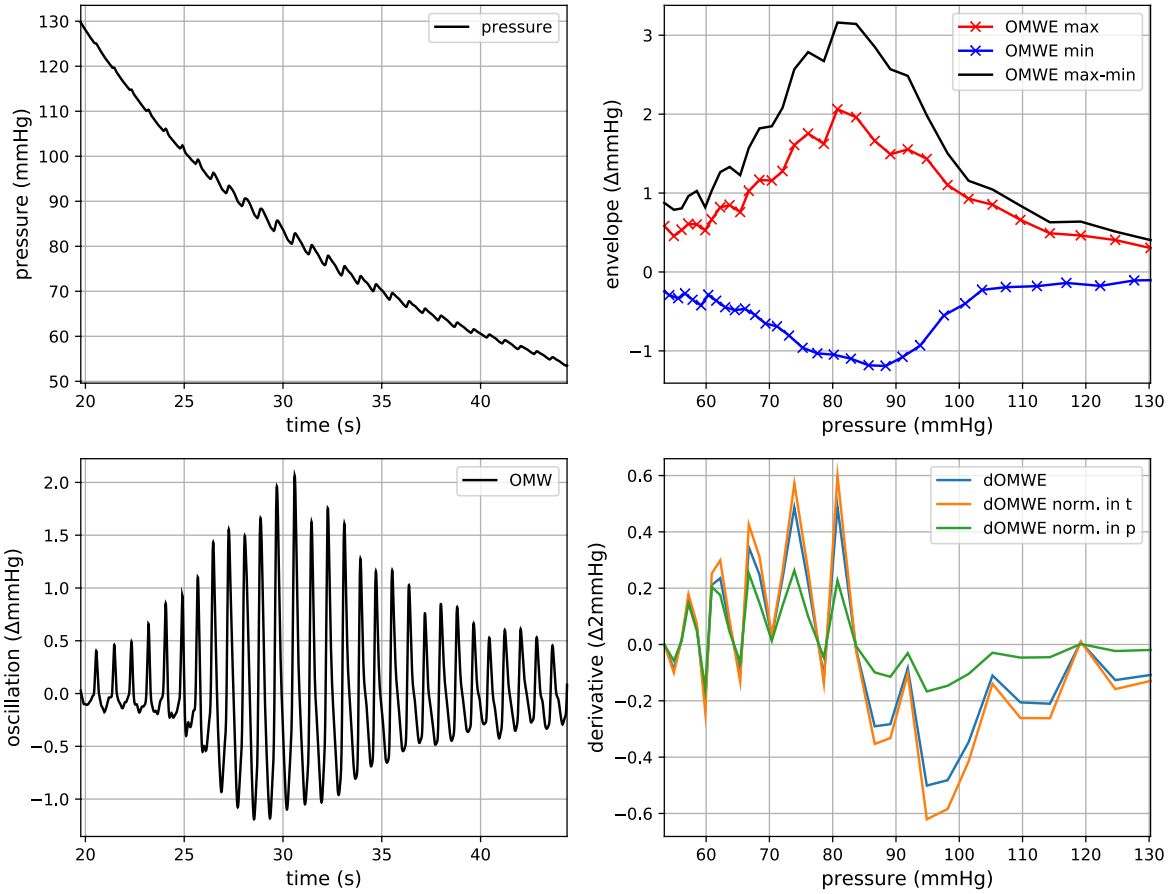

Figure 6.3: The derivative algorithm is tested with python. The left-hand side shows the known plots of deflating pressure (top) and oscillations (bottom). The right-hand side shows the formation of the OMWE on the top. Note that the x-axis is the pressure when the oscillations occurred. The bottom right is the derivative of the OMWE normalised in different ways.

The plot on the top right shows how this OMWE is formed from the detected maxima and minima. The bottom-right plot shows the derivative of the OMWE. The blue trace is the difference between two successive data points. Because they are spaced unevenly, the orange trace has the values normalised

	not normalised	normalised in time	normalised in pressure
SBP (mmHg)	94.87	94.87	94.87
DBP (mmHg)	80.76	80.76	73.94

Table 6.2: Comparison of blood pressure values calculated by the derivative algorithm for differently normalised derivatives.

by the time difference between them. The green track normalises the derivatives with the pressure difference. While the green curve seems to make the most sense logically, they all look similar, except for the green one being compressed compared to the others. A variation of this figure, where all derivative traces have been normalised by their maximal value for comparison, can be found in the appedix A in figure A.1.

Taking the maximum value of the derived OMWE results in the DBP and the minimum value in the SBP, as explained in section 2.3.2 Derivative Algorithm. Table 6.1.2 lists the values for SBP and DBP that were computed for each of the OMWE methods. SBP is identified at 94.87 mmHg and DBP at 80.87 mmHg or 73.94 mmHg. The only difference in the three approaches is the DBP that is estimated lower by the derivative that was normalised in pressure. The lower is most likely the closest to the actual value because it relates to the one determined with the fixed-ratio algorithm.

Other tests, using only the maxima or minima for derivation, have produced plots that are even more ambiguous. For this particular example, the minima are smooth, and the derivative had a clear indication for the SBP. The plots for this test are located in the appendix A in figure A.2.

Additionally, it has to be noted that the tests were done using an immaculate data set. If the deflation curve is not as stable as in the example, the derivative algorithm does not work at all. Similarly, even if the deflation is steady, but there are any other artefacts in the oscillations, e.g. from micro-movements or natural blood pressure variations over time, the wrong blood pressure will be measured. Figure A.3 in the appendix A shows the same algorithm using non-ideal data that was recorded within minutes of the data shown above. All methods determined SBP at 84.65 mmHg and systolic DBP at 62.58 mmHg. Both values are 10 mmHg lower compared to the previous measurement analysed by both the derivative and the fixed-ratio algorithm.

6.1.3 Summary

	fixed-ratio interpolated	derrivative normalised in pressure
MAP (mmHg)	82.49	-
SBP (mmHg)	99.14	94.87
DBP (mmHg)	71.83	73.94

Table 6.3: Comparison of blood pressure values calculated by the fixed-ratio and the derivative algorithm.

Table 6.1.3 lists the values of the results from the two best options for the fixed-ratio and deriv-

ative algorithm. For the fixed-ratio algorithm, the interpolated version is chosen because it has the smoothest curve. The derivative algorithm is logically and in the current measurement best for the version normalised in pressure. However, even using clean data that is optimal for the derivative algorithm, the values have little confidence. There is no apparent rising and falling curve that has a distinct maximum and minimum, but rather an assembly of maxima and minima. Even the smallest changes in amplitude or time difference have a significant impact on the results. Therefore, this approach is not implemented in the application.

As expected, the fixed-ratio algorithm produced stable estimates of MAP. Of course, it also depends on how the OMWE is defined. The interpolated version has the least sensitivity to noise because it considers the time difference between minima and maxima. SBP and DBP are highly dependant on the chosen ratios. For this test, the ratios were selected as recommended by Geddes et al. (1982) ($r_S = 0.5$ and $r_D = 0.8$).

6.2 Application Implementation

To assess the results, C++ calculations are compared to python. Next, Korotkoff sounds are compared to the OMWE. Finally, a series of measurements are made within a short period to test reproducibility.

6.2.1 Comparison to Python Algorithm

To make sure the in C++ implemented algorithm does what it is expected to, a measurement is performed and compared against the python algorithm. From the application, not just the raw data was saved, also low and high-pass filtered data and the OMWE that is used by the algorithm were written to a file. The raw data was analysed by the same python script described above (section 6.1.1 Fixed-Ratio Algorithm). The filtered and calculated data from the application is plotted over it in figure 6.4. The used filters are the same and perform correctly, as can be seen in the pressure plot at the top and the oscillation plot in the middle.

The bottom plot shows the OMWE calculated by the application matches the interpolated version in python. Because interpolation is done linearly in python, only calculating the edge values results in the same trace as the fully interpolated version, with considerably fewer computations.

Table 6.2.1 shows the calculated values for the python and application implementation. The dif-

	C++ Application	Python Script
MAP (mmHg)	71	71.87
SBP (mmHg)	95	94.50
DBP (mmHg)	67	66.05

Table 6.4: Blood pressure values calculated by the C++ application and the python script from the same data.

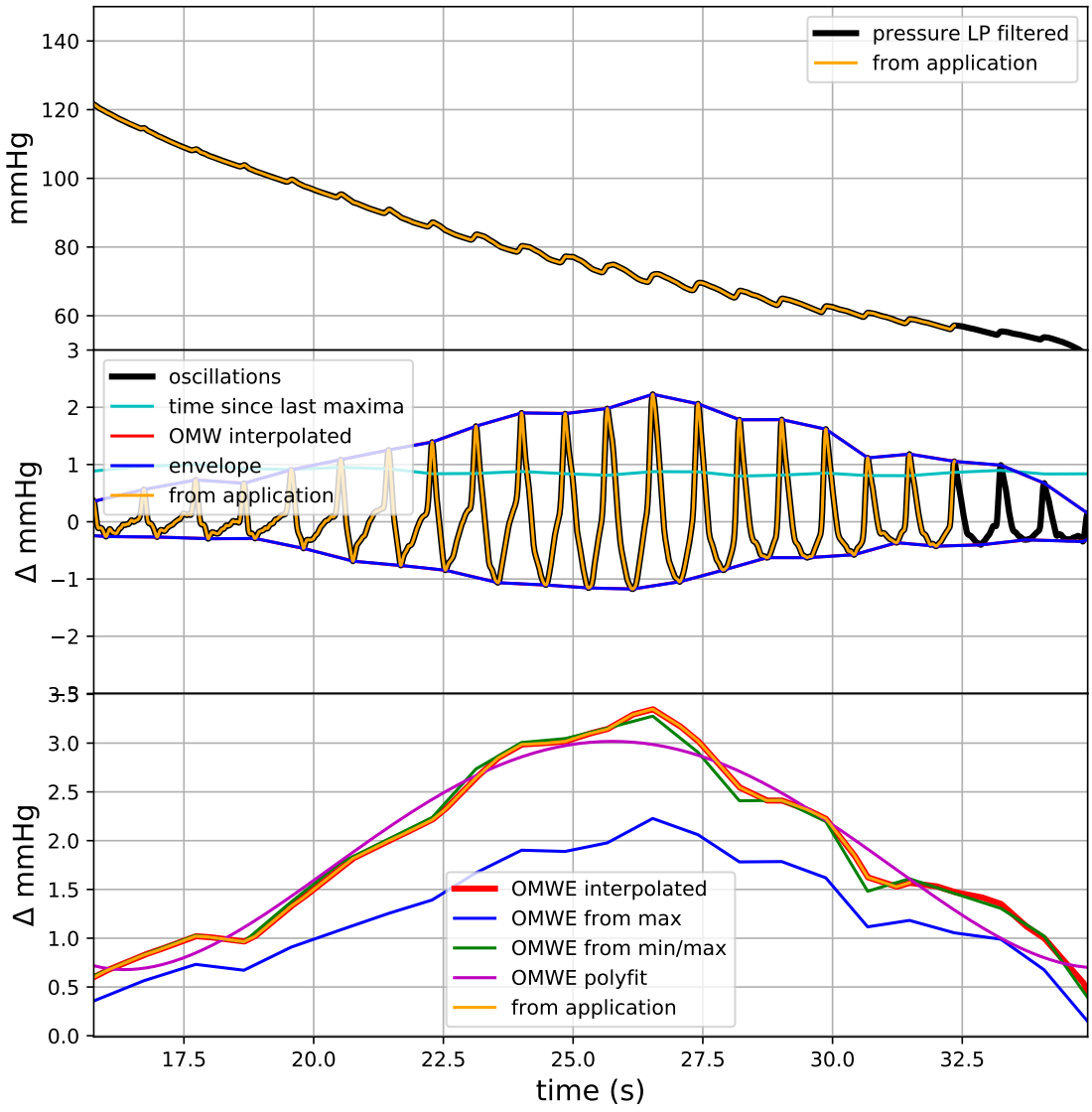

Figure 6.4: The results from the python script are compared to the results of the application using the same raw data.

ference is that the application uses an average pressure value around the determined time, whereas the python script directly looks up the pressure value at the given time.

6.2.2 Korotkoff Sounds

Figure 6.5 shows a test where a stethoscope was placed under the cuff to record Korotkoff sounds while performing the measurement. The resulting values are; 109 mmHg for SBP, 77 mmHg for MAP

and 71 mmHg for DBP with an average heart rate of 74 beats/min. Korotkoff sounds only allow estimations of DBP and SBP.

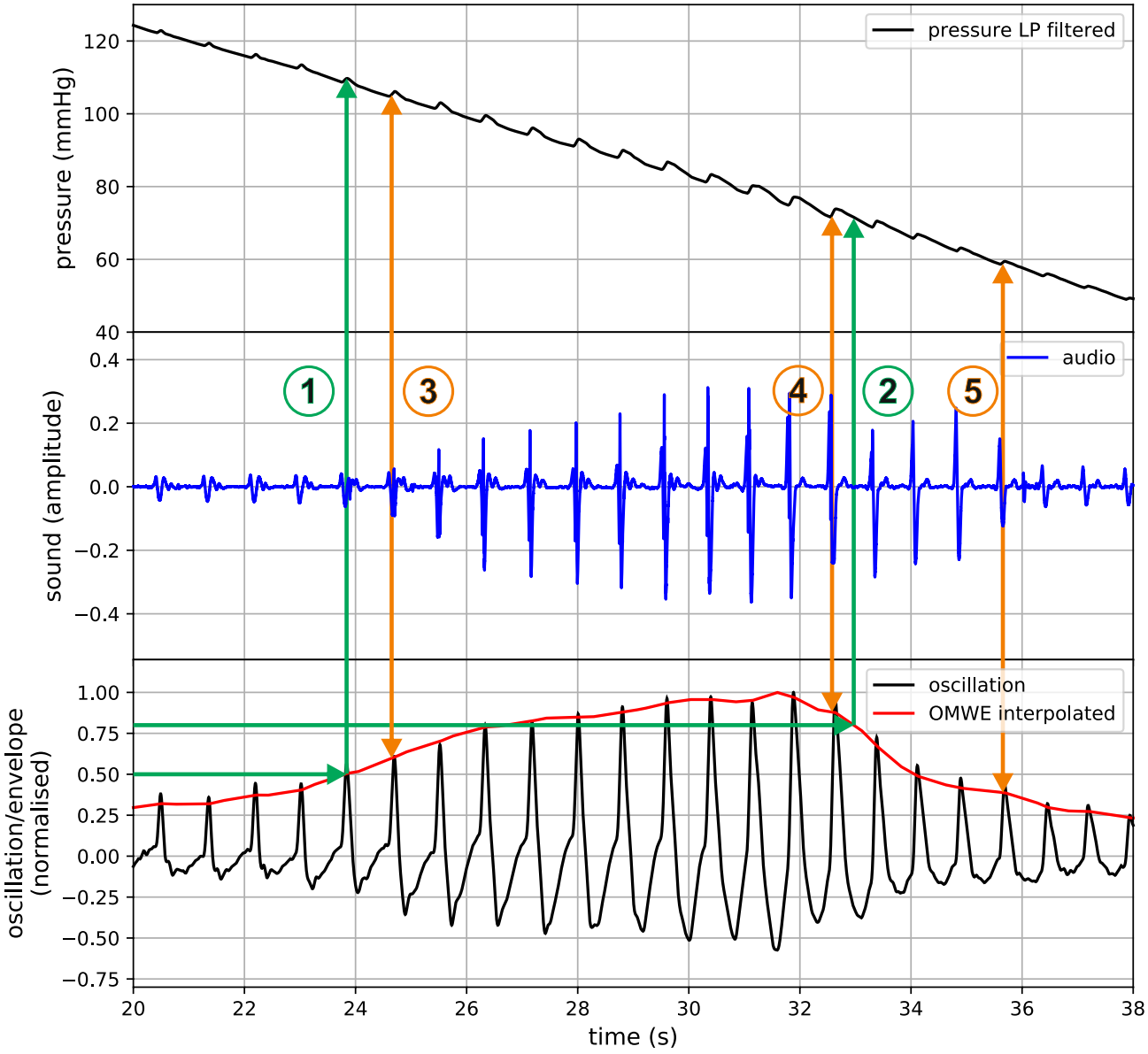

Figure 6.5: The OMWE is compared to the Korotkoff sounds recorded with a microphone.

In figure 6.5, the green arrows are linked to the OMWE, which is displayed normalised to identify the ratios. As before, the values are 0.5 for r_S and 0.8 for r_D. ① shows where the algorithm expects systolic pressure and ② marks diastolic pressure. The orange arrows relate to the sounds displayed in the central plot. ③ is where the sounds first appear, ④ where they are muffled and ⑤ where the sounds disappear entirely. According to Boron and Boulpaep (2012), DBP is located where the sounds are muffled. This point is difficult to see in the plot, but easy to hear. It corresponds well with the ratio of 0.8 for this measurement. Because the ratios are known to be dependant on factors like age and health, the software allows to change them in the settings. On the other hand, if the guidelines

are followed that DSP is located where Korotkoff sounds disappear (Lloyd, 2018; Reeves, 1995), the ratio should be less than 0.5.

Altogether, the chosen ratios work decently. According to Sapinski (1996), the auscultatory method underestimates SBP and overestimates DBP, which fits with our findings. However, the ratios are known to be highly dependent on BP, age and health of the subject and the pressures calculated from them should only be used as indications.

6.2.3 Repeated Measurements

Unfortunately, the ethical application to perform experiments with test subjects was rejected given the current circumstances. Therefore, the only tests were performed on the developer.

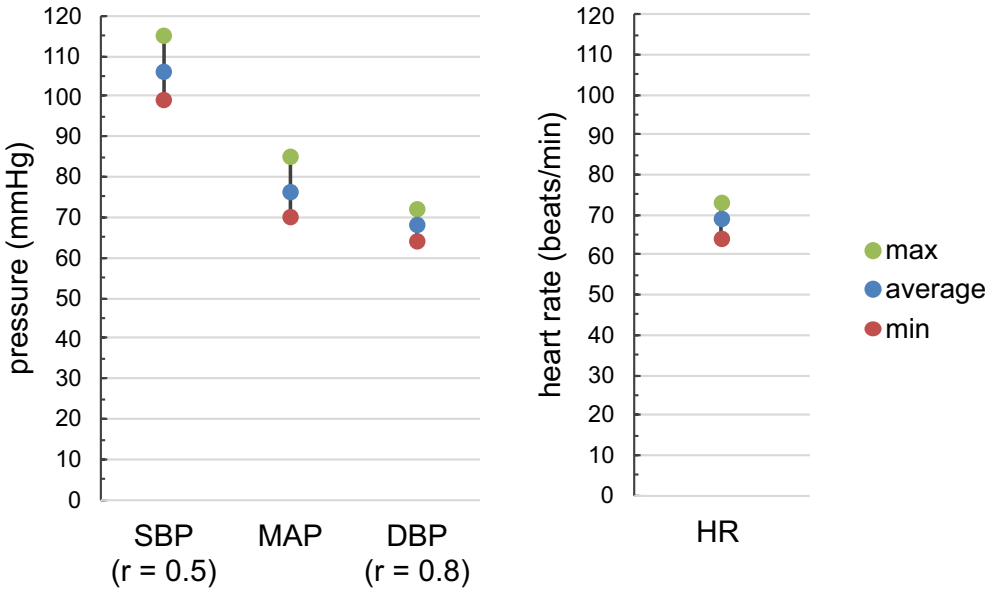

Figure 6.6: Ten measurements were performed within twenty minutes, using the application. The minimal, maximal and average values are shown in the plot.

Figure 6.6 shows how the measured values vary in a period of twenty minutes, performing ten measurements in a row. The ratios for systolic and diastolic BP were 0.5 and 0.8. For each determined value type, the maximal, minimal and average is indicated. The individual measurements can be found in the appendix B. Besides MAP, DBP and SBP, the heart rate was noted as an indicator of natural variations. The heart rate is the signal that can be registered most accurately. Both MAP and SBP have differences of 16 mmHg and 15 mmHg. The heart rate and DBP vary less than 10 mmHg. For the DBP, this is surprising. The research with python has shown that irregularities in amplitude are more common in the diastolic range. One explanation is because oscillations decline quicker than they increase, the pressure range is smaller for DBP. However, this explanation is based on subjective observations and might be misleading.

A manual blood pressure measurement was performed before and after the automatic ones. Before, BP was determined at 110/80 and after at 100/70. These should only be used as a reference and not as the 'right' values. The tester performed them on themselves, with the stethoscope tucked under the cuff, which is known to influence the measurement. Additionally, the person is not trained to take BP.

Still, it shows that it is likely that the average blood pressure dropped within the twenty minute time frame, which can account for part of the variations.

All tests were successful because the tester/developer knows what to pay attention to during a measurement. Experiments with untrained people would have been interesting. It would also have provided feedback on the usability of the GUI, and if it guides the user sufficiently, so they can take successful measurements.

Chapter 7

Conclusion

This chapter discusses the outcome of the project and proposes the next steps to take.

The goal of this project was to be able to conduct experiments with test subjects and to record datasets. Unfortunately, due to the ongoing situation when this project was done, this was not possible. Even though all possible safety measurements were considered and approved by the University's risk assessment department, the approval process was rendered impossible to go through within the given time frame. Apart from not being able to record any datasets, the algorithm might suffer from systematic errors due to subjective characteristics in the developer's blood pressure oscillations.

7.1 Application and Algorithm Evaluation

The developed program guides the user through taking their measurements. This application could be used in the future to acquire datasets. The prefered way is that the test subject does not move. This can be achieved if an examiner performs inflation and deflation of the cuff. The instructions in the GUI are designed to obey social distancing guidelines and would have to be updated.

An even better option is equipping the setup with an electric pump and valve, so no human interaction is required to take the measurements. It would also make the process more stable.

A common problem during deflation is inconsistency. For the implemented algorithm, a consistent deflation rate is more important than the exact speed of 3 mmHg/s. Therefore, the decision was made not to pursue the implementation of a more detailed deflation rate feedback. It would only encourage the user to change the valve opening more frequently to get the perfect deflation speed, which is not needed. The best feedback for consistency is a steadily falling needle. Excessively fast or slow deflation can cause inaccuracies in the measurement, but the algorithm will still determine results. The OMWE will have fewer or more values. Fewer values can mean not enough data to assess BP accurately. Too many can result in a flat OMWE with no clear maxima.

If the deflation is too fast and the user closes the valve, this influences oscillations. A large amplitude might be observed where a small one is expected. Similarly, if deflation is continuous and at

a correct speed of 3 mmHg/s in high-pressure regions, it is possible to get stuck around MAP. The deflation rate decreases if the opening of the valve stays the same as the pressure in the cuff decreases. Often, this is minor, but if the starting pressure is considerably above BP, it can cause the deflation to stop around MAP. In this case, the valve has to be opened further. If this is done carelessly, deflation will be too fast. An automated valve would solve this problem.

A second problem is if the user is swift to take the measurement, pumps up the pressure quickly and immediately releases it at the right speed, oscillations from the quick changes before deflation started can have an impact on the measurement. They might have a valid pulse peak but an invalidly large amplitude. Worst case scenario, this peak will be detected as MAP. Because the OMWE is calculated after data acquisition, changing this part of the algorithm is not trivial. The first 1.2 s of the deflation is ignored to account for this. Increasing this value could solve this problem, but might introduce new ones if it is too high.

As stated before, the MAP is the only characteristic that can be determined confidently from the oscillations. The implemented GUI tries to address this by displaying the results in a fashion that makes it clear that only the MAP should be trusted. Because many people know about systolic and diastolic BP, but not about the MAP, they are still included. The ratios used to calculate SBP and DBP can easily be adapted in the settings menu.

7.2 Proposed Software Improvements

Because no experiments could be performed with the implemented application, the algorithm may have a subjective bias. Hopefully, this can be improved by adjusting the configurable parameters in the OBPDetection class. In any way, a series of tests, using people of different age and with different blood pressures should be conducted next.

Afterwards, the user interface should be updated with the new insights that will be gained from people interacting with the application. One missing feature is most likely user feedback. When an error occurs in the software, it is printed to the log file, but no information is presented to the user.

There is currently no implementation of deflation detection. The algorithm assumes a continuously deflating pressure curve but does not check for it. If an electric pump is available and controllable in software, it would be possible to measure BP during inflation of the cuff. Provided the pump does not add further noise. At the very least, the linearly increasing pressure could be used to estimate the range of BP and adjust the maximally required pumped-up value accordingly.

As every other algorithm that was discussed before, the implemented one is susceptible to noise and artefacts, e.g. movements. From the information gathered in chapter 2, this is due to the method of oscillometry in general. However, some aspects have room for improvements. The maxima and minima detection are dependent and rely on a minimum height for the maxima. A possibility is the Persistence1D class by Weinkauf et al. (2020). It is written for precisely this purpose, but was found

late in the project and was not investigated.

Furthermore, smoothing the calculated OMWE has the potential to improve repetition accuracy because small variations would have less of an impact.

The current implementation of the algorithm is speedy, and calculations do not impact the data acquisition enough to be visible on the GUI. In case the calculation time increases, the final part of the processing could be outsourced into a third thread while data acquisition can continue.

Currently, software testing is minimal. Only the OBPDetection is tested. Sample data is read from files, containing pressure and oscillation values, and fed to the OBPDetection class. If the algorithm can determine blood pressure values from that, the test is passed. Unit testing should be extended. Likewise, the project should be set up for continuous integration.

7.3 Beyond Oscillometry

Blood pressure used to be measured with the auscultatory method, which is suitable to determine SBP and DBP accurately. Oscillometric blood pressure measurements are not suited for that, as the last 40 years of research has shown. However, it is useful to determine the MAP, and it should be used for that. A YouTube video by Joe (2019) addressed at nurses working in the ICU, who calculate MAP from the SBP and DBP values, displays how little medical professionals are aware of this. Manufacturers of automatic devices should avoid giving inaccurate estimates of systolic and diastolic BP or make it clear that MAP is more precise.

If systolic and diastolic BP is needed, other methods should be considered. Using a microphone to listen to Korotkoff sounds while the cuff is deflating is an inexpensive addition to the system that renders ratios useless and improves accuracy for those values. The test done in 6.2.2 shows this. Automated devices that use this approach exist, but they rare. Another method is to use pulse transit time (PTT) to improve the accuracy of measurements, as proposed by Forouzanfar et al. (2015).

It is essential to know that blood pressure varies naturally to a great extent, also during a measurement. Additionally, it depends on which arm it was performed on. That limits the accuracy of blood pressure measurements in general. After all, it is a physiological parameter and not a fixed value.

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Appendix A

Python Plots

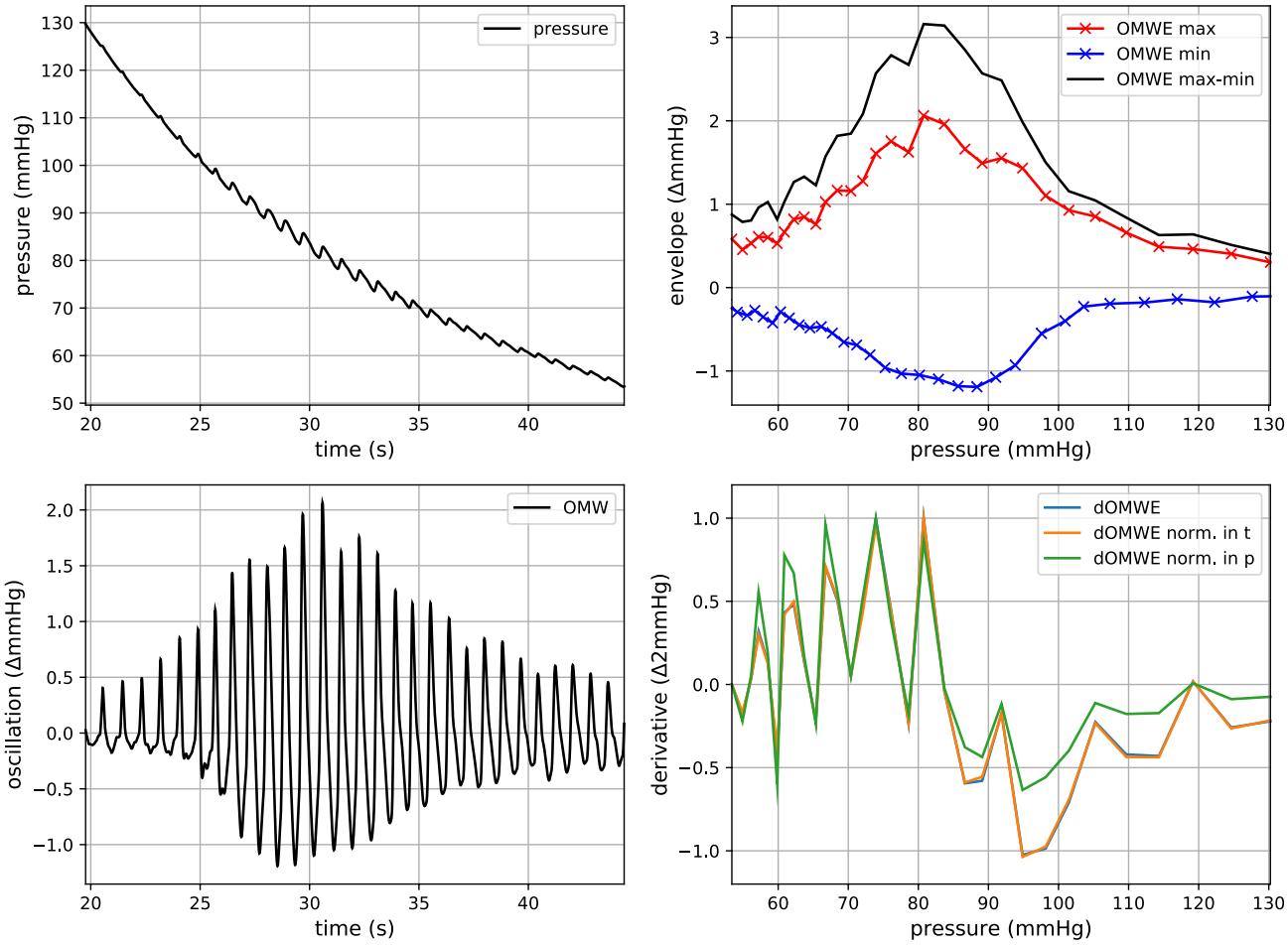

Figure A.1: The derivative algorithm is tested with python. The left-hand side shows the known plots of deflating pressure (top) and oscillations (bottom). The right-hand side shows the formation of the OMWE on the top. Note that the x-axis is the pressure when the oscillations occurred. The bottom right is the derivative of the OMWE normalised in different ways. For comparison, the traces are normalised a second time by their maximal value.

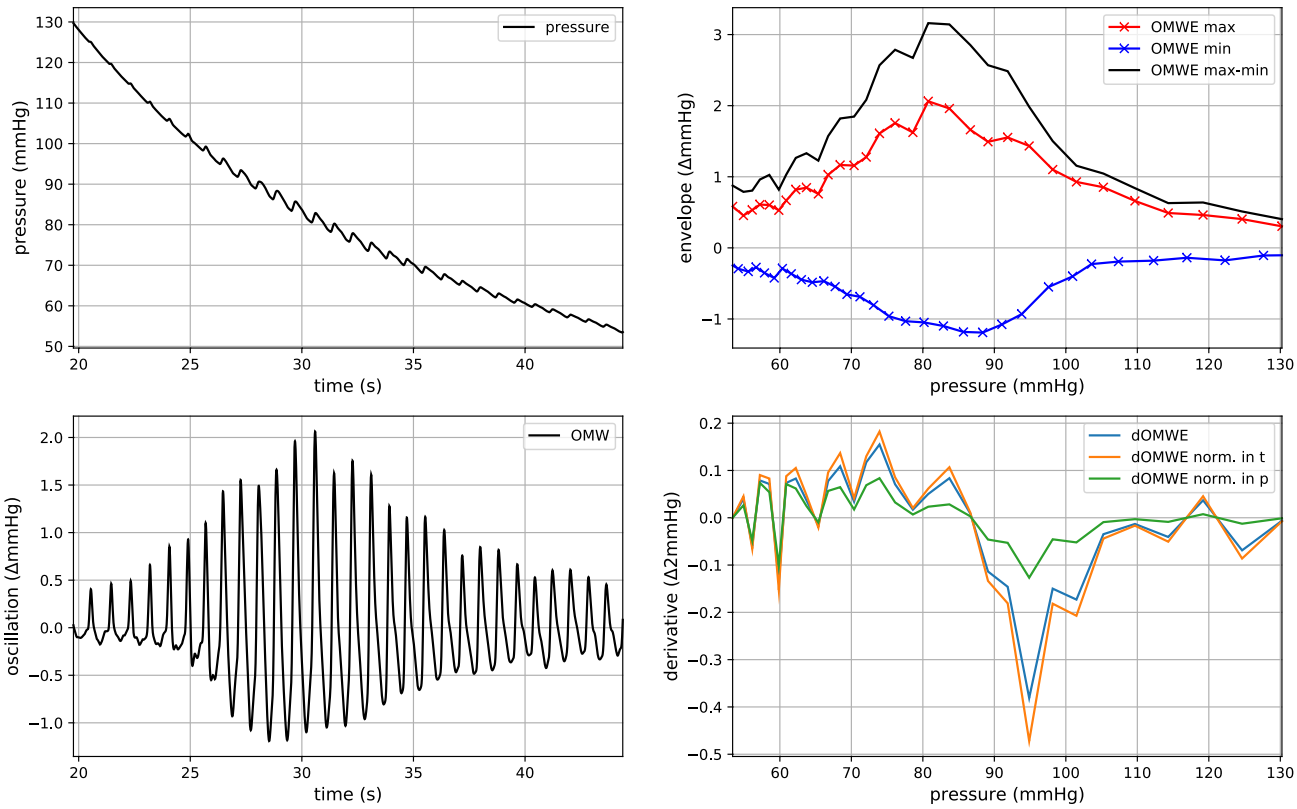

Figure A.2: The derivative algorithm applied to the curve of the minima shows a very distinctive trough where the systolic blood pressure is expected.

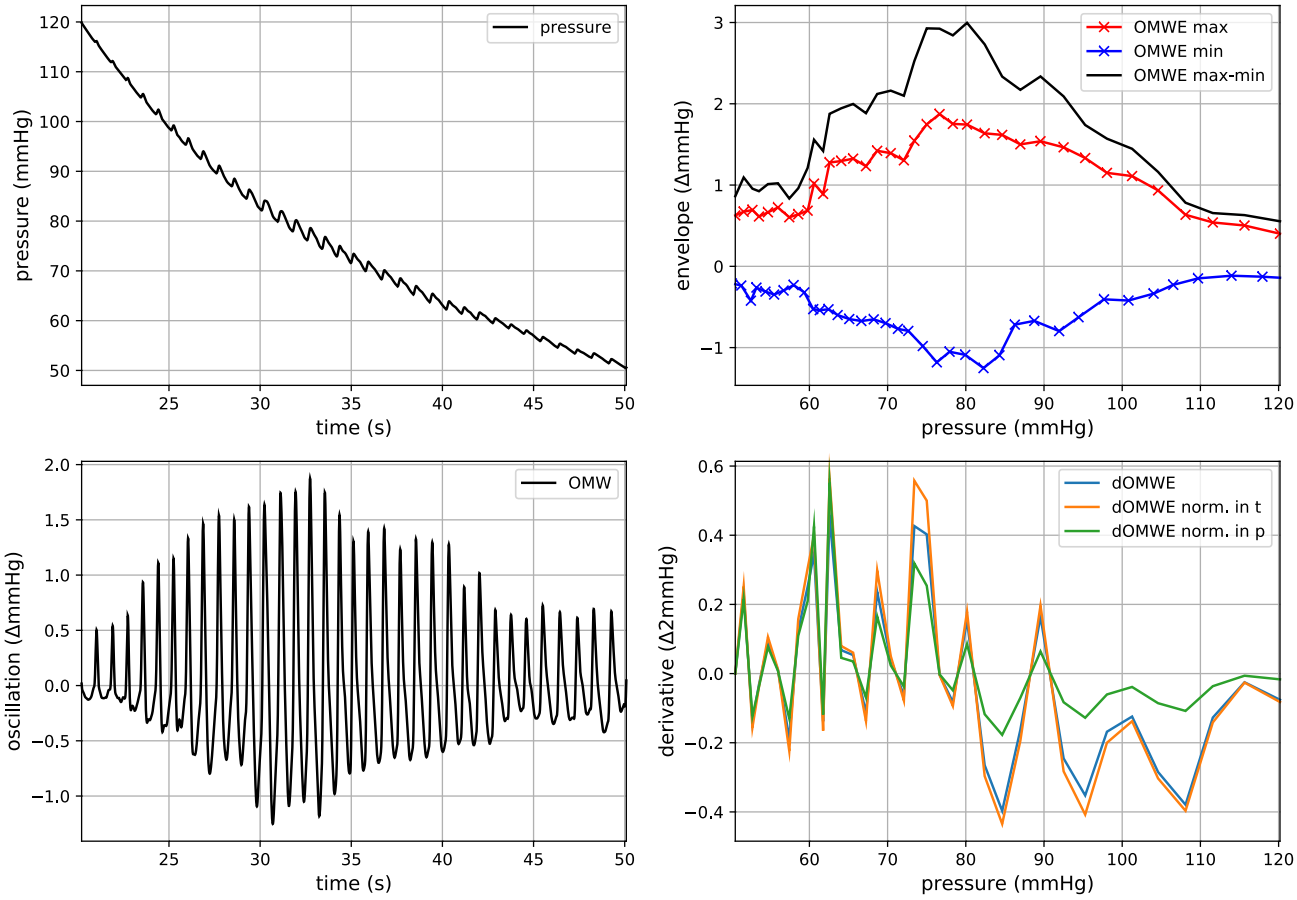

Figure A.3: A second measurement, taken within minutes of the first (shown in figure 6.3), results in a very different derivative graph.

Appendix B

Measurements

Nbr.	SBP (mmHg)	MAP (mmHg)	DBP (mmHg)	HR (beats/min)
1	115	85	70	71
2	112	77	69	73
3	104	70	64	67
4	107	78	72	70
5	103	79	68	64
6	109	80	68	68
7	107	73	68	69
8	99	71	67	68
9	100	73	69	69
10	104	76	66	71

Table B.1: Repeated BP measurements performed with the application within 20 minutes with $r_S = 0.5$ and $r_D = 0.8$.