Non-invasive SpO2 Monitoring Using Reflective PPG: A Low-Cost Calibration Method

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***Abstract*— The increasing availability of wearable devices has resulted in a rise in the use of non-invasive physiological monitoring applications. In this paper, we develop a reflective-type photoplethysmography system. A low-cost calibration method is established by implementing noise reduction and signal quality control. The proposed method eliminates the need for subject inhalation of low concentration oxygen during calibration, making it more convenient and cost-effective.**

Keywords—photoplethysmography (PPG), pulse oximeter, SpO2, signal processing, non-invasive, calibration

I. INTRODUCTION

The growing availability of wearable devices has led to a surge in non-invasive physiological monitoring applications. Photoplethysmography (PPG) is a cost-effective and non-invasive method that detects changes in blood volume in the microvascular bed, enabling the measurement of key physiological data such as heart rate, and blood oxygen saturation in real time [1].

One widely used PPG device is the pulse oximeter, which utilizes red and infrared light to detect PPG signals and determine blood oxygen saturation (SpO2). According to the Beer-Lambert law, R-value, which can be used as an indicator of SpO2, can be calculated based on the AC and DC intensity of both wavelengths, taking into account the different absorption spectra of oxygenated and deoxygenated hemoglobin in response to red and infrared light [2].

To design a reliable pulse oximeter, whether it is transmissive or reflective, a signal processing step is necessary to remove low-frequency noises caused by motion artifacts and high-frequency noises caused by electrode impedance and ambient light [3]. The frequency range that contains the relevant information is mainly between 0.4~10Hz. Subsequently, calibration is typically required with an existing pulse oximeter serving as a reference to establish the correlation between R-value and actual SpO2. During this calibration process, it is common for the subject to inhale low-concentration oxygen to measure lower blood oxygen levels [4], which incurs certain costs and takes time.

The objective of this experiment is to establish a reflective PPG system for measuring blood oxygen. By implementing noise reduction and signal quality control, we propose a low-cost method that enables the subject to complete the pulse oximeter calibration by simply adjusting their breathing.

II. SYSTEM ARCHITECTURE

A. Hardware

The proposed system architecture for non-invasive SPO2 monitoring incorporates a green LED (525 nm), a red LED (660 nm), and a infrared LED (950 nm) as transmitters. A silicon photodiode (with a spectral range of 400 nm to 1100 nm) serves as the detector. The current output from the photodiode is directed to the front end (AFE), where it is converted to a voltage using a transimpedance amplifier (TIA) and then digitized using an analog-to-digital converter (ADC). The ADC code can be read out using an I2C interface. The system is controlled using an Arduino Mega 2560 microcontroller unit, ensuring efficient and effective monitoring.

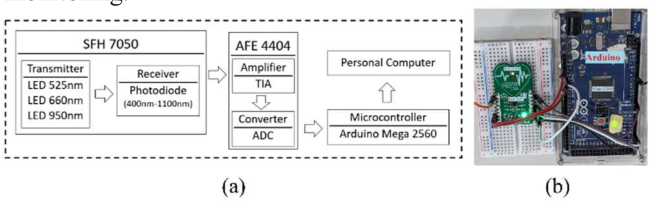

Fig. 1. (a) System architecture (b) The real circuit corresponds to the system architecture

Fig. 1a illustrates the working methodology of the non-invasive SpO2 monitoring system. Specifically, the MIKROE 2036 module incorporates the SFH 7050 and AFE 4404 components. The SFH 7050 receives reflected light in the form of current, while the AFE 4404 converts this current into voltage and then transforms it into a digital signal, which is sent to the Arduino microcontroller unit. The Arduino Mega 2560 serves as a microcontroller unit (MCU) and uses the I2C interface to send data to a personal computer for SpO2 prediction through signal processing. In contrast, Fig.1b illustrates the actual circuit that corresponds to the system architecture.

B. Signal processing

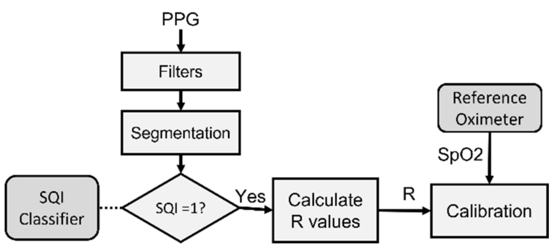

Fig. 2. Flow chart of the signal processing and calibration system

All PPG signals are measured from finger tips and processed in MATLAB R2022b. The method of signal processing and calibration is shown in Fig.2. A raw PPG signal is first filtered out high-frequency noise and low-frequency noise relatively by a moving average filter and a Butterworth high-pass filter. The filtered signal is segmented into individual pulse segments by the method of slope sum function (SSF) [5].

Next, signal quality index(SQI) of each segment will be determined by SQI classifier trained by machine learning. In this step, every pulse will be classified into 2 categories: “acceptable” (SQI=1) and “unfit” (SQI=0).

$$R = \frac{Red_{AC} / Red_{DC}}{IR_{AC} / IR_{DC}} \tag{1}$$

We choose only the acceptable ones to calculate the R-value for each pulse segment using the formula above, and then calibrated it with the blood oxygen values measured by a commercial pulse oximeter.

III. Experiment

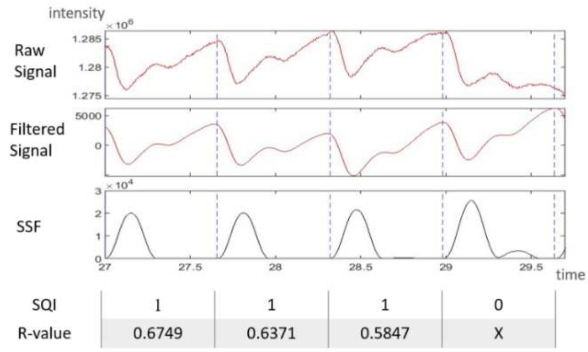

Fig. 3. Each stage of signal processing

As shown in Fig. 3, we filter the raw signal and identify the onset of each pulse using the SSF. Then, we employ a classifier to determine the Signal SQI of each segment and calculate R-values using (1). The specifics of the classifier and calibration are explained in detail below.

A. SQI classifier

PPG signals were collected from the fingers of six individuals, and 2425 pulse segments were manually labeled as "acceptable" or "unfit." From each segment, we extracted five features: skewness, kurtosis, zero-crossing rate, max-to-min value, and max-to-mean value. We trained and cross-validated a Support Vector Machine (SVM) model with the features. The SVM model achieved an accuracy rate of 96.44% with a sensitivity of 93.83% and a specificity of 97.27%. This trained model will be adopted as the classifier for subsequent blood oxygen measurement.

B. Calibration of the oximeter

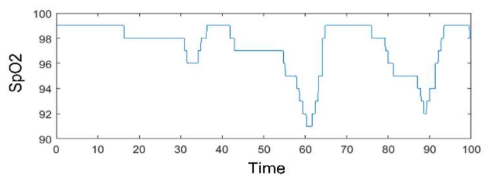

Fig. 4. the variation of the SpO2 while holding breath intermittently

The subjects intermittently held their breath for 100 seconds while we measured the PPG signals with our device and a reference oximeter. Fig.4 shows the variation of the SpO2 during the measurement. After signal processing, we segmented the PPG into pulse segments and calculated the R-value of each segment, which corresponded to the blood oxygen value at the time. The SQI classifier classified each segment as usable or not.

As shown in Fig.3, the high-frequency part of the PPG was filtered out after signal processing, and the PPG was segmented into pulse segments. The R-value of each segment was calculated and corresponded to the blood oxygen value at the time, and each segment was classified as usable or not using the SQI classifier.

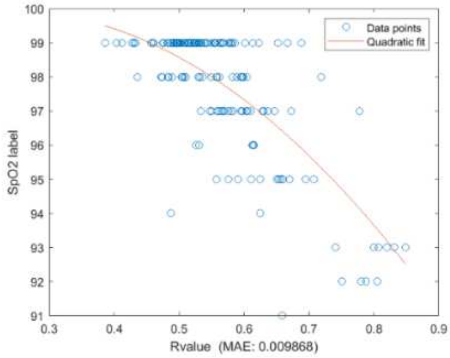

Fig. 5. SpO2 vs R-value

After filtering out unusable segments, we performed a quadratic regression on the R-values and blood oxygen values of each segment, as shown in Fig.5. We achieved a mean absolute error of 0.98%. Future studies will be conducted to further validate the accuracy and applicability of this method.

This architecture can be further modified for glucose monitoring devices [6], as features can be extracted from each segment for machine learning, with blood oxygen level carrying significant weight in glucose monitoring.

IV. Conclusion

We propose a reflective PPG system and develop an SQI classifier trained by machine learning, which achieves an accuracy rate of 92.81% in determining the quality of pulse segments. With the help of the SQI classifier and signal processing, a low-cost calibration method is demonstrated, resulting in the measurement of SpO2 with an error of around 1% for a subject. Further research is needed to improve the accuracy and reliability of the system and to expand its potential applications.

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