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Measuring Pulse Rate with a Webcam – a Non-contact Method for Evaluating Cardiac Activity

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Abstract—**In this paper the simple and robust method of measuring the pulse rate is presented. Elaborated algorithm allows for efficient pulse rate registration directly from face image captured from webcam. The desired signal was obtained by proper channel selection and principal component analysis. A developed non-contact method of heart rate monitoring is shown in the paper. The proposed technique may have a great value in monitoring person at home after adequate enhancements are introduced.**

I. Introduction

HOME health care is nowadays growing and changing discipline. The remote monitoring of vital signs includes not only the high accuracy diagnostic devices but also simple ones and accessible for everyone. One of the most frequent examinations performed in health care monitoring is cardiac pulse measurement. There are many different methods of contact measurement of a heart rate among which the golden standard is an electrocardiography (ECG). However, recording electric potential generated by the heart requires appropriate application of the electrodes what may be too complicated and annoying in home conditions. Other methods of measuring cardiac pulse involve thermal imaging [1], Doppler phenomenon both optical [2] and ultrasonic [3] or piezoelectric measurements [4]. Photoplethysmography (PPG) is another method that is being used in detecting pulse rate [5]. It utilizes changes of the optical properties of a selected skin area involved by pulsating blood contents. The typical implementation of PPG uses dedicated light sources, e. g. near-infrared light. Changes of the light intensity reflected from the skin correspond to a volume of tissue blood perfusion. Moreover, it has been proved that pulse measurement from human face is also possible using daylight as the illumination source [6]. *Poh et al.* has developed a robust method for computation of the heart rate from digital color video recordings of the human face [7]. The method is based on blind source separation of the color channels into independent components.

A principal component analysis is used in our procedure. It is applied to video channels and in effect it reduces computational complexity in comparison to independent component analysis. We also show that it is possible to determine a pulse rate based on small rectangular region of the face image and only on two color channels. It is important when considering computational efficiency of the home health care monitoring system and its operation in real time.

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II. Methods

A. Experimental setup and measurement procedure

The experimental setup consisted of web and thermographic cameras, and synchronized recorder of ECG (Fig. 1).

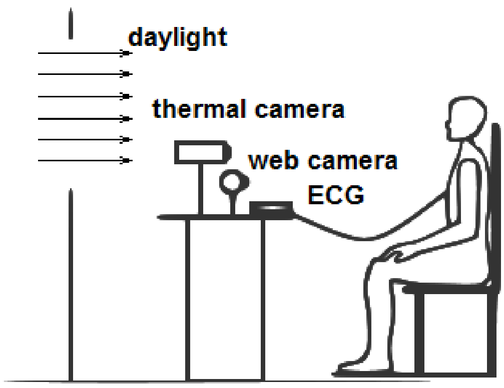


Fig.1 Experimental setup

The measurements were performed indoor and the only light source was sunlight. The 30 seconds long video sequences were recorded by means of a Logitech Webcam 9000 Pro. The resolution of the videos was 640x480 pixels and the frame rate was 20 fps. Sequences of images were saved in AVI format without compression. While the video was being recorded the ECG signal was collected using the AsCARD electrocardiograph (AsCARD MrGrey v.201, Aspel). The sampling rate of ECG signal was 400 Hz.

Together 10 white volunteers, 2 women and 8 men, of different age (20 - 64 years), were examined. During the measurements they were sitting still and distant 1 m in front of the camera. Experiments were performed in room naturally lighted at midday (Fig. 1).

B. ROI's selection

The analysis was performed for two different ROI's (regions of interest) sizes. First, the rectangle containing the face region was selected at the first frame of video recording (Fig. 2a). Coordinates of the selected face region remained the same for the whole sequence of images. The second ROI was a rectangular-shaped part of the forehead area. It was defined basing on pupils' coordinates and distance calculated between them (Fig. 2b). It was expected that it would be possible to find a part of forehead to be visible "uniformly". To prove this assumption thermographic images were taken for all examined persons. Thermograms were recorded by the FLIR ThermaCam SC3000 thermal camera having temperature resolution equal 0.1°K.

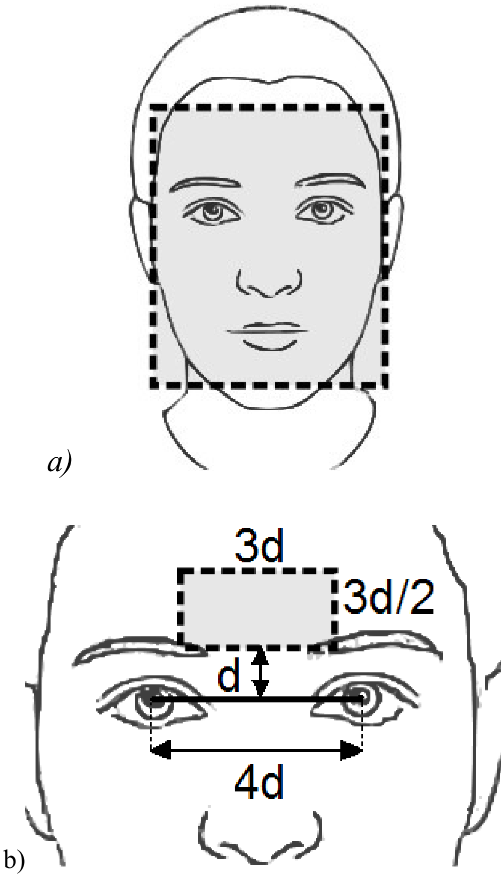


Fig.2 Definition of ROI's for two approaches utilized in the paper, a) the whole face as a ROI, b) selected part of the forehead as a ROI

C. Image decomposition

The ROI's were decomposed into three RGB channels. Analyses were performed for a different channels combination: RGB, RG, GB, RB.

D. Methods of analysis

The Independent Component Analysis (ICA) is a statistical and computational technique used to separate independent signals from a set of observations that consist of linear mixtures of the underlying sources [8]. The ICA model assumes that the observed signals $\mathbf{y}(t)$ are linear mixtures of the unknown sources $\mathbf{x}(t)$:

$$\mathbf{y}(t) = \mathbf{A}\mathbf{x}(t) \quad (1)$$

where the mixing matrix $\mathbf{A}$ is also unknown. To estimate both $\mathbf{A}$ and $\mathbf{x}(t)$ we assume that the components of vector $\mathbf{x}$ are statistically independent and nongaussian. After estimating $\mathbf{A}$ matrix its inverse $\mathbf{W}$ (demixing matrix) can be computed. Then the independent components can be obtained:

$$\mathbf{x}(t) = \mathbf{W}\mathbf{y}(t) \quad (2)$$

To evaluate the demixing matrix many algorithms have been proposed. In the present study the FastICA algorithm was used [9].

The Principal Component Analysis, (PCA), is sometimes called the Karhunen-Loeve Transformation, which is a technique commonly used for data reduction in statistical pattern recognition and signal processing. The PCA is a transformation that identifies patterns in data, and expresses the data in such way that it highlights the similarities and differences. That makes PCA a powerful tool for analyzing data [10].

The basic idea in PCA is to find the components $s_1; s_2;.. s_N$ so that they explain the maximum amount of variance possible by N linearly transformed components. The principal components are then given by $s_i = w_i^T \cdot x$. The computation of the w_i can be accomplished by using the covariance matrix $E\{xx^T\} = C$. The vectors w_i are the eigenvectors of C that corresponds to the N largest eigenvalues of C .

These components should be ordered in such way that the first component, s_1, points in the direction where the inputs have the highest variance. The second component is orthogonal to the first and points in the direction of highest variance when the first projection has been subtracted, and so forth.

Suppose we have two zero mean random vectors, $\mathbf{X}$ and $\mathbf{Y}$, that gives $E[\mathbf{X}] = 0$ and $E[\mathbf{Y}] = 0$. Let u denote a unit vector, onto which the $\mathbf{X}$ is to be projected. This projection is defined by the inner product of the vectors $\mathbf{X}$ and $\mathbf{U}$, as shown by

$$\mathbf{Y} = \mathbf{U}^T\mathbf{X} \quad (2)$$

where $\mathbf{U}$ is an orthonormal matrix. The principal components are columns of $\mathbf{U}$ and they are found by seeking the directions of maximum data variance, under the orthogonality constraint. Columns of $\mathbf{U}$ are eigenvectors of the covariance matrix ordered with decreasing variance [11].

E. Algorithm

For every ROI's channel, pixels values were added separately for each frame. The signals obtained this way were filtered using a FIR bandpass filter (0.5–3.7 Hz, 32-

point Hamming window, designed with MATLAB FDATool). Next, independent and principal component analyses were performed. The ICA was performed using FastICA algorithm implemented in MATLAB. Principal components were obtained with the use of MATLAB *processpca* function.

III. Results

The images of examined volunteers were processed so as to find regions of interest to further analysis (Fig. 3).

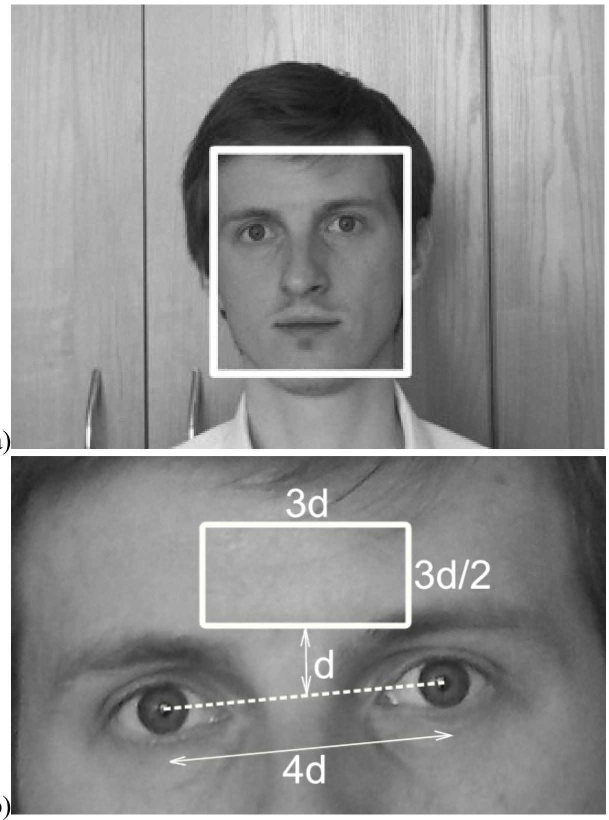
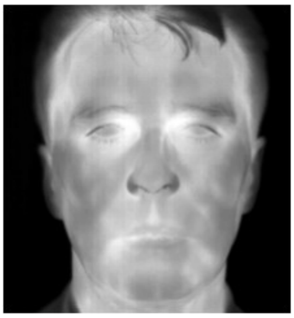


Fig. 3 Selection of the analyzed region: a) whole face ROI, b) forehead ROI

The uniformity of ROI localized on the forehead was analyzed using thermal images. The mean pixel value and the variance σ^2 were calculated for face and forehead ROI. Examples of obtained images with calculated $\bar{x}$ and σ^2 are shown in Fig. 4. The images support the assumption that it is possible to select almost uniform part of face to be analyzed.

Video sequences were processed in order to obtain a desired time - dependent signals. A sum of pixels values was calculated for each channel throughout the ROI (Fig. 5). Obtained signals were bandpass filtered (0.5–3.7 Hz).

Independent component analysis and principal component analysis were conducted for different sets of data (Fig. 6 - 7). Firstly, analyses were performed for the ROI containing whole face area, and then a rectangular shape ROI selected on the forehead center was analyzed. Signals from three channels R, G and B were an input to ICA and PCA.



Face ROI: $\bar{x}$ = 152; σ^2 = 2073
Forehead ROI: $\bar{x}$ = 158; σ^2 = 52

Face ROI: $\bar{x}$ = 162; σ^2 = 2465
Forehead ROI: $\bar{x}$ = 180; σ^2 = 309

Face ROI: $\bar{x}$ = 136; σ^2 = 3734
Forehead ROI: $\bar{x}$ = 166; σ^2 = 197

Face ROI: $\bar{x}$ = 139; σ^2 = 4600
Forehead ROI: $\bar{x}$ = 159; σ^2 = 90

Fig. 4 Temperature distribution of the face for selected persons examined in the study

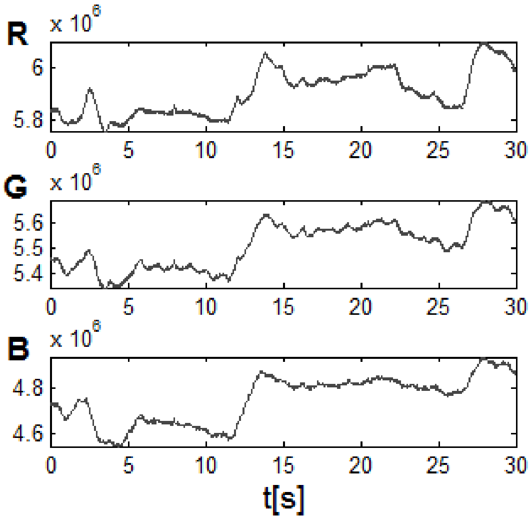


Fig. 5 Sum of pixels values of video sequence for whole face ROI; R, G and B stands for RGB channels

The result of PCA was compared with that obtained by ICA (Fig. 8). Time of calculation for ICA performed on the face ROI was equal to 223 ms, while for forehead ROI 94 ms. The time of calculation when using PCA for the same data set was respectively 1.4 ms and 1.2 ms.

To check whether obtained “pulse” signal changes are related to the heart rate the results obtained from PCA were compared with an ECG signal that was measured during video recordings (Fig. 9).

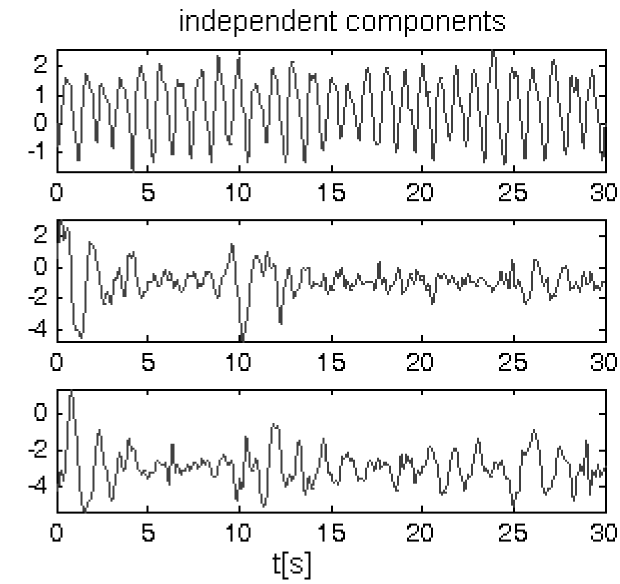


Fig. 6 Bandpass filtered result of independent component analysis for three RGB channels, ROI – the whole face

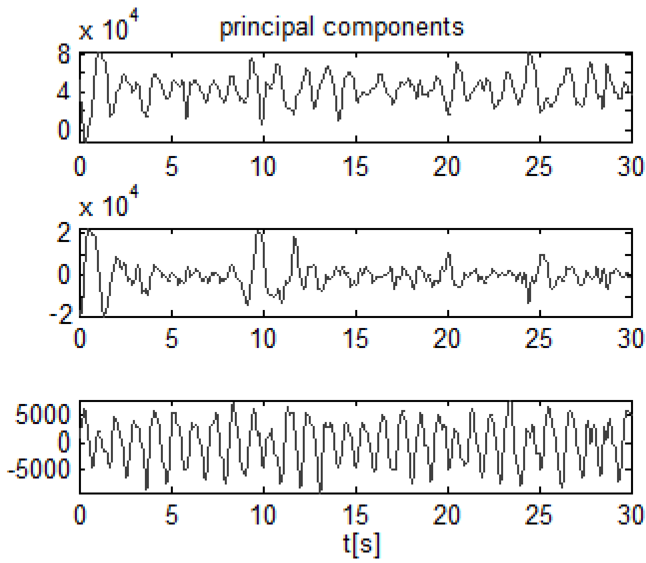


Fig. 7 Bandpass filtered result of principal component analysis for three RGB channels, whole face ROI

In Table I mean heart rates of four selected patients are presented. Results obtained from webcam measurements are compared to that obtained from ECG (R-R interval). Mean heart rate was calculated using two methods: one based on the interval between positive slope zero-crossings of the 2nd or 3rd PC and the second using maximum of the power spectral density function. Results obtained with the use of the second method are the same for face and forehead ROI in all cases.

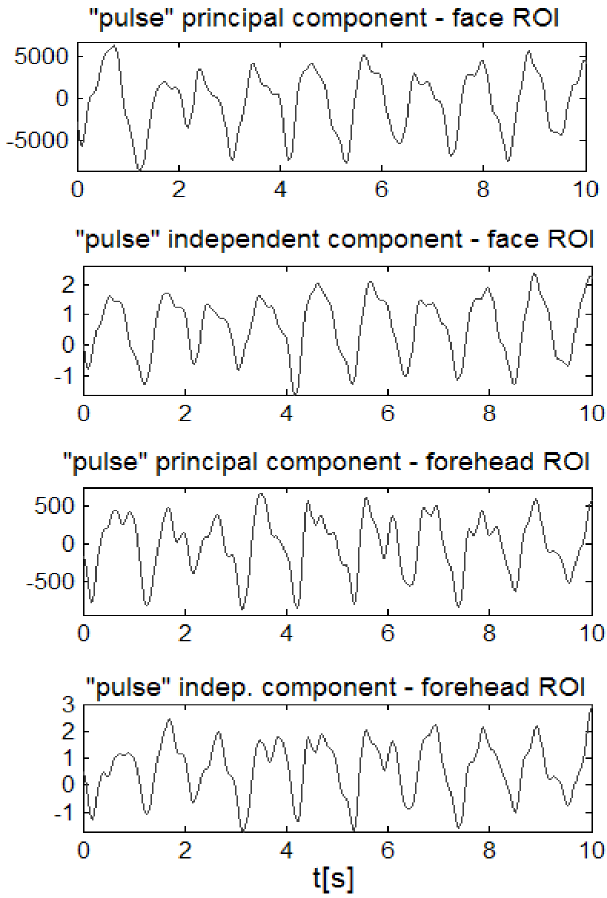


Fig. 8 Comparison of results obtained for ICA and PCA for the same data set

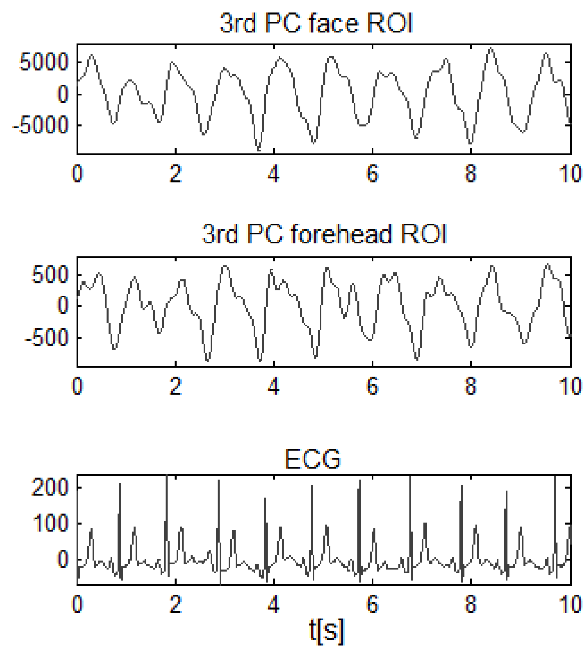


Fig. 9 Third principal component for two different ROI's: face and forehead, compared to ECG signal; it can be noticed that components of registered video signals are changing with heart rate

TABLE I.
HEART RATES OF FOUR SELECTED PATIENTS

Mean heart rate [bpm](measurement time = 30s)				
Patient Id	**Web camera**			**ECG**
	zero crossing		**fft**	
	face ROI	**forehead ROI**	**face/forehead ROI**	
1.	87.56	100.67	91.41	87.89
2.	59.32	59.18	58.01	58.59
3.	94.84	104.35	98.44	99.61
4.	60.07	76.85	59.76	58.66

When analyzing signals from only two channels, detection of a pulse rate was most effective when RG combination was considered (Fig. 10 - 11). However, compared to the analysis using three channels the "pulse" component (2^{nd} PC) was more distorted, especially when forehead ROI was analyzed (Fig. 11). Spectra of principal components containing pulse signals are presented in Fig. 12. Pulse component extracted from R and G channels apart from 1 Hz component contains also frequencies from 0.3 – 1 Hz range.

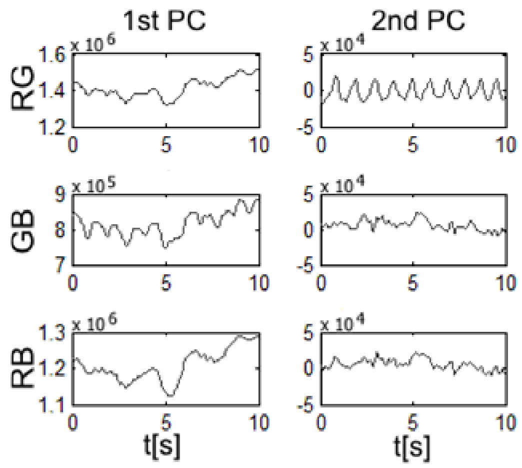


Fig. 10 Principal components for different channel combination: RG, GB, RB; face ROI

IV. DISCUSSION

Using the methods detailed in Section III, we estimated pulse rate based on webcam recordings. To reduce both complexity and number of calculations a smaller ROI was selected (the rectangular region of the forehead) as well as fewer color channels and less complex method of analysis was chosen.

The results obtained from independent and principal component analysis' show that those two methods extract the "pulse" component with similar accuracy. However, comparison of time of calculation and other studies [12] allows for the conclusion that PCA is less computationally complex so it is reasonable to choose that method to reduce time and complexity of analysis. The obtained results show that when only pulse rate is considered there is no need to use the more computationally complex ICA method. The accuracy of extraction of cardiac pulse signal by PCA is comparable to that obtained by ICA and is sufficient for our purposes. Moreover, the time of calculation obtained for PCA suggests possibility of using this approach in real-time applications.

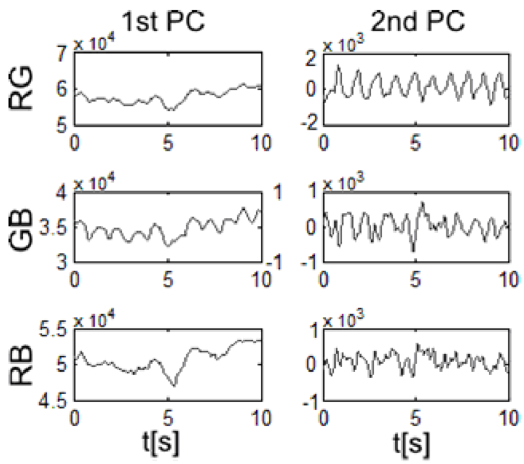


Fig. 11 Principal components for different channel combination: RG, GB, RB; forehead ROI

Selected forehead rectangular area is a region of the face with a temperature relatively constant for healthy male and female of different age. As shown in Fig. 4 the selected part of the forehead area, in contrast to other parts of the face, e.g. nose, has almost the same temperature for examined subjects. Furthermore, assuming that the examined object is kept still it does not contain any "moving" elements, like blinking eyes or moving lips. Based on the analysis performed on the forehead ROI it was possible to determine the pulse rate with sufficient accuracy for the selected group of patients. The results indicate that the selected forehead ROI is representative for the whole face region.

As it is shown in Fig. 10 and Fig. 11 the selected R and G channels contained most of the information about color changes corresponding to the blood volume pulse. So it was possible to reduce the number of analyzed signals from three to two. Decrease in ROI's size or number of channels increases the level of noise (Fig. 12). However, taking into account that these measurements are destined for daily monitoring of vital signs not for clinical purposes, the high accuracy is not the most important factor.

To improve the accuracy of the presented algorithm it is important to provide proper experiment conditions. The object of research needs to be motionless, so the examination have to be performed in the sitting or supine position. The proper lightening conditions are also very important because when analyzed face images are under- or overexposed information about color changes may be lost.

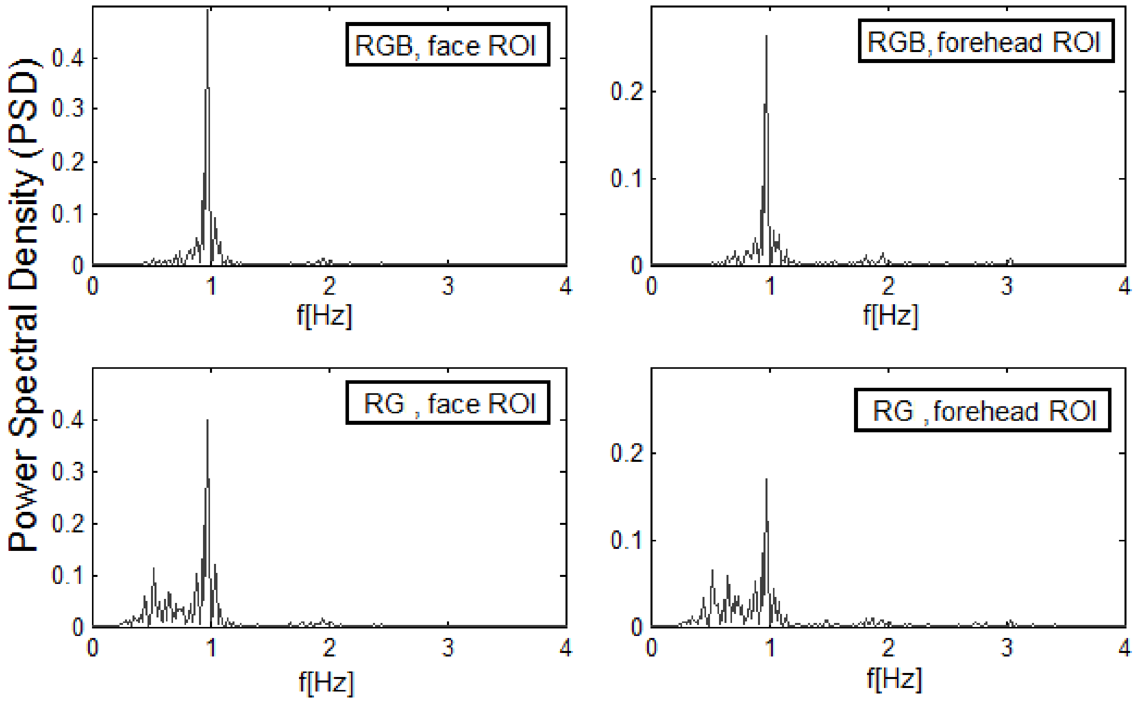


Fig. 12 Spectral density of two different ROI's (face and forehead) and two different channel combination (RGB and RG)

V. Conclusions

A simple processing of image data and then applying PCA allows extracting the changeable component containing information of the heart rate. The presented algorithm seems to be quite effective and easy to use in the daily monitoring of home care patients. However, a further study has to be performed on moving persons and the same with more than one camera.

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