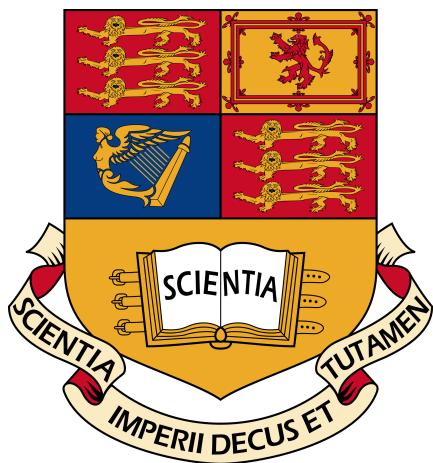


Imperial College London

Department of Electrical and Electronic Engineering

Final Year Project Report 2016



Project Title: **Non-invasive Estimation of Blood Pressure and Heart Rate using Smartphone**

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Abstract

Blood Pressure and Heart Beat rate are the most commonly physiological parameters used for health evaluation. Moreover, hypertensive patients have the need for continuously monitoring their Blood Pressure throughout the day. This will assist their physicians to provide them with the correct treatment. The instruments that are used for Blood Pressure measurement are either cuff based instruments or invasive devices. A non-invasive method which will not interrupt with user activities will be very advantageous compared to the traditional ways of measuring Blood Pressure. At the same time the evolution of smartphones in combination with the important role they have in our life, has motivated a lot of studies of how these devices could be involved and utilised in healthcare. In this project the photoplethysmographic (PPG) signal obtained from a smartphone is analysed in an effort to identify the parameters of the signal that are varied with Blood Pressure in order to predict the Diastolic and Systolic values. In addition the Mean Heart Rate is calculated again using the PPG waveform. Furthermore, the conditions that the photoplethysmographic signal should be recorded are examined. Data is collected and analysed from many participants and statistical analysis is presented. Different linear regression models for four different features of are compared and 1/3 Pulse width model produce the most accurate results. Furthermore, real time implementation was developed through an iOS application.

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Chapter 1

Introduction

Generally, Hypertension (HTN) or High Blood Pressure is a major chronic and growing public health problem which could lead to heart disease, stroke, aortic aneurysm and atherosclerosis [1]. Information from the National Health and Nutrition Examination Survey which occurred in 2012 demonstrated that roughly one billion individuals worldwide have been diagnosed with Hypertension. Based on data from 2011-2012, only 48.9% of adults have their Hypertension under control which is relatively small compare to the Healthy People 2020¹ target of 61.2%. These statistics prove that the efforts for better control of Hypertension should be continued [3].

Blood Pressure(BP) is the force of blood pushing against the walls of arteries, which transfer blood from the heart to different parts of the body. During the day the BP can have a lot of variations (rises and falls). In the situation that it remains high for quite a while, it can harm the heart and may cause various health problems [2]. High Blood Pressure infrequently has detectable indications, yet in the event that it remains untreated it might have disastrous consequences. Self-Management of BP (SMBP) can be a viable method for reducing Blood Pressure levels. SMBP along with an additional form of support such as medication and educational materials, has appeared to accomplish extraordinary results in the diminishment of Blood Pressure [1].

¹Healthy People is a program of nationwide health-promotion and disease-prevention goals set by the United States Department of Health and Human Services.

Ordinarily, the most widely recognised device for BP estimation is the sphygmomanometer. It is an instrument that comprises of an inflatable rubber cuff which is connected to the arm and associated with a segment of mercury alongside a graduated scale. It is empowering the measurement of systolic and diastolic BP by expanding and steadily discharging the pressure in the cuff. Sphygmomanometer cannot provide beat-to-beat determination of BP. Constant monitoring of Blood Pressure might give more valuable data about a person's health. Likewise, a cuff-less outline will be simpler and more convenient to use [5].

A widely used non-invasive technique that can estimate vital health parameters is known as photoplethysmogram (PPG). It is a method that allows continuously track variations in blood pressure and it has the benefits of not being intrusive and subsequently disposing the need to embed a device to calculate the arterial pressure and thus eliminating the risk of infection [6].

As cell phones proliferate throughout society, the chance to leverage these devices to study, understand, and positively influence human behaviour has increased drastically. The popularity of mobile phones, in combination with people's habit to carry their phones have made mobile technologies as the pointing focus for helping people deal with their chronic diseases [4]. Hence, the utilisation of smartphones can be an effective tool for advancing the Self Management of Hypertension.

The motivation of this undertaking is the use and examination of the PPG signal in an attempt to attempt to infer Blood Pressure and Heart-Rate, in a non-invasively and continuously way. The PPG waveform was chosen because it has been observed that the patients PPG disappears when an external cuff is inflated, it re-appears when the pressure in the cuff decreases. Since it is inconvenient for people to carry special equipment to measure their Blood Pressure and Heart Rate(HR), the non-invasive video photoplethysmographic method will be examined as an alternative solution to that problem.

Chapter 2

Background Theory

2.1 Introduction

In recent years scientists have increasingly started to use smartphones for delivering solutions in the healthcare system. These rapid technological developments and the widespread adoption of smartphones have raised the question of whether mobile phones could provide a powerful mechanism for handling problems and challenges related to the global population's health and well-being. This chapter of the report, aims to present the influences and related work in mobile applications for Hypertension and non-invasive methods to measure Blood pressure and HR, all of which aim to improve the health of patients, whether they are children, adults or elderly people.

2.2 Cardiac Cycle

The heart is a muscular organ which pumps blood through the blood vessels of the circulatory system with a rhythmic activity. It pumps blood by its contraction and relaxation. The contraction of the heart is called systole and the relaxation is called diastole. The contraction and relaxation together constitute the heartbeat. The heart beats at the rate of 72 beats per minute. The changes

that occur in the heart during one beat is repeated in the same order in the next beat. This cyclical repetition is called cardiac cycle. During the cardiac cycle, blood flows through the cardiac chambers in a specific manner and direction. The backward flow is being prevented by specific valves. In humans the heart is divided into four chambers, upper left and right atria and lower left and right ventricles Fig.2.1.

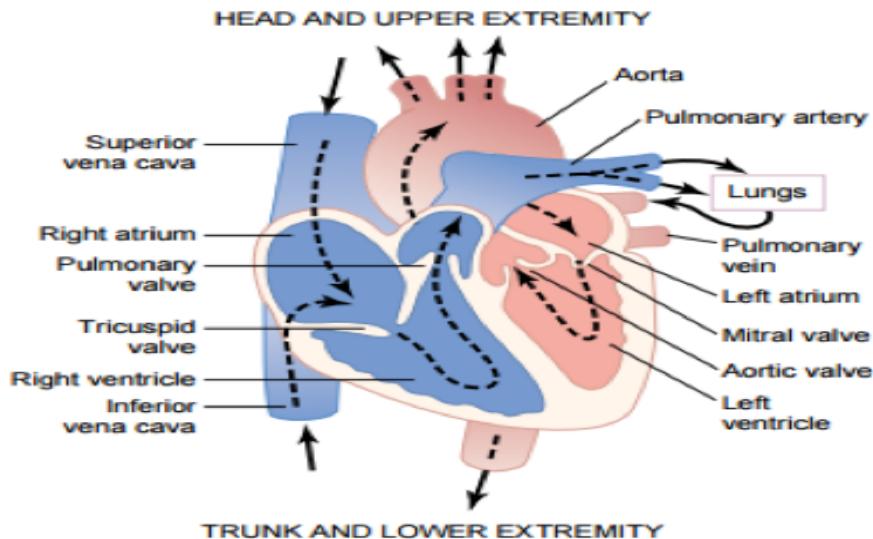


Figure 2.1: Systole and Diastole [21]

The left atrium and left ventricle constitute the left heart and the right atrium together with right ventricle constitute the right heart. The heart pumps blood through the body by receiving blood with low oxygen from the systemic circulation enters the right atrium and passes to the right ventricle. From here it is pumped into the pulmonary circulation, through the lungs where it receives oxygen and gives off carbon dioxide. Oxygenated blood then returns to the left atrium, passes through the left ventricle and is pumped out through the aorta to the systemic circulation where the oxygen is used and metabolized to carbon dioxide [21].

A cardiac cycle is a complete heartbeat from its creation to the beginning of the next beat and it passes through five stages. The heart rate is expressed as beats per minute. During the first two stages the blood moves from the atria into the ventricles. The next three stages involve the movement of blood from the ventricles to the pulmonary artery (in the case of the right ventricle) and the aorta (in the case of the left ventricle) [22].

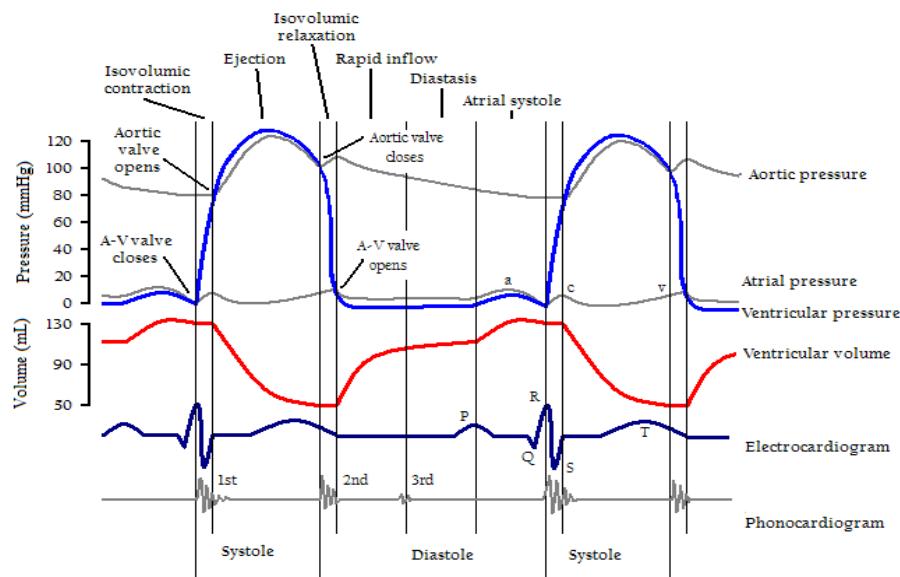


Figure 2.2: Wigger's Diagram [11]

- The first stage, "diastole," is when the semilunar valves (the pulmonary valve and the aortic valve) close, the atrioventricular (AV) valves (the mitral valve and the tricuspid valve) open, and the whole heart is relaxed [10].
- The second stage, "atrial systole," is when the atrium contracts and blood flows from atrium to the ventricle.
- The third stage, "isovolumic contraction" is when the ventricles begin to contract, the AV and semilunar valves close, and there is no change in volume [10].
- The fourth stage, "ventricular ejection," is when the ventricles are contracting and emptying and the semilunar valves are open [10].
- During the fifth stage, "isovolumic relaxation time", pressure decreases, no blood enters the ventricles, the ventricles stop contracting and begin to relax and the semilunar valves close due to the pressure of blood in the aorta. Fig 2.2 shows two complete cardiac cycles [10].

2.3 Hypertension

Throughout the cardiac cycle, Blood Pressure increases and decreases. Under normal circumstances, each cycle takes 0.8 seconds. Blood pressure is typically recorded in two numbers. The highest value represents the blood pressure in the arteries when the heart beats (when the heart muscle contracts). This is called the Systolic Pressure (SBP). The lowest value represents the pressure in the arteries between heartbeats (when the heart muscle is resting between beats and refilling with blood). This is called the Diastolic Pressure (DBP).

The term Hypertension refers to the situation where there is too much pressure in the blood vessels as the heart pumps blood around the body to deliver energy and oxygen. Through each pulse, a stream of blood is pumped out of heart and cause an increase in pressure [50]. A particular volume of pressure in the blood vessel walls is needed to achieve this (see Figure 2.3). However, if there is too much pressure in your blood vessels, it puts extra strain on your arteries and heart leading to serious conditions for your health [49].

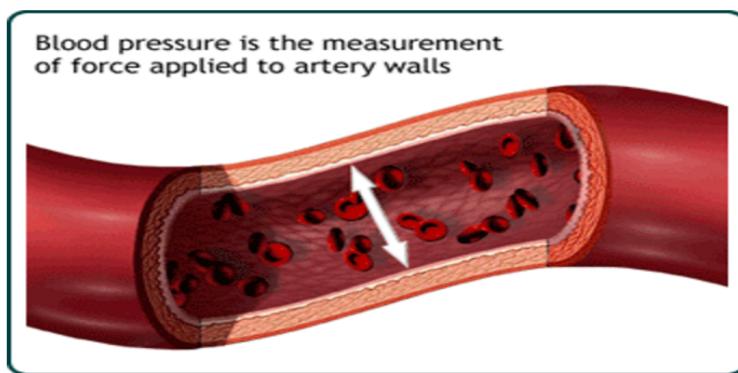


Figure 2.3: Blood Pressure [2]

2.3.1 Classification of Hypertension

Hypertension is classified according to the readings of Diastolic and Systolic Blood Pressure. The classification as given by the joint National Committee on Prevention, Detection, Evaluation, and Treatment of High Blood Pressure is defined in Figure 2.4 [51].

Blood Pressure Classification	SBP(mmHg)	DBP(mmHg)
Normal	<120	and <80
Prehypertension	120-139	or 80-89
Stage 1 Hypertension	140-159	or 90-99
Stage 2 Hypertension	≥160	or ≥100

Figure 2.4: Classification of Hypertension

2.3.2 Causes of Hypertension

The actual reasons behind Hypertension are unknown but several factors play significant role in its development. Consuming a lot sodium intake in the form of sodium chloride as table salt or in processed food has been heavily connected to the increase of BP [49]. The sensitivity to react to salt and be able to affect your blood pressure is strongly related with the age. Sedentariness and being overweight is another reason that can cause Hypertension in the long term. Drinking alcohol and smoking increase the risk of developing High Blood Pressure and related diseases. Furthermore, the possibilities of a person who has genetics and family history of High Blood Pressure, to develop Hypertension at some point in his life are extremely high. Finally, highly related to this condition are the patients who have chronic kidney disease, adrenal and thyroid disorders or sleep apnea [52].

2.3.3 Management of Hypertension

Management of HTN is a sequential approach. Adjustments of the way of living of hypertensive patients is needed. Dietary changes are a must, eating healthy and avoiding salt will be a good start. Moreover, exercising in daily base will help the better control of Blood Pressure. The next stage of HTN Management is the addition of drug therapy.

2.4 Methods to Estimate Blood Pressure and Heart Rate

Throughout the last years, ambulatory monitoring of arterial BP has been endorsed to people suspected to experience Hypertension [3] in an attempt to control their condition. The equipment that was given to those patients was depended on mechanical or oscillometric recordings. A pressure cuff was placed on the patient's upper arm to acquire those readings. In general, people find the periodic inflation of the cuff uncomfortable and noisy. For this reason many studies focus on alternative ways to monitor BP.

Arteta et al. [7] composed and built up a framework that contains low-cost peripherals with insignificant hardware, focusing to offload the main processing to the mobile phone. The oscillometric method was used to calculate BP and HR. Parallel with the hardware they developed an Android based application to control the data they received.

Further research into mobile applications led to the Shivaraman and Pooja [8] implementation of a cuffless continuous Blood Pressure monitoring device, which is comprised of two acquisition modules and an Android smartphone. In contrast with Arteta, the data were transmitted via Bluetooth to the system. The Blood Pressure was estimated by consolidating ECG and Heartbeat wave signals.

Several recent works have presented various ways of measuring BP using various sensors. Alair Dias Junior et al. [9], presented a new smartphone based method to measure pulse transmit time and BP using the sensors that smartphones have. Their approach included the determination of the pulse transmitted time while they simultaneously measured the time the blood leaves the heart. The pulse transmitted time was calculated with the help of the phone's video camera. The smartphones' microphone allowed them to measure the time the blood leaves the heart.

Another related work to the subject was implemented at [14]. A PPG sensor was applied to the finger of the patient where at the same time a wrist cuff was put on the wrist. Meanwhile, the system was able to analyse the PPG signal was receiving from the sensor and extract the systolic and diastolic blood pressure. Then these values were compared with the wrist cuff measurements. This technique had in general positive results with good accuracy. Moreover,

the authors of that paper emphasised that the main issue of PPG technique is the distortion of the signal due to the movement of the subject during the measurement. This is something that would be considered during this project.

The notion of developing a non-invasive system that would provide real-time data for heart-rate variations was also examined in other studies. In [15] and [16] the mobile video camera was used to record the PPG signal and the peak detection algorithm was applied to estimate the Heart Rate. The accuracy of the peak detection algorithm is inspected by comparing the experimental results with the actual values of BP (use of electronic device to determine BP). The outcome showed low levels of correlation between the actual and the experimental results.

Domenico Grimaldi et al. [19] implemented and examined the photoplethysmographic method using only the video camera of a mobile phone. Their approach was tested for different mobile models. Conversely in [17], the authors considered one and only mobile phone device the Nokia E63 and their observations suggested that the strongest channel of the PPG signal (better to analyse) is the green. On other hand, the authors of [19] suggested that only the red channel has the same features in different smartphones. The outcome from the experiments in both cases confirmed the accuracy and suitability of the proposed technique.

2.5 Photoplethysmography

2.5.1 Principles

Photoplethysmography is a basic and low cost optical technique that can be used to detect blood volume changes in the microvascular bed of tissue [36]. The light is travelling though biological tissue and can be consumed by different substance,for example, pigments in the skin, bone, and arterial and venous blood. Most changes in blood stream happen essentially in the veins and arterioles. For instance, arteries contain more blood volume during the systolic phase of the cardiac cycle than during the diastolic phase. PPG sensors (like oximeter) optically could distinguish the adjustments in the light intensity of the microvascular bed of tissue via reflection

or transmission. [37].

The PPG signal consists of two parts as Figure 2.5 shows; the AC which is the pulsatile part and the DC which is the steady part. The AC waveform is known as physiological waveform and represents the blood volume variations which occur during the cardiac cycle phases(systolic and diastolic phases). The DC component of the signal is the result of the signal's reflection in the tissue and depends on the average blood volume of both arterial and venous blood [37].

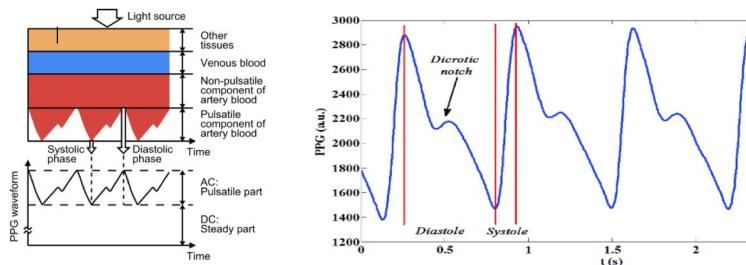


Figure 2.5: PPG Signal [37]

This non-invasive method to measure the BP and the HR consists of two modes: transmission and reflection. Therefore, to be able to monitor important health parameters with this technique, special equipment is needed. In the transmission mode, with the assistance of a light emitting diode (LED), light is transmitted through the medium and a photodetector (PD) is used to detect the reflected light from the tissue. For efficiency purposes the PPG sensors should be placed on body parts where the transmitted light could be easily detected like the fingertip and the earlobe (see Figure 2.6).

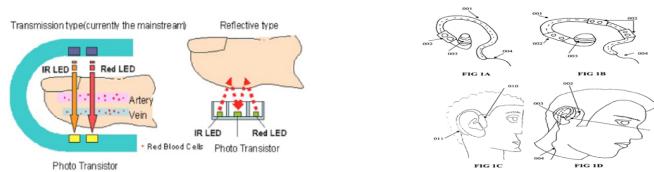


Figure 2.6: Photophlysmography is applied in the finger and earlobe

Photoplethysmographic signal is often acquired by using a pulse oximeter and is presented in Figure 2.7. It illuminates the skin and measures progressions over light absorption. This kind of sensor is very popular and very common for continuous measurement of heart rate and

respiration.



Figure 2.7: Pulse Oximeter [12]

To implement PPG method will require from people to have photoplethysmographic sensors such as the pulse oximeter. In the meantime, cell phones have become part of our daily life and people tend to bring them almost everywhere. The powerful hardware and the multifunctional interfaces of smartphones have spread their usage in a very wide spheres. Mobile technology can possibly reshape significantly the Health industry , changing the way that health services are delivered and received. The new mobile devices and services will allow people to take care of themselves in a regular base. The main target of these technologies is to make healthcare more accessible to communities that are undeserved. Simultaneously, living in the era where information dominates, the use of mobile phone will allow researchers to saddle the power of big data on a vast scale [38]. Extracting relevant information from these enormous data sets and identifying new patterns, will impact the future of healthcare industry [42].

2.5.2 Video Plethysmography

Most of the recent mobile technologies are equipped with high resolution cameras and light emitting diodes (flash). This is very similar to the pulse oximeter the most common PPG sensor. The video camera can be used as a photodetector and the new term for our method is video plethysmography. Video plethysmography is divided into two types:(a) Contactless for long distance measurements and (b) contact type for short distance measurements.

In the long distance type, the plethysmographic signals were measured remotely (bigger than 1m) using ambient light and a video camera of a cell phone as PD [47, 48]. While the strongest PPG signal characteristics were found in the green channel, the blue and red channels also contain

some plethysmography information. The observations recommend that the encompassing light of PPG could be utilised for medical reasons in order to measure vital signs, such as HR and RR.

The other video type, which it will be investigated during this project, is the contact one. The correct way to acquire the PPG signal using this method is shown in Figure 2.8. The user's finger should be placed on the smartphone's camera covering at the same time the lighting emitting diode (LED). The light from the LED manages to pass the finger and the camera makes adjustments in order to record the volumetric variations of blood in the finger. These changes can be used to compute the PPG signal [17]. A major issue of this methodology is that the accuracy of the entire system depends entirely on the user.

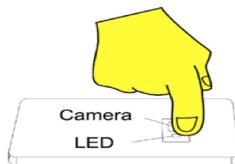


Figure 2.8: Video PPG using Mobile Phone [17]

2.6 Mobile Applications for Hypertension Management

Management of Hypertension requires both lifestyle modifications and pharmacotherapy. The control and management of High Blood Pressure could receive huge boost from user friendly mobile systems. In [23] Morium et al. developed an android based system for the management of diabetic Hypertension. A treatment plan and advices for the patients were included in the application. Intelligent Life Solutions Portugal [24] developed an android application for helping people dealing with Hypertension. The system describes the classification of the Hypertension according to "The Seventh Report of the Joint National Committee on Prevention, Detection, Evaluation, and Treatment of High Blood Pressure". Additionally, the cardiovascular risk is calculated according to the score as it is defined by the "European Society of Cardiology".

Anchoret in his applications at [26] and [27], assists the users to track their BP statues. Moreover, is providing medication list, graphical trends and weekly reports to the patients. The systems

in [28] and [29] can collect and analyze the Blood Pressure records and present them in a pie chart. The application in [29] can back up the data as well.

Chapter 3

Analysis of Photoplethysmography

3.1 PPG Types

Five main types of plethysmography exist. All types are used to measure the volume and volume displacement of blood. Each one uses different transducer and their use are depended on the application type. Table 3.1 below shows a list of plethysmograph types with the associated transducer and application to be used.

Table 3.1: Different Types of Photoplethysmography [20]

Type of Photoplethysmograph	Transducer	Applications
Air	- Air-filled Cuf	- Evaluation of venous hemodynamics - Measures parameters of global venous function
Water	- Water-filled cuff - Water-filled body - Water-filled chamber	- Measuring penile blood flow - Measuring Pulmonary Capillary Blood Flow - Measuring maximal blood flow
Photoelectric	- Photodetector	- Monitoring of heart and respiratory rates - Monitoring of oxygen saturation - Assessment of blood vessel viscosity - Assessment of venous function - Measuring the ankle pressure - Measuring genital responses - Measuring blood pressure
Strain Gauge	- Fine rubber tube	- Evaluation of peripheral circulation in spinal cord injury cases - Evaluation of acute and chronic venous insufficiency - Evaluation of peripheral vascular disease - Measurement of deep venous thromboses
Impedance	- Electrodes	- Detection of blood flow disorders - Assessment of fat-free mass of the human body

3.2 Photo-plethysmography approach to measure BP

For the needs of this paper the photoelectric plethysmography also known as Photo-plethysmography and it is abbreviated as PPG will be examined and used for the estimation of the blood pressure. PPG is very easy to set up, simple, convenient and provides a relatively economical solution compared with the other types of plethysmographs. It only needs a light source and a detector to detect the cardio-vascular pulse wave that propagates through the body. An invisible infrared light is sent into the tissue and the amount of the backscattered light is recorded [20]. The result of this reflection is a wave-like motion as shown in Figure 3.1

Hertzman in 1938 [30] was the first who discovered a relationship between the intensity of the reflected light with the variation of blood volume. As shown in Fig. 3.1a the PPG signal is simple and is very difficult to detect changes in the phase of the infections. Ozawa [18] in order to facilitate the interpretation of the PPG waveform applied the first and second derivative of the PPG signal as it is shown on the Fig.3.1b and 3.1c. Therefore the infection points can be recognised with more accuracy and the original PPG signal is easier investigated.

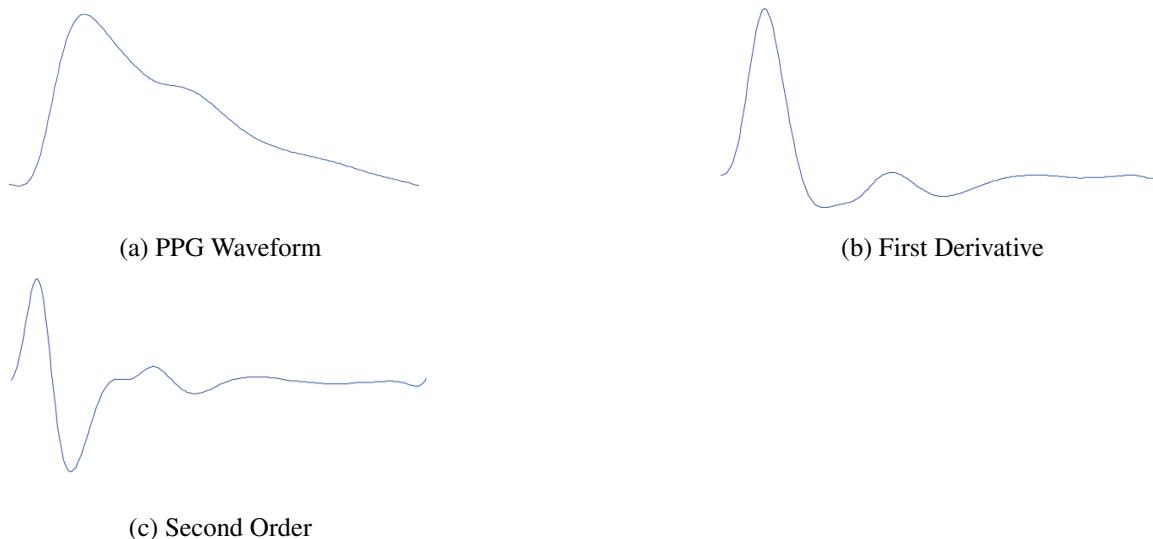


Figure 3.1: PPG [20]

The PPG signal is very much affected from many factors like skin structure, skin temperature, blood flow rate, measuring environment and the blood oxygen saturation [20]. In order to maintain the good quality of the PPG signal different techniques like high pass filters shall be

applied.

A lot of research has been taken place to explore the different features of the photoplethysmogram and transform them to helpful information that will be useful for many healthcare problems. In spite of the fact that the morphology of the PPG signal appears to be like the blood vessel weight beat, the signal varies and it is not the same . Millaseua et al [25] have quantified the relationship between the PPG sigal and the pressure pulse. Moreover, the evolution of semiconductor technology makes the possibility to build a more accurate and delicate PPG sensors a reality.This will drive the medical industry to use the PPG signals in many applications. Consequently a deeper analysis and exploration of the PPG signal is anticipated.

3.2.1 Phases and Features

The appearance of the PPG pulse can be described as having two phases,the anacrotic and the catacrotic. The anacrotic phase is the rising edge of the beat (systolic phase) and the catacrotic stage is the falling edge of the beat (diastolic phase). If a dicrotic notch, appeared in the signal during diastole is an indication of a healthy arterial. Some of the characteristics of this waveform and their applications are mentioned in this section [20].

1) Systolic Amplitude: The amplitude x in Fig. 3.2 is the systolic amplitude. It is an indicator of the blood volume changes at the fingertip(point of measurement).It has been suggested at [57] that Systolic Amplitude could be used for blood pressure estimation.

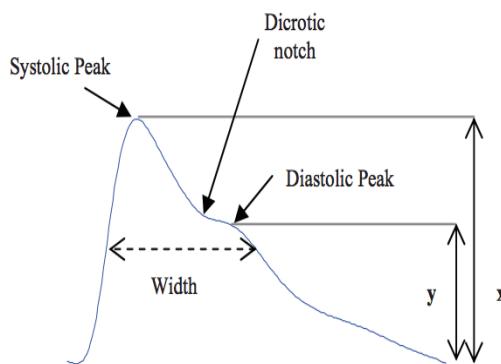


Figure 3.2: Characteristic parameters of PPG [20]

2) Pulse Width: Another important characteristic of the PPG signal is the width from Figure 3.2. Pulse width has been used in [32] as the pulse width at the half height of the systolic peak. The outcome of that research has suggested that pulse width has much better correlation with the vascular resistance compared to the systolic amplitude.

3) Peak to Peak Interval: The distance between two diastolic peaks is known as the peak to peak interval. The R-R heart variability interval in the electrocardiogram (ECG) signal and the Peak to peak interval in PPG both represent a whole heart cycle. For this reason the Peak-Peak interval has been utilised for heart-rate estimation.

4) Pulse Interval: As can be seen from Fig. 3.3a, the pulse interval is the distance from the point where the PPG signal starts until the point where the signal ends. The pulse interval was used for the determination of Heart Rate Variability (HRV) [41].



Figure 3.3: ΔT Feature [20]

5) ΔT calculation: Another important feature is the time ΔT can be seen in Fig. 3.3b It is the time difference between the systolic peak and the diastolic notch. In other words, is the time that pressure wave needs to travel from heart to the periphery and back. Since the contour of PPG varies in different individuals the ΔT varies as well.

6) Crest time (CT) or Systolic Time (ST): Crest time is defined as the time needed from the minimum point in the PPG waveform to reach its peak Fig. 3.4. Otherwise is known as the systolic Time of the signal. The literature [54] suggests that this feature can be used for cardiovascular symptoms evaluation.

7) Diastolic Time: It is defined as the time between the systolic peak and the diastolic minimum. It is the time for the diastolic phase to be executed. Similarly with the Systolic Time, Diastolic has been used in many cases for cardiovascular symptoms evaluation.

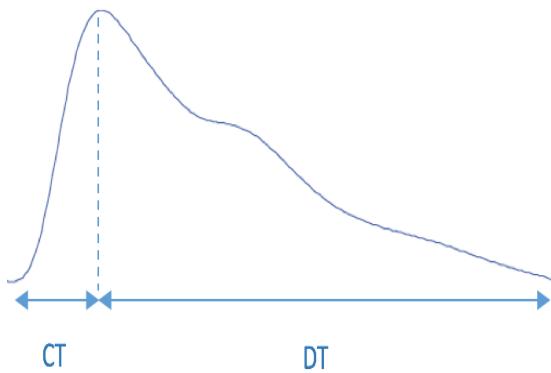


Figure 3.4: Crest and Diastolic Time [20]

Photoplethysmography is an extremely encouraging innovation because of its simplicity, low cost and non-invasiveness. For this reason in this project a lot of the characteristics that mentioned in this chapter are investigated in order to correlate PPG with Heart Rate and Blood Pressure.

Chapter 4

Hardware and Software

4.1 Hardware

The camera and the LED flash from the mobile are forming the PPG sensor which is going to record the photoplethysmographic waveform. Meanwhile, devices for recording the truth values for blood pressure and HR from the experimental participants were selected.

iPhone 5 was chosen as the main device for this project. It has the ability to record video at a rate of 30 frames per second, speed that is suitable for PPG processing. The specifications of iPhone's video camera are the following [39]:

- Panorama Video recording, HD (1080p) up to 30 frames per second with audio.
- HD camera with 1.2MP photos and HD video (720p) up to 30 frames per second LED flash. Improved video stabilisation.

iPhone's ergonomic design it was ideal for recording the video photoplethysmogram correctly. The LED and the camera are very close to each other making thus the

Figure 4.1: iPhone5



video capturing very easy.

4.1.1 Measuring Heart Rate

Truth values for heart rate and blood pressure should be obtained as stated above for the evaluation of the new methods accuracy. A lot of commercial devices exist that could serve this task. Forrester Research [34] suggested that the preferred location for heart rate sensors must be on the wrist.

Most commercial products nowadays deploy PPG to measure the HR. Unfortunately, the outcome of Lu et al. [40] study has shown that PPG is prone to noise and error due to movement. Furthermore they have suggested that heart-rate variability cannot be measured accurately using PPG. However, this method performs extremely well for the mean Heart-Rate measurement which is examined in this project.

Since the majority of activity trackers and smartwatches use similar hardware sensors, the final choice for HR sensor was an Apple Watch. Apple has implemented photoplethysmography in the watch for tracking the Heart Rate. The way that Apple watch operates as described by Apple is the following:

"Apple Watch uses green LED lights paired with light-sensitive photodiodes to detect the amount of blood flowing through your wrist at any given moment. When your heart beats, the blood flow in your wrist - and the green light absorption - is greater. Between beats, it's less. By flashing its LED lights hundreds of times per second, Apple Watch can calculate the number of times the heart beats each minute — your heart rate. In addition, the heart rate sensor is designed to compensate for low signal levels by increasing both LED brightness and sampling rate" [35].

Even this is a commercial device inaccurate readings could be obtained. If the wrist band in the watch is too loose may cause problems which lead to false measurements or no measurements

Figure 4.2: Apple watch



at all. Furthermore, skin perfusion could affect the result. Also extensive movement and the weather could be the cause of wrong readings.

Evaluation of Apple watch

The accuracy of the apple Watch was compared with the readings obtained from a Polar H7, which uses ECG to measure HR. To evaluate the performance of the watch measurements for 15 minutes were taken for a week from each of the two devices from 7 different subjects. At the same time the subjects were wearing the polar H7 strip and the Apple Watch. The Mean Heart was acquired and the final results are presented in Figure 4.3. The test interval was over 15 minutes and illustrates a strong correlation between the two sensors. This confirms that the Watch is a suitable sensor for continuously measuring HR.

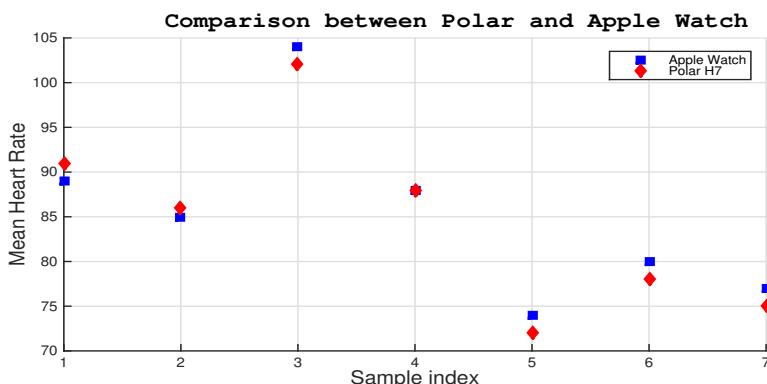


Figure 4.3: Evaluation of Apple watch

The results show that the two devices are highly correlated and the correlation is found to be 0.9870. This confirms that the Watch is an accurate sensor for measuring HR.

4.1.2 Measuring Blood Pressure

For the blood pressure measurements the Withings Blood Pressure monitor was selected. Withings monitor is a self-measurement device which is placed at the arm level and uses oscillometric method to perform the measurement.

An electric air pump in the cuff is responsible for the inflation that is happening at 15 mmHg/s and the deflation is performed by an electrical controller releasing air from a discharge valve [44].

The specifications of the above device are:

- It weights around 600 g
- It needs 4 - “AAA” batteries to operate
- Cuff dimensions are 150 (W) x 600 (L) mm
- It can be deployed to an arm range between 22 to 42 cm.

The Withings blood pressure monitor has the ability to measure:(a) Systolic and Diastolic blood pressure, (b) Pulse Rate, (c) Date and time.

4.1.3 Evaluation of Withings Blood Pressure

Asmar et al. [44] validated this blood pressure monitor device in 2011. The way that validation was performed, was that readings from both cuff mercury sphygmomanometer at arm level and readings from the Withings device were taken into account. The mercury sphygmomanometer method was used since is generally being accepted as the standard approach to calculate the blood pressure. They used 33 subjects for the purpose of this experiment and their results could sum up in the Fig. 4.5.



Figure 4.4: Withings Blood Pressure Monitor

This study showed that the accuracy of the WITHINGS oscillometric device fulfils the Hypertension International Protocol. However, it should be mentioned that all BP measurements taken while the participants were seated and their arm was supported at the heart level.

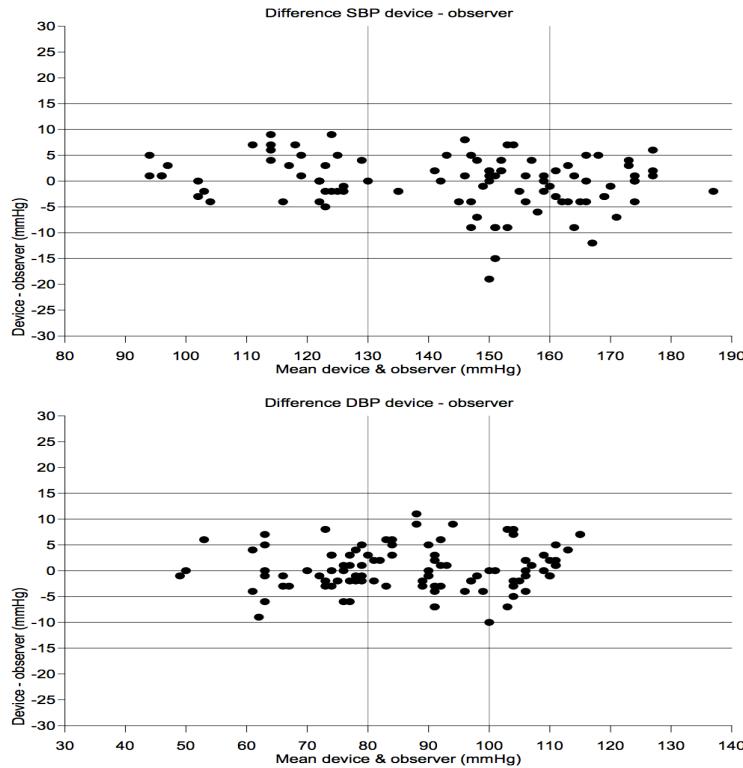


Figure 4.5: Evaluation of Withings Blood Pressure Monitor [44]

4.2 Software

MATLAB is the short name of Matrix Laboratory and was created by Mathworks. It is a programming language that is extensively used in the science and engineering world. It provides the perfect environment for mathematical analysis, data manipulation, modelling and visualisation. Overall, the mathematical, matrix-based structure of the MATLAB language is suitable for signal processing algorithms that can be expressed as mathematical functions. MATLAB gives the benefit of implementing an algorithm in a few lines, something that is impossible with other programming tools.

The signal processing toolbox that MATLAB provides makes the use of MATLAB suitable for this project. Predefined functions, filters, graphical representation methods are all included in

the toolbox which give a big advantage to MATLAB over other programming languages. All the code for this research has been written and implemented in MATLAB.

Chapter 5

Estimation Heart Rate Through the Camera

5.1 Introduction

Tracking HR from the smartphone's camera is simple and does not require any special knowledge from the user. The only essential tool that is needed is a mobile phone with a camera and an LED. The user by placing his finger to cover both camera and the LED can record the photoplethysmographic signal for about 20 seconds. Then the video is uploaded in the computer for further processing.

As the heart pumps, it pushes the blood to all parts of the body. As the blood flows in the fingers, the shading and murkiness of the skin changes. These changes are recorded by the video camera and can be distinguished by breaking down the normal red channel from the video.

5.2 Algorithm Flowchart

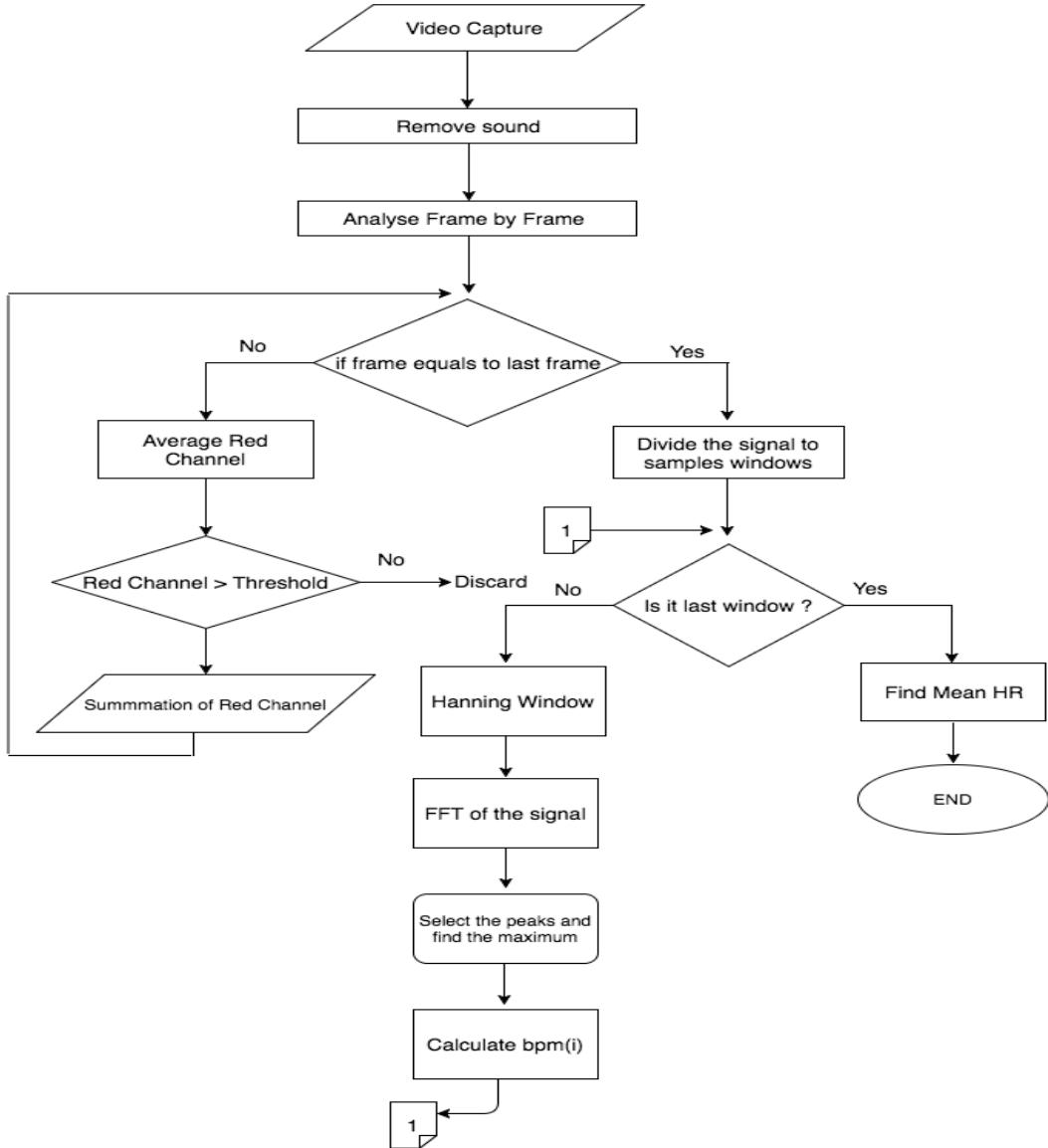


Figure 5.1: Alogrithm Flow Chart

The algorithm that has been implemented for the detection of average Heart Rate is available in Figure 5.1. The algorithm is proposed by Ignacio Manella [62]. A lot of factors can affect the final result of the process. In Self-monitoring of Heart Rate or Blood Pressure, the only person that is responsible for the correctness of the procedure is the user. For instance, by placing the fingertip in the wrong position, or moving of the fingertip as the video is recorded can affect the outcome. These circumstances are taken into consideration during the experiments.

5.3 Analysis of the Algorithm

5.3.1 Capturing the Frames

The colour saturation in the frames depends on the environmental conditions or by smartphone type used. Since in this project iPhone 5 was used, different lighting conditions or circumstances were applied during the recording process. Figure 5.2 presents the histograms of the 3 channels that exist in the RGB (Red-Green-Blue) space. For this research only the iPhone 5 was used. The quality of the PPG signal was assessed in different circumstances.

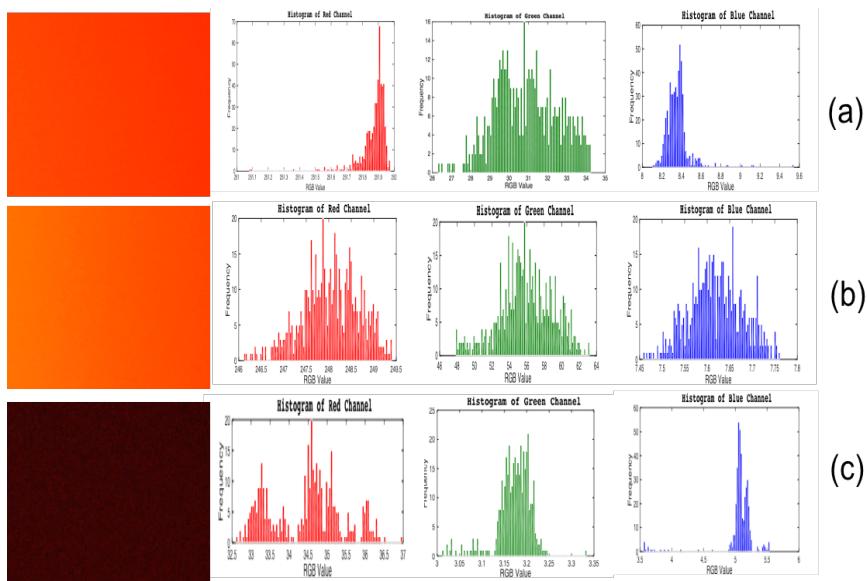


Figure 5.2: Different conditions:(a) Pressure on the LED flash,(b)low-level of pressure, (c) No LED

Observations

Figure 5.2 shows the histograms of the three channels (Red, Blue, Green) taken from a subject in a room with good lighting. The subject was asked to apply in the first case pressure on the camera, on the second case to apply less pressure and in the third case to turn off the LED and perform the experiment. The investigation of the results received (Figure 5.2) grants the following conclusions:

- In normal conditions with LED turned on, the brightness level of the green channel is

low between 25-35 (RGB values). When the LED is turned off the values of the green channel are almost 0. In the case of low pressure in the camera, the green channel has greater values compared to the high pressure case.

- The red component of the frame normally lies in the range 250-252 RGB. However, this is not fixed and could vary by the use of different device or by different subject. Nevertheless, to suggest that the frame is good for processing it must exceed a specified threshold value. The small variation of the values, which happens when the illumination is not sufficient could create problems during the analysis of the signal.
- The values of the blue channel are very small whatever the case is and very close to 0.

Hence, having in mind the above observations it is suggested that use of LED is essential for photoplethysmography and natural light cannot be used as a substitute. Furthermore, green and red channel will be used to form the PPG signal.

The same experiment was performed in an environment with different lighting conditions. The samples for the three different cases were recorded and the result can be seen in Fig. 5.5.

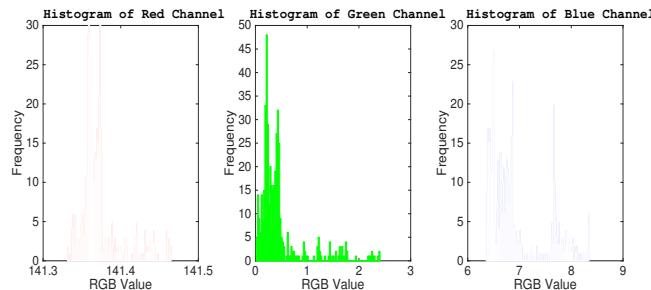


Figure 5.3: Outside environment protected from the sun

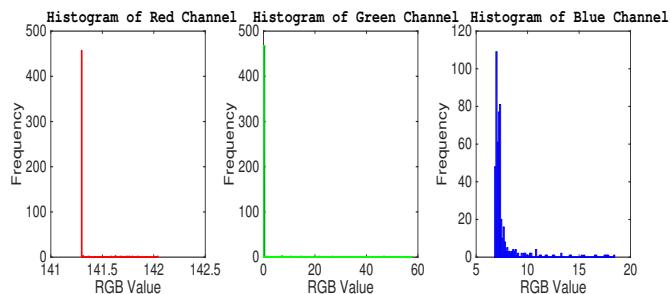


Figure 5.4: Outside environment exposed in the sun

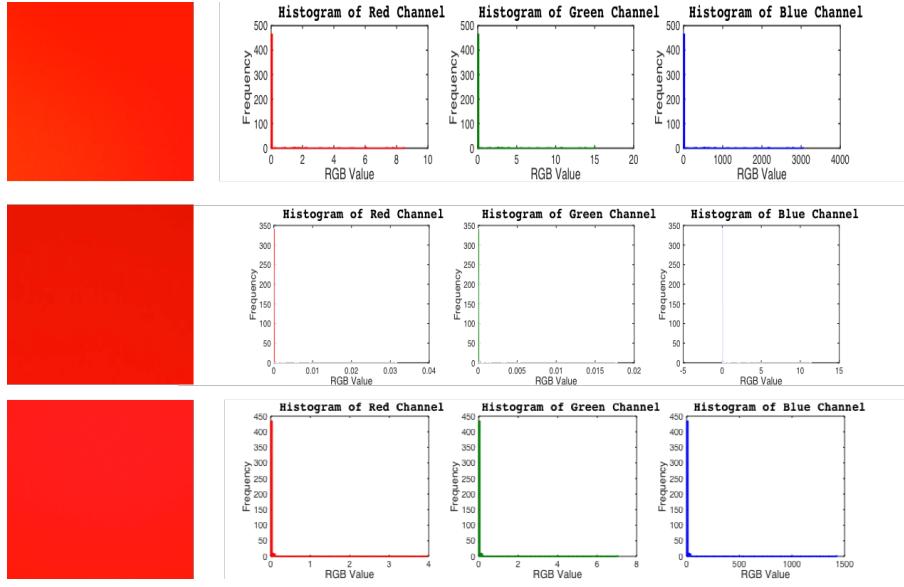


Figure 5.5: Day light conditions:(a) Pressure on the LED flash,(b)low-level of pressure, (c) No LED

Further experiments were carried under bright lighting conditions. The RGB values are presented on Fig. 5.4 and 5.5. The brightness level has been significantly reduced due to the interference of external light.

The use of the photoplethysmographic method in an environment where the intensity of daylight is high then the red,green and blue channel could not provide sufficient data that could be used for extracting any information. Therefore it was decided that any experiments relevant to the project should be done in a quiet room, thus any external noise would be reduced, and the lighting will be at normal levels. Also all the participants were asked to exercise pressure to the camera during the experiments to minimise the possibility of external light to interrupt the process.

Domenico Grimaldi et al. [58] proposed following ranges for the correct assessment of the video frames.

- $\text{mean}(\text{Green}) + \sigma_{\text{Green}} \geq \text{GreenThreshold}$
- $\text{mean}(\text{Red}) - \sigma_{\text{Red}} \geq \text{RedThreshold}$
- $\text{mean}(\text{Green}) + \sigma_{\text{Green}} \geq \text{MaxThreshold}$ AND $\sigma_{\text{Red}}, \sigma_{\text{Green}}, \sigma_{\text{Blue}} < \sigma_{\text{Max}}$

The mean(Red), mean(Green) and mean(Blue) are the average values of each component in each frame. Also the σ is the Standard deviation of each component. The Threshold values that are mentioned above as they are defined by [58] are: GreenThreshold= 10, RedThreshold= 128, Gmax = 128, Bmax = 128, $\sigma = 40$, σ_G, σ_B are the standard deviation values, computed for each frame and each color channel. The propose threshold value for the red channel is used in this project.

5.3.2 Motion Artifacts

Apart from the lightening conditions another factor that could affect the the accuracy of the PPG signal is the shifting of the finger during the video recording. For this reason for 7 subsequent days a capture was received in order to examine how any movement during the experiment could affect the final result.

Experiment Setup:

(1) For a week the PPG signal was obtain from a subject. The subject was asked to use the iPhone 5 and record two videos for 15 seconds. During the first video, the participant was advised to keep his hand and his finger stable, while in the second it was asked to move his finger or his hand while the phone was recording.

(2) At the same time MotionLogger application was turned on, measuring the accelerometer data from the phone. The x,y,z positions of the phone were stored and they were exported in the form of a csv file.

(3) The waveform of the PPG signals from the two cases were compared, as well as the heart rate results. The first three samples that were taken are shown on Figure5.6, 5.7, 5.8

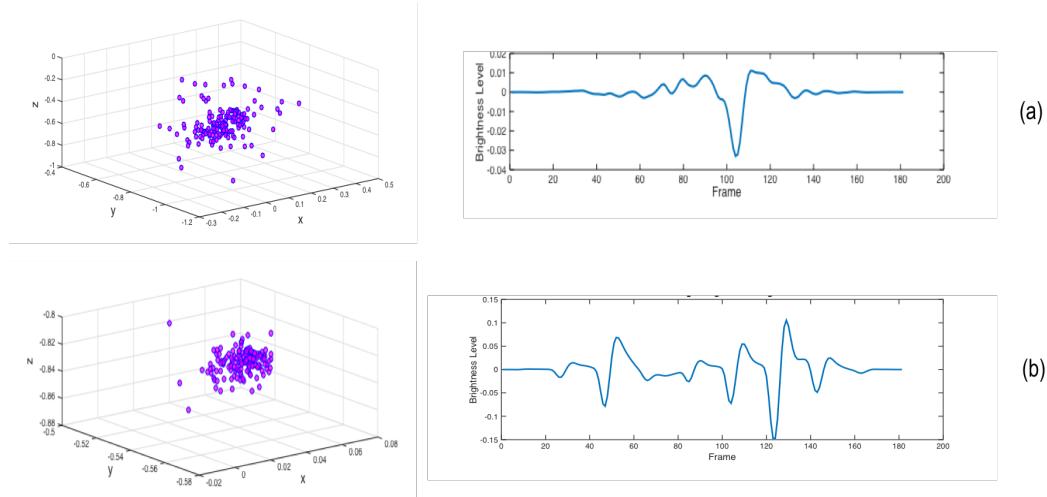


Figure 5.6: Day 1-Movement: (a)movement, (b) no movement

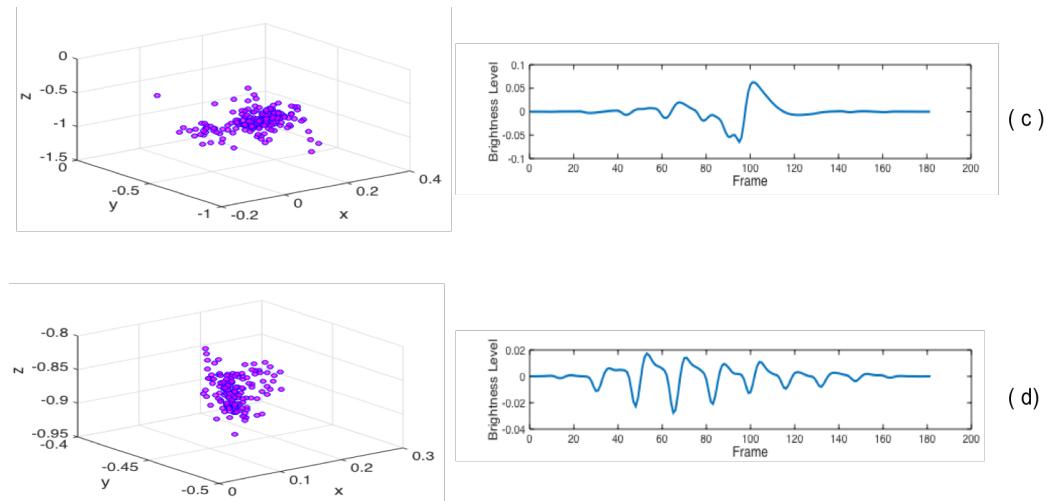


Figure 5.7: Day 2 - Movement: (a)movement, (b) no movement

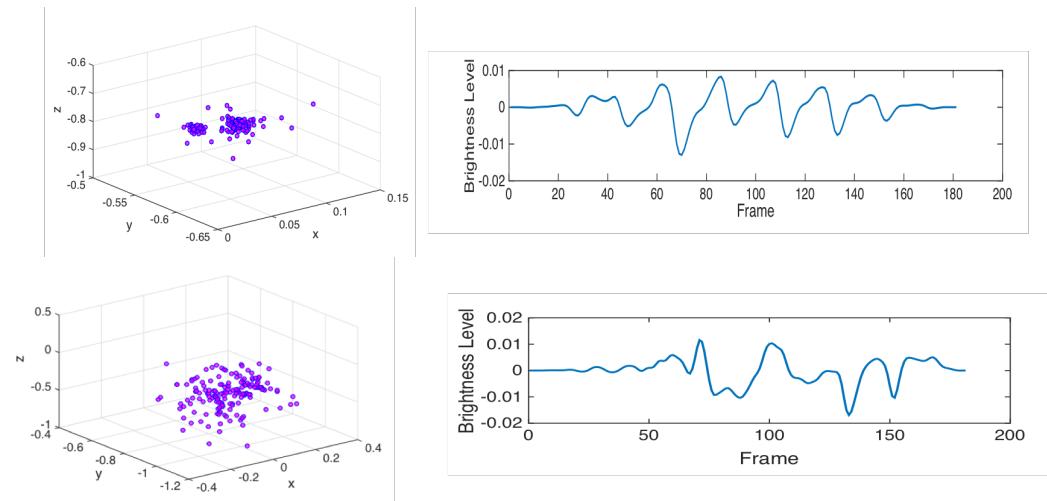


Figure 5.8: Day 3 - Movement: (a)movement, (b) no movement

Fig. 5.6 and Fig 5.7 shows the results from the first two days of the experiment. It can be observed clearly that there is a difference between the PPG waveform that is obtained in the two states: (a) movement and (b) no movement.

Conclusion: Further experiments for this project all were taken place in a quiet room and all the participants were asked to keep the phone stable and do not move during the recording.

5.4 Implementing the Algorithm

The algorithm proposed in Section 5.2 was implemented. The first step was the capture of the video plethysmogram. Then the sound from the video was removed. This objective was achieved with the help of iMovie App.

The choice to remove the sound before further processing of the signal was affected by the reduction of the computational time. It was observed that before the removal of the sound the time for reading the frames of the video was significantly long. However, cancelling the sound has resulted to a huge amount of computational time improvement. The table 5.1 shows the computational time between the two cases for 5 examples. It is clearly indicated that the processing time is much less when the sound has been removed.

Table 5.1: Computational Time for frame processing

	Sound (s)	No Sound (s)
Subject 1	212.7245	89.1627
Subject 2	282.3641	105.5940
Subject 3	128.5140	117.3854
Subject 4	283.9952	119.1716
Subject 5	276.8874	109.3527

5.4.1 Construct the PPG signal

The photoplethysmographic signal that must be constructed can be characterised as the skin brightness over a period. The proposed algorithm suggests to add all the frames of a pixel

and find the average values. For computation reasons the blue, green and red channels were not combined. Instead, the average value of red and green channel were found and are used separately to form the required signal. From the research that is was done for this project it was suggested that the red channel has most of the information, since most of the energy is concentrated in that plane. The formula below from [62]was used to find the average values:

$$\text{signal}[i] = \frac{1}{\text{Width} \times \text{Height}} \sum_x^{\text{Height}} \sum_y^{\text{Width}} s[i, x, y, 1] \quad (5.1)$$

Width is the width of the image in pixel and the Height is the Height of the image in pixel. Finally, s is the channel in the i frame. The number 1 in $s[i, x, y, 1]$ is an indicator for the red plane.

Noise Signal

Figure 5.9 displays the PPG waveform that is constructed by averaging the values of red channel. The waveform indicates that the first seconds could be noisy. This could be due to the fact that the camera needs some time to auto-focus. Therefore the first few seconds of the capture should be ignored.

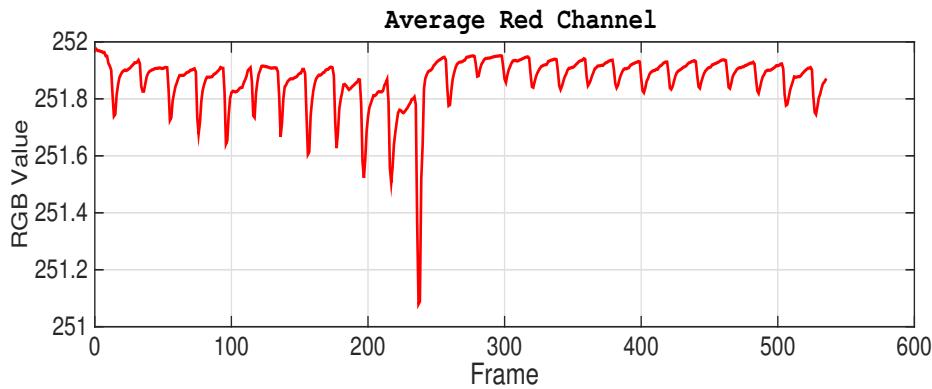


Figure 5.9: Noise Signal

The average heart rate of human is between 60 and 100 beats per minute. This can be affected by various factors. The physical condition of the human and the age are some of these factors. The range between 40 beats per minute (bpm) and 240 bpm was assumed to be the range

that heart beat could be found. These values should be converted in the frequency domain by applying: $Frequency = \frac{BeatPerMinute}{60}$. The resulting range in frequency domain is 0.6667 Hz and 4 Hz respectively. From that, the sampling frequency can be specified. In order to avoid aliasing sampling frequency must be twice the maximum frequency. As the Nyquist states: $SamplingFrequency = 2 \times 4 = 8Hz$. The frame rate that iPhone 5 is capturing the frame is 29.9826 HZ which is greater than the Nyquist Sampling frequency.

Signal Filtering

To remove the unwanted frequencies from the signal a second order Butterworth filter is applied. The frequency range of the filter is equal to the expected frequency range which is defined above (0.6667-4Hz).

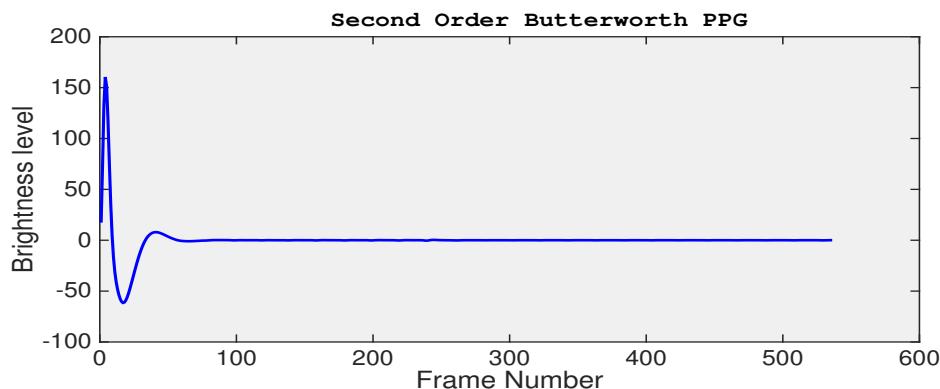


Figure 5.10: Signal after Second Order Butterworth signal

The filter selected belongs to the Infinite Impulse response (IIR) category of filters. The particular filter was chosen because the order that requires is much less than using a Finite Impulse Response Filter (FIR). A comparison between an IIR and FIR can be seen in Fig. 5.11 . This means less computational complexity. This kind of filter by having flat pass-band and stop-bands does not favoring certain frequencies over other. Butter-worth filter has only two design parameters that should be considered: (1) the order of the filter and (2) the cut-off

frequency. The magnitude response of a Butterworth filter has the following form [33]:

$$\left| H_{BW}(e^{j\omega}) \right|^2 = \frac{1}{1 + \left[\frac{\tan(\omega/2)}{\tan(\omega_c/2)} \right]^2} \quad (5.2)$$

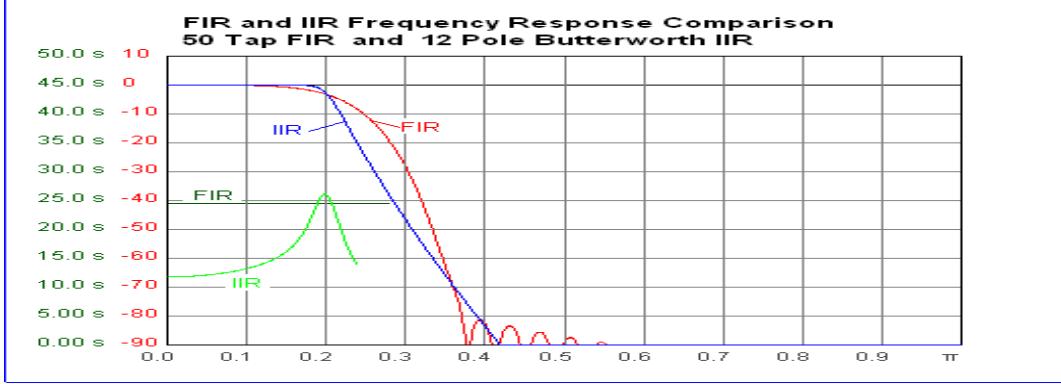


Figure 5.11: Second Order Butterworth Signal

By looking at Figure 5.10 there is an initial stabilisation time. This time is found between the 1st and the 2nd second. Therefore to remove this stabilisation time further processing is required. The initialisation time that is needed is around 29.3 *frames/s* which is the 1st second of our waveform. The signal in Figure 5.12 is the outcome of removing the initialisation time [62].

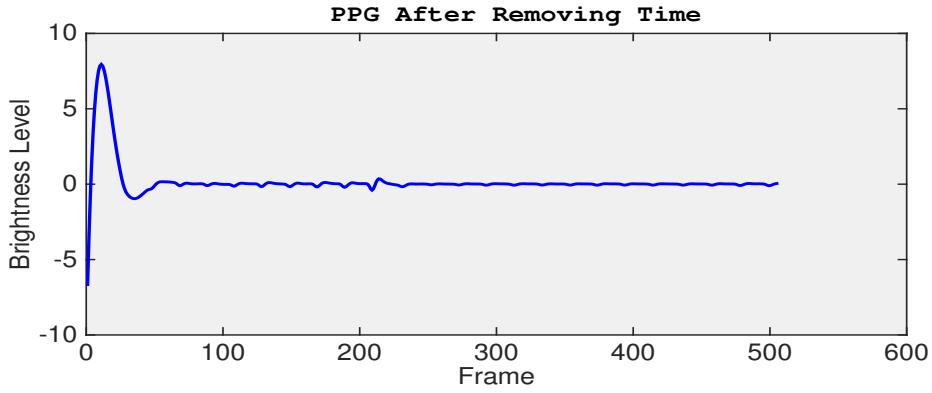


Figure 5.12: PPG without initialisation time

Sliding Window

Continuous estimation of the Heart-rate and Blood pressure is achieved by using the sliding window method. By considering a small "window" of the signal, this algorithm look for evidence

of a step occurring within the window. The window "slides" across the time series, one step at a time.

A window is initialised to contain the last 6 seconds of the signal samples. Therefore inside the window 180 samples will be examined since the sampling frequency is equal to 30 frames per second. The duration of the sliding window is very important and will affect the frequency resolution and as a consequence the accuracy of our estimation.

The following procedures will be carried out inside each window:

- Hanning window
- Fourier Transform
- Peak Detection

Hanning Window

Inside the sliding window processing a Hanning window is used to bring edges to zero. In this way, no artificial high frequencies appear when the signal is treated as periodic by the Fast Fourier Transform (FFT).

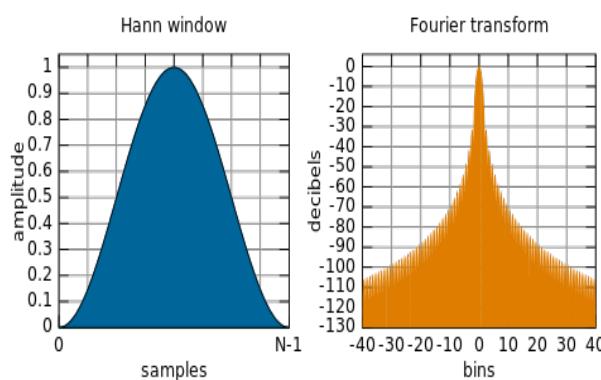


Figure 5.13: Hanning Window [45]

5.4.2 FFT

The original PPG signal is very noisy and for this reason the frequency domain transformation is required to clearly observe the peaks of the signal which are related to the HR estimation. The Discrete Fourier Transform (DFT) is used to translate the signal from the time domain to the frequency domain. The Fast Fourier Transform algorithm was used to save processing time when computing the DFT. While the computational complexity of the DFT is $O(N^2)$ for a set of N points, the FFT gets the same results with $O(N \cdot \log_2(N))$, which means a huge speed-up when N is high [62].

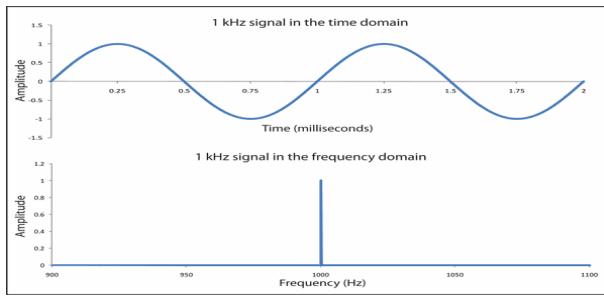


Figure 5.14: Frequency domain [46]

Fig 5.13 presents the time and frequency domain of a signal. It is clear that it is simple to plot the frequency domain. The benefit of this transformation is that the peak amplitude and frequency of the signal can be easily extracted in this domain.

In MATLAB the FFT can be easily calculated by using standard MATLAB command `fft`. Since the `fft` is a complex number giving information for both the magnitude and the phase of the signal. The absolute value is taken into consideration while the phase is discarded.

The choice of 6 seconds as the time of the sliding window is strongly related to the frequency resolution as it is mentioned above. In FFT it can be said that a signal sampled N times and having a sample frequency $F_{sampling}$ it has N bins. Therefore the distance between two consecutive bins is $F_{sampling}/N$. This is known as the Resolution Frequency [62].

$$F_{Resolution} = \frac{F_{sampling}}{N} = \frac{\frac{N}{T_w}}{N} = \frac{1}{T_w} \quad (5.3)$$

From the above equation it is concluded that the higher the window period the better the frequency resolution. However, this will result to decrease the time accuracy. Using a 6s window this gives a fair frequency and time accuracy 6s and 5 bmp respectively. The duration of steps of the sliding window is 0.5, this was selected in order to produce more samples heart rate which will result to better estimation.

Figure 5.15 (b) shows the FFT spectra are plotted as the power density versus frequency in the range of 40-240 bpm, corresponding to 0.66 to 4 Hz. For each time interval, the spectra show the 4 main peaks, which are respectively labeled according to their power as Peak 1 is the strongest peak, Peak 2, Peak 3, and Peak 4 the weakest peak.

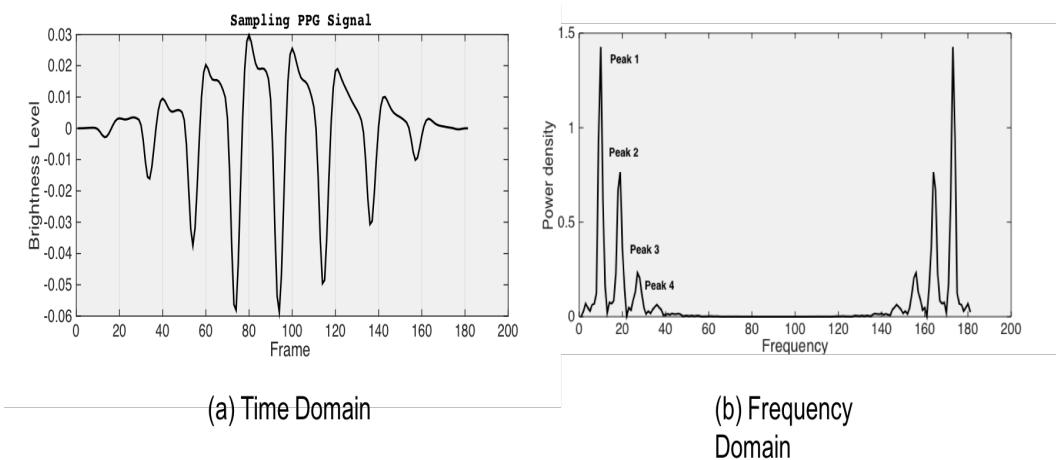


Figure 5.15: FFT spectra

5.4.3 HR Estimation

The Peak-Peak interval has been used to detect the HR in PPG signals. The Bits per minute heart rate is estimated by finding peaks in the interest frequency range and locate the highest. The interest range frequency is defined as the range of frequencies where the human heart beat is. It is defined by the following equations:

$$Frequency_L = \frac{BPM_L}{60} \quad (5.4)$$

$$Frequency_H = \frac{BPM_H}{60} \quad (5.5)$$

Therefore by calculating the maximum peak for each sample the heart rate is defined by [62]:

$$BPM = (MaxIndexFrequency - 1) * \left(\frac{SamplingFrequency}{NumberOfSamples} \right) * 60 \quad (5.6)$$

These calculations are done for all the samples of the sliding window and at the end an average value of the heart rate is obtained.

5.4.4 Evaluation

Participants

A convenience sample of 33 adults, aged 21–50, volunteered and participated in the study. The diverse sample of participants consisted of 9 females and 25 males. Participants gave a brief information about their medical history, whether they are athletes or not and their age. These information are presented in Table 5.2.

All the subjects during the experiments were given an Apple Watch and an iPhone 5. Apple watch was measuring the heart rate every 1 second. These values were automatically stored in Healthkit. The participants were asked to sit quietly and place their finger index in the correct position. The video was recorded for a period of 20 seconds. When the recording stopped , video was sent for offline processing and the Healthkit values were extracted to calculate the average HR.

Data Analysis

The Apple Watch data were averaged and compared with the HR values recorded from the cell phone at their respective time periods. Pearson correlation coefficients and standard errors of estimate (SEE) were calculated. The standard error of the estimate is a measure of the accuracy of predictions and Pearson correlation is a coefficient which has value between -1 and 1 showing

the linear relationship of two variables. The SEE can be calculated using the following formula:

$$SEE = \sqrt{\frac{(Y - Y')^2}{N}} \quad (5.7)$$

Table 5.2: Descriptive Characteristics of Sample

Sex	Age	Athlete/Not Athlete	Chronic Disease
M	28	Not	-
M	25	Not	-
M	21	Not	-
F	20	Not	-
M	24	Athlete	-
M	23	Athlete	-
M	24	Not	-
M	24	Not	-
F	23	Athlete	-
F	23	Not	Diabetes
M	28	Not	-
M	24	Not	-
M	24	Not	-
M	22	Not	-
M	23	Not	-
M	24	Not	-
M	25	Athlete	-
M	24	Not	-
M	24	Not	-
M	27	Not	-
M	26	Not	-
M	24	Not	-
F	26	Not	-
F	24	Not	-
F	24	Not	-
M	25	Not	-
F	23	Not	-
M	47	Not	-
F	43	Not	-Thrombosis
F	25	Not	-
M	50	Not	-
M	46	Not	-

SEE is the standard estimation error. Y represents the truth values , Y' represents the predicted values, and N is the number of samples. The numerator is the sum of squared differences between the actual values and the predicted values. Another important statistics that is going to

be used in this project is the mean absolute difference which is defined by:

$$MD = \frac{1}{n} \sum_{i=1}^n \sum_{j=1}^n |y_i - y_j| \quad (5.8)$$

5.4.5 Results and Discussions

All the experiments were finalised and the results are tabulated in the following tables. Table 5.3 shows the mean heart rate and standard deviation of the truth values obtained from the Apple Watch and the iPhone 5. Table 5.4 displays the standard error of estimate and the correlation coefficient

Table 5.3: Heart rate means and SD across methods

Device	Mean Heart Rate
Apple Watch	78.0312 ± 12.9178
iPhone 5	78.7592 ± 13.0340

The SEE is the other standard mistake measurement most regularly utilised by analysts. This measurement is utilised with the correlation measure, the Pearson R. It can permit the scientist to build a confidence interval between the true values and the experimental values. The calculations got from the r and the SEE of the evaluation can be used to describe the accuracy of the results.

Table 5.4: Standard Estimation

	Result
r	0.9019
SEE	4.1177

To determine if adequate agreement existed across the experimental and the truth methods, Bland Altman plots were developed for all the possible pairs. Fig. 5.16 shows that all the experimental result in the range of ± 8 except from two extreme cases. The outcome showed an agreement in the results, 19 samples were having an accuracy over 95%, 7 subjects had accuracy in the range of 90%-95%, 8 line between 85%-90% and 2 have low accuracy results. Figure 5.17 can verify these observations. Overall, HR results from the video camera could be characterised as accurate.

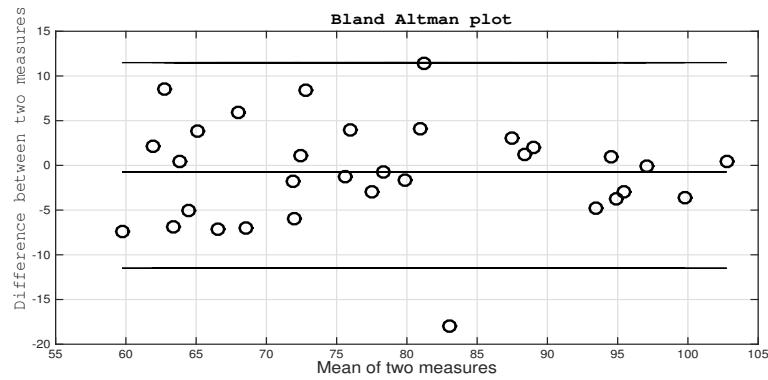


Figure 5.16: Bland Atman

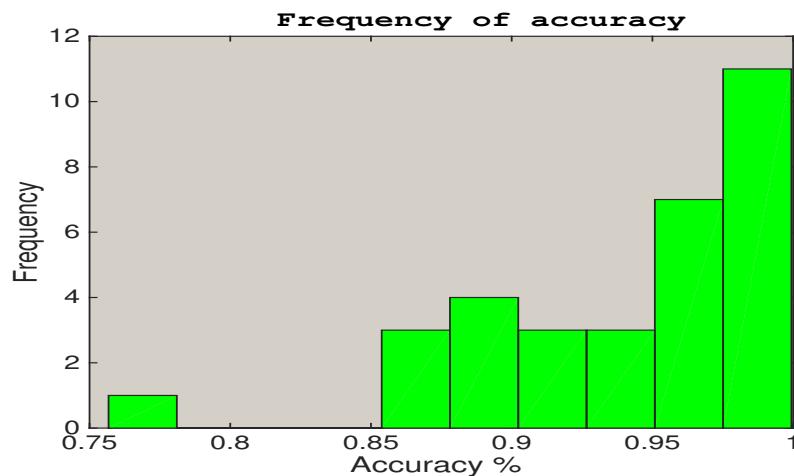


Figure 5.17: FFT spectra

Chapter 6

Blood Pressure Estimation

6.1 Introduction

A lot of research has been done during the last years about methods to calculate Systolic and diastolic Blood Pressure from the characteristics of the photoplethysmographic signal. Most of the studies used PPG sensors such as pulse oximeters or other lab equipment to acquire the signal. In addition, the huge evolution of mobile technology allowed us to replace these devices and use instead the smartphone as the PPG Sensor.

Furthermore there is a large number of existing applications which are claiming that they can be used for tracking Blood pressure. In this chapter linear regression analysis is used to correlate blood pressure with different features of the PPG.

6.2 Method used

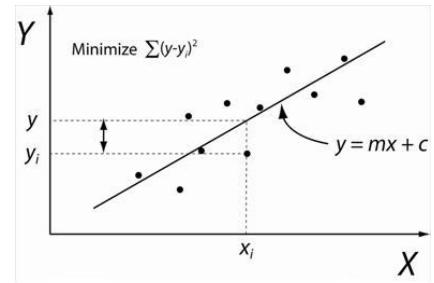
Linear regression modelling is the approach that is selected to correlate PPG with Blood Pressure. This decision has been influenced by the satisfactory results that the research of Teng et al. has produced [31] by using Linear Regression for Blood Pressure estimation. For their study a pulse oximeter was used, in contrast with this project where the smartphone has been used instead.

Linear regression is a method of building a linear relationship between different variables. In this study the relation between the actual BP measurements and PPG features are examined. Therefore simple linear regression is implemented since only one variable is used.

Regression allows us to model the relationship between two or more variables using simple algebra. In the Blood Pressure estimation problem, the features in the PPG signal represents the independent variable and the Systolic and Diastolic values of BP the dependent variable.

Least squared criterion is used to formulate the model. The goal during the formulation of the best fit line is to minimise the sum of squared differences between the observed and the predicted value $\sum(y - \bar{y})^2$ [53]. The Figure 6.1 shows an example of linear regression. In our case y is the truth value of either Systolic or Diastolic Pressure and \bar{y} the predicted. The simplest form of such a model is [64]:

Figure 6.1: Linear Model [55]



$$y_i = x_i\beta_1 + \beta_0 + e \quad (6.1)$$

- y_i can be called the response variable
- x_i is the input variable
- β_1 is the regression coefficient of the best fit line. It is calculated by:

$$\frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sum(x_i - \bar{x})^2} \quad (6.2)$$

\bar{x} is the mean of the independent variable, x_i value of independent variable, \bar{y} is the mean of the dependent variable and y_i is the value of the dependent variable.

- β_0 is defined by the formula:

$$\beta_0 = \bar{y} - \beta_1 \bar{x} \quad (6.3)$$

- e is a random variable which sometimes it cannot be observed and is adding noise to the linear relationship.

Y is defined as the output for the model and will be used for the Systolic or Diastolic blood pressure. The input x is the dependant random variable which could represent one of the following four features of the PPG signal: (a) Systolic Time, (b) Diastolic Time, (c) Pulse Time(Cardiac Cycle Time, (d) 1/3 Pulse Width(W1)

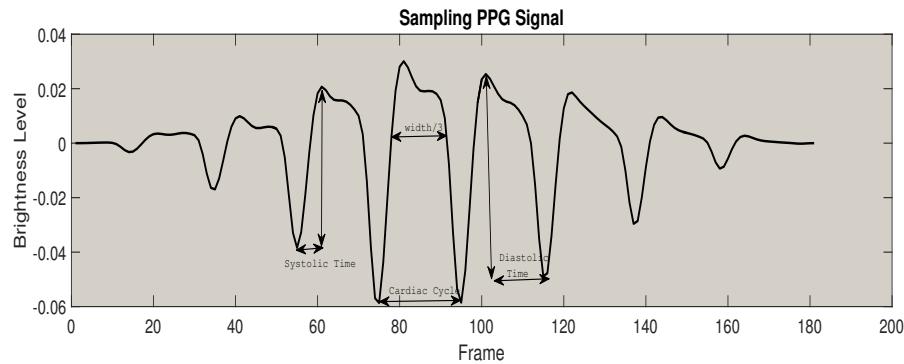


Figure 6.2: PPG Signal

6.3 Building the Model

The linear regression was divided into two phases, the training and the testing phase. Therefore data were collected for each phase separately. Training data were used to build and train the model. In the testing phase the testing data were used as inputs to the already built model and the Blood Pressure was predicted and compared with the truth values.

In the proposed methodology PPG features are extracted from the training dataset. Peaks and minimum values of the signal are automatically distinguished and used to determine the features which are correlated with BP.

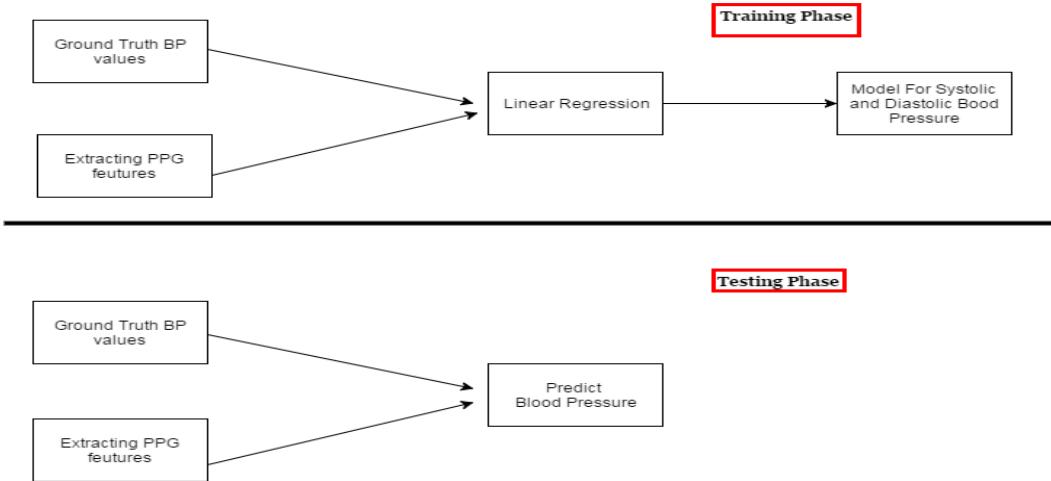


Figure 6.3: Block diagram of proposed methodology

6.4 Experimental Setup

Blood Pressure Measurements were taken with the help of the Withings Blood Pressure monitor, while the video photoplethysmographic signal was obtained from the iPhone 5. The data from iPhone and the Withings device couldn't be obtained at the same time. When the cuff increases its pressure in the arm of the subject the PPG signal disappears, and reappears when the pressure is decreased. This is proved by the research at [43]. In their study they examined the behaviour of the PPG signal during the cuff inflation and deflation. Their observations are available in Fig. 6.4.

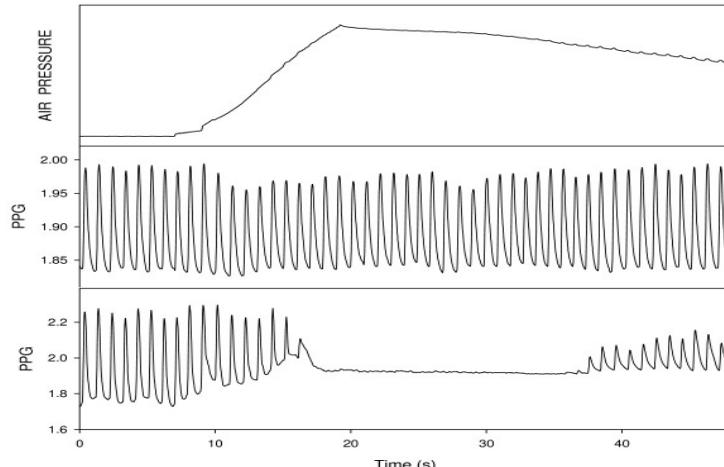


Figure 6.4: PPG [43]

The PPG pulses observed above is obtained from different hands. The finger that is in the hand where the cuff is placed it is the one where the pulses disappear. This phenomenon is observed when the pressure is greater than the Systolic Blood Pressure value and reappears when the value of the pressure is lower than the Systolic pressure.

It was decided to measure the Blood pressure and record the PPG pulses from the same hand. For this reason since these two tasks could not be obtained simultaneously, the smartphone was used to capture the video at first. Then the readings from the Blood pressure monitor were obtained.

Samples from 21 participants were taken from randomly chosen people. The conditions to record the PPG signal were identical to those used in previous part of this project for the determination of HR.

From the data obtained, 11 samples were used for training of the model and the other 10 were used for testing.

6.4.1 Extracting PPG Features

Figure 6.2 shows the four features of the PPG Signal which are correlated with Systolic and Diastolic pressure. These characteristics of the photoplethysmographic waveform were selected since a correlation has been found between them and BP.

(1) Systolic Time: Systolic Time is the interval from the onset of ventricular depolarization to the beginning of aortic ejection. It is defined as the distance between a minimum value of the PPG waveform and the next peak value.

(2) Diastolic Time: Diastolic Time is when the semilunar valves close, the atrioventricular valves open, and the whole heart is relaxed. It is defined as the distance between a systolic peak and the next diastolic minimum.

(3) Cardiac Cycle: Cardiac Cycle refers to a complete heartbeat from its generation to the beginning of the next beat, and so includes the diastole, the systole, and the intervening pause. It can be defined as either the distance between two systolic peaks or two diastolic minimum values.

(4) 1/3 Pulse Width: Some studies like [31] showed that 1/3 Width could be an indicator for observing Blood Pressure.

6.5 Algorithm

The procedure to record the video is the same with the one used in section 5.3.1. The experiments took place in a quiet room. The duration of the video was 20s. Similarly to HR estimation method, for better processing time, the sound was removed from the videos.

Then sliding window is applied to the PPG waveform and the signal is divided into samples. Inside the loop Hanning window is used again for leakage reduction and to remove the edges. Then the PPG features are extracted from the signal. For instance, average systolic time is found in each iteration. Similarly, averages values are found for all the characteristics that

are investigated: $AverageF = \frac{1}{n} \sum \bar{F}_i$. The mean value of each F is calculated and it is fitted to the correct model. Since we have 4 features 4 different linear regression models have been developed.

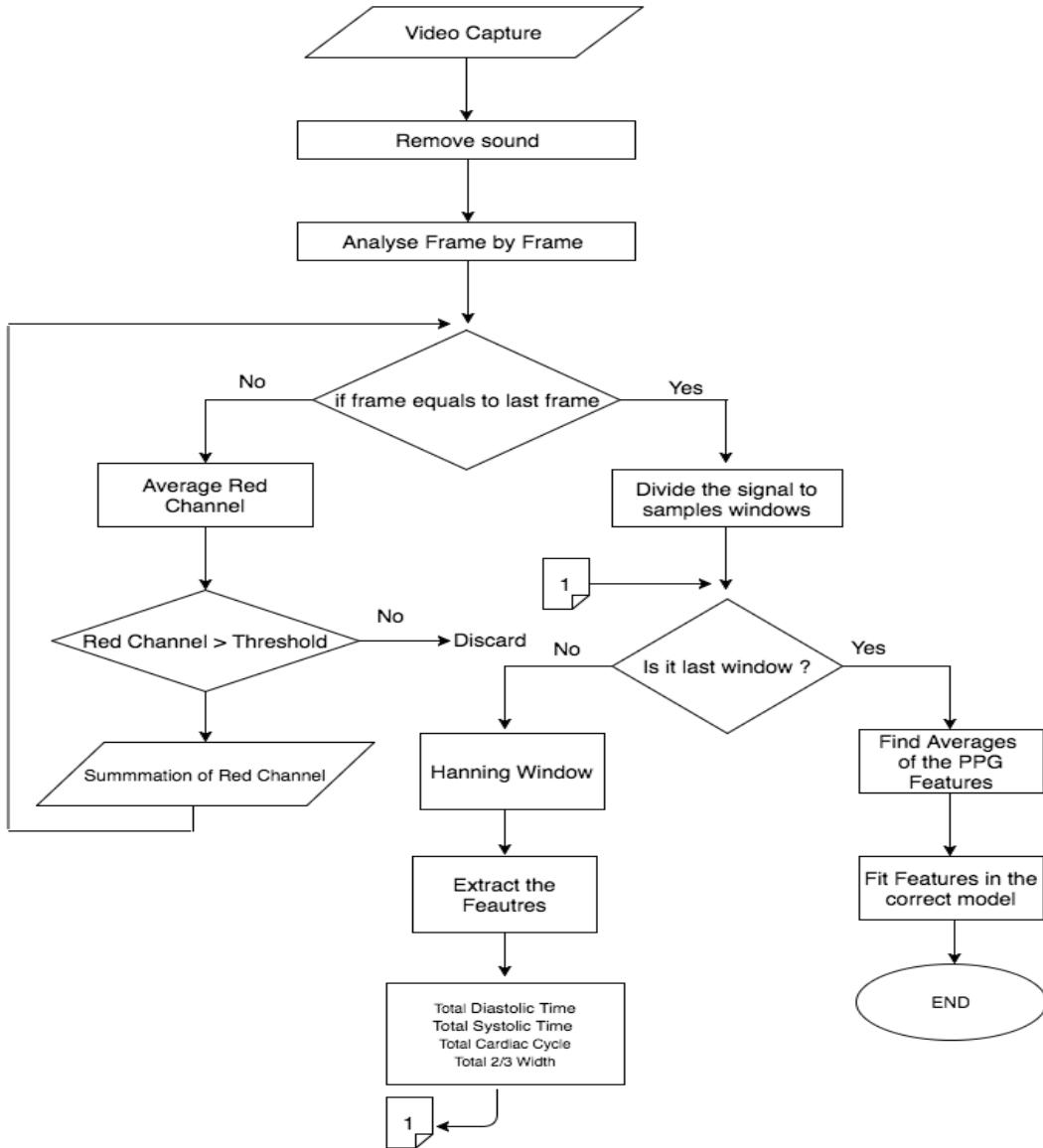


Figure 6.5: Alogrithm Flow Chart

6.6 Training Period

Building the linear regression model as it is stated in section 6.3 the training data were used. For this purpose a CSV file was created. In this file the Ground Truth values of Blood Pressure, systolic, diastolic, cardiac cycle time and the 1/3 pulse amplitude were included.

During the training period the regresses coefficients were obtained for each feature. The correlation between features, Diastolic and Systolic BP were calculated, together with some descriptive statistics. The results are presented below.

6.6.1 Systolic Blood Pressure

Table 6.1: Systolic Blood Pressure Correlation Results

Features	R	P-Values	Upper Bound Coefficient	Lower Bound Coefficient
Systolic Time	-0.7796	0.5826	-0.4420	0.6815
Diastolic Time	0.1768	0.0028	-0.9351	-0.3722
Cardiac Cycle	0.7950	0.0020	-0.9400	-0.4067
Width 1/3	-0.8711	0.0002	-0.9634	-0.5943

- The correlation coefficient is an indicator of how strong is the relationship between two variables. The value range of correlation coefficient is between -1 and 1. The -1 value represent a negative correlation, 0 represents that there is no relation and 1 that the there is a direct positive relationship. The higher the value of the correlation coefficient the better the model.
- P-values is between [0-1]. When p is close to 0 corresponds to large correlation in R and a low probability of observing a null hypothesis. The lower the P-value the better.
- Upper Bound Coefficient is the 95% confidence interval upper bound for the corresponding coefficient in R.
- Lower bound Coefficient is the 95% confidence interval lower bound for the corresponding coefficient in R

The width 1/3 and cardiac cycle had the highest correlation with the Systolic Blood Pressure. This can be supported by the small P-Values. The Diastolic time has the smallest correlation value and the greatest P-value.

Diastolic Time Regression Model

Firstly, the Diastolic time model was implemented. The results of the coefficient are shown in the table below:

Table 6.2: Diastolic Time Results

Coefficients	R^2
$\beta_0 = 117.0293$,	0.0313
$\beta_1 = 11.5147$	

Linear Regression Model For Systolic Blood Pressure using Diastolic Time:

$$\text{Systolic Pressure} = 117.0292 + 11.5147 \times \text{Diastolic Time} \quad (6.4)$$

The training data were used as input to the linear model and the SBP outputs are available in Fig. 6.6

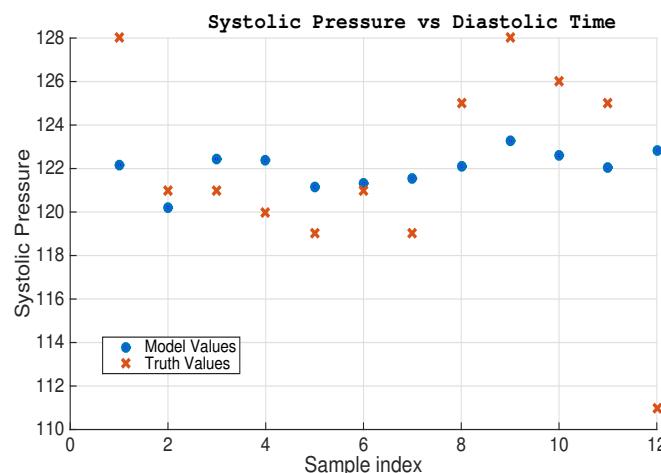


Figure 6.6: Systolic Pressure Estimation using Diastolic Time

The diastolic model provides accurate results when the diastolic pressure is between 119-123 mmHg. The range that the values varies is between $\pm 4\text{mmHg}$. For SBP measurements above 125mmHg or below 118 mmHg the estimated values are not very accurate. The mean and standard deviation is 122 ± 0.8462 .

Systolic Time

Similarly to the Diastolic time, Systolic time Model was implemented. The results of the coefficients and R^2 are shown in the table below:

Table 6.3: Systolic Time Results

Coefficients	R^2
$\beta_0 = 131.3428$,	0.6077
$\beta_1 = -27.1239$	

Linear Regression Model For Systolic Blood Pressure using Diastolic Time:

$$\text{Systolic Pressure} = 131.3428 - 27.1239 \times \text{Systolic Time} \quad (6.5)$$

The training data were used as input to the linear model and the systolic blood pressure output are available in Fig. 6.7.

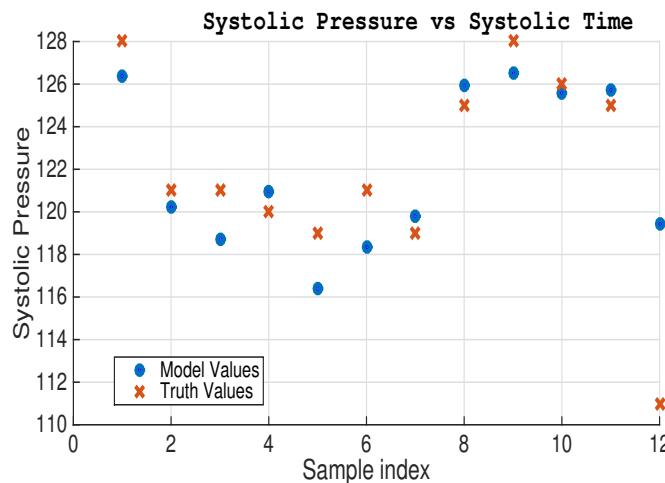


Figure 6.7: Systolic Pressure Estimation using Systolic Time

Overall systolic time appeared to be a good estimator for the Systolic Blood Pressure. All the predicted values are very close to the truth values and are in the range ± 2 . Apart from the value 111 mmHg the difference is much higher than expected. Furthermore, Systolic Time model has high R^2 value. The mean and standard deviation is 122 ± 0.37313 .

Cardiac Cycle Time

Cardiac Cycle time model was implemented. The results of the coefficients and R^2 are shown in the table below:

Table 6.4: Systolic Time Results

Coefficients	R^2
$\beta_0 = 147.8605$,	0.6321
$\beta_1 = -33.5176$	

Linear Regression Model For Systolic Blood Pressure using Cardiac Cycle Time:

$$\text{Systolic Pressure} = -33.5176 \times \text{Cardiac Cycle Time} + 147.8605 \quad (6.6)$$

The training data were used as input to the linear model and the systolic blood pressure output are available in Fig. 6.8

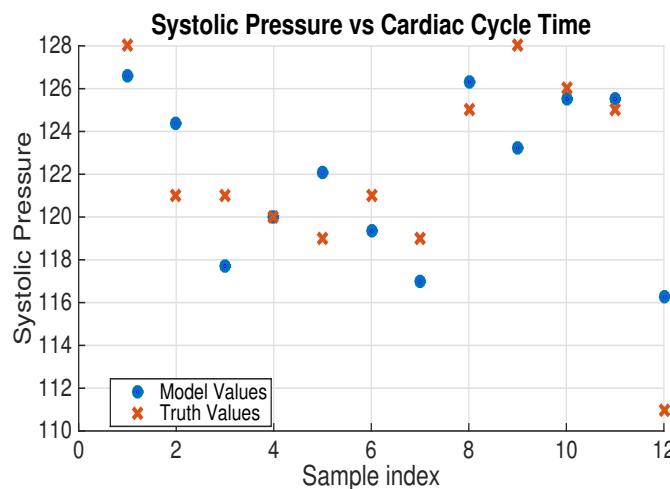


Figure 6.8: Systolic Pressure Estimation using Cardiac Cycle Time

The average difference between the truth and the model values is ± 2.2596 . This model is slightly better than the Systolic Time model. This can be supported by the fact that $R^2 = 0.6321$, which is greater than the value of Systolic Time model. The mean and standard deviation of experimental results is: 122 ± 3.8053

Width 1/3 Interval

The 1/3 Pulse width amplitude model was implemented. The results of the coefficients and R^2 are shown in the table below:

Table 6.5: Width Results

Coefficients	R^2
$\beta_0 = 136.1336$,	0.7588
$\beta_1 = -51.7367$	

Linear Regression Model For Systolic Blood Pressure using Cardiac Cycle Time:

$$\text{Systolic Pressure} = 136.1336 - 51.7367 \times W1 \quad (6.7)$$

The training data were used as input to the linear model and the systolic blood pressure output are available in Fig. 6.9

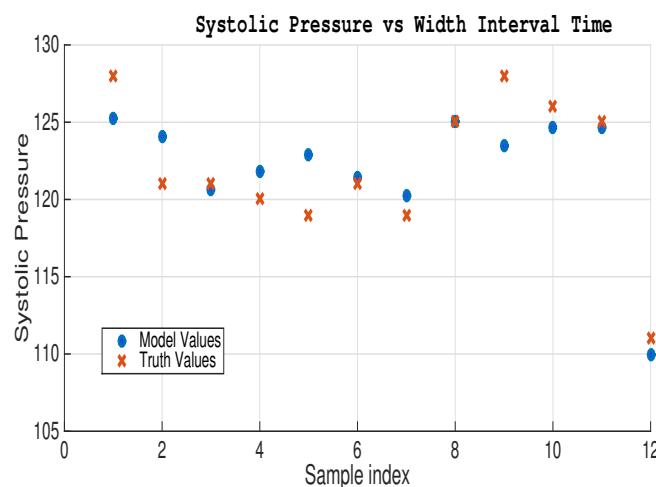


Figure 6.9: Systolic Pressure Estimation using w1

The mean difference between the truth and the model's values is ± 1.7501 . The mean and standard deviation of the truth and the experimental values respectively are: 122 ± 4.1694 , $122 \pm 122 \pm 4.1694$. This model has generated the most accurate results and it has $R^2 = 0.7588$.

6.6.2 Diastolic Blood Pressure

In the same way as the model trained for Systolic Blood Pressure, Diastolic Blood Pressure models were trained. Correlation between Diastolic Pressure and the Features of PPG was computed and the results are shown in the following Table.

Table 6.6: Diastolic Blood Pressure Correlation Results

Features	R	P-Values	Upper Bound Coefficient	Lower Bound Coefficient
Systolic Time	-0.5339	0.0738	-0.4435	0.0576
Diastolic Time	0.1750	0.5865	-0.4435	0.6805
Cardiac Cycle	-0.5162	0.0857	-0.8410	0.0819
Width 1/3	-0.6722	0.0166	-0.8992	-0.1600

Table 6.6 shows the correlation results for Diastolic Blood Pressure. W1 and Systolic Time extracted from the waveform have the highest correlation values.

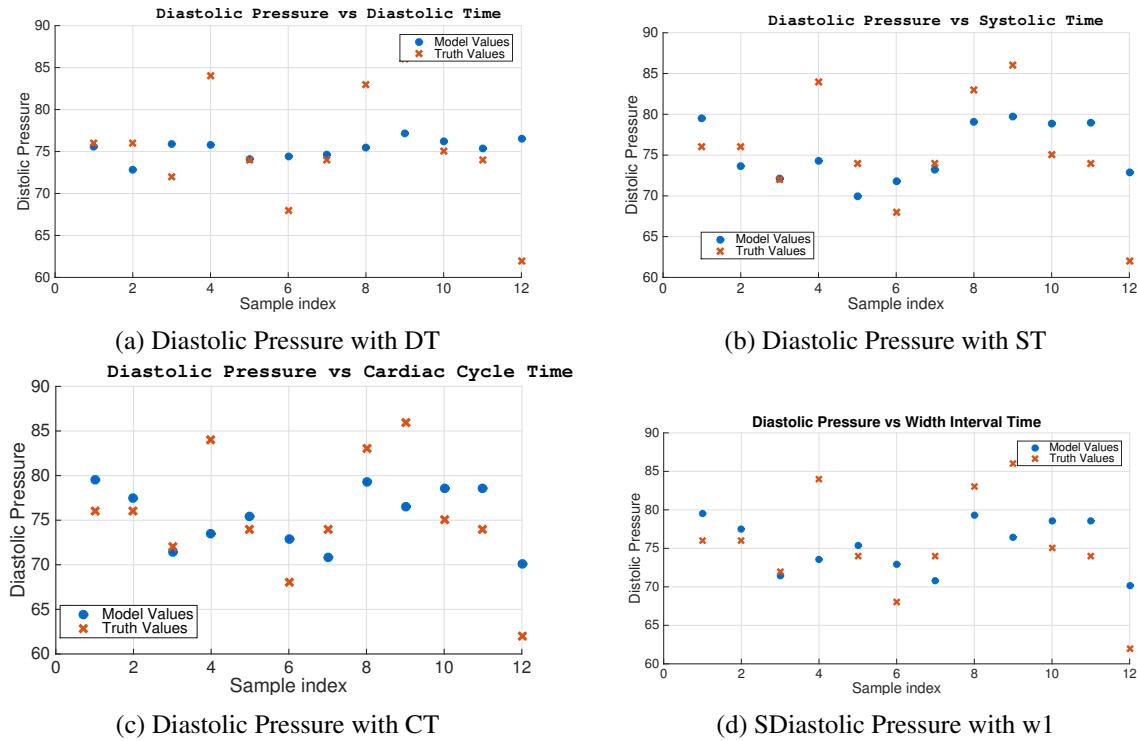


Figure 6.10: PPG [20]

Table 6.7: Diastolic Results

Features	Coefficient	R^2
Diastolic Time	$\beta_0 = 68.4269,$ $\beta_1 = 15.9989$	0.0306
Systolic Time	$\beta_0 = 84.3168,$ $\beta_1 = -26.0806$	0.28509
Cardiac Cycle	$\beta_0 = 98.9077,$ $\beta_1 = -30.5546$	0.26651
Width 1	$\beta_0 = 90.6446,$ $\beta_1 = -56.0475$	0.45184

The estimated results using diastolic time are better than the results using systolic upstroke time. Generally, the DBP estimation is more accurate than the SBP estimation. The mean difference is ± 3.8 and is greater compare to the SBP case.

6.6.3 Testing Period

Testing data were gathered in similar way to the training data. For testing, 10 subjects participated. The data were applied in the models that were built and described in the above section. Systolic and Diastolic Blood Pressures were calculated. Systolic and Diastolic Pressure results are presented together with Bland-Atman plots.

Table 6.8: Systolic Pressure

Features	Correlation	SEE	P-Value	SD
Diastolic Time	-0.8313	1.4473	0.7427	3.0692
Systolic Time	0.0864	5.7412	0.3155	3.9319
Cardiac Cycle	0.7383	10.5163	0.0689	3.8439
Width 1	0.7383	3.5608	0.4483	3.2480

Table 6.9: Diastolic Pressure

Features	Correlation	SEE	P-Value	SD
Diastolic Time	-0.5762	1.5563	0.7233	3.0599
Systolic Time	-0.0774	2.6297	0.6318	3.8148
Cardiac Cycle	0.5484	6.7749	0.2068	3.6582
Width 1	0.5484	0.7743	0.8670	3.2236

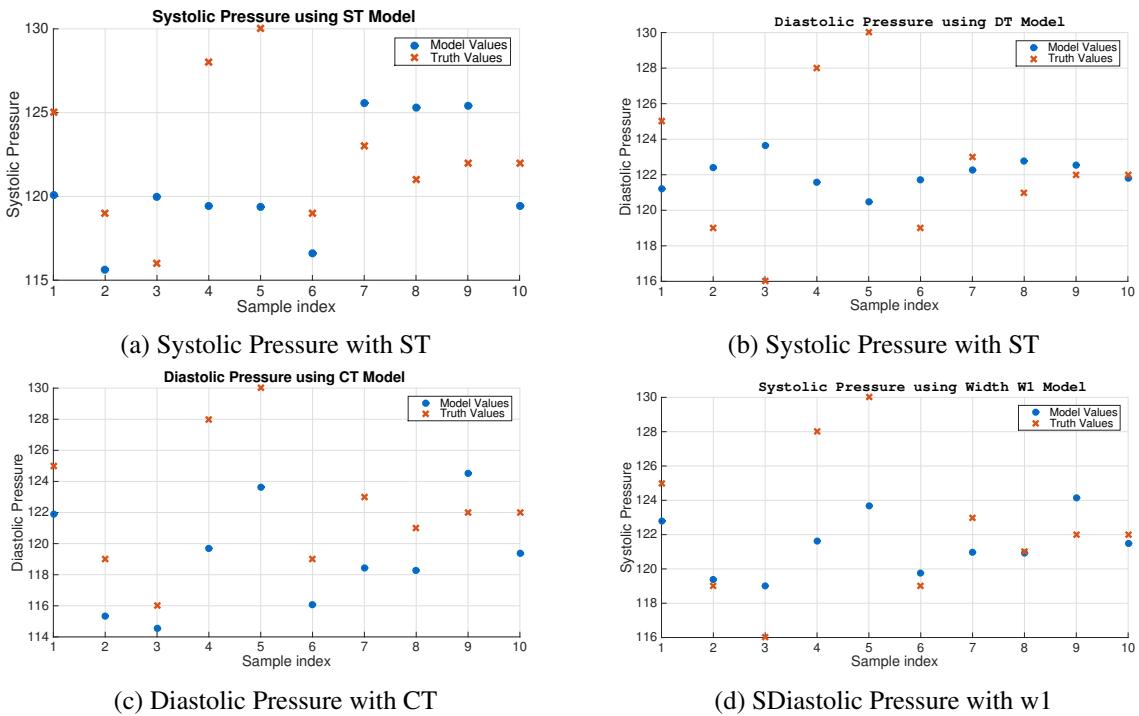


Figure 6.11: Systolic Pressure Estimation

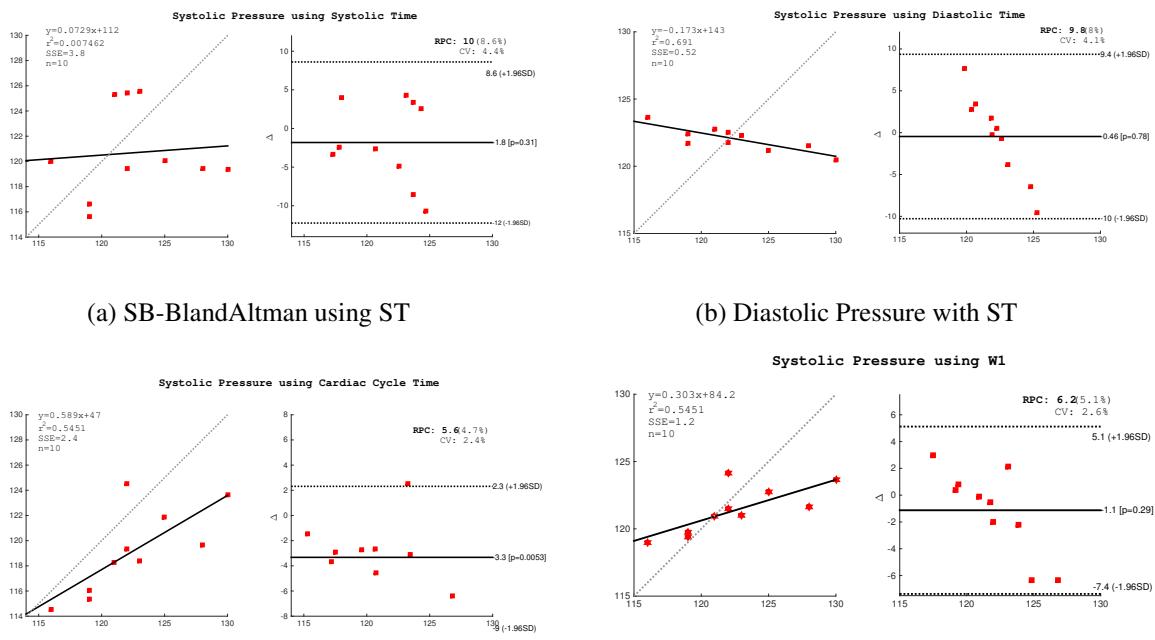


Figure 6.12: Systolic Pressure BlandAltman plots

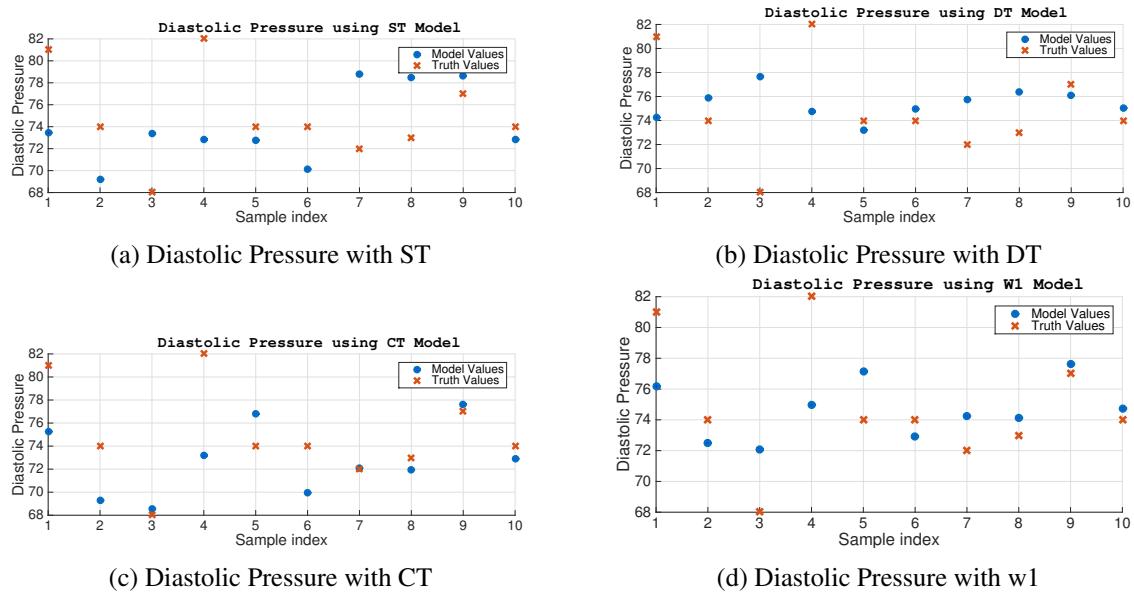


Figure 6.13: Diastolic Pressure Estimation

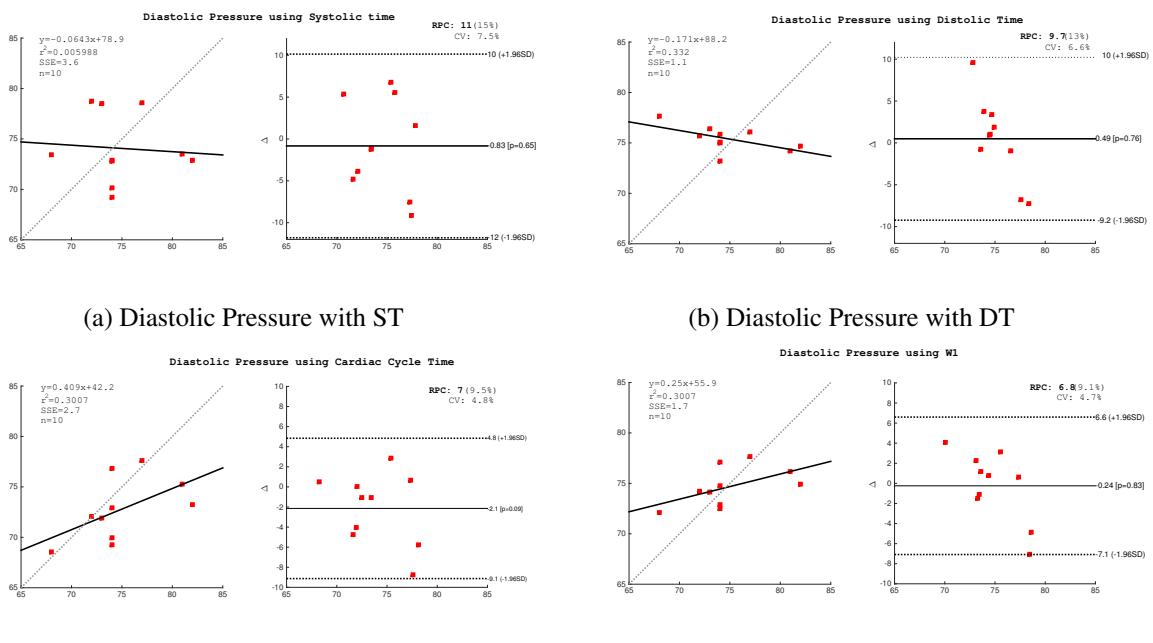


Figure 6.14: Diastolic Pressure Estimation

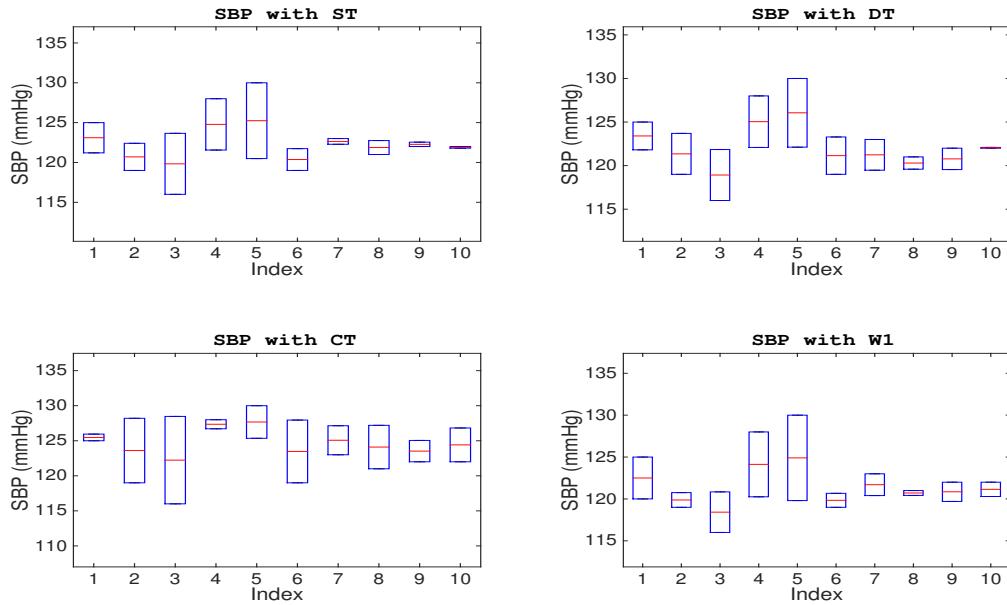


Figure 6.15: Systolic Pressure Estimations Box Plot

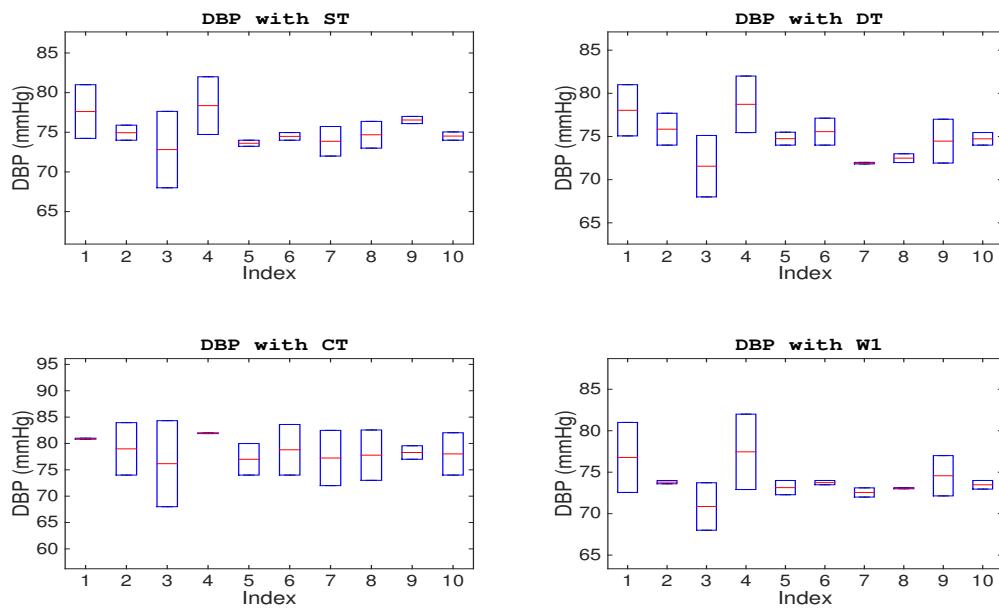


Figure 6.16: Diastolic Pressure Estimation Box Plot

The box plots presented in Figure 6.15 and 6.16 used to show the the largest and the lowest value of the data that are compared. The edges at the box represents these two values. The red line in the middle of each box represents the mean between the two measurements.

6.7 Evaluation

Figures 6.11 and 6.13 show the estimated values for diastolic and systolic blood pressure that were calculated using the linear regression models . For Systolic Pressure the maximum difference and the mean difference between theoretical and experimental data are:

- (a) Model A: Maximum Difference is -10.6432 Mean Difference: 4.6788 (b) Model B: Maximum Difference is -9.514 Mean Difference: 3.6767 (c) Model C: Maximum Difference is 8.333 Mean Difference: 3.83 (d) Model D: Maximum Difference is 6.3613 Mean Difference: 2.3857

Despite the fact that during the training period Diastolic Time had the lowest correlation value compared to the other features, it has acquired the highest value during the testing period. Furthermore, W1 and Pulse Time has scored again high correlation measurements as table 6.8 shows. Furthermore, diastolic time scored the lowest standard estimation error(SEE) equals to 1.4473. The Pearson r-value squared, otherwise the coefficient of determination that is available in the Bland-Atman plots, shows that the diastolic time is greater than the other features but very close with Width 1 and Cardiac Cycle Time. The larger R^2 value is indicating better fit and 1 represents a perfect fit. Finally, the sum of squared error(SSE) for DT feature is the smallest together with the W1.

In addition, the standard deviation of all the subjects was lower than 10% of the actual pressure. Therefore the small variation will not affect the Blood pressure classification of the participants. For example, if someone has blood pressure 128mmHg having in mind the smallest mean difference which is 2.3857 therefore the error is significantly small and the subjects' hypertension status could no be misclassified for the Systolic blood pressure. To conclude, the 1/3 width of the PPG signal is the feature that produced the best results for the Systolic Pressure estimation.

Similarly to the Systolic Pressure, the Diastolic Pressure results were examined. For Diastolic Pressure the maximum differences between theoretical and experimental data are:

- (a) Model A: Maximum Difference is -9.1352 Mean Difference: 4.6975 (b) Model B: Maximum Difference is 9.6358 Mean Difference: 3.6361 (c) Model C: Maximum Difference is -8.7734

Mean Difference: 2.9582 (d) Model D: Maximum Difference is -7.0581 Mean Difference: 2.6435

Diastolic Time had the highest correlation coefficient compare to the other characteristics of the PPG signal. However it has greater average data variation from Cardiac Cycle time and the 1/3 Pulse width amplitude. The amplitude scored the lowest SEE value 0.7743.

The standard deviation of subjects was again small compare to the original values acquired from the Withings blood pressure monitor. Moreover, it was observed that the biggest mean difference was occurred when the SB of the participant was above 80 mmHg. However, overall the outcome of the experiments suggests that W1 could be used as a good indicator of the Diastolic Blood pressure.

The best linear fit of Bland-Altman plots for Systolic and Diastolic Pressure is presented in Figures 6.12 and 6.14. The smaller the slope of the graphs the better fit and thus the estimated and actual results are closer to each other.

6.8 Polynomial Regression

Polynomial regression with polynomial and non-polynomial coefficients were implemented in an attempt to improve the accuracy of the Blood Pressure estimator. The polynomial regression is the modelling of the the relationship between independent variable x and dependent variable y as an nth degree polynomial. It is often used for modeling non - linear relationships. In case the polynomial model fail to produce good results linear relationship with non-polynomial terms is used.

Second degree polynomial models for the features of PPG that are used in this project are deployed. The equation [56] of a such a model is the following:

$$y = a_2t^2 + a_1t + a_0 \quad (6.8)$$

- y is the output

- $a_i, i = 0, 1, 2$ are defined as the polynomial coefficients

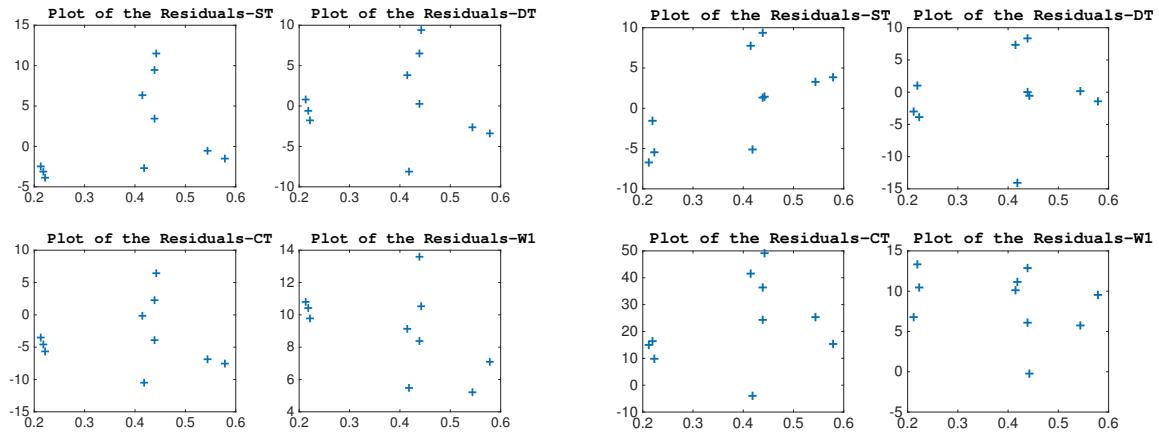
The results of the polynomial coefficients for all the characteristics are summarised in the table 6.17. To evaluate polynomial regression the residuals for each model are found and the plots are shown in the Fig.6.18. The residual is defined as the difference between the actual and the experimental value.

	a0	a1	a2		a0	a1	a2
DT	143.18	-109.18	120.82	DT	86.745	-42.913	24.782
ST	120.21	-4.5242	19.565	ST	101.08	-148.62	200.81
CT	109.3	66.765	-63.924	CT	-77.278	427.59	-292.04
W1	149.67	-136.22	118.47	W1	85.473	-23.764	-45.271

(a) Polynomial Coef. SBP

(b) Polynomial Coef. DBP

Figure 6.17: Polynomial Coefficients



(a) Residuals of SBP

(b) Residuals of DBP

Figure 6.18: Residuals Plot

The residuals plots suggest that there are big differences between the actual values of BP and the estimated ones. Therefore polynomial models are worst than the simple linear regression method.

When the results of polynomial models are not satisfactory, linear model with non-polynomial

terms is used. The formula of this model is defined as [56]:

$$y = s_0 + s_1 e^{-t} + s_2 \times t \times e^{-t} \quad (6.9)$$

	s0	s1	s2		s0	s1	s2
DT	-329.51	-182.29	329.34	DT	-24.885	19.859	66.957
ST	-47.882	43.009	104.88	ST	-43.108	31.345	64.721
CT	-29.962	54.979	101.09	CT	-30.509	46.768	58.322
W1	-19.259	62.954	78.95	W1	-14.783	70.714	25.202

(a) Coef. of SBP

(b) Coef. of DBP

Figure 6.19: Coefficients

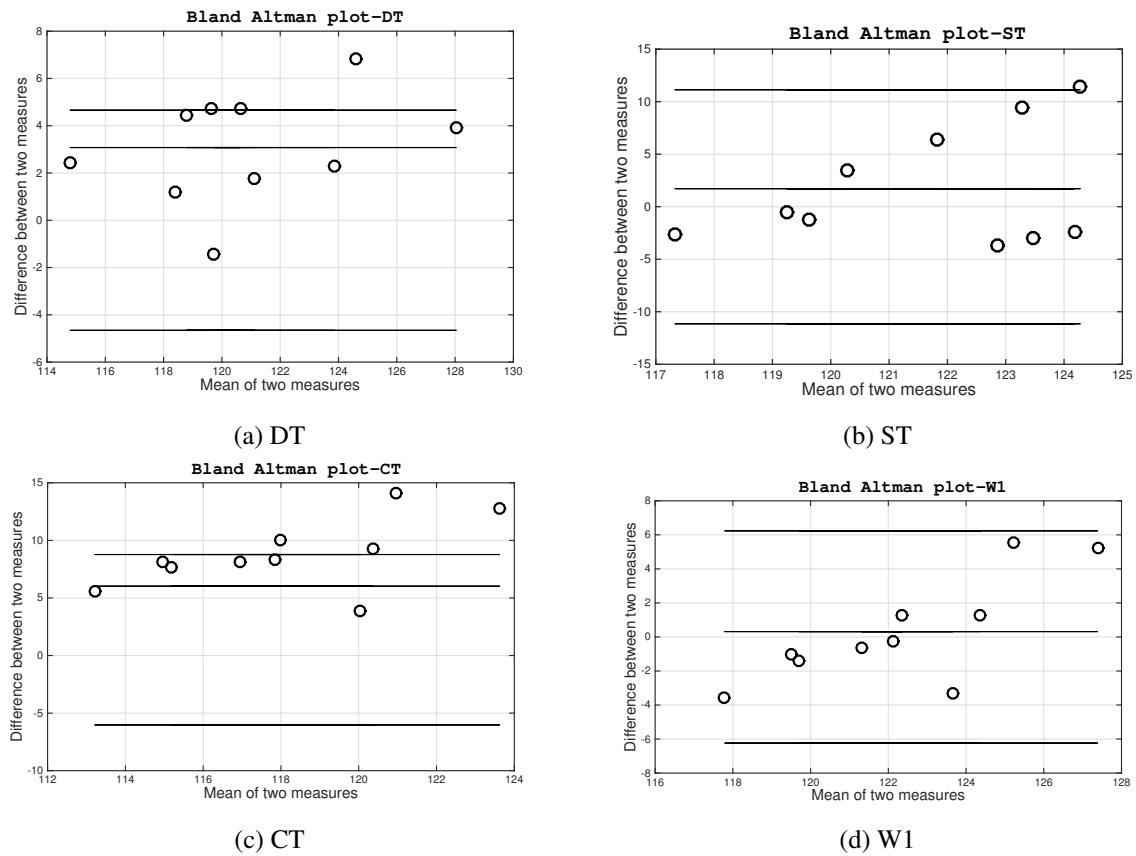


Figure 6.20: Bland Altman plots for linear models with non-polynomial terms, SBP

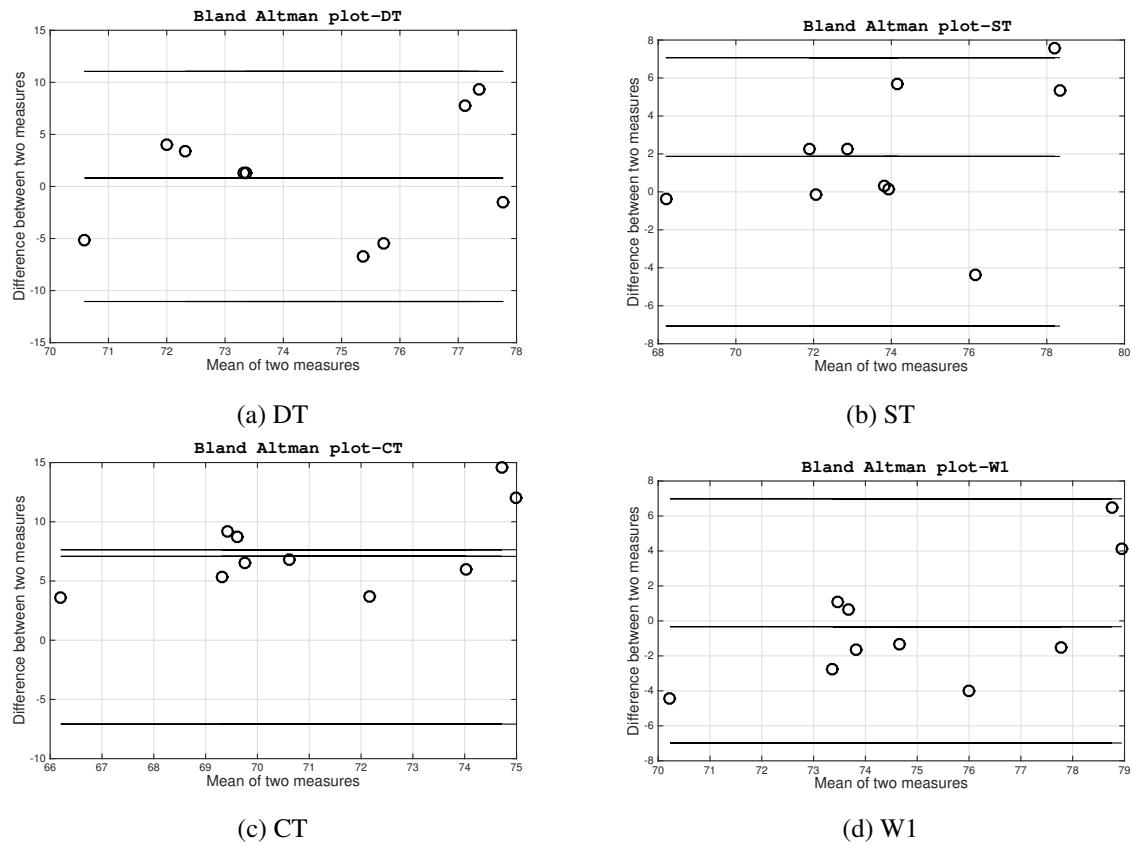


Figure 6.21: Bland Altman plots for linear models with non-polynomial terms, DBP

The Bland Altman plots in Fig 6.20 and 6.21 suggests that linear regression with non-polynomial terms had better outcome for Diastolic and Systolic Blood Pressure compare with the polynomial coefficients. The best model is when 1/3 Pulse Width is used in both cases. The equations of the two models are the following:

$$SBP = -19.259 + 62.954e^{-w1} + 78.95 \times w1 \times e^{-w1} \quad (6.10)$$

$$DBP = -14.783 + 70.714e^{-w1} + 25.202 \times w1 \times e^{-w1} \quad (6.11)$$

The results obtained are compared with the simple linear regression in order to find which is the best technique. In both methods the feature with the best results is the 1/3 Pulse Width for both SBP and DBP. The comparison is sum up in the following table.

Table 6.10: Comparison for Systolic Pressure results

Model	R^2	SEE	SSE	SD	Mean Difference	Correlation	P-Value
SLR	0.7588	3.5608	1.2	1.7445	2.386	0.7383	0.0148
LR-NP	0.7213	0.9957	1.4	1.9550	2.348	0.7314	0.0162

Table 6.11: Comparison for Diastolic Pressure results

Model	R^2	SEE	SSE	SD	Mean Difference	Correlation	P-Value
SLR	0.4518	0.7743	1.7	1.8899	2.644	0.5484	0.1007
LR-NP	0.4309	1.0469	1.8	2.0706	2.803	0.5420	0.1055

The statistical analysis showed that both methods have similar results for the Systolic Pressure. For Diastolic Pressure simple linear regression had slightly better performance compare to linear regression with non polynomial coefficients.

6.9 Limitations

During this project the vulnerabilities of the PPG signal were exposed. PPG was discovered to be very vulnerable to motion artifacts. This has affected a lot the quality of our samples, since the slightest movement could affect the whole waveform. Furthermore the lighting of the room, has influenced the results of video plethysmogram. An example of a problematic signal can be found in Fig.6.22.

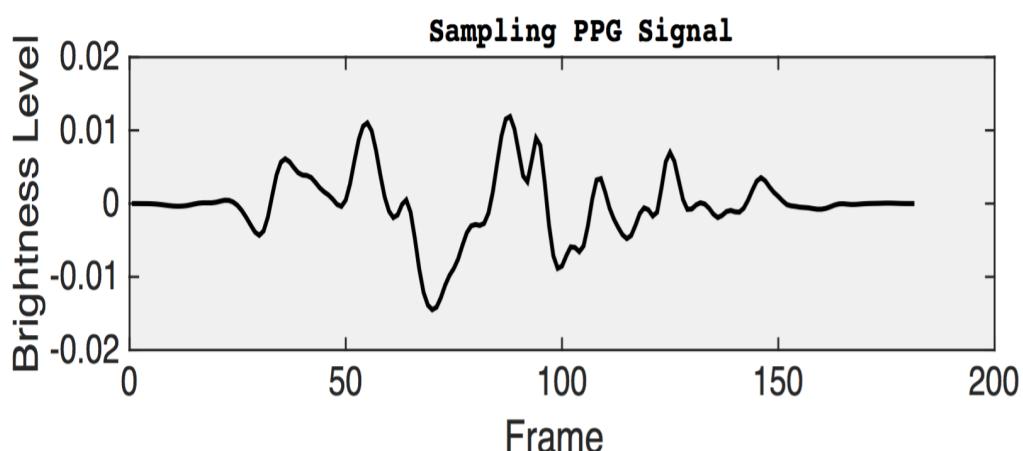


Figure 6.22: Bad Signal

To overcome this problem, as the study [20] proposed the features of the PPG could be found easier identified using the first derivative of the signal. However, even using the first derivative of PPG this issue couldn't be solved. An example of such a signal is available in the Fig 6.22.

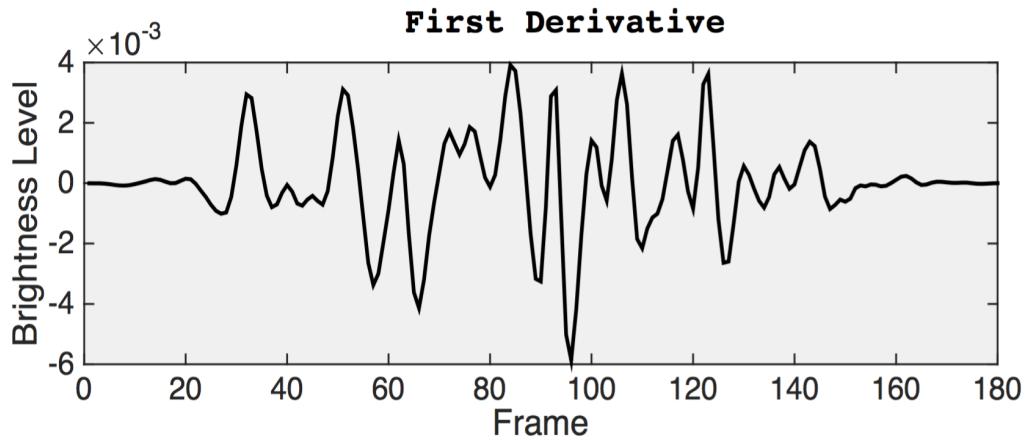


Figure 6.23: Bad Signal

These limitations restricted the number of sample that could be used in the training and testing phase. In total 45 subjects took part in the experiments. Only 21 signals were characterised as good in order to be used for this Project which is approximately 47%.

Chapter 7

Real Time Implementation

7.1 System Design

7.1.1 Choosing the Development Platform

When developing a mobile application, the very first decision that must be taken is the development platform. There are numerous platforms nowadays but the two frameworks that dominate the market are Apple's iOS and Google's Android. Other technologies companies such as Microsoft, Blackberry are also distributing apps however they hold much smaller market share. [61].

There are a lot of factors should be taken into consideration before choosing the development platform such as working environment, configuration, user experience design, programming language, data sharing. The comparison was made between the two market dominant platforms, iOS and Google's Android. The table in Figure 7.1 summarises the comparison between the two frameworks. The cells that are highlighted with green indicate an advantage. The outcome of the comparison showed a clear winner which in this case is the Apple's iOS. The result of the comparison proved that despite the advantages that Android has overall, it remains significantly easier to write good iOS apps than good Android apps.

Table 7.1: Comparison between iOS and Android

Categories	iOS	Android
UI Design	Xcode: Fast, powerful, fast and responsive simulator Objective C and Swift:	Android Studio: background compilation and will quickly highlight errors
Language	Better and Cleaner. Does not require to wrap up the code with try exceptions	Java: Better stack traces, for one thing, which means tracking down bugs is easier
Internet	iOs provides facilities but they are all pretty low and unsatisfying	AsyncTask class easy to determine when you are online
Sharing		Same difficulty to share things from the app

7.1.2 Design and Develop the System

Designing and developing a mobile application is a sequential procedure. The software development life cycle is divided into 5 major parts:



Figure 7.1: Development Cycle

Mobile Life Cycle Overview

The inception stage is all about clarifying the purpose of the application. The UI Design phase is where colors and graphics, are introduced and finalised. Following the UI design, the development stage is taking place. In fact, once an idea has some progress, a working prototype is going to be developed to provide an understanding of the scope of the work. Two elements are required for this phase: 1) a complete set of design specification and 2) proper processes, standards and tools. Stabilisation succeeds the development stage with ultimate goal to improve the quality of the solution in order to meet the criteria for the product release. Finally, when the application is ready deployment occurs.

Application Characteristics

Before the design phase starts, the characteristics of the application must be specified. As a major contributor to cardiovascular disease, effective management of HTN is critical. Therefore, understanding what features a Hypertension Management app must have, is very substantial.

Poor adherence to therapeutic treatment is regularly referred as a major issue in the management of a chronic medical condition. McGillicuddy et al. [67] showed in their investigation an improvement in the obedience to medical therapy by hypertensive patients. The positive results were obtained using reminders/notifications method. Additional support to these results was given by Verloet et al [68]. They used SMS-based reminder to support the therapy of patients. The majority of their outcomes suggest this technique has positive effects on short-term medication adherence.

The ability to share data with physicians is pretty intuitive. In a study by Earle et al. [72] the Systolic Blood Pressure was reduced by 2.9 mmHg utilising mobile Health intervention.

Another important aspect of Blood Pressure assessment at home is the use of proper way to measure it. It is essential for the applications to offer that functionality. Further research showed in [65] that consumers have a strong tendency to download apps that advertise to monitor BP, HR or weight. For the purpose of this project it was decided for this stage to focus in the tracking of Blood Pressure and HR in real time through the video camera.

Design the User Interface

After understanding the requirements of the application, the design phase begins. Don Norman said “User experience encompasses all aspects of the end-user’s interaction with the company, its services, and its products”. True user experience goes far beyond to just give people what they want or providing some features. High quality user experience is a combination of multiple disciplines, including engineering marketing, graphical and industrial design, as well as interface design [63].

Number one priority is to create an enjoyable environment for the users. Positive experiences will help to build loyalty between clients and products. Creating a successful user-centered environment requires the knowledge of the human-computer interaction principles: useful, usable, findable, credible, accessible, desirable.

Planning the User Interface of the application needs to combine the application requirements and the UI standards. The interface of the application is presented Figure 7.2.

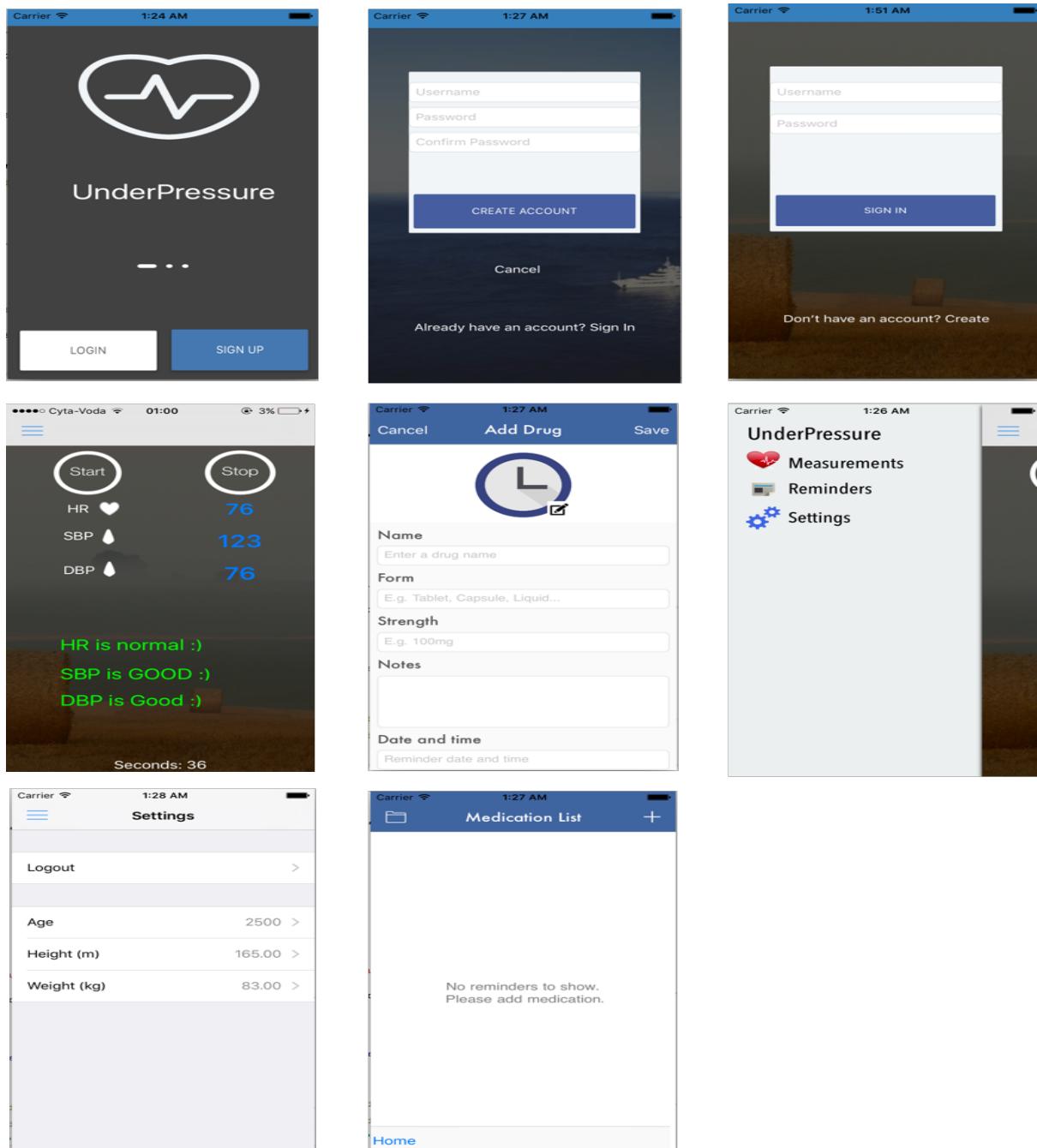


Figure 7.2: Interface

UI Overview

UnderPressure has been designed to integrate multiple functions and provide a system to offer more value to the user than any other Hypertension management app. Each client is required to register before the access to utilise the application is granted to him. Sign In and Sign Up pages are responsible to offer this functionality.

After the enrolment, the user is directed to the Home Page. The standard functionalities of the application are the measurement of BP, HR and the addition of medical subscription with a reminder to receive medication. The reminder is send in the form of a notification(see figure 7.3). For accessibility purposes every page can make utilisation of a navigation menu through the symbol in the upper left corner. The menu will permit the client to direct to pages.

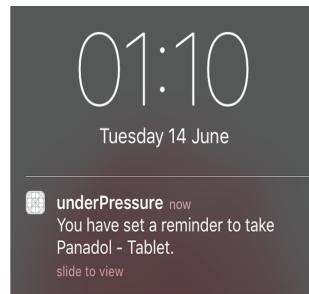


Figure 7.3: Medicine Notification

Application Back-End

In software engineering, a platform consists of the presentation layer (Front-End) and the data access layer (Back-End). Designing and implementing the UI is part of the front-end process. The Back-End of an application is responsible to offer services to the front-end. For this project Firebase has been chosen to support the User Interface together with the device memory.

Firebase is a cloud service provider which can offer data storage, user authentication and many other functionalities to the application. Each client can synchronise its information progressively with the database however in the meantime Firebase can stay responsive regardless the network connectivity . Another key feature is the security that it offers to the clients. These are the main reasons Firebase was chosen to support the Back-End of UnderPressure. The users' are

registered to Firebase using the app and have access to the application through that cloud service provider [70].

7.1.3 Architecture Overview

A complete overview of the components that are integrated into the UnderPressure system is shown in Figure 7.4. The iOS app provides the graphical interface to our platform and is also responsible for any processing. The users in order to gain access to the application's functionalities will have to register in the online database. Registration and user authentication is achieved through Firebase. The user is registered with his email and a password that he desires.

One of the most significant aspects that must be taken into consideration when designing and developing a healthcare system is data privacy. Data concerning an individual's health can be a very sensitive subject. Threats to sensitive data have reached a critical point over the last few years, with an escalation in sophistication and frequency of cyberattacks. It is imperative that healthcare organisations implement security solutions that will not only protect important data assets, but also satisfy the compliance mandates for which they are held accountable [71]. For this reason information about the pills or any medicines that the user's need to take are stored locally in device's memory. Furthermore in the future where Heart Rate and Blood Pressure values will also going to be stored in the phone's memory in order to avoid the danger of exposing sensitive data.

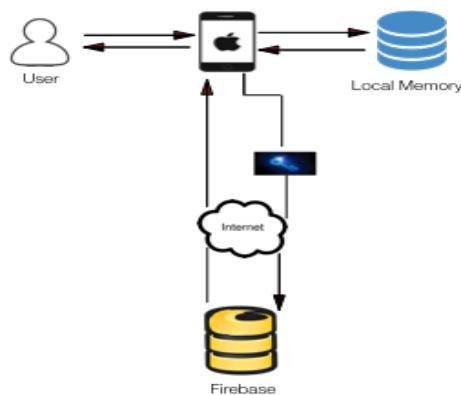


Figure 7.4: Architecture diagram of the Application

7.2 Method and Evaluation

For estimating Blood Pressure in Real time the W1 feature's simple linear regression models which are found in the previous chapter are used.

$$SBP = -51.7367 * W1 + 136.1336$$

$$DBP = 90.6446 - 56.0475 * W1$$

Heart-Rate is estimated using the Peak-Peak interval in the Frequency domain. The application displays the average value of HR and BP from a period of 20s. The first 15s are used for calibration and camera adjustments and the next 20s for taking pulse amplitude values in order to find the average.

The protocol of the experiments performed were similar to the offline procedures and the results are shown in the following graphs. In the experiments for the evaluation of the applications 10 subjects participated.

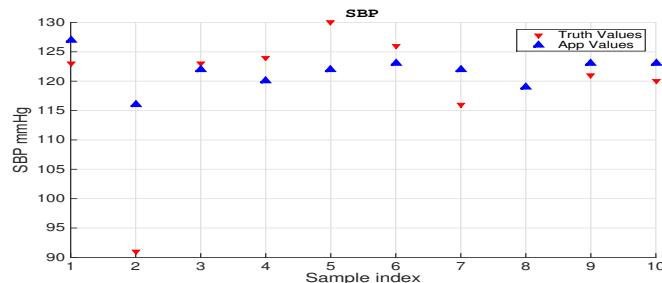


Figure 7.5: SBP results

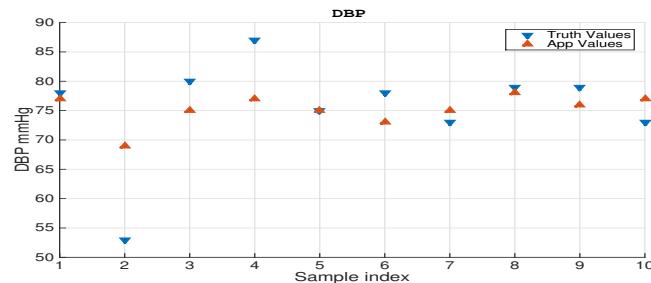


Figure 7.6: DBP results

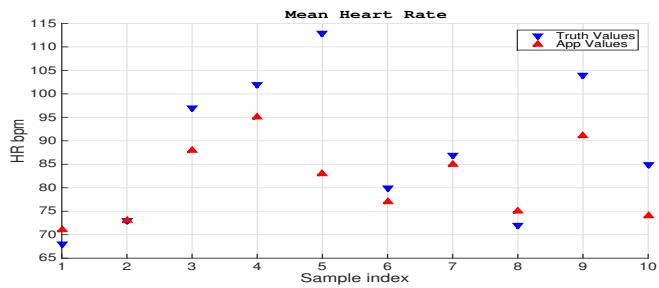


Figure 7.7: HR results

Table 7.2: Real Time Results

Statistics	SBP	DBP	HR
Correlation	0.5974	0.7994	0.8096
P-Value	0.0682	0.0055	0.0045
Mean Difference	6.300	4.700	8.1
SEE	5.3759	0.9487	21.8197

7.3 Discussion

The samples were taken mostly from healthy people where their blood pressure was lying in the normal range measurements. It can be observed that for healthy people the estimated values from the application and the actual values were closed to each other. However, in the case of sample 2 where the person appeared to be hypotensive the estimated and the actual results for SBP and DBP have large difference. As a consequence, the application misclassified the hypotensive person as healthy.

Overall, the correlation coefficients were high as the table 7.2 shows, especially for Diastolic Pressure and Heart Rate. The relation between the actual and the experimental values is supported by the low values of p. Despite the high correlation coefficient that was achieved for Heart Rate, HR produced the biggest Mean difference 8.1 and it had the highest SEE which is equal 21.8197 which could be characterised as high value.

To conclude, estimating values from people with normal Blood Pressure the result produced could be classified as accurate. On the other hand hypertensive or hypotensive people could be misclassified by the application. The reason that this may happened is that during training

period of where the models fro DBP an SBP were created, the data were mostly acquired from healthy people. Therefore, a bigger range of training data with people of different condition could improve the accuracy of this implementation.

It was observed during this project that PPG signal is different for people. Another way to improve the accuracy of the application is to create user adapted application. A user adapted application will be able to build the model specifically for the user. A two weeks period of training will happen where the user will enter its Truth BP measurements and the application will record the W1 in the background. After the two weeks a model for the specific user will be created. In this way a since the model will be built according to the user characteristics will have more accurate results.

7.4 Future Implementations of the Application

UnderPressure has a target to become a great Hypertension management app in the future which will provide huge assistance to Hypertensive people. Currently, the main purpose of the app is to examine how accurate blood Pressure and HR could be measured. However, expansion to the capabilities of the application should be done in order to become a helping tool.

The following pages must be developed: (1) Health Plan, (2) Sharing Data, (3) Review History, (4) Tracking Steps , (5) Notifications/Reminding (6), Instant Feedback.

- **Health Plan:** It includes daily tasks that patients should complete such as: Walking minimum 30 minutes per day (this could be monitored from GPS data). Also taking his medication and improve blood pressure diet. Moreover for alcoholics or smokers the challenge of avoiding cigarette or alcohol will be raised in order to stop their bad habits which affect their problem.
- **Sharing Data with the physicians:** Users will have the option to send their weekly data to their physicians automatically by the end of each week or month or send them manually. Medical advice by specialist is always useful.

- Review History: Past measurements of BP and HR will be available in this section. Graphs that will show the stored data over a period of time.
- Tracking Steps: Measuring the Steps and setting challenges to Hypertensive people is very important, since physicians advice them to walk at least 30 mins per day.
- Notifications/Reminder: From the research in the background theory section, reminding the user about his responsibilities is critical for good management of the blood pressure.
- Instant Feedback: Immediately after blood pressure or heart rate is calculated, feedback will be provided.

Chapter 8

Conclusion

The outcome of this study supports the use of photoplethysmographic signal to estimate the HR and Blood Pressure. Peaks detection algorithm in the frequency domain was the approach that was followed for the estimation of Mean Heart Rate. The results from the 33 subjects that participated in the experiments showed positive results and high correlation between PPG and Heart Rate. Furthermore the conditions that video should be recorded were analysed. It was found that the waveform could be easily affected by the environmental conditions. Light intensity and movement can result to wrong measurements.

This research suggests four different models to calculate PPG from the video plethysmogram. The most consistent model during training and testing phase proved to be the 1/3 Pulse Amplitude Width for both Diastolic and Systolic Pressure. Systolic Pressure was estimated with higher Accuracy compared to the Diastolic measurements.

The American National Standards of the Association for the Advancement of Medical Instrumentation recommend that the minimum number of subjects that should be used for evaluation of any new method for estimating BP is 85. Furthermore, the mean difference and standard deviation of the non-invasive method must be less than the range of 5 ± 8 mmHg from a reference technique. The validity of the propose procedure should also be verified with people that are having pathological symptoms. Therefore more experiments should be conducted before any final conclusions made.

Finally, the rapid evolution of mobile technologies allows people to be more proactive in the monitoring of their medical conditions. A lot of research has been undertaken in this area which is believed that could change and impact the medical services industry positively. However, the integration of these technologies requires a proof about reliability, validity, and responsiveness for each application over the scope of different diseases. A mobile application has been designed and developed for real-time investigation of PPG. Further improvements could be done to improve the accuracy and also the integration of helpful features could transform the application to a desirable HTN management tool.

Appendix A

Data

Table A.1: Training Data

Training Data						
SBP	DBP	HR	ST	CT	DT	Width 1/3
128	76	97	0.1834	0.6337	0.4447	0.211233333
121	76	78	0.4086	0.7004	0.2735	0.233466667
121	72	71	0.4669	0.9	0.4693	0.3
120	84	78	0.3836	0.8308	0.4634	0.276933333
119	74	67	0.5503	0.7701	0.3574	0.2567
121	68	73	0.4803	0.8505	0.372	0.2835
119	74	67	0.4252	0.9205	0.3902	0.306833333
125	83	93	0.2001	0.642	0.4419	0.214
128	86	81	0.1779	0.7338	0.5447	0.2446
126	75	89	0.2112	0.6671	0.486	0.222366667
125	74	94	0.2068	0.6671	0.4336	0.222366667
111	62	64	0.4391	0.9426	0.5035	0.5062

Table A.2: Real Time data: From Withings and iOS App

SBP	DBP	HR	SBP_APP	DBP_APP	HR_APP
123	78	68	127	77	71
91	53	73	116	69	73
123	80	97	122	75	88
124	87	102	120	77	95
130	75	113	122	75	83
126	78	80	123	73	77
116	73	87	122	75	85
126	79	72	119	78	75
121	79	104	123	76	91
120	73	85	123	77	74

Table A.3: Testing Data

Testing Data					
SBP	DBP	ST	DT	CT	Width 1/3
125	81	0.4151	0.3627	0.7745	0.258166667
119	74	0.5791	0.4669	0.9703	0.323433333
116	70	0.4182	0.5756	0.9938	0.331266667
128	82	0.4391	0.3936	0.8405	0.280166667
130	74	0.4419	0.3002	0.7226	0.240866667
119	74	0.5435	0.4086	0.9485	0.316166667
123	72	0.2121	0.4563	0.8783	0.292766667
121	73	0.2223	0.4967	0.8833	0.294433333
122	77	0.2186	0.4794	0.6962	0.232066667
122	74	0.4396	0.4136	0.8505	0.2835

Table A.4: HR results obtained from 33 subjects

HR from Apple Watch	HR from camera
63	60.8
71	65.014
89	86
78	74
65	72
64	63.599
67	58.46
74	77
77	68.65
56	63.445
90	88
95	94
89	87.745
76	79
60	66.83
73	71.9582
69	74.9956
63	70.1304
98	101.545
71	72.7277
91	95.8216
67	63.1417
79	80.6532
78	78.7329
93	96.802
62	67
87	75.5357
103	102.5254
75	76.2638
83	78.9261
97	97.059
94	96.9322

Appendix B

Matlab Code

B.1 Building and Testing Simple Linear Regression

```
%
```

```
=====
```

```
% This file is used to build the Simple Linear Regression  
Model for Blood Pressure for training  
% period and testing period  
  
clear;  
clc;  
close all;  
  
format short  
  
% Reading Training - Training Period  
  
data = csvread('training_data2.csv');
```

```
% Truth Values

SB = data(:,1);
DB = data(:,2);
HR = data(:,3);

% Features values

systolic_time = data(:,4);
diastolic_time = data(:,7);
cardio_time = data(:,5);
summation_time = data(:,6);

w1 = data(:,8);

feuture1 = 'diastolic Time';
feuture2 = 'systolic Time';
feuture3 = 'cardio Time';
feuture4 = 'summation Time';
feuture5 = 'w1';

indices=[]; % Find correlation bigger than 0.3

BP = SB

%BP = DB

% Find correlation coefficients values

for i = 1:size(data,1)

    [r1, p, ru, rl] = corrcoef(BP, diastolic_time);
    [r2, p2, ru2, rl2] = corrcoef(BP, systolic_time);
    [r3, p3, ru3, rl3] = corrcoef(BP, cardio_time);
    [r4, p4, ru4, rl4] = corrcoef(BP, summation_time);
    [r5, p5, ru5, rl5] = corrcoef(BP, w1);
```

```
end

% Find the absolute values of correlation coefficients

rr(1)=abs(r1(1,2));

rr(2)=abs(r2(1,2));

rr(3)=abs(r3(1,2));

rr(4)=abs(r4(1,2));

rr(5)=abs(r5(1,2));

% Find the Feature with maximum correlation

[maximun_correlation,index] = max(rr);

disp('The feauter with greater correlation with Systolic
Blood Pressure is :')

switch index

    case 1

        disp('Diastolic Time')
        disp(r1(1,2))

    case 2

        disp('Systolic Time')
        disp(r2(1,2))

    case 3

        disp('Total Cardio Cycle Time')
        disp(r3(1,2))

    case 4

        disp('Summation Time')
        disp(r4(1,2))

    case 5
```

```
    disp('Width');

    disp(r5(1,2))

end

%
=====
% Building the Linear regression Model

% Initialise Predictor Variable
X = ones(length(systolic_time),1);

% Concatenate predictor variables in one structure
X=[X systolic_time];

% Use regress to find Linear regression coefficients and
% build a model
[b, bint, r, rint, stats] = regress(BP,X);

%
=====

train_period=length(systolic_time); % Length of training
period

%
=====

output=zeros(train_period,1);
x_train = systolic_time; % Predictor variable change it
according what feature is examined

%
=====
```

```
i=1;

noise = randn(train_period,1)
noise = (noise - mean(noise)) / std(noise);
%

=====
% Use training Data to find the output
for j = 1:train_period
    l = (i - 1) * train_period + j;
    output(j,i) = output(j,i) + b(2) * x_train(j)
    output(j,i) = output(j,i) + b(1);
end

display(['Total R^2 for Systolic Pressure: ' num2str(stats(1))]);
% Training Period Results
figure()
scatter(1:length(output),output)
hold on
scatter(1:length(BP),BP)
grid on
legend('Model Values','Truth Values');
title('Systolic Pressure vs Systolic Time');
ylabel('Systolic Pressure');
xlabel('Sample index');
set(findobj('type','axes'),'fontsize',16)

% Calculate Mean Difference
```

```
MD = 0.1*sum(abs(output-SB))

% Calculate Standard error of estimation

SEE = sqrt(sum(SB-output)^2/length(output));

bland_altman(SB, output); % Bland Altman plots

BlandAltman(SB, output); % Differernt Bland Altman
```

Implementaon

```
%
```

```
=====
```

```
% Testing Period
```

```
data_test = csvread('test.csv');

SB_Test = data_test(:,1);

DB_Test = data_test(:,2);

DiastolicTimeTest = data_test(:,4);

SystolicTimeTest = data_test(:,3);

PulseTimeTest = data_test(:,5);

w1_test = data_test(:,6);
```

```
test_period = length(SystolicTimeTest);
```

```
output_test=zeros(test_period,1);
```

```
% Check both Systolic and Diastolic Pressure
```

```
BP_Test=SB_Test;
```

```
% BP_Test= DB_Test;
```

```
% The same procedure is repeated for all the Feutures
```

```
x_test = SystolicTimeTest; % Predictor variable change it  
according what feature is examined  
%  
%  
%  
%  
=====  
  
i=1;  
noise = randn(test_period,1)  
noise = (noise - mean(noise)) / std(noise);  
%  
=====  
  
% Use training Data to find the output  
for j = 1:test_period  
    l = (i - 1) * test_period + j;  
    output_test(j,i) = output_test(j,i) + b(2) * x_test(j)  
);  
    output_test(j,i) = output_test(j,i) + b(1);  
end  
  
% Testing Period Results  
figure()  
scatter(1:length(output),output)  
hold on  
scatter(1:length(SB),SB)  
grid on
```

```
legend('Model Values','Truth Values');

title('Systolic Pressure vs Systolic Time');

ylabel('Systolic Pressure');

xlabel('Sample index');

set(findobj('type','axes'),'fontsize',16)

% Calculate Mean Difference

MD = 0.1*sum(abs(output_test-BP_Test))

% Calculate Standard error of estimation

SEE = sqrt(sum(BP_Test-output_test)^2/length(output_test));

bland_altman(BP_Test, output_test); % Bland Altman plots

BlandAltman(BP_Test, output_test); % Differernt Bland Altman

    Implementaon

accuracy = 1-abs(BP_test-output_test)./BP_Test

figure()

histogram(accuracy)

title('Frequency of accuracy');

xlabel('Accuracy %');

ylabel('Frequency');

set(findobj('type','axes'),'fontsize',16)

s=1;

s2=1;

s3=1;

s4=1;
```

```
% Find the frequency that accuracy occurs

for i=1:test_period

    if (accuracy(i)*100>95)

        s=s+1;

    end

    if (accuracy(i)*100>90 && accuracy(i)*100<95)

        s2=s2+1;

    end

    if (accuracy(i)*100<90&& accuracy(i)*100>85)

        s3=s3+1;

    end

    if (accuracy(i)*100<85)

        s4=s4+1;

    end

end
```

B.2 Building and Testing Polynomial Linear Regression

```
%% Polynomial Models
%
=====
% This file is used to build and test
% the Polynomial Linear Regression Models for Blood Pressure
%
=====

% Reading Training Data
data = csvread('training_data2.csv');
SB = data(:,1);
DB = data(:,2);
systolic_time = data(:,4);
diastolic_time = data(:,7);
cardio_time = data(:,5);
summation_time = data(:,6);
w1 = data(:,8);

%
%
=====

% Reading Testing Data
data_test = csvread('test.csv');
SB_Test=data_test(:,1);
DB_groundTruthTest=data_test(:,2);
DiastolicTimeTest=data_test(:,4);
```

```
SystolicTimeTest=data_test(:,3);  
PulseTimeTest=data_test(:,5);  
w1_test=data_test(:,6);  
  
% Building The polynomial Model  
y=SB;  
%y=DB  
t1 = polyfit(systolic_time,y,5);  
t2 = polyfit(diastolic_time,y,5);  
t3 = polyfit(cardio_time,y,5);  
t4 = polyfit(w1,y,5);  
  
% Constructing Table to Present the data  
feautures = {'DT'; 'ST'; 'CT'; 'W1'}  
  
a2=[t1(1);t2(1);t3(1);t4(1)];  
a1=[t1(2);t2(2);t3(2);t4(2)];  
a0=[t1(3);t2(3);t3(3);t4(3)];  
  
T = table(a0,a1,a2,...  
    'RowNames',feautures)  
% Testing Period  
y1 = polyval(t1,SystolicTimeTest);  
y2 = polyval(t2,DiastolicTimeTest);  
y3 = polyval(t3,DiastolicTimeTest);  
y4 = polyval(t4,DiastolicTimeTest);  
  
% Find Correlation between Testing Outcome and Actual Values  
r=corrcoef(y1,SB_groundTruthTest);
```

```
r2=corrcoef(y2,SB_groundTruthTest);  
r3=corrcoef(y3,SB_groundTruthTest);  
r4=corrcoef(y4,SB_groundTruthTest);  
  
correlation=[abs(r(1,2));abs(r2(1,2));abs(r3(1,2));abs(r4  
(1,2));]  
  
% Calcualte the Residual  
res1 = SB_Test - y1;  
res2 = SB_Test - y2;  
res3 = SB_Test - y3;  
res4 = SB_Test - y4;  
  
% Plot the Residuals  
figure()  
subplot(2,2,1)  
plot(SystolicTimeTest,res1,'+')  
title('Plot of the Residuals')  
set(findobj('type','axes'),'fontsize',16)  
subplot(2,2,2)  
  
plot(SystolicTimeTest,res2,'+')  
title('Plot of the Residuals')  
set(findobj('type','axes'),'fontsize',16)  
subplot(2,2,3)  
plot(SystolicTimeTest,res3,'+')  
title('Plot of the Residuals')  
set(findobj('type','axes'),'fontsize',16)  
subplot(2,2,4)
```

```
plot(SystolicTimeTest,res4,'+')  
title('Plot of the Residuals')  
set(findobj('type','axes'),'fontsize',16)  
  
%% Regression with non-polynomial Terms  
  
% Reading Data  
data = csvread('training_data2.csv');  
SB = data(:,1);  
DB = data(:,2);  
systolic_time = data(:,4);  
diastolic_time = data(:,7);  
cardio_time = data(:,5);  
summation_time = data(:,6);  
w1 = data(:,8);  
  
% Testing Data  
data_test = csvread('test.csv');  
SB_Test=data_test(:,1);  
DB_Test=data_test(:,2);  
DiastolicTimeTest=data_test(:,4);  
SystolicTimeTest=data_test(:,3);  
PulseTimeTest=data_test(:,5);  
w1_test=data_test(:,6);  
  
% Feature extraction  
t1=systolic_time  
t2=diastolic_time  
t3=cardio_time  
t4=w1
```

```
%  
=====  
  
% Training Period  
% Same procedure for both Systolic and diastolic Pressure  
y=DB;  
% y=SB;  
% Initialize Predictor Variables  
X1 = [ones(size(t1)) exp(-t1) t1.*exp(-t1)];  
X2 = [ones(size(t2)) exp(-t2) t1.*exp(-t2)];  
X3 = [ones(size(t3)) exp(-t3) t1.*exp(-t3)];  
X4 = [ones(size(t4)) exp(-t4) t1.*exp(-t4)];  
% Find non-linear Terms  
a1 = X1\y;  
a2 = X2\y;  
a3 = X3\y;  
a4 = X4\y;  
%  
=====  
  
% Testing Period  
  
% Testing Input  
T1=SystolicTimeTest;  
T2=DiastolicTimeTest;  
T3=PulseTimeTest;  
T4=w1;  
BP_Test = DB_Test;
```

```
% BP_Test = SB_Test;

Y1 = [ones(size(T1)) exp(-T1) T1.*exp(-T1)]*a1;
Y2 = [ones(size(T2)) exp(-T2) T2.*exp(-T2)]*a2;
Y3 = [ones(size(T3)) exp(-T3) T3.*exp(-T3)]*a3;
Y4 = [ones(size(T4)) exp(-T4) T4.*exp(-T4)]*a4;

% Bland Altman Plots

bland_altman(BP_Test,Y1)
bland_altman(BP_Test,Y2)
bland_altman(BP_Test,Y3)
bland_altman(BP_Test,Y4)

% Statistics

[r,p]=corrcoef(BP_Test,Y1)
[r2,p2]=corrcoef(BP_Test,Y2)
[r3,p3]=corrcoef(BP_Test,Y3)
[r4,p4]=corrcoef(BP_Test,Y4)

% Statistics of the best model: Feature W1

SEE = sqrt(sum((BP_Test-Y4)^2/length(Y4)); % Statistical error
           of Estimation

MD = 0.1*sum(abs(Y4-BP_Test)) % Mean Difference

Rsq1 = 1 - sum((y - Y4).^2)/sum((y - mean(y)).^2);
standard=std(Y4); % Standard Deviation
BlandAltman(BP_Test,Y4);
std(Y4); % Standard Deviation
varrr=var(Y4,BP_Test); % Variance
```

```
% Constructing the table with Results
feautures = {'DT'; 'ST'; 'CT'; 'W1'}
s2=[a1(1);a2(1);a3(1);a4(1)];
s1=[a1(2);a2(2);a3(2);a4(2)];
s0=[a1(3);a2(3);a3(3);a4(3)];

T = table(s0,s1,s2,...  

'RowNames',feautures)
```

B.3 Signal Processing and HR Estimation

```
%
```

```
=====
```

```
% Read the frames from the video , Calculate HR and extract  
    Feauture  
  
clear all;  
clc;  
close all;  
  
v = VideoReader('VideoName.mp4');  
first_der1 = VideoReader('VideoName.mp4');  
  
number_Of_Frames = first_der1.NumberOfFrames  
sampling_frequency = v.FrameRate;  
  
% Initialise the singals  
signal = zeros(1, number_Of_Frames);  
signal2 = zeros(1, number_Of_Frames);  
signal3 = zeros(1, number_Of_Frames);  
  
tic  
i=1  
  
% Initialiase threshold value  
threshold = 128;  
  
% Find Red Channel Average  
while hasFrame(v)  
    frame = readFrame(v);
```

```
N=size(frame, 1);

redChannel = frame(:, :, 1);
greenChannel=frame(:, :, 2);
blueChannel=frame(:, :, 3);

if mean(redChannel)>= threshold

    signal(i) = sum(sum(redChannel))/(N^2);
    signal2(i) = sum(sum(greenChannel))/(N^2);
    signal3(i) = sum(sum(blueChannel))/(N^2);

    i=i+1;
end

end

% Plot the Original Signal
figure(1)
plot(signal)
title('Average Red Channel');
xlabel('Frame');
ylabel('RGB Value')
grid on
set(findobj('type','axes'), 'fontsize',16)
%
=====
% Initialisations
window = 6; % Length of the sliding
widnow
step = 0.5; % Step value between HR

% Heart Rate Normal range
```

```
bpm_low = 40;
bpm_high = 240;
%
=====
%
% Build and apply input filter
% construct a second order low pass filter
% Apply second order butterworth filter to the signal
[b, a] = butter(2, [(((40)/60)/30*2) (((240)/60)/30*2)]);
filtered_signal = filter(b, a, signal);

n = size(filtered_signal, 2); % Number of pixels

figure(3)
plot (filtered_signal);
title('Second Order Butterworth PPG','fontsize',14)
xlabel('Frame Number')
ylabel('Brightness level')
set(findobj('type','axes'), 'fontsize',16)

%
% Cut the stabilisation time
signal = filtered_signal((sampling_frequency+1:n));

figure (4);
plot(signal);
title('PPG After Removing Time','fontsize',16)
ylabel('Brightness Level');
xlabel('Frame');
set(findobj('type','axes'), 'fontsize',16)
```

```
%
```

```
=====
```

```
%
```

```
=====
```

```
% Some initializations and precalculations
```

```
Nsamples = round(window * sampling_frequency); %
```

```
Calculate number of samples inside the window
```

```
samplesInWindow = round(step * sampling_frequency);
```

```
num_bpm_samples = floor((size(signal, 2) - Nsamples) /  
samplesInWindow);
```

```
% Transalte beats per minute to frequencies
```

```
frequency_low = bpm_low / 60;
```

```
frequency_high = bpm_high / 60;
```

```
original_signal = signal;
```

```
% Find systolic peaks and diastolic minimun of the signal
```

```
k = 1;
```

```
diastolic_New = - signal
```

```
[~,diastolic_indexes]= findpeaks(diastolic_New)
```

```
[~,Systolic_indexes] = findpeaks(signal)
```

```
sys = Systolic_indexes(3:end)
```

```
dia = diastolic_indexes(2:end-1)

% Calculate Systolic, Diastolic Time and Pulse Time
SystolicTime = mean((sys(3:end)-dia(2:end-1)))/v.FrameRate;
DiastolicTime = mean((dia(3:end)-sys(2:end-1)))/v.FrameRate;
PulseTime = mean((dia(3:end)-dia(2:end-1)))/v.FrameRate;
%
=====

bpm=zeros(num_bpm_samples,1);

for i=1:num_bpm_samples,
%
=====

    % Sliding Window
    newSignal = original_signal(((i-1)*samplesInWindow+1):((i
        -1)*samplesInWindow+1)+Nsamples);

    % Leakage reduction using hanning window
    signal = newSignal .* hann(size(newSignal, 2))';
    n2 = size(signal, 2);
    gain = abs(fft(signal));

    % FFT indices of frequencies where the human heartbeat is
    low = floor(frequency_low * (n2 / sampling_frequency));
    upper = ceil(frequency_high * (n2 / sampling_frequency));
    index_range = low+1:upper+1;
```

```
% Find peaks and allocate the maximum peak
[peaks, locations] = findpeaks(gain(index_range));
[~, maxPeak] = max(peaks);
indexMaxPeak = index_range(locations(maxPeak));

% Estimate beat per minute in the window sample
bpm(i) = (indexMaxPeak-1) * (sampling_frequency / size(
    signal, 2)) * 60;

%
=====

end

% Find Systolic and Diastolic time using First Derivative
first_der=diff(signal);
figure(5)
plot(first_der)

% Initialisations
begin = false;
mystart = [];
myfinish = [];

for t=1:length(first_der)-1

    % Find the indexes where the sign changes
    if (begin == false) && first_der(t)<0 && first_der(t+1)
        >0
        mystart = [mystart, t];
    end
end
```

```
begin=true;

end

if (begin == true) && first_der1(t)>0 && first_der1(t+1)

<0

myfinish=[myfinish,t];

begin = false;

end

end

if length(mystart) > length(myfinish)

mystart = mystart(1:end-1);

end

b=length(mystart);

d=length(myfinish);

diastolicpressure = myfinish-mystart;

DTIME = diastolicpressure(2:end);

Mean_DT = mean(DTIME)/sampling_frequency % Convert

frames to Time

%=====Systolic Time
=====

% Calculate Systolic Time from first derivative

begin = false;

mystart2 = [];

myfinish2 = [];

for t=1:length(first_der1)-1
```

```
if (begin == false) && first_der1(t)>0 && first_der1(t+1)
<0
    mystart2 = [mystart2, t];
    begin=true;
end

if (begin == true) && first_der1(t)<0 && first_der1(t+1)
>0
    myfinish2=[myfinish2,t];
    begin = false;
end

end

if length(mystart2) > length(myfinish2)
    mystart2 = mystart2(1:end-1);
end

rr = myfinish2-mystart2;
DT2 = rr(2:end);

% Find Average Systolic time
mean_ST = mean(DT2)/sampling_frequency
%
=====
disp(['Average Heart Rate: ' num2str(mean(bpm)) ' bpm']);

% Plot the results
figure(6);
plot(signal);
title('Sampling PPG Signal','fontsize',14)
```

```
xlabel('Frame');  
ylabel('Brightness Level');  
figure(7)  
plot(gain)  
xlabel('Frequency')  
ylabel('Power density')  
set(findobj('type','axes'), 'fontsize', 16)
```

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