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Adaptive Comb Filtering for Motion Artifact Reduction from PPG with a Structure of Adaptive Lattice IIR Notch Filter

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Abstract—**Photoplethysmographic (PPG) signal can provide important information about cardiovascular and respiratory conditions of individuals in a hospital or daily life. However, PPG can be distorted by motion artifacts significantly. Therefore, the reduction of the effects of motion artifacts is very important procedure for monitoring cardio-respiratory system by PPG. There have been many adaptive techniques to reduce motion artifacts from PPG signal including normalized least mean squares (NLMS) method, recursive least squares (RLS) filter, and Kalman filter. In the present study, we propose the adaptive comb filter (ACF) for reducing the effects of motion artifacts from PPG signal. ACF with adaptive lattice infinite impulse response (IIR) notch filter (ALNF) successfully reduced the motion artifacts from the quasi-periodic PPG signal.**

I. INTRODUCTION

PHOTOPLETHYSMOGRAPHY (PPG) signal provides very useful information about cardiovascular and respiratory physiology like arterial oxygen saturation, heart rate and respiratory rate [1]. PPG signal can replace electrocardiography (ECG) to estimate heart rate variability (HRV) [2] and can be also used to calculate pulse transit time (PAT) to estimate blood pressure [3]. PPG recording can provide a very convenient tool for continuous monitoring of hemodynamic status of healthy persons or patients and can also be developed for portable devices so as to monitor physiologic condition during daily lives [4].

However, PPG signal is very easily contaminated by motion artifact both in bed-side patient-monitoring and during continuous mobile monitoring by portable devices [5]. Motion artifacts distorted the information found in the PPG signals, so that the removal of motion artifact is a very important step for the exact estimation of physiological variables to exactly assess the cardio-respiratory conditions.

Until now, so many methods have been suggested for the motion artifact removal from physiological signals including PPG and ECG. Kim et al. proposed independent component analysis exploiting the quasi-periodicity of PPG signals [6]. In addition, wavelet-based methods [7] or non-linear methods [5] have been also suggested for the same purpose.

On the other hand, there were several attempts to utilize adaptive filtering techniques for the on-line reduction of the motion artifacts. In [7], the least mean square (LMS) iterative recursive algorithm was presented and recursive least squares (RLS) noise cancellation technique [8] was also used to recover clean PPG signals from those corrupted by motion artifacts. Seyedtabaii [9] reported that adaptive formula based on Kalman filter successfully reduced the motion artifacts from the contaminated PPG signals. Recently, our team applied a fixed-interval Kalman smoother to the problem of motion artifact reduction for PPG monitoring [10].

In the present study, we proposed an adaptive comb filtering (ACF) with a structure of adaptive lattice IIR notch filter (ALNF) to reduce motion artifacts from PPG signal. ACF for quasi-periodic signal enhancement can be expected to be successfully applied to the biomedical signals such as ECG and PPG because of their quasi-periodicity [11]. In addition, ALNF structure can provide an efficient way for extracting the fundamental frequency and rational approximation of the ideal notch filter [12]. Since we use an adaptive notch filter with a lattice structure and a least-squares estimation as an adaptation algorithm, we can obtain an unbiased estimator and outstanding tracking performance.

The organization of this paper is as follows. In section II, we will explain the algorithm in detail. Next, section III will show the results of simulation and actual experiments processed by the algorithm presented in the previous section. In the last section, some considerations will be discussed with regard to the proposed method and the results of simulation test and real experiment.

II. ALGORITHM

In this section, the algorithm will be introduced by four steps: i) adaptive lattice IIR notch filter (ALNF), ii) a priori information, iii) tunable comb filter and iv) ACF with ALNF structures.

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A. Adaptive Lattice IIR Notch Filter (ALNF)

The frequency response of the ideal notch filter can be approximated by L_2 norm and there are two candidate realizations which can be approximated in rational transfer function. One is a direct from structure whose numerator has a monic mirror symmetric polynomial and whose denominator has a similar structure parameterized with a pole-zero contraction factor. Recursive maximum likelihood (RML) algorithm for this structure was proposed by Nehorai [11]. Another form suggested by Cho and Lee [12] is the lattice IIR notch filter as follows:

$$H_l(z^{-1}) = \frac{N(z^{-1})}{D(z^{-1})} = \frac{1+2k_0 z^{-1}+z^{-2}}{1+k_0(1+\alpha)z^{-1}+\alpha z^{-2}} \cdot \qquad (1)$$

They combined this lattice IIR notch filter and the method of least-squares for adaptation algorithm, which is proposed as the adaptive lattice IIR notch filter (ALNF). k_0 is the adaptation parameter and it is independent of pole-zero contraction factor α. One of the possible realizations is described in Figure 1 (a).

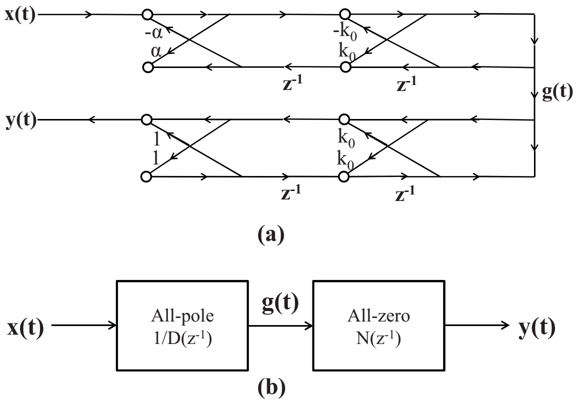

Fig. 1. Adaptive lattice IIR notch filter (a) structure of the ALNF (b) cascade of the ALNF system function.

To derive the weighted least squares as an adaptation algorithm, the system function (1) is separated into two parts: all-pole and all-zero lattice filters (Figure 1(b)). Let the cost function J be the output power $E[y^2(t)]$, then we solve $\min_{k_0} E[y^2(t)]$ where k_0 is related with the notch frequency of the ALNF:

$$\hat{f}_0(t) = \frac{1}{2\pi}\arccos(-\hat{k}_0(t)) \cdot \qquad (2)$$

Since $\partial J/\partial k_0 = 0$, $g(t) = x(t) - k_0(1+\alpha)g(t-1) - rg(t-2)$ and $y(t) = g(t) + 2k_0 g(t-1) + g(t-2)$, we get the value of the adaptation parameter k_0:

$$k_0 = -\frac{E[g(t-1)\{g(t)+g(t-2)\}]}{E[2g^2(t-1)]} = -\frac{R_g(1)}{R_g(0)} \qquad (3)$$

where $R_g(0)$ and $R_g(1)$ are the autocorrelation function of $g(t)$. If the random process $\{\, x(t) \,\}$ is autocorrelation ergodic, then the autocorrelation function of $g(t)$ can be represented by time average as follows:

$$R_g(k) = E[g(t)g(t-k)] = \lim_{N\to\infty}\frac{1}{N}\sum_{t=0}^{N-1} g(t)g(t-k) \qquad (4)$$

and for sufficient large N,

$$R_g(1)\big/R_g(0) \cong \sum_{t=0}^{N-1} g(t)g(t-1)\Big/\sum_{t=0}^{N-1} g^2(t) \cdot \qquad (5)$$

By introducing a forgetting factor λ and a smoothing factor γ, recursive algorithm for evaluating k_0 can be implemented like

$$\frac{R_g^{(i)}(1)}{R_g^{(i)}(0)} = \frac{\lambda R_g^{(i-1)}(1) + (1-\lambda)g(t-1)\{g(t)+g(t-2)\}}{\lambda R_g^{(i-1)}(0) + (1-\lambda)2g^2(t-1)} \qquad (6)$$

with the initial conditions such as $R_g^{(0)}(0) = 1$ and $R_g^{(0)}(1) = 0$. From (6), we get the following adaptation step:

$$R_g^{(i)}(0) = \lambda R_g^{(i-1)}(0) + (1-\lambda)2g^2(t-1)\,, \qquad (7a)$$

$$R_g^{(i)}(1) = \lambda R_g^{(i-1)}(1) + (1-\lambda)g(t-1)\{g(t)+g(t-2)\}\,, \qquad (7b)$$

$$\breve{k}_0(t) = -R_g^{(i)}(1)\big/R_g^{(i)}(0)\,, \qquad (7c)$$

$$\breve{k}_0(t) = \begin{cases} \breve{k}_0(t), \text{if } -1 \le \breve{k}_0(t) \le 1 \\ 1, \quad\quad \text{if } \breve{k}_0(t) > 1 \\ -1, \quad\quad \text{if } \breve{k}_0(t) < -1 \end{cases}, \qquad (7d)$$

$$\hat{k}_0(t) = \gamma\breve{k}_0(t-1) + (1-\gamma)\breve{k}_0(t)\,. \qquad (7e)$$

B. A Priori Information

Since the ALNF estimates the fundamental frequency by minimizing the cost function over the entire frequency range, the convergences take a long time and the mean square error (MSE) of the frequency estimate is large because of the low signal-to-noise ratio (SNR). However, if the filtering objects are confined to the quasi-periodic physiological signals, we can obtain a priori knowledge. That is, the physiological signals are band limited and the feasible range of the fundamental frequency is bounded. Therefore, when we use the ALNF for frequency estimation, we can improve the performance by searching for the frequency in the feasible range. To use this information for the performance improvement of the ALNF, we designed a bandpass filter and placed the filter in front of the ALNF. This procedure makes the ALNF accurately search for the true fundamental frequency in the feasible region.

C. Tunable Comb Filter

Due to the fact that the physiological signals have harmonic structure, we propose a tunable filter, so-called comb filter, because the shape of the magnitude response is like a comb whose notches are adjustable. Since the tunable comb filter is constructed by linearly cascading several identical 2nd-order notch filters, the overall system function is just a product of the 2nd-order notch filter as follows:

$$H(z^{-1};\boldsymbol{\varphi}) = \left(\frac{b_0}{a_0}\right)\prod_{j=1}^{N}\frac{1+2k_j z^{-1}+z^{-2}}{1+k_j(1+\alpha_j)z^{-1}+\alpha_j z^{-2}} \qquad (8)$$

where a_0 and b_0 determine the overall gain of the ACF, N is the total number of the 2nd-order notch filter used, α_j is the pole-zero contraction factor of the j-th notch filter and k_j determines the notch frequency of the j-th 2nd-order notch filter. The parameter vector $\boldsymbol{\varphi}$ is defined by $\boldsymbol{\varphi} = (\frac{b_0}{a_0}, N, \alpha_j, k_j)$ and let $\{k_j\}_{j=1}^{N}$ be related following

$$k_j(t) = -\cos(2\pi(j-0.5)\hat{f}_0(t)) \;\; (j = 1, 2, \cdots), \tag{9}$$

then (8) is controlled by a single parameter so it retrieves harmonic component of the input sequence and suppresses inter-harmonic noise.

D. ACF with ALNF structures

The proposed system consists of three stages: 1) frequency selective or shaping filter, 2) ALNF which is used to estimate the fundamental frequency and 3) the tunable comb filter. Figure 2 shows the overall structure of the proposed ACF.

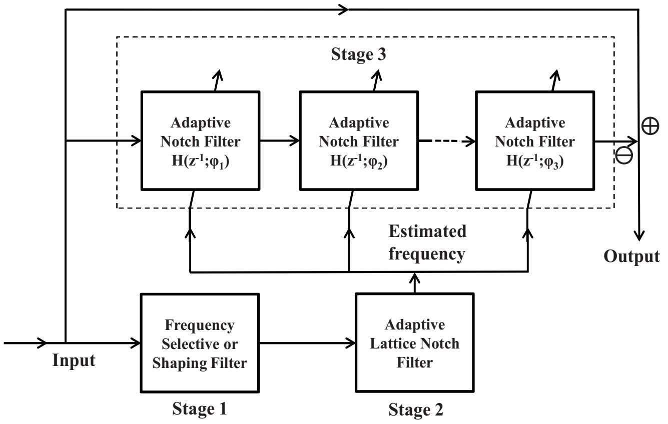

Fig. 2. Overall structure of the proposed ACF.

First, if the input sequence enters into the proposed system, the band-pass filter of the first stage extracts the feasible frequency component from the physiological signal. At the same time, the input sequence also enters into the third stage input, i.e., the tunable comb filter. After these processes are completed, the ALNF stage estimates and tracks the true fundamental frequency by minimization of the output power. Since local minima points on the performance surface of the input sequence are filtered out by the first stage, the estimation performance may be more accurate than in the absence of the first stage. Finally, the estimated frequency is transmitted to the third stage. The tunable comb filter parameterized with the estimated frequency enhances the harmonic component of the input sequence and suppresses the inter-harmonic noises.

III. SIMULATION AND EXPERIMENT

In this section, the proposed algorithm will be applied to the simulation data and then real experimental data. The tests were performed under MATLAB (MathWorks Inc., USA) programming environment.

A. Simulation

To construct the simulation data set, the motion artifacts are modeled by sine functions because finger and arm movements during real life were low-frequency motions. This artificial signal composed of motion artifact and white Gaussian noise were merged with the real PPG signals having the same time-points which are obtained using commercial PPG sensor and customized acquisition device.

We applied the proposed algorithm to the simulated PPG signal as in Figure 3. The uppermost panel shows the original PPG signal measured in one index finger at rest, the middle panel represents the simulated PPG with artificial motion artifact, and the bottom panel shows the result after being filtered by our adaptive method of ACF with ALNF structure. By inspection, the final result reconstructed the original PPG signal almost perfectly.

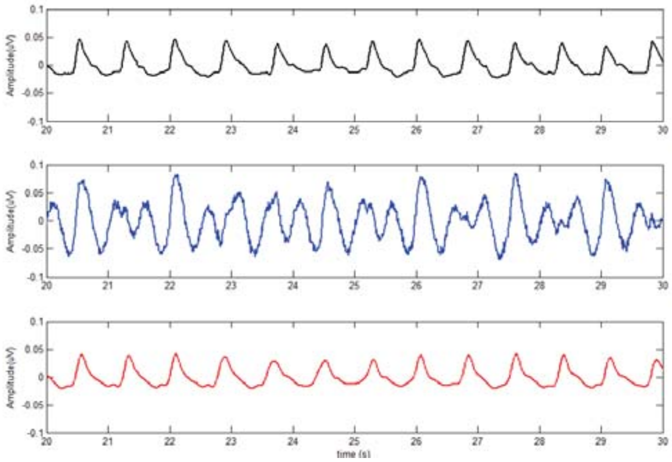

Fig. 3. Upper: original PPG signal, middle: PPG distorted by artificial motion artifact, bottom: PPG reconstructed by adaptive comb filter.

B. Experiment

Now, the PPG signal was measured in real situation. That is, PPG signal was acquired during intermittent finger movement with commercial transmitted-type finger sensor (NONIN finger clip 8000R). The data were acquired with sampling rate of 128 Hz using our in-house potable device composed of 12bit AD converter, 32MB flash memory and USB connection with computer. Reference PPG signal was also measured in the other hand that was in fixed position.

The proposed algorithm was applied to the PPG signal corrupted by the finger movement as in Figure 4. The uppermost panel shows the reference PPG signal measured in the left index finger at rest, the middle panel represents the

PPG with motion artifact measured in the other index finger during finger bending motion, and the bottom panel shows the result after being filtered by our adaptive method of ACF with ALNF structure. By inspection, the reconstructed PPG signal produce very similar pattern as the reference PPG signal.

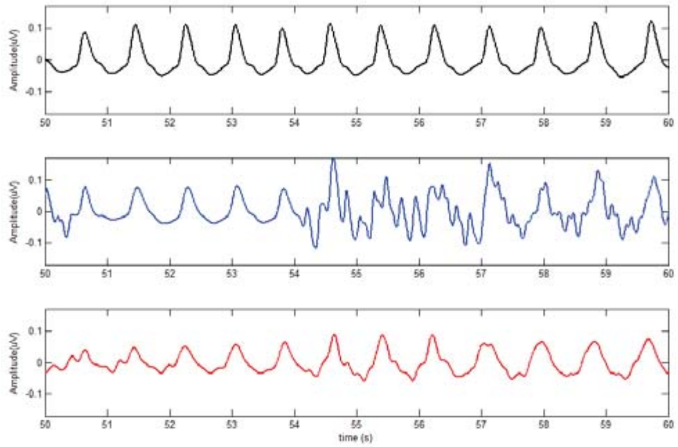

Fig. 4. Upper: reference PPG signal, middle: PPG contaminated with finger movement in real situation, bottom: PPG reconstructed by ACF.

IV. DISCUSSION AND CONCLUSION

In the present study, we proposed an adaptive comb filter (ACF) with adaptive lattice notch filter (ALNF) structures to eliminate the motion artifacts from photoplethysmographic signal. In both tests of simulation and real experimental data, the results produced by this method were reasonable by inspection. That is, ACF provided an efficient tool for motion artifact rejection without any other reference signal such as accelerometer signal for adaptive filtering.

To validate the performance of this method, we have to carry out more rigorous quantitative evaluation including simulation and real experiments in future studies.

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