Non-contact Physiological Parameters Extraction Using Camera

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Abstract. Physiological parameters such as Heart Rate (HR), Beat-to-Beat Interval (IBI) and Respiration Rate (RR) are vital indicators of people's physiological state and important to monitor. However, most of the measurements methods are connection based, i.e. sensors are connected to the body which is often complicated and requires personal assistance. This paper proposed a simple, low-cost and non-contact approach for measuring multiple physiological parameters using a web camera in real time. Here, the heart rate and respiration rate are obtained through facial skin colour variation caused by body 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 colour channels in video recordings and the blood volume pulse (BVP) is extracted from the facial regions. HR, IBI and RR are subsequently quantified and compared to corresponding reference measurements. High degrees of agreement are achieved between the measurements across all physiological parameters. This technology has significant potential for advancing personal health care and telemedicine.

Keywords: Heart rate · Respiration rate · Inter-Bit-Interval · Camera

1 Introduction

The ability to monitor physiological signals by a remote, non-contact methods include lasers Doppler [1], microwave Doppler radar [2], and thermal imaging [3, 4], but these systems are very expensive and require complex hardware. Using photoplethysmography (PPG) to measure BVP and then Heart-rate-variability (HRV) has been widely used in clinics and research labs, due to its simplicity, convenience and accuracy. The principle of PPG method is to illuminate the skin with a light-emitting diode (LED) and then measure the amount of light reflected or transmitted to a photodiode. In the past few years several papers proposed colour-based methods for remote heart rate measurement using ordinary commercial cameras [5, 6]. Poh et al. [7] explored the possibility to measure HR from 1-minute face videos recorded by a web-cam.

In this paper, a new framework for non-connected physiological parameters measurement is proposed which can work for any length of time. The information of the heart rate and respiration rate is obtained through facial skin colour variation caused by body blood circulation. Three different signal processing methods such as Fast Fourier

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Transform (FFT), Independent Component Analysis (ICA) and Principal Component Analysis (PCA) have been applied on the colour channels in video recordings and the Blood Volume Pulse (BVP) is extracted from the facial regions. The outcomes of the system using three methods are compared with existing ECG and respiration sensors system named cStress[1]. The paper is organized as: the measurement methods, its application and a real-time measurement system are described is chapter 2, Verification and validation of the designed real time measurement system is presented in chapter 3. Finally, the paper is summarized.

2 Materials and Methods

Data acquisition is conducted using 9 participants of different genders (3 females, 6 males), ages (25 to 40 years) and skin colours. The experiments are conducted indoors and with a varying amount of ambient sunlight entering through windows as the only source of illumination. Two out of nine experiments were conducted in artificial light environment and the result does not change so much. The test subjects were asked to sit without any movement. Participants are informed the aim of the study and they seated at a table in front of a laptop at a distance of approximately 0.5 m from the built-in webcam (HP HD webcam). During the experiment, participants are asked to keep still, breathe spontaneously, and face the webcam while their video was recorded for 10 min. All videos are recorded in colour (24-bit RGB) at 30 frames per second (fps) with pixel resolution of 640×480 and saved in AVI format in the laptop. Simultaneously HR, RR and IBI are also recorded using ECG sensors and cStress system.

All the videos and physiological recordings are analysed offline using custom software written in MATLAB 2013b. After extracting all the frames from the video automatic face detection is used using Viola and Jones methods [11] to identify the coordinates of the face location in the first frame and a boosted cascade classifier is used for the x and y-coordinates along with the height and width that define a box around the face. We select the centre 60 % width and full height of the box as the region of interest (ROI) for our subsequent calculations. The ROI is then separated into the three RGB channels and spatially averaged over all pixels in the ROI to yield a red, blue, and green measurement point for each frame and form the raw signals respectively. Each trace is 10 min long. The raw traces are detrended using a procedure based on a smoothness priors approach [12] and normalized. The normalized RGB traces are sent to three different algorithms ICA [8], PCA [9] and FFT [10] to quantify HR, RR and IBI.

For the ICA, the normalized raw traces are decomposed into three independent source signals using ICA based on the joint approximate diagonalization of Eigen matrices (JADE) algorithm [12]. ICA is able to perform motion-artifact removal by separating the fluctuations caused predominantly by the BVP from the observed raw signals. However, the order in which ICA returns the independent components is random. Thus, the component whose power spectrum contained the highest peak was then selected for further analysis. Similarly the normalized raw traces are also

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

decomposed by PCA to find the principal components. This transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it is 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. The pulse frequency was designated as the frequency that corresponded to the higst power of the spectrum within an operational frequency band.

As the frame rate of the video is 30 fps so every 30 image frames are passed together through the algorithm to find the physiological parameters for one second. In this way all the image frames are passed as a bundle of 30 images to calculate physiological parameters for whole session and the extracted data are saved in an excel file which are used later for further analysis. Before applying PCA, ICA and FFT the RGB signal is filtered by Hamming window (128 point, 0.6-4 Hz, Heart rate 36–240) for heart rate extraction and Hamming window (64 points, 0.15–0.5 Hz, respiration rate 9–30) for the RR. Then the HR is calculated as HR = $60{*}f_h$ and RR = $60{*}f_r$ where f_h is the extracted frequency of the Heart rate and f_r is the extracted frequency of respiration rate. IBI is calculated from the number of peak points in which HR is calculated.

3 Experimental Works

The physiological parameters are extracted from 7 out of 10 min (first 2 and last 1 min are excluded) for all the 9 test persons using webcam and cStress system. For the first two minutes it is observed how the system works properly and the last minute is also deducted because of preparation of shutting down the system. For the statistical analysis minimum, maximum, average, median and standard deviations are calculated for both the web camera and cStress data. Finally, calculating Root Mean Square (RSQ) value and slope compares both the statistical values. The statistical analyses of HR, IBI, and RR for the 9 test subjects are presented in Table 1.

As can be seen from Table 1, both the RSQ and Slope values are close to 90 % or more than 90 %. Here, RSQ and Slope values represent the Goodness-of-fit or correlation co-efficient compare to the reference measurements, where 1 means 100 % accuracy. The average RSQ and Slope of 9 subjects are also calculated for HR, IBI and RR by applying three methods presented through bar charts as Figs. 1, 2 and 3. According to the Figures, PCA method shows its best performance compare to the other methods.

Table 1. Statistical analysis of HR, IBI and RR

Subject	Criteria	HR			IBI			RR		
		FFT	PCA	ICA	FFT	PCA	ICA	FFT	PCA	ICA
1	RSQ	0.98	0.99	0.98	0.96	0.98	0.95	0.89	0.91	0.86
	SLOPE	0.97	0.95	0.91	0.94	0.95	0.92	0.90	0.92	0.89
2	RSQ	0.99	0.99	0.95	0.93	0.97	0.90	0.91	0.95	0.90
	SLOPE	0.94	0.93	0.92	0.93	0.96	0.91	0.92	0.96	0.89
3	RSQ	0.95	0.99	0.96	0.90	0.91	0.88	0.89	0.95	0.88
	SLOPE	0.96	0.95	0.95	0.91	0.93	0.90	0.92	0.94	0.90
4	RSQ	0.99	0.99	0.98	0.93	0.98	0.89	0.93	0.95	0.91
	SLOPE	0.92	0.98	0.95	0.93	0.96	0.90	0.92	0.97	0.90
5	RSQ	0.99	0.99	0.98	0.91	0.94	0.88	0.91	0.95	0.88
	SLOPE	0.86	0.94	0.95	0.94	0.95	0.91	0.88	0.93	0.88
6	RSQ	0.99	0.99	0.97	0.90	0.96	0.86	0.89	0.93	0.90
	SLOPE	0.91	0.97	0.95	0.93	0.95	0.89	0.90	0.96	0.88
7	RSQ	0.99	0.99	0.98	0.92	0.93	0.89	0.91	0.95	0.90
	SLOPE	0.90	0.96	0.95	0.95	0.99	0.91	0.92	0.96	0.91
8	RSQ	0.99	0.99	0.99	0.90	0.95	0.88	0.91	0.95	0.90
	SLOPE	0.88	0.94	0.93	0.93	0.96	0.91	0.90	0.92	0.90
9	RSQ	0.99	0.99	0.99	0.93	0.99	0.91	0.89	0.91	0.88
	SLOPE	0.82	0.92	0.93	0.91	0.96	0.89	0.88	0.92	0.87

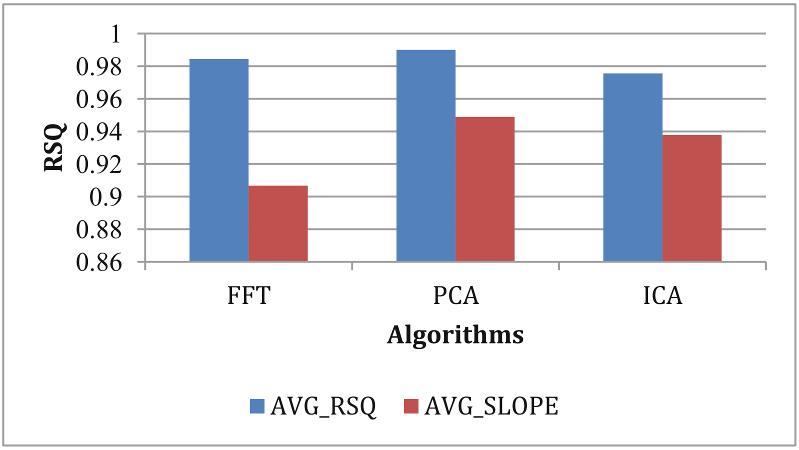

Fig. 1. Comparison between FFT, PCA and ICA methods considering HR

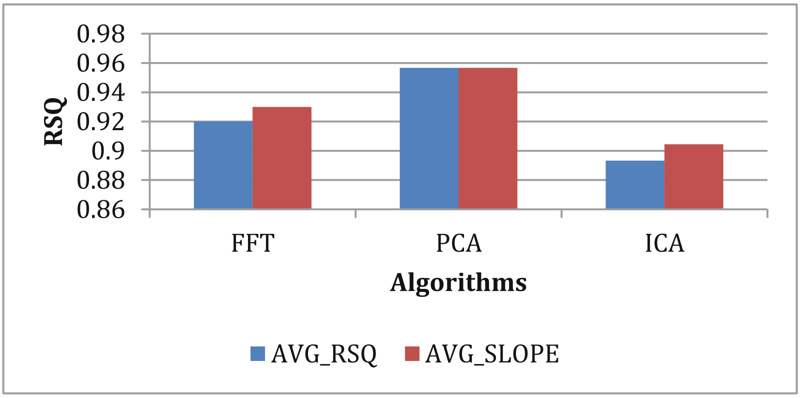

Fig. 2. Comparison between FFT, PCA and ICA methods considering IBI

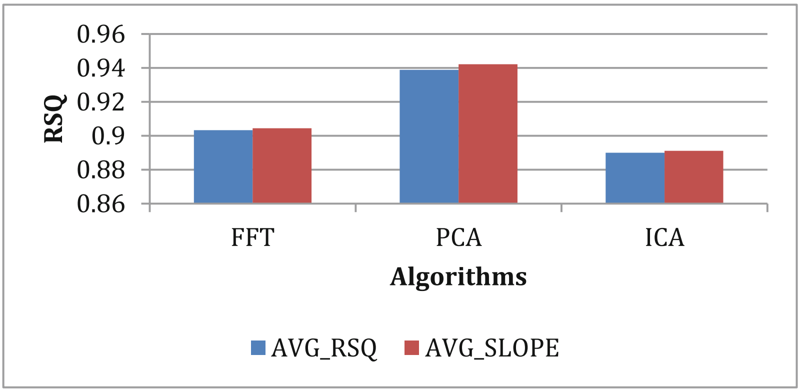

Fig. 3. Comparison between FFT, PCA and ICA methods considering RR

4 Conclusion

An easy to implement, low cost and non-contact physiological parameters detection method based on facial video image processing technology and blind source component technologies are described in this paper. Here, the methodology for recovering the cardiac pulse rate from video recordings of the human face and an implementation using a simple webcam with ambient daylight providing illumination are demonstrated. According to the experimental works, both the RSQ and slope values shows highest closeness (i.e. > 94 %) with the reference measurements while considering PCA methods for all the parameters. From the table and the figures presented in earlier chapter it is noted that RSQ gives better result than Slope and among the three methods PCA works the best and FFT works better. Given the low cost and widespread availability of webcams, this technology is promising for extending and improving access to medical care if the experiment is done by more test subjects and more verifying systems.

Although this paper only addressed the recovery of the cardiac HR, RR, IBI but many other important physiological parameters such as, heart rate variability and arterial blood oxygen saturation can potentially be estimated using the proposed technique. Creating a real-time, multi-parameter physiological measurement platform based on this technology will be the subject of future work.

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References

1. Ulyanov, S., Tuchin, V.: Pulse-wave monitoring by means of focused laser beams scattered by skin surface and membranes. In: Proceedings of the SPIE, Los Angeles, CA, pp. 160–167 (1884)
2. Greneker, E.: Radar sensing of heartbeat and respiration at a distance with applications of the technology. In: Proceedings of Conference on RADAR, Edinburgh, U.K., pp. 150–154 (1997)
3. Garbey, M., Sun, N., Merla, A., Pavlidis, I.: Contact-free measurement of cardiac pulse based on the analysis of thermal imagery. IEEE Trans. Biomed. Eng. **54**(8), 1418–1426 (2007)
4. Fei, J., Pavlidis, I.: Thermistor at a distance: Unobtrusive measurement of breathing. IEEE Trans. Biomed. Eng. **57**(4), 988–998 (2009)
5. Zhang, Q., Xu, G., Wang, M., Zhou, Y., Feng, W.: Webcam based non-contact real-time monitoring for physiological parameters of drivers. In: The 4th Annual IEEE International Conference on Cyber Technology in Automation Control and Intelligent Systems, Hong Kong, China, pp. 4–7 (2014)
6. Guo, Z., Jane, Z., Shen, Z.: Physiological Parameter monitoring of drivers based on video data and independent vector analysis. In: IEEE Int. Conf. on Acoustic, Speech and Signal Processing (ICASSP), pp. 4374–4378 (2014)
7. Poh, M.Z., McDuff, J.D., Picard, R.W.: Advancement in noncontact, multiparameter physiological measurement using a webcam. IEEE Trans. Biomed. Eng. **58**(1), 7–11 (2011)
8. Comon, P.: Independent component analysis, a new concept. J. Trans. Signal. Process. **36**, 287–314 (1994)
9. Krammer, M.A.: Nonlinear principal component analysis using autoassociative neural networks. AICHE **37**(2), 233–243 (1991)
10. Veenkant, R.L.: A serial-minded FFT. IEEE Trans. Audio Electroacoust. **20**, 180–185 (1972)
11. Viola, P., Jones, M.: Rapid object detection using a boosted cascade of simple features. In: Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition CVPR 2001, vol. 1, pp. I–511. IEEE (2011)
12. Tarvainen, M.P., Ranta-Aho, P.O., Karjalainen, P.A.: An advanced detrending method with application to HRV analysis. IEEE Trans. Biomed. Eng. **49**(2), 172–175 (2002)