Real Time Heart Rate Monitoring From Facial RGB Color Video Using Webcam

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***Abstract*— Heart Rate (HR) is one of the most important Physiological parameter and a vital indicator of people's physiological state and is therefore important to monitor. Monitoring of HR often involves high costs and complex application of sensors and sensor systems. Research progressing during last decade focuses more on noncontact based systems which are simple, low-cost and comfortable to use. Still most of the noncontact based systems are fit for lab environments in offline situation but needs to progress considerably before they can be applied in real time applications. This paper presents a real time HR monitoring method using a webcam of a laptop computer. The heart rate is obtained through facial skin color variation caused by blood circulation. Three different signal processing methods such as Fast Fourier Transform (FFT), Independent Component Analysis (ICA) and Principal Component Analysis (PCA) have been applied on the color channels in video recordings and the blood volume pulse (BVP) is extracted from the facial regions. HR is subsequently quantified and compared to corresponding reference measurements. The obtained results show that there is a high degrees of agreement between the proposed experiments and reference measurements. This technology has significant potential for advancing personal health care and telemedicine. Further improvements of the proposed algorithm considering environmental illumination and movement can be very useful in many real time applications such as driver monitoring.**

I. Introduction

The non-contact physiological parameters monitoring idea has come from the cardiovascular system of human body. The cardiovascular system permits blood to circulate in the body due to continuous blood pumping by heart. Our Heart pumps blood through the blood vessels of this system and for each heart beat blood circulation creates color variation in Facial skin. Therefore, it is possible to extract HR from the color variation of the facial skin. In 1995, the first noncontact health monitoring system was investigated by Costa et al. [1]. They used camera images in order to extract physiological parameters using color variation of the skin. But their approaches did not report quantitative results; they reported only a graph of heartbeats and also failed to show any correlation with reference ECG signals. After this first attempt further progress was moderate and in 2005 another novel method was introduced for the measurement of computer user's emotional state using the facial thermal image using a thermal camera [2]. The experiment was conducted by 12 users and the authors found some interesting fact between stress and blood flow. According to their experiment user stress is correlated with increased blood flow in the frontal vessel of the forehead. In 2006, Takano et al. shows that RR (Respiratory Rate), HR and BVP are possible to extract simultaneously using a camera [3]. They captured images of a part of the subject's skin and then the changes in the average image brightness of the region of interest (ROI) are measured for a short time. They used MATLAB custom functions for filtering and spectral analysis. Finally, they could able to extract HR and HRV (Heart Rate Variability). The system can detect HR for a certain period of time but the efficiency of their system is unknown. Later in 2007, Garbey et al. developed a contact-free measurement of cardiac pulse based on the analysis of thermal images using FFT algorithm [4]. Their experiment shows that the temperature of the vessel is modulated by pulsative blood flow is directed at recovering the frequency of the component signal with the highest energy content. The effort is directed at recovering the frequency of the component signal with the highest energy content. After appropriate processing, the thermal image signal can yield quantitative information about blood flow velocity, respiratory function etc. The noncontact methods using camera further improved in the same year by Kenneth et al [5]. They presented a system capable of capturing two PPG (Photoplethysmogram) signals simultaneously at two different wavelengths using non-contact system. Ten test persons participated in their experiment where both camera and PPG sensors were used for data collection. Their proposed system extracted oxygen saturation (SpO2) successfully but the efficiency is not compared. Additionally, they showed that the system was capable of obtaining good quality PPG signals from deep tissue. Another successful attempt was done in 2008 by Verkruysse et al. [6]. Few Simple, inexpensive digital cameras were used to extract HR and RR from facial video recorded in ambient light. Their system is able to extract HR and RR from 30 seconds to a few minutes which is a major flaw to apply in real time applications.

Noncontact based method for physiological parameters extraction has been further improved in recent years. A novel method was presented by Banitsas et al. in 2009 which is able

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to extract HR information from a user using the camera of a smart phone using user's finger [7]. In different experiments HR and RR were extracted by smart phone camera using user's finger in [8], [9] and [10]. In 2011, Poh et al. proposed an algorithm to extract underlying source signals from R, G, and B color bands using computer webcam [11]. The experiments were conducted using built-in webcam (iSight camera) in indoor environment. BVP was also recorded with spontaneous breathing using a finger BVP sensor and chest belt respiration sensor respectively at a sampling rate of 256 Hz. Finally they extracted HR from 1 minute color facial video using FFT. Similar experiments were taken place using different cameras for physiological parameters extraction which are referred in [12], [13] and [14]. A main drawback of systems for use in personal health care, telemedicine and real time applications such as driver monitoring are that they are not real time and they did not show that how much time the system can extract physiological parameters.

In 2013, Parnandi et al. approached an algorithm to extract HRV using a remote eye tracker [15]. HRV was estimated from the relative distribution of energy in the low frequency (0.04 to 0.15 Hz) and high frequency (0.15 to 0.4 Hz) bands of the power spectrum of the time series of pupillary fluctuations. The system was validated under a range of breathing conditions and under different illumination levels in offline situation. In the same year, several attempts were taken place for non-contact physiological parameters such as [16], [17], [18], [19], [20] and [21]. In 2014, Zhang et al. developed a webcam based noncontact monitoring system for the physiological parameters of drivers [22]. Using iSight camera the facial images are captured for several minutes which are separated into three RGB channels and each channel. FFT is used to measure HR and RR. In the same year, Guo et al. showed similar approach to monitor driver's HRV continuously under real world driving circumstances [23]. Using normal computer webcam one video sequence (15 fps and 640 x 480 resolutions) is taken of the driver face and then HRV is calculated from BVP. Dividing the Face regions into 7 sub regions and average HRV was extracted using ICA method for all the regions. Another approach by Xiaobai Li et al. was proposed for HR measurement framework under realistic human computer interaction (HCI) situations [12]. Some others similar works were done in [8, 24-31].

The most successful noncontact based physiological parameters extraction system has been proposed by Rahman et al. in 2015 [32]. They have developed a simple laptop web camera based method to detect HR, RR and IBI (inter bit interval). The results show about 90% accuracy for physiological parameters extraction using this system. This experiment can extract three physiological parameters in offline for any length of time. From all the related literatures it is seen that most of the noncontact systems to monitor physiological parameters are done in offline and most of them are good for a certain amount of time in lab environment. This paper presents a noncontact HR monitoring system in real time for unlimited amount of time using a web camera which overcomes most of the flaws of the previous works.

The rest of the paper is organized as follows: chapter II describes materials and methods, chapter III highlights feature extraction using image processing tasks for noncontact experiments, chapter IV discusses real time HR monitoring method and the experiments and results have been focused on in chapter V. Finally, chapter VI summarizes the work.

II. Materials and Methods

The experiment was taken place in two phases: firstly the real time HR extraction was conducted along with cStress system as a reference. All the facial image frames were saved for offline testing. Secondly HR was extracted again in offline using the saved film image sequences.

A. Data Collection

Data acquisition was conducted by 10 participants (all are male) of different ages (25 to 50 years) and skin colors. The experiments were carried out in indoors and with a sufficient amount of ambient sunlight. The participants were informed the aim of the study and they seated at a table in front of a laptop computer at a distance of approximately 0.5 m from the built-in webcam (HP HD webcam). During the experiment, participants were asked to keep still, breathe spontaneously, and face the webcam while their video was recorded for 5 minutes. HR was extracted in real time and saved in an excel file. All facial image frames (24-bit RGB) during real time HR extraction were recorded sequentially at 30 frames per second (fps) with pixel resolution of 640 × 480 and saved in PNG (Portable Network Graphics) format in the laptop. Simultaneously HR was also recorded using ECG sensors and cStress system[1]. After the real time extraction, HR was also extracted again in offline from the saved film image sequences.

B. Applied Algorithms

Three algorithms such as FFT, ICA and PCA have been applied at the same time but separately to extract HR in real time using only facial video. The average of the R, G and B signals were calculated for FFT method. For the ICA method [33], the normalized raw traces were decomposed into three independent source signals (R, G and B) based on the joint approximate diagonalization of Eigen matrices (JADE) algorithm [34]. The data collection was supposed to perform in sitting position without any movement but in reality the test persons moved their hands and heads little bit which is the cause of motion artifacts. Therefore, ICA is used which is able to remove motion-artifact by separating the fluctuations caused by small motions or movement. Interestingly, ICA returns the independent components randomly and the component whose power spectrum contained the highest peak is then selected for further analysis. Similarly the normalized raw traces are also decomposed by PCA to find the principal components [35]. This transformation is defined in such a way that the first principal component has the largest possible variance and each succeeding component in turn has the highest variance possible under the constraint that it is

[1] http://stressmedicin.se/neuro-psykofysilogiska-matsystem/cstress-matsystem/.

orthogonal to the preceding components. The resulting vectors are an uncorrelated orthogonal basis set. The principal components are orthogonal because they are the eigenvectors of the covariance matrix, which is symmetric. PCA is sensitive to the relative scaling of the original variables. Finally, the Fast Fourier Transform (FFT) is applied on the selected source signal to obtain the power spectrum [36]. The pulse frequency was designated as the frequency that corresponded to the highest power of the spectrum within an operational frequency band.

III. FEATURE EXTRACTION

The main features of the proposed method is 3 independent signals which are called Red signals, Green signals and Blue signals and these signals were produced from the red, blue and green color values of each pixel of all the facial image frames.

A. *Reading Image Frames*

An image frame is the fundamental part of a video or any image source that indicates the start and end point of a video which represents a silent part of that video. Fig. 1(a) shows the real time HR monitoring system to extract a number of image frames one by one at a certain period of time defined by the user. It is also important to notice that the resolution of the video should remain same during each image frame extraction for further calculations. Therefore a novel key frame video extraction algorithm has been used to maintain same resolution that can read image frames automatically one by one [37].

B. *Face Tracking*

Facial image is the input of the proposed non-contact HR monitoring algorithm and therefore it is very important to track facial part of the user. The real time method needs a powerful face tracking method to perform higher face detection rate. After extracting an image frame in real time, the automatic face detection function '*CascadeObjectDetector'* of Computer Vision Toolbox provided by MATLAB[2] was applied which has been implemented using Viola and Jones method [38]. Later the function was modified to fulfill our own purposes. Fig. 1(b) indicates the detected face.

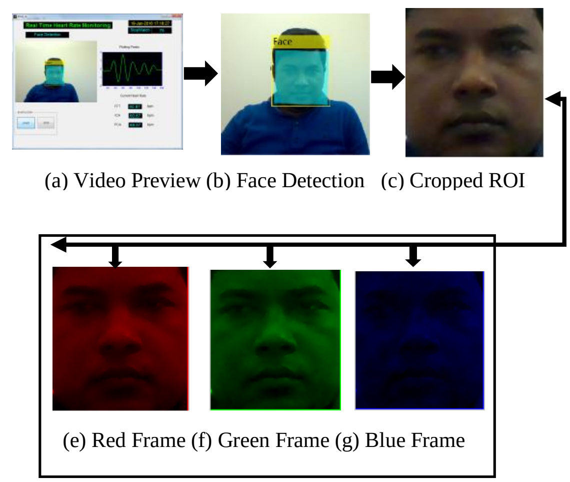
C. *Region of Interest Selection*

R, G and B color values of each pixel of the facial image frames are the most essential part for this experiment. Hence it was searched a perfect Region of Interest (ROI) over the detected face. The detected face using Viola and Jones method contains some unwanted part which needs to eliminate. To identify the coordinates of the face location in the first frame a boosted cascade classifier was used for the x and y-coordinates along with the height and width that define a box around the face according to the method in [39]. Therefore the center was selected as 60% width and 80% height of the box as the region of interest which is free from unwanted parts. Only the ROI was then separated from the entire facial image shown in Fig. 1(c) and this ROI is used for further calculations.

[2] "MATLAB Computer Vision Toolbox," R2013a ed: The MathWorks Inc., pp. Natick, Massachusetts, United States.

D. *RGB Signals Extraction*

R, G, B color values are the fundamental elements of R, G and B signals (together they are called RGB signals) which were extracted from the facial cropped RIO image [40]. Each pixel of the image has 3x1 matrix of color values which consists of Red (R), Green (G) and Blue (B) color of the image. Then the three desired signals Red, Green and Blue signals are produced in two phases. In the first phase the average R, G and B color values are calculated for each image frame shown in Fig. 1(d) and in the second phase the red, green and blue signals are calculated from the summation of all the averaged R, G and B color values indicated in Fig. 1(e-g).



(a) Video Preview (b) Face Detection (c) Cropped ROI

(e) Red Frame (f) Green Frame (g) Blue Frame

(d) RGB Frames

Figure 1. Feature Extraction from each image frame

E. *Signal Detrending*

Detrending is an important signal processing concept which is used to remove unwanted trend from the series. Detrending of signal is useful when it is thought that a feature is distorted from the relationships of interest. In our case, when environmental parameters changes such as temperature or external noise, the collected RGB signals will be drifting and noising. Therefore the signals need to detrend. The RGB signal has been detrended using the method used in [41] based on smoothnes priors approach with the smoothing parameter λ =10 and cutoff frequency = 0.059 Hz shown in Fig. 2(h).

E. *Filtering*

Before applying PCA, ICA and FFT the Red, Green and Blue signals in Fig. 2(d-f) formed from all red, green and blue image frames in Fig. 2(a-c) are filtered by Hamming window (128 point, 0.6-2 Hz, for normal HR 36-120) for heart rate [42] shown in Fig. 2(j).

F. *Normalization*

The signal needs to be normalized and the normalization has been performed according to the method mentioned in [43] in Fig. 2(i). Equation (1) shows the normalization formula as below:

$$X_i(t) = \frac{Y_i(t) - \mu_i(t)}{\delta_i} \qquad (1)$$

For each i = R, G and B signals where μ_i is the mean and δ_i is the standard deviation of Y_i.

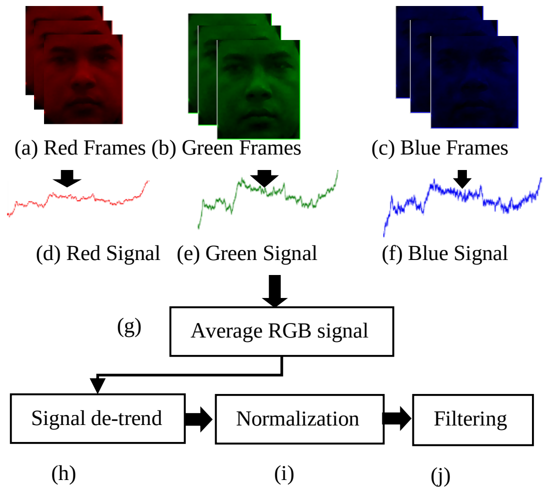


Figure 2. RGB Signals Pre-processing

IV. Real Time Monitoring System

The physiological parameters extraction methods in [32] presents for physiological parameters (HR, RR and IBI) extraction for any length of time in offline. In order to use physiological parameters extraction in real life application like driver monitoring [44] or driver monitoring in semi-autonomous vehicle [45] or in any other health applications [46], a real-time HR extraction method has been implemented in this paper. The proposed method has four main parts which are (i) video display and extract each image frame, (ii) face detection and facial image extraction, (iii) RGB signal extraction and pre-processing and (iv) Extraction of HR using ICA, PCA, FFT methods and displaying the results. For real time HR extraction it is not necessary to save any facial video during experiment. But all the facial images have been saved to extract HR in offline which is also a part of this paper. At first the system previews the user's video in continuous mode and it performs all the works described in fig. 1. When the system reads 50 image frames one by one it stores all the R, G and B color values of the cropped facial image in a temporary database which are sent to the processing unit for further processing. Before applying ICA, PCA and FFT the signals are processed according to the steps in fig. 2 and also described vividly in section III.

To minimize the update time of the results it was investigated using different number of image frames to extract HR and it was found that the system can able to perform best HR monitoring for 50 image frames for the first time which needs 2-3 seconds and after that the update is possible for reading each image frame which is around 500 milliseconds (ms). The update of the result depends on how fast the system can read each image frames. It was investigated that the average update time was about 300 ms to read every image frame and display the results. Hence the system can extract physiological parameters of the user in real time for any length of time. To extract HR in real time at first the number of peaks in frequency domain was calculated for first 50 image frames and also the required time was recorded. Therefore HR is calculated as HR = 60*f_h bpm (beat per minute) where f_h is the extracted frequency of the HR. For example Fig. 3 shows 25 peaks for 600 image frames. The frame rate was 30 fps and

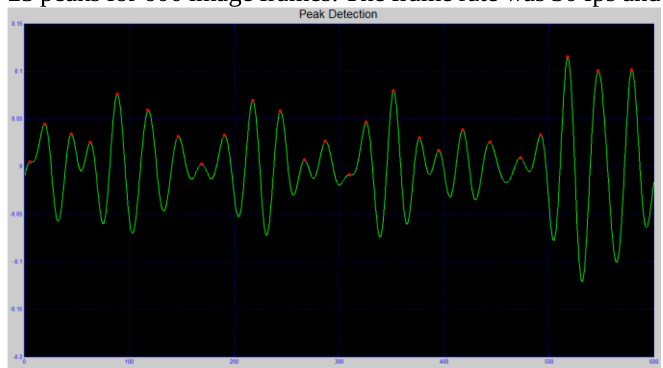


Figure 3. Real Time HR monitoring GUI

therefore the required time to read 600 image frames was 20 second. HR is calculated as below:

HR = 60*f_h bpm
= [60 x (number of Peaks/Time)] bpm
= 60 x (25/20) bpm
= 75 bpm.

When the first 50 image frames are read, the real time HR extraction begins and after that each image frame is added to the data base and the method provides new HR.

A Graphical User Interface (GUI) has been developed using MATLAB to monitor HR in real time which has 3 main sub-sections. Fig. 3 shows the real time HR monitoring Graphical User Interface (GUI) which displays the 3 subsections such as detected face, pulse peak and current HR using the three methods.

Figure 4. Real Time HR monitoring GUI

V. Experiment and Results

HR was extracted and recorded for 5 minutes for all the 10 test persons in real time using webcam and cStress system using ECG sensors and the extracted HR values were saved in two different excel files. After 5 minutes the real time session was over and HR was extracted again in offline using the saved film sequences using the proposed algorithms of [32]. For each test subject there were 3 separate excel files for the extracted HR; one was for real time method, another one for cStress system for reference and the last one for offline

TABLE I. STATISTICAL ANALYSIS OF HR IN REAL TIME VS OFFLINE CONSIDERING CSTRESS SYSTEM

SUBJECT	PARAMETERS	Real Time			Offline			CSTRESS
		FFT	PCA	ICA	FFT	PCA	ICA	
1	min	46	51	52	63	54	60	64
	max	98	99	90	88	98	88	87
	mean	71	73	70	77	76	78	76
	std	7	9	7	5	7	4	4
	median	70	72	69	77	76	78	76
2	min	57	59	57	58	51	64	53
	max	89	91	89	99	99	99	64
	mean	73	76	73	74	76	74	56
	std	6	5	6	5	6	5	2
	median	73	76	73	73	77	73	56
3	min	57	59	57	61	63	64	58
	max	90	99	90	99	99	99	71
	mean	76	75	76	79	80	80	64
	std	7	5	7	4	5	4	3
	median	78	75	78	80	80	80	64
4	min	54	61	54	54	60	54	64
	max	91	99	91	94	90	94	85
	mean	82	78	82	82	77	82	73
	std	6	6	6	6	4	6	4
	median	83	78	83	84	77	84	72
5	min	51	50	59	55	50	61	41
	max	99	99	99	99	99	99	93
	mean	71	74	72	72	75	75	61
	std	6	6	6	6	7	7	8
	median	71	74	72	71	75	74	61
6	min	63	59	63	55	61	55	71
	max	90	96	90	94	95	94	90
	mean	78	77	78	79	77	79	77
	std	5	7	5	6	6	6	3
	median	77	78	78	79	77	79	77
7	min	46	51	52	64	58	64	61
	max	98	99	90	95	99	95	99
	mean	72	74	70	77	78	77	70
	std	7	10	7	6	5	6	7
	median	70	72	69	76	77	76	68
8	min	51	50	59	54	51	67	71
	max	99	99	99	99	90	99	98
	mean	71	74	72	82	77	83	83
	std	6	6	6	6	5	6	4
	median	71	74	72	83	77	83	84
9	min	65	58	74	66	52	74	66
	max	98	97	98	92	99	92	95
	mean	87	84	87	87	84	87	81
	std	3	4	3	3	5	3	5
	median	70	72	69	77	76	78	76
10	min	47	50	48	61	53	58	66
	max	98	99	88	87	96	90	87
	mean	72	73	68	76	74	76	76
	std	7	8	7	6	7	5	4
	median	71	72	69	75	76	78	75

method. It is necessary to do statistical analysis to find out the efficiency of the proposed method with respect to reference sensor system. Therefore several parameters such as minimum, maximum, average, median and standard deviations were calculated from the extracted HR for the real time extraction method, cStress system and offline method. These statistical parameters for all the 10 test persons are presented in table I. For the evaluation then it is necessary to calculate some statistical analysis. Therefore, the evaluation was made using 2 important statistical parameters such as RSQ (R-squared) and CORREL (Correlation Coefficient) for both real time and offline HR extraction considering cStress system.

It should be noted here that the RSQ parameter is used to see how close the obtained signals of HR to the reference signal. RSQ ranges 0 to 1 where 0 indicates that the two signals are not correlated with each other where 1 indicates that the signals are fully correlated which means that the model explains all the variability of the response data around its mean. CORREL (also known as The Pearson product-moment correlation coefficient) is another statistical measurement of the correlation (linear association) between two sets of values. The CORREL value ranges -1 to +1 where +1 indicates a strong positive correlation and -1 indicates a strong negative correlation. These statistical parameters were calculated both for real time and offline with respect to cStress using the parameters from Table I. The statistical analyses of HR in real time for the 10 test subjects are presented in Table II.

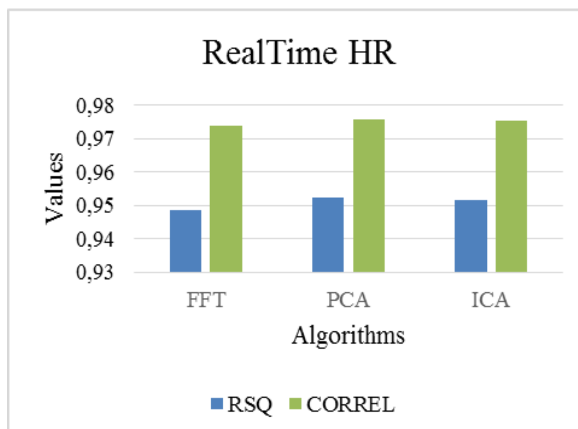


Figure 5a. Comparison among three methods for Real time HR Extraction considering cStress System

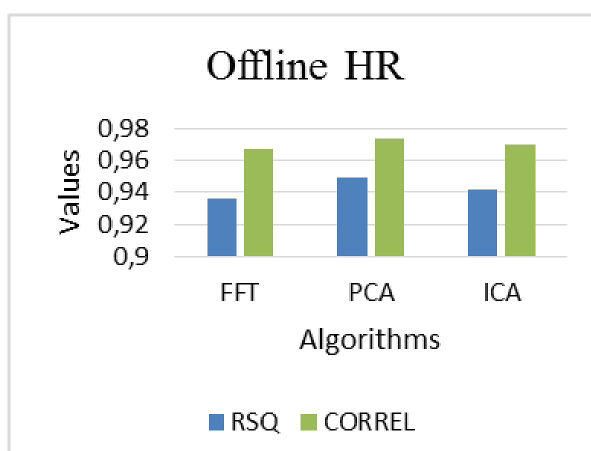


Figure 5b. Comparison among three methods for Offline HR Extraction considering cStress System

TABLE II. STATISTICAL ANALYSIS OF HR IN REAL TIME VS OFFLINE CONSIDERING CSTRESS SYSTEM

SUBJECT	PARAMETER	Real Time			Offline		
		FFT	*ICA*	*PCA*	*FFT*	*ICA*	*PCA*
1	RSQ	0.90	0.89	0.96	0.99	0.95	0.99
	CORREL	0.95	0.94	0.98	0.99	0.97	0.99
2	RSQ	0.95	0.96	0.95	0.91	0.86	0.94
	CORREL	0.97	0.98	0.97	0.96	0.93	0.97
3	RSQ	0.95	0.93	0.95	0.92	0.95	0.94
	CORREL	0.98	0.97	0.97	0.96	0.98	0.97
4	RSQ	0.94	0.97	0.94	0.94	0.99	0.94
	CORREL	0.97	0.98	0.97	0.97	0.99	0.97
5	RSQ	0.99	0.98	0.96	0.97	0.98	0.98
	CORREL	0.99	0.99	0.98	0.98	0.99	0.97
6	RSQ	0.98	0.96	0.98	0.94	0.97	0.94
	CORREL	0.99	0.98	0.99	0.97	0.98	0.97
7	RSQ	0.89	0.94	0.86	0.81	0.90	0.81
	CORREL	0.95	0.97	0.93	0.91	0.95	0.90
8	RSQ	0.93	0.94	0.96	0.94	0.96	0.99
	CORREL	0.966	0.97	0.98	0.97	0.98	0.99
9	RSQ	0.98	0.98	0.97	0.96	0.96	0.95
	CORREL	0.99	0.99	0.98	0.98	0.98	0.97
10	RSQ	0.97	0.97	0.96	0.95	0.95	0.94
	CORREL	0.98	0.98	0.97	0.97	0.97	0.96

As can be seen from Table 1, both the RSQ and CORREL values are close to 90% or more than 90%. CORREL function gives better result than RSQ both in real time and offline. The average RSQ and CORREL values of 10 subjects were also calculated for real time HR methods and offline HR methods by applying three algorithms and presented through bar charts as fig.4a and fig.4b. Average CORREL value is 0.97 for real time and 0.95 for offline which indicates that there is a strong positive correlation between the proposed methods and the reference system. Average RSQ value for real time is 0.93 and offline is 0.91 which also indicates a perfect fitness between the two methods. According to the Figures, real time method shows its best performance compare to the offline methods. It may happen because of the loss of R, G and B color values of the film image sequences during saving in local disk. Lower resolution of the video may be another reason of this performance. It is also seen from the fig.4 that PCA method gives the best results both in real time and offline and ICA methods show better result than FFT.

VI. CONCLUSION

A real time noncontact based HR extraction method is described in this paper using facial video which is easy to implement, low cost and comfortable for real time applications. Here, the main idea is to extract HR from the color variation in the facial skin due to cardiac pulse and the implementation has been done using a simple webcam in indoor environment with constant ambient light. According to the experimental works, both the RSQ and CORREL values shows highest closeness (i.e. >90%) with the reference measurements. From the table and the figures presented in earlier chapter it is noted that the correlation using CORREL parameters (97.5%) is higher than RSQ (96.5%) in real time and among the three methods PCA shows the highest accuracy and ICA works better. Better results (i.e. 99%) can be achieved by taking the average of the three methods and using HD (High Definition) video (1280 x 720 or even 1980 x 1080). This non-contact technology is promising for medical care and others indoor applications due to widespread availability of camera specially webcams. For applications in outdoor environment for example driver monitoring, few things such as variable environmental illumination or head movement should be considered. Also to increase the efficiency, the experiment needs to be done by more test subjects and more verifying systems. Although this paper only addressed the recovery of the cardiac HR, many other important physiological parameters such as, RR, HRV and arterial blood oxygen saturation can potentially be estimated using the proposed technique. Creating a real-time, multi-parameter physiological measurement platform with higher resolution of video based on this technology in driving situation will be the subject of future work.

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