A Wearable Photoplethysmographic System Realization with Efficient Motion Artifact Reduction Method Based on Recursive Least Squares Adaptive Filtering Algorithm

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***Abstract*—The appearances of Motion Artifacts (MAs) in the photoplethysmographic (PPG) signals is one of the major obstacles to improve the accuracy and the stability of the signals analysis. In this paper, we present an effective and adaptive method based on DC Remover method and Recursive Least Squares (RLS) adaptive filter for reducing MAs disturbances from PPG signals. The results achieved by the presented methodology show a high correlation coefficient between Electrocardiography derived heart rate and PPG-derived heart rate (R=0.8054), moreover, the accuracy of heart rate monitoring was improved. The proposed system was implemented in hardware design for wearable and home-care applications.**

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

I. INTRODUCTION

The use of Photoplethysmography (PPG) is prevalent for clinical applications, as it is a non-invasive and low-cost instrumentation to monitor continuously blood volume changes in tissue. 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 change of pulsatile blood volume has effect on the AC component with a fundamental frequency depending on the heart rate value. The DC component, without the pulsatile signal, reflects the background absorption [1].

However, Motion Artifacts (MAs), interferences caused by subject's movements, easily contaminate PPG signals. In order to track a subject's heart rate by analyzing a sampled PPG signal, signal-processing methods to circumvent the MAs have to be introduced [1]. There are some methods that have been applied on the PPG signal processing for MAs reduction, such as Fast Fourier Transform (FFT) Filter[2], Discrete Wavelet Transform (DWT)[3], and Least Mean Square (LMS) method, the adaptive filtering algorithm[4]. RLS is also an adaptive digital filter that can automatically adjust the filter's parameters according to the cost function. Compared to the LMS algorithm, the RLS algorithm has a faster convergence speed and a lower error rate.

This study presents an adaptive and effective method to reduce MAs in corrupted PPG signals based on the DC Remover method and Recursive Least Squares (RLS) adaptive filter.

II. SYSTEM DESCRIPTION

This study proposes an integrated system implemented with the analog front-end circuit ADXL355, a 3-axis accelerometer, the reflection PPG front-end Max30100, and the Bluno Microcontroller Unit. The Max30100 is a digital front-end optimized optics IC integrated with a 16-bit ADC with 125 Hz sample rate, two LEDs (Red/IR 660/880), and a photodetector. We acquire the raw PPG signals from the PPG front-end circuit, Max30100, and simultaneously record 3-axis motion signals from the accelerometer as the noises of reference for the front-end circuit ADXL335. After collecting all of the PPG signal and motion reference noise, these signals will be sent to Bluno Microcontroller, the processor of the motion artifact elimination. Figure 1 shows an overview of the proposed system. The detail data flow of the proposed system is shown in figure 2.

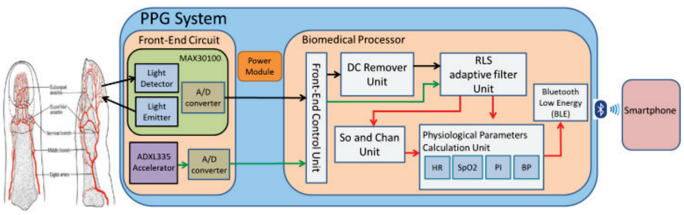

Figure 1. An overview of the proposed PPG system.

A. *DC Remover*

The PPG signals corrupted by MAs are mainly concentrated in the AC component of the reflection PPG [5]. The DC Remover as a kind of IIR filter is often applied to separate the DC bias interference contained in the signal. We apply DC Remover method to divide the DC and AC components from the PPG signals. In the next step, the RLS adaptive filter can process the motion artifact elimination algorithm solely on the AC component, which reduces the number of required operations. The operation formulas are as follows:

$$w = x(t) + \alpha \times w(t-1) \quad (1.1)$$

$$y(t) = w(t) - w(t-1) \quad (1.2)$$

$$\frac{Y(z)}{X(z)} = \frac{1-z^{-1}}{1-\alpha z^{-1}} \quad (1.3)$$

x(t) represents the sampling point of the PPG signal each time as the input in the above equation(1.1). The *w(t)* in the equation(1.2) records the DC drift of the PPG signals. The α (range: 0~1) in the equation (1.3) is an operating parameter for adjusting the speed of the response and the cutoff frequency of the filter band. As α is getting closer to 1, the band of DC cutoff frequency becomes narrower, and the speed of response becomes slower. Conversely, the DC cutoff frequency band will be wider, and the speed of response will be faster.

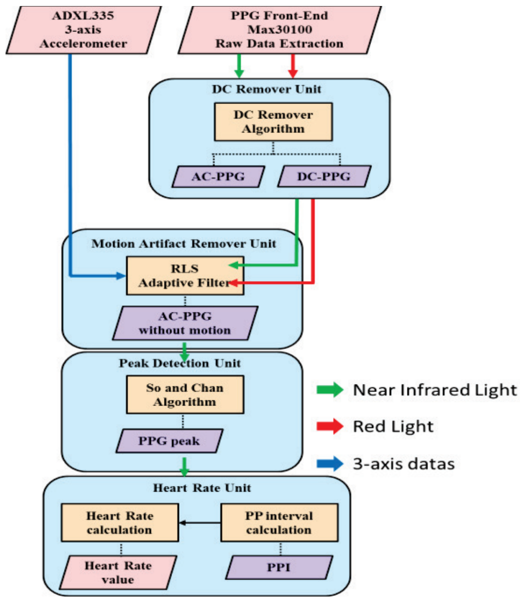

Figure 2. A detail data flow of the proposed motion artifacts elimination system.

B. *Recursive Least Squares Adaptive Filter (RLS)*

1).RLS Algorithm

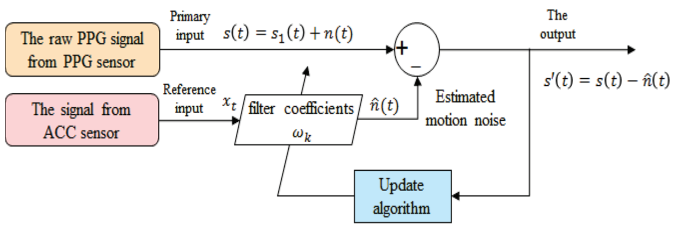

Figure 3. RLS Algorithm Block Diagram

The adaptive filter algorithm employs a feedback architecture to adapt the filter coefficients and the frequency response. By using a cost function, the filter can determine new filter coefficients to reduce the cost of the next iteration of the operation [6]. The block diagram of the RLS algorithm is shown on Figure 3 and the related equation is as follows:

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

The two principal input signals are the input data of PPG signal with motion noise (AC component): $s(t)$ and x_t the input reference noise of motion artifacts. The reference signal of the motion artifacts is measured by the 3-axis accelerometer paralleled to the direction of the blood flow in the finger [6]. The $s_1(t)$ represents the noise-free PPG signal after the process of the operation, $n(t)$ represents the action noise, ω_k corresponds to the coefficients of the RLS filter, and the t represents the sampling time. The θ is the n*1 matrix composed of the coefficients of the RLS filter, $\theta=[\omega_1,...\omega_n]^T$. The φ_t is the n*1 matrix of the reference signal of the motion artifacts in the direction of x-axis, $\varphi_t=[x_{(t-n)},\ldots x_t]^T$. The algorithm performs a matrix operation to acquire the estimated motion noise: $\hat{n}$, then subtracts $\hat{n}$ from the original PPG signal $s(t)$ to acquire the clean PPG signal $s'(t)$. According to our experiments, the quantity of MAs removed starts saturating for all the selected matrix order superior at 10.

2). Updating the Filter Coefficients

The RLS algorithm makes a recursive calculation of the reference noise of motion artifacts $\hat{n}$ at every sampling time and automatically updates the coefficients in the filter matrix. That makes the $\hat{n}$ being closer to the real motion noise as shown in equations (1.5).

$$\theta_t = \theta_{t-1} + \beta(S_t - \hat{n}_t) \quad , \quad \beta = \frac{P_{t-1}\varphi_t}{1+\varphi_t P_{t-1}\varphi_t^T} \qquad (1.5)$$

$$P_t = P_{t-1} - \frac{P_{t-1}\varphi_t\varphi_t^T P_{t-1}}{1+\varphi_t P_{t-1}\varphi_t^T} \qquad (1.6)$$

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 $s_t - \hat{n}_t$, in equation (1.5). 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 (1.6).

III. Experimental Results

To validate the functional simulation and performance of the proposed algorithm, the experimental PPG signals are measured from 10 subjects by the prototype system with a 125 Hz sampling rate and x-axis reference signal of motion artifacts. The subject's heart rate is collected by the CSI/CRITICARE 8100e nGenuity Bedside Monitor at the ground-truth of the stationary chest. The MAs actions type of the set of the experiment are scratching and slight shaking [7]. The figure 4 shows the result of the DC Remover applied on the PPG signal.

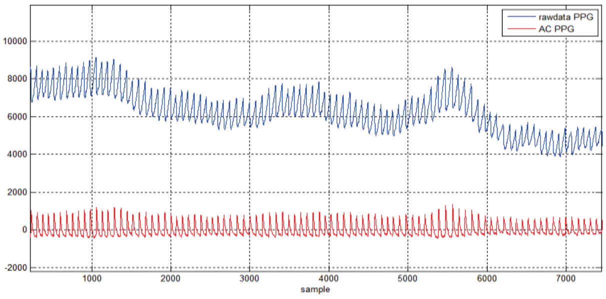

Figure 4. The effect of the DC Remover applied on the PPG signal. The blue line is the PPG raw data (AC and DC components), The red line is the processed PPG signal (AC component).

Figure 5 shows the mean PPG signals of 10 subjects with MAs (scratching and slight shaking) in the frequency domain analysis by the FFT. On the Figure 5b, the frequency components of MAs corrupts the intrinsic frequency of PPG. On the Figure 5a, the RLS adaptive filter algorithm eliminates these frequency components of MAs and leaves the characteristic frequency of PPG signals. Figure 6 shows the Correlation Coefficient analysis of heart rates from the database with PPG's MAs after the RLS processing, the result presents a high correlation of R=0.8504.

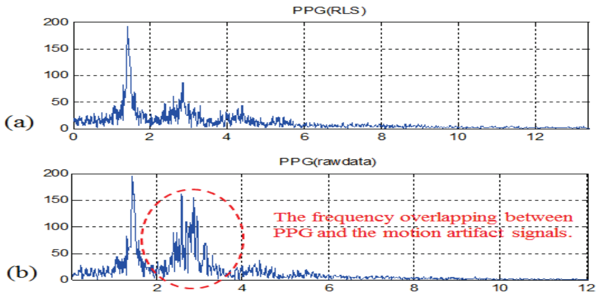

Figure 5. (a) The frequency spectrum of the mean PPG signal after the RLS adaptive filter; (b) The frequency spectrum of the mean MAs-corrupted PPG signal.

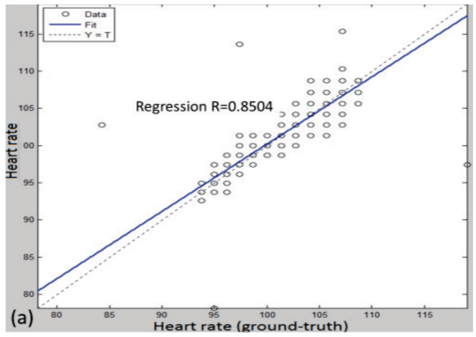

Figure 6. The Correlation Coefficient analysis from the database of 10 subjects.

IV. Conclusion

This study presents an effective motion elimination algorithm based on the conjunction of DC Remover and RLS adaptive filter. The proposed algorithm eliminates the motion artifacts of corrupted PPG signals. The results show a high correlation, with a correlation coefficient R higher than 0.8504 and a standard deviation of 3.81 BPM. This work has been implemented in hardware for wearable and home-care applications. It makes the at-home care possible and can contribute to lower the damages of cardiovascular diseases and medical expenses through a long-term monitoring.

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