2018 4th International Conference for Convergence in Technology (I2CT)
SDMIT Ujire, Mangalore, India. Oct 27-28, 2018

Heart Rate Measurement using Face Video with Noise Suppression

B.A Sujathakumari
Associate Professor,
Dept.of E&C, SJCE, Mysore
Karnataka, India
basujatha@yahoo.com

Shreeharsha BS
Dept.of E&C
SJCE, Mysore
Karnataka, India
harsha11235813@gmail.com

Prince Verma
Dept.of E&C
SJCE, Mysore
Karnataka, India
princeverma1711@gmail.com

Sathvik Shivram
Dept.of E&C
SJCE, Mysore
Karnataka, India
sathvik321@gmail.com

Raksha A.R
Dept.of E&C
SJCE, Mysore
Karnataka, India
rakshaar15@gmail.com

Abstract— **Heart rate is an important parameter to measure peoples health and physiological state. In this paper we propose a method which uses face tracking, heart rate estimation using Photoplethysmography and noise reduction using wavelet transforms. Remote photoplethysmography is a technique in which we can estimate heart rate, oxygen saturation etc from live or previously recorded video taken by a simple web camera. The reason we can estimate these physiological parameters is that blood flow in our arteries shows some periodic flow because the heartbeat is usually very regular over a small interval of time. The arteries and blood vessels in our face hence show minor variations in the amount of light reflected from the face which can be captured by the camera and then processed as a Blind Source Separation (BSS) problem. Here the rPPG signal was obtained from ICA, which is a statistical method of solving the BSS problem. In this context we use ICA in separating the reflected light signal into constituents such that each constituent is a result of reflection from a distinct source such as skin, lighting etc. ICA does not require any knowledge of the source at all. The non contact method developed here to measure the heart rate can have great value for home monitoring or security purpose.**

Index Terms—**Photoplethysmography (PPG),Independent component analysis(ICA), Blind source separation(BSS), heart rate, wavelet transforms.**

I. Introduction

Heart rate (HR) monitoring during fitness is important for enabling exercisers to control their training load. In past few years, humans physiological state has gained a lot of attention. Heart rate is the most important indicator of humans health state.In Recent years, we have seen increased attention being given to non-contact HR measurement. Non-contact HR measurement gives a great alternative compared to other electrocardiography (ECG) and photoplethysmography(PPG) based methods as direct contact of any sensors with skin should be avoided. [10]

A. Background

The heart rate measurements can be done in two ways:

1. Making contact with the patient.
2. Making no contact with the patient.

1) Contact based HR measurement: HR measurement is made by making contact with test subject, some of them are as follows:

1. Taking the pulse manually : The two most common locations used to take a pulse are at the radial artery in the wrist and the carotid artery in the neck. Position the fingers just below the base of the thumb to take the radial pulse at the wrist [2]. One way to manually take the pulse is to measure the radial pulse [4].
2. HR measurement using optical method : The design and development of a low powered HRM device provides an accurate reading of the heart rate using optical technology. It uses standard Light Emitting Diode(LED) and photo-sensor to measure the heart rate within seconds using index finger. A micro-controller is programmed to count the pulse.
3. HR measurement using ECG : The majority of ECG's are based on the need to place some electrodes on standard positions on the body surface. The main limitation is the requirement of maintaining direct contact between the bare skin of the subject and the electrodes which is fixed in the environment that limits the application of fixed-in-the-environment electrodes to a few cases [5].

2) Non-contact methods for heart monitoring: The other alternatives to standard heart monitor may require contacts and leads for its accurate placement and control. This may be possible or undesirable in many situations. This method has been divided into four categories, based on the working principle,

1. Electromagnetic-based HR monitoring system : A radar transmits a radio signal towards the target. The back scattered signals strength is measured. This method consists of two types of radar sensing used for heart rate

978-1-5386-5232-9/18/$31.00 ©2018 IEEE

monitoring i.e..., continuous wave (CW) and wide band pulsed radar (UBW)[4].
2. Laser-based HR monitoring system : It uses optic fiber cable, movement of blood in artery was measured in embedded blood vessel. The maximum gradient of skin displacement is proportional to the time derivative of the blood profile within underlying blood vessel. Thus detection of vibrations from human gives the performance of human heart [5].
3. Image-based HR monitoring system : The image based heart rate monitoring method is based on, the blood flowing in our arteries shows some periodic flow because the heartbeat is usually very regular over a small interval of time. The arteries and blood vessels in our face hence show minor variations in the amount of light reflected from the face which can be captured by the camera and then processed as a Blind Source Separation (BSS) problem. [6]

   The implementation using image based method is more preferred because this technique is much simpler compared to other non-contact based HRM systems since it does not involves the emission of electromagnetic radiations from a source (RADAR). The electromagnetic radiations are harmful for the human beings and involves a complex testing procedure. This method requires no contact with the patient, it is more comfortable and can be used in remote heart rate measurement.

B. Motivation

1. This is a very new technology to find the heart rate of an individual.
2. Most of the infants that undergo ECG several number of times, might unknowingly invite skin irritations and diseases.
3. ECG method also causes skin burns due to which it is less preferable.
4. It can be used for security and health monitoring purposes.
5. Electrical hazards due to appliances.

C. Objective

1. To detect the individuals face.
2. To keep track of facial parameters.
3. To display heart rate with maximum noise reduction.

II. Proposed Method

The block diagram of HR measurement using facial video shows the interfacing of the web camera with the computer system.The proposed method estimates HR by extraction of a raw PPG signal using ICA.

The method contains three main stage, i.e., Pre-processing to remove Motion artifacts, Face detection using Viola Jones algorithm and Face tracking algorithm using KLT algorithm, a spectral peak selection stage to estimate HR using ICA (maximum kurtosis), and a post-processing stage to reduce false peaks using discrete wavelet transforms and refine the estimated HR. The method is demonstrated in Fig 1.

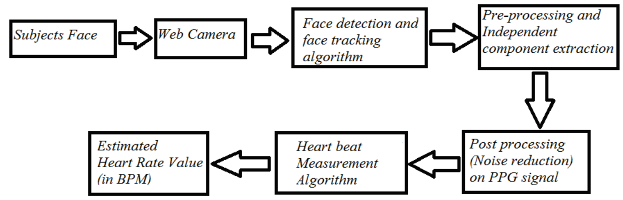

Fig. 1. Block diagram of the framework for HR monitoring.

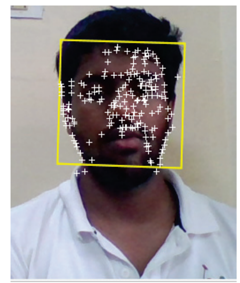

Fig. 2. Face Detection and Tracking of a person

A. Face detection and Face tracking

The Region of interest (ROI) is the face from which the heart rate is obtained using PPG technique. Hence we need to detect and track the face in real time.

1) Face Detection: Face Detection is performed using Viola Jones Algorithm [7]. A simple implementation of Viola Jones works by detecting high frequency components in the image such as transition from the eye to skin as shown in Fig 2.

The algorithm has four stages

1) Haar feature selection
2) Creating an integral image
3) Adaboost training
4) Cascading classifiers

This algorithm is chosen because it is robust and works well in real time.

2) Face Tracking: Face tracking is performed using KLT Algorithm [15]. It tracks certain feature points under translations and rotations of the face. This is implemented by using minimum eigenvalue algorithm, which detects points that look like corners and looks for attributes which are known to permit stability while tracking as shown in Fig 2.

B. Pre-processing And ICA

Pre-processing techniques are used to facilitate independent component extraction from the face ROI. This is performed by demeaning and centering the image data described by equation (1).

$$x_{ij} \leftarrow x_{ij} - \frac{\sum_{j'} x_{ij'}}{M} \tag{1}$$

where x(i,j) are the pixel intensity values at location (i,j) and M is number of mixed signals obtained from the image.

Independent Component Analysis : ICA is a statistical method of implementing Blind source separation which allows us to separate mixed signals originating from different sources without actually knowing the sources or its properties. Because it is a statistical method it assumes three things,

1) The number of sources is known.
2) The sources are independent of each other.
3) The source signals have a non-Gaussian probability distribution.

ICA is, in general, a change of basis operation such that the individual components obtained after the change of basis are the same signals that originate from the different individual sources. There are two types of reflections of light from an irregular surface or a surface with different chemical composition (e.g. Human Face):

i) Specular reflection
ii) Diffuse reflection.

Diffuse reflection does not follow Snell's law of equal angles between reflected ray and incident ray as shown in Fig 3.

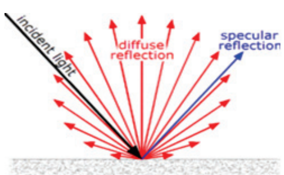

Fig. 3. Types of reflection that occur at the instant when frame is being considered

Now suppose we have 3 incident light rays and their diffuse reflections travel to the camera's lens and we obtain an image with non-zero intensity at only two locations. This means that at least two of the rays have been mixed after reflection. There are possibilities now. One of the signals has not mixed with the other and the other two have mixed or one of the signals has mixed with both the signals: A total of six combinations. Here we can see the usefulness of a statistical method in separating the signals as shown in Fig 4.

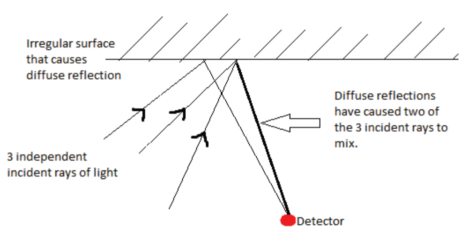

Fig. 4. An Example of mixing of source signals

One example is shown above. The detector is placed at the point of intersection. If they do not intersect a camera lens with a convex lens can converge them to a point [11].

Now the problem is to separate the image intensities from each other. The solution is to make the components as independent as possible i.e. finding out what the intensities would be if the signals were specularly reflected. This is done by taking the intensities at the two locations and rotating the vector to make it as though it were specularly reflected by using the rotation matrix described by equations (2a) and (2b).

$$P' = RP \tag{2a}$$

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} cos\theta & -sin\theta \\ sin\theta & cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \tag{2b}$$

This process is done iteratively over a large time period until convergence is obtained i.e. the resulting vector converges and its value does not change even after many iterations.

The angle θ is a varying quantity and is found from the image intensities/vector itself. Many algorithms exist to find θ at each step from the vector. Maximum kurtosis (4th order moment) is the algorithm used in this project.

The problem of Blind Source Separation(BSS) can be formulated as, Given the signals $x_j(t)$ from m number of sources n is the Received image size ($m \geq n$), one wants to recover the components of the separated signals $s_i(t)$ as described by equations (3a) and (3b).

$$x_i(t) = \sum_{j=1}^{n} a_{ij} s_j(t) \qquad (i = 1, 2, ...m) \tag{3a}$$

$$\begin{bmatrix} x_1 \\ \vdots \\ x_m \end{bmatrix} = \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \dots & \dots & \dots \\ a_{n1} & \dots & a_{mn} \end{bmatrix} \begin{bmatrix} s_1 \\ \vdots \\ s_n \end{bmatrix} \tag{3b}$$

The estimation $\mathbf{y} = Wx$ of the source variables $s_j(t)$ the independent components, and the linear combination matrix $\mathbf{A}$. This is called as Blind Source Separation (BSS) which separates linearly mixed source signals into set of independent signals. Blind, in this context actually means that no assumption is done regarding any prior knowledge about sources $\mathbf{s}$ or the mixing process $\mathbf{A}$ i.e ..., the source signals s_i are statistically independent.

Basically we are trying to solve an over-determined system of equations and there doesn't exist a unique solution to this problem. So we need certain parameters to get a unique solution. This is done by looking at the correlations and the independence of the solution components and selecting the ones that were exactly independent.

Since BSS problem seems severely under constrained, the independent component analysis (ICA) finds nearly unique solutions that satisfies certain properties of BSS. ICA is a more powerful method in the sense that it satisfies a stronger requirement of finding $\mathbf{W}$ so that the components of $\mathbf{y} = Wx$ are independent (and therefore are also necessarily uncorrelated).

The resulting vector/image components are the independent components and are separated signals from each source. The aim of ICA in this project was to separate the component of the image that varied periodically (because of the blood variations in the face) due to the heart. Thus we can also conclude that this component is proportional to the heart rate and we can measure the heart rate from it.

The ICA method depends on certain measurement of the non-Gaussianity. The method employed by us, is kurtosis.

Kurtosis: Kurtosis is defined as the normalized form of the fourth central moment of a distribution described by equation (4).

$$kurt(x) = E(x^4) - 3(E(x^2))^2 \tag{4}$$

If we assume x to have zero mean $\mu_x = E\{x\} = 0$ and unit variance $\sigma_x^2 = E\{x^2\} - \mu_x^2 = 1$, then $E\{x^2\} = 1$ and $kurt(x) = E\{x^4\} - 3$.

Kurtosis is the 4th moment of a probability distribution X. There are certain incorrect interpretations that involve looking at the kurtosis as a measure of some sort of peakedness of a distribution or the density of the tail distribution. One of the correct interpretations is that it measures the dispersion of a transformed random variable ,$Z = (X - mean(X))/standard - deviation(X)$. It is 0 for a gaussian distribution as shown in Fig 5.

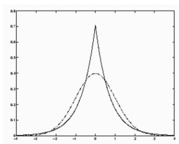

Fig. 5. Measure of non-Gaussianity of a distribution.

C. Post processing (Noise Suppression using wavelets)

The PPG signal obtained from the ICA method contains noise due to variations in background lighting and noise from other sources that cannot be unmixed by ICA. These noises are highly localized in time and have large amplitudes so the use of filters designed using Fourier basis will not produce good results because of signal leakage and variations in phase.

So Wavelets are employed in filtering process, because wavelet decomposition and reconstruction after filtering is more exact and effective in removing these types of noises. A general block diagram is shown in Fig 6.

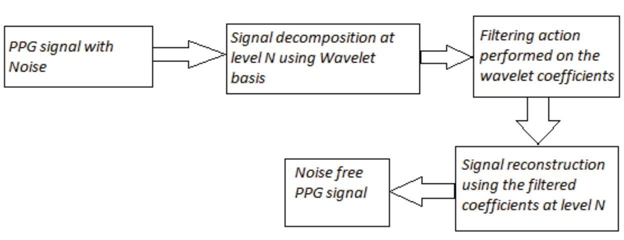

Fig. 6. General Block Diagram of Noise Suppression using Wavelets

The choice of wavelet used depends on the type of noise encountered. To reduce computation time a simple wavelet basis (Shannon basis) set has been used in this project. The PPG signal is decomposed to level 3 (again, to reduce

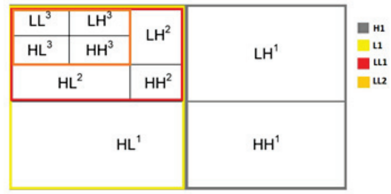

Fig. 7. Structure of Decomposed Wavelet coefficients

computation time) and four sets of wavelet coefficients are obtained as shown in Fig 7.

The coefficients used for filtering and reconstruction are:

1) 3rd level approximation coefficients LL3 (Smoothened signal)
2) 3rd level detail coefficients HH3 (High frequency component of smoothened signal)
3) 2nd level detail coefficients HL2 (High frequency component of less smoothened signal)
4) 1st level detail coefficients H1 (High frequency component of original signal)

Another advantage of using Wavelet decomposition is that the coefficients obtained are already categorized into high frequency and low frequency components so filtering actions can be simply algebraic.

A simple low pass filtering action would be to reconstruct the signal as R = a*LL3+b*HH3+c*HL2+d*H1, which removes the higher frequency components. We introduce parameters (a,b,c,d) while reconstructing the signal to obtain required result.

After de-noising the PPG signal it is sent to the Heart Rate Measurement algorithm.

D. Heart Rate Measurement Algorithm

To measure the heart rate, the independent component which corresponds to the heart rate must be found. This signal is referred to as PPG signal. The heart rate is proportional to the changes in PPG signal.

1) Photoplethysmography (PPG): It is a term describing the measurement of changes in volume in different parts of the body. These changes are often due to fluctuations in the amount of blood in a specific body part. Hence by plethysmography is meant the detection of the pulse wave travelling through the body. The word photo refers to the use of light for plethysmography. From a PPG signal it is relatively easy to derive the heart rate from the time between two consecutive peaks. An example of a PPG signal is shown in Fig 8.

The function of the red blood cells is to carry oxygen. To do this each cell contains a vast amount of the protein hemoglobin (Hb) which can bond oxygen molecules. When blood is flowing from the heart to the body, it contains oxygenated hemoglobin (HbO2) and when it flows back to the heart, it contains deoxygenated hemoglobin (Hb). As PPG

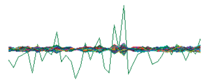

Fig. 8. Frequency domain representation of PPG signal with other independent components.

measures fluctuations in the amount of blood in the body part by its colour, it is relevant to examine the absorption spectra of Hb and HbO2. It shows that both Hb and HbO2 have absorption peaks between 530 nm and 590 nm which corresponds to green and yellow colours.

Since the wavelengths corresponding to green colours have large absorptivities, changes in blood volume will be more evident at these wavelengths whereas the changes will be much less evident at red wavelengths since the absorptivity is much lower here. Thus in the RGB colour space the strongest PPG signal is present in the green channel which is used to find heart rate.

2) PPG signal Extraction: After calculation of the ICA on the mixed signals, it is not known which component is the sought after PPG signal. To identify this, begin by normalizing the variance of each ICA component. Afterwards the FFTs of all the signals are calculated. Then the one with the largest amplitude in the interval from 40 to 150 BPM is chosen as the PPG signal. The frequency of this peak, f is converted to BPM, which yields the heart rate described by equation (5).

$$HeartRate = \frac{60 \times FPS \times (idx - 1)}{LengthofFFTofPPGsignal} \tag{5}$$

where idx is the index of the peaks in the Fourier transform.

III. Experimental Results

Eight trials were conducted on different persons to examine the effectiveness of remote Heart rate measurement. All eight trials were conducted under the same environment with no changes in background illumination.

During experimentation the HRM algorithm was not run without the Noise Suppression technique as is done in most papers to check the effectiveness of the technique because some noises which were easily identifiable would give rise to ridiculous values in the Heart rate obtained. The trials were run concurrently on the persons using rPPG method and was also verified(compared) by another Independent measuring device (FitBit) and the heart rates were obtained. The resulting heart rates were tabulated and compared with the Heart rates obtained by the Independent measuring device.

Table 1 lists the obtained results and the Relative error for each trial. Fig 10 shows an example of a segment of clean PPG signal. Plot (a) shows the waveform of input image and Plot(b) shows the spectrum of a clean PPG signal. Plot (c) and Plot (d) shows the waveform and the spectrum of the Updated PPG signal after Noise suppression and Heart Rate in

TABLE I
TABLE OF EXPERIMENTAL RESULTS (UNITS IN BPM)

Trial No.	HRM Algorithm Output	HR from Independent device	Relative Error
1	57.46	55	0.0447
2	60.5	59	0.0254
3	64.5	60	0.075
4	60.5	57	0.0614
5	60	60.6	0.0099
6	64	65.5	0.0229
7	55.5	55.9	0.0072
8	66	66.6	0.009

BPM, respectively. Fig 11 shows the graphical representation of the comparison of Heart Rate between HRM algorithm and Independent device.

The relative error was calculated because it is known that noise is relatively large for larger frequencies of PPG signal (hence higher Heart Rate). To find the relative error (δx) it is assumed that the value given by the Independent device is the true value (x) and the Heart rate obtained by rPPG method is (x_0). Then the relative error is described by equation (6).

$$\delta x = \frac{\Delta x}{x} = \frac{x_0 - x}{x} = \frac{x_0}{x} - 1 \tag{6}$$

It is found that the maximum Relative error was 0.075.

IV. Flowchart of MATLAB implementation

MATLAB is a convenient tool to implement video and image processing applications. Its built in functions reduce the computation time while processing the images and videos significantly.

Fig. 9 shows the flowchart of the MATLAB program. Firstly video frames are captured by the web camera. Then using Face detection and Face tracking algorithms, face is detected and tracked. The face Region of interest (ROI) is extracted from it. This image is given to maxKurt algorithm for ICA. Noise suppression algorithms are applied to the obtained PPG signal and this PPG signal is sent to HRM algorithm that measures the heart rate. The above process iterates and it stores a heart rate value for each iteration, until the frame Count is less than 50. The final heart rate is the mean of the heart rate values stored earlier for each iteration.

V. Conclusion

We have successfully recreated the method for obtaining the heart rate in beats per minute from a remote PPG (rPPG) signals originating from the face and achieved comparable/similar results to earlier implementations. We have examined the green color spaces in extracting the PPG signal. We have created a real time system which extracts Independent components using MaxKurt algorithm which achieved good performance on our samples. Furthermore, we have identified that a window length of at least 300-400 frames (10-13 seconds) is reasonable

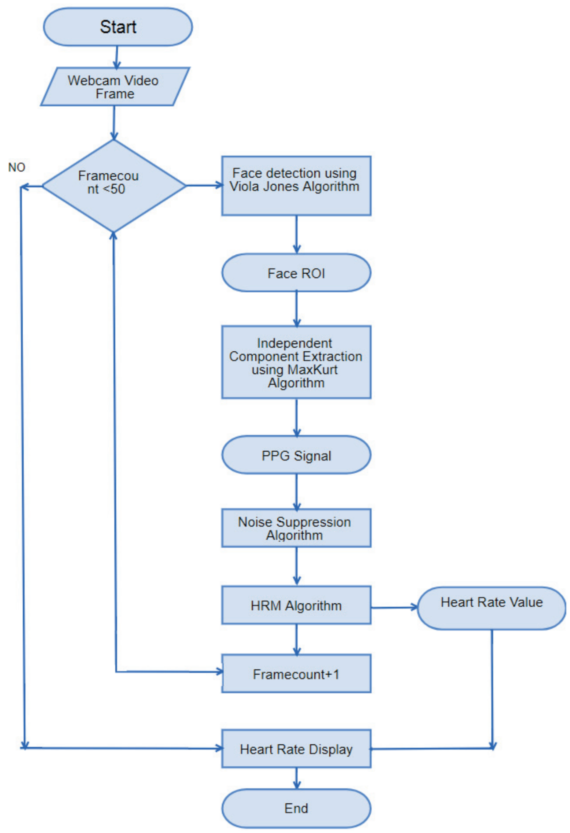

Fig. 9. Flowchart of Heart rate monitoring system

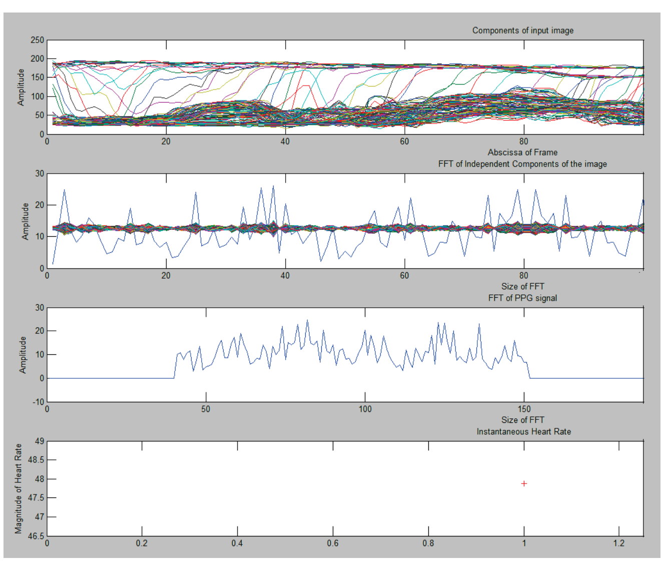

Fig. 10. Independent Components Extraction and Heart Rate Estimation

for real time measurements. We have also developed a novel method of eliminating high intensity low duration noise using Wavelet Analysis. This noise suppression algorithm greatly improves the performance of the heart rate algorithm used in this project. The maximum relative error obtained was 0.075,

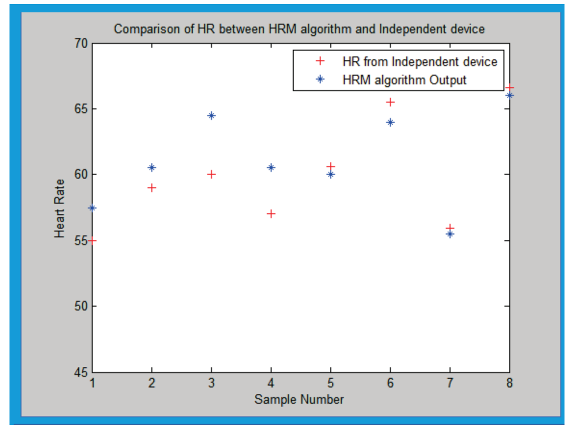

Fig. 11. Comparison of Heart Rate between HRM algorithm and Independent device

so we can conclude that this method works well under static illumination condition.

There are several topics for future work. One of them is improving the face detection location accuracy. Viola-Jones eye detection could possibly increase the position accuracy and compensate for small rotations in the face. Also by using the KLT feature tracker, we can detect and follow specific faces in a sea of faces from a video. Another topic for future work is the PPG signal identification, which can possibly be improved by using machine learning techniques such as training a classifier of different measures and using that to identify the correct ICA component. Another topic is improving Noise suppression techniques to account for different types of noises emanating from background sources such as long duration and lower intensity noises.

Acknowledgment

The authors would like to thank for the help and contributions of their lecturer and project guide Mrs B A Sujathakumari, Associate Professor. They would also like to thank reviewers for their thorough feedback on the manuscript.

References

[1] F. Guede-Fernandez, V. Ferrer-Mileo, J. Ramos-Castro,"Real Time Heart Rate Variability Assessment From Android Smartphone Camera Photo Plethysmography: Postural And Device Influences", IEEE international conference on pattern recognition, Vol 4, 2015.

[2] Richard Macwan, Yannick Benezeth, Alamin Mansouri, Randy Gomez, "Remote Photo Plethysmography Measurement Using Constrained ICA", 6^{th} IEEE conference on E-health and Bioengineering, 2017.

[3] Janus Jensen, Morten Hannemose,"Camera-Based Heart Rate Monitoring", B.Sc. engineering 2016.

[4] Gerard de Haan and Vincent Jeanne,"Robust Pulse Rate From Chrominance-Based rPPG", IEEE transactions on biomedical engineering Vol.60, October 2014.

[5] Bing-Fei Wu, Po-Wei Huang, Meng-liang Chung,"Camera-Based Heart Rate Measurement Using Continuous Wavelet Transforms", International Conference on System Science and Engineering (ICSSE), 2017.

[6] T.Pursche, Jarek Krajeswki,"Video-Based Heart Rate Measurement Form Human Faces", IEEE conference on consumer electronics, 2016.

[7] "Remote Detection of Photoplethysmography Sysytolic And Diastolic Peaks Using a Digital Camera" ,IEEE Journal of Bio-medical Engineering, 2015.

[8] ”Illimination Variation Video Based HRM Using Joint BSS and Empirical decompostion” ,IEEE Journal of Bio-medical and Health Informatics, 2017.
[9] John Allen, ”Photoplethysmography and its application in clinical physiological measurement”, Physiological Measurement, vol. 28, no. 3, pp. R1R39, February 2007.
[10] Nina Golyandina, Vladimir Nekrutkin, and Anatoly A. Zhigljavsky,”Analysis of Time Series Structure: SSA and related techniques ”, CRC Press, 2001.
[11] Zhilin Zhang, Zhouyue Pi, and Benyuan Liu, ”TROIKA: A general framework for heart rate monitoring using wrist-type photoplethysmographic signals during intensive physical exercise”, IEEE Transactions on Biomedical Engineering, vol. 62, no. 2, pp. 522531, February 2015.