An Implementation of Motion Artifacts Elimination for PPG Signal Processing Based on Recursive Least Squares Adaptive Filter

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***Abstract*—In Photoplethysmographic (PPG) signals analysis, the accuracy and stability are highly affected by Motion Artifacts (MAs) disturbances. In this paper, we adopt an adaptive and efficient approach based on the developed DC Remover method and Recursive Least Squares (RLS) adaptive filter for reducing MAs from PPG signals in real time. The experimental results of this work show a high correlation coefficient between Electrocardiography (ECG)-derived heart rate and PPG-derived heart rate, which is higher than 0.8504 of the R value, a high agreement by Bland-Altman analysis in the limits of agreement represent the 95% confidence interval and the standard deviation is 3.81 BPM (Beats Per Minutes). An overall PPG signal with higher signal quality is obtained. Further, the precision of heart rate calculated by PPG is improved.**

Keywords—Photoplethysmography ; DC Remover ; Recursive Least Squares filter ; Motion Artifact ; adaptive filter

I. Introduction

Photoplethysmography (PPG) has been widely used for clinical setting and home care due to low-cost, non-invasive, long time monitoring, and easy operation, and can get the two important information of vital signs: respiration and heart rates. PPG is a simple and inexpensive optical technique that can be used to detect blood volume changes in the microvascular bed of tissue [1]. The arterial pulse in the finger changes the blood perfusion, which causes a change in optical properties especially in the optical intensity detected after optical stimulation. PPG is a non-invasive method and can be measured from the surface of the human body, it will not cause any physical harm to subjects. According to the absorption and transmission characteristics, the intensity of red light and infrared light passing through the finger will relate to the changes in the blood volume. PPG signal contains two major components, which are pulsatile (AC) component and non-pulsatile (DC) component. The AC component is caused by the change of pulsatile blood volume and has its fundamental frequency, depending on heart rate. The DC component represents the background absorption which is the component without a pulsatile signal [2]. Using PPG to monitor cardiac activity is a low-cost and a convenient method because the light source and phototransistors are easily embedded in a wearable system. Therefore, PPG has been widely developed in biomedical research and applications.

However, PPG signal is easily contaminated by Motion Artifacts (MAs), interferences caused by subject's movements. In order to track a subject's heart rate by analyzing the sampled PPG signal, signal processing methods have to be introduced to circumvent the MAs. [1][2]

There are some methods have been applied on the PPG signal processing for MAs reduction, such as Fast Fourier Transform (FFT) Filter, Discrete Wavelet Transform (DWT), and Least Mean Square (LMS) method, which is a kind of adaptive filter algorithm.

FFT Filter retains that main cardiac portion frequency (0.5-4 Hz) and respiratory activity (0.2-0.35 Hz) of PPG and sets other component frequency to zero [3]. However, the frequency ranges of MAs are not always fixed, FFT Filter will not be applicable if the MAs are in the component frequency of PPG.

DWT is used to decompose the PPG signals into low and high frequency components of same lengths. Then it reconstructs to the noise free PPG signal based on both low and high frequency components. But the mother wavelets are determined in advance, it will lead to loss of certain important physiological information because of the non-stationary and non-linear characteristic [4].

The adaptive filter algorithm LMS assumes that the reference noise received from the accelerometer is statistically correlated with the MA component in the corrupted PPG signal, while the MA is uncorrelated with the noise-free PPG signal. A cost function (also termed error signal) is used to adjust the filter coefficients (or named filter's weights) continuously in order to improve the signal quality of the noise-corrected PPG signal [5].

This study adopts an adaptive and efficient approach based on the developed DC Remover method and Recursive Least Squares (RLS) adaptive filter to reduce MAs in distorted PPG signals.

DC Remover is a kind of IIR filter design that is often used to remove the DC bias interference contained in the signal. The purpose of the DC Remover digital filter is to extract the low-frequency voltage offset (DC) of PPG signals. RLS is also an adaptive digital filter that can automatically adjust the filter parameters according to the cost function, and compared to the LMS algorithm, the RLS algorithm has a faster convergence speed and lower error.

II. System Description

To improve the overall accuracy, we combine two algorithms, a DC Remover and a Recursive Least Squares adaptive filter. Our work implements the integrated system

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with reflection PPG front end Max30100, the analog front-end circuit, ADXL355, the 3-axis accelerometer, and the Bluno Microcontroller Unit. The Max30100 is composed of optimized optics, it combines two LEDs (Red/IR 660/880), a photodetector, and a 16-bit sigma delta ADC with 125 Hz sample rate. We extract the raw PPG signals through the analog front-end circuit and the 3-axis motion signals as the reference noises through the ADXL335 simultaneously, and sent them to the Bluno Microcontroller. Fig. 1 describes the detail data flow of the proposed system.

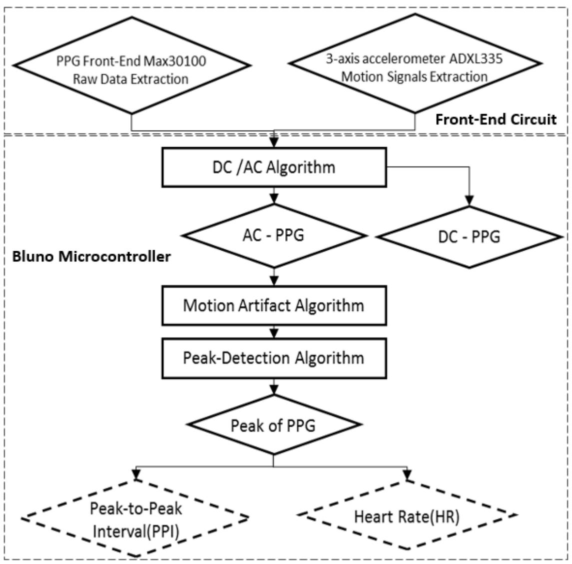

Fig. 1 A detail data flow of the proposed motion artifacts elimination system.

A. DC Remover

In this work, the DC bias in PPG signals is troublesome. Because the MAs corrupted on PPG signals are mainly concentrated in the AC component of the reflection PPG [6], we apply DC Remover method to separate the DC and AC components of the PPG signals, and receive the AC component of the PPG signals. The operation formulas are as follows:

$$w = x(\mathrm{t}) + a \times w(t-1) \tag{1.1}$$

$$y(t) = w(t) - w(t-1) \tag{1.2}$$

$$\frac{Y(z)}{X(z)} = \frac{1-z^{-1}}{1-az^{-1}} \tag{1.3}$$

The PPG sampling point input for each time is represented by $x(t)$ in the above equation (1.1). The $w(t)$ is the calculated value of the operation process, which will record the DC drift of the PPG signal in the equation (1.2). The value a is an operation parameter for controlling the filter cutoff band range and the response speed, and the range is 0 to 1. It can be seen from the transfer function (1.3) that the value of a must be less than 1, and if it is 1, the filtering effect is lost. When a is closer to 1, the DC cutoff frequency band becomes narrow, and the response speed is slow. Conversely, the DC cutoff frequency band is wide, and the response speed is fast. As shown in Fig. 2.

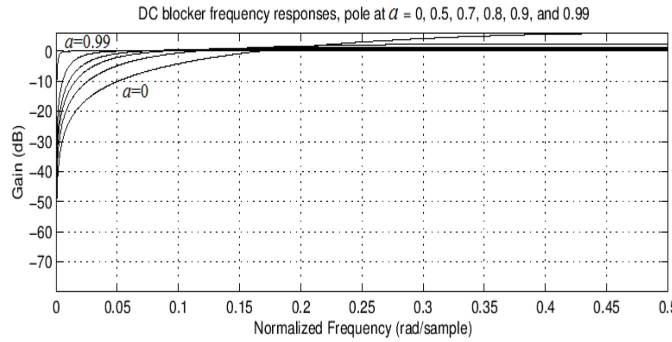

Fig. 2 DC Remover: The amplitude response under different parameters of a.

B. Recursive Least Squares Adaptive Filter (RLS)

1).RLS Algorithm

The adaptive filter can use feedback to adjust the filter coefficients, and the frequency response, as well as the process involve using a cost function (or error signal) to determine how the filter coefficients are changed so as to reduce the cost of the next iterative process of the operation [7].

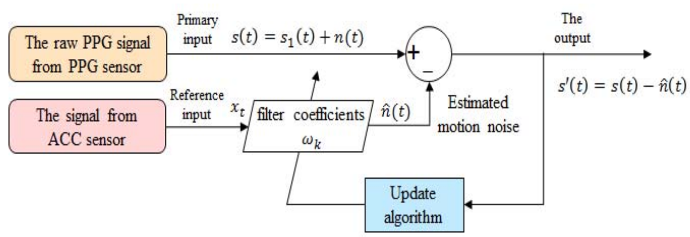

Fig. 3 RLS Algorithm Block Diagram

The RLS algorithm block diagram is shown in Fig. 3, the formula is as follows:

$$\hat{n}(t) = \sum_{k=0}^{t} \omega_k^T x_k = \theta^T \varphi_t \tag{1.4}$$

In the RLS algorithm, the two input signals are primary input, $s(t)$ and reference input, x_t . Those two inputs respectively represent the PPG signal with motion noise (AC component), and the accelerometer signal is measured by the 3-axis accelerator parallel to the direction of the finger's blood flow. This directional acceleration is selected as the reference signal in that it has a high correlation with the motion noise on the finger PPG signal [6]. The $s_1(t)$ represents the noise-free PPG signal, and $n(t)$ represents the action noise.

In the equation (1.4), ω_k represents the coefficients of the RLS filter; θ is the n*1 matrix composed of these coefficients $\theta = [\omega_1, \omega_2 \ldots \omega_n]^T$; φ_t is the n*1 matrix of acceleration signals in the x-axis direction $\varphi_t = [x_{(t-n)}, x_{(t-n+1)} \ldots x_t]^T$; t is the sampling time. Through the filter coefficient matrix θ and the X-axis acceleration signal matrix φ_t, the algorithm performs matrix operation to obtain the estimated motion noise $\hat{n}$. And then subtracting the estimated motion noise $\hat{n}$ from the original PPG signal $s(t)$ to obtain the clean PPG signal $s'(t)$ with respect to the original PPG signal $s(t)$. After several experiments, we find that the effect of removing the MAs will be saturated when the selected matrix θ is 10 orders or even higher ones, so we set θ to 10 for our PPG signal processing.

2). Updating the Filter Coefficients

After the RLS algorithm recursively calculates the estimated motion noise $\hat{n}$ each sampling time, the coefficients in the filter matrix are updated automatically. After this operation, the estimated motion noise $\hat{n}$ obtained next time is closer to the actual motion noise. The operations are shown in equations (1.5) and (1.6).

$$\theta_t = \theta_{t-1} + \beta(S_t - \hat{n}_t) \tag{1.5}$$

$$\beta = \frac{P_{t-1}\varphi_t}{1+\varphi_t P_{t-1}\varphi_t^T} \tag{1.6}$$

$$P_t = P_{t-1} - \frac{P_{t-1}\varphi_t\varphi_t^T P_{t-1}}{1+\varphi_t P_{t-1}\varphi_t^T} \tag{1.7}$$

In equation (1.5), the new filter coefficient matrix θ_t will be the product of the gain vector ß and the original coefficient matrix $\theta_{(t-1)}$ plus the cost function $s_t - \hat{n}_t$. P_t is the correlation inverse matrix of the input signal φ_t produced by the process of calculating the gain vector, as shown in (1.7).

III. Experimental Results

In order to verify the efficiency of the proposed algorithm, two databases are used in this experiment. First one is MIMIC (Multi-parameter Intelligent Monitoring for Intensive Care) online database [8] of 5 groups of PPG and ECG sampled simultaneously at 125Hz (without MAs), Second is the PPG signal measured from the 10 subjects by the experimental system of the 125 Hz sampling rate with MAs and X-axis acceleration signal (parallel to the vector of the finger's blood flow) and their heart rate collected by the CSI/CRITICARE 8100e nGenuity Bedside Monitor at the stationary chest to be the ground-truth. The MAs of this experiment set the actions type as scratches and slight shakings.

The effect of the DC Remover applied on the PPG signal is showed on the Fig. 4.

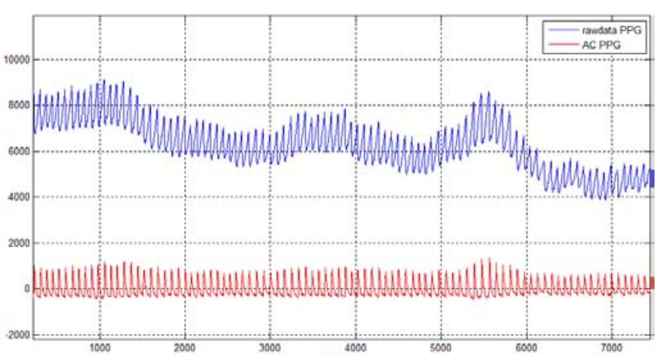

Fig. 4 The effect of the DC Remover applied on the PPG signal. The blue line is the PPG rawdata (AC and DC components), The red line is the processed PPG signal (AC component) which is separated from non-constant DC component.

Fig. 5 shows that the Correlation Coefficient analysis of the 5 MIMIC datasets of PPG-derived PP intervals (PPI) and ECG-derived RR intervals (RRI), and the result is highly correlated (R=0.99132) which indirectly means that the estimated HR values derived from PPG are very close to the one derived from ECG when MAs are faint.

Then the degree of agreement between two datasets is estimated using Bland-Altman analysis (Fig. 6). In the Bland-Altman plot, the corresponding limits of 95% confidence interval of PPI and RRI is [-0.024, 0.024] second.

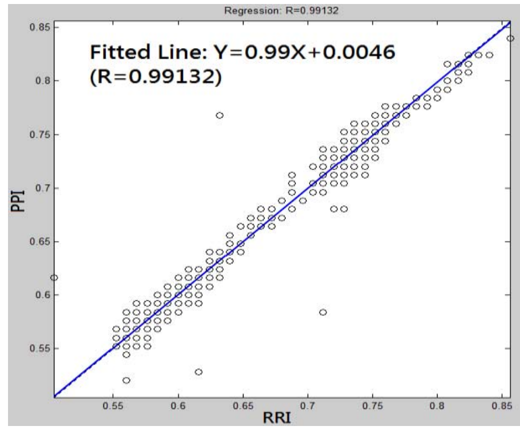

Fig. 5 The Correlation Coefficient analysis between beat-to-beat changes of PPG and ECG from 5 groups MIMIC online database. The fitted line is Y=0.99X+0.0046 where X signifies the ECG RRI values, and Y indicates PPG PPI values; the R value is 0.99132 which expresses that the estimated HR derived from PPG is very close to the one derived from ECG when MAs are faint.

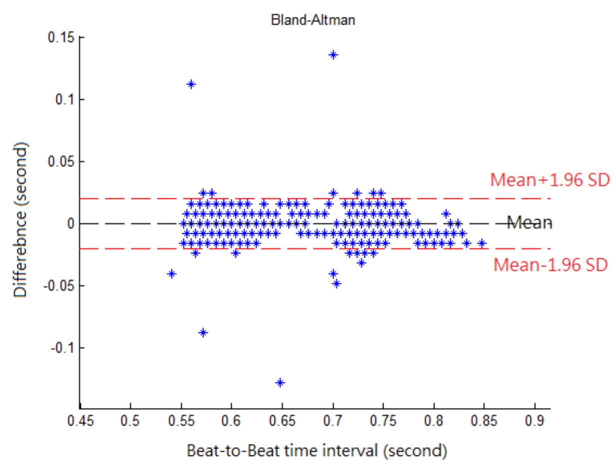

Fig. 6 The Bland-Altman agreement analysis between beat-to-beat changes of PPG and ECG from 5 groups MIMIC online database. The corresponding limits of 95% confidence interval is [-0.024, 0.024] second and the standard deviation is 0.0102s.

Fig. 7 shows the mean PPG signals of 10 subjects with MAs (scratches and slight shakings) in the frequency domain analysis by the FFT. In the Fig. 8b, the frequency component of MAs appears on the intrinsic frequency of PPG. After the RLS adaptive filter, the frequency components of MAs are removed and the PPG characteristic frequency components remain.

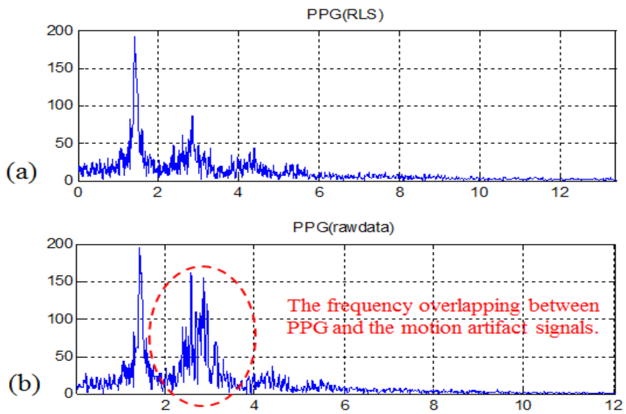

Fig. 7 (a) The frequency spectrum of the mean PPG signal after the RLS adaptive filter; (b) The frequency spectrum of the mean MAs-corrupted PPG signal.

The Fig. 8 shows the Correlation Coefficient analysis of heart rates from the second database with PPG's MAs after the RLS processing, the result presents high correlation (R=0.8504). Fig. 9 is the Bland-Altman plot of heart rates from the second database, and the corresponding 95% limits of heart rate and ground-truth heart rate is [-4.29, 4.26] BPM and the standard deviation is 3.81 BPM.

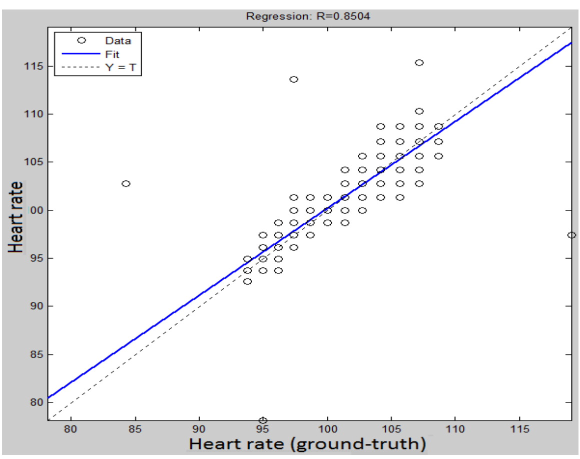

Fig. 8 The Correlation Coefficient analysis of the second database from 10 subjects. The R value is 0.8504 which presents the high correlation of the heart rate (calculated by PPI) and ground-truth.

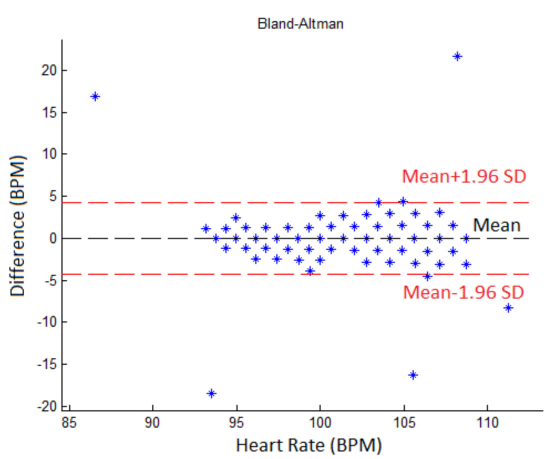

Fig. 9 The Bland-Altman agreement analysis of the second database from 10 subjects. The corresponding limits of 95% confidence interval is [-4.29, 4.26] BPM and the standard deviation is 3.81 BPM.

IV. Conclusion

This paper has presented an efficient algorithm based on the combination of DC Remover and RLS adaptive filter for eliminating motion artifacts corrupted on raw PPG signals in real time. Two kinds of the database were used to test the algorithm. The results show high correlation, the correlation coefficient R is higher than 0.8504, and high consistency, the agreement of the corresponding limits of 95% confidence interval is [-4.29, 4.26] BPM and the standard deviation is 3.81 BPM. Moreover, all the methods of signal processing are based on real time design, and have been implemented in hardware design for wearable and home-care applications. It makes the at-home care possible and lowers the rate of cardiovascular diseases and medical expenses through a long-term monitoring.

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