



Illuminance Color Independent in Remote Photoplethysmography for Pulse Rate Variability and Respiration Rate Measurement

Suryasari^{a,*}, Aminuddin Rizal^b, Sri Kusumastuti^b, Taufiqurrachman^c

^a Information System, Universitas Multimedia Nusantara, Jl. Scientia Boulevard, Tangerang, Indonesia

^b Electrical Engineering Department, Politeknik Negeri Semarang, Jl. Prof. H. Soedarto, Semarang, Indonesia

^c Telecommunication Research Center, Badan Riset dan Inovasi Nasional (BRIN), Jl. Sangkuriang No 21, Bandung, Indonesia,

Corresponding author: *suryasari@umn.ac.id

Abstract— Remote photoplethysmography (rPPG) is now becoming a new trend method to measure human physiological parameters. Especially due to its noncontact measurement which is safe and suitable to use in this new era condition. Pulse rate variability (PRV) and respiration rate (RR) included as parameters can be measured by using rPPG. PRV and RR are used to measure both physical and psychological wellness of the subject. However, current performance challenges in rPPG algorithm in measuring PRV and RR are illuminance invariant and motion. Especially in different light conditions which represent real-life environment, signal-to-noise ratio (SNR) will be affected and directly reduce the measurement accuracy. Therefore in this study, we develop rPPG algorithm and then investigate the performance of rPPG in different illuminance scenarios. We perform PRV and RR measurement under each scenario. On this study, for the pulse signal extraction, we use an algorithm based on the modification of plane orthogonal-to-skin (POS) algorithm. While, for respiration signal extraction is done in CIE Lab color space. Our experimental results show the mean absolute error (MAE) of each measured parameter are 3.25 BPM and 2 BPM for PRV and RR respectively compared with clinical apparatus. The proposed method proved to be more reliable to use in real environments measurement. However, limitation of our proposed algorithm is still running in offline mode, hence for the future we want to try to make our algorithm run in real time.

Keywords— CIE Lab; pulse rate variability; plane-orthogonal-to-skin; remote photoplethysmography; respiration rate

Manuscript received 31 Aug. 2022; ; revised 21 Oct. 2022; accepted 10 Dec. 2022. Date of publication 10 Sep. 2023. International Journal on Informatics Visualization is licensed under a Creative Commons Attribution-Share Alike 4.0 International License.



I. INTRODUCTION

A regular physiological parameter check can improve the quality of life and guide the person to have a better habit. Especially our social health status after Covid-19, where individuals have to check their health condition in any place. Not only physical health affected by Covid-19, but also psychological of individuals that may lead to stress, anxiety, and depression [1]. Heart rate variability (HRV) and respiration rate (RR) is a physiological parameter used as the indicator of a health status, wellness, and physical condition [2]. Traditionally, the acquisition of HRV and RR is done by using electrocardiogram (ECG). However, since the ECG sensors (electrodes) are needed to be placed in contact with the skin, with potentially spread virus or bacteria and may cause discomfort to the user [3]. Therefore, several methods based on non-contact systems developed to overcome the limitations of contact-based systems. One reliable contactless method to sense human vital signs parameters is using a camera as the sensor and well-known as remote photoplethysmography

(rPPG). Similarly, to contact-based photoplethysmography (cPPG), rPPG also refers to an electro-optic technique for non-invasively measuring the tissue blood volume pulses in the microvascular tissue bed underneath the skin [4].

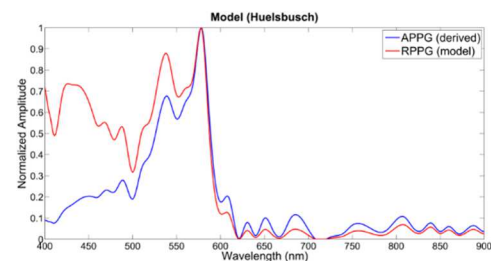


Fig. 1 The model of relative PPG spectrum

Since photoplethysmography basically measures the blood pulse under vessels and does not exactly measure the heartbeat. Study by Schäfer [5] reveals the possibility of measuring pulse variability (PRV) as a surrogate of HRV, showing the close

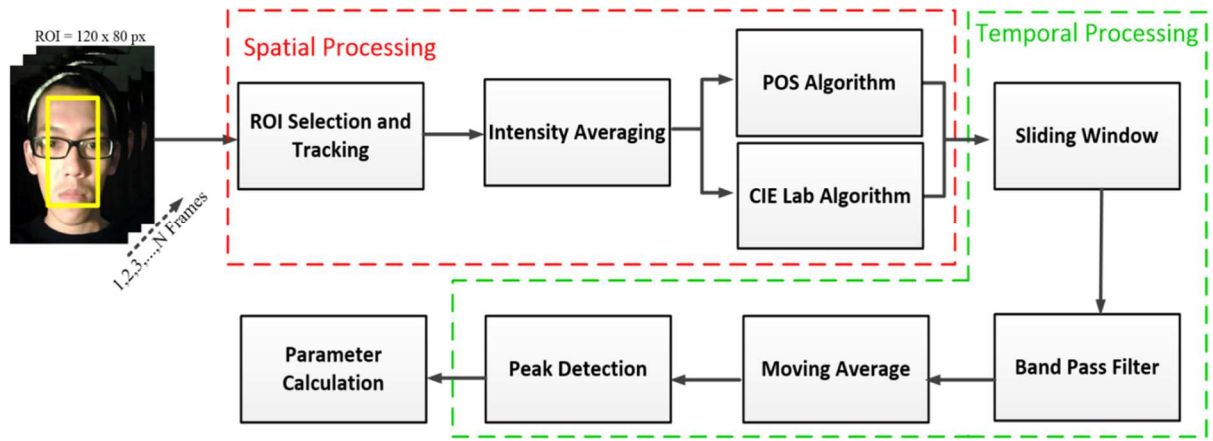


Fig. 2 Proposed method

agreement. Thus, a PRV analysis constitutes a good, reliable, and more comfortable for measuring HRV [6]. As this far, the usage of rPPG able to cover vital signs parameter including pulse rate [7][8], respiration rate [9][10], blood oxygen saturation [11][12], blood pressure [13][14], and PRV [5][6][15]-[17].

Different rPPG method has been proposed to deal with PRV measurement. Started in 2011, Poh et al. [18] presented a multiparameter physiological measurement including PRV parameter by using independent component analysis (ICA) method. The comparison performance between ICA and principle component analysis (PCA) for PRV measurement were investigated by Alghoul [15] in 2017. in 2018 a study about PRV was done by A. M. Rodríguez [4], he proposed a system for PRV measurement used in application including motion activity. And most recent study were done by Yu SG., et al. [16] and M. M. Shoushan, et al. [17].

For RR measurement, various algorithms have been presented as well. Most of the studies are focusing on ROI selection (e.g. face and chest) [19] and color space used in signal extraction (e.g. visible light and NIR) [20]. The recent study was done by Sanyal [21], the work present RR measurement in Hue color space.

Currently, there are two major challenges from using rPPG method for PRV and RR measurement, those are invariant color illumination and subject's motion. The previous studies investigated only focus on subject's motion problem and using static light source in their experiment. In fact, the invariant light source will make the physiological signal has low signal-to-ratoin (SNR). Fig. 1 shows the relationship between relative amplitude between rPPG signal and luminance spectrum modeled by Hulsbusch [22] and derived by Gastel [23]. In a short, the rPPG signal quality depends on the incoming wavelength spectra.

The goal of this paper is to investigate our developed rPPG algorithm to measure PRV and RR in different illuminance scenarios. For the hardware cost, we use a personal computer (PC) as processing unit and one consumer grade RGB webcam as the sensor. All processing stages will be run in offline performance. We believe in the future, our system improves the usability of rPPG in different environmental condition. Moreover, our algorithms are applicable for application with high dynamic illuminance condition such as driving activity.

II. MATERIAL AND METHOD

Illustration of our used method is shown in Fig. 2, the substantial of rPPG algorithm consists of spatial (image) processing and temporal (signal) processing. The spatial processing has main function to select and track the region of interest (ROI) and then convert the 2 dimensional data (pixels) into 1 dimensional signal. Since the converted signal still raw and usually has low SNR, temporal processing employed to improve the SNR there are 4 stages in the temporal processing including sliding window, band pass filtering, moving average and peak detection. Finally, after clean signal obtained the parameter calculation can be done.

A. ROI Selection and Tracking

We select forehead-to-cheek area as the ROI, based on our preliminary analysis stage those area has good SNR for both PRV and RR parameter. The area formed for ROI is 120 x 80 pixels. Kanade-Lucas-Tomasi (KLT) tracking algorithm [24] was used to track the ROI.

B. Intensity Averaging

To convert the pixels data into 1 dimension signal, we simply employ intensity averaging for each R, G, and B channel. Our operation in this stage was using Equation (1). Where $Intensity_n(x_i, y_j)$ is the intensity of each color channel located in (x_i, y_j) , and n is the current frame number.

$$R, G, B [n] = \frac{1}{ROI_{area}} \sum_{i=1}^{120} \sum_{j=1}^{80} Intensity_n(x_i, y_j) \quad (1)$$

C. Signal Extraction

We decided to use different signal extraction algorithm for PR and RR parameter. For PR signal we were extracted by using plane-orthogonal-to-skin (POS) algorithm. The algorithm was proposed by Wang [7] which demonstrated robust to both motion and light source. The core of POS algorithm is using the plane orthogonal to the skin tone in the temporally normalized RGB space. As our best knowledge, no study investigates the usage of POS algorithm for PRV measurement. The detail of algorithm can see thoroughly from his paper [7]. In the other hand, we use CIE Lab color space instead of RGB color space. The idea is to separate diffused and specular reflection from incoming luminance. Specular reflection is the component from surface of the skin

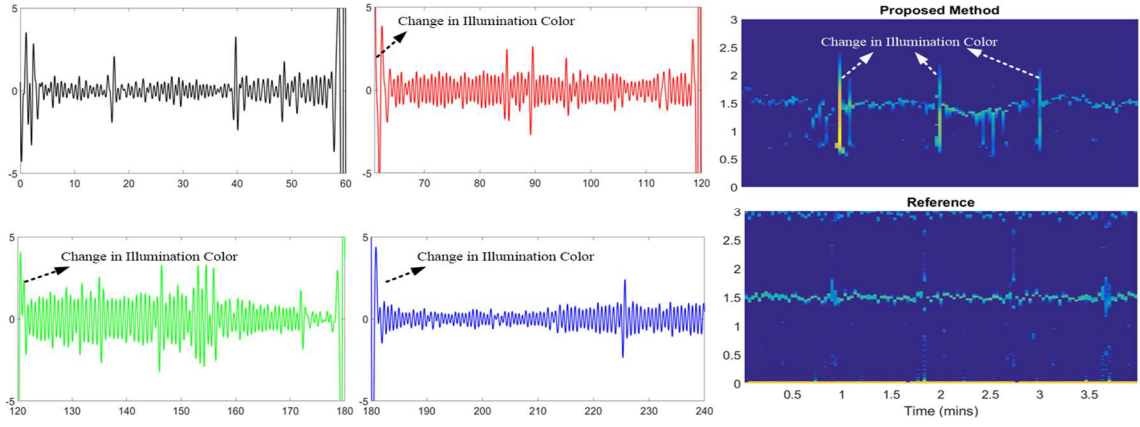


Fig. 3 Final PR signal in different illumination color: white (black signal), red, green, blue, respectively and PR Spectrogram proposed method vs reference

where respiration motion can be detected. An experiment had been done by Yang [20], she had used CIE Lab color space to perform motion robust rPPG. In their method, PR signals are estimated by calculating the a^* channel component which based on her work is robust to motion. Moreover, a^* is experimentally better SNR for PR measurement than b^* and L^* channel. While L^* channel is more sensitive to motion. Therefore, in our proposed method we decide to use L^* channel to extract RR signal.

Bare core of our modification CIE Lab based method for rPPG is shown in Algorithm 1 (we only calculate L^* channel). We adopt RGB normalization in line 5 from POS algorithm and implement to line 5 of our modified CIE Lab algorithm. Equation (2) is used to perform normalization which has function to eliminate non-uniformity of signal caused by different skin types. Then convert RGB color space to XYZ color space first before convert to CIE Lab. But, we only calculate Y channel which only related to L^* channel CIE Lab color space by employing Equation (3). We need to divide Y channel with Y_n of the CIE XYZ tristimulus values of white color to create W by using Equation (4). Next step is construct L^* channel signal from W with parameter set by default of CIE Lab conversion. Lastly, after overlap-adding process, CIE Lab RR signal (P) is produced.

Algorithm 1 CIE Lab (Modification RGB to CIE Lab)

Input: A video sequence containing N frames

- 1: **Initialize:** $H = \text{zeros}(1, N)$
- 2: **For** $n = 1, 2, \dots, N$ **do**
- 3: $C(n) = [R(n), G(n), B(n)]^T$
- 4: **If** $m = n - 1 + 1 > 0$ **then**
- 5: $C_n^i = \frac{C_{m \rightarrow n}^i}{\mu(C_{m \rightarrow n}^i)}$ (2)
- 6: $Y = (0.222 \ 0.07 \ 0.71) \cdot C_n$ (3)
- 7: $W = \frac{Y}{Y_n}$ (4)
- 8: **If** $W > 0.008856$
- 9: $L^* = 116 \times W^{\frac{1}{3}} - 16$ (5)
- 10: **Else**
- 11: $L^* = 903 \times W$ (6)
- 12: **End if**
- 13: $P_{m \rightarrow n} = P_{m \rightarrow n} + (L^* - \mu(L^*))$ (7)
- 14: **End if**
- 15: **End for**

Output: raw respiration rate signal (P)

D. Sliding Window

After signal from full video frames were extracted, for further processing we applied sliding window processing. The window lengths of two parameters were also different. For PR signal, 5 second window and 1 second overlap were used since the fast changing in PR. While for RR parameter had longer window with 8 second length and 2 second overlap. Since we proceed all the process in offline mode the length of sliding window was not significantly different in result. However, to give better understanding what our algorithms perform in real-time we set as mentioned before.

E. Band Pass Filter

Afterwards, the signal filtering process is applied to remove the redundant noises. Because PR and RR signals are located in different bandwidths, we construct two bandpass Butterworth coefficient filters with different cutoff frequencies for pulse rate signal [0.4, 2.5] Hz and respiratory rate signal [0.1, 0.5] Hz. The raw POS signal will be filtered with PR filter, and raw signal from CIE Lab will be filtered with RR filter. We set our filter parameter similar to related studies [25] – [27].

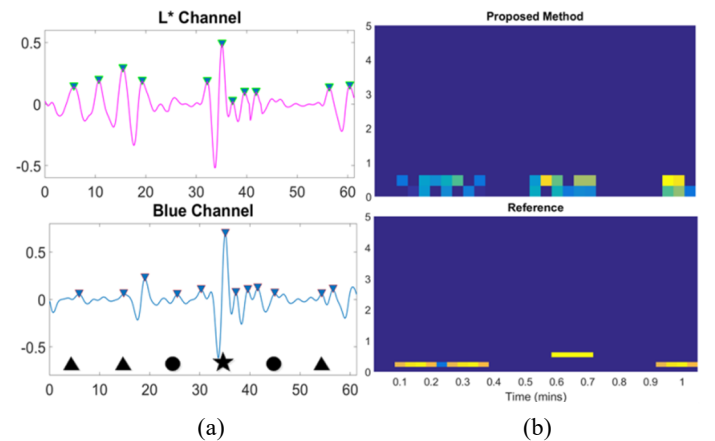


Fig. 4 (a) RR signal L^* vs Blue Channel, (b) spectrogram RR

F. Moving Average

Due to non-ideal IIR filter performance, there are still some noises left on the both PR and RR signals. To avoid false positives PR and RR signal peak detection [28] - [30], we simply employ moving average operation using Equation (8)

$$SMA = \frac{y_1 + y_2 + \dots + y_n}{n} \quad (8)$$

Where SMA is the output signal, y_n is the input signal from IIR filter, n presents as an average order, which is set as 10 here. Fig. 3 shows the PR final signal after this stage with (a), (b), (c), and (d) are the signal formed from different illumination color and also (e) is the spectrogram between signals from proposed method and the reference device. Fig. 4 is the example of RR signal from red illumination with (a) is comparison signal using CIE Lab algorithm and RGB color space and also (b) is the spectrogram from L^* channel signal with the reference signal.

G. Peak Detection

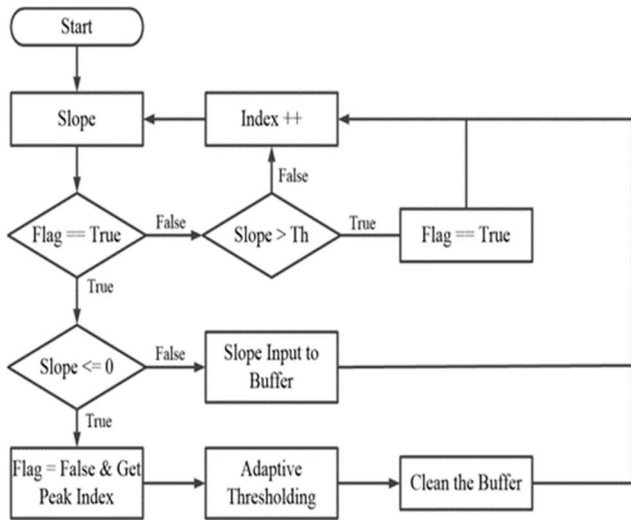


Fig. 5 Peak detection

Both PR and RR signal need a peak detection algorithm to determine the parameter for further processing. We use peak detection algorithm based on study [31]. Fig. 5 depicts the peak detection flow used in this study. In the beginning of the test, the Flag is set to false. When the slope value is larger than the threshold (Th), the Flag is set to true and this slope is recorded in the buffer. While the Flag is true and the slope value is smaller than or equal to 0, a peak index (peak position) is recorded. The maximum slope value from the buffer will be used to update the new threshold as adaptive thresholding and then clean the buffer to restart the peak detection. A peak-to-peak interval (PPI) check is applied after peak detection to prevent noise contaminations. When the PPI is in the requested range, a peak is detected.

H. Parameter Calculation

For PRV parameter, we calculated both time and frequency domain. The detail equation used for PRV parameter presented by Table 1 where NN is same with peak-to-peak interval (PPI) from peak detection stage. The time domain parameter presented by Equation (9) – (11) and frequency domain presented by Equation (12) – (14).

In other side, for respiration rate parameter we use operation from Equation (15). Where $PPI(RR)$ is peak-to-peak interval from respiration rate signal.

TABLE I
PRV PARAMETER

Parameter	Description	Equation
Time Domain		
$AVNN$	Average of all NN interval (peak-to-peak)	$\frac{1}{r} \sum_{k=1}^r NN_k$ (9)
$SDNN$	Standard deviation NN interval	$\sqrt{\frac{1}{r} \sum_{k=1}^r (NN_k - AVNN)^2}$ (10)
$RMSSD$	Root mean square of successive differences between adjacent NN intervals	$\sqrt{\frac{1}{r-1} \sum_{k=1}^{r-1} (NN_{k+1} - RR_k)^2}$ (11)
Frequency Domain		
LF	Total spectral power of all NN interval between 0.4 and 0.15	$\frac{\sum_{f1=0.04}^{0.15} P_{NN}(f1)}{\sum_{f2=0}^{fs/2} P_{NN}(f2)} \cdot 100$ (12)
HF	Total spectral power of all NN interval between 0.15 and 0.4	$\frac{\sum_{f1=0.15}^{0.4} P_{NN}(f1)}{\sum_{f2=0}^{fs/2} P_{NN}(f2)} \cdot 100$ (13)
LF/HF	Ratio of low to high frequency power	$\frac{LF}{HF}$ (14)

III. RESULT AND DISCUSSION

To evaluate the performance of our method, we built benchmark dataset. The video sequence was recorded twice from 5 health subjects. Hardware cost for the experiment were a low cost Logitech C920 pro HD RGB camera (setting in 480 x 640 pixels resolution, 8 bit depth, and run on average 30 fps), Philips Hue 7 W LED lamp (smartphone controllable to change the LED color), a laptop with an Intel Core i5 processor and the ground-truth data was recorded from contact-based PPG DASH 3000. All analyses and implementation were developed offline in MATLAB.

The experimental setup and procedures and the illumination exposure to the subject presented in Fig. 6. Each subject was asked to stand 50 cm in front of a desk with camera. The LED lamp was positioned around 1 m side from camera. Each video had same procedure and 4 minute overall long, for every 1 minute the illumination color changed

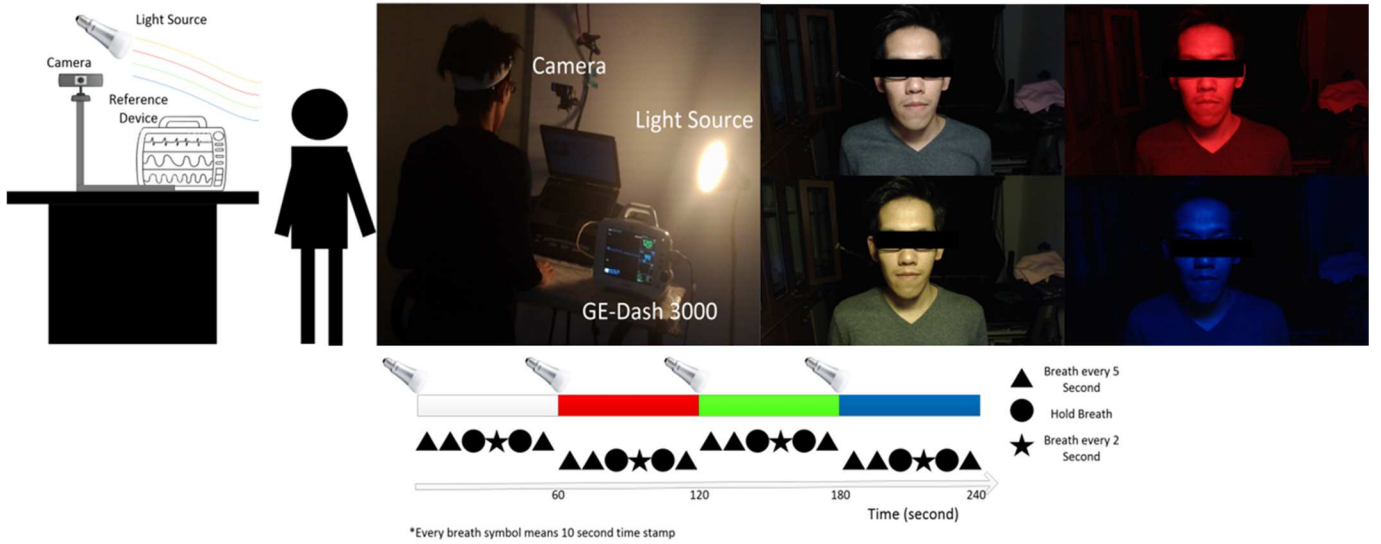


Fig. 6 Experimental setup and procedure

(white-red-green-blue). Also, we close the window and the door to avoid another light source (e.g. sun light or lamp from other room). All subject need to control their breath corresponding to our scenario. Therefore, all of subject would have same respiration rate pattern. The breath procedure in 1 minute describe as follow: first 20 second breath for every 5 second (4 breath), then hold breath for 10 second, after that breath for every 2 second in 10 second span (5 breath), then hold breath again for 10 second and the next 10 second breath every 5 second (2 breath). This 1 minute breath procedure was repeated for every LED color illumination.

We used standard evaluation metrics: mean absolute error (MAE) from Equation (17) and root mean square error (RMSE) from Equation (18) for each PRV and RR parameter. For PRV parameter we done fair comparison with recently related method [15], the same processing technique from reference study was applied to our dataset.

$$\chi = |\text{parameter}_{test} - \text{parameter}_{ref}| \quad (16)$$

$$MAE = \frac{\sum_{j=1}^N \chi_j}{N} \quad (17)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{j=1}^N |\chi_j - \text{mean}(\chi)|^2} \quad (18)$$

The results from PRV and RR measurement are presented in Table 2 and Table 3 respectively.

TABLE II
PRV MEASUREMENT RESULT

Parameter	ICA [15]		Proposed Method	
	RSME	MAE	RSME	MAE
AVNN (ms)	15.2	11.8	10.6	9.6
SDNN (ms)	2.3	1.88	0.09	0.06
RMSSD (ms)	0.31	0.22	0.25	0.18
LF (n.u)	2.75	2.56	0.18	0.15
HF (n.u)	7	6.3	2.62	2.2
LF/HF	5.3	4.9	2.1	1.3

From the result, our proposed method has better performance and compared to related work at some parameters. To be noted, we also performed experiment in different light source condition to represent real condition of some applications, this experiment scheme is only few study to attempt. Furthermore, we tested the respiration rate measurement with scheme represent no breath, normal breath and fast breath also only few study to conduct this scenario.

The reason our proposed method is better from related study is because we use better rPPG algorithm to extract pixel image for PR and RR signal (POS algorithm currently one of the best rPPG method). Also we use correct spatial processing to deal with both PR and RR signal. For PR measurement, in a harmony with study [7] ICA method including in [15] is still not capable to give better result in different luminance color. And also this algorithm is very sensitive to large motion distortion. ICA will provide better result if only under good illumination and less motion noise, because the key of ICA algorithm is estimation (in PR frequency band) and component selection. For RR measurement case, most of rPPG method are detect movement caused by respiration and then calculate the RR. In this case, one of best accurate method to detect motion is by employing L^* of CIELab color space. Based on our result, we outperformed blue channel from RGB color space which most study used this channel to compute their RR. Blue channel will have huge distortion if the illumination color are different. In contrast with blue channel method, L^* channel are more illuminance color independent due to brightness component representation of color.

TABLE III
RR MEASUREMENT RESULT

Parameter	Blue channel (BPM)	Proposed Method (BPM)
	Mean RR	6
RSME	4.8	1.26
MAE	3.5	0.6

As for the difference occurs between our proposed method and reference device were because the change of illumination color simultaneously (camera need to stable 1-2 second), ambient light that still captured by camera, and also motion noise. The frame rate of the camera had slightly drop when low brightness illumination applied (blue and red). When that happen our filter will not work optimally. In additional to be consideration, the frame rate of camera need to be fast enough. A clinical medical equipment are usually runs in more than 250 Hz of sampling rate frequency.

The limitations of our method, for current version follows: our algorithm are still run in offline mode. However, based on complexity of the algorithm we use, real-time performance is possible to made. The parts having more computational effort shown in Equation (2) and Equation (7) where we need to allocate amount memory in both process and take cearefully if data complexity is exponentially growth. Our algorithm is less robust for respiration rate measurement if subjects do more movements. We had not test our algorithm in different movement when measurement taken. But we found short-time spike on our signal when more motion happened.

Our plan for future work, we will build application for our rPPG method which can work in real-time that will work in different light condition and for different kind of biometric from people of worldwide. We also strongly want to fulfill our desire to build an API framework, so our application can run in different platform (e.g. android, apple, Linux, and etc.). We also will try to verify our algorithm in different activities that include different movements (e.g. fitness, exercise activity).

IV. CONCLUSION

This paper presented robust rPPG algorithm to extract pulse rate variability (PRV) parameters and respiration rate (RR) in different illumination color and skin type. POS-based algorithm is utilized to convert frames pixels into pulse rate signal, while CIELab-based algorithm covers the RR signal conversion. We had done tested our method to 15 different subjects with various illumination scenarios. In the result section shown, proposed rPPG method is able to outperform most recent related study in state of the art of PRV and respiration rate measurement. And for RR measurement we also achieve performance compare to the conventional method. Our main focus for future work, we want to develop an application using our method runs in real-time and different platform.

ACKNOWLEDGMENT

The authors would like to acknowledge the research funding by Universitas Multimedia Nusantara under the grant of research of international publications, numbers 075/PI/LPPM-UMN/III/2021; 085/PI/LPPM-UMN/IX/2020.

DECLARATION

Author contribution. All authors contributed equally to the main contributor to this paper. All authors read and approved the final paper.

Funding statement. The research funded by Universitas Multimedia Nusantara under the grant of research of

international publications, numbers 075/PI/LPPM-UMN/III/2021 and 085/PI/LPPM-UMN/IX/2020.

Conflict of interest. The authors declare no conflict of interest.

Additional information. No additional information is available for this paper.

REFERENCES

- [1] Passavanti M, Argentieri A, Barbieri DM, Lou B, Wijayaratra K, Foroutan Mirhosseini AS, Wang F, Naseri S, Qamhia I, Tangerang M, Pelliciaro M, Ho CH, "The psychological impact of COVID-19 and restrictive measures in the world" *J Affect Disord*, 2021 Mar 15;283:36-51, doi: 10.1016/j.jad.2021.01.020.
- [2] Prinsloo, Gabriell E., HG Laurie Rauch, and Wayne E. Derman, "A brief review and clinical application of heart rate variability biofeedback in sports, exercise, and rehabilitation medicine," *The Physician and sportsmedicine*, vol. 42, no. 2, pp. 88-99, 2014.
- [3] Dasari, A., Prakash, S.K.A., Jeni, L.A. et al., "Evaluation of biases in remote photoplethysmography methods", *npj Digital Medicine*, vol 4 paper number 91 (2021), doi: 10.1038/s41746-021-00462-z.
- [4] A. B. Hertzman and C. R. Speelman, "Observations on the finger volume pulse recorded photoelectrically," *Amer. J. Physiol. Meas.*, vol. 119, pp. 334-335, 1937.
- [5] Schäfer A, Vagedes J., "How accurate is pulse rate variability as an estimate of heart rate variability? A review on studies comparing photoplethysmographic technology with an electrocardiogram." *Int J Cardiol.*, 2013;166(1):15-29.
- [6] Melchor Rodríguez, Angel, and J. Ramos-Castro., "Video Pulse Rate Variability Analysis in Stationary and Motion Conditions." *BioMedical Engineering*, OnLine 17 (2018): 11. PMC. Web. 14 Aug. 2018.
- [7] W. Wang, A. C. den Brinker, S. Stuijk and G. de Haan, "Algorithmic Principles of Remote PPG," *IEEE Transactions on Biomedical Engineering*, vol. 64, no. 7, pp. 1479-1491, July 2017.
- [8] Y. -C. Chou, B. -Y. Ye, H. -R. Chen and Y. -H. Lin, "A Real-Time and Non-contact Pulse Rate Measurement System on Fitness Equipment," *IEEE Transactions on Instrumentation and Measurement*, vol. 71, pp. 1-11, 2022, Art no. 5002711, doi: 10.1109/TIM.2021.3136173.
- [9] A. Rizal, K. Chiang, J. Lin and Y. Lin, "An SoC-Based System for Real-time Contactless Measurement of Human Vital Signs and Soft Biometrics," *2019 6th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI)*, 2019, pp. 55-59, doi: 10.23919/EECSI48112.2019.8976953.
- [10] D. Shao, Y. Yang, C. Liu, F. Tsow, H. Yu and N. Tao, "Noncontact Monitoring Breathing Pattern, Exhalation Flow Rate and Pulse Transit Time," *IEEE Transactions on Biomedical Engineering*, vol. 61, no. 11, pp. 2760-2767, Nov. 2014.
- [11] D. Shao et al., "Noncontact Monitoring of Blood Oxygen Saturation Using Camera and Dual-Wavelength Imaging System," in *IEEE Transactions on Biomedical Engineering*, vol. 63, no. 6, June 2016.
- [12] Rizal, A. (2019)" Study: Pengukuran Saturasi Oksigen dengan Konsumer Grade RGB Kamera" *Ultima Computing : Jurnal Sistem Komputer*, 11(1), 29-33, doi: 10.31937/sk.v11i1.1038.
- [13] A. Rizal, Y. Lin and Y. Lin, "Contactless vital signs measurement for self-service healthcare kiosk in intelligent building," *2018 3rd International Conference on Intelligent Green Building and Smart Grid (IGBSG)*, Yi-Lan, 2018, pp. 1-4.
- [14] F. Tabei, J. M. Gresham, B. Askarian, K. Jung and J. W. Chong, "Cuff-Less Blood Pressure Monitoring System Using Smartphones," in *IEEE Access*, vol. 8, pp. 11534-11545, 2020, doi: 10.1109/ACCESS.2020.2965082.
- [15] K. Alghoul, S. Alharthi, H. Al Osman and A. El Saddik, "Heart Rate Variability Extraction From Videos Signals: ICA vs. EVM Comparison," in *IEEE Access*, vol. 5, pp. 4711-4719, 2017.
- [16] Yu SG, Kim SE, Kim NH, Suh KH, Lee EC. "Pulse Rate Variability Analysis Using Remote Photoplethysmography Signals." *Sensors (Basel)*. 2021 Sep 17;21(18):6241. doi: 10.3390/s21186241.
- [17] M. M. Shoushan, B. A. Reyes, A. R. M. Rodríguez and J. W. Chong, "Contactless Monitoring of Heart Rate Variability During Respiratory Maneuvers," in *IEEE Sensors Journal*, vol. 22, no. 14, pp. 14563-14573, 15 July 15, 2022, doi: 10.1109/JSEN.2022.3174779.
- [18] M. Poh, D. J. McDuff and R. W. Picard, "Advancements in Noncontact, Multiparameter Physiological Measurements Using a

- Webcam," in *IEEE Transactions on Biomedical Engineering*, vol. 58, no. 1, pp. 7-11, Jan. 2011.
- [19] Van Gastel, M., Stuijk, S., & de Haan, G. (2016). Robust respiration detection from remote photoplethysmography. *Biomedical Optics Express*, 7(12), 4941–4957.
- [20] A Yang, Yuting et al. "Motion Robust Remote Photoplethysmography in CIE Lab Color Space." *Journal of Biomedical Optics*. 2016;21(11):117001.
- [21] S. Sanyal and K. K. Nundy, "Algorithms for Monitoring Heart Rate and Respiratory Rate From the Video of a User's Face," in *IEEE Journal of Translational Engineering in Health and Medicine*, vol. 6, pp. 1-11, 2018.
- [22] M. Hulsbusch, "An image-based functional method for opto-electronic detection of skin-perfusion (in German)," Ph.D. dissertation, RWTH Aachen, 2008.
- [23] M. van Gastel, S. Stuijk and G. de Haan, "Motion Robust Remote-PPG in Infrared," in *IEEE Transactions on Biomedical Engineering*, vol. 62, no. 5, pp. 1425-1433, May 2015.
- [24] Carlo Tomasi and Takeo Kanade. Detection and Tracking of Point Features. Carnegie Mellon University Technical Report CMU-CS-91-132, April 1991.
- [25] X. Yu, T. Laurentius, C. Bollheimer, S. Leonhardt and C. H. Antink, "Noncontact Monitoring of Heart Rate and Heart Rate Variability in Geriatric Patients Using Photoplethysmography Imaging," in *IEEE Journal of Biomedical and Health Informatics*, vol. 25, no. 5, pp. 1781-1792, May 2021, doi: 10.1109/JBHI.2020.3018394.
- [26] S. Sanyal and K. K. Nundy, "Algorithms for Monitoring Heart Rate and Respiratory Rate From the Video of a User's Face," in *IEEE Journal of Translational Engineering in Health and Medicine*, vol. 6, pp. 1-11, 2018, Art no. 2700111, doi: 10.1109/JTEHM.2018.2818687.
- [27] G. Bai, J. Huang and H. Liu, "Real-Time Robust Noncontact Heart Rate Monitoring With a Camera," in *IEEE Access*, vol. 6, pp. 33682-33691, 2018, doi: 10.1109/ACCESS.2018.2837086.
- [28] J. Lin, M. Lu and Y. Lin, "A Contactless Healthcare System with Face Recognition," *2019 4th International Conference on Intelligent Green Building and Smart Grid (IGBSG)*, 2019, pp. 296-299, doi: 10.1109/IGBSG.2019.8886237.
- [29] Y. Lin and Y. Lin, "Step Count and Pulse Rate Detection Based on the Contactless Image Measurement Method," in *IEEE Transactions on Multimedia*, vol. 20, no. 8, pp. 2223-2231, Aug. 2018, doi: 10.1109/TMM.2018.2790172.
- [30] S. Yu, Y. Lin and Y. Lin, "Contactless pulse rate measurement based on smart TV," *2017 IEEE International Conference on Consumer Electronics - Taiwan (ICCE-TW)*, 2017, pp. 397-398, doi: 10.1109/ICCE-China.2017.7991163.
- [31] Lin, S.-T., Chen, W.-H., & Lin, Y.-H. "A Pulse Rate Detection Method for Mouse Application Based on Multi-PPG Sensors". *Sensors*, 17(7). 2017.