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E-Health monitoring using camera: Measurement of vital parameters in a noisy environment

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***Abstract*—We investigated contact-less solution to study micro circulation and its spatial heterogeneity by means of RGB imaging and to estimate blood oxygenation and heart rate. Oxygen saturation SpO_2 and heart rate *HR* are indicators directly related to the cardiovascular diseases. Detecting low level of oxygen and abnormal heart rate can be an indicator of fatal heart problem and require urgent medical attention. Traditionally, measurement of *HR* and SpO_2 is made through the probes or pulse oximeter attached to the skin surface and hence could be a potential way of spreading contagious infections. For a non-contact assessment of pulse rate, imaging photoplethysmogram *iPPG* has been proposed, where data is acquired through the video frames and different image analysis-based methods are used to extract required information. We detects face from the sequence of images using Viola Jones algorithm, followed by the extraction of region of interest, filtering performed in spatial domain removed artifacts, and intensity signal gives iPPG estimation by using CHROM method. The estimation of *HR* and SpO_2 from these signals are evaluated on publicly available data set containing facial videos and reference contact photoplethysmogram. Furthermore, we also investigate the performance of these methods on data acquired under diverse illumination conditions. Relative correlation and $\%$ error gives satisfactory results to extend the method for more diverse scenario.**

***Index Terms*—Vital parameter, heart rate, oxygen saturation, imaging photoplethysmogram, Face detection, illumination.**

I. Introduction

Recent development in the field of telemedicine allows patients to use devices, which can monitor certain physiological parameters remotely. More recently, the mobile or e-health technologies played a vital role during epidemiological situations (COVID), as they allowed patients not only to monitor physiological parameters themselves but can be used in remote connection with the physicians, while staying at home or during quarantine. Most of these parameters are related to the human respiratory and cardiovascular systems. The use of such self-monitoring systems can measure these parameters without causing any discomfort or limiting the patient's daily routine or disturbance. Oxygen saturation (SpO_2), heart rate (*HR*) and body temperature etc. are the most important physiological indicators of the person health and well-being. These parameters indicate the sufficient supply of oxygen in the blood and are directly related to the cardio respiratory system and hence, frequent monitoring of these indicators plays a significant role in the diagnosis of health conditions and predicting abnormal behaviour. In the past, even during remote monitoring of critically ill patients, most of the developed systems are relatively expensive and are based on the sensors which require physical connection with the patients and be a cause of discomfort and constrain patient movement. Therefore, it requires a new frontier for self-healthcare systems to develop alternative methods without any type of physical connection.

With the advancement in the camera-based health monitoring applications during last decade where patients can use personal mobile devices to monitor continuously their vital parameters, several methodologies have been proposed which use camera based monitoring system. Recently, Selvaraju *et al.* provides an overview of these technologies based on image and signal processing and their respective application areas [1]. They highlighted that *HR* and respiratory rate can reliably be monitored using visible cameras in controlled settings. Similarly, Sun *et al.* presented techniques from contact to non contact and from points to images to estimate vital parameters [2]. Their study presents an overview of the wide range of imaging photoplethysmogram (*iPPG*) systems being introduced and they discussed their methods in various physiological assessments. Unakafov *et al.* also discussed different methods and compared performance on a publicly available data set [3], containing facial video and reference contact photoplethysmogram (PPG). Rahman *et al.*, specifically discussed vital physiological parameters extracted from visible camera, in driving situations by selecting region of interest (ROI) [4]. Similarly, Stricker *et al.* presented their findings on of pulse measurement system implemented on mobile robot, they also compared methods for face segmentation [5]. Their proposed method consider motion robustness and computational complexity. More recently, Casalino *et al.* derived an estimate of SpO_2 from the video frames of the patient's face acquired by a camera [6]. Each frame is processed in real time by using combination of signal processing and computer vision techniques to extract remote photoplethysmography signal that measures the change of cardiovascular tissue coming from some regions of the face. In another study, Casalino *et al.* proposed contact-less device composed of a see-through mirror equipped with a camera [7]. The device detects the face of the subject through the camera mounted on the mirror and process video frames using photoplethysmography to estimate multiple physiological parameters. In addition to that, their method detects different feature of the face by using clustering-based color quantization. Moreover, Hassan *et al.* presented a critical review of camera based methods to detects heart rate from face. They presented their analysis in the presence of low signal quality, insufficient illumination conditions and motion artifacts [8]. Similarly, Shao *et al.* presents an overview of the recent advances in contactless methods for the estimation of *iPPG* signal [9]. they discussed different physiological parameters, data processing and algorithms. They also presented the application of these methods in different fields, including security, health and wellness *etc.* The advancement in the field of e-health monitoring grows rapidly during recent years specifically during COVID-19, the devices based on such technologies allow patients to monitor their health conditions while staying in remote connection with the physicians (despite the quarantine). However, most of the previously proposed methods monitored vital parameters in controlled environment with sufficient illumination and position of the subject. Such controlled environment may not be possible in certain scenario, where it is not possible to change the position of the subject. In this work, we present a pilot study to estimate vital parameters in uncontrolled environment in different illuminating conditions. As already explained, the monitoring of these physiological parameters in a contactless manner involves data acquisition from contcat less source e.g camera, infrared sensor *etc.*, followed by the data transmission to the processing unit and finally biomedical and signal processing to extract information from the acquired data. The two vital indicators discussed in this paper are *HR* and SpO_2. We will present a brief explanation of these parameters in next coming section.

A. Heart Rate

HR is one of most important vital physiological parameter and indicator of the physiological state. It is typically defined as the number of cardiac beats each minute, and expressed as beats per minute (beat/min). In general, the normal range of heart rate for an adult varies from 60 to 100 bpm [1] [3]. The abnormal value of heart rate can be an indicator of possible emotional stress *e.g.*, hypertension or can be an early warning of possible myocardial infarctions. Traditionally, heart rate is measured from electrocardiogram by measuring pulse rate and more indirect methods includes photoplethysmogram. However, both techniques require contact based sensors and have disadvantages as explained before. Recent advancement have enabled doctors and physicians to measure heart rate with out any type of physical contact and is useful in several applications for detecting drowsiness or sudden cardiovascular events [1] [3].

B. Oxygen Saturation

SpO_2 is another important clinical sign and represents the amount of oxygen carried by the haemoglobin in the blood. It is defined as the ratio of concentration of oxygenated haemoglobin carried by blood cells to the total concentra-

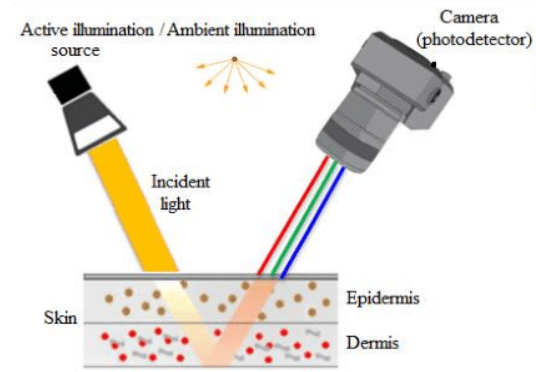

Fig. 1. Principle of iPPG method. A camera capture the optical properties of the skin tissue in the presence of illumination [12].

tion of haemoglobin and can be expressed by the following equation [10]:

$$SpO_2 = \frac{[HbO_2]}{[HbO_2 + Hb]} * 100\% \quad (1)$$

Where $[HbO_2]$ is the concentration of the oxygenated haemoglobin and $[Hb]$ is the concentration of deoxygenated haemoglobin. The normal range of SpO_2 lies in between 95–98$\%$ or even up to 100$\%$ in some cases [10]. The abnormal values less than this range are termed as hypoxemia. Constant decreased of SpO_2 level is a sign of various diseases including Asthma, lung cancer, chronic disease, and COVID-19. The abnormal values indicates the warning of possible anomaly or infection. Furthermore, in the case of COVID-19 the low SpO_2 level appears earlier then rest of the symptoms and even if the blood oxygen level is reducing, the patients does not feel short of breath. Measurement of SpO_2 is traditionally made through the pulse oximeter. Oximeter requires a physical contact with the skin surface and could be a potential source of spreading contagious infections ($e.g.$ COVID-19). Recent advancements in the field of imaging based contactless solution enabled us to monitor SpO_2 without any physical contact. In this work, we present our findings on such solutions in diverse scenario. In the next coming sections, we will present the acquisition, importance and measurement methods these physiological parameters.

The rest of the paper is organized as follows: Section I introduces the subject and gives the background of vital parameter estimation by using contact and contactless methods. The Principle of the method, data set used and explanation of acquired data is mentioned in II. In section III, the detailed explanation of pre-processing, filtering techniques and iPPG signal extraction method is given. We further explained in detail, the formulation given in literature for the estimation of *HR* and SpO_2. Section IV discussed the statistical analysis in multiple illumination conditions. We also report our findings on PURE data set in result section. Section V finally concludes the paper with challenges and future perspectives.

Fig. 2. The images were acquired from webcam viewing the face of the subject and oximeter monitoring the parameters in the presence of illuminating source at different positions.

II. Principle of Method

PPG is a non-invasive technique for detecting micro vascular blood volume changes in tissues and provide information about cardio respiratory activity in biomedical and clinical environments [11] [2]. In clinical terms, detection of the cardiovascular pulse wave traveling through the body is referred to as plethysmography. The word 'photoplethysmography' is widely used in camera system and composed of photo refers to the light source and plethysmography means increase (Greek word plethysmos), first introduced by Hertzman [11] [13]. The heart pumps the blood which flow through the body, as blood absorbs more light as compared to the associated tissues and ultimately variations occur in the optical properties of the skin due the associated haemoglobin in the superficial tissues. In general, a dedicated illumination source and photo detector is required to analyze the variations, though these variations are not visible with the naked eye [2]. Such techniques require skin contact and hence could be a potential way of spreading contagious infections. Recent studies use camera as a photo detector source to detect variations and came up as an alternate solution without any physical connection with the skin surface, termed as *iPPG* as explained in Fig. 1, when a light from any source falls on the skin surface, the superficial layers (epidermis and dermis) absorb certain amount of light and the camera system capture these variations and store them in the form of images [2]. Most of the research focused on extracting *iPPG* data in light controlled environment and to the best of author's knowledge, limited study is available to estimate these physiological parameters in uncontrolled environment. In this pilot study, we investigate *iPPG* signal and estimate physiological parameter from the images acquired in different illumination conditions without any dedicated setup.

A. Acquisition and Dataset

The data set used in this work is taken from the database of "Pulse Rate Detection Dataset - PURE" [14] [5]. PURE data set consists of 10 subjects sitting in front of the camera, performing different, controlled head motions. However, for the current work we tested the algorithm only on the steady position (01). The ten person includes 8 males and 2 females sitting at the average distance of 1.1 meters from the camera. The videos were acquired with a frame rate of *30 Hz* and resolution of 640x480 pixels and a 4.8mm lens in a relatively controlled indoor daylight conditions. During image acquisition, reference data which includes SpO_2 and *HR* from finger clip pulse oximeter were also captured for the evaluation purposes. Oximeter uses the principle of *PPG*, the skin is illuminated with light source, and based on the proportion of the blood volume flowing through the tissues, some light is absorbed by the body while the rest is reflected. By monitoring the amount of the reflected light, oximeter estimate the parameters [18]. The data obtained from PURE data set is acquired in a controlled environment with the fixed distance and illumination conditions. However, as explained in previous sections, in this work we addressed uncontrolled environment with varying illumination conditions. In the proposed data-collection method, sequence of images were acquired from the "Hp HD webcam" camera for 15sec with the frame rate of *30 Hz* from the subject facing towards the camera in a steady position with little head motion as illustrated in Fig. 2. A finger clip pulse oximeter is also attached with the subject's finger to measure contact-based measurement of *HR* and SpO_2 for the evaluation purposes. The acquired images from some of the captured video sequences is shown in Fig. 3, it can be seen from the images that the illumination conditions are varying, however the position of the subject is approximately same with slight head movement.

Fig. 3. The images acquired from webcam in different illuminating conditions.

III. Methods

We present a method for extracting heart rate and oxygen saturation from video sequences. The complete schematic diagram of processing is shown in Fig. 4, where series of signal and image processing techniques are applied to extract physiological parameters. The basic frame work includes data acquisition, face detection, extraction of intensity components followed by the filtering techniques and estimation of vital parameters. In the next coming section, we explained each of these steps in detail with theoretical background.

A. ROI Selection

For the estimation of vital physiological parameters from the skin surface, we selected face area for the estimation purposes. With the advancement of computer vision techniques,

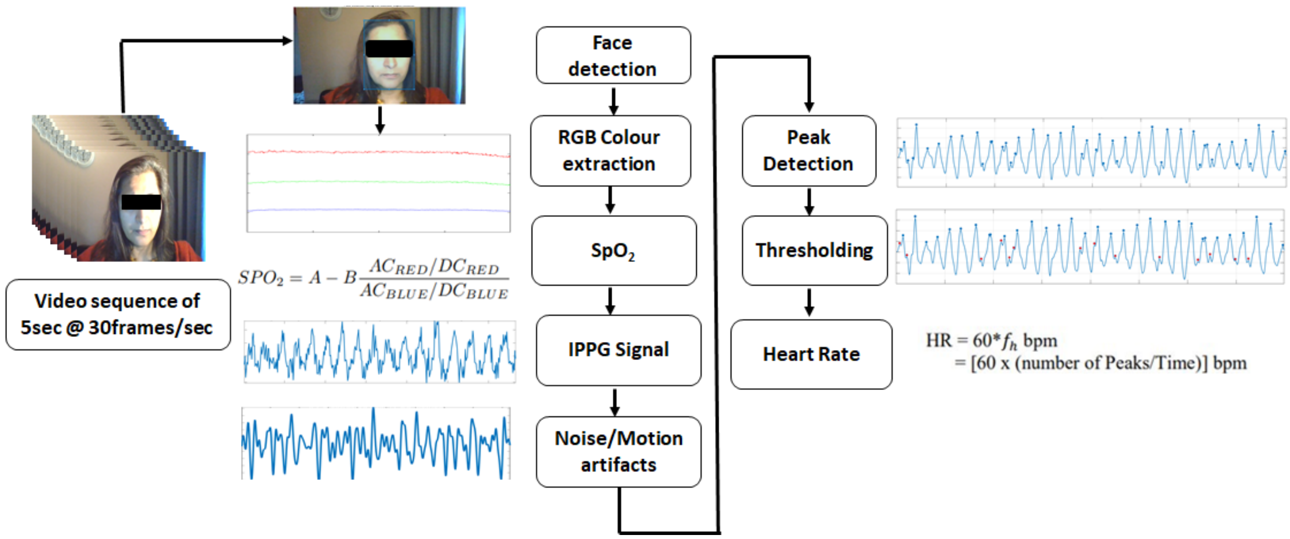

Fig. 4. Illustration of the complete processing which includes data acquisition, face detection, extraction of intensity components followed by the filtering techniques and estimation of vital parameters [15].

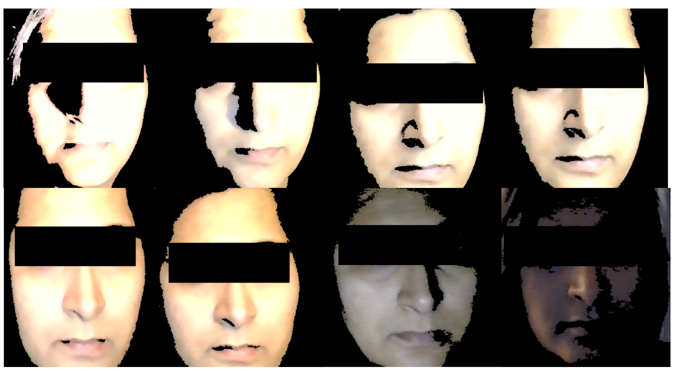

Fig. 5. Segmented face area acquired in the presence of illuminating source, placed at different positions. Viola Jones algorithm detects face followed by the segmentation.

face detection has been a major field of interest due to its application in the variety of fields including, security, surveillance, health care *etc.* Viola and Jones in 2001, presented an algorithm to detect different objects including face [15]. The main steps to detect face comprises of Haar feature selection, Adaboost training and cascade filters. The method detect and localize face in each video frame as shown in Fig. 5. The implementation of face detection is done by using Matlab Computer Vision toolbox and in each frame, face area is detected and localized, termed as ROI for further processing of color channel detection.

B. Extracting Color Channel

The images obtained from the colored camera consist of three channels including red, green and blue. Several approaches have been proposed in the past for color channel selection [12]. We extracted three channel from the segmented ROI by calculating the spatial average of pixel value in the respective ROI for each frame by using intensity-based method that uses spatial averaging as:

$$I_R = \frac{\sum_1^n \sum_1^m R_i}{nm}, I_G = \frac{\sum_1^n \sum_1^m G_i}{nm}, I_B = \frac{\sum_1^n \sum_1^m B_i}{nm} \tag{2}$$

where n x m is the dimension of the ROI. For each ROI, the average signals (I_R, I_G, I_B) are collected on the N frames of the sequence and we obtain I_{RGB} with $3N$ dimension for each video sequence. The aim of averaging each color channel is to reduce the noise in each sequence to improve signal to noise ratio.

C. Pre-processing

The averaged I_R, I_G, I_B signal from each frame is individual red, green and blue channels in each ROI. Signals in I_{RGB} represents the reflected signal obtained through the detector which includes the reflected light and other noise. In order to reduce the impact of these fluctuations and unwanted noise, the I_{RGB} signals are improved through a pre-processing phase which includes multiple signal processing techniques, median and band pass filtering followed by the chrominance-based methods.

D. Extraction of iPPG signal

After pre-processing, *iPPG* signals were estimated as a combination of refined signal by using recently proposed POS method of Wang *et al.* [16] shown in Fig. 6. Their method is considered as an improved version of previous method (CHROM) [3]:

$$iPPG(t) = x_1(t) + \frac{\sigma_1(t, L)}{\sigma_2(t, L)} x_2(t) \tag{3}$$

where $\sigma_1(t, L)$ and $\sigma_2(t, L)$ are L-point running standard deviations of $x_1(t) = g(t) - b(t)$ and $x_2(t) = g(t) - b(t) - 2r(t)$ respectively [3]. where r, g and b represents the

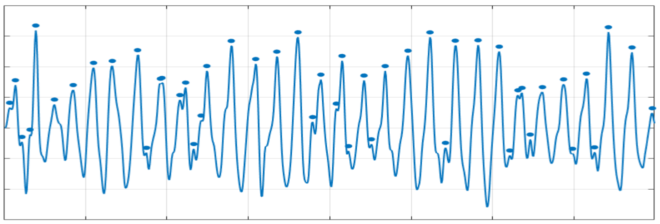

Fig. 6. Obtained *iPPG* signal: combination of red, green and blue signals by using recently proposed POS method [16]. Peaks correspond to pulse rate, and detected through adaptive thresholding.

red, green and blue components of the channels respectively. From *iPPG* signal, the next step is to estimate physiological parameters.

E. Estimation of Vital signs: HR and SpO_2

AC_{RED} and AC_{BLUE} computed as standard deviations of the red and blue signals in I_{RGB}, while DC_{RED} and DC_{BLUE} are computed as the mean of the red and blue values. The coefficients A = 125 and B = 26 according to the empirical evaluation mentioned in [6], using following expression:

$$SpO_2 = A - B\frac{AC_{RED}/DC_{RED}}{AC_{BLUE}/DC_{BLUE}} \tag{4}$$

We estimate pulse rate from the filtered iPPG signal (Fig. 6) through the peaks, detected by using MATLAB functions where each peak in *iPPG* signal correspond to the heart beat. We observed false positives due to the presence of noise artifacts and in order to eliminate those peaks, adaptive thresholding is applied finally pulse rate are estimated through the number of peaks per minuted by using following expression:

$$HeartRate = [60 * (no.of peaks/Time)]bpm \tag{5}$$

IV. Results

The algorithms are implemented in MATLAB R2020b with *Image processing Toolbox* and *Computer Vision Toolbox*. To evaluate the performance of vital sign measurement method, we initially performed analysis on "Pulse Rate Detection Data set - PURE" with the video sequence of 10 subjects at steady state. The contact based indicators from oximeter are also given for evaluation purposes. The obtained statistics are illustrated in graphical from in Fig. 7, where the obtained results are approximately similar to the reference indicator. Similarly, the approximation of SpO_2 is given in Fig. 8 with similar results.

At the second stage, we tested the performance of the method in diverse illumination conditions, where a dedicated source is mounted at different position for each video sequence. We acquired data using HD webcam in un-controlled environment as explained in previous sections. The duration of each video sequence is of 15 sec with the frame rate of *30 Hz* from the subject facing towards the camera in a steady position with little head motion. A finger clip pulse oximeter is

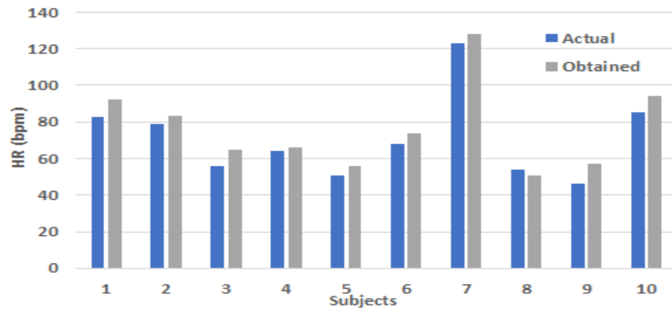

Fig. 7. *HR* obtained on PURE data set with the subjects sitting still and looks directly into the camera without any movement.

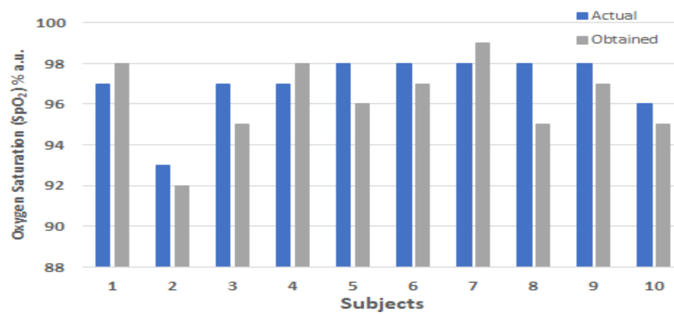

Fig. 8. SpO_2 on PURE data set with the subjects sitting still and looks directly into the camera without any movement.

attached to the finger as a reference indicator for the evaluation purposes.

We performed statistical analysis of the signal extracted from the images in the presence of diverse illumination sources to quantitatively assess the performance of the method. Since, in this work we focused on evaluation the performance of method under different illumination condition, therefore we assume the video sequence acquired in ambient conditions are consider as a referenced image and the performance of the sequences obtained with illuminating source placed at different positions are compared with the referenced sequence. In order to find the similarity between the current image with the referenced image in ambient light, we use Pearson's correlation coefficient which estimate the statistical measure of the similarity and is defined by [17]:

$$Corr = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m}(x_{ij}-\overline{x})(y_{ij}-\overline{y})}{\sqrt{(\sum_{i=1}^{n}\sum_{j=1}^{m}(x_{ij}-\overline{x})^2)(\sum_{i=1}^{n}\sum_{j=1}^{m}(y_{ij}-\overline{y})^2)}} \tag{6}$$

where, x_{ij} and y_{ij} are the individual sample points of the two images (reference images in ambient conditions and images acquired in dedicated illuminating source), which indicate the pixel content of the two images (x and y), $\overline{x}$ and $\overline{y}$ represent the sample mean. A correlation coefficient value indicates the similarity between two images. We performed methods explained in previous sections on all recordings and calculated the error of obtained heart rate from each sequence with respect to the referenced sequence in ambient conditions by

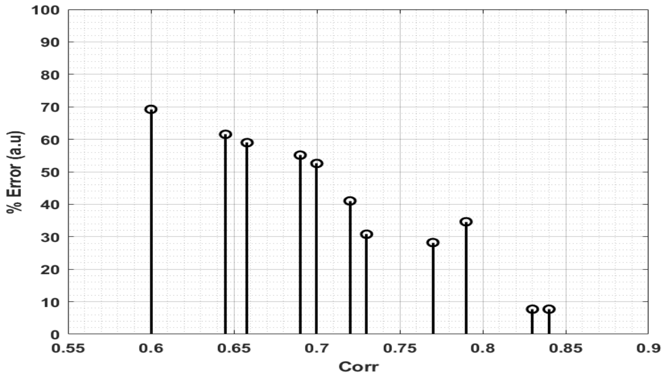

Fig. 9. $\%\epsilon(Error)$ vs to the correlation of acquired data under different illumination conditions with minor head movement.

using:

$$\%Error = \frac{|Estimated - Actual|}{Actual} * 100 \tag{7}$$

We observed reduced % error with increase correlation of images as shown in Fig. 9. The initial findings depicts that the contactless solution are reliable and the measurements are consistent with the pulse oximeter even in extreme illumination conditions, achieving measurement errors that are within acceptable margins. Insufficient illumination and extreme brightness, with pre-processing filtering, image processing techniques can reduce the effects and improve the performance of the methods.

Preliminary experimental result shows that the estimation of SpO_2 obtained through the contactless solution are comparable and consistent with the reference device.

V. Conclusion

We investigated a contactless, e-Health solution for self-measurement of vital parameters which are of extreme importance. Initially, we tested the methods on PURE data set obtained in controlled environmental conditions. In order to illustrate the performance in diverse illumination conditions, video sequences of 30 frames/second of subject face are acquired through HD webcam in the presence of illuminating source, placed at different position. The acquired data is extracted, filtered through the signal and image processing techniques to extract *iPPG* signal. When light is reflected from the skin surface, a slight variation in colour of the skin can be monitored through *iPPG* signal and we estimated heart rate and oxygen saturation from these signals with minimal % error. We demonstrated that with increased correlation, the % error decreases and the obtained results are comparable and consistent with the reference contact device even in the presence of diverse illumination conditions. In future, we propose to use more transformation of the color space to separate *PPG* from distortions and to develop deep neural models for better classification of normal and abnormal indicators from video frames.

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