Accurate Detection of Heart Rate and Blood Oxygen Saturation in Reflective Photoplethysmography

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***Abstract*— In recent years, the demand for wrist wearable devices to monitor continuously critical physiological parameters in real time that are limited by designated hospital monitoring equipment is steadily increasing. In the medical field, one of the main issues that wearable devices could sufficiently address is the pervasive monitoring of vital signs and the corresponding health status assessment of the rapidly growing elderly population in real time. Main advantages in the adoption of wearable devices for the real time monitoring are the significant decrease of the cost both for the health system and subsequently the patient as well as the dramatic decrease of the waiting time in the hospital emergency rooms.**

Reflectance pulse oximetry being the right mode to be used at the wrist for measurements such as Heart Rate (HR), Peripheral Capillary Oxygen Saturation (SpO2) and Respiratory Rate (RR) imposes many technical challenges with its excessive sensitivity to all types of entailed artifacts due to arm/hand/body motions to be amongst the major ones.

This work introduces a low-power wrist wearable device comprising a Photoplethysmography (PPG) array sensor and special extraction algorithms to estimate HR and SpO2 parameters and a Multiple Linear Regression model, which after training performs considerable reduction of the imposed Motion Artifacts (Mas) thus enabling more accurate reading outputs.

Keywords*— *Reflective Photoplethysmography, Wrist Wearable Device, HR, SpO2, Linear Regression

I. Introduction

PPG-based monitoring is often used in vital-sign monitoring for the estimation of HR, SpO2 and RR. The ability of the PPG acquisition to be integrated into wearable devices provides the potential for unobtrusive tracking of vital signs suitable for continuous monitoring of patient's conditions. Clinically validated pulse oximeters are typically based on transmission-mode PPG, which requires the user to wear a probe on a finger or an earlobe. Recently wearables sensors and smart watches have started using reflectance-mode PPG on wrist to gather vital signs, usually for fitness purposes. However, they have not been widely used in everyday clinical practice, as the PPG signals are vulnerable to Motion Artifacts MAs [1], which significantly affect the accuracy of the estimated physiological parameters.

The main challenge in the use of reflectance pulse oximeters is their sensitivity to artifacts imposed by any type of motion. This paper aims to improving the quality of PPG signals gathered from wrist to enable robust estimation of physiological parameters. We developed a wrist wearable monitoring device that entails HR and SpO2 measurements based on continuous PPG recording. This device is a low cost non-invasive, lightweight integrated system with low power consumption. Its circuit board incorporates the Espressif platform, ESP-WROOM-02D, which is based on the ESP8266 chip implementing the WiFi communication protocol. Additionally, a 3-axis accelerometer is included on its circuit board to continuously record the movements in x-y-z directions. The sensor board is Maxim's Integrated MAXREFDES117 development board featuring the MAX30102 PPG sensor [2], [3]. MAX30102 PPG sensor is a high-sensitivity optical sensor comprising two light sources, one red with a wavelength of 660nm and one infrared with a wavelength of 880nm, and a photodetector.

The rest of the paper is structured as following: Section II outlines the existing knowledge for eliminating the interference of human MAs on physiological signals. Section III depicts our approach and our proposed system. Section IV outlines the performance of the proposed system in real environments while Section V highlights the progress made so far along with the future steps to follow.

II. Related WorK

In order to effectively extract the physiological parameters from a PPG signal, there is a need for eliminating the interference of human MAs on those signals. The existing reduction methods for the aforementioned MAs fall into three

main categories. Those are: i) methods using a single sourced PPG signal ii) methods using a multi-channel approach and iii) combining PPG signal with a motion reference signal.

A motion reference signal is acquired from additional hardware, an accelerometer, or a transducer. With an accelerometer, it is possible to measure movement, produce a reference signal based on it and remove that from the PPG signal, resulting in a clean trace. This becomes possible through adaptive digital filtering [4].

A different approach on the efficient use of adaptive filtering is using a synthetic reference signal to model the noise. This can be simply generated by applying a Fast Fourier Transform (FFT) on the corrupted signal without the need for external hardware. The noise signal is then applied to a filter, such as an adaptive step-size least mean squares (AS-LMS), a time-varying step size LMS (TVS-LMS) or a constant step-size LMS (CS-LMS) [5].

Another technique which can be applied in low-motion environments is Independent Component Analysis (ICA) [6]. One proposed model consists of a pre-processor that enhances the PPG component of the captured signal and the ICA that separates the PPG from the pre-processed signal. The pre-processing step consists of period detection, block interleaving, lowpass filtering and block de-interleaving [7]. Later, a frequency domain-based approach was introduced [8]. The shortcoming of those methods is that the ICA algorithm is based on the assumption that all source signal component pairs are statistically independent. Apart from that, the ICA algorithm utilizes multiple PPG sensors, which can increase complexity for wearable design.

We propose a non-invasive wrist wearable device with algorithms which require borderline processing power to identify the physiological parameters. The removal of the corresponding MAs is done through digital processing of the PPG signal in the time domain and the estimation of the desired parameters considers the motion reference signal acquired from accelerometer.

III. System Description

To measure HR one wavelength source is sufficient. In contrary, SpO2 is determined by the pulse oximetry measurement technique which requires two LEDs, operating at two different wavelengths [9]. The measured substance is a protein called hemoglobin being responsible to transmit oxygen from the lungs to different organs / tissues of the body. The assessment of HR and SpO2 is highly sensitive to almost any rapid movement of the subject which results in un-accurate data acquisition and identification. As depicted in Fig. 1, the collected from the wrist signal is weak, it has a variable offset (DC component of PPG waveform), and it contains noise and interference. In addition to MAs, the collected wrist PPG signal has wicked quality due to some other factors, such as improper sensor placement on the wrist, low blood perfusion in the wrist area, interference from ambient light, skin type, hairy skin. However, MAs affect the PPG signal to the greatest extent. In fact, motion introduces, in some cases, noise with wider range than the pulsatile PPG element (AC component of PPG waveform), resulting to great distortion of the PPG signal and its parameters. To identify the physiological parameters, various algorithms are being implemented on our proposed wearable device that do not require significant processing power. More specifically, to extract the HR in the time-domain the collected PPG signal must be preprocessed so that the peak detection algorithm can locate the peaks. The simplest and most common approach is to use a bandpass filter that reduces the noise and eliminates the constant component of the signal [10]. All the processing to identify the HR is done on the filtered infrared signal, while the DC offset and the AC component of red and infrared waveforms, needed to calculate the SpO2 parameter, are identified through the acquired signals.

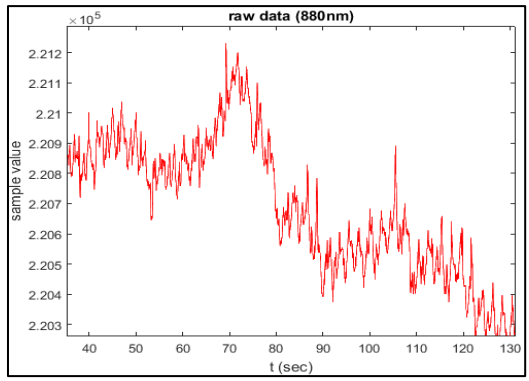

Fig. 1 Raw data acquired from 880 nm light sources

By using a peak detection algorithm, which we developed, the peak values of the filtered PPG signal are detected, and the instantaneous HR is calculated using the time between consecutive peaks. Since two consecutive samples are 40 ms apart, as the sampling frequency is 25Hz (fs), we estimate the time difference (d) between two consecutive peaks and consequently the instantaneous HR is obtained from the equation (1):

$$\text{inst\_HR} = \text{fs} * 60/d \quad (1)$$

The HR is then calculated from the average of the instantaneous HR values corresponding to a 4 sec time window. SpO2 is calculated using a formula contained in Maxim's Integrated sample code [10]. At first, the AC and DC components of the pulsative waveform are calculated for both the red and infrared signals as a mean of existed peaks/valleys in a 4 sec time window. Then a ratio R of the AC and DC is calculated by the equation (2):

$$\text{R} = (\text{AC}_{\text{Red}}/\text{DC}_{\text{Red}})/(\text{AC}_{\text{IR}}/\text{DC}_{\text{IR}}) \quad (2)$$

Eventually, from the mean AC and DC values, the SpO2 value is calculated using the formula (3):

$$\text{SpO2} = -45.060 * \text{R}^2 + 30.354 * \text{R} + 94.84 \quad (3)$$

The DC component represents the constant absorption of light passing through the tissues, while the AC component is produced by the heart beats that affects the volume of blood that light passes through. Oxygenated hemoglobin absorbs less red light than infrared light, so when SpO2 in the blood is high the AC component of the red signal is less than that of the infrared signal.

In order to validate our proposed system's accuracy, we compared its measurements with the corresponding measurements of a commercial medical device. As a matter of fact, there were deviations between the respective HR and SpO2 entailed values that appear to be strongly associated with the user's movement. Hence, the user's movement was recorded via the on-board accelerometer and the variation of motion on the x, y, z axes was calculated. Then, a multiple linear regression was launched to make the correlation and reduce the discrepancies on the measurements between the two devices. Multiple Linear regression is a general method for exploring the relation between a collection of independent variables to a target value. It is among the most highly used statistical analyses in the behavioral sciences. One general form of the multiple regression equation written for an individual case, i, is given by the formula (4):

$$\hat{Y} = b_0 + b_1 * X_{i1} + b_2 * X_{i2} + \cdots + b_p * X_{ip} \qquad (4)$$

where X_{i1} , X_{i2} ,… X_{ip} are the scores of case i on the n=1, 2,...p predictors; b_1 , b_2 , … b_p are partial regression coefficients (or regression weights), and b_0 is the regression intercept [11]. For our model's training regarding SpO2 and HR predictions, we use as target values the medical device's values while as independent predictors the corresponding measurements from our wrist wearable device along with the variation of movement on the x, y, z axes. After collecting a large amount of training data, we proceeded to the training of the model to extract the relative regression weights and intercept. Then we applied the new equations, and we achieved considerable results as presented in the next section.

IV. System Evaluation

A. Trials

The performance of our proposed wearable wrist device was evaluated in real hospital conditions, by applying it patients under the close supervision of the doctors on duty. A finger pulse oximeter was also used to assess the accuracy of our wrist device measurements, as currently there is no wearable wrist device on the market for continuous monitoring of HR and SpO2 parameters. The commercial finger pulse oximeter chosen is a certified medical device manufactured by Berry [12]. As shown in Fig. 2, each patient was fitted with our wearable wrist device applied at the bottom of the wrist, and the Berry medical device, which comprises a bracelet with a finger pulse oximeter extension.

B. Outcomes

The following figures show the HR and SpO2 measurements concerning two patients. Each figure presents the recorded measurements by both the commercial medical device and our wearable wrist device as well as the predicted values from the Linear Regression model. Fig. 3 and Fig. 4 shows the HR and SpO2 entailed values respectively for patient 1, while Fig. 5 and Fig. 6 correspond to patient 2.

Fig. 2 Devices Placement

As can be seen, the predicted values by the Linear Regression model achieve a lower Root Mean Square Error (RMSE) that leads to a significant reduction in the initial deviations of the HR and SpO2 measurements calculated by our wearable wrist device in relation with the commercial medical device. Feeding the model with larger training data, it can be further improved and produce more accurate predictions. Few minor deviations among the devices' outputs are acceptable, since the system's overall performance ensures the detection of abnormal HR and SpO2 cases, which is our operational goal.

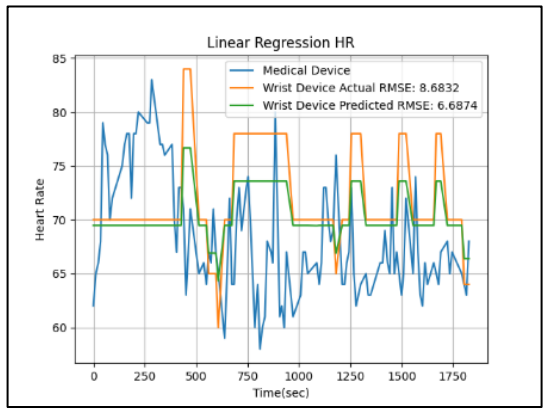

Fig. 3 HR measurement for the first patient

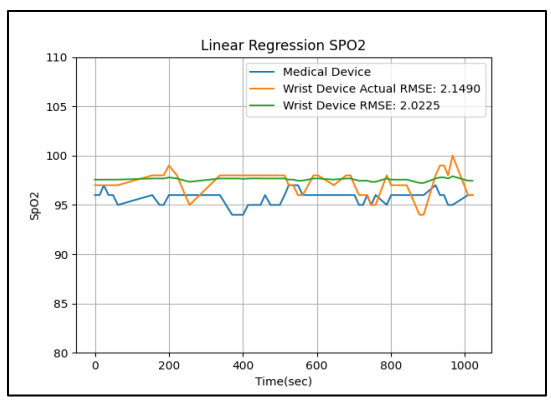

Fig. 4 SpO2 measurements for the first patient

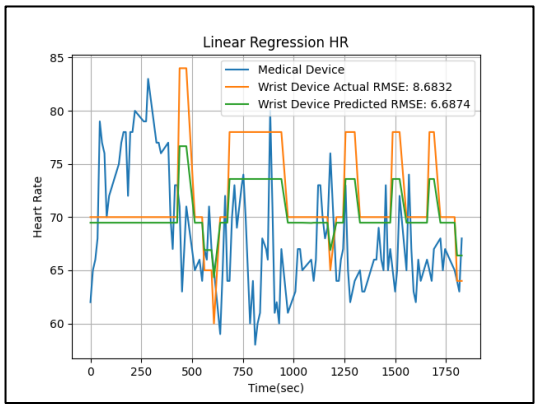

Fig. 5 HR measurements for the second patient

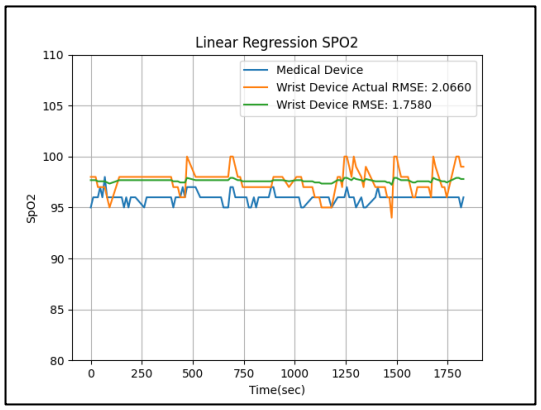

Fig. 6 SpO2 measurements for the second patient

V. Conclusion

The main objective is to continuously measure the percentage of haemoglobin binding sites in the bloodstream occupied by oxygen, commonly referred to as SpO2, as well as to estimate the HR through the PPG signal acquired from patients' wrist, thus imposing critical specifications for the required hardware and software. Moreover, the adoption of pulse reflectance pulse oximetry, which is suitable for the wrist area, highlights many challenges mainly due to its excessive sensitivity to all types of entailed arm/hand/body motion artifacts, low blood perfusion in the specific area, interference from ambient light, skin type. This work introduces a lightweight, low power, non-invasive wearable device able to identify the required physiological parameters of HR and SpO2 from the PPG signal acquired from patients' wrist. The device adopts a reliable signal processing approach to eliminate the noise of PPG signal by applying bandpass filtering. Additionally, it implements functions that require minimum processing power in order to estimate the physiological parameters from the filtered PPG. Moreover, a properly developed and well trained linear regression algorithm correlates the entailed arm/hand/body motion artifacts with the initial estimated parameters and generates more accurate predicted values for the HR and SpO2, which are then continuously pushed over the device's WiFi to a hospital server thus, enabling medical experts / doctors to efficiently monitor their patients and assess their health status. The overall performance of the proposed wearable wrist device was evaluated through a series of tests to patients in real hospital situations at the department of emergency and its reliability was compared against a commercial medical device. The accrued results of the extensive tests verified its good performance and its reliability of our device. Context of future work is to apply our wrist wearable device to more patients, to collect larger amount of corresponding data sets for the creation of a more robust training of the linear regression model that will further enhance its reliability in terms of accuracy. Moreover, our endeavour towards greater accuracy will bring upgrades in both the hardware as well the software components.

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