Effects of Illuminance Intensity on the Green Channel of Remote Photoplethysmography (rPPG) Signals

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Abstract

Point-of-care remote photoplethysmography (rPPG) devices that utilize low-cost RGB cameras have drawn considerable attention due to their convenience in contactless and non-invasive vital signs monitoring. In rPPG, sufficient lighting conditions are essential for obtaining accurate diagnostics by observing the complete signal morphology. The effects of illuminance intensity and light source settings play a significant role in rPPG assessment quality, and it was previously observed that different lighting schemes result in different signal quality and morphology. This study presents a quantitative empirical analysis where the quality and morphology of rPPG signals were assessed under different light settings. Participants' faces were exposed to the white LED spotlight, first when the sources were installed directly behind the video camera, and then when the sources were installed in a cross-polarized scheme. Hence, the effect of specular reflectance on rPPG signals could be observed in an increasing projection. The signal qualities were analyzed in each intensity level using a signal-to-noise (SNR) ratio metric. In 3 of 7 participants, placing the video camera on the same level as the light source led to signal quality loss of up to 3 dB for the range 30-60 Lux. In addition, two fundamental morphological features were analyzed, and the derivative-related feature was found to be increasing with illuminance intensity in 6 of 7 participants.

Keywords: remote photoplethysmography (rPPG), vital signs measurements, heart rate, digital health, health-care applications

1 Introduction

Advancements in mobile technologies have led to a new era in transferring and processing a wide range of data types Abd Elaziz et al (2021); Attiya et al (2022). Integration with smart devices facilitated access to healthcare services Acar et al (2019). Recent advancements in image processing have made the extraction of vital signs from remote, contactless, photoplethysmographic (rPPG) signals possible Rouast et al (2018). The fundamental principle governing rPPG is similar to that of contact PPG; they both exploit the light absorption differences of oxygenated and deoxygenated hemoglobin in capillary blood vessels Kamshilin and Margaryants (2017). While PPG primarily uses visible and near-infrared light sources, rPPG merely acquires visible wavelength as modern video cameras compose images in the RGB color channels Sun and Thakor (2016); Allen (2007). The rPPG measures the blood that circulates through the facial capillaries in every heartbeat resulting in imperceptible color variations on the skin, and modern video cameras can capture those variations under sufficient ambient conditions. It has been previously shown that the green channel has the most robust pulse information amongst the three RGB channels since the hemoglobin absorption is at its highest under green light Verkruysse et al (2008). This is the main reason why we attempted to investigate the effects only on the denoised green channel.

Different methods have been proposed for generating pulse signals in rPPG. These methods have recently been classified under three subsections as design-based, model-based, and blind source separation methods Sinhal et al (2020). Design-based methods involve the algorithms where the spatial representation is redefined, and they usually do not require a priori information of skin tone or illuminant Eaton et al (2018); Xu et al (2014). However, they are mostly dependent on the number of pixels in the region of interest (ROI) mask Wang et al (2016b). Model-based methods, on the other hand, are very useful for motion robustness de Haan and van Leest (2014). Chrominance-based method (CHROM) was introduced which builds two orthogonal chrominance signal components (X,Y); then it generates the pulse signal as combinations of X,Y de Haan and Jeanne (2013). Blind source separation methods are also effective when the original RGB signals are contaminated with noise or motion artifacts. Their principle is to exploit the signals as statistical data sets rather than to process them in a time or a frequency domain directly. JADE-ICA algorithm was successfully implemented in rPPG for heart rate (HR) predicting with 12 participants Poh et al (2010). Later, component analysis techniques were improved and tailored in rPPG applications for better accuracy Tsouri et al (2012); Macwan et al (2019). However, in cases where subjects have less or no motion at all, there is usually no need to use source separation methods for heart rate estimation as the raw signals have already sufficient pulse information.

The quality of an rPPG signal depends on several things such as illuminance level, type of camera lenses, skin type, skin color, environmental conditions, and make up Wang and Shan (2019). However, it is essential to consider the principles of skin reflection properties prior to collecting data for measurements. Wang et al. described the skin reflection model in detail and explained how the pulsatile information could be interpreted mathematically as depicted in Figure 1 Wang et al (2016a). Their analysis was purely based on the dichromatic reflection model Tominaga (1994). The skin pixels of RGB channels were defined as a time-varying function as in Equation 1;

$$C_k(t) = I(t) * [v_s(t) + v_d(t)] + v_n(t) \tag{1}$$

where $I(t)$ represents the luminance intensity, $v_s(t)$ represents the specular reflection, $v_d(t)$ represents the diffuse reflection, and $v_n(t)$ represents the noise induced by the camera sensor. The specular reflection phenomenon was described as a mirror-like effect which has no pulsatile information whatsoever. However, diffuse reflection is directly related to the light absorption of the skin, and it contains information regarding blood volume changes.

Light variance is one of the common challenges in rPPG and researchers have attempted to improve light tolerance with different methods. Jeanne et al. presented a method using infra-red reference light for remote HR measurements where the ambient light conditions are highly dynamic Jeanne et al (2013). Li et al. implemented an adaptive least mean square filter in their algorithm to reduce the noise induced by light variation for HR measurements Li et al (2014). Tulyakov et al.'s method calculates the HR while simultaneously determining suitable ROI depending on the environmental conditions such as motion or illumination variation Tulyakov et al (2016). Wu et al. proposed a neural network-based method for denoising pulse signals of a driver under ambient traffic lights Wu et al (2019). In addition to the techniques proposed to overcome those challenges regarding light conditions, Blackford et al. proposed a spectroscopy analysis to investigate the spectral properties of blood volume pulses Blackford et al (2018).

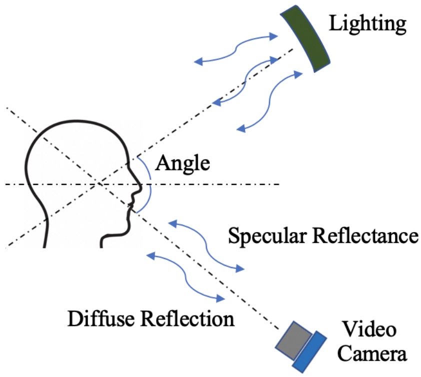


Fig. 1: Skin Reflection Model explains the reflection properties of skin, and it helps to justify the pulsatile information extracted from rPPG.

One of the significant effects of light variance is on rPPG pulse morphology. Unlike the conventional PPG, rPPG signals do not have a characteristic pulse morphology as it varies according to several factors (e.g., lighting, sensor, recording device). This situation calls some of the vital signs measurements in question (i.e., blood pressure [BP]). Especially for BP measurements, an accurate feature extraction process is essential when training the artificial neural networks being used Luo et al (2019). The studies published so far do not prove that the rPPG features are reliable enough to be fed into the neural networks for running solid health applications/algorithms. This is one of the main reasons why all aspects of the rPPG signal morphology must be studied thoroughly; the ambient light conditions (light settings, light intensity), subject's skin tone (as this may have an effect on the reflectivity, which is related to the quality of the pulsatile information taken from the rPPG measurement), and skin conditions (cleanness, oil, make-up, local melanin variations, etc.).

Several physiological models have been proposed in cPPG to explain the light interaction in reflective photoplethysmography Kamshilin and Margaryants (2017). While each model has its own advantages in justifying the signal morphology and behavior, more empirical analyses are needed for hypothesizing similar models in rPPG-based sensing applications. The findings in this study, therefore, are essential to find the answers of the following questions; (1) How does the illuminance intensity affect the rPPG signal quality? (2) Does the illuminance intensity affect the morphological features in rPPG, and if so, to what extent and what are the associated experimental challenges?

Although there are studies associated with the effects of light intensity variations on PPG signals, this is the first attempt to quantify the signal quality under different illuminance intensities systematically. We established two experimental setups and analyzed the illuminance intensity effects on 42 rPPG recordings with a signal quality metric and two morphological features.

2 Methods

2.1 Experimental Setup & Participants

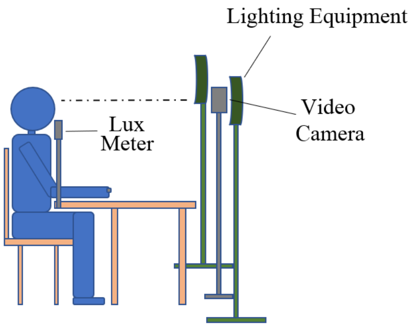
The experiments were carried out in the physiology laboratory in Bournemouth University (BU) where the Research Panel of BU approved the study. Seven Caucasian volunteers aged between 24 and 38 participated in the study. Darker skin tones are excluded for this trial as they require different biases and assumptions when processing rPPG signals Nowara et al (2020). The informed consent of each participant was obtained prior to the sessions. They were priorly requested not to wear make-up as such a factor requires additional assumptions and knowledge such as the type or quantity of the material that covered the specific parts of the face Wang and Shan (2019).

First, the subjects' faces were exposed to 30-60-100 lux respectively in a direct scheme as shown in Figure 2a; then they were exposed to 60-90-130 lux in a cross-polarized scheme as shown in Figure 2b. The illuminance ranges were so selected because our empirical pre-studies had shown that those lux levels would not irritate and induce discomfort to the human eye under those settings.

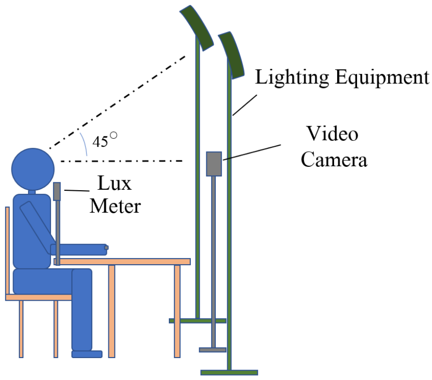
Controlled lighting equipment (Neewer 480 LED Panel Light) was used as the illuminant source. Illuminance was measured with a lux meter installed directly in front of the participant's face (Urceri MT-912 Light Meter). The RGB video camera was a CCD Sony DSCH300, and it was stabilized on an adjustable tripod. No additional lenses were attached, and no artificial effects were used. The distance between the participant and lighting equipment was 70 cm. The position of the equipment was so arranged that the regions of interest were not exposed to any potential shadow fall induced by the rays of light. As Kwon et al. and Lempe et al.'s analyses showed that the best ROI for spatial averaging is the cheeks, we manually created ROI masks for each participant Lempe et al (2013); Sungjun Kwon et al (2015). Participants were asked to keep as still as possible throughout the sessions. The recordings were taken in 30 frames per second, and video lengths were 30 seconds for each illuminance level.

2.2 Signal Analysis

All signal processing operations were carried out in custom-written scripts in MATLAB (MathWorks, Natick, Massachusetts, USA). The rPPG pulse data were presented as the normalized green channel only by taking the spatial average of the ROI pixels in every frame. This can be formalized as in the Equation 2 where $\mu(G_i)$ is the spatial mean in time domain. The multiplication of -1 is due to the need for inverting the signal as the *video camera rPPG* exhibits a reflectance oximetry behaviour, and it needs to be flipped over after normalization. In order to observe the morphological changes, a 3rd order Savitzky-Golay filter was used because of its better transient capturing properties for removing high frequency components from all the signals.



(a)



(b)

Fig. 2: In direct scheme (a), video camera and lighting were in the same horizontal plane. In cross-polarized scheme (b), 45 degree was set between the camera and lighting.

$$G_n = -1 * \frac{G_i}{\mu(G_i)} \tag{2}$$

We have implemented De Haan et al.'s signal-to-noise ratio (SNR) metric to assess the usability and quality of rPPG signals de Haan and Jeanne (2013). The 30-second filtered temporal datasets were assessed in frequency domain. This method calculates the energy around the harmonics and remaining portion in the power spectrum; then an SNR score in dB is presented by taking the ratio of both. Signal and noise calculations are formulated as in Equation 3 and 4 where $S(f)$ represents the spectrum and $U_t(f)$ represents the binary template.

$$Signal = \sum_{f=0.2}^{15} (U_t(f)S(f)) \tag{3}$$

$$Noise = \sum_{f=0.2}^{15} ((1 - U_t(f))(S(f))) \tag{4}$$

$$SNR\, score = 10\, log_{10} \left(\frac{Signal}{Noise} \right) \tag{5}$$

Since all the participants were asked to keep as still as possible during the recordings, the predictions extracted from the frequency domain were consistent and the spectra were clean.

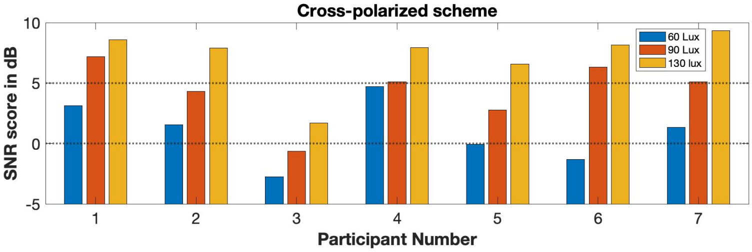
3 Results

Pulse signal qualities were assessed using the SNR metric to see the illuminance intensity effect on rPPG signals. The SNR scores of the normalized green channel are presented in Figures 3a and 3b.

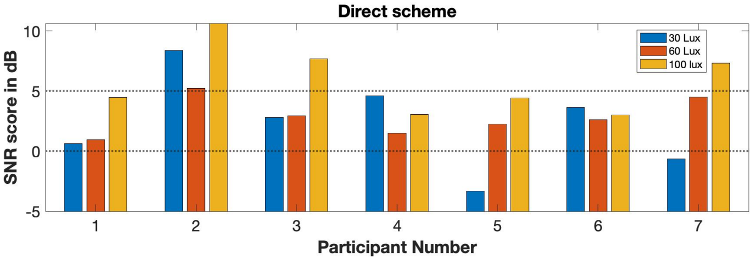
Beside the signal quality, the two main features of the rPPG signals were analyzed to observe the change in morphology in the normalized green channel. The first feature is the time in seconds between the maxima of the first derivative of the pulse signal (where it rises rapidly) and the crest point. This is shown with a participant image in Figure 4 as "Length A." The second feature, on the other hand, is simply the amplitude of the pulse signal; it is the distance in y axis between the start and crest points of the pulse. This is shown as "Length B." Signal morphology analyses were made by detecting each pulse in the time domain. The values presented in tables are the mean values of the features extracted from each pulse in 30-second recordings. Standard deviation (SD) for the pulse amplitude in each intensity level was within the range of 0.1-0.2, and SD for the time between the maxima of the first derivative of the pulse signal and the crest point was within the range of 0.01-0.1. The only linearity observed in morphology analyses was in the distance between the maxima of the first derivative of the pulse signal and crest point. In 6 participants, the feature "Length A" increased with the illuminance intensity as can be followed in Table 1. The pulse amplitude did not exhibit a linearity in distance between the start and crest points of the pulse (Length B) in any case whatsoever. However, in the cross-polarized scheme, the amplitudes have been shown to vary by up to 0.1 (RGB colour unit), and in direct scheme, they have been shown to vary by up to 0.13 (RGB colour unit) in the y axis.

4 Discussion

The prevailing opinion in remote measurements is that "the illuminance intensity will affect the rPPG assessment positively", however, our results have shown that this notion is likely to be refuted when the video camera is placed within the same horizontal direction as the light source. The effect of the light setting in the direct scheme where there is zero angle between the light source and video capturing device, might reduce the usability of the rPPG signals. Figure 3b shows how such an inappropriate setup design could introduce an unpredictability in the pulse signal quality where high illuminance increased the mirror-like effect in 3 of the participants.



(a)



(b)

Fig. 3: SNR scores of the green channel in cross-polarized scheme form an increasing projection in all participants (a). When the video camera and light source are in the same horizontal plane with no angle, SNRs exhibited an unpredictability in 3 participants (b).

The SNR analyses have shown that the readability of the pulsatile information increases with higher illuminance intensity where the illuminant is set up in a cross-polarized scheme. When there is no angle between the illuminant and the video recording device (i.e., direct scheme), the mirror-like phenomenon of the skin-light interaction (i.e., specular reflectance) engenders a signal quality loss and this potentially might lead to an inaccurate rPPG assessment in which case an advanced algorithm can be implemented to the application Jeanne et al (2013). Though the sample size was small in this trial, these findings show that the raw signal morphology concept needs more detailed spectroscopy studies

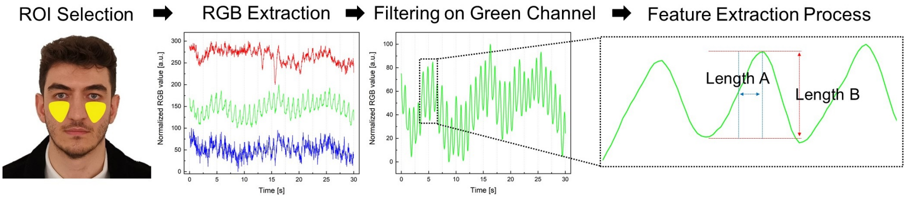


Fig. 4: Once the RGB channel data were extracted from the same region in all participants, the green channel was filtered with a smoothing Sav-Gol. Finally, morphological features were extracted.

	Cross-Polarized Scheme			Direct Scheme		
	60 Lux	90 Lux	130 Lux	30 Lux	60 Lux	100 Lux
Participant 1	0.1836	0.2266	0.1946	0.1941	0.2395	0.196
Participant 2	**0.1891**	**0.2377**	**0.2753**	0.1768	0.2378	0.2108
Participant 3	**0.2219**	**0.2267**	**0.2472**	0.2381	0.2079	0.2213
Participant 4	**0.3161**	**0.3233**	**0.3596**	0.3587	0.2709	0.2834
Participant 5	**0.2261**	**0.2229**	**0.244**	0.1202	0.2454	0.1883
Participant 6	**0.167**	**0.1756**	**0.1905**	0.2209	0.1908	0.1966
Participant 7	**0.216**	**0.2451**	**0.2706**	0.2377	0.2617	0.2482

Table 1: Average Length A. The time in seconds between the maxima of the first derivative of the pulse signal and the crest point.

to improve understanding of the rPPG theory better. The factors to be investigated might be the types of camera (whether it is an RGB color model or not), and the color sensors embedded in the recording device (CCD, CMOS or a combination of those technologies). The major limitation in our study, on the other hand, was the illuminance intensity range. Safety was an important matter, and it was decided not to risk causing any eye discomfort to the participants. However, with light-blocking glasses, the study can be extended in the future with different light wavelengths. Also, the sample size could be extended including darker skin tones. It is still not clear that if rPPG features carry vital information about blood pressure as cPPG features do Rong and Li (2021). We expect this study to initiate a trend in which morphological features are deeply investigated from the spectroscopic and light intensity aspects.

5 Conclusion

Remote photoplethysmography (rPPG) signals carry vital information about human cardiovascular dynamics. Here, we investigated how the green channel in rPPG reacts to illuminance intensity change in the ranges 30-60-90 and 60-90-130 lux. We reported signal qualities in SNR metric and analyzed the morphological changes by observing the two main features of photoplethysmography signals in two different experimental setups. It was hypothesized that the specular reflectance leads to signal quality loss in rPPG signals, and we found that in the range of 60-130 lux, which is considered to be low level in comparison with a typical office environment, illuminance intensity can affect the SNR up to 7 dB. The derivative-related morphological feature, on the other hand, was observed to vary up to 0.1 (RGB color unit) in both settings. Additionally, linearity was observed when the light setting was in a cross-polarized scheme. This study confirms that the placement of light sources significantly affects rPPG assessments and must be carefully considered when designing such an application in rPPG. The results encourage us to propose more detailed studies to determine the best pulse generation methods in various environmental conditions and ambient settings to get an accurate rPPG assessment. In future works, we plan to extend the study where more volunteers from multiple backgrounds are recruited, especially females and the elderly. Thus we will be able to investigate not only the effects of skin homogeneity but also the skin color on rPPG signals as well.

6 Statements and Declarations

This study was partially funded by the Sabanci University research fund.

Conflict of Interest. The authors declare no conflicts of interest.

Ethical approval. The experiments were conducted in Bournemouth University (BU) and The Research Ethics Panel of BU approved the study which was performed in accordance with the ethical standards as laid down in the 1964 Declaration of Helsinki and its later amendments.

Consent to participate. The informed consent of each participant was obtained prior to the sessions. The authors affirm that all participants provided informed consent for publication of the images and relevant data that were collected during the experiments.

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