Vision-Based Remote Heart Rate Variability Monitoring Using Camera

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Abstract. Heart Rate Variability (HRV) is one of the important physiological parameter which is used to early detect many fatal disease. In this paper a non-contact remote Heart Rate Variability (HRV) monitoring system is developed using the facial video based on color variation of facial skin caused by cardiac pulse. The lab color space of the facial video is used to extract color values of skin and signal processing algorithms i.e., Fast Fourier Transform (FFT), Independent Component Analysis (ICA), Principle Component Analysis (PCA) are applied to monitor HRV. First, R peak is detected from the color variation of skin and then Inter-Beat-Interval (IBI) is calculated for every consecutive R-R peak. HRV features are then calculated based on IBI both in time and frequency domain. MySQL and PHP programming language is used to store, monitor and display HRV parameters remotely. In this study, HRV is quantified and compared with a reference measurement where a high degree of similarities is achieved. This technology has significant potential for advancing personal health care especially for telemedicine.

Keywords: Physiological signals · Heart rate · Inter-beat-interval
Heart-rate-variability · Non-contact · Remote monitoring

1 Introduction

Remote health monitoring is an important topic by the research community and growing so fast [20, 21]. Here, most of the systems are developed using sensors that is attached with patients [22, 23]. However, non-contact based physiological parameters monitoring using camera is limited and one of the pioneer and advanced technology today. Recently, non-contact system have been developed both in offline and real time using different color space such as RGB [1], Lab [2], YCbCr [3] etc. This kind of technology is not attached with the body and therefore it is completely electrical interference free.

HRV is one of the important physiological parameters which is calculated from the variation of time interval between two consecutive heart beats. Many fatal diseases can be detected early using the HRV measurement, i.e. HRV is used to detect mortality after myocardial infarction [4]. HRV is related to acute myocardial infarction which can be detected from mean HR [5]. HRV is also useful to estimate stress level, cognitive

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load, pain etc. For example, HRV features are used to estimate cognitive performance of workers [6] and stress level has been estimated using facial video in [7]. There are several approaches to calculate HRV such as [8–11] where RGB color space is used to extract color variation of facial skin. A number of HRV features both in time domain and frequency domain have been extracted using smart phone PPG [12]. Other methods such as adaptive facial regions [13] and pupillary fluctuations are used to calculate HRV features [14]. In 2014, Xiaobi et al. have used Normalized Mean Least Square (NLMS) adaptive filter to reduce environmental illumination from RGB facial images to calculate HR and HRV [15]. NMLS filter is very sensitive to the scaling of the input light source and the calculation is also very complex. Another method has been proposed by Zhang et al. to eliminate environmental illuminance during real time HR monitoring using YCbCr images of the facial skin [3]. Most of the remote monitoring technologies use the word 'remote' in abstract form which means monitoring physiological parameters from 0.5–1 m away from test subject [9, 15–17].

This paper presents a non-contact remote monitoring system of HRV based on Lab color space using a web camera. Even though our intention is to estimate HRV for stress management, but only HRV features estimation are limited in this article. Here, three signal processing algorithms (FFT, ICA and PCA) have been applied on the color channels to detect R-peaks from where HR, IBI and HRV are extracted. 1st HR is calculated from R-peaks and IBI is calculated from all consecutive R-R intervals in a certain time length. Subsequently, both the time domain and the frequency domain HRV features are calculated based on IBI. A reference sensor system called cStress[1] is used to quantify the proposed system.

The rest of the paper is organized as follows: Sect. 2 describes materials and methods including data collection procedures, feature extraction, approach color signal processing, and Sect. 3 presents results and evaluation. Finally, Sect. 4 summarizes the work.

2 Materials and Methods

2.1 Data Collection

Data acquisition is conducted on 10 participants (all are Male) of different ages (25 to 50 years) and the participants have different skin colors. The ethnicity of two participants is European, other two are Arabian and the rest six are from south Asian. The experiments have been conducted in a Lab in normal sitting position where there is a varying amount of ambient sunlight and artificial electrical light. All the participants signed a letter of consent and they are informed about the aim of the study. They sit on a chair in front of a laptop computer at a distance of approximately 0.5 m and they are allowed to move their hands and body. A built-in webcam (HP HD webcam) is used to record the facial video of the test participants for five minutes and all the videos are

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

saved in a local computer in .avi format. During the experiment, the average frame rate of the camera was 12 frames per second (fps). First, RGB color values of facial skin are extracted and then it is converted into Lab color space [2]. All these raw color values are uploaded in the cloud server into MySQL database using MATLAB R2017a. Then HR, IBI and HRV features are calculated based on the raw signals and stored them again into MySQL database in the cloud sever. Simultaneously, HR and IBI are also recorded using cStress system with a sampling frequency of 4 Hz and saved in a excel file in the local computer which are then transferred into a cloud server in MySQL database.

2.2 Methods

A non-contact based HRV features monitoring system is developed to monitor patient remotely. Here, a patient can sit in front of a camera at his/her home and doctor can see his/her HRV from a distance place.

Even though, in this small study, both the uploading and downloading activities have been conducted in a local computer but these activities can be done using e.g., Wired/Wireless, VSAT, GPS connection and similarly it can be displayed in e.g., mobile phone, laptop, ipad or any other display using any of the above connection. First both the raw data of the camera and sensor are sent to cloud server using Matlab R2017a. The raw data of the camera is an average color values of Lab color space are extracted from ROI for every frame with a sampling frequency of 12 Hz. From the reference sensor system, HR and IBI are recorded directly where sampling frequency is 4 Hz. For HRV feature calculation, a Matlab script is running as a service in the cloud which retrieved the raw data from the MySQL database server, calculated the features and stored them again to the MySQL database server using a moving time window.

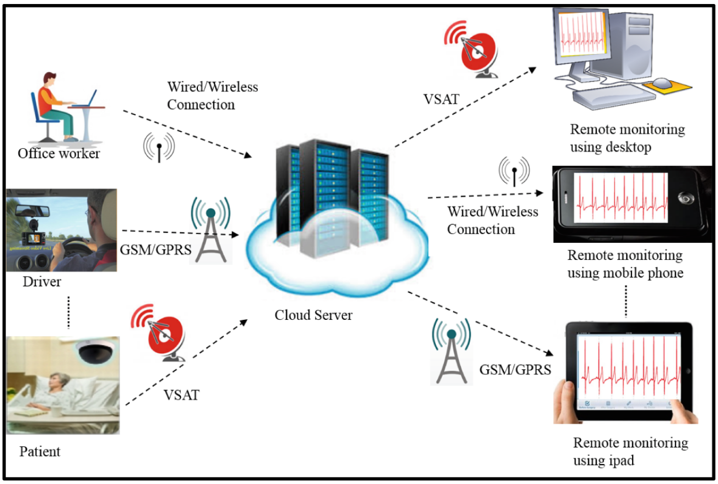

Fig. 1. Remote monitoring of HRV framework

A webpage is developed using PHP and Java script to present the features in real-time from remote places. A framework of remote monitoring is shown in Fig. 1.

2.2.1 Color Signal Pre-processing

Face detection is performed using Viola and Jones algorithm for each frame and region of interest (ROI) is selected from facial part where 80% of height and 60% of width of face is selected for ROI. Then KLT (Kanade-Lucas-Thomasi) algorithm is used to facial tracking for all consecutive frames. First RGB color values are extracted from ROI and the procedure is presented in Fig. 2. The RGB color values are converted into Lab color space. Lab color space has three independent color signals which are L, a and b where L represents the lightness of the images, a and b represents other color channels [2]. The advantage of Lab color space is that it is device independent and able to filter environmental illumination. To consider environmental illumination, another signal ab is constructed using only color signal a and b and signal L is discarded. This ab signal is able to filter ambient illumination.

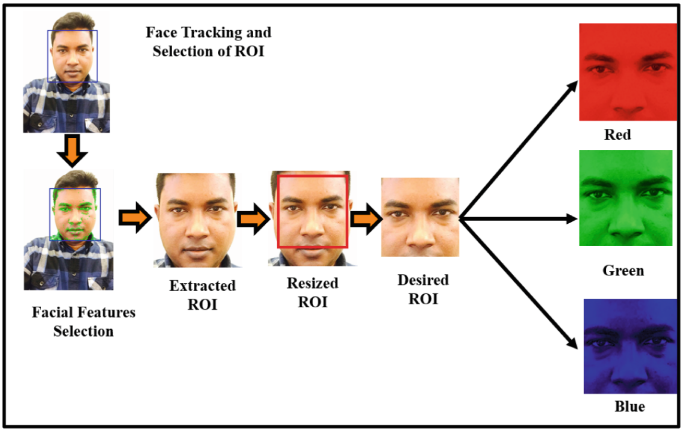

Fig. 2. Color signal extraction from facial images (Color figure online)

2.2.2 HR, IBI and HRV Feature Extraction

Human eyes cannot see the variation of facial color caused by cardiovascular system for each heart beat and hence a non-contact computer program is developed to detect color variation from where HR and IBI is calculated [1, 2, 18, 19].

Based on Lab color space the raw color signal ab is normalized and filtered using band pass filter [40–120 Hz]. Three algorithms such as FFT, ICA and PCA are used to extract HR and IBI from the lab color channel ab and then the average value is obtained. An example of major peaks and IBI are shown in Fig. 3. HRV features are calculated both in time domain and frequency domain. Definition of Time Domain Features and Frequency Domain Features are shown in Tables 1 and 2 respectively.

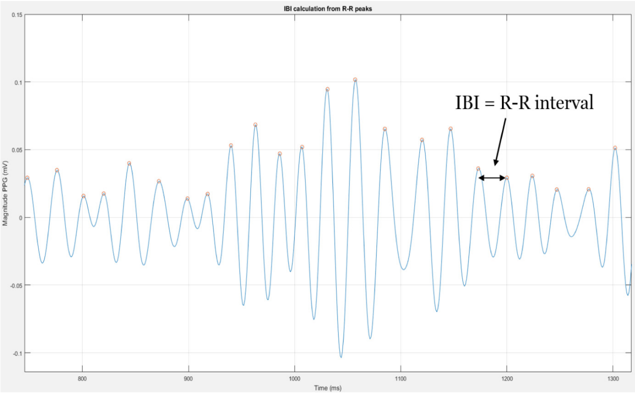

Fig. 3. Major peaks: IBI indicates time interval between two consecutive peaks

Table 1. HRV time domain features

No	Feature	Definition
1	meanNN	Average of all NN intervals
2	SDNN	Standard deviations of all NN intervals
3	RMSSD	Root mean square of successive differences between adjacent NN intervals
4	SDSD	Standard deviation of successive differences between adjacent NN intervals
5	NN50	Number of pairs of successive NN intervals which more than 50 ms
6	pNN50	Proportion of NN50 divided by total number of NN intervals

Table 2. HRV frequency domain features

No	Feature	Definition
1	LF	Low frequency power (0.04–0.15 Hz)
2	HF	High frequency power (0.15–0.4 Hz)
3	TotalPower	The variance of NN intervals over temporal segment
4	LF/HF ratio	Ratio of LF to HF

3 Results and Evaluation

The raw camera data is segmented into three parts each for one minute and HR is calculated from number of major peaks for each minute using FFT, ICA and PCA and then average HR of these three algorithms are taken. Therefore, for each subject we obtain three HR for minute one, two and three respectively. Then statistical parameters MAX, MIN, AVG, STD and MEDIAN of three HR of each subject are calculated. All these statistical parameters are also calculated for cStress measurement which are presented in Table 3 for ten subjects both for camera and sensor. For test subject 1, the statistical parameters of MAX, MIN, AVG, STD and MEDIAN of HR for sensor is 78,

Table 3. Statistical measurements of HR of three minute camera and cStress data

Test subject	MAX		MIN		AVG		STD		MEDIAN	
	Sensor	Camera	Sensor	Camera	Sensor	Camera	Sensor	Camera	Sensor	Camera
1	78	77	75	74	76.33	75.67	1.53	1.53	76	76
2	78	77	76	75	77.00	76.00	1.00	1.00	77	76
3	56	55	54	54	55.33	54.67	1.15	0.58	56	55
4	76	71	66	69	69.67	70.00	5.51	1.00	67	70
5	72	71	71	69	71.67	69.67	0.58	1.15	72	69
6	83	82	81	82	82.33	82.00	1.15	0.00	83	82
7	66	65	62	64	63.33	64.67	2.31	0.58	62	65
8	62	60	57	59	59.33	59.67	2.52	0.58	59	60
9	62	61	56	58	58.33	59.33	3.21	1.53	57	59
10	84	81	79	80	81.33	80.33	2.52	0.58	81	80
AVG (10 Subjects)	71.7	70	67.7	68.4	69.47	69.20	2.15	0.85	69	69.2

75, 76.33, 1.53 and 76 and for camera is 77, 74, 75.67, 1.53 and 76 which are closely related. The statistical parameters of other test subject also show that both sensor and camera parameters are closely related.

To calculate HRV features both in time domain and frequency domain first IBI is calculated for three minutes both for sensor and camera where sampling frequency of sensor and camera are 4 Hz and 12 Hz respectively. In time domain, statistical methods are applied on the Inter-beat-interval (IBI) signals to extract average of all NN intervals (meanNN), standard deviation of RR intervals (SDNN), root mean square of the all successive RR interval difference (RMSSD), standard deviation of differences between adjacent NN intervals (SDSD), number of pairs of adjacent NN intervals differing by more than 50 ms (NN50) features and percentage of NN50 count (pNN50). All these HRV time domain features are calculated and presented in Table 4.

Table 4. Comparison between sensor and camera system on time domain features.

Subject	meanNN		SDNN		RMSSD		SDSD		NN50		pNN50	
	Sensor	Camera	Sensor	Camera	Sensor	Camera	Sensor	Camera	Sensor	Camera	Sensor	Camera
1	785.81	799.15	35.35	36.44	7.12	12.34	7.11	12.35	0	0	0	0
2	778.22	791.17	24.51	25.43	8.16	12.79	8.16	12.80	2	2	0.36	0.35
3	1075.45	1088.53	34.17	34.94	7.83	13.00	7.83	13.00	1	1	0.13	0.12
4	864.05	877.11	74.41	74.84	15.08	18.22	15.08	18.22	10	12	1.60	1.90
5	833.72	846.66	37.69	38.47	9.14	13.69	9.13	13.69	0	1	0	0.16
6	727.03	740.19	35.01	35.39	9.68	14.01	9.68	14.01	0	3	0	0.56
7	941.78	954.90	39.06	39.79	9.31	13.87	9.31	13.87	2	4	0.29	0.58
8	1014.27	1027.23	68.89	69.01	23.09	25.59	23.09	25.59	38	47	5.20	6.35
9	1040.77	1053.99	133.61	134.00	55.04	55.89	55.04	55.89	97	91	12.94	11.99
10	735.75	749.17	41.54	41.89	14.01	17.52	14.01	17.52	10	11	1.88	2.03
AVG of 10 subjects	879.68	892.81	52.42	53.02	15.84	19.69	15.85	19.69	16	17.2	2.24	2.40

For frequency domain features, first IBI is transformed into frequency domain using FFT and PSD (power spectral density) is calculated considering 1024 FFT points. Then HRV frequency features such as Low frequency power (LF) (0.04–0.15 Hz), high frequency power (HF) (0.15–0.4 Hz), total power, and Ratio of LF to HF (LF/HF) are calculated and presented in Table 5. From Table 5 it is shown that frequency domain features both for sensor and camera are closely related.

Table 5. Comparison between sensor and camera system on frequency domain features.

Subject	LF		HF		TotalPower		LFHFratio	
	Sensor	Camera	Sensor	Camera	Sensor	Camera	Sensor	Camera
1	299.97	298.95	81.67	79.55	10264.78	10155.75	3.67	3.75
2	313.54	313.62	77.22	74.13	10055.41	9959.33	4.06	4.23
3	571.20	568.18	139.17	133.88	19210.03	18861.68	4.10	4.24
4	389.56	390.31	111.07	106.64	12471.12	12321.39	3.50	3.66
5	370.51	371.53	82.215	78.11	11555.06	11429.71	4.50	4.75
6	272.59	274.47	54.52	52.68	8787.64	8738.05	4.99	5.20
7	453.36	451.65	96.97	93.68	14747.83	14522.22	4.67	4.82
8	519.04	512.64	125.54	124.14	17118.14	16838.19	4.13	4.12
9	649.06	641.84	204.97	215.56	18125.50	17831.36	3.16	2.97
10	268.11	271.74	74.38	69.83	8997.96	8931.53	3.60	3.89
AVG of 10 subjects	410.69	409.49	104.77	102.82	13133.35	12958.92	4.04	4.16

4 Conclusion

The paper presented an approach for a non-contact based remote HRV monitoring using camera. Here, Lab color space approach is applied to extract physiological parameters from video recordings of the human face using a simple webcam with ambient daylight providing illumination. Both the time domain and frequency domain HRV features are extracted based on IBI and compared with a reference sensor system. Currently, the system is running in a local computer where HRV features are monitored via website in offline. However, the development of a real-time, remote, multi-physiological parameters measurement platform based on the proposed approach is ongoing.

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References

1. Rahman, H., Ahmed, M.U., Begum, S.: Non-contact physiological parameters extraction using camera. In: The 1st Workshop on Embedded Sensor Systems for Health through Internet of Things (ESS-H IoT), October 2015
2. Rahman, H., Ahmed, M.U., Begum, S.: Non-contact heart rate monitoring using lab color space. In: 13th International Conference on Wearable, Micro & Nano Technologies for Personalized Health (pHealth2016), Crete, Greece, 29–31 May 2016
3. Qi, Z., Guo-qing, X., Ming, W., Yimin, Z., Wei, F.: Webcam based non-contact real-time monitoring for the physiological parameters of drivers. In: 2014 IEEE 4th Annual International Conference on Cyber Technology in Automation, Control, and Intelligent Systems (CYBER), pp. 648–652 (2014)
4. Abildstrom, S.Z., Jensen, B.T., Agner, E., Torp-Pedersen, C., Nyvad, O.L.E., Wachtell, K., et al.: Heart rate versus heart rate variability in risk prediction after myocardial infarction. J. Cardiovasc. Electrophysiol. **14**, 168–173 (2003)
5. Kleiger, R.E., Miller, J.P., Bigger Jr., J.T., Moss, A.J.: Decreased heart rate variability and its association with increased mortality after acute myocardial infarction. Am. J. Cardiol. **59**, 256–262 (1987)
6. Tsunoda, K., Chiba, A., Chigira, H., Yoshida, K., Watanabe, T., Mizuno, O.: Online estimation of a cognitive performance using heart rate variability. In: 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 761–765 (2016)
7. McDuff, D., Gontarek, S., Picard, R.: Remote measurement of cognitive stress via heart rate variability. In: 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 2957–2960 (2014)
8. Bousefsaf, F., Maaoui, C., Pruski, A.: Remote assessment of the heart rate variability to detect mental stress. In: 2013 7th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth), pp. 348–351 (2013)
9. Bousefsaf, F., Maaoui, C., Pruski, A.: Remote assessment of physiological parameters by non-contact technologies to quantify and detect mental stress states. In: 2014 International Conference on Control, Decision and Information Technologies (CoDIT), pp. 719–723 (2014)
10. Kranjec, J., Beguš, S., Geršak, G., Drnovšek, J.: Non-contact heart rate and heart rate variability measurements: a review. Biomed. Sig. Process. Control **13**, 102–112 (2014)
11. Parnandi, A., Gutierrez-Osuna, R.: Contactless measurement of heart rate variability from pupillary fluctuations. In: 2013 Humaine Association Conference on Affective Computing and Intelligent Interaction (ACII), pp. 191–196 (2013)
12. Peng, R.C., Zhou, X.L., Lin, W.H., Zhang, Y.T.: Extraction of heart rate variability from smartphone photoplethysmograms. Comput. Math. Methods Med. **2015**, 1–11 (2015)
13. Tasli, H.E., Gudi, A., den Uyl, M.: Remote PPG based vital sign measurement using adaptive facial regions. In: 2014 IEEE International Conference on Image Processing (ICIP), pp. 1410–1414 (2014)
14. Parnandi, A., Gutierrez-Osuna, R.: Contactless measurement of heart rate variability from pupillary fluctuations. In: 2013 Humaine Association Conference on Affective Computing and Intelligent Interaction, pp. 191–196 (2013)
15. Li, X., Chen, J., Zhao, G., Pietikainen, M.: Remote heart rate measurement from face videos under realistic situations. In: 2014 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 4264–4271 (2014)

16. Verkruysse, W., Svaasand, L.O., Nelson, J.S.: Remote plethysmographic imaging using ambient light. Opt. Express **16**, 21434–21445 (2008)
17. Zhao, F., Li, M., Qian, Y., Tsien, J.Z.: Remote measurements of heart and respiration rates for telemedicine. PLoS ONE **8**, e71384 (2013)
18. Rahman, H., Begum, S., Ahmed, M.U., Funk, P.: Real time heart rate monitoring from facial RGB color video using webcam. In: 29th Annual Workshop of the Swedish Artificial Intelligence Society (SAIS), Malmö, Sweden (2016)
19. Rahman, H., Iyer, S., Meusburger, C., Dobrovoljski, K., Stoycheva, M., Turkulov, V., et al.: SmartMirror: an embedded non-contact system for health monitoring at home. Presented at the the 3rd EAI International Conference on IoT Technologies for HealthCare (Healthy-IoT-2016), Västerås, Sweden, 18–19 October 2016
20. Ahmed, M.U.: An intelligent healthcare service to monitor vital signs in daily life – a case study on health-IoT. Int. J. Eng. Res. Appl. (IJERA) **7**(3), 43–55 (2017)
21. Ahmed, M.U., Björkman, M., Causevic, A., Fotouhi, H., Lindén, M.: An overview on the internet of things for health monitoring systems. In: 2nd EAI International Conference on IoT Technologies for HealthCare (HealthyIoT2015), October 2015
22. Ahmed, M.U.: A personalized health-monitoring system for elderly by combining rules and case-based reasoning. In: 12th International Conference on Wearable Micro and Nano Technologies for Personalized Health (pHealth 2015), June 2015
23. Ahmed, M.U., Espinosa, J.R., Reissner, A., Domingo, À., Banaee, H., Loutfi, A., Rafael-Palou, X.: Self-serve ICT-based health monitoring to support active ageing. In: 8th International Conference on Health Informatics (HEALTHINF), January 2015