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Abstract:	Photo plethysmography(PPG) signals are universally accounted for in healthcare units due to their non-invasive nature and effectiveness. They are used to calculate heart rate(HR), heart rate variability(HRV), and other parameters. The PPG measurement is moving from the traditional setup to acquire the data with the help of LED and photodetector to image-based data acquisition with the help of cameras called i-PPG signals. This study compares PPG with i-PPG signals captured using a smartphone's front camera, especially in calculating heart rate and its variability. Fifteen healthy volunteers participated for this purpose. Data were recorded in a calm and quiet environment to avoid interference in the signals. The reference value of the volunteers' heart rate was obtained using a commercially available standard pulse-oximeter and Omron BP monitor. PPG signals were collected using a red LED with a wavelength of 660nm in the circuit built with the MAX30102 sensor. Then videos of the right index finger of the volunteers were captured for a duration of 2 minutes. The videos were processed to extract the i-PPG signals, and then both signals (i-PPG and PPG) were pre-processed to remove baseline drift. The heart rate series of both signals was obtained by calculating the time interval between adjacent peaks and multiplying its inverse by 60. The heart rate variability series was also calculated by taking the difference between two adjacent inter-peak intervals. The heart rate obtained from the sensor circuit has a positive correlation of 0.87, and 0.94 with that from Pulse oximeter and BP monitor respectively. Similarly, the HR values obtained from i-PPG signals have a positive correlation of 0.79, and 0.86 with that obtained from reference methods. However the HRV values were in the range of 650 to 900ms which is much higher than the normal range. It is significant to note that there were fluctuations while obtaining reference heart rate values.

Comparison of PPG Signals with i- PPG signals for the calculation of heart rate and heart rate variability

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Abstract

Photoplethysmography(PPG) signals are universally accounted for in healthcare units due to their non-invasive nature and effectiveness. They are used to calculate heart rate(HR), heart rate variability(HRV), and other parameters. The PPG measurement is moving from the traditional setup to acquire the data with the help of LED and photodetector to image-based data acquisition with the help of cameras called i-PPG signals. This study compares PPG with i-PPG signals captured using a smartphone's front camera, especially in calculating heart rate and its variability. Fifteen healthy volunteers participated for this purpose. Data were recorded in a calm and quiet environment to avoid interference in the signals. The reference value of the volunteers' heart rate was obtained using a commercially available standard pulse-oximeter and Omron BP monitor. PPG signals were collected using a red LED with a wavelength of 660nm in the circuit built with the MAX30102 sensor. Then videos of the right index finger of the volunteers were captured for a duration of 2 minutes. The videos were processed to extract the i-PPG signals, and then both signals (i-PPG and PPG) were pre-processed to remove baseline drift. The heart rate series of both signals was obtained by calculating the time interval between adjacent peaks and multiplying its inverse by 60. The heart rate variability series was also calculated by taking the difference between two adjacent inter-peak intervals. The heart rate obtained from the sensor circuit has a positive correlation of 0.87, and 0.94 with that from Pulseoximeter and BP monitor respectively. Similarly, the HR values obtained from i-PPG signals have a positive correlation of 0.79,

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Keywords: , i-PPG, PPG, HR, HRV

1. Introduction

Heart rate (HR) in beats per minute (BPM) is the most common yet most significant parameter to check one's health condition even during and post COVID pandemic. The conventional ways to determine heart rate include manual palpation and other assistive devices like pulse oximeter and BP monitor. Now fitness trackers like smart watches, and smartphone applications are also available for the same. They make use of PPG signals from the wrist or fingertip to calculate the same [1]. The PPG signals recorded with the help of a camera are called image-based photoplethysmography signals (i-PPG) and it has more significance [2-7] Many researchers have published papers utilizing the features of i-PPG signals.

Lin Qi et al estimated heart rate from rPPG (remote photoplethysmography) obtained from facial video of subjects using the method called 'Project ICA' along with temporal filtering and Fast Fourier Transform and compared the results with four other methods. Their dataset comprises 112 videos of 28 subjects including people of pale and dark skin tones and they concluded that they got the correlation value of 0.98 and 0.50 for respective skin tones under stationary conditions [8]. Mejia-Mejia et al reviewed the potential of PPG signals that can be used to determine heart rate, heart rate variability, prediction of hypertension, assessment of diabetes, etc. It is concluded that the PPG signals not only possess information on the cardiovascular system but also autonomic diseases[9]. Similarly Ge Xu et al worked on disease classification based on IPPG [10].Geng et al estimated heart rate from facial videos from two sets of cameras under resting, talking, and head rotating conditions. They used the green channel data for which they obtained lower MAE[11]. Mc Duff et al employed the Lomb-Scargle method and Bayesian Spectral method for evaluating pulse rate variability from iPPG signals and contact-type PPG signals. They concluded that the Bayesian Spectral method has more advantages compared to the other method. [12].Luo et al developed algorithms to classify cardiovascular diseases by analyzing the facial videos with the forehead as the region of interest. Features from i-PPG signals were obtained and got a weighted F1 score of 0.900 [13]. Hernandez-de la Cruz et al conducted a study to calculate heart rate and respiratory rate from the smartphone-based i-PPG signals of 5 healthy volunteers and compared them to ECG waveform and respiratory effort band. They got mean correlation index around 0.69 for respiration rates and MAE of around 1 for heart rate[14]. Arya Deo Mehta et al calculated heart rate from web and phone camera videos by using homomorphic filtering, color space transformation, Empirical Wavelet Transform (EWT), and PCA techniques. The estimated results have an MAE of 1.81 and a Standard deviation of 3.77 [15].Neha Singh et al estimated heart rate and respiratory rate from facial webcam videos under ambient light using green channels and non-negative matrix factorization [16]Wurtenberger et al. collected videos using a fast hyperspectral imager using the wavelengths of 799nm and 861nm and calculated heart rate with MAE of 1.67 bpm. [17].Quoc-Viet Tran et al captured subtle face changes using a Logitech camera parallelly with fingertip PPG using a MAX30105 sensor under different scenarios such as translation, rotation, mix-motion, biking, running to estimate heart rate and obtained average RMSE of 6.93 bpm[18].Ryan S. McGinnis et al proposed an algorithm for the estimation of heart rate for panic attack tracking by collecting videos of a fingertip pressed on a smartphone camera for 30 seconds and comparison of the same with ECG signals obtained a correlation value $r > 0.99$[19].From all the literature cited above we find that i-PPG signals are used to determine HR values and they have obtained good correlation when compared to gold standard.

Several papers suggest that the word pulse rate and heart can be used interchangeably under controlled conditions. The gold standard method to compare the obtained HR values is ECG signals but the validity of comparing ECG-based HR to smartphone-based i-PPG signals' HR has been studied and the correlation was found to be more than 0.98.[19] Some literatures support on the usage of green channel[5, 16, 10] for the calculation of HR and HRV,some support the usage of red channel[20] and some used combined channels[4].The scope of this study is to compare the smartphone-based i-PPG signals with MAX30102-based PPG signals by estimating HR and HRV. In that regard, PPG and i-PPG signals were collected from healthy individuals and then compared with commercially available pulse-oximeter and digital BP monitor as reference.

2. METHODOLOGY

The methodology followed to determine the HR and HRV from PPG signals is explained in detail.

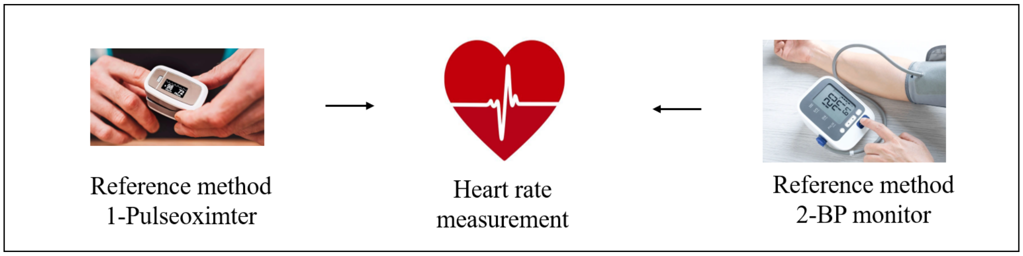
2.1. Experimental setup

The hardware setup developed consists of a MAX30102 sensor which has Red (660nm) and IR (880nm) LEDs, a photodetector with a range of response between 600nm and 900nm connected to a microcontroller. It has the dimensions of 5 x 6 x 2 cm. For the measurement of heart rate, only the signals from the red LED were used.

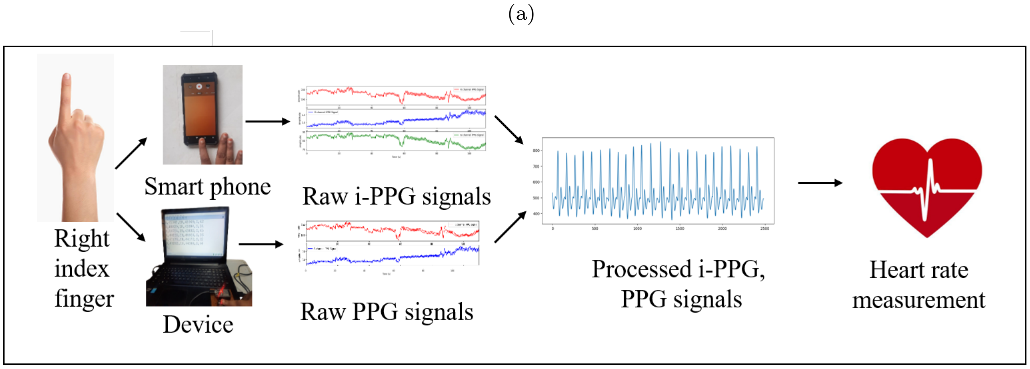
2.2. Data collection

Ethical committee clearance was obtained from Institutional Ethical Committee for Students on Human Subjects (IECH) of Vellore Institute of Technology, Vellore. Then informed consent forms were obtained from the volunteers who participated in the study. Fifteen healthy individuals including 9 women and 6 men with the age group of 21 and 55 were involved. The reference heart rate values were observed using a commercially available digital blood pressure monitor from OMRON and the DR Trust pulse-oximeter. The test PPG signals were collected with the help of the hardware setup constructed in the lab and the test i-PPG signals were collected from the smartphone SAMSUNG M31S for 2 minutes.

The entire data collection took place for a total duration of approximately 7 minutes per person in a calm environment with ambient light. Each volunteer was seated comfortably and the reference heart rate from both devices was observed as shown in Fig1(a). Then the volunteers were asked to place their right index finger on the hardware setup connected to the personal computer for 2 minutes. The sampling rate of the hardware setup is 16.5 samples per second. After that, they were asked to place their right index finger on the front camera of the smartphone to record the video for 2 minutes. The mobile camera operates at 30 frames per second. The recorded video was converted into i-PPG signals and then pre-processed for the calculation of heart rate as shown in Fig1(b).



(a)



(b)

Figure 1: (a)reference methods for heart rate measurement and (b) Proposed methods for heart rate measurement

2.3. Data pre-processing

i-PPG signals (S) were obtained from the collected videos by converting them into frames and taking the average of each frame for RGB channels [21]. Motion artifact, baseline drift, and 50 HZ interference are the most common noises present in both i-PPG and PPG signals. i-PPG signals obtained from the red channel and PPG signals obtained from the red LED were considered for this study. The first and last 30 seconds of data from both signals were removed to reduce the motion artifacts. These signals were filtered using the 4th order butterworth bandpass filter [19] with a frequency range of 0.9Hz – 7Hz (S1). The moving average of the signal was taken and this operation is equivalent to applying an average low pass filter. The moving average equation is given in the equation (1)

$$MA = \frac{1}{k} \sum_{i=n-k+1}^{n} P_i \tag{1}$$

where MA is the moving average, k is the size of the window and is based on the frequency of the data used (for PPG k = 16, iPPG = 30), Pi is the signal, n is the number of data points in the signal Pi [8]. Then the difference between a sample signal and its moving average values was obtained to smoothen the signal (S2) and it is in the form of a 1D array. This is equivalent to the operation of a high-pass filter. Hilbert transform is used to get the envelope of the signal. The Hilbert transform formula is given in the equation(2).

$$Ht(x(t)) = \tilde{x} = \frac{1}{\pi}\int_{-\infty}^{\infty}\frac{x(\tau)}{t^{\tau}}d\tau \tag{2}$$

where Ht(x(t)) is the Hilbert transform of the signal x(t). The ratio of this smoothened array (S2) to the moving average of the Hilbert-transformed signal (S3) resulted in normalized noise-reduced PPG signals (S4)[22]. The pre-processing steps are shown in Fig.2

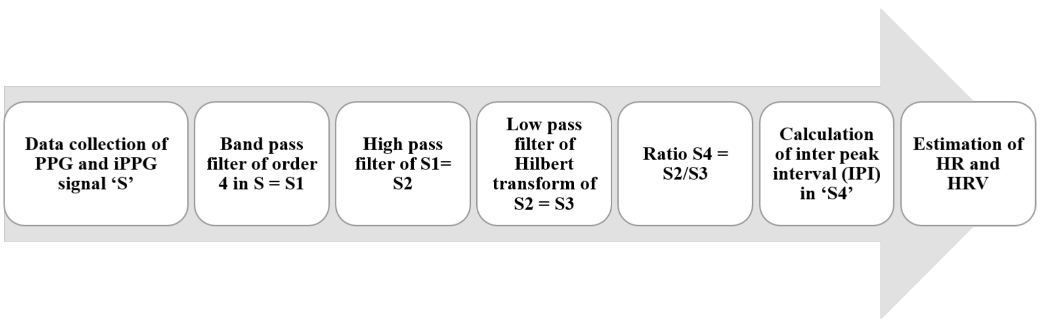


Figure 2: Data processing

2.4. Signal quality analysis

The preprocessed signal is analyzed for its quality. This step is important to remove the outliers in the dataset. It is done by calculating the perfusion index of the signal as expressed in the equation (3).

$$PI = \frac{SD[x(t)]}{Mean[x(t)]} \tag{3}$$

where PI = perfusion index, x(t) = signal (S4), SD = standard deviation. The signal whose PI value is more than 100 was considered as an outlier and was removed.

2.5. Calculation of HR, HRV

The signals were then processed to detect the peaks and the time interval between consecutive peaks were noted. The ratio of 60 and the time interval difference was calculated and a heart rate series was obtained from both PPG and i-PPG signals using the equation (4).

$$HR = \frac{60}{IPI} \tag{4}$$

where IPI is the inter-peak intervals [5]. Then the outliers in the heart rate series were removed with the help of median absolute deviation (MAD) [19] as in the equation (5).

$$m = |x_i - med(x_i)| \tag{5}$$

where m is the median absolute difference, x_i is the data series, $med(x_i)$ is the median of the data series. The data with m value greater than 10 were removed. The difference between consecutive IPI gives heart rate variability (HRV) series If 'n' number of peaks were noted, (n-1) number of heart rate and (n-1) number of heart rate variability readings would be obtained from the signal. In this study, the minimum number of peaks considered is, n = 80.

2.6. Evaluation metrics

To evaluate the correctness of the results obtained the metrics such as Spearman correlation, mean absolute error, and Bland-Altman plots were used to analyze the data.

2.6.1. Spearman correlation coefficient (r)

'r' was obtained between two series by using the equation (6). It reveals whether two inputs are highly related or not.

$$r = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \tag{6}$$

where d_i^2 is the square of difference between the ranks assigned to variables 1, 2, and n is the number of data points. If the r value is nearly equal to 1 the variables are closely and positively correlated, and if it is nearly -1, then they are negatively correlated. If r=0, then they are uncorrelated.

2.6.2. Mean Absolute Error (MAE)

MAE was obtained using the equation (7). It is the measure of the difference between reference data (yi) and obtained values (xi) for n number of data points.

$$MAE = \frac{\sum i = 1^n |y_i - x_i}{n} \tag{7}$$

2.6.3. Bland Altman (BA) plot

It is used to find the terms of agreement between the output of two methods (I and II) for the same volunteers. It is obtained by taking the difference between the variables and plotting against their means. Then the mean difference is calculated and drawn. Finally, the upper and lower limit with a 95 percent confidence interval is calculated with the help of the formula in the equation (8).

$$Limits = \bar{d} \pm (1.96 \times std(d_i)) \tag{8}$$

where $\bar{d}$ is the mean of differences and std(d_i) is the standard deviation of differences di. If the upper limit is A and lower limit is B then it is concluded that the output calculated using method II might be A units above or B units below method I[4].

3. Results and discussion

Once the series of heart rate and heart rate variability data were obtained, mean heart rate and heart rate variabilities from i-PPG (mHR3, mHRV1) and PPG (mHR4, mHRV2) were calculated and tabulated along with the HR values observed using a pulse oximeter (HR1) and BP monitor (HR2), gender, and age of the subjects in Table 1. The HR values observed and obtained were in the range of 64 and 100 beats per minute. The maximum HRV of 0.91 and 0.95 seconds with an average HR value of 65.16 beats per minute was observed for subject 2 and the minimum HRV of 0.67 and 0.66 seconds was observed for subject 5 with an average HR value of 95.18 beats per minute. All the HRV values were under 0.96 seconds which are 10 times higher than normal values.

Table 1: Calculation of HR using pulse-oximeter (HR1), digital BP monitor (HR2), IPPG (HR3), PPG (HR4) and HRV using IPPG (HRV1) and PPG (HRV2)

SNO	Age	Gender	HR1 bpm	HR2 bpm	mHR3 bpm	mHRV1 seconds	mHR4 bpm	mHRV2 seconds
1	21	F	70	69	75.00	0.80	73.84	0.79
2	29	M	65	65	66.66	0.91	64.0	0.95
3	30	F	78	77	75.00	0.78	73.84	0.79
4	33	M	70	77	81.81	0.71	76.92	0.76
5	37	F	90	100	94.73	0.67	96.00	0.66
6	42	F	76	74	78.26	0.80	73.84	0.78
7	42	F	80	77	75.00	0.79	73.84	0.82
8	52	M	83	84	85.71	0.73	80.00	0.80
9	52	F	90	87	85.71	0.69	80.00	0.72
10	55	F	82	85	81.81	0.75	80.00	0.73

Mean absolute error was calculated among reference values and calculated values. These were tabulated in Table 2. The maximum MAE was obtained between HR1 and HR3 with the value of 11.81 BPM for subject 4 and the minimum MAE = 0.07 was obtained for the same subject when calculated between HR2 and HR4. This is may be due to the vast difference observed between the reference values of heart rate, especially for the subject 4,5.

The Spearman correlation was calculated among HR1, HR2, HR3, and HR4. The values are shown in the form of a matrix in the Fig 3. It is evident that the values obtained from i-PPG and PPG signals are correlated with an r-value of 0.96 and the same recorded from reference methods has an r-value of 0.93. The r value is greater when the reference method 2 (BP monitor) is involved.

The Bland Altman (BA) plots between the HR series with a 95% limit of agreement are shown in Fig4. The Fig 4(a) is the B A plot between the two reference methods (HR1 and HR2) and has a mean difference of -1.1 bpm and the same between PPG and i-PPG signals were 2.74 as in Fig 4(e). The least mean difference of -0.47 bpm was observed in the B A plot between the HR values from the BP monitor (HR2) with those from the i-PPG signals (HR3) as shown in Fig 4(d) compared to the mean difference of 1.57 bpm

Table 2: Mean Absolute Error calculated between IPPG and PPG with pulse-oximeter and BP monitor readings

SNO	MAE in bpm				
	HR1 with HR2	HR1 with HR3	HR2 with HR3	HR1 with HR4	HR2 with HR4
1	1	5.00	6.00	3.84	4.84
2	0	1.66	1.66	1.00	1.00
3	1	3.00	2.00	4.15	3.15
4	7	11.81	4.81	6.92	0.07
5	10	4.73	5.26	6.00	4.00
6	2	2.26	4.2	2.15	0.15
7	3	5.00	2.00	6.15	3.15
8	1	2.71	1.71	3.00	4.00
9	3	4.28	1.28	10.00	7.00
10	3	0.18	3.18	2.00	5.00

Correlation	Pulse-oximeter	BP monitor	IPPG	PPG
Pulse-oximeter	1	0.93	0.79	0.87
BP monitor	0.93	1	0.86	0.94
IPPG	0.79	0.86	1	0.96
PPG	0.87	0.94	0.96	1

Figure 3: Correlation of heart rate calculated among 4 methods

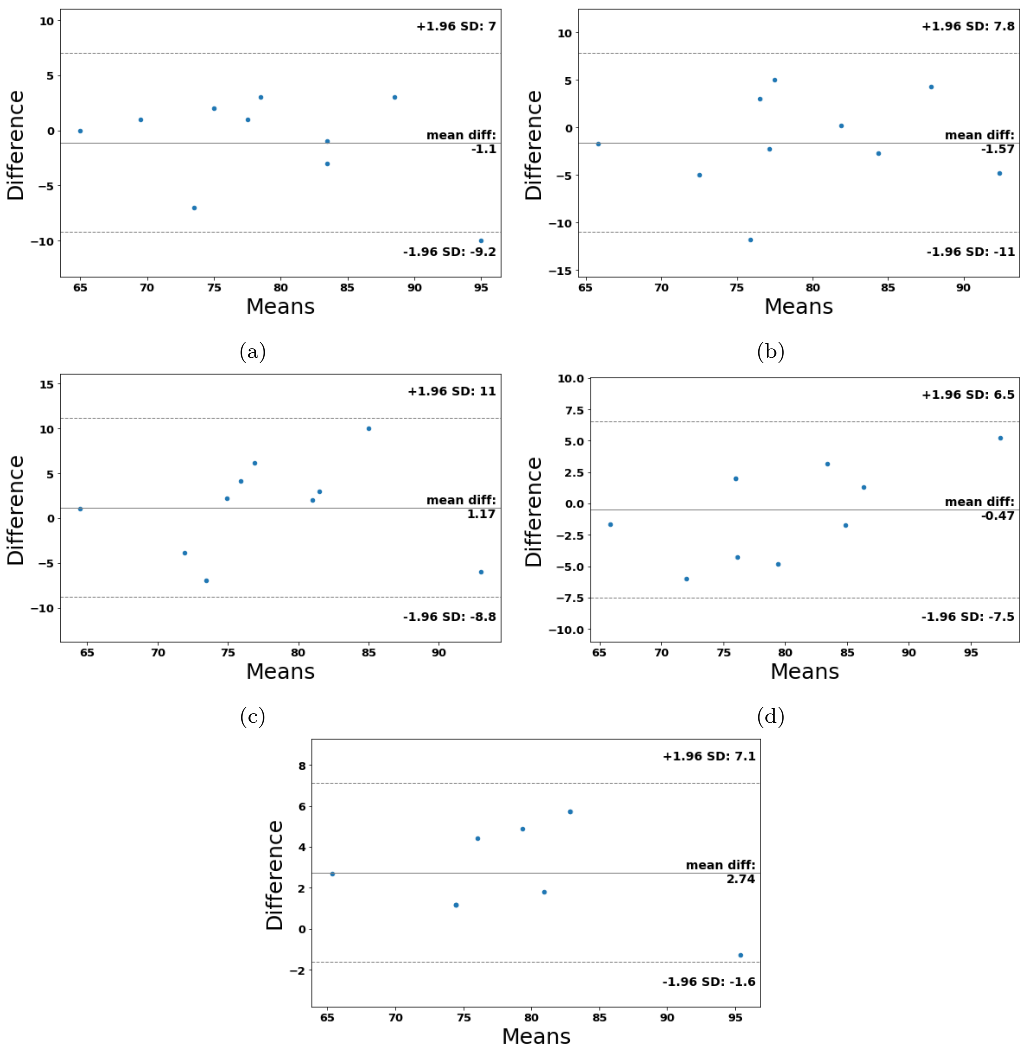
between HR1 and HR3 as in Fig 4(b) and of -1.17bpm between HR1 and HR4 as in Fig 4(c) It should be noted that the range of upper and lower limits is also less for the same plot compared to the other plots.

4. Conclusion

In this study, an algorithm was developed to calculate HR and HRV from i-PPG and PPG signals. In that regard video of the right index finger for 2 minutes and a PPG signal from the circuit for the same duration were recorded for the 15 healthy volunteers. The HR values observed using commercially available pulse-oximeter and BP monitor were taken as reference methods 1 and 2. For calculating heart rate all r,g,b channels, and r,ir signals were considered and calculated. Based on the results obtained only the red channel from the smartphone and hardware setup designed were more suitable than the other signals.

Once the results were obtained interquartile-based outlier removal methods were used. The Spearman correlation r-values between i-PPG and reference methods 1 and 2 were 0.78 and 0.88 and r-values between PPG and reference methods were 0.77 and 0.84. when the outliers were removed using median absolute deviation (MAD) based methods the r-values for i-PPG signals were found to be 0.79 and 0.89 and the same for PPG signals were improved to 0.87 and 0.94. These results can be compared to HR calculation by Xinchi Yu et al in 2020 [23] and Anusha Krishnamoorthy et al. in 2023[24]. Empirically the MAD methods are more suitable for this study. Both the i-PPG and PPG signals were more correlated to the values observed from the BP monitor. This fact is evident in the BA plots also.

The HR values obtained were in the range of 65 and 100. This algorithm works well for people with no co-morbidities. The results can be compared to the study by Robert Avram et al [25]. The HRV values were below 1 second. The volunteers who participated in the study are people who do physical work and the readings were taken during their break time. The study has to be expanded to more number subjects of different ages, geographical locations, and skin color. The results of PPG signals were better compared to i-PPG signals but the efficiency of the algorithm for i-PPG signals can be improved by the inclusion of lightweight machine learning and neural networks. It can be upgraded in the form of a smartphone application which enables the



(a) (b) (c) (d) (e)

Figure 4: Bland Altman plots of a) HR1 with HR2, b) HR1 with HR3, c) HR1 with HR4, d) HR2 with HR3, e) HR4 with HR3

subject to use the application in their comfort zone and in case of emergencies to estimate not only HR, HRV but blood pressure, oxygen saturation.

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