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Improvement of the Heart Rate Estimation from the Human Facial Video Images

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Abstract- Human facial video captured with a webcam can be processed to extract the heart rate. This paper shows that the color space of processed video images, the distance of the person from a webcam and processed segment of the face are important parameters in the accuracy of the estimated heart rate. Our results show that the heart rate ought to be extracted from the facial videos in the HSV color space, also our results show that the accuracy of the estimated heart rate are decreased, by increasing the distance of the person from the webcam. Therefore, our proposed scheme using the video images captured by two webcams, improves the accuracy of the estimated heart rate. Subsequently, we segmented facial region to several blocks and found regions with higher accuracy in heart rate estimation. We have carried out experiments on a data set of 12 subjects. The results of experiment have been compared with the heart rates recorded by a fingertip pulse Oximeter in a statistical analysis framework.

Keywords- *Distance, Heart rate, HSV color space, Independent component analysis*

I. INTRODUCTION

Heart rate is one of the most important physiological characteristics in medicine. Heart rate estimation has been identified as an independent risk factor for cardiovascular disease [1]. Contact methods of measuring heart rate, such as electrocardiogram (ECG) and fingertips or earlobes pulse Oximeter sensors, are uncomfortable and sometimes inaccessible for the patient. Therefore, the non-contact methods of heart rate measurement are non-invasive and appropriate than contact methods. One of the non-contact methods of measuring heart rate is utilization and processing of video images of the face.

Our investigation shows that in the heart rate estimation from facial video images, some parameters such as the color space, the distance from a webcam and processed segment of face are important in the accuracy of the heart rate estimation. Heart rate estimation from recorded video images at the distance can be used to increase security in airports and conference halls based on the information in the thermal signal emitted from major superficial vessels have estimated the heart rate by using a thermal camera in the distance range between 3 and 10 feet [2]. Since the RGB (red, green, blue) video images in webcam only a small part of the range of the infrared spectrum are included, obviously, with increasing distance, accuracy in estimating heart rate by RGB video images is less than accuracy in estimating heart rate by infrared video images. In our knowledge, estimating the heart rate of RGB video images that are recorded with the webcam at distances greater than one-half meter, have not been studied seriously. Takano and Ohta have proposed a method for heart rate measurement from the recorded images from a CCD (Charge-Coupled Device) camera at close distance [3]. Balakrishnan et al have extracted the heart rate from head motion on the video images that recorded at close distance [4], also Wei et al have presented a method using Laplacian Eigenmap (LE) for heart rate measurement at close distance [5]. Another method for the heart rate estimation is the independent component analysis (ICA) implementation on the three RGB channels of recorded video images with webcam in distance about 0.5 meter which was proposed by Poh et al [6,7].

In this study, we investigate the effect of the color space of video images, the distance of the person from a webcam, and processed segment of face, in the accuracy of the estimated heart rate, from facial video images. We explore the adverse effect of distance on heart rate estimation and propose a very simple but powerful way to handle the problem. To evaluate the effect of these parameters on the accurately of heart rate estimations, we have mainly adopted previously proposed algorithm for heart rate estimation by Poh. Firstly, we implement the ICA method on RGB and HSV (Hue, Saturation, Value) color space of facial video images, and then select the best color space for heart rate estimation. Then, we implement the ICA method on HSV color space of facial video images, which recorded at distances of 0.5m and 3m from the webcam and show by increasing the distance from the webcam, the accuracy of the estimated heart rate is decreased. Continuously, using the video images captured by two webcams improve the accuracy of the estimated heart rate in distance. Finally, we segment facial region in video images to the several segment and find the segments with high accuracy in the heart rate estimation rather than other segments. The effect of these parameters in the estimated heart rate from facial video image, in different conditions has been compared with the heart rates recorded by a fingertip pulse Oximeter in a Bland-Altman statistical analysis.

The paper is organized as follows: in section II, the algorithm of Heart rate estimation from facial video images and proposed methods for improvement the heart rate accuracy are explained. Then the method of comparison estimated heart rate from face video images with extracted heart rate from pulse Oximeter is explained. In section III, the experimental results on video images that were taken of 12 people are shown. In final section, conclusion is provided.

II. MATERIALS AND METHODS

In this section, first we explained the independent component analysis and the algorithm of the heart rate estimation from facial video images, by implementation the ICA on the average of pixels intensity in color channels. Then, the proposed methods for improvement the adverse effect of RGB color space and distance from the webcam on estimated heart rate accuracy are explained. Finally, the proposed method for extraction heart rate from pulse oximeter and statistical method are described.

A. *Independent component analysis*

Stated simply, imagine that two people are speaking simultaneously in a room and two microphones, which are hold in different locations, recorded time speaking signals. We could denote recorded signals by $x_1(t), x_2(t)$, each one of these recorded signals is a weighted sum of the speech signals emitted by the two speakers, which we denote by $s_1(t), s_2(t)$ as (1) and (2).

$$x_1(t) = a_{11}s_1(t) + a_{12}s_2(t) \quad (1)$$

$$x_2(t) = a_{21}s_1(t) + a_{22}s_2(t) \quad (2)$$

If you could estimate a_{11}, a_{12}, a_{21} and a_{22} , two speech signals are extracted from recorded signals. An independent component analysis are used to estimate a_{11}, a_{12}, a_{21} and a_{22}.

In independent component analysis, assume that observe n linear mixture $x_1(t), \dots, x_n(t)$ of n independent components (3). The matrix with element a_{ij} is denoted by A and (3) is written as (4). Therefore independent components are extracted from $x_i(t)$ by (5)[8].

$$x_i(t) = \sum_{j=1}^{k} a_{ij}s_j \ ; i = 1,2,\dots,k \quad (3)$$

$$x(t) = As(t) \quad (4)$$

$$s(t) = A^{-1}x(t) \quad (5)$$

In heart rate estimation from face video images, the average of pixels intensity color space channels, in facial region are $x_1(t), x_2(t), x_3(t)$. These raw traces were decomposed into three independent components $(s_1(t), s_2(t), s_3(t))$ by using ICA (6).

$$x_i(t) = \sum_{j=1}^{3} a_{ij}s_j \ ; i = 1,2,3 \quad (6)$$

B. *Heart rate estimation algorithm based on facial video images*

In this study, recorded video images were processed by MATLAB software and OpenCV (Open Computer vision) libraries, and then for using the OpenCV libraries in the MATLAB software, MEX (Matlab Excusable) were used.

For face detection in video images, we used the OpenCV face detection algorithm based on the Viola-Jones algorithm, this algorithm is extremely rapidly with high detection rate and it is an appropriate for face detection in different distances [9,10]. After face detection from face video images, in next step, the average of R, G and B color channels pixels intensity, in facial region were plotted versus the time. Then, raw RGB traces were passed from a high-pass filter with a finite impulse response (FIR)[11]. In next step, we normalized the RGB traces to zero mean and unit variance as (7).

$$X_i(t) = \frac{x_i(t)-\mu_i}{\sigma_i} \quad (7)$$

In Equation (7), for each i=1, 2, 3 where μ_i and σ_i are mean and standard division (SD) of $X_i(t)$. The normalized raw traces were decomposed into three independent components by using ICA [12-14]. Then the Fourier transform were implemented on these and the peak of any components was detected, finally we estimated heart rate from these peaks as (8) and (9).

$$P = \max(p_1, p_2, p_3) \quad (8)$$

$$\text{Heart Rate} = 60 * F \quad (9)$$

According to the (8), maximum peak was detected, then frequency response with P coefficient (F) was multiplied in 60 and heart rate was estimated by (9) (Fig. 1).

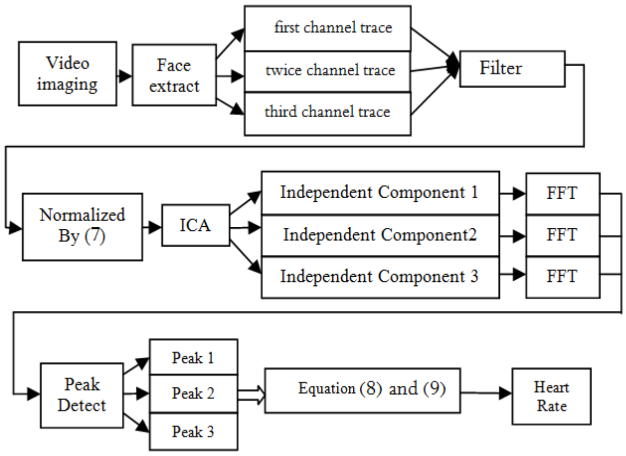

Figure 1. Heart rate estimation algorithm from video images

We will perform experiments on the explained algorithm to investigate the effect of the color space, distance from webcam and processed segment of face in the accuracy of the estimate heart rate.

C. *Color space as a parameter*

In this section, first, we explain HSV color space and reason of RGB to HSV transformation for the heart rate estimation. Then algorithm of the heart rate estimation from HSV color space is described.

The HSV (hue, saturation, value) color space is very similar to the color space of human vision system. In HSV, hue is amount of pure color, such as pure yellow or pure red, hue channel determine color type from 0 to 360 degree. Saturation is shown the mixture amount of pure color with light or white. Value is related to the brightness. HSV is non-linear, but very intuitive color space. Generally this space is obtained from linear transformation of RGB.

Sometimes applying ICA to signals may lead to poor results. For improving ICA result, we can preprocess signals by grouping into clusters, and then implement ICA on every cluster [15]. By preprocessing, correlation between signals is reduced. Therefore results of implement ICA on ICA incoming signals are better if these signals have a low correlation.

R, G, and B channels are high correlation, while correlation between H, S, and V channel is lower. Since, RGB to HSV transformation is similar to preprocessing, in this study we will show that RGB to HSV transformation lead to the improvement of the heart rate estimation results.

The Heart rate estimation from HSV channels is similar to heart rate estimation from RGB channels, except just after face detection, RGB color space is converted to HSV color space and then other steps of the algorithm are the same.

D. Distance of the person from webcam as a parameter

In fact, with increasing the distance of the person from a webcam, facial region is limited and the resolution of the video image is diminished which eventually leads to decrease in the accuracy of the estimated heart rate. To evaluate the effect of distance from the webcam on the accurately of heart rate estimation, we implement the algorithm from Fig. 1 on facial video images, that recorded at intervals of 0.5 m and 3 m from the webcam, The results of experiment (in result section) show that the accuracy of estimated heart rate is decreased by distance increase. The results indicated that in measuring heart rate at the distance, we need to increase the image resolution, while information lies in face that brings us heart rate, are maintained. So, we proposed the simple method based on using the video images captured by two webcams, for heart rate estimation at distance.

Firstly video images captured by two webcams, synchrony, then by face detection library in OpenCV, face is detected in every frame of the every captured video. In next step, the average of color channels pixels intensity, in facial region (in every face region of two videos) were made two matrix, then average of two matrix was computed over the time and other steps of heart rate estimation algorithm (Fig. 1) are implemented on it.

E. Face segmantation in facial video images

If we search for a part of face region that heart rate shows more than other regions in it, will reduce the amount of calculations. Since, there are major vessels on face and the relationship between this vessel's color changes with heart rate, heart rate was estimated from video images [2]. So we can assume that the heart rate in the parts of the face that contains more blood vessels (such as temple and species), more than in other parts (such as the eyes) are shown. To test this hypothesis, we consider two face segmentation schemes. Firstly, face is divided into four segments (Fig. 2) and by processing every segments, heart rate is estimated for every segment. Then estimated heart rates from every segment are compared with extraction heart rate from pulse Oximeter and best segment of face for heart rate estimation is selected by a statistical method.

Blood vessels of the face in the cheeks and temples are more than other segments (Fig. 3). As it is shown in section 3, face segmentation to four segments was not useful for our purpose, because face vessels in every four segments are same, so in next step, we segment face to three segments (Fig. 4). Then estimated heart rates from every segment are compared with extraction heart rate from pulse Oximeter and best segment of face for heart rate estimation is selected by a statistical method.

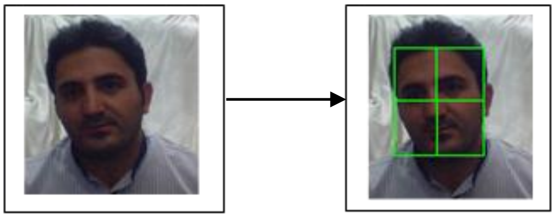

Figure 2. Face segmentation to four segments

Figure 3. Blood vessels in face

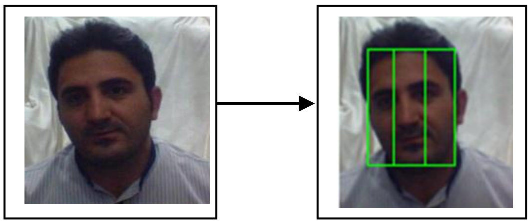

Figure 4. Face segmentation to three segments

F. Extarct the heart rate from pulse oximeter

In this study, for heart rate measurement, the finger pulse Oximeter CMS-50D model was used (Fig. 5). The extracted values of the pulse Oximeter were used as a reference in subsequent comparisons, in the next step, extraction of the displayed Heart rate on the pulse Oximeter screen and transfer them to computer were considered. By reading pulse Oximeter catalog, was found that the displayed values on the screen of the device can transfer into the computer via USB cable, However, by installing the drivers, the data transfer from pulse Oximeter to computer was not solved [16]. So, to enter the values shown on the screen to a computer, we were forced to use image processing methods.

By mobile phone camera (Sony Ericsson w150), a video from the pulse Oximeter screen (attached to the finger) was recorded (Fig. 6), this video was transformed to numbers by using image processing techniques.

For extraction pulse oximeter displayed number, firstly, each frame of the input video was converted to the binary image, then we separated each digits of this number, but, due to light scattering in pulse oximeter screen, often in the video frames, digits were attached to each other and separating them by using connected components and morphology algorithms, was not possible. So to separate the digits, K-means clustering algorithms was used [17]. The next step was to identify the separated digits. At this stage, each separated digit was compared with pre-stored templates and recognition done (Fig. 7).

Now, the estimated heart rates of video recordings in the different experimental condition, and the extracted heart rates from pulse Oximeter were compared in a statistical method.

G. Bland-Altman statistic

To compare estimated heart from webcam with the extracted heart rate from pulse Oximeter, the bland-Altman statistical method was applied [18]. The main characteristic of this statistical method is to compare a new clinical method with other methods (old) is used, while in the comparison, do not fully trust on these clinical methods. In this statistical method, the difference between the two methods is plotted versus the average of them on a distribution graph. Then, the average data and standard deviation data are calculated and these calculated values are specified on the scatter diagram (Fig. 8).

Figure 5. Pulse Oximeter CMS-50D

Figure 6. Video record from Pulse oximeter digits, with a mobile

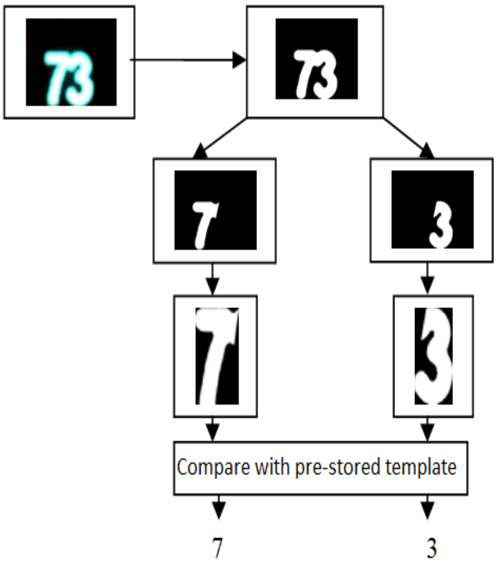

Figure 7. Heart rate extaraction from pulse oximeter.

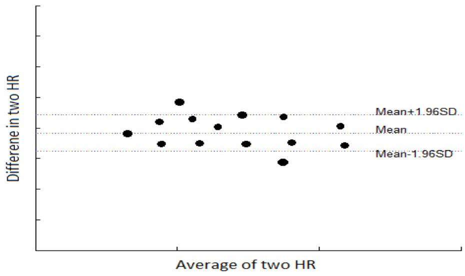

Figure 8. Statistic method graph

III. RESULTS

A. Experimental setup

In this study our samples featured 12 participants of both genders (8 females, 4 male) and different ages (22-35 years). Participants were seated in front of a laptop webcam or webcams at a distance of approximately 0.5m (or 3m). During the experiment, participants were asked to keep face in webcam cadre, while webcam was recording video from face and mobile camera was recording video from pulse Oximeter screen, these videos was recorded for 30 second (Fig. 9). In this experiment, 9000 frames of every participant were collected, and RGB videos were recorded at 30 frames per second (fps) and were saved in mpeg format.

Therefore databases are collected follow as:

- Database 1: Participants were seated in front of the HP webcam at the distance of approximately 0.5m.
- Database 2: Participants were seated in front of the HP webcam at the distance of approximately 3m.

- Database 3: Participants were seated in front of the HP and DEL webcams at the distance of approximately 3m.

B. Result of experiments

In this section, firstly we provide results of change color space by implementing the heart rate estimation algorithm on database 1. Then, the results of heart rate estimation at distance 0.5m and 3m are provided by database 1 and 2. Then, we show results of heart rate estimation at distance 3m from two webcam by implementing proposed algorithm on database 3. Finally, the results of facial region segmentation on heart rate estimation algorithm, by using database 1, are provided.

- Results of heart rate estimation by change color space parameter

For every color space, we implemented heart rate estimation algorithm on recorded video images at the distance 0.5m and estimated heart rates. Using the algorithm detailed in Section 2, heart rates are estimated from RGB and HSV color spaces. The results of processing 30 frames of video for HSV color space is shown in Fig. 10. Heart rate estimation from RGB channels is similar to HSV just do not convert RGB to HSV color space.

Using Bland-Altman method, the difference between the estimated heart rate from the HSV color channels and the extracted heart rate from the pulse Oximeter were plotted versus average heart rate in Fig. 11 (a). Similarly, the scatter diagrams for the estimated heart rate from RGB color channels were plotted in Fig. 11 (b). Root mean square error (RMSE), standard division and mean value were calculated, the root mean square error was reduced from 24.53 (from RGB channels heart rate estimation) to 8.68 (from HSV channels heart rate estimation) (TABLE I). Statistic values in TABLE I and coherence in Fig. 11 (a) indicated that RGB to HSV transformation is similar to preprocessing in ICA and improve heart rate estimation results.

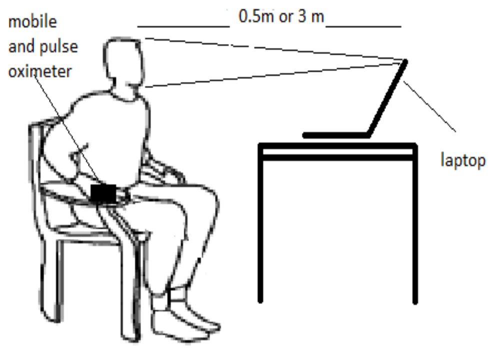

Figure 9. Experimental setup

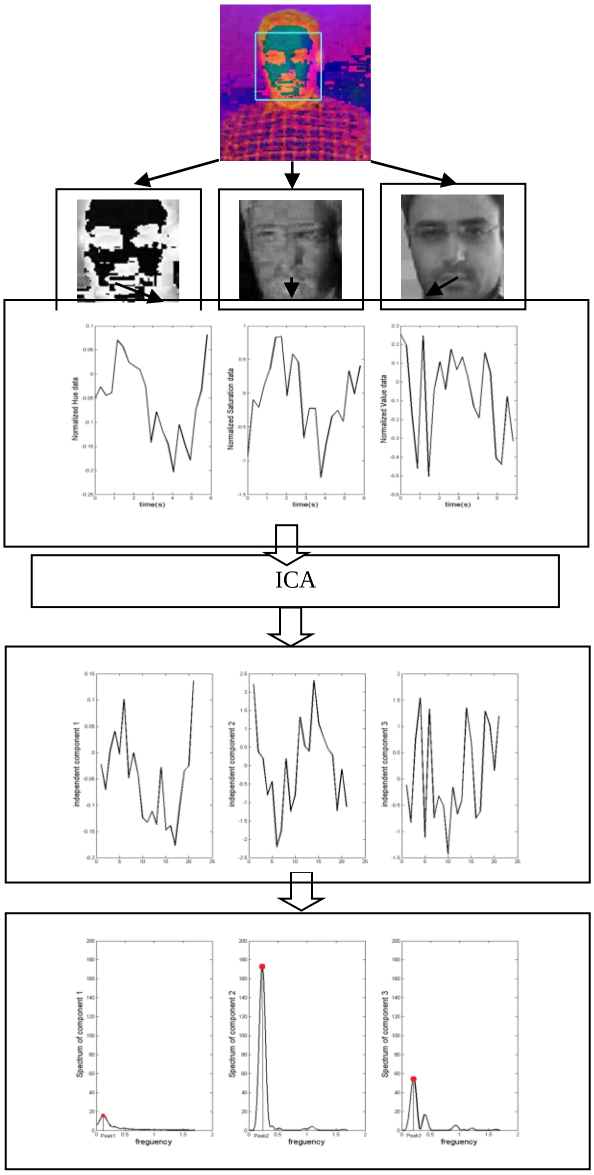

Figure 10. After face extraction, RGB converts to HSV, draw traces of each HSVchannels,implement ICA on filtered and normalized trace, three independent components, fourier transform of these, detect peak of each component.

- Results of heart rate estimation at distances 0.5m and 3m from a webcam

For heart rate estimation, the recorded video images at the distance of 3m were used. Using the algorithm from section 2, heart rate was estimated. The difference between the estimated heart rate from the recorded video at the distance of 0.5 meter and the extracted heart rate from the pulse Oximeter were plotted versus average heart rate in Fig. 12 (b). Similarly, the scatter diagrams for the estimated heart rate of the video images recorded at the distance of 3 meters were plotted in Fig. 12(a). For both distance, statistical values are obtained, the results showed that the RMSE value of 8.68 (at the distance of 0.5m) to 14.37 (at the distance of 3m) was increased (TABLE I). Comparison of data in TABLE I, and that the data dispersion in Fig. 12 (a) was less than the Fig. 12 (b), shown that the distance from the webcam to capture video images effects on the statistical results. As a result, increasing distance from the webcam, by limiting the face and reducing the intensity of the received signals, resulting was an increase in root mean square error between heart rate extraction from pulse Oximeter and heart rate can be estimated.

- Results of heart rate estimation at distance 3m from two webcams

For improving the effect of the distance from webcam in accuracy of estimated heart rate, captured video images by two webcams (Hp and Del) at the distance 3m are used. The algorithm from section 2 again is used to estimate the heart rates.

The difference between the estimated heart rate from the recorded video at the distance of 3m of two webcam and the extracted heart rate from the pulse Oximeter were plotted versus average heart rate in Fig. 13. Statistical values are obtained. The result showed that the RMSE value of 17.37 (at the distance of 3m of one webcam) to 9.05 (at the distance of 3m of two webcam) was decreased (TABLE I). Data dispersion in Fig. 13 was less than the Fig. 12 (a), so by using two webcam we can improve the adverse effect of the distance from webcam on estimated heart rate accuracy. Finally, RMSE in heart rate estimation from recorded video at the distance 3m from two webcam and RMSE in heart rate estimation from recorded video at the distance 0.5m from one webcam, approximately are same.

- Results of heart rate estimation by facial region segmentation

Herat rate estimation from a part of face region in facial video images will reduce the amount of calculations. Therefore, we segmented facial region in four segments (Fig. 2) and three segments (Fig. 4) and estimate the heart rate from every segment. In this section statistics results of comparing estimated heart rate from face and extracted heart rate from pulse Oximeter are provided.

We have two scenarios to segment the facial video images: four blocks and three blocks. For every segment in each scenario, we apply the algorithm from section 2 to estimate the heart rates on recorded video images at the distance 0.5m.

Using Bland-Altman method, in four blocks segmentation, Root mean square error (RMSE), standard division and mean value were calculated and shown in TABLE II. Since, blood vessels of the face in these four segments are approximately same, so, RMSEs for every block are approximately equal and this form of facial region segmentation was not useful for our purposes.

Statistics values for three block segmentation were provided in TABLE III. Since, blood vessels of the face in block one and block three are approximately same and rather than block two , so, RMSEs for block one and block three are less than block two. These results shown that block one and block three that contain most blood vessels, have most information about heart rate, rather than block two.

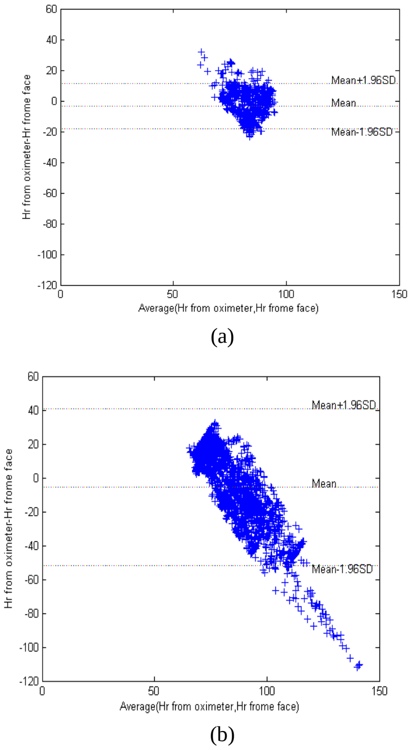

Figure 11. Statistics diagram for heart rate estimition (a) from HSV color space and (b) from RGB color space.

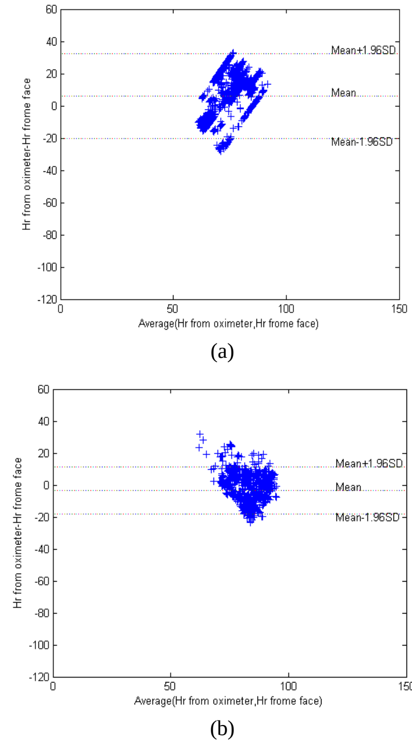

Figure 12. Statistics diagram for heart rate estimition (a) at the distance 3m and (b) at the distance 0.5m.

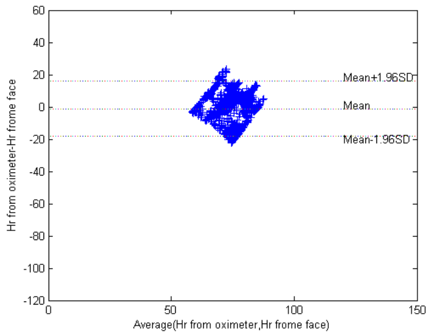

Figure 13. Statistics diagram for heart rate estimition at the distance 3m of two webcam.

TABLE I. STATISTICS RESULTS IN DIFFERENT CONDITION

Experimental setup			Statistics		
Distance from webcam	***Color space***	***Webcam model***	***RMSE***	***SD***	***mean***
0.5m	HSV	Hp	8.6827	7.5547	-3.2823
	RGB	Hp	24.5251	23.6527	-5.4994
3m	HSV	Hp	14.3733	13.4615	6.0473
		Dell	13.9366	13.9336	0.5971
		Hp,Del	9.0457	8.7868	-1.1579

TABLE II. STATISTICS RESULTS FOR FACE SEGMENTATION TO FOUR SEGMENTS.

Block number	***RMSE***	***SD***	***Mean***
Block one	14.8172	13.4816	-5.1552
Block two	15.7122	15.0528	5.5168
Block three	15.7702	15.1301	5.4602
Block four	15.5144	15.4356	2.6037

TABLE III. STATISTICS RESULTS IN FACE SEGMENTATION TO THREE SEGMENTS.

Block number	***RMSE***	***SD***	***Mean***
Block one	12.6451	12.6360	0.4359
Block two	42.4714	41.4376	-8.3651
Block three	15.3034	15.0627	3.7268

IV. CONCLUSION

In this article, the heart rate estimation from on the human facial video images was improved. So in this paper, the effect of the color space of video images, the distance of the person from a webcam and processed segment of face in the accuracy of the estimated heart rate was studied and then the methods were proposed for improvement accuracy in estimated heart rate. For this study, facial video images of the database with 12 persons at intervals of 0.5 m and 3m were processed. The estimated heart rates were compared with the extracted heart rates from the pulse Oximeter, using the Bland-Altman statistical method. The Comparison in color space parameter, show that the heart rate should be extracted from HSV (hue, saturation, value) color space video images, scatter diagrams show that RMSE was reduced from 24.53 from RGB channels heart rate estimation to 8.68 from HSV channels heart rate estimation. Also the results of distance parameter show, by increasing the distance form webcam, the accuracy of the estimated heart rate is decreased. The RMSE value of 8.68 (at the distance of 0.5m) to 14.37 (at the distance of 3m) was increased. Therefore, we proposed the method based on the video images captured by two webcams and improved the accuracy of the estimated heart rate in distance. The RMSE value of 17.37 at the distance of 3m of one webcam to 9.05 at the distance of 3m of two webcam was decreased. Subsequently, we segmented facial region to several region and found the region with high accuracy in heart rate estimation. The Bland-Altman diagram shown that, in three segmentation form, block one and block three that contain most blood vessels, have most information about heart rate, rather than two block.

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