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A non-contact oxygen saturation detection method based on dynamic spectrum

Tian Lan, Gang Li, Ling Lin*

State Key Laboratory of Precision Measurement Technology and Instruments, Tianjin University, Tianjin 300072, China

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ABSTRACT

Blood oxygen saturation (SpO₂) is an important monitoring indicator for many respiratory diseases. Non-contact oximetry offers outstanding advantages in both coronavirus pandemic monitoring and sleep monitoring, but at the same time poses both challenges regarding technology and environment. Therefore, we propose a method for non-contact SpO₂ measurement based on the principle of DS (dynamic spectrum) in this paper. A multispectral camera with 24 wavelengths (range in 660 nm-950 nm) is used to capture video of the people’s cheek region, and then the two-dimensional images are converted into a one-dimensional temporal PPG signal. After pre-processing the PPG signal, the 24 wavelengths DS values are extracted. The optimal wavelength combination is obtained by wavelength screening using the one-by-one elimination method, and a PLS (partial least squares) model is established using the SpO₂ values measured simultaneously by pulse oximetry as the modeled true values. The facial videos of eight healthy subjects were collected, and a total of 140 valid samples were obtained. By analyzing the modeling results, the regression coefficient (R) and root mean square error (RMSE) of the modeled set were 0.6366 and 0.9906, respectively. This method can significantly respond to the variation of SpO₂, and the prediction results are approaching to the prediction accuracy (±2%) of most pulse oximeters in the market. Using DS theory in this method eliminates in principle the interference of static tissue, individual differences, and environment. It fully meets the strong demand for non-contact oximetry and provides a new measurement idea.

1. Introduction

Oxygen saturation (SpO₂) is often an important test for several diseases, such as hypoxia, chronic obstructive pulmonary disease[1], and OSA (obstructive sleep apnea)[2]. Among them, OSA when occurred during sleep with multiple episodes can lead to oxygen desaturations, oxidative stress, blood pressure and heart rate changes, and sleep disruption [3], for which non-contact would be more strongly demanded for such tests that require long-term continuous testing at night. In addition, the emergence of coronavirus pandemic, which pose a huge threat to the people’s life safety all over the world. It not only changes the body temperature, but also affects the variability of the person’s oxygen saturation [4], and the ability to achieve rapid non-contact measurements in congregate locations helps to avoid cross-contamination.

Imaging photoplethysmography (iPPG), with its advantages of non-contact and large information content in clinical applications, has attracted many scholars to explore[5-7], including heart rate [8-11], oxygen saturation [12-14], respiratory rate, and blood pressure [15-17]. Wieringa et al. [18] first validated the feasibility of non-contact blood oxygen using a camera and a light source of three wavelengths measurement, but it was not well used due to limitations such as low SNR (signal-to-noise ratio). Humphreys et al. [19] achieved the first prediction of SpO2 using a dual-wavelength light-emitting diode array and a semiconductor camera, but could not achieve high prediction accuracy due to the low acquisition frame rate. Shao et al. [20] screened a combination of orange and near-infrared wavelengths by SNR for illumination, using a CMOS camera and selecting the lips as the ROI region, and calculated the oxygen saturation, but the environmental requirements were demanding. Kong et al. [21] used two cameras with narrowband filters in ambient light to achieve oxygen saturation measurements, which dispensed with the environmental requirements but had high equipment complexity. Guazzi et al. [22] used the three color-channels of RGB camera, and the AC-DC component ratio of the red and blue channels was used as the basis to calculating the SpO₂. However, the factors such as the camera frame rate and the environment have certain influence on the prediction results.

However, it is easy to see that non-contact measurements pose many...
challenges to researchers, such as lower signal-to-noise ratios and harsher environmental requirements. In addition, for the detection of SpO$_2$ are used the traditional detection method [23]. The peak-to-peak value of PPG signal is used as the AC component, the average value is used as the DC component. Then the AC and DC components ratio of two wavelengths is used to obtain the predicted value of SpO$_2$. However, for the traditional measurement method, its measurement principle, measurement conditions, and individual differences have a certain impact on the results.

To address these problems, Li et al. [24] proposed the theory of dynamic spectrum (DS) in 2004, explaining in principle its advantages in terms of suppressing individual differences and measurement conditions. During the development of dynamic spectroscopy, several dynamic spectral extraction methods have been proposed, such as frequency domain extraction [25], single-edge extraction [26], and differential extraction [27]. Basing this method has remarkable results in noninvasive blood component detection, such as red blood cells [28], hemoglobin [29], globulin [30], cholesterol [31], blood glucose [32], and so on. Li et al. [33] applied this idea to extract the DS from the frequency domain of the PPG signal to calculate SpO$_2$. Since then, Li et al. [34] and Song et al. [35] have made further efforts in signal acquisition. Nonetheless only applied to contact oximetry.

From the principle of blood oxygen saturation measurement, we know that at least 2 wavelengths of PPG signal are required. Combined with the use of a spectrometer in dynamic spectroscopy based noninvasive blood component testing, the multispectral camera meets our needs. Multispectral cameras assume an important role in the detection of substance components based on the spectral imaging, enabling fast and non-contact substance detection and identification [36,37]. There are also attempts in the DS measurement, Maria et al. [38] used spectral camera to collect the wrist images and calculated SpO$_2$ through neural network modeling to realize the real-time detection, but there were certain limitations in the model training process and individual differences.

In this paper, a non-contact method for SpO$_2$ detection is proposed using a multispectral camera and combining DS theory. A multispectral camera is used to obtain multiple wavelengths of facial video images and downscale to obtain multiple wavelengths of PPG signals. Then, the multiple wavelength DS values are extracted from the signals, and the blood oxygen values collected simultaneously by pulse oximetry are used as the modeling true values. Finally, the detection results of blood oxygen saturation are obtained by the PLS (partial least squares) modeling. This method has low environmental requirements, can effectively suppress individual differences, convenient and fast, and fully meets the strong demand for non-contact oxygen saturation measurement.

2. Methods

This section introduces the principle of blood oxygen saturation measurement based on DS theory. The DS theory is introduced from the conventional oxygen saturation measurement. Moreover, the DS value extraction method and the SpO2 measurement method are introduced.

2.1. Conventional oximetry

The human arteries throb can cause fluctuations in blood volume, thus causing changes in the optical absorption amount, while the optical absorption amount of non-blood tissues (skin, muscle, bone, etc.) is constant. The SpO2 measurement technology is to detect the optical absorption change caused by blood volume fluctuation to obtain the SpO2 on the premise of eliminating the non-blood tissue influence.

According to the Lambert-Beer law, a substance absorbance is:

$$ A = -\lg \frac{I}{I_0} = \varepsilon c l $$  \hspace{1cm} (1)
changes regularly with the heart beating, thus forming PPG signal. Due to the influence of the blood components absorbance, PPG signals at different wavelengths will be different, and contain the absorbance information of blood components. During arterial dilation, the volume of blood is at its maximum during the cycle. At this time, the incident light $I_0$ is absorbed by the pulsating arterial blood to the maximally, resulting in the minimum value of the outgoing light intensity. On the contrary, when the blood vessels are contracting, the outgoing light intensity reaches its maximum value.

If there are $i$ blood components, according to the modified Lambert-Beer law, the absorbance coefficient $A'$ at wavelength $\lambda$ can be obtained:

$$A' = \log \frac{I}{I_0} = \sum_{i=1}^{n} c_i \epsilon_i$$

Where, $c_i$ and $\epsilon_i$ respectively represents the concentration of blood component $i$ and its molar extinction coefficient. $I$ represents the equivalent optical path of blood vessel filling. Absorbance difference of arterial vessels $\Delta A'$ in systole and diastole:

$$\Delta A' = \log \frac{I_{\text{max}}}{I_0} - \log \frac{I_{\text{min}}}{I_0} = \log \frac{I_{\text{max}}}{I_{\text{min}}} = \sum_{i=1}^{n} c_i \Delta I$$

The absorbance of the static tissue such as skin and bone can be considered to fixedness in one blood pulsation cycle, therefore, the difference method of DS can theoretically eliminate the static tissue influence, so that the absorbance change is only related to the absorption state of pulsating arterial blood. And the DS size has nothing to do with incident light, so the influence of the ambient light and the light source intensity change can be ignored in the measurement process, greatly reducing the measurement conditions requirements.

### 2.3. Dynamic spectrum extraction

Since any signal in nature can be expressed as a continuous function $x(t)$, it can always be expressed by the Fourier transform, and its fundamental wave value is.

$$X_{\text{base}} = \frac{1}{T} \int_{t} x(t)e^{-i2\pi ft} \, dt$$

(8)

The fundamental wave value is undoubtedly proportional to the original function. The ratio between fundamental wave amplitude components in the frequency domain can replace the ratio between signal peak-to-peak values in the time domain.

$$\Delta A' = \log \frac{I_{\text{max}}}{I_{\text{min}}} \propto X_{\text{base}}$$

(9)

Where, $k$ is the proportional coefficient, which represents the proportional relationship between signal peak-to-peak value and fundamental wave value.

Thus, when the logarithmic pulse wave is obtained by taking the logarithm of the PPG signal, the fundamental amplitude of this signal can be used as the absorbance value, which is the extracted DS value.

### 2.4. Non-contact oxygen saturation measurement based on dynamic spectrum

The overall process of non-contact oxygen saturation measurement based on DS broadly includes five stages: PPG signal acquisition, PPG signal pre-processing, dynamic spectrum extraction, dynamic spectrum data processing, and model building.

1. PPG signal acquisition.
2. PPG signal pre-processing.
3. Dynamic spectrum extraction.
4. Dynamic spectrum data processing.
5. Modeling.

In this paper, the non-contact oximetry method based on DS, which is non-contact while ensuring the measurement accuracy, is of great significance to avoid cross-infection in the current situation of the coronavirus pandemic. In addition, the extraction of dynamic spectrum eliminates in principle the interference of static tissue, individual differences, and environment.

### 3. Experiments

This experiment seeks eight volunteers, including three males and five females. All measurements are performed in a room with stable ambient light, avoiding the influence of sudden changes in light intensity on experimental results.

#### 3.1. Data acquisition

The platform for collecting PPG signals in the experiment is shown in...
This experimental setup includes light source, multispectral camera, medical pulse oximeter, and computer. Light source: 50 W halogen lamp (light intensity adjustable). Multispectral camera: developed by Tianjin Jinhang Institute of Technology and Physics, model JHS-C-SN24-VN, mosaic imaging technology, adjustable focal length, frame rate of 120fps (adjustable by software), pixel resolution of 2048*1088, 24 wavelengths, wavelength range of 660–950 nm, spectral band half-wavelength of 6–16 nm, single wavelength image pixel resolution of 409*216, exposure time of 6.32 μs (adjustable by software). Medical POM model number: PO3M. The computer model used to process the images and signals is Nitro N50-610.

During data acquisition, to facilitate the procedure, the subject is required seated quietly and breathe steadily, ensuring that the unilateral cheek area filled the entire frame. The light source is adjusted to the appropriate light intensity to ensure the subject’s comfort. The focus of the multispectral camera is manually adjusted to ensure clear imaging. The medical pulse oximeter is clipped to the index finger of the left hand, and the oximeter’s indicated value is recorded in real time and corresponds to the acquired facial PPG signal. Subjects were performed to multiple trials, with each acquisition lasting 30 s. And 5 s of data was taken as a sample, yielding a total of 176 sets of samples.

Considering that a short measurement time is needed to collect samples with sufficient accuracy, 5 s is finally chosen as the acquisition time of one sample. From Eq. (10), the frequency resolution of Fourier transform is 0.2 Hz when the sampling time is 5 s. The human heart rate frequency is basically between 0.5 and 2.0 Hz, if the time is too short, the frequency resolution is poor, and the selected fundamental amplitude will be affected, if the time is too long, it does not meet the needs of fast, so 5 s is more appropriate.

\[ \Delta f = \frac{f_s}{N} \]  

Where, \( \Delta f \) is the frequency resolution, \( f_s \) is the sampling frequency, \( N \) is the total number of adoptions.

3.2. Data processing

(1) PPG signal extraction and preprocessing.

The whole PPG signal extraction and pre-processing is shown in Fig. 3. The images acquired by the multispectral camera are re-arranged from the original image of 2048*1088 to obtain a multilayer matrix of 409*216*25 according to the law of mosaic arrangement. In this multilayer matrix, each point is multiplied by the spectral correction matrix (24*25) corresponding to the camera to obtain the spectral feature data (24*1) for that point, for a total of 24 spectral bands (The 24 wavelengths in this paper are the central wavelengths of these 24 spectral bands). In simple terms, each point under each band is calculated using 25 pixel-values at the corresponding position in the original image. When the image corresponding to the 24 wavelengths of 409*246 is obtained, all the pixel-values in the image are superimposed and used as the PPG signal value at this moment. 600 frames of data are combined to obtain a 5 s temporal PPG signal. As for the pre-processing of the PPG signal, the logarithmic pulse wave is first obtained, followed by WT to filter out low-frequency interferences and retain components in the heart rate frequency range (0.5–2.0 Hz), which is reconstructed to obtain the final PPG signal used to extract the dynamic spectrum \( X^\lambda_i \).

In this process, by double screening the PPG signal waveform in the time domain as well as in the frequency domain, the samples with poor PPG quality are removed, and 140 valid samples are screened.

(2) Dynamic spectrum data extraction and processing.

The Fourier transform of \( X^\lambda_i \) is performed to obtain the amplitude and frequency diagram, as shown in Fig. 4. Find the amplitude \( X^i \) from the original image of 2048*1088 to obtain a multilayer matrix of 409*216*25 according to the law of mosaic arrangement. In this multilayer matrix, each point is multiplied by the spectral correction matrix (24*25) corresponding to the camera to obtain the spectral feature data (24*1) for that point, for a total of 24 spectral bands (The 24 wavelengths in this paper are the central wavelengths of these 24 spectral bands). In simple terms, each point under each band is calculated using 25 pixel-values at the corresponding position in the original image. When the image corresponding to the 24 wavelengths of 409*246 is obtained, all the pixel-values in the image are superimposed and used as the PPG signal value at this moment. 600 frames of data are combined to obtain a 5 s temporal PPG signal. As for the pre-processing of the PPG signal, the logarithmic pulse wave is first obtained, followed by WT to filter out low-frequency interferences and retain components in the heart rate frequency range (0.5–2.0 Hz), which is reconstructed to obtain the final PPG signal used to extract the dynamic spectrum \( X^\lambda_i \).

In this process, by double screening the PPG signal waveform in the time domain as well as in the frequency domain, the samples with poor PPG quality are removed, and 140 valid samples are screened.

Fig. 2. This experimental setup includes light source, multispectral camera, medical pulse oximeter, and computer. Light source: 50 W halogen lamp (light intensity adjustable). Multispectral camera: developed by Tianjin Jinhang Institute of Technology and Physics, model JHS-C-SN24-VN, mosaic imaging technology, adjustable focal length, frame rate of 120fps (adjustable by software), pixel resolution of 2048*1088, 24 wavelengths, wavelength range of 660–950 nm, spectral band half-wavelength of 6–16 nm, single wavelength image pixel resolution of 409*216, exposure time of 6.32 μs (adjustable by software). Medical POM model number: PO3M. The computer model used to process the images and signals is Nitro N50-610.

Fig. 3. Extraction and pre-processing flow of PPG signal at 24 wavelengths.

Fig. 4. Fourier transform spectrum to find the log PPG fundamental amplitude (The graph shows the result for \( i = 24 \)).
corresponding to the fundamental frequency of the logarithmic PPG signal to complete the extraction of the DS value.

The dynamic spectral values collected by the spectral camera contained a total of 24 wavelengths. A portion of the wavelengths were removed by wavelength screening, and the retained dynamic spectral data were subjected to partial least squares modeling, and the results were evaluated using R and RMSE.

4. Results and discussion

The spectral camera used in this paper contains a total of 24 wavelengths, and wavelength screening is performed using a one-by-one rejection method. In the screening process, the correlation coefficient R between the modeling results after eliminating a single wavelength and the full modeling results is compared to decide whether this wavelength is eliminated or not. Finally, the dynamic spectrum data of 16 wavelengths are retained for the final PLS modeling. The wavelength distribution is shown in Fig. 5.

We recorded the R and RMSE of the modeling before and after wavelength screening as shown in Table 1. After analysis, the screened R reached 0.6366, a relative improvement of 8% and a 4.8% reduction in RMSE. In addition, the filtered model master score has 11, accounting for 68.8% of the total score involved in modeling, with higher wavelength utilization.

The models before and after wavelength screening are shown in Fig. 6. Where (a) is the prediction result of the model before screening and (b) is the prediction result of the model after screening. We counted

![Fig. 5. Wavelength distribution chart (• indicates the rejected wavelength).](image1.jpg)

![Table 1](image2.jpg)

| Model | PLS Components | R    | RMSE | Max (True-Pre) |
|-------|----------------|------|------|---------------|
| Before| 6              | 0.5894 | 1.0377 | 2.618         |
| After | 11             | 0.6366 | 0.9906 | 2.137         |

![Fig. 6.](image3.jpg)
the differences between the predicted and true values before and after screening, as shown in Table 1. The accuracy after screening is closer to the POM accuracy.

In the future work, the focus is on improving prediction accuracy, for example, we can add face detection to reduce interference due to slight shaking caused by breathing. The modeling can also be enhanced by increasing the sample size and sample variety to enrich the sample.

5. Conclusion

In this paper, we propose a non-contact method for measuring SpO\textsubscript{2} based on the DS. Using IPPG technology as the technical background, a multispectral camera with 24 wavelengths is used to acquire video images of the cheek region of the human face. And then the two-dimensional images are converted into one-dimensional time-series PPG signals. After pre-processing the PPG signal, the DS is extracted. Wavelength screening is performed using the one-by-one rejection method to select the optimal wavelength combination. A PLS model is established by using the blood oxygen value measured simultaneously by the POM as the modeled true value. By analyzing the results, this method can clearly respond to the changes of SpO\textsubscript{2}. Moreover, the prediction results are similar to the prediction accuracy (~2\%) of most POM in the market. Among them, the application of DS can effectively suppress the effects of individual differences and ambient light intensity. It fully satisfies the strong demand for non-contact oxygen saturation measurement and provides a new measurement idea.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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