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Heart-Rate Evaluation Using Remote Photoplethy Smography - A Case Study

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ABSTRACT—Heart rate of a person is a very crucial parameter concerning a person's physical state. It's directly related to a person's well-being. Although, several devices such as smart watches, portable heart-rate monitor etc. are available in the market which can be used to monitor heart-rate on a regular basis and have the capability to send alerts if any unexpected curve is observed in the pattern, these devices usually require a contact with the skin to measure the heart-rate and are expensive. Since there is an increasing widespread use of camera equipped devices in our daily lives, the prospects to employ remote photoplethysmography (rPPG) are vast. A camera can be used to perceive variations in reflection and absorption of light from skin that is otherwise not noticeable with naked eye. Camera based remote photoplethysmography assists non-contact and low-cost vascular activity monitoring. It is very important to manage the aspects such as illumination, selection of proper region of interest, correct estimation of signal and escalation of signal to noise ratio to remove any unwanted disturbances in order to get accurate results. In this paper, steps involved in remote photoplethysmography and the implementation of these steps are discussed.

Keywords—OpenCV, rPPG, Machine learning, plethysmographic signal, Affine Transformation, PCA, ICA, measurements, photoplethysmography, autonomous

I. INTRODUCTION

With the advancement in technology, apart from many other areas such as smart home devices, autonomous systems, etc. remote heart rate monitoring has also gained a lot of importance. This is because heart rate measurement plays a key role in understanding a person's cardiovascular activity. Further, it can help diagnose and assess a person's stress level. For instance, in the fitness industry accurate heart rate measurement helps in controlling the training load. In the healthcare industry, it can help in detection of a possible cardiac arrest.

PPG is a simple contact based technique used in wearables such as smart bands to measure the variations in the heart rate of a person. In this technique the blood volume of the venous and artillery blood is compared to measure the heart rate. The blood volume of artillery blood is comparatively lower than the venous blood for obvious reasons as the venous blood contains impurities and hence indicates a pulse. To observe this change in volume two sensors are used one which emits a green light and the other one which receives the reflected light through the blood[1]. Whereas RPPG is a contactless technique to measure the heart rate which uses a similar approach. In this technique a camera is used to observe the change in intensity of the light being reflected directly through the skin and the light being reflected from the blood. The reflection of light which is reflected by the skin directly is known as specular reflection whereas the reflection of light reflected by the blood is known as diffused reflection.

In the past literature, many platforms have been designed for remote heart monitoring such as wearables. These devices record the Photoplethysmographic (PPG) signals from the wearers' wrist to predict the heart -rate. For this purpose, the wearables are embedded with a pulse oximeter sensor. The sensor is used to measure the intensity change in the light reflected from the wearer's skin whenever the skin is illuminated using a light emitting diode (LED). This technique has been adopted widely for heart rate measurements. But, in order to calculate the heart rate, they require physical contact with the person. The skin contact might become uncomfortable especially for the elderly people. Hence, the focus in this work is based on contactless rate monitoring measurements using face videos. This has an added benefit for people with skin conditions. The contactless solution is based on real time video processing. In such a technique, image processing using OpenCV is used to analyse the user's video in real time and measure the heart rate. In order to predict accurate

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heart rate, contactless based solutions require good ambient light in the environment. In case of optimal ambient light, it can give good results in just a few seconds[2].So this paper will mainly focus on the implementation of remote photoplethysmography algorithms. The following sections will be based on different steps involved in the implementation of rPPG algorithm and it's representation with the help of flowchart.

II. LITERATURE SURVEY

Feng L et al.[3], in 2014, analysed the effects of moving objects on rPPG signals, as movement of the subject was a big problem for rPPG. To overcome this problem, region of interest (ROI) was stabilized by the use of face tracking based on characteristic points tracking. And to normalise the remaining movements a bandpass filter was used. An independent component analysis (ICA) was implemented and the result was correlated with the derived reference sine signals and the ICA component with highest correlation coefficient was automatically picked up as cardiac pulse wave. Fourteen subjects were used to test the robustness of the suggested method with maximum movement. In 2015, Zhang Z et al.[4] projected a universal framework termed TROIKA, consisting of decomposing the signal for denoising, reconstructing the sparse signal for high resolution spectrum estimation, and tracking and verifying the spectral peak. TROIKA was highly accurate in estimating and robust to strong motion artefacts. 12 subjects were made to sprint at a speed of 4.16 m/s to record the datasets. The experimental results showed that 2.34 beats per minute was the average absolute error in heart rate estimation and the earson correlation was 0.992.

Later on, in 2016**,** Edgars et al. [5] invented a prototype device which monitors the pulsations in blood volume from the human skin based on remote photoplethysmography. The device is made up of an electronic board with a high speed camera, twelve circularly positioned infrared LEDs and battery charger circuit. The device was lab tested and blood volume changes could be monitored using human palm without any contact. Richards et al.[6] used rPPG for measuring heart rate using a conventional camera. He used the fact that, due to the heartbeats the blood flowing in the arteries show some regularity and there are very minor periodic changes in the colour of the skin which are evident for these regularities. These variations in colour can be separated and enumerated by signal and image processing methods. And to isolate these signals from other sources like lighting, ICA was used. As the basic ICA was believed to be blind, they suggested the constrained ICA (cICA) where a CHROM constraint was used sideways with the prior information about the periodicity of blood flow signal. Maximizing the autocorrelation applied the periodicity and some restrictions were also set inevitably by the CHROM constraint. This model was rivalled with the conventional ICA models and tested on MMSE-HR database for accuracy and robustness.

In 2019, Fouad et al. [7]**,** stated that accuracy and reliability of HR estimation algorithm is directly proportional to choosing the correct ROI. They performed downsizing on the ROI for extracting only the skin pixels and after this step they experimented with the conventional rPPG method and the results were compared. They also used signal fusion to examine the effect of subtracting the HR from three ROIs. The output of their algorithm was also compared with the output of viable pulse oximeters and hence improved the results of the rPPG technique

III. IMPLEMENTATION

A. ALGORITHM

A standard remote photoplethysmography algorithm can be divided into three major steps. These steps include extracting raw signal from different frames of a video, estimating the obtained plethysmographic signal and estimation of heart-rate from that signal. Facial color variation is being used as a raw signal for contactless photoplethysmography in most of the studies.[8] The light which is absorbed by skin changes according to human cardiac cycle. These variations can be noted by using an RGB camera. A few studies are also based on episodic head movements which occur due to pumping of blood to head via the aorta with every single cardiac cycle. Every step in the algorithm comprises a number of constituents which are represented by figure-1 and are further described in the following subsections.

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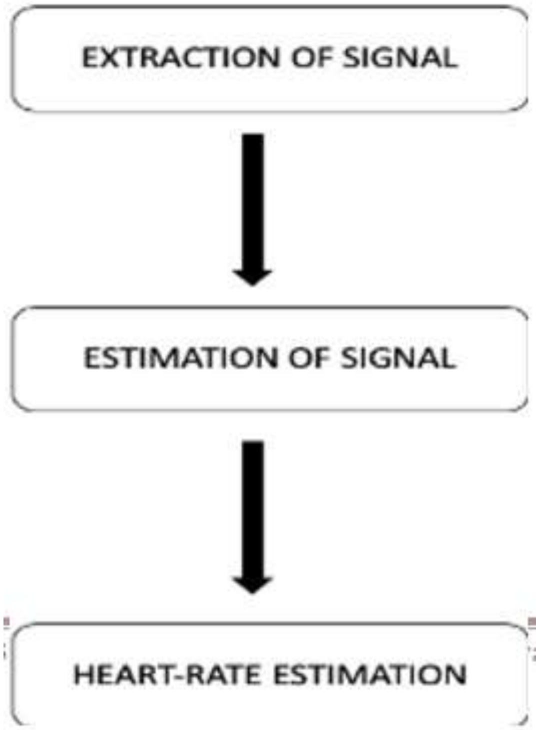

Fig. 1. General steps involved in a rppg algorithm

B. Extraction of Signal

1) **Detection of ROI**: Because we considered rPPG algorithms standing on a human face, a ROI detection is necessary to make the boundaries of the face in a telegenic frame. Earlier, the subject was left still and the first frame was selected manually as the frame of the face.

The most widely used technique for ROI detection is the Viola and Jones algorithm which categorizes faces using a series of simple functions of machine learning. Viola-Jones algorithm provides a boundary box for the face as a result.

Instead of detecting the face Lee proposed to apply an algorithm which detects skin regions. A neural network classifier was used to select skin like pixels so that the ROI can include a wider area like the neck. A drawback of using this algorithm is that there might be some noises present in the background which may have similar colour as that of the skin. Hence this algorithm was combined with the Viola-Jones algorithm for selection of skin within the bounds.

Active appearance models (AAM) [9] are statistical models of human faces were used to extract a set of coordinates of known facial landmarks. These coordinates provide a more detailed ROI definition and ROI tracking. This step is applied after the face detection by Viola-Jones algorithm in the rPPG algorithm. Several approaches have been used in the literature to detect the facial landmarks. For instance, discriminative response map fitting (DMRF) based approach has been used by Li et al. [10], deformable model fitting based approach is also used. Further, Daniel et al. [11] Mcduff et al. [12] used a combination of regression based approach and probabilistic face shape model. Facial landmarks can be directly extracted using the last two algorithms without detecting the face.

2) **Defining ROI**: The video frame contains a region where the raw signal for the algorithm is focused known as the ROI. It was an easy choice for the researchers to use the results produced by Viola-Jones algorithm or detecting the face manually as the ROI [13]. The bounding box produced by the Viola-Jones algorithm contains pixels from the background on both the sides, and is suggested to cover 0.6 width. To define more precise and robust ROIs, the researchers used two prominent subdivisions of the bounding box that are the cheeks and the forehead.A region was defined by Li et al. [10] which includes the cheeks without any noises using the nine landmark points.Recently, another approach based on multiple ROIs has been proposed. The technique is to define multiple ROIs and generate a RGB signal for later analysis. Demirezen et al. [14] proposed a more stringent approach wherein they apply a large array of small ROIs. Depending on the signal quality, a subset of available ROIs are selected for further studies. This results in a dynamic ROI

3) **Tracking ROI**: It is obvious that whenever the subject moves a noise is introduced in the signal, making it ineffectual for rPPG. So a new technique of ROI tracking was intended whose motive is to make sure that the pixels of the ROI does not change as the object moves. Earlier, tracking was not used as it was expected that the object is stationary. ROI tracking can be directly obtained by simply redetermining the ROI for every frame. A drawback of this method was that the object sensor in Viola-Jones is used very often, so an uninvited noise can be produced for the ROIs based on mutable outputs. As it was very difficult to start over detecting the ROI for all the frames due to computational complexity, using a set of tracking points and a tracking algorithm is much easier, which can update the location of ROI frame by frame. As the subject

moves the ROI is revised by using an affine transformation which is grounded on the Kanade-Lucas-Tomasi (KLT) function tracker. The points detected using the accelerated robust services algorithm forms the base for the KLT detection algorithm. Body tracking algorithms which are built on kernels can be exercised to renovate the skin regions present in the ROI.

4) **Extraction of Raw Signal:** The raw signal extraction is done according to the position of the ROI where the video is processed frame by frame. For different colour channels i∈{R, G, B}, such extraction results in the series Ti (t) in case of colour based methods. The ROI of the frame consists of several pixels of corresponding colour channels, the values are given by calculating the average of these channels at a particular time t. Thus, the camera noise is averaged in each pixel and this process is called spatial aggregation. The image can be resized with a very small ROI to avoid noise

[16]. Localized spatial pooling is the technique used to note variations over time, firstly the image is divided into different spatial frequency bands without clearly printing each value per frame.The tracking points inside the ROI are carefully chosen for extracting the raw signal for head movement built methods. A tracing array was used by [17], whereas [18] exercised only the best recognized point. The path of each point was calculated using the KLT tracking algorithm.The raw signal is then constructed using the series Ti, axis a and i for tracking point. While both [17] and [18] used the same technique to construct the raw signal, they differ in the axes being used. The former uses only the vertical axis, whereas the latter uses both vertical and horizontal axes.

C. Estimation of Signal

1) **Filtering**: Regardless of performing ROI tracking,some undesirable noises are still present in the raw signal which might be the result of subject movement or variation in lighting conditions or any other factor. Digital filters were applied on the raw signals based on the knowledge present on the feasible HR frequencies and the expected noise frequencies. The value of the estimated plethysmographic signal is enhanced by escalating the signal-to-noise ratio. This is the main motive of filtering. Several filters are operated on the raw signal before reducing its dimensionality. It's totally the researcher's choice to apply filters either, after downsizing or scaling, or both before and after scaling as it is more important to centralize and normalize the raw signals first for evaluating periodicity. The procedure of deduction of a mean μS from a signal S is called centralizing. And in addition to this, dividing the signal by its standard deviation σS is called normalization. Bandpass filters are used to remove undesirable frequency noises. To do this, the feasible human HR frequency band must be assumed. A band of frequency [0.7 Hz, 4 Hz] [10] is generally selected which leads to an HR ranging from 42 to 240 beats per minute (bpm). To signify a low pass equivalent, the filter with moving average is used in which the window is rolled which gives the average of a given number of values. This is considered to be a high pass equivalent. A new element in recent publications is adaptive bandwidth [16], which dynamically changes cut off frequencies based on previous estimations of HR, thereby directing the algorithm to produce reliable HR estimates. Researchers also cut off some noisy frequencies by using various methods, for example, Li et al. [10] removed the noisiest segments which are measured by standard deviation in a considered signal. To deal with noise introduced by lighting variations, he also used background illumination as a reference and employed an adaptive filter to remove the background illumination from the signal.

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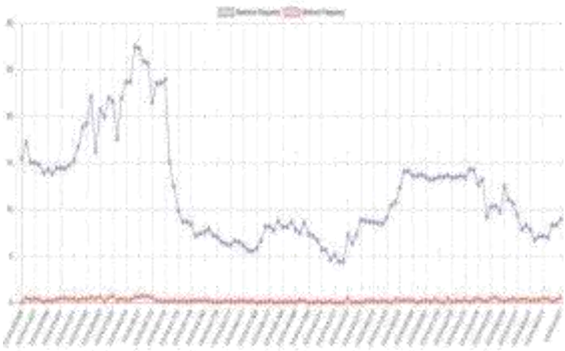

Fig. 2. Graph representing maximum and minimum frequencies after reading

2) **Reducing Dimensionality**: Signals corresponding to RGB channels is a type of raw signal that consists of more than one series. These have been used by several authors. There is an assumption about a one-dimensional (t) plethysmographic signal, often represented as a linear combination of weighted sum of raw signals, being contained in the raw signals. Estimation of the weights for this combination is wearisome and it remains one of the highly debated issues in literature on rPPG. The initial approach to use an algorithm for BSS to search the optical combination of raw signals was proposed by Poh at el. [19]. ICA techniques were used to segregate the raw signals into independent non gaussian signals. As discovered by Poh et al. in their original rPPG algorithm, the plethysmographic signal (t) imitates the second component produced by ICA which was the most periodic one. This method was adopted by many authors [20,21]. Since the arrangement of components of ICA seemed random, Poh et al. introduced a selection criteria in an improved version of their rPPG algorithm. This criterion selects a component with high periodicity. There is another related criterion which chooses the highest periodicity based on the percentage of spectral power raised by the first harmonic [15,18]. To determine the best component a correlation with the reference sine function was put to use. The second popular algorithm of BSS, used by [15], Principal component analysis (PCA), used by [15], is the second famous algorithm of BSS which linearly decomposes raw signals into uncorrelated components and classifies them according to variance. The basis used to make a selection of the components of the ICA apply equally to the components produced by the PCA. In order to choose the most appropriate part manufactured by ICA, machine learning was also used by [22]. Likewise, to deduct the frequency range of the plethysmographic signal, Hsu et al. [13] used supporting vector regression (SVR). The Linear discriminant analysis (LDA) was used to decrease the size, by Tran et al. Class values were generated from the red channel and data was assembled from the other two channels. On the contrary, various authors highlighted the use of fixed weights through BSS. However, the brute force technique determined the fixed weights, according to Ibrahim et al. [20], rest were derived from skin illumination models. De Haan and Jeanne

[23] theoretically suggested a motion robust method, based on standardized skin colour assumptions, that makes use of all three RGB colour channels to generate two orthogonal colour difference signals. Combination of these yields the estimate of p(t). Having recognised many shortcomings of their method, the authors [23] suggested to support component selection by combining it with BSS. The adaptive green red difference (GRD), which is an estimate of a p(t), was also derived from the skin model and its relationship to plethysmographic signs. Also, usage of a model of interaction with human skin has been made, which considers the time quotient of raw signal values in order to obtain varied estimation of plethysmographic signals. As an alternative, the raw color sequence of each pixel can be transformed by individual erythema transformation and used to estimate PPG based on Bayesian estimation. There was a comparison between performance of nonlinear BSS techniques with other techniques which concluded that the Laplacian eigenmap performs best.

D. Heart rate estimation

1) **Frequency analysis**: To measure the frequency of HR, frequency analysis technique has been adopted widely. The analysis depends on the estimation of p (t) in the plethysmographic estimate. In this regard, Discrete Fourier Transform is used to convert the signal consisting of a separate periodicity to its frequency domain. Among the many types of transformation techniques, FFT is the most widely used. But there are some exceptions to it such as in [17] which uses DCT. Further, in [10] the author's use short term Fourier transform (STFT) and Welch's method to estimate density. To estimate the HR frequency,

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the index with highest spectral power in the frequency range is chosen. The frequency corresponding to this index is selected as the final estimate.

2) **Peak Detection:** Interpolation methods such as a cubic spline function [12] can be used to further refine the signal of the peak sensor. Such methods help in easy identification of the peaks using a moving window methodology. This is because the window represents the maxima of the signal. Peak detection method is important as it can provide additional information such as the variability of HR based on collision intervals.

IV. WORKING

The front end of the project is developed using html and css. Real time video recording is being done with the help of opencv. The attained frame rate for real time video is dynamic and totally depends upon rate of computation. When enough raw data is available, estimates start getting produced. The process is visualized on the graphical user interface. Based upon the previous researches we have also used the Viola-Jones object detector. A haar cascade is being used to detect a face and a bounding box of the object detected is returned. Once the coordinates of the bounding box are obtained and the face detection is done, this data is used to select the region of interest using a rectangle on the forehead as shown in figure 2. The Region of Interest and the bounding box are traced in succeeding frames. Noticeable sets of tracking points are found and selected within the ROI. Then Kanade-Lucas-Tomasi algorithm [24] is used to track points in succeeding frames. The calculation of the points in succeeding frames is done by using affine transform. Hence ROI is calculated without the need to use face detection for each frame. For every frame, the average of RGB channels is extracted from the raw signal obtained from ROI. The length of the signal depends upon the window size and operational frame rate.

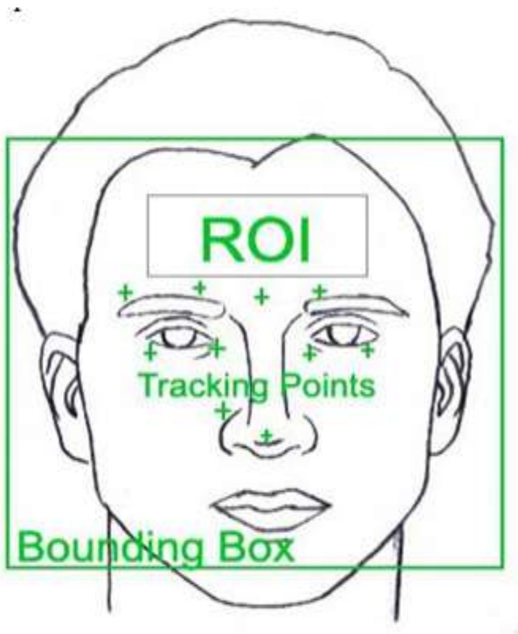

Fig. 3. Representation of ROI and tracking points

The undesirable low and high frequency noise is then removed. The resulting signal which has been denoised is then normalized. At the end, high and low frequency noises are removed. The steps discussed above are employed to the 1-D green channel to generate plethysmographic signals with discrete periodicity. All the first three steps are applied to every channel discreetly. After that Principle component analysis is used upon filtered RGB channels. The component with highest discrete periodicity is selected. After this, each component is converted to corresponding frequency domain using discrete fourier transform. Within these components, the one with highest power response for single frequency is chosen and the left over high frequency noise is removed. Finally an approximate plethysmographic signal is obtained. The rest of the work is explained in figure-3.

V. RESULT

The growing concept of rPPG has been demonstrated in this project. A systematic literature review has been provided to describe the previous findings till now. It is shown that several studies have been made in this field of detecting HRM using rPPG and continuing that, we have tried to obtain a more accurate model. We have described the latest skin colour and head movement based development of rPPG. Technical explanations of various physical features and software algorithms for rPPG were also included in this project. The core challenges in this area of interest were examined and recommendations are made for further research.

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Two of the core challenges currently examined in the rPPG were: the robust ability of the algorithm to handle the noise level and low signal strength of the object due to lighting and skin kind. In this project, these encounters are being addressed much

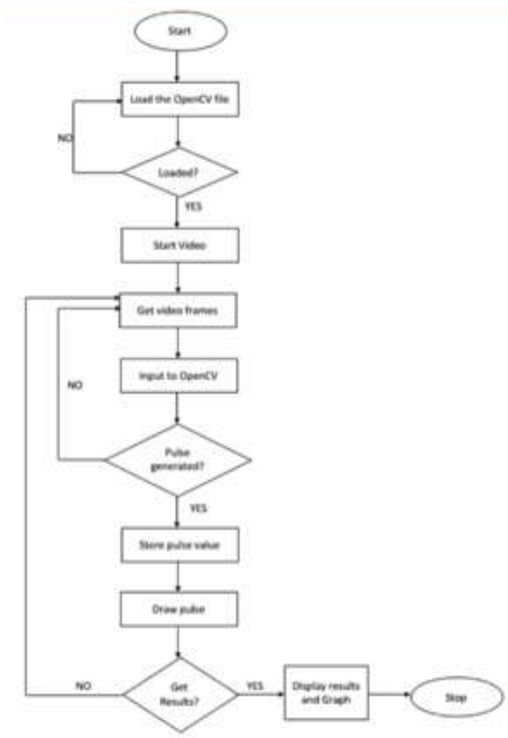

Fig. 4. Working of project

More effectively, but the use cases uncovered are typically far from the actual real life situations. More precisely, the upcoming rPPG algorithms should be emphasized on balancing the amount of information being processed and the complexity of algorithms as the real time applications will limit the computation time. Obviously, remote HRM can be performed with less expensive video equipment, and previous studies show rPPG is becoming increasingly sophisticated. The increase in the number of reports and publications during the period of our survey indicates that there is an increasing concern for dependable rPPG algorithms. This is mainly because the demand for contactless HRM solutions has increased in various industry sectors such as in medical, professional and consumer sectors

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