ABSTRACT

This project is a Fourth year project on building a “Non-Invasive Way Of Heart Diagnosis” under supervision of **Dr. Uttam Kumar Roy**. In this project we tried to research and develop an application that can measure various heart related parameters in a non-invasive manner. The parameters are like heart rate ,blood pressure ,respiration rate and SPO2. The smart phones with multiple inbuilt sensors can be used to design and develop application to collect different biomedical signals. The method works by placing the index finger over the cell phone camera and passing the flash light through the finger and computing the amount of light absorbed by the finger tissue. The phone acquires the Photoplethysmographic (PPG) signal. This is achieved by using the phone’s ability to record and detect variations in colour signals in a fingertip placed in contact with its optical sensor, i.e. camera. The PPG signal is further explored to find health related parameters.

ACKNOWLEDGEMENT

It is our privilege to express our sincerest regards to our project coordinator, **Dr Uttam Kumar Roy** for his valuable inputs, able guidance, encouragement, whole-hearted cooperation throughout the duration of our project. We deeply express our sincere thanks to our Head of Department Dr Bhaskar Sardar for allowing us to present the project on the topic “Non-Invasive Way of Heart Monitoring" at our department premises We take this opportunity to thank all our lecturers who have directly or indirectly helped in our project. Last but not the least we express our thanks to our friends for their cooperation and support.

CONTENTS

1. INTRODUCTION TO PROJECT

1.1 PROBLEMS

Heart related problem is one of the major concern in these days as majority of the people die from this problem annually. Statistics from Centers for Disease Control and Prevention, in 2008, around 616K people died of heart disease and 25% cause of total death and in 2010 the percentage grew up to 31%. High blood pressure, high cholesterol, diabetes, smoking, overweight are some of the real cause of heart disease. 31% of the total death i.e (17.7 million lifes) were estimated due to these diseases in 2015. The number is increasing alarmingly and sources claimed that total estimated global cost of cardiovascular disease was $863 billion in 2010 and it might likely to increase by 2030 to $1044 billion.

Heart disease including Coronary Heart Disease, Hypertension, and Stroke claims the top rank in most of the countries to end a life.

1.2 OUR TARGET

Our target is to develop a Smart Cardiovascular Health Monitoring Tool which will be able to measure for different health related parameters with the help of Mobile Camera using a flash light to capture continuous video of blood flowing inside the arteries due to the cardiac cycle, and further analysis on feature extraction in the form of image & signal processing and collecting necessary health related data of the patient. This signal and data are then used for deriving various health related parameters.

Here we have primarily focused on PPG signal and possibilities to measure important blood parameters like

- Heart Rate.
- Blood Pressure.
- Respiration Rate.
- Oxygen Saturation - spO2.

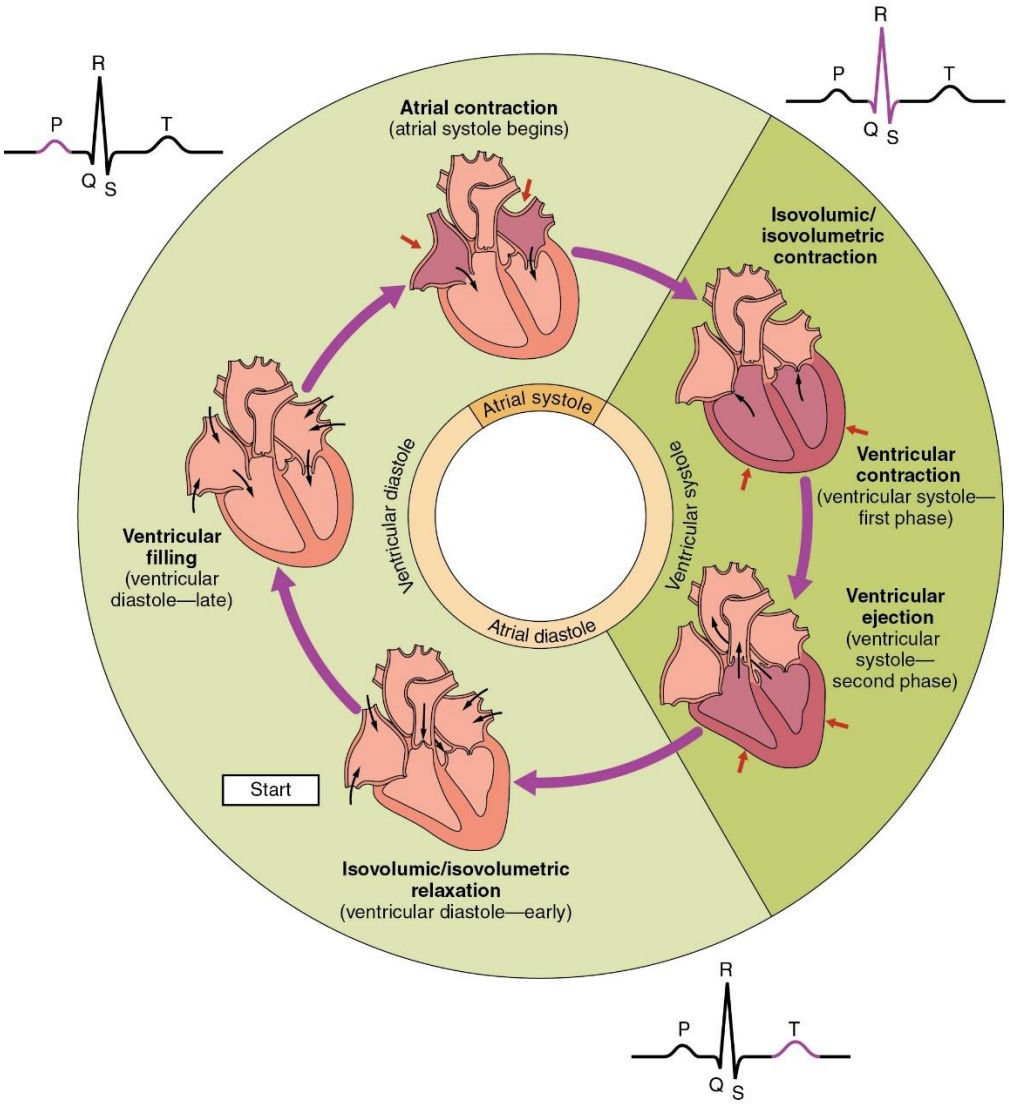
These parameters indirectly or directly can provide us a status of our health when required. Accurate measurement of PPG can open up new possibilities in non-invasive computer aided cardiac research.

In addition, PPG depends on location, skin (structure, temperature), blood oxygen saturation, blood flow rate, added artifacts like motion, baseline drift, low amplitude PPG, and premature ventricular contraction and creates noise in the signal. Higher order derivatives of PPG sharpens the signal and helps in calculation. Sharpening PPG signal with reduced noise is also another challenge.

2. GENERATION OF PPG SIGNAL

2.1 CARDIAC CYCLE

The **cardiac cycle** is the performance of the human heart from the beginning of one **heartbeat** to the beginning of the next. It consists of two periods: one during which the heart muscle relaxes and refills with blood, called diastole(die-ASS-toe-lee), followed by a period of robust contraction and pumping of blood, dubbed systole (SIS-toe-lee). After emptying, the heart immediately relaxes and expands to receive another influx of blood *returning from* the lungs and other systems of the body—before again contracting to *pump blood to* the lungs and those systems. A normally performing heart must be fully expanded before it can efficiently pump again. Assuming a healthy heart and a typical rate of 70 to 75 beats per minute, each cardiac cycle, or heartbeat, takes about 0.8 second to compete the cycle

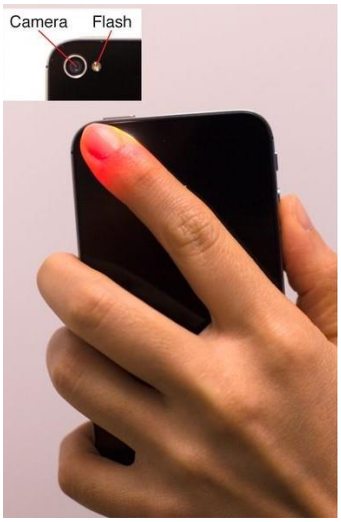


2.2 METHODOLOGY

The model works on the principle that, every heart beat pertains to a rush of blood in the blood vessels, even in the capillaries at the finger-tips. Whenever the capillaries are rich in blood during a systolic pulse, more light is getting absorbed by the blood, leading to low reflective index and darker frame intensities. Likewise, during a diastolic pulse, most of the light gets reflected leading to bright frames. This change in intensity of light which can pass through the finger creates an alternative pattern of waves similar to a pulse. These changes in intensity with time gives the heart rate of a person.

In the proposed method, we record a video of short duration, with the finger placed over the lens of the mobile camera. The flash is turned ON, so that adequate amount of light can reach the finger for proper measurement.

For this experiment, we developed an application to keep the LED flash consistently ON while recording video from camera. Initially the CMOS sensor of the camera tries to focus when turned ON. Also, the camera doesn't need to be focused, as the results rely only on the amount of light entering the video feed. It was generally hard to detect the fluctuations in the frames unless the pulses are distinct.

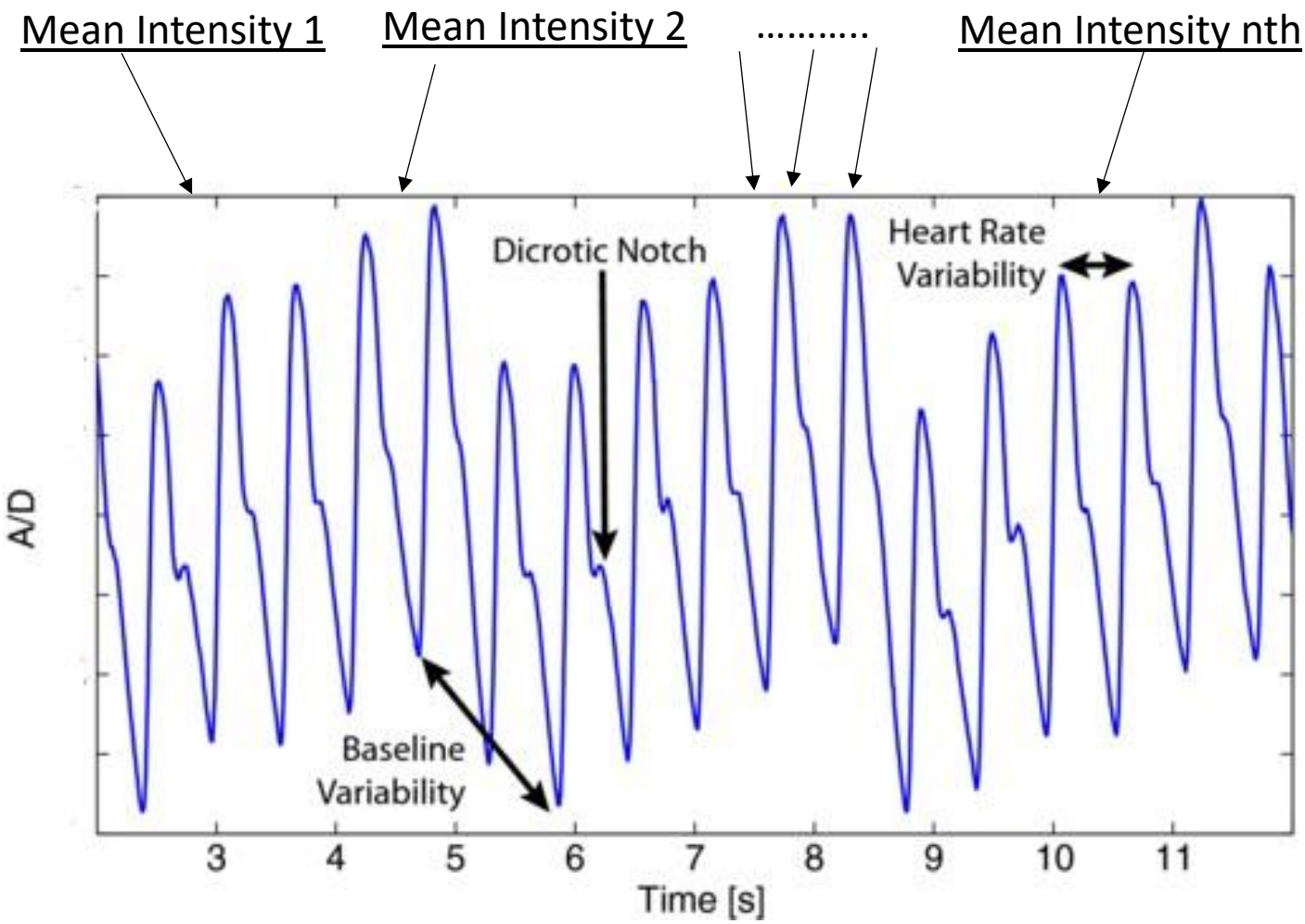


FINGER APPLIED ON CAMERA RECORDING THE VIDEO

A SINGLE FRAME

88	82	84	88	85	83	80	93	102
88	80	78	80	80	78	73	94	100
85	79	80	78	77	74	65	91	99
38	35	40	35	39	74	77	70	65
20	25	23	28	37	69	64	60	57
22	26	22	28	40	65	64	59	34
24	28	24	30	37	60	58	56	66
21	22	23	27	38	60	67	65	67
23	22	22	25	38	59	64	67	66

INTENSITY VALUES AT EACH PIXEL OF CORRESPONDING FRAME

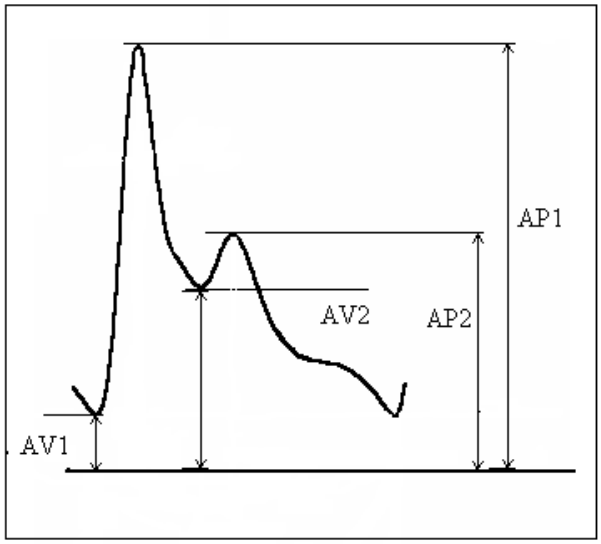


The mean intensity value is then calculated for each frame of the video. These intensity values are then plotted against time to give us the PPG Waveform.

Now these frames intensity values and the PPG waveform obtained helps us in deriving the different health related parameters.

2.3 PPG CURVE

The final PPG curve obtained can be shown in the figure.



Typical Volume or Pressure pulse wave:
AP1-systolic peak amplitude,
AP2-dicrotic peak amplitude,
AV1 and AV2 are the corresponding valley amplitude

3. HEART RATE ESTIMATION

3.1 INTRODUCTION

Detection of peaks often forms an essential part of time domain analysis of biomedical signals and patient monitoring. Peak detection is the process of finding the locations and amplitudes of local maxima in a signal that satisfies certain properties. Generally, a signal sample x(n) is considered as a peak when it is greater than its previous sample and next sample ($x(n-1) < x(n) > x(n+1)$). Fortunately, the peak detection algorithms for Electrocardiogram (ECG) signals are well developed and widely available.

Most of the algorithms for detection of QRS complexes in ECG combine a band pass filter with a transformation, such as the signal derivative or the wavelet transform, to exploit the large slope and high frequency content of the QRS complex (10 to 25 Hz). This transformation generates a feature signal in which QRS complexes can be detected easily by a threshold. In contrast, PPG signals are more sinusoidal and less impulsive than ECG signals and most of its power is in a lower frequency range, typically from 0.7–3.5 Hz. Thus, the algorithms that rely on the impulsive shape of the QRS complex are inappropriate for PPG signals and cannot yield accurate results.

Thus, we need a altogether different algorithm for peak detection in a PPG signal.

3.2 METHODOLOGY

3.2.1 OVERVIEW

There are two peaks corresponding to two waves, systolic wave and dicrotic wave. The valley between these two waves is called dicrotic notch. The location of the dicrotic notch changes from subject to subject and also depends on the age [. This prevents the use of simple threshold to detect systolic peaks as compared to peak detection in ECG. The algorithm uses the relative amplitudes of corresponding systolic and dicrotic waves to distinguish the systolic peaks from the dicrotic peaks. The algorithm detects the systolic peaks from the PPG signal and takes care to eliminate the minor peaks due to dicrotic notches and noise by using the wave amplitudes in combination with a moving average technique. The difference between successive valley amplitude and peak amplitude (valley – peak difference (VPD)) gives the amplitudes of systolic and dicrotic waves. The algorithm employs moving average of valley- peak differences along with local threshold filters to identify the systolic peaks. All the spurious peaks due to noise and dicrotic peaks are eliminated by looping, until the number of peaks remains unchanged in two successive iterations.

3.2.2 PREPROCESSING

The first step in the algorithm is to process the signal to enhance the signal components by using a 3-point moving average smoothing filter. The filter is applied forward and backward to eliminate any phase shift produced due to filtering the signal.

3.2.3 MAXIMA AND MINIMA DETECTION

The second step detects all the peaks and valleys and their locations in the signal. Given the PPG signal time series

S(n)={s1 ,s2 ,s3…..sN},

the peaks and the valleys are those points that satisfy the following criteria

Peaks , $P(n) = S(n): S(n-1)<S(n)>S(n+1)$;
$n=1,2,3...N$ (1)

And Peak locations $L_p(i) = n : S(n-1)<S(n)>S(n+1)$;
$i=1,2,3...m$ (2)

Valleys, $V(n) = S(n): S(n-1)>S(n)<S(n+1);$
$n=1,2,3...N$ (3)

And Valley locations $L_v(j) = n : S(n-1)>S(n)<S(n+1);$
$j=1,2,3...m$ (4)
respectively.

Here m = number of peaks = number of valleys

3.2.4 VPD PROCESSING

In this stage, it is ensured that the processing begins with a valley. The location of first peak and first valley are compared and if the peak comes first, then it is discarded and the signal is taken starting from the valley. This implies that the discarded peak has no corresponding valley

$S(n)= \{s_1,s_2,s_3.....s_N\}$ is the original signal;
$n = 1,2,3,\ldots\ldots\ldots, N$

$P(i)=\{p_1,p_2,p_3...p_m\}$ is the series of all peaks;
$i = 1,2,3,\ldots\ldots\ldots,m$

$L_p(i)=(l_{p1}, l_{p2}, l_{p3}... l_{pm})$ is the series of locations of peaks; $i = 1,2,3,\ldots\ldots\ldots,m$

$V(j)=(v_1,v_2,v_3 \ldots v_m)$ is the time series of all valleys;
$j = 1,2,3,\ldots\ldots,m$

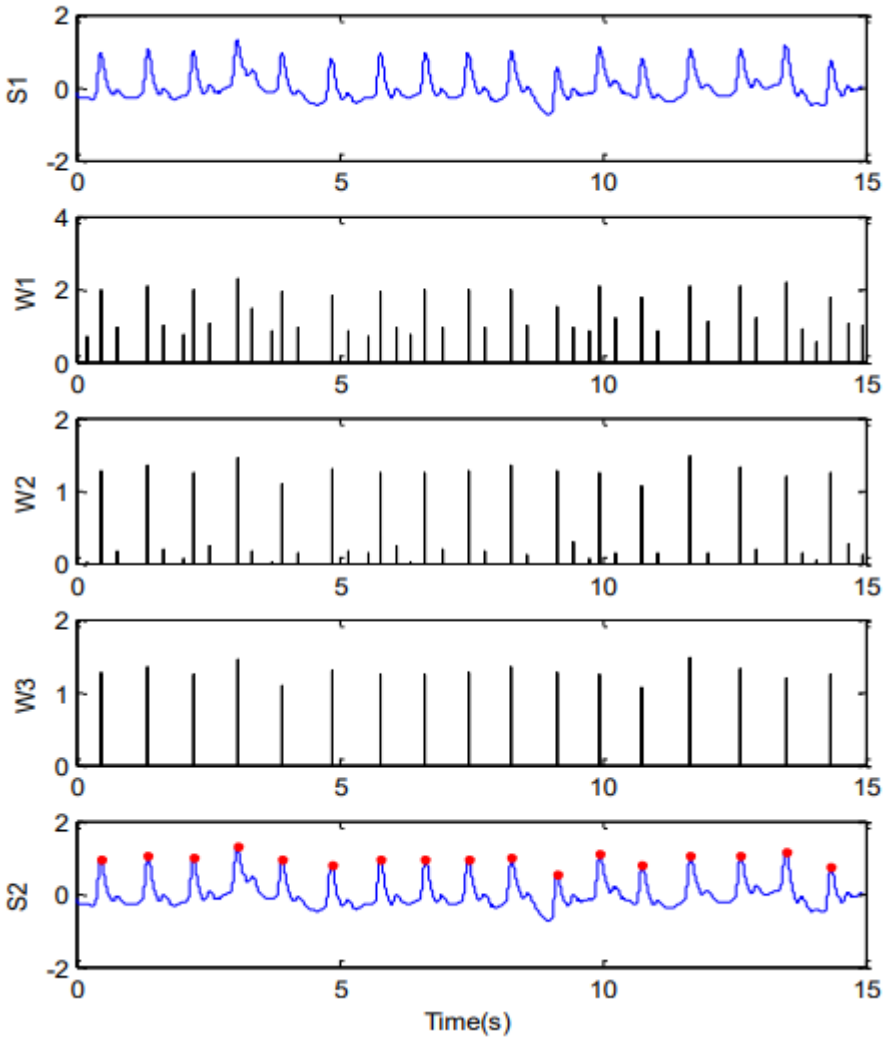
$L_v(i)=(l_{v1}, l_{v2}, l_{v3} \ldots l_{vm})$ is the series of locations of valleys; $j = 1,2,3,\ldots\ldots,m$

$$VPD(k)=P(k)-V(k); \quad k = 1,2,3,\ldots\ldots,m \qquad (5)$$

After the calculation of *VPDs*, the algorithm searches the *VPD* series for the instances where

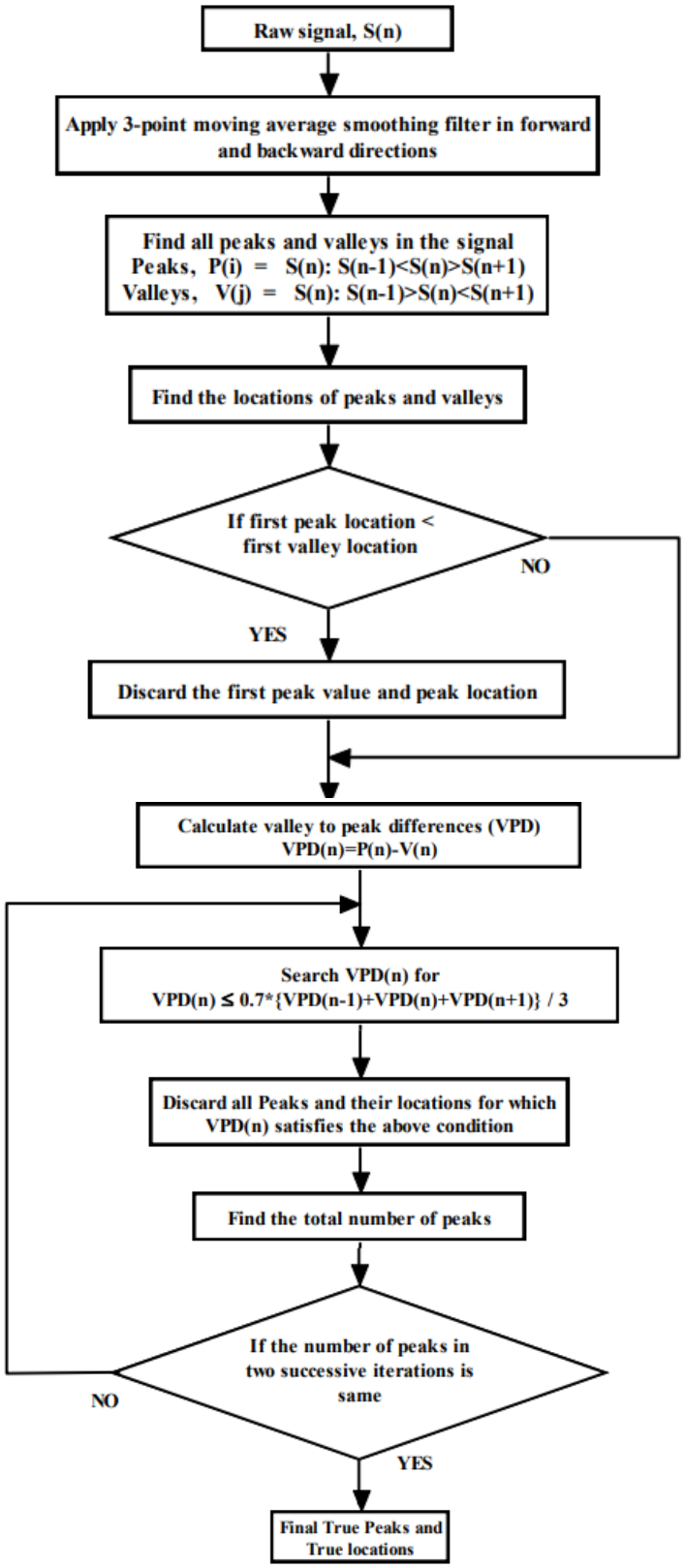
$$VPD(k) < 0.7*\{VPD(k-1)+VPD(k)+VPD(k+1)\}/3 \qquad (6)$$

This is considered as an over detection so, corresponding P(i) and P(i) location, Lp (i) is removed from the candidate series. This VPD processing is repeated until the number of peaks in the two successive iterations remains the same. This eliminates all the dicrotic peaks and peaks due to noise.



Different stages while processing a Signal.

3.2.5 FLOWCHART



4. RESPIRATION RATE

4.1 INTRODUCTION

A person's respiratory rate is the number of breaths you take per minute. The normal respiration rate for an adult at rest is **12 to 20 breaths per minute**. A respiration rate under 12 or over **25 breaths per minute** while resting is considered abnormal.

Current respiration rate sensing is commonly done using contact sensor such as chest straps, electrodes or finger clips. However, these sensors are uncomfortable and introduce additional costs to the users.

RR (Respiration Rate) measurement is important because it could help subjects to achieve a calm state and to detect and prevent abnormal respiratory rates that may lead to cardiac arrest, stroke and chronic obstructive pulmonary diseases.

RR is calculated based on the effects of respiratory sinus arrhythmia (RSA). That refers to the variation in heart rate when breathing. During inspiration the HR accelerates and during expiration the HR slows down.
The peaks under the red line correspond to the heartbeats, and the peaks shaped by the red line are the respiration rate traced by the heart rate over time.

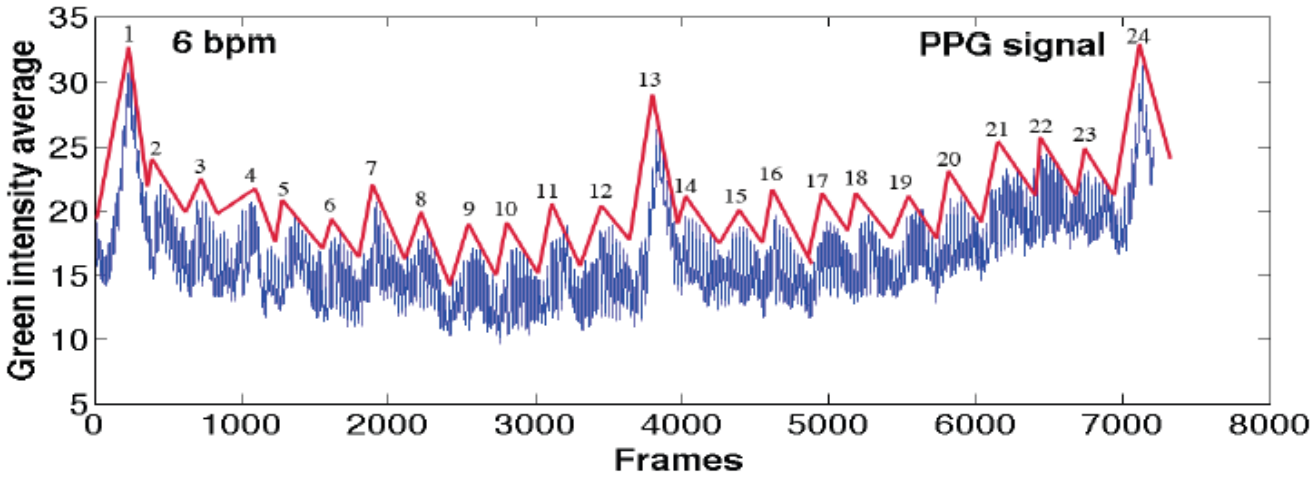


Figure 1. Photoplethysmographic signal and Respiratory sinus arrhythmia

The PPG signal was recorded for four minutes at a breathing rate of 6 breaths per minute. The graph clearly shows twenty-four peaks that correspond to the breathing rate.

4.2 METHODOLOGY

5.2.1 OVERVIEW

The method started with an individual placing his finger over the cell phone camera without
pressing down any additional force and the smartphone camera's flash turned on.

For the first phase of this experiment , a smartphone was used to record a video of the light absorbed by the finger index tissue. The length of the videos was around 10sec. The videos were recording at a sampling rate of 30fps. From the recoded video frames were extracted.
The RGB components were extracted from every frame. However only the green values
were used to compute the average of light absorbed by the finger tissue in every frame.

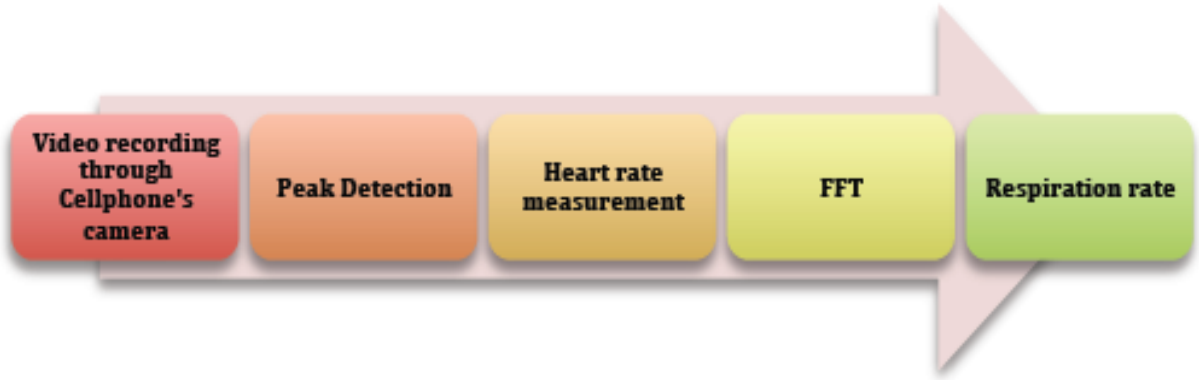


Figure 2. Overview of the method

4.2.2 RESPIRATION RATE DETECTION

Respiration rate can be extracted from Heart Rate in the spectrum domain. This is possible because respiration rate modulates amplitude and frequency of a signal. Before spectral analysis, the HR signal was interpolated in order to address the issue of irregular sampling from the cellphone. After this , the fast Fourier transform (FFT) of the HR was computed. The frequency that corresponds to the maximum peak is the respiration rate.

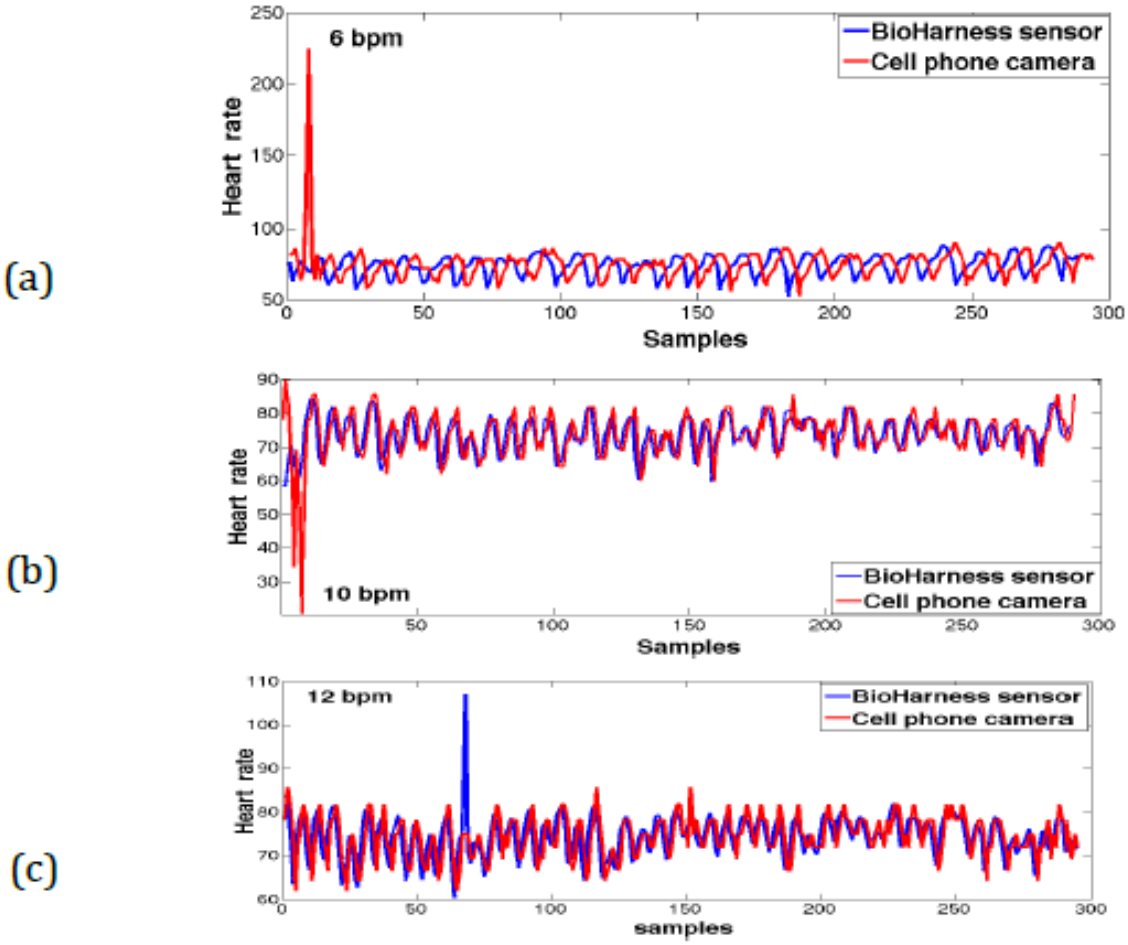


Figure Represents heart rate correlation between the commercial sensor measurements and the HR estimation from the iPhone camera recordings at (a) 6, (b) 10 and (c) 12 bpm.

(a)

(b)

(c)

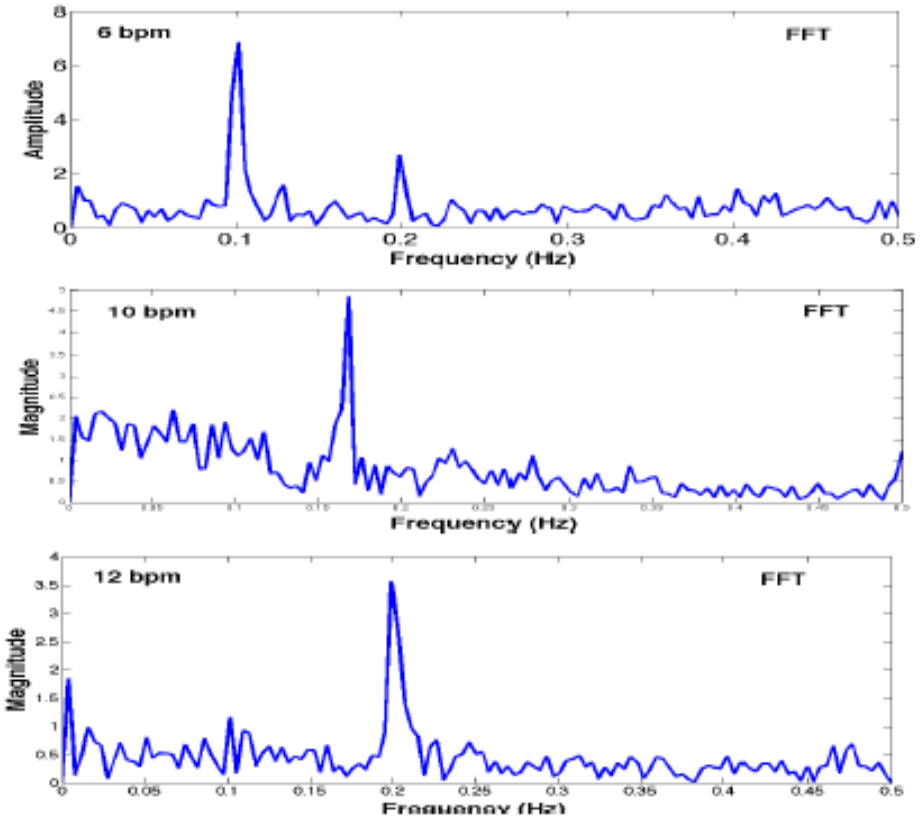


Figure Represents the fast Fourier transform plots. Each harmonic peak corresponded to the respective breathing frequency, in which the samples were collected. (a) Breathing frequency of 0.1hz corresponds to 6bpm, (b) 0.16 corresponds to 10bpm and (c) 0.2Hz corresponds to 12bpm.

5. SPO2(Oxygen Saturation)

5.1 INTRODUCTION

The amount of oxygen saturation (SpO2) in the blood is a very important parameter for detection and prevention of cardiovascular disease. Haemoglobin is an essential component of blood; however it has very low solubility in it. To induce solubility, oxygen binds with it to form oxyhaemoglobin. Hence, we define a parameter called SpO2 which is the ratio of the oxyhaemoglobin present in blood to the total haemoglobin content of the blood. SpO2 levels are a measure of physical well-being. Normal SpO2 levels are considered to lie in the range of 95-99. If the level is below 90 percent, it is considered low, resulting in conditions like hypoxemia. Blood oxygen levels below 80 percent may compromise organ function, such as the brain and heart, and should be promptly addressed. There is a need for low-cost physiological monitoring solutions that are easy to use, accurate.

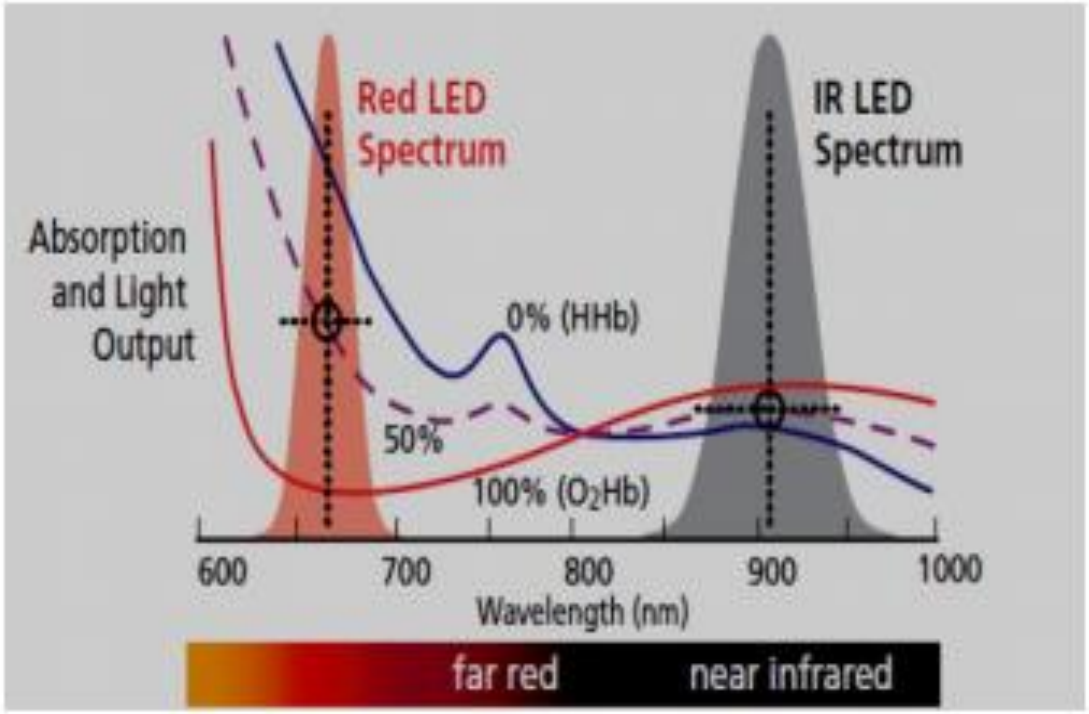


Figure Light Spectrum for SPO2

5.2 ALGORITHM

Pulse oximetry is a method used to determine the SpO2 level of the blood. Light which is not absorbed by the tissue is measured by photo detector. Pulse oximetry is based on the principle that pulsatile blood absorbance of IR or red light changes with regard to degree of oxygenation.

The signal at the receiver is divided into two parts:

The AC component which is due to the pulsatile arterial blood

The DC component which is due to tissue background, venous blood and constant part of arterial blood flow.

The DC component is subtracted while the AC component is amplified.

The DC and AC parts can be used to calculate the SpO2 level in the blood as given by the formula:

$$SpO_2 = A - B\frac{AC_{RED}/DC_{RED}}{AC_{BLUE}/DC_{BLUE}}$$

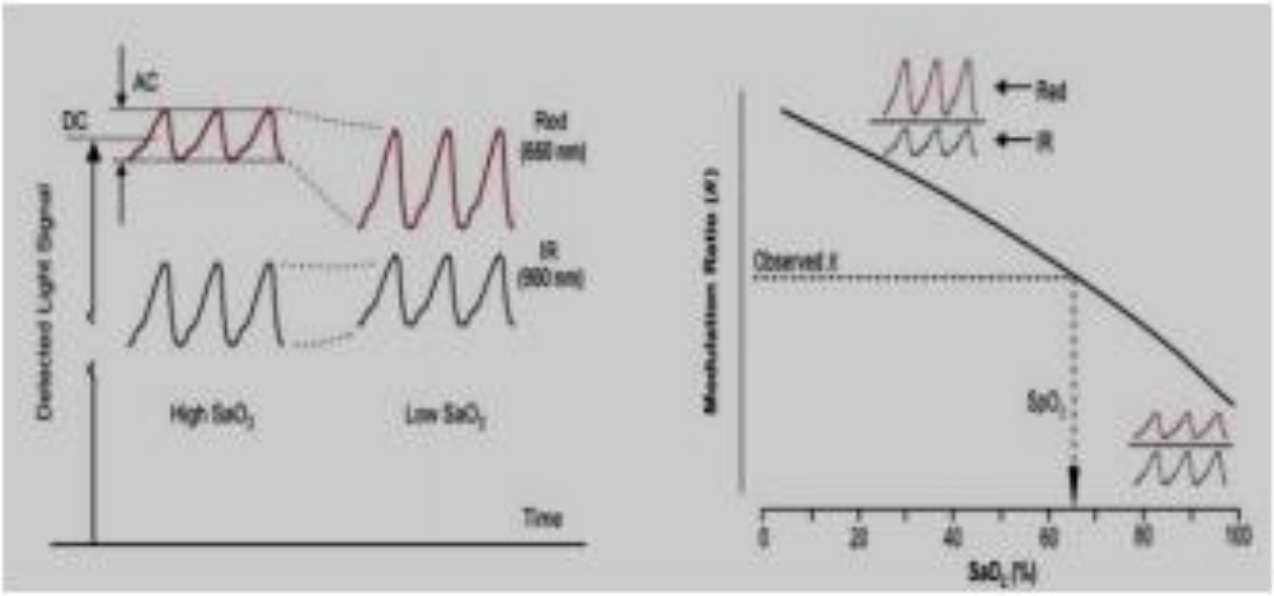


Figure AC & DC component for SPO2

Where, A and B are parameters that can be obtained by matching the SpO2 graph obtained here with a graph that is obtained by a standard pulse oximeter.

A and B values are found to be 5 and 100 respecively.

5.3 IMPLEMENTATION

Generally receivers look for the amount of absorption in red and infrared light . However, to do away with the need for a separate infrared light source, blue light can be used as substitute. This is possible because results obtained with blue light are similar to those obtained within infrared light.

The detailed steps are:

A. First Step

The first step of the algorithm involves the recording of a small video clip of around 20 seconds. Around 20 second is essential for the calculated values to stabilize. The user has to keep his index finger on the lens for the duration the video is to be recorded. Then the flash light of camera passes through finger.

B. Second Step

Then all the frames of video are extracted.

C. Third Step

After the extraction of the frames, they are parsed into an image holder where they were processed one by one. Each frame is resized to 320X240 pixels for reduced computation time. Each frame is separated into its red and blue constituents. The following parameters are calculated for each image: mean of red color component (mr), mean of blue color component (mb), standard deviation of red color component (sdr) and the standard deviation of blue color component (sdb). Here, mr corresponds to the red DC value, mb to the blue DC value, sdr to the red AC value and sdb to the blue AC value. These values are substituted in equation , to calculate the SpO2 level.

D. Final Step

1. SpO2 calculated between 96 and 99 ……Result → Healthy
2. SpO2 calculated <95…… Result→The user should try again, if values persist, he should cross check his values with standard equipment.
3. SpO2 calculated <95…… Result→ Case of worry and should consult a doctor immediately.

6. BLOOD PRESSURE ESTIMATION

6.1 INTRODUCTION

Blood pressure, commonly abbreviated as BP is the pressure exerted by blood, on blood vessels. Following the periodic nature of blood pumping by the human heart, BP goes through a periodic change. However, the maximum (systolic) and minimum (diastolic) BPs measured are considered to reflect heart condition well enough. Abnormal BP can cause hypotension (low BP) or hypertension (high BP). Detection of these medical conditions helps physicians to perform a root cause analysis of the visible symptoms, e.g. a high BP can be a direct result of vessel narrowing, or vasoconstriction, low BP can lead to low heart rate, heart valve problems and so on.

In this project we have proposed several time and frequency domain features, to achieve robustness in BP estimation from PPG. These features are further processed to form a subset of features, using Maximal Information Coefficient (MIC). Machine learning based approach has been deployed to estimate BP values.

Table 1. Blood Pressure Bin Levels (in mm Hg)

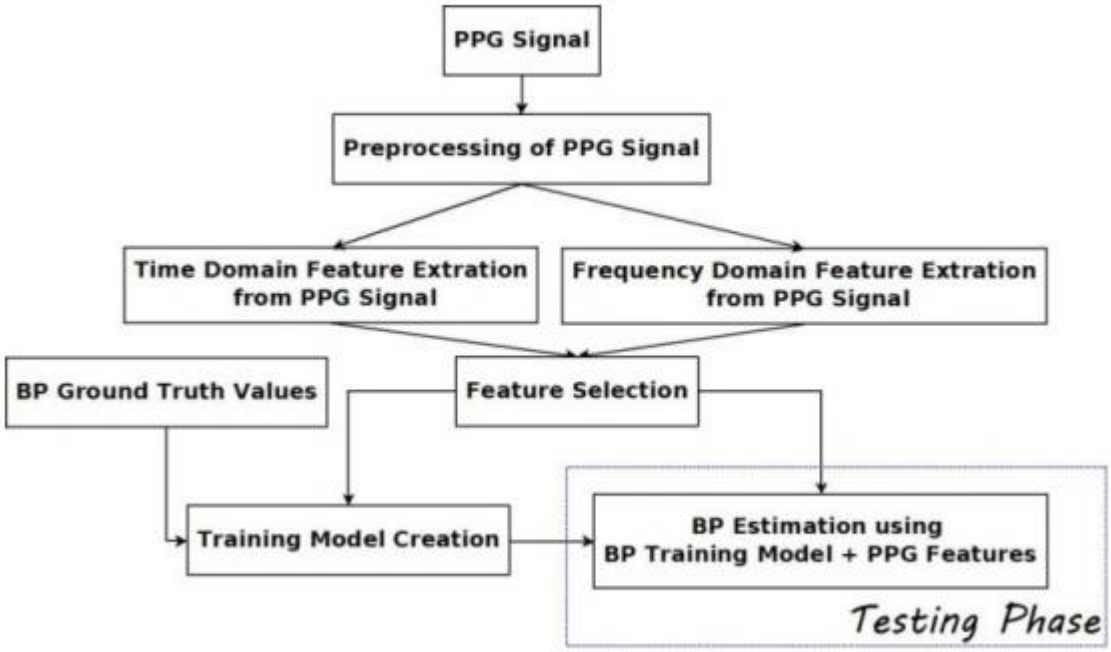
BP Level	Systolic (P_s)	Diastolic (P_d)
Hypotension	<90	<60
Desired	90-119	60-79
Prehypertension	120-139	80-89
Stage 1 hypertension	140-159	90-99
Stage 2 hypertension	160-179	100-109
Hypertensive emergency	>=180	>=110

6.2 METHODOLOGY

6.2.1 OVERVIEW

We first preprocess the PPG signal and derive certain features from it thereby establishing relationship between arterial BP with certain selected PPG features, namely systolic upstroke time,diastolic time,width of half pulse amplitude, and width of two-third pulse amplitude.

Fast Fourier Transform is also applied on the PPG signal to transform the signal into frequency domain. Now from this frequency domain signal certain are extracted. The most dominant spike in the frequency spectrum corresponds to cardiac beat and the remaining spikes are associated with the location and amplitude of the waves reflected from the periphery towards the aorta, the frequency spectrum in reality gives us a picture of the blood flow which is in turn related to the BP.



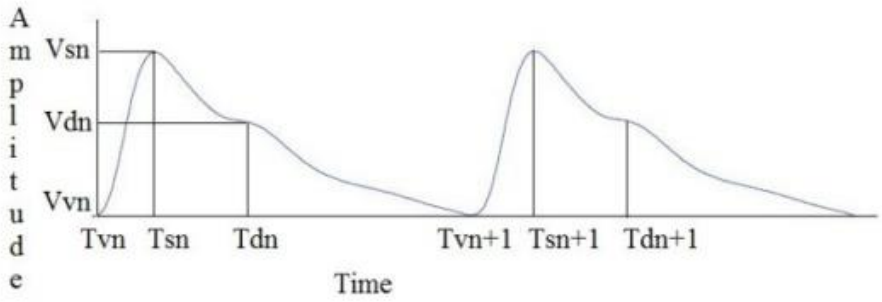
BP Estimation methodology from PPG Signal

6.2.2 FEATURE EXTRACTION FROM PPG SIGNAL

Twelve time domain features and seven frequency domain features are extracted from the PPG signal, which are used for creatingtraining models for BP estimation.

6.2.2.1 TIME DOMAIN FEATURE EXTRACTION

The peaks of the PPG signal are analysed along with their neighbouring troughs and dicrotic notch points. Fig. 2 shows 2 cycles of a sample PPG signal, where (Tsn, Vsn) is the peak point, (Tvn, Vvn) is the trough point and (Tdn, Vdn) is the dicrotic notch. Based on the above 3 important points, features can be calculated for each cycle in the PPG signal. The 12 time domain features, FT= [f1 , f2 , f3 ,…f11,f15], used in this method are shown in Table.

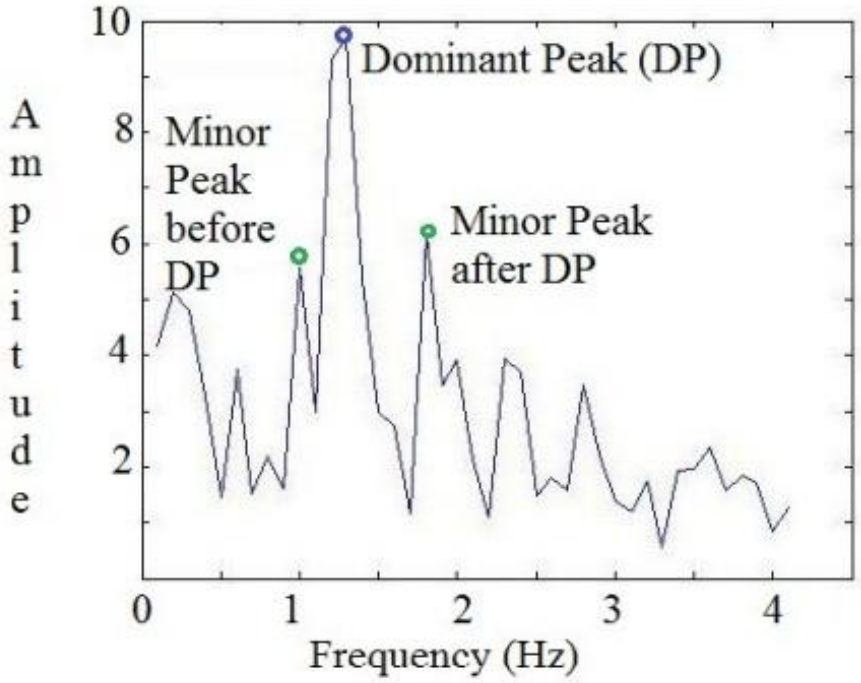


PPG signal for Time Domain Feature Extraction

f_1: Trough Point V_{vn}		
f_2: Systolic Peak Amplitude V_{sn}	f_7: Area Ratio f_6/f_5	
f_3: Dicrotic Notch Amplitude V_{dn}	f_8: Peak Interval T_{sn+1}-T_{sn}	f_{12}: Age of the subject in year
f_4: Pulse Area f_5+f_6	f_9: Pulse Interval T_{vn+1}-T_{vn}	f_{13}: Height of the subject in cm
f_5: Systolic Area $\Sigma_{Tsn}^{T}{}_{dn}$ PS	f_{10}: Crest Time T_{sn}-T_{vn}	f_{14}: Weight of the subject in kg
f_6: Dicrotic Notch Area Σ_{Tdn}^{Tvn+1} PS	f_{11}: Delta Time T_{dn}-T_{sn}	f_{15}: Pulse Height V_{sn}-V_{vn}

6.2.2.2 FREQUENCY DOMAIN FEATURE SELECTION

To enhance the training model and to improve the estimation accuracy, a combined approach of time domain features and frequency domain features needs to be used. The Frequency spectrum of the PPG signal is obtained by applying Short Time Fourier Transform, which consists of several peaks, with the dominant peak related to the heart rate of the person. Based on the dominant peak and the neighboring peak before and after the dominant peak, seven features are extracted, FF=[f16, f17, …,f22], as shown in Table.



f_{16}: Dominant Peak Location	
f_{17}: Distance between minor peak locations, one before and after the dominant peak.	f_{20}: Dominant Peak Amplitude
f_{18}: Distance between dominant peak and previous peak	f_{21}: Width of Dominant Peak
f_{19}: Distance between dominant peak and next peak	f_{22}: Spectral Centroid

6.2.3 FEATURE SELECTION

Features, having little or no predictive content and redundant features can be successfully eliminated by applying a feature selection algorithm. Feature selection can significantly improve the transparency of the classifier model and in most cases, boost up the classification accuracy up to a certain level.

In this project we have proposed an effective feature extraction approach using the concept of Maximal Information Coefficient (MIC).

It states that if a relationship (linear or non-linear) exists between two real data variables, then constructing optimized grids with various sizes to find the largest mutual information between a pair of data will return a fractional number between 0 and 1. This MIC value indicates the dependency between the pair of number. Higher the MIC value, stronger is the association between the data pair. Mathematically, for a pair of dataset x and y, if I denotes the mutual information for a grid G, then MIC of a set D of pairwise data with sample size n and grid size (xy),less than B(n) is given by

$$MIC(D) = max_{xy<B(n)} \{M(D)_{x,y}\}$$

Where $B(n)$ is a function of sample size (usually $B(n)=n^{0.6}$).

Our aim is to maximize I/ log min(x,y) – which gives the MIC score.

For a particular BP parameter, the subset of features to be used is determined if the MIC value for a particular feature is greater than the median value of the set of MIC values found for all the features. Using this approach, the feature subset for Ps and Pd is determined to be f1, f3, f12-f22.

6.2.4 MODEL CREATION AND ESTIMATION

The subset of features thus obtained by performing feature selection is used for training the linear regression model using cross validation technique in matlab. The Final model thus created and trained on the PPG features are then loaded into the application system for future prediction of the Blood Pressure values. The data on which the model is trained is taken from the Queensland Vital Signs Dataset.

7.OUR APPLICATION

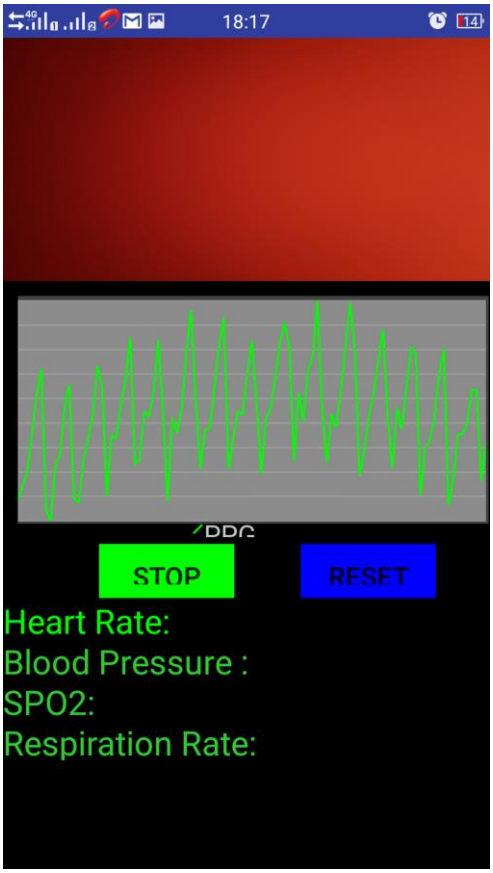
Finally, we were able to develop the application incorporating all the above theories and algorithms. Below is our application user – interface.

Figure. The user should first

1.Open the application and then

2. Place the index finger behind the camera.

3.Tap the start button.



Continuous recording of the changing intensities of blood at the finger-tip.

The real time PPG signal being constructed by plotting the mean blood intensities of the incoming frames against time.

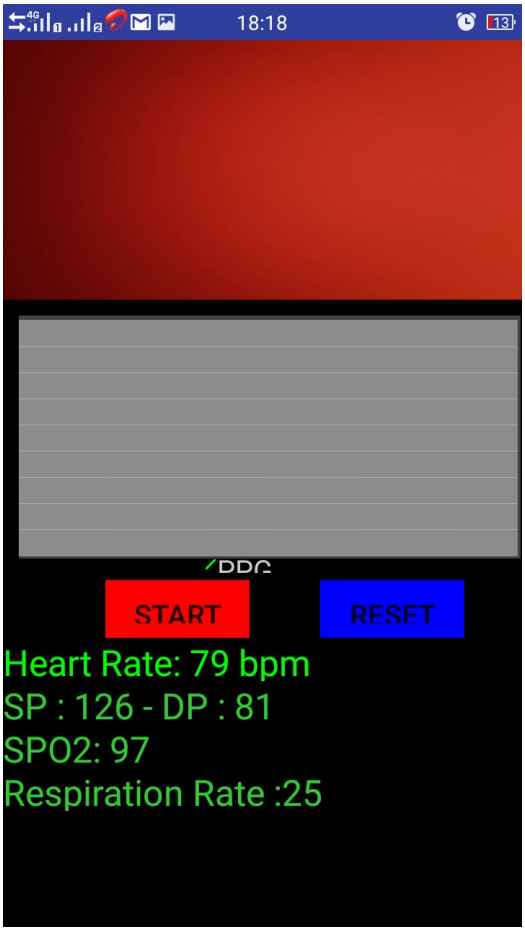
After user stops the recording the respective fields will show the respective values calculated.

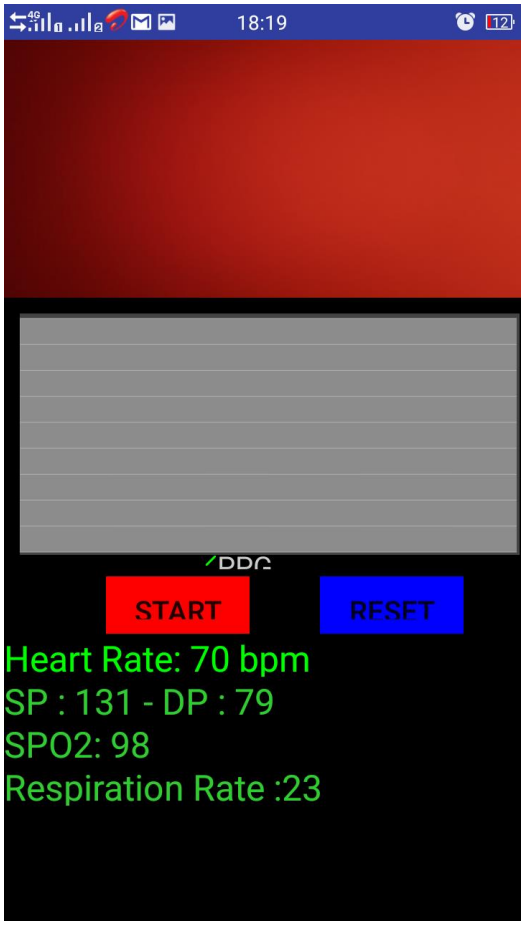
OUR APPLICATION UI

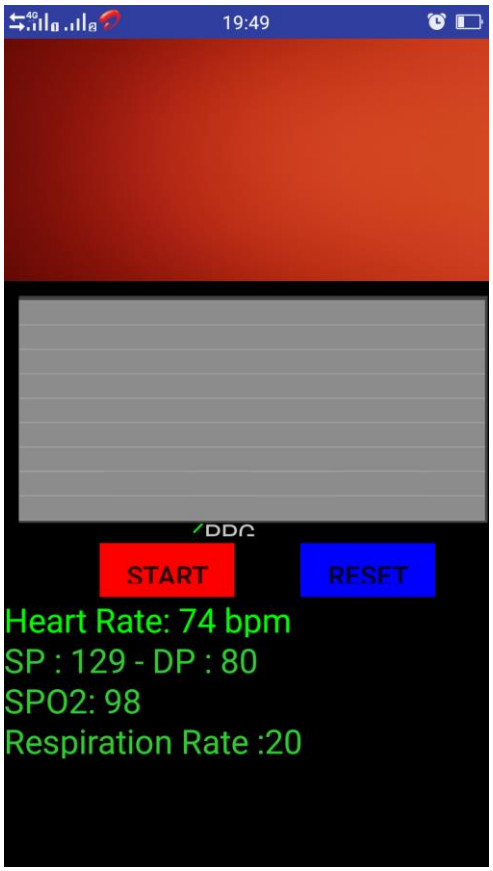
8. EXPERIMENTAL RESULTS

Finally the application was tested on 5 different persons with different health conditions.

The screenshots of the respective results are attached.







The accuracy level for our application is good but not perfect, but we tried to get closely accurate result.

CHALLENGES

- It requires high quality camera –
    - To measure even the slight change in the intensity of blood.
- It is affected by change in pressure of finger applied on the camera.
    - The pressure should be kept as constant as possible.
    - Change in pressure results in change of intensity of the frame
        - Which in turn affects the ppg waveform.
        - Thus, affecting heart rate and other health parameters. (BP ,SPO2,RR).
- This technique is not suitable for people suffering from involuntary muscle movement disorder(for example tremor).
- Due inaccuracy of the PPG waveform obtained it is very difficult to calculate the different features of the signal.

CONCLUSION

Android Smart phone with good quality camera has come to the reach of common people and has become one of the most necessary and powerful device for today and of course, for future generation. We can use its powerful features to solve or assess some novel problems occurring in our daily health and we can also enhance existing features to make smart phone more powerful without using any additional device for health monitoring . Preventive cardiology, holds lot of promise, but easy to use and widely available hardware is necessary to make it an effective tool against cardiovascular diseases. In this project we had seen that mobile camera can be effectively used for recording important parameters like heart rate , blood pressure, respiration rate and SPO2.

FUTURE SCOPE

Till now we have implemented some of the Health related parameters. Our target is to develop an Accurate Cardiovascular Health Monitoring Tool with the help of Android Camera and other Android Sensors available to capture video, movements. Some other parameters like glucose, blood sugar etc can also be incorporated. In future an algorithm can be implemented for gesture recognition and emotion detection. The accuracy of the application can also be improved in future.