Spatiotemporal monitoring of changes in oxy/deoxy-hemoglobin concentration and blood pulsation on human skin using smartphone-enabled remote multispectral photoplethysmography

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Abstract: We propose a smartphone-enabled remote multispectral photoplethysmography (SP-rmPPG) system and method to realize spatiotemporal monitoring of perfusion changes and pulsations of the oxyhemoglobin (HbO2) and deoxyhemoglobin (Hb) information of the effective blood volume within light interrogated skin tissue beds. The system is implemented on an unmodified smartphone utilizing its built-in camera and flashlight to acquire videos of the skin reflectance. The SP-rmPPG method converts the RGB video into multispectral cubes, upon which to decouple the dynamic changes in HbO2 and Hb information using a modified Beer-Lambert law and the selective wavelength bands of 500nm and 650nm. Blood pulsation amplitudes are then obtained by applying a window-based lock-in amplification on the derived spatiotemporal changes in HbO2 or Hb signals. To demonstrate the feasibility of proposed method, we conduct two experiments on the skin tissue beds that are conditioned by occlusive maneuver of supplying arteries: one using the popular blood cuff pressure maneuver on the upper arm, and another artificially inducing a transient ischemic condition on the facial skin tissue beds by finger pressing on the supplying external carotid artery. The cuff experiment shows that the measured dynamic information of HbO2 and Hb in the downstream agrees well with the parallel measurements of oxygenation saturation given by the standard pulse oximeter. We also observe the expected imbalance of spatiotemporal changes in the HbO2 and Hb between the right and left cheeks when the transient ischemic condition is induced in the one side of facial skin tissue beds. The results from the two experiments sufficiently demonstrate the feasibility of the proposed method to monitor the spatiotemporal changes in the skin hemodynamics, including blood oxygenation and pulsation amplitudes. Considering the ever-growing accessibility and affordability of the smartphone to the general public, the proposed strategy promises the early screening of vascular diseases and improving general public health particularly in rural areas with low resource settings.

1. Introduction

The primary function of the microcirculation is to supply oxygen and nutrients to the local tissue [1]. Microcirculation status, hence capillary hemodynamics, plays an important role in regulating blood flow and tissue oxygenation, thus being well recognized in the vital sign monitoring, as well as in the study of vascular function, peripheral artery diseases [2–6] and cardiovascular disorders [7–9]. Therefore, non-invasive and contactless techniques to assess microcirculatory behaviors and hemodynamic contents are indispensable for clinical practices and daily assessment of medical conditions [10,11].
Skin, being the largest and capillary-rich organ, provides an easily accessible window for developing such techniques to access the hemodynamic information inside the human body [12–15]. Thanks to the translucent property of skin at visible and near infrared (NIR) wavelengths, numerous optical methods have been developed to derive signals (measurands) that are indicative of blood hemodynamics, for example blood perfusion, oxygen saturation, pulsation etc. [16–20]. Among these optical methods, photoplethysmography (PPG) is becoming one of the most popular techniques and being widely used for in-hospital monitoring and even in wearable devices nowadays [21–23]. Due to the strong absorption of blood to the light, PPG works by recording time-elapsed optical reflectance modulated by the effective blood volume within light interrogated tissue volume to indicate the dynamic pulsatile behavior of the blood flow (volume) caused by cardiac heartbeat [24]. With this dynamic and pulsatile blood flow behavior directly obtained from the human skin tissue, PPG can be used to monitor the heart rate [25], cardiac cycle [26] and respiration [27]. However, PPG is often implemented through a contact approach between sensors and skin, prone to motion artifacts. To solve this problem, remote PPG (rPPG) has been proposed and developed [28,29]. rPPG is typically implemented by a camera-based system that is used to acquire the video of skin surface, from which to derive the pulse waveforms [30]. Using dedicated signal processing algorithms, subtle momentary changes in the skin reflection in the video can be extracted. The remote attribute of rPPG is its most attractive advantage compared to the conventional PPG [29]. However, since global parameters are addressed in the above applications, there is still a demand to develop techniques that can be used to perform the spatiotemporal analysis of rPPG and explore its potential applications.

As exciting as the rPPG delivers, however, previous developments were not able to decouple the hemoglobin compositions from the acquired signals, e.g., oxygenated (HbO2) and deoxygenated (Hb) blood. This additional information is critical for our improved understanding of the microcirculatory function and hemodynamic regulations [31]. In most cases, changes in pulsation and oxygenation detected at the peripheral site would manifest changes in supplying arteries or systemic blood flow [12,32,33]. Although previous rPPG studies have explored the changes in pulse waveforms (e.g., shape, intensity) upon conditioning the blood flow, they have not been able to decouple the modulation of HbO2 and Hb from the tissue volume, making the techniques less effective and accurate in assessing blood flow obstruction and microvascular disorders. In addition, achieving all these detections with the use of a widely available and cost-effective device is an additional challenge that, to our best knowledge, has not been addressed. In our previous study, we have developed smartphone-enabled transdermal optical imaging techniques to investigate the spatial blood perfusion on the human skin [34]. This work has shown that snapshot RGB-mode photographs of the skin can be reconstructed into multispectral images to map the contents of bio-chromophores [35], which proves it possible to integrate the smartphone-enabled transdermal optical imaging technique with rPPG to measure and monitor the cutaneous hemodynamics in both time and spatial scales.

Herein, we propose a smartphone-enabled remote multispectral photoplethysmography (SP-rmPPG) system and method to provide a spatiotemporal monitoring of the perfusion changes and pulsations of HbO2 and Hb in the human skin. The method first converts the RGB video into the multispectral data cube, upon which to derive and decouple spatiotemporal HbO2 and Hb information within the effective blood volume utilizing a modified Beer-Lambert law and dual-waveband processing method. We then describe a method to obtain the spatiotemporal pulsation amplitudes of both two types of oxygenated and deoxygenated bloods by applying a window-based lock-in amplification approach. To demonstrate the feasibility and performance of our proposed method, two experiments are performed by imaging two peripheral skin sites in health volunteers while conditioning the upstream blood supply and drainage, with an aim to delineate the changes in HbO2 and Hb modulation and pulsation strength upon the challenging.
2. Methods and Materials

2.1. Set up and data recording

Schematic of the experimental setup to demonstrate the proposed SP-rmPPG method is illustrated in Fig. 1(A), where an unmodified smartphone was used to acquire video images of dynamic light reflectance emerging at the skin surface upon which to derive blood oxygenation and hemodynamics. In this study, an iPhone 8 (Apple, USA) was used for the demonstration purpose, but any types of smartphones can be used. The videos were collected by the smartphone rear camera under illumination from the built-in flashlight. The spectral power distribution of the flashlight is shown in Fig. 1(B). The relative spectral sensitivities of the R, G and B channels in the smartphone camera are given in Fig. 1(C). We placed a polarizer film in front of the flashlight and an analyzer film in front of the camera lens. The film pairs were arranged orthogonally to minimize specular reflections from the skin surface. The illumination uniformity in the field of view (FOV) was tested with a standard 95% reflection board. U1 (Minimum/Average lux) and U2 (Minimum/Maximum lux) were assessed to be 0.99 and 0.92, respectively, indicating that the illumination is relatively uniform across the sample target.

The room temperature was kept at around 23°C and the humidity was around 50% during the experiments of video recording. Before recording the video, the volunteer was allowed to calmly sit in a chair for 5 minutes to get acquainted to the room environment and stabilize the heartbeat. The smartphone was placed 30 cm away from the skin surface. In the smartphone, we installed “ProMovie” from the App Store and used it to acquire videos, representing the light reflectance emerging at the skin surface. The image resolution was set at 2160 × 3840 pixels. The shutter speed, ISO and white balance were set to be 1/60 seconds (i.e. frame rate of 60 fps), 100 and
4000 K, respectively. Before data processing described below, a proprietary sub-pixel registration algorithm was used to pre-process the videos to minimize subtle motion artifacts in the results.

Normal healthy volunteers were enrolled in this study to demonstrate the feasibility of proposed methods. This study adhered to the tenets of the Declaration of Helsinki and was performed in accordance with the Health Insurance Portability and Accountability Act. Informed consent was obtained from the subjects prior to the start of each study session. Ethical approval was obtained from the Institutional Review Board of the University of Washington.

2.2. Smartphone camera calibration to perform multi-spectral imaging

We applied Wiener estimation method to calibrate the built-in RGB-mode camera in the smartphone to perform multi-spectral imaging. The details of this method can be found in our previous study [34,36]. Briefly, a standard color checker (X-Rite ColorChecker Classic, Fig. 1(D)) was used in this study to calibrate the smartphone camera, where the images (or video) captured from the standard color checker were used as the training data set to determine a transformation matrix that is needed to convert the RGB color images into the multi-spectral images. Under the illumination provided by the built-in flashlight, the transformation matrix can be determined by the following equation:

$$W = \langle V'V \rangle \langle VV \rangle^{-1}$$

where $W$ is the reconstructed transformation matrix. $<>$ is an ensemble-averaging operator. $V'V$ is the correlation matrix between the multispectral reflectance of the color checker and the RGB responses in the smartphone camera. The standard reflectance data of the color checker was provided by the manufacturer. Here, we selected 450, 500, 550, 600, 650 and 700 nm as the wavelengths of interest in the calibration, though other wavelengths can be selected if needed. $VV$ is the autocorrelation matrix of the RGB sensor responses in the camera.

To verify the accuracy, the derived transformation matrix was firstly applied on the RGB-mode image of the color checker that was used for calibration to calculate its reconstructed reflectance data at multiple wavelengths of interest. We evaluated the goodness of fit coefficients (GFC) between the standard and reconstructed reflectance data [37,38]. The minimum, average and maximum GFC values were measured to be 0.9533, 0.9898 and 0.9999, indicating excellent performance of the derived transformation matrix. We then tested the matrix on a set of 14 unique skin tone colors in ColorChecker Digital SG (X-Rite) that were not used for the calibration. The comparison of standard and reconstructed reflectance data is shown in Fig. 2, with corresponding GFC values shown. The minimum, average and maximum GFC values were measured to be 0.9928, 0.9971 and 0.9999, demonstrating that the derived transformation matrix is accurate enough to estimate the real reflectance of the targets from their RGB-mode images.

2.3. Analysis of changes in HbO2 and Hb within blood perfusion

With the transformation matrix $W$ obtained in the last Section 2.2, the RGB-mode videos of the skin can then be converted into multispectral data cubes. The multispectral cube thus obtained represents the spectral information at the six wavelengths of 450, 500, 550, 600, 650 and 700 nm, which can be written as,

$$
\begin{bmatrix}
    M_1(x, y, t) \\
    M_2(x, y, t) \\
    \vdots \\
    M_6(x, y, t)
\end{bmatrix} = W \times 
\begin{bmatrix}
    R(x, y, t) \\
    G(x, y, t) \\
    B(x, y, t)
\end{bmatrix}
$$

where $M_i(x, y, t)$ is the reconstructed spectral value at pixel $(x, y)$ and time $t$. $i$ is the channel number ($i = 1, 2, \ldots, 6$, representing 450, 500, 550, 600, 650 and 700 nm, respectively). $R(x, y, t)$,
Fig. 2. The comparison between the standard reflectance and the reconstructed reflectance from the transformation matrix for each block of 14 unique skin tone colors in ColorChecker Digital SG (SR: standard reflectance; RR: reconstructed reflectance). Numeric values shown in each block are the goodness of fit coefficients between SR and RR.

$G(x, y, t)$ and $B(x, y, t)$ are the values at the pixel $(x, y)$ and time $t$ of the video from the red, green, and blue channels, respectively.

Since here we are interested in extracting HbO2 and Hb information in the dynamic blood perfusion, the wavelength selection could follow the requirements of pulse oximetry [39]. That is, the absorption coefficients of HbO2 and Hb should be approximately equal at one wavelength and differ considerably at another wavelength. Therefore, we selected the channel 2 (500 nm, approximately at the isosbestic point) and channel 5 (650 nm, having considerable difference in absorption between HbO2 and Hb) as the target wavelengths in further processing steps to derive oxygenation information. For the reconstructed signals at each channel, we estimated the changes in light absorption with reference to the time zero by using the modified Beer-Lambert law [40], i.e.,

$$\Delta A = A_t - A_0 = -\log(I_t/I_s) - (-\log(I_0/I_s)) = -\log(I_t/I_0)$$

(3)

where $\Delta A$ is the change in light absorption from the time $t_0$ to $t$. $A_t$ and $A_0$ are the light absorbance at the time $t$ and $t_0$. $I_t$ and $I_0$ are the signal intensities in selected channels at the time $t$ and $t_0$. $I_s$ is the intensity of incident light. Assume that the light absorption in the skin is caused by melanin, HbO2 and Hb chromophores. In the current study, we can safely assume the melanin concentration and skin tissue scattering are relatively constant over time [41]. Thus, the change in light absorption (Eq. (3)) would be dominated by the changes in HbO2 and Hb concentrations within the blood volume. Consequently, Eq.3 could be rewritten as,

$$\Delta A = \Delta c_{HbO2} \varepsilon_{HbO2} l + \Delta c_{Hb} \varepsilon_{Hb} l$$

(4)

where $\Delta c$ is the change in either HbO2 or Hb concentrations. $\varepsilon$ is the absorption extinction coefficient of either HbO2 or Hb. $l$ is the light interaction path length. We assume that the light interaction path lengths at different wavelengths to be the same. In order to decouple the changes
in HbO2 and Hb in Eq.4, we constructed a weighting formula below,
\[
\Delta = \Delta A_2 - k \Delta A_5 = \Delta c^{HbO_2}l(e_2^{HbO_2} - k e_5^{HbO_2}) + \Delta c^{Hb}l(e_2^{Hb} - k e_5^{Hb})
\]
(5)
where \(\Delta\) is the result after weighted subtraction. \(\Delta A_2\) and \(\Delta A_5\) are the changes in the light absorbance at 500 nm and 650 nm, respectively. \(k\) is the subtraction weighting factor to be determined. \(e_2^{HbO_2}\), \(e_5^{HbO_2}\), \(e_2^{Hb}\) and \(e_5^{Hb}\) are the absorption extinction coefficients of HbO2 and Hb at 500 nm and 650 nm, respectively. It is clear that if the factor \(k\) is set to be \(e_2^{Hb}/e_5^{Hb}\), then the effect of the Hb changes on Eq. (5) would be eliminated. Thus, the change in HbO2 concentration can be derived as,
\[
\Delta c^{HbO_2} = \frac{\Delta A_2 - k \Delta A_5}{l(e_2^{HbO_2} - k e_5^{HbO_2})} \quad \text{(where } k = \frac{e_2^{Hb}}{e_5^{Hb}}\text{)}
\]
(6)
Likewise, if the factor \(k\) is set to \(\frac{e_2^{HbO_2}}{e_5^{HbO_2}}\), then the effect of the HbO2 changes on Eq. 5 is eliminated. Thus,
\[
\Delta c^{Hb} = \frac{\Delta A_2 - k \Delta A_5}{l(e_2^{Hb} - k e_5^{Hb})} \quad \text{(where } k = \frac{e_2^{HbO_2}}{e_5^{HbO_2}}\text{)}
\]
(7)
Thus far, we have decoupled the effects of the changes in HbO2 and Hb concentrations on the Eq. (3) that can be estimated from the color images captured over time by the smartphone after multispectral conversion (Eq. (2)). In doing so at each pixel in the video image, the spatiotemporal changes of decoupled HbO2 and Hb concentrations (i.e., \(\Delta c^{HbO_2}\) and \(\Delta c^{Hb}\)) within the dynamic blood perfusion within the light interrogated tissue volume can be obtained, but scaled by the light interaction path length. For simplicity, we assume that the light interaction path length for HbO2 and Hb is constant and takes a value of 1 mm in the current study. A further discussion about this assumption is provided in Discussion Section.

2.4. Analysis of blood pulsations

It is known that heart pumping leads to pulsatile blood volume propagating throughout the body tissue. This pulsatile modulation of the blood volume results in the absorption modulation of the light propagating within the skin, which in turn leads to the intensity modulation of light reflected from the skin tissue. Assuming that the oxygenated and deoxygenated bloods are responsible for this absorption, the derived spatiotemporal changes in HbO2 and Hb concentrations in the last Section would also behave pulsatile, which can be used to analyze and indicate the blood volume pulsations within the light interrogated skin tissue volume in this study.

To recover spatiotemporal pulsation of the dynamic blood perfusion, we applied a window-based lock-in amplification algorithm [42] on the time varying HbO2 and Hb signals obtained by Eq. (6) and Eq. (7). First, we selected a 5-second time window starting from the first frame. In the window, we built a standard function with its temporal heart rate frequency. The heart rate was extracted by conducting fast Fourier transformation of the global perfusion data in the window. The standard function can be expressed as:
\[
R(t) = \cos(\omega_h t) - i \sin(\omega_h t) = e^{-i\omega_h t}
\]
(8)
where \(R(t)\) is the standard reference function constructed by the known heart beating frequency \(\omega_h\). The dynamic blood perfusion signal at each pixel \((x, y)\) obtained from the last Section can be
expressed through Fourier series expansion:

\[
\Delta c(x, y, t) = \sum_m \sum_n AM_{mn}(x, y) \cos[\omega_m t + \theta_m(x, y)] \\
= \sum_m \sum_n \frac{AM_{mn}(x, y)}{2} \{e^{i(\omega_m t + \theta_m(x, y))} + e^{-i(\omega_m t + \theta_m(x, y))}\} \tag{9}
\]

where \(\Delta c(x, y, t)\) is the input signal representing the changes in hemoglobin concentration contained in the dynamic blood volume at time \(t\). \(AM_{mn}(x, y)\), \(\omega_m\) and \(\theta_m(x, y)\) are the amplitude, frequency and phase of the input signal at the pixel \((x, y)\). Therefore, the signals solely due to the heartbeat at the frequency \(\omega_h\) embedded within \(\Delta c(x, y, t)\) can be recovered by applying lock-in detection [43]:

\[
Z(x, y) = \sum_t R(t)\Delta c(x, y, t) = \sum_t \sum_m \sum_n \frac{AM_{mn}(x, y)}{2} \{e^{i(\omega_m - \omega_h)t + \theta_m(x, y)} + e^{-i(\omega_m + \omega_h)t + \theta_m(x, y)}\} \tag{10}
\]

where \(Z(x, y)\) is the time integral of the product of the standard reference function \(R(t)\) and the input signal of \(\Delta c(x, y, t)\). Per lock-in detection mechanism, when the components of input signals have the frequencies that differ from the standard reference frequency (i.e., \(\omega_h\)), the product would oscillate in time and approach to zero. However, when the signal is of the same frequency as \(\omega_h\), the product would be retained and amplified. Assuming the phase of the heart cycle at pixel \((x, y)\) is constant over time, the output of the lock-in detection can be simplified as,

\[
Z(x, y) = \frac{AM_h(x, y)}{2} e^{j\theta_h(x, y)} \tag{11}
\]

where \(AM_h(x, y)\) and \(\theta_h(x, y)\) are the amplitude and phase of the extracted cardiac pulsation signal, respectively. Consequently, the pulsation amplitude at pixel \((x, y)\) can be calculated as below:

\[
AM_h(x, y) = 2\text{abs}\{Z(x, y)\} = 2\text{abs} \left[\sum_t R(t)\Delta c(x, y, t)\right] \tag{12}
\]

By moving the evaluating time window along the time axis across the entire video frames, the spatial and time-resolved pulsation of blood perfusion within the light interrogated skin tissue volume can be obtained. Since the dynamic blood contains oxygenated and deoxygenated blood, the pulsation amplitudes separately evaluated from the HbO2 and Hb signals (i.e. Equation (6) or Eq. (7)) must be equal and the same as the pulsation amplitude of the whole blood volume.

A flow chart for the signal processing procedures described above is given in Fig. 3. After the videos are captured by the smartphone, the time trace of signals in the RGB channels are first converted into the multispectral data cube through the transformation matrix obtained by calibration (Eq. (2)). In this study to achieve our purpose, we converted the RGB colors into the six spectral wavelengths at 450, 500, 550, 600, 650 and 700 nm, respectively. Then, the changes in light absorbance at 500 and 650 nm were calculated (Eq. (3)) with reference to the frame at the time zero (i.e., the start of video frame of interest). Afterwards, the spatiotemporal changes in HbO2 and Hb concentrations within the dynamic blood volume are decoupled by weighted subtraction method (Eq. (6) and Eq. (7)). Finally, the spatiotemporal pulsation is mapped by the window-based lock-in detection mechanism (Eq. (10) and Eq. (12)).

2.5. Experimental demonstration considerations

Having described the methods and formulations of SP-rmPPG to monitor the changes in HbO2 and Hb concentrations and pulsatile blood volume in the light interrogated skin tissue from smartphone recorded videos, we conducted two experiments to demonstrate its feasibility to
Fig. 3. The schematic of signal processing steps to derive the spatiotemporal changes in HbO2 and Hb and their pulsation amplitudes from the video images captured by the smartphone. (A) The RGB color video is first converted to hyperspectral video cube, where hyperspectral cube contains 6 wavelengths of 450, 500, 550, 600, 650 and 700 nm in this study. (B) The time-varying spectral signals of selected wavelengths at 500 nm and 650 nm are used to calculate (C) the spatiotemporal changes in the HbO2 and Hb concentrations in the blood volume within the light interrogated tissue volume. (D) Finally, the spatial pulsation amplitude is evaluated from either dynamic HbO2 or Hb signals resulted in the step (C).

reveal oxygenation and pulsation changes during flow-challenged conditions. The first experiment was designed around the popular blood cuff maneuver at the upper arm to gradually occlude the blood draining venules. The second experiment was designed to simulate the occlusive external carotid artery (or more precisely the facial artery) that supplies the facial skin tissue beds.

In the 1st experiment (Experiment I), we applied a standard medical grade manual blood cuff to condition the blood supply and drainage in the left upper arm, and then used our proposed SP-rmPPG system to monitor the development and evolution of blood hemodynamics in the dorsal skin of the left hand. With the hand placed on the desk steadily to avoid relatively large motion, videos were taken by the smartphone while the cuff pressure was being applied. In parallel, a medical grade contact-mode sensor-based pulse oximeter (PC-66H Handheld Pulse Oximeter, CMI Health, USA) was used to monitor the peripheral oxygen saturation (SaO2) at the left little finger. Five trials of the experiments were conducted by applying 0 (control), 50, 70, 90 and 110 mmHg cuff pressures on the upper arm until the SaO2 as measured by the pulse oximeter reached a level of 97% (control), 96%, 95%, 94% and 93%, respectively. For each experimental trial, we started the video recording at the time when the cuff pressure was applied. After the target SaO2 level was reached as monitored by the pulse meter and stabilized for 20 seconds, we released the cuff pressure and continued the video recording for next 10 seconds. We labeled these 5 trials as: c1 – 0 mmHg/97% (control), c2 – 50 mmHg/96%, c3 – 70 mmHg/95%, c4 – 90 mmHg/94%, c5 – 110 mmHg/93%. For example, for the trial c5 (110 mmHg/93%), the cuff pressure applied was 110 mmHg. The onset of the continuous video recording was at the time when the cuff pressure started at the upper arm. The cuff pressure was continuously being applied until the SaO2 value measured by the pulse oximeter reached at the level of 93%, at which time the pressure was released. And the video recording continued for another 10 seconds.
The 2nd experiment (Experiment II) was designed to demonstrate whether the smartphone system is able to observe the changes in blood oxygenation and associated blood pulse strength at the facial skin when the external carotid artery that supplies maxillofacial region is challenged. There are two branches of the facial arteries symmetrically located at the lower jaw region near neck, supplying the nutritive blood to the facial skin tissue beds. We simulated partial occlusive (or ischemic) condition within the skin tissue beds by gently pressing on the facial artery while continuously recording the videos of the light reflectance emerging at the facial skin surface using the smartphone. To avoid motion, the head was placed on the chin rest in a slit lamp setup. Below are the brief procedures of the experiment. First, the volunteer used finger-touching method to locate the artery position by feeling pulse below the jawbone. Then, the smartphone started to continuously record the skin videos, initially without applying finger pressure on the artery. Approximately 15 seconds after the onset of the video recording, the volunteer applied a gentle pressure to press the artery to produce partial occlusion on the artery to limit the blood supply to the corresponding facial skin tissue beds. The applied pressure lasted for 20 seconds and then removed. The video recording was finally ended at the time when a period of 60 seconds was reached. We conducted two separate experiments using this procedure on the facial artery located at both sides of lower jaws: first on the left, and then on the right. Another set of experiment was also conducted without applying the pressure on the artery, which was treated as the control.

3. Results

3.1. Experiment I: changes in HbO2 and Hb concentrations due to blood cuff maneuver on the arm

The maneuver of blood cuff pressure on the upper arm progressively occludes relatively superficial venules that drain the blood from the forearm. This action would expect a gradual increase of the deoxygenated blood pooling at the downstream of skin beds and a gradual decrease of oxygenated blood. Figure 4(A) show the representative maps indicating the changes in HbO2 and Hb concentrations at the dorsal skin tissue beds of the challenged left hand, extracted from the spatiotemporal images at four observation time points of each experimental trial: 1) the onset of the application of pressure cuff on the upper arm, 2) the time instant at the halfway of the video recording, 3) the time instant when the pressure cuff was released, and 4) the finishing time of the video recording. For all the experimental trials except for the zero-cuff pressure (i.e., the control), the decrease in HbO2 concentration within the skin tissue beds were observed with the application of pressure cuff, whereas the opposite trends were true for Hb concentration. After releasing the cuff pressure on the upper arm, a rapid recovery of the HbO2 and Hb was seen. Comparing among different trials, the degree of changes in HbO2 and Hb concentration from onset to release agrees positively with the level of pressure applied.

To demonstrate the temporal profile of the measured signal, we selected a region of interest (ROI) on the dorsal hand skin and calculated the averaged values of the changes at each frame in the time course of spatiotemporal dynamic images. The averaging operation for a selected region was for the purpose of improving the signal quality and reducing the noises because the smartphone camera that we used was only of 8-bit depth. The time traces of the measured SaO2 values are shown in Fig. 4(B). In Fig. 4(C), we show the time traces of decoupled HbO2 and Hb. As expected, the changes in HbO2 concentration show a continuous decrease with the cuff on and a rapid recovery right after the cuff was released. The opposite trends are observed for the changes in Hb concentration. These results match well with the values of oxygen saturations given by the pulse oximeter (Fig. 4(B)). Decreased oxygenation values indicate decreased concentration of the oxygenated blood within the skin tissue beds. We also calculated the changes in total hemoglobin concentration for each experimental trial by summing corresponding changes in HbO2 and Hb together (Fig. 4(D)). Except for the control, the changes in total hemoglobin concentration increase in all trials. Since venules are located more superficially than arteries in
the upper arm, the application of cuff pressure causes severer occlusion in venules than arteries, leading to gradual blood pooling in the downstream of the forearm, indicating the validity of the results observed in the experiments. It is worthy to mention that all the values of concentration changes ($\Delta c$) were calculated when the light interaction path length ($l$) was assumed to be 1 mm. The real values of $\Delta c$ can be affected by this assumption and can be improved by a more realistic $l$ under specific illumination and imaging conditions.

Fig. 4. The SP-rmPPG can provide information about spatiotemporal changes in oxygenated and deoxygenated blood within the light interrogated dorsal skin tissue in the hand during a routine blood cuff procedure applied on the upper arm. The changes in HbO2 and Hb concentrations were estimated from the smartphone recorded videos of a volunteer’s hand when the upper arm was applied with a pressure by the cuff, using the proposed SP-rmPPG algorithms. The results shown were obtained from 5 experimental trials: c1 – 0 mmHg/97% (control), c2 – 50 mmHg/96%, c3 – 70 mmHg/95%, c4 – 90 mmHg/94%, c5 – 110 mmHg/93%. (A) Representative reflectance (rf), Hb (d) and HbO2 (o) images extracted from the spatiotemporal images at four-time instants: 1) the onset of the application of pressure cuff on the upper arm, 2) the time instant at the halfway of the video recording, 3) the time instant when the pressure cuff was released, and 4) the finishing time of the video recording. (B) The time trace of measured oxygen saturation values from the pulse oximeter. (C) The time traces of averaged values of decoupled HbO2 and Hb changes within the selected region of interest (ROI) shown in the top left figure in (A). (D) Time traces of averaged values of the total hemoglobin changes within the selected ROI. rf – reflectance image, o – oxygenated blood, d – deoxygenated blood.
3.2. **Experiment I: pulsations of oxygenated and deoxygenated blood in cuff pressure experiments**

With the obtained spatiotemporal changes of oxygenated and deoxygenated blood due to the blood cuff maneuver at the upper arm, we applied a window-based lock-in amplification algorithm described in Section 2.4 to map the spatial pulsation amplitudes at the skin tissue beds as imaged by the smartphone. Since the experiment was conducted with the subject in sitting position that made the forearm about 20 cm below the heat level, the blood pulsation in the hand skin beds would be relatively weaker when compared to the positions that are above the heart level, due to the gravity effect. Therefore, we applied a longer time window of 10 seconds to maximally extract the heart frequency signal. It was successful to map the blood pulsation strengths for all the experimental trials conducted. As an example, Fig. 5(A) show the spatial pulsation maps resulted from the respective spatiotemporal changes of HbO2 and Hb concentrations, when 110 mmHg cuff pressure was applied at the upper arm of the subject (i.e., the trial c5). Figure 5(B) illustrates the corresponding time traces of the pulsation strength averaged within the selected ROI (square region marked in the upper left figure in Fig. 4). It can be observed that the blood pulsations remain relatively weak when the cuff pressure was applied, while being approximately the same strength for both the oxygenated and deoxygenated blood volumes. These are expected because mathematically and physically, the pulsation derived from the dynamic concentrations of either HbO2 or Hb should be the same as the total effective blood volume. Upon after releasing the cuff pressure, the blood pulsation shows a significant re-bound, indicating that both oxygenated and deoxygenated blood are experiencing a recovery associated with a strong pulsation, which is more clearly illustrated in the time trace curves of the average pulsation intensity in the selected ROI (Fig. 5(B)).

3.3. **Experiment II: changes in HbO2 and Hb concentrations in facial skin**

After conducted feasibility study using the popular blood cuff maneuver on the subject’s upper arm, we next performed the experiments to demonstrate whether the proposed SP-rmPPG can monitor the changes of HbO2 and Hb within the facial skin tissue beds (See the procedure in Section 2.5). With the finger pressed on the facial arteries located at the lower jaw region to partially occlude the blood supply to the facial skin tissue beds for ∼20s duration at ∼15s after the onset of the video recording, Fig. 6(A) shows the representative dynamic facial skin maps of the changes in HbO2 and Hb at the time instants of 1s, 30s and 60s, respectively, when the left facial artery branch was pressurized. The corresponding time traces of HbO2 and Hb changes on left and right cheeks are shown in Fig. 6(B) that were assessed by averaging the values within the regions of interest (the region marked by white boxes in the top left figure) at each frame for the entire time-period of video recording. During the first 15s, both the HbO2 and Hb signals are fluctuating around the zero level. At the time when the left facial artery was challenged by applying pressure on it, the HbO2 started to rapidly decrease and Hb to increase at the left cheek, while the changes at the right cheek region were minimal. With the pressure sustained at the position for a period of 20s, the decrease in HbO2 and increase in Hb sustained in the left cheek, but at a much slower rate. Afterwards, the changes rapidly re-bounded when the pressure was released and then slowly approaching the initial normal level. Such behaviors of changes in HbO2 and Hb are expected from normal physiology for a tissue region that experiences a temporary shortage of blood supply (i.e., a transient ischemic attack) [44]. However, a slight opposite trend of changes in HbO2 and Hb was observed at the contralateral right cheek, where the blood supply was not limited, but the HbO2 was seen slightly increase and Hb decrease during the partial occlusive maneuver on the left facial artery, and then the trend reversed after the pressure was lifted. This may be explained by the symmetrical relationship of arterial supply and venular drainage between the left and right cheeks where an ischemic impairment at one side
Fig. 5. Dynamic blood pulsation maps can be obtained from the spatiotemporal changes in HbO2 and Hb concentrations as evaluated from the smartphone recorded videos. (A) Representative pulsation maps at the time instants as shown derived from the respective Hb (top row) and HbO2 signals (bottom row) when a 110-mmHg cuff pressure was applied at the upper arm until the oxygen saturation at the little finger reached 93% as monitored by the pulse oximeter, i.e., the experimental trial c5: 110 mmHg/93%. (B) Corresponding time traces of the pulsation strengths averaged from the selected ROI, derived from both the HbO2 (Top) and Hb signals (bottom), respectively, evaluated from a time window of 10s sliding through the entire recording time with a step time length of 0.5s. Cuff releasing time was at ∼80s. Oxygenated blood is indicated by the label of “o”, and deoxygenated blood by “d” in the figure.

would likely evoke a response at its dependent contralateral side, trying to balance circulation system likely due to microvascular or sympathetic nerve autoregulations [45].

Figures 6(C) and (D) show the spatiotemporal changes in the HbO2 and Hb of the skin tissue beds at both the right and left cheeks, albeit with the right facial artery challenged to limit the blood supply to right facial regions. The changes are observed the same as that of left-pressing experiment but with the trend reversed. However, the changes are in much smaller magnitude in this case, likely due to insufficient pressure on the right facial artery applied by the finger pressing. In Figs. 6(E) and (F), we also show the spatiotemporal results of the control group. As expected, the perfusion changes are moderate and stable over the time period of smartphone video recording. These results sufficiently demonstrate that the proposed SP-rmPPG method is feasible to detect the dynamic oxygenation status within the facial skin tissue beds, simply by the use of a widely available and cost-effective smartphone.

3.4. Experiment II: pulsations of oxygenated and deoxygenated blood in facial skin

The spatiotemporal pulsation maps of the facial skin derived from the spatiotemporal changes in HbO2 and Hb are shown in Fig. 7 for the facial artery challenging experiments. The representative pulsation maps at the time instant of 20s extracted from the spatiotemporal images are shown in Fig. 7(A), for the experimental trials of 1) left facial artery being challenged, 2) right facial artery being challenged, and 3) control. For the case of occluding left artery, lower pulsation amplitudes for both the HbO2 and Hb are seen at the left side of the cheek compared to its
Fig. 6. The proposed SP-rmPPG can provide dynamic information of HbO₂ and Hb within the facial skin tissue beds when blood supply is limited by pressing the facial arteries in the lower jaw region. (A) The representative maps of HbO₂ (top row) and Hb (bottom row) changes of the facial skin at three time points (1, 30 and 60s) when the left facial artery was pressed at the time of ≈15 s after the onset of the video recording. White box area in the top left figure indicates the selected ROIs for evaluating the temporal time trace signals. (B) Time traces of averaged values of HbO₂ and Hb changes within the selected ROIs (R: right cheek, L: left cheek) shown in (A). (C) and (D) the same as in (A) and (B), respectively, but the right facial artery was limited. (E) and (F), the same as in (A) and (B), but the control experiment, i.e. no pressing on the facial artery was applied.
contralateral right cheek, indicating that limiting the blood supply to the skin tissue beds in the left cheek reduces its blood pulsation. The opposite change is true for the case of right artery challenging. However, there is no observed difference between the left and right cheeks for the control group, i.e., they remain symmetrical. Since the signal to noise ratio is relatively low due to the use of smartphone that has limited bit-depths (8-bits), we calculated the averaged pulsation amplitudes within the selected regions of interest (ROI) at each frame in order to improve the signal to noise ratio. The ROIs were selected symmetrically at the right and left cheeks, marked as white boxes in left figure of Fig. 7(A). We then calculated the ratio of pulsation amplitudes between right and left cheeks in each time window to further contrast the imbalance of blood pulsation within the skin tissue beds at the right and left cheeks. In doing so, the time traces of the ratios of either Hb (Fig. 7(B)) or HbO2 (Fig. 7(C)) pulsation amplitude in three trials can be obtained. It is observed that for the control group, the ratio sways between 0.8 and 1.0. However, for the left artery challenging case, the ratio reaches more than 1.3, while it becomes ≈0.5 for the right artery challenge case. The ratios resulted from Hb (Fig. 7(B)) and HbO2 (Fig. 7(C)) are almost identical, which is expected because the pulsations so evaluated should be the same and equal to the pulsation of total blood volume within the skin tissue beds. These results support the

![Fig. 7](image-url)

**Fig. 7.** The proposed SP-rmPPG is able to image dynamic changes of blood pulsation within the facial skin tissue beds upon the challenging of the blood supplying facial arteries. (A) Representative pulsation maps extracted from dynamic images at the time of 20-second, derived from the spatiotemporal HbO2 (o) and Hb (d) signals obtained from the facial skin for three experimental trials (l: challenging on left supplying artery; r: challenging on right supplying artery; n: control group without challenging). (B) The time traces of temporal ratios of averaged pulsation intensity values derived from dynamic Hb signals between right and left cheeks at the selected ROIs (right/left). (C) The time traces of temporal ratios of averaged pulsation intensity values derived from dynamic HbO2 signals between right and left cheeks at the selected ROIs (right/left).
conclusion that the changes in blood pulsation due to the induced ischemia at the facial tissue beds can be measured by the smartphone, which may be useful in the applications of assessing cardiovascular diseases, for example strokes at risk where the obstruction of internal carotid artery is often the cause of stroke.

4. Discussions

We proposed a SP-rmPPG method and system to monitor the spatiotemporal changes in oxygenated and deoxygenated hemoglobin concentrations in the effective blood volume within the light interrogated skin tissue beds, and further to map the blood pulsation amplitudes. The results of cuff pressure experiments on the upper arm provided the feasibility of the proposed method to reflect the impact of the occlusion at the upstream blood vessels on the downstream blood perfusion at the extremity of skin tissue beds. The results obtained by the proposed method agreed well with the parallel peripheral oxygenation measurements by the pulse oximeter. The spatiotemporal HbO2 and Hb changes and the blood pulsations of the skin tissue beds at the challenged hand with and without cuff pressure at the upper arm also agreed with the expected changes in the cutaneous blood oxygenation in this well-known and popular blood cuff maneuver. We also demonstrated that the proposed method is capable of measuring the spatiotemporal changes in the oxygenated and deoxygenated blood within the facial skin when it was challenged by a transient ischemic event induced by artificially limiting the blood supply to the tissue region at the external carotid artery. The observed imbalance of the oxygen supply and the blood pulsations within the facial skin tissue beds between the left and right cheeks indicates that the proposed method may be useful in detecting or monitoring certain cardiovascular diseases like carotid stenosis, and in doing so by only taking selfie videos with a cost-effective smartphone.

The values of spatiotemporal HbO2 and Hb changes that we obtained were scaled by the light interaction path length in the skin tissue (Eq.6 and Eq.7). While this path length may be of complicated relationship with tissue optical properties and wavelength used [46,47], we assumed it to be 1 mm in this study. From the measurements, we estimated that the averaged concentration changes of Hb and HbO2 was ~16.5 µM for every 1% decrease of the SaO2 value from Fig. 4(C). For a normal male subject, the concentration of total hemoglobin in the whole blood is approximately ~2500 µM [48]. In this case, every 1% decrease of SaO2 would be theoretically caused by the concentration changes of Hb and HbO2 at ~25 µM. Consequently, the measured changes by the smartphone were approximately in line with the theoretical predictions (which on the other hand, indicates the validity of the proposed SP-rmPPG method). Given the limited penetration depth of visible lights [49], thickness of epidermis and dermis in the dorsal skin of hand [50] and relatively weak illumination of the smartphone flashlight, the actual light interaction path length in our study is likely to be smaller than 1 mm. If this is the case, then the measured values would be closer to the theoretical value. Therefore, we believe that there is still a room to improve the accuracy of the measured changes in HbO2 and Hb by carefully determining the practical and more realistic values of the light interaction path length in biological tissue through, for example, Monte Carlo simulations of the light (with the wavelengths of interest) propagating within the skin tissue [51,52] taking into account the consideration of its proper optical properties [53] possibly combined with the measurements of optical coherence tomography of depth-resolved skin morphology and microcirculation information [54,55].

Compared with the conventional single-wavelength PPG (swPPG), the multiple-wavelength PPG (mwPPG) has been demonstrated to have superior performance in detecting the blood pulsation in terms of its signal quality and robustness, thus increasingly gaining attentions from both academic researchers and industrial entrepreneurs [56]. Most mwPPG sensors rely on the use of multiple light sources each with different wavelength or a more complicated spectrometer-like photodetector array, leading to a bulky system setup and associated complicated control to implement, let alone the cost issues [57]. Nevertheless, such strategy has been adopted by
many remote PPG (rm-PPG) systems [58]. Due to the demand of the wide-field illumination and imaging, the system setup of a rm-PPG becomes even more complicated than mw-PPG does. In this study, we provided a simple solution to realize rm-PPG by employing unmodified and intact commercial smartphones through an algorithm that can convert the color images (video) captured by the built-in cameras into the multispectral video cubes. Due to the minimal constraints in hardware requirements, the proposed method provided an advantage of flexibility to select the wavelengths of interest and multi-channel processing. Though it is a “pseudo” multispectral imaging that we achieved, the method can still be used to decouple the dominant bio-chromophores from the videos of the dynamic light reflectance emerging at the skin tissue surface to realize a refined monitoring of skin hemodynamics. Besides, rather than simply detecting the heart rate and pulse waves, our method offers another perspective for the analysis and monitoring of spatiotemporal hemodynamic activities. For example, from the imbalanced hemodynamic responses between the left and right sides of the cheek, we may speculate the existence of vascular disorder in corresponding carotid arteries.

The experiments we conducted and analyzed in this study may be directly relevant to some clinical applications. The cuff pressure experiments on the upper limb could be a useful method in the assessment and monitoring of peripheral vascular diseases that cause the blood vessels outside of the heart and brain to narrow, block, or spasm, for example in the cases of arteriosclerosis, or even diabetes. The facial tissue imaging experiments may be useful in the assessment or prediction of possible obstruction of major blood supplying arteries to the downstream tissue beds, which might cause transient ischemic attacks and even stroke. The proposed method can also be used to derive and spatially localize the lesion area from the field of view. In addition to the potential usage in clinical scenarios, there would also be a potential space for the SP-rmPPG system to be applied in general health care because of the current ever-growing accessibility and affordability of the smartphone to the general public. It may be envisioned that the future smartphone can have an ability to perform daily monitoring of the skin hemodynamics to support the early screening and interventions of the potential cardiovascular diseases.

Though as promising as it has been demonstrated, the limitations in the use of smartphone to realize rmPPG cannot be ignored. Since current commercial smartphones are not designed to fulfill the requirements for biomedical imaging, there are inherent limitations in their hardware design, including the camera sensor and the flashlight with limited wavelength range. Most smartphones employ 8~10-bit camera sensors and produce compressed 8-bit videos, presenting challenges to acquire blood pulse waveforms with high fidelity. Even with the compensation of illumination uniformity, the flashlight still provides limited irradiance to the target samples for imaging purposes and its available wavelengths are confined within the visible range limited by a near infrared filter within the housing. Due to these constraints, the measured spatiotemporal changes in HbO2 and Hb by the proposed SP-rmPPG were inevitably noisy. We had to perform a good averaging within a selected region of interest to improve the signal to noise ratio of temporal change signals to derive HbO2, Hb and blood pulsation information. These limitations may be partly reduced if one has the ability to access its raw videos and to remove its near infrared filter by working together with the smartphone manufacturers. Alternatively, if resources permit, these limitations can be removed by configuring a dedicated high-performance system that employs high bit-depth camera sensors and high irradiance light sources with appropriate working wavelengths of interest that extend from visible to near infrared region.

Currently, the experiments we conducted were used to simulate vascular diseases for a proof-of-concept study. It can be imagined that the real situation would be much more complicated and individualized. In future, we plan to apply the proposed system and method in clinical medical imaging for further refinements and optimizations, and to conduct proper clinical trials to determine its clinical utility. Meanwhile, due to the large data used in our method, the storage consumption and tedious signal processing also limit the usability. An alternate solution to
mitigate this problem would be to adopt cloud computing and deep learning technologies to store and process the acquired data.

5. Conclusions

We have proposed and described a smartphone-based remote PPG (SP-rmPPG) system and method to spatiotemporally monitor the perfusion changes and pulsations of the circulating blood volume within the light interrogated skin tissue beds. In the method, the skin color videos captured by an unmodified smartphone camera was first converted into the multispectral data cubes, upon which to derive the spatiotemporal changes in oxygenation status within the skin beds through a novel algorithm that can decouple the chromophore determinants of oxygenated and deoxygenated hemoglobin. The corresponding spatiotemporal blood pulsation were then mapped by a window-based lock-in amplification method. We have demonstrated the feasibility of the proposed SP-rmPPG method using the popular blood cuff pressure maneuver on the upper arm to occlude the blood supply to the downstream tissue beds, where the measured dynamic information of oxygenated and deoxygenated blood in the downstream agreed well with the parallel measurements of oxygenation saturation provided by the standard pulse oximeter. We have also showed the ability of the SP-rmPPG method to monitor the hemodynamic information within the facial skin tissue beds that were challenged by a transient ischemic event. Due to the ever-growing accessibility and affordability of the smartphone to the general public, the proposed system and method are expected to be useful in the vital sign monitoring, in the early screening of peripheral artery diseases and cardiovascular disorders, as well as in the investigations of vascular functions. In particular, due to its attributes of low-cost, compactness and usability, it is expected to serve the health care systems well in the rural areas where the medical resources are severely limited.

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