Technical Note

Motion Artifact Reduction in Electrocardiogram Using Adaptive Filter

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Abstract

Removing motion artifacts from an electrocardiogram (ECG) is one of the important issues to be considered during real-time heart rate measurements in telemetric health care. However, motion artifacts are part of the transient baseline change caused by the electrode motions that are the results of a subject's movement. Therefore, an accelerometer was used to measure the acceleration signal of the vibrations or movement of the trunk as the reference inputs of the adaptive filter. The optimal weight of the adaptive filter could be adjusted by a least mean square algorithm. Experiments with synthetic and real data were performed to demonstrate the efficacy of this proposed method. We have found that the QRS complex of the filtered ECG was clearly appeared.

Keywords: Electrocardiogram, Accelerometer, Adaptive filter

1. Introduction

The electrocardiogram (ECG) has not only been used for diagnosing heart diseases and evaluating the efficiency of therapeutic drugs, but is also widely used for the diagnosis of obstructive sleep apnea or wearable physiological monitor [1,2]. ECG recordings are often corrupted by various kinds of noise such as power line interference, motion artifacts, electromyogram effects, and baseline drift with respiration. Recently, portable monitors incorporating the computational power of microprocessors have allowed us to implement digital filters for noise cancellation in real-time execution. However, motion artifacts that are part of the transient baseline change are caused by changes in the electrode-skin impedance with electrode motion. This is assumed to be vibrations or movement of the subject. In particular, the spectrum of motion artifact completely overlaps with the ECG signal when the subject is walking or running. Thus, motion artifacts are the most difficult type of noise to cancel.

There are several studies on reducing motion artifacts with the filtered or differential method [3-10]. Friesen et al. compared many methods to detect the QRS complex of ECG from the simulated noise. The baseline noise could be fully reduced by several methods [3]. Ruha et al. thought that the bandwidth of motion artifacts was below 5 Hz. They filtered and detected the QRS complex for recording of ambulatory heart rate variability in real time [4]. Furthermore, adaptive filtering technique has been considered as a high-pass filter or band-stop filter with applications related to 60-Hz powerline interference cancellation and the recording of fetal ECGs [5]. A reference signal representing the powerline interference from another part of the body or a 60-Hz sine wave generator could be used to cancel powerline interference from the ECG signal. In fetal ECG recordings, the mother's ECG recording from one of the conventional leads could be used as a reference signal to filter the mother's ECG recording from the abdominal leads. Other interesting applications include improving the signal-to-noise ratio (SNR), which uses multiple surface leads for adaptive filtering to discriminate the *P*-wave [6], or cancels the cardiogenic interference from the thoractic impedance signal [7]. Thakor and Zhu designed an adaptive recurrent filter structure for noise cancellation whereby the reference input is an impulse train coinciding with the QRS complex [8]. Tong et al. proposed an adaptive filter to reduce the motion artifact of ECG with an accelerometer [9]. Yoon et al. proposed that the motion information of the subject had relation to the motion artifact of the ECG [10]. They used another electrode to measure the motion artifact's reference as the reference input of the adaptive filter, and the accelerometer to measure the motion information as the signal. The relation could be constructed and used to reduce the motion artifact of ECG.

This paper proposes a portable ECG recorder which uses a triaxial accelerometer to detect the subject's movement. The triaxial acceleration signals are used as reference signals for the adaptive filter to cancel the ECG motion artifact. The portable ECG recorder uses Bluetooth technology to transmit data. The experimental results showed that the adaptive filter could reduce the motional artifacts of the ECG signal, and let the QRS complex of the filtered ECG be clearly appeared.

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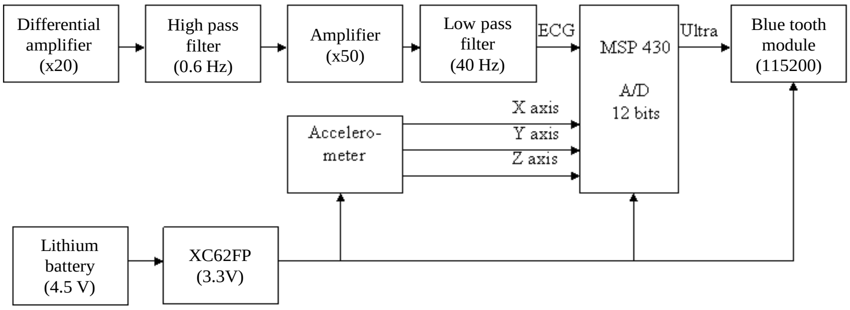

Figure 1. The block diagram of portable ECG recorder system.

2. Methods

When a subject is moving his/her trunk, a motion artifact is produced by a change in the impedance between the skin and electrode which could be considered as the transient change in the baseline signal. The baseline shift signals include the slow baseline change and the quick transient change. The lower the cutoff frequency of the high-pass filter is, the larger the slower baseline change. Therefore, when the impedance between the skin and the electrode has an instantaneous change, the slow baseline change will occurr. The quick baseline change always occurs when the electrode is continuously moved by the subject's motion.

2.1 Hardware

Figure 1 shows the block diagram of the portable ECG recorder system, which includes the analog circuit of a differential amplifier (gain: 20), a band-pass filter (frequency range: 0.67 to 40 Hz), and a gain amplifier (gain: 50). In the digital circuit, we used the TI MSP430 F1611 microcontroller (MCU), which has eight 12-bit A/D channels. The sampling rate was 250 Hz. The MCU used the serial communication port (baud rate: 115,200) to connect to a Bluetooth module (MB-C04, SMART Design Group, Taiwan). The accelerometer (KXM52-L20, Kionix, USA) has a range of $\pm 2\,g$ with the three-axis output signals in rectangular coordinates being placed at the electrode's side. The power supply to the measurement system was a 4.5-V lithium battery. A voltage regulator (XC62FP) was used to regulate a 3.3-voltage for this circuit. The monitoring interface was written in 'LabView' software to display and record the signals. Because the A/D converter of the MCU is 12 bits, the sample data were separated into low and high bytes. Therefore, in one sample point, there are 4 sample data from the ECG and triaxial signals of the accelerometer which are separated into 8 bytes and stored in a buffer. When the Bluetooth was suddenly interrupted to stop the communication, some bytes were still being stored in the buffer of the Bluetooth model, and when the Bluetooth transmitted data again, these bytes would appear before the new data. Hence, we transmitted 2 bytes, FF and FF, as the code before the 4 sample data to distinguish each sample data. When the Bluetooth model received the data, 10 bytes were considered as a segment. We first found the position of the identification code. Then, one sample point's data would be acquired between two distinguishing codes.

2.2 Adaptive filter structure

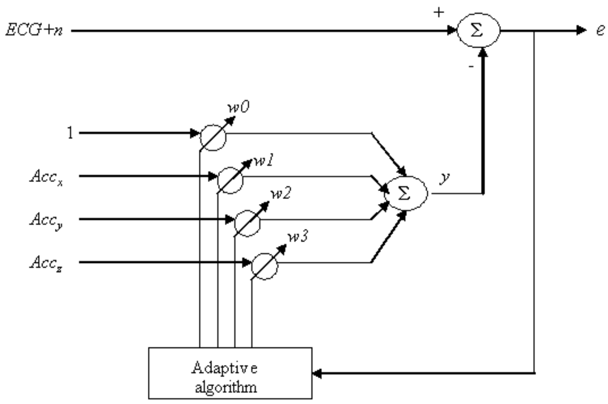

Figure 2. The structure of the adaptive filter.

Figure 2 shows an adaptive filter with the primary input being the ECG signal with motion artifact, *s*+*n*, while the reference inputs are the triaxial signals of the accelerometer and a bias, $X(n) = [\,C, Acc_x(n), Acc_y(n), Acc_z(n)]$. Because there was no need to match the phase of the signal, the first element of the reference input vector was set to a constant value, *C*, which was set to 1. The filter coefficients are $W = [w0, w1, w2, w3]$, the filter output is $y = XW^T$. A bias weight, *w*0, in an adaptive filter had been proven to be a high-pass filter with zero on the unit circle at zero frequency [5]. The filter error is defined as the difference between the primary input and the filter output,

$$e = s + n - XW^T, \tag{1}$$

$$e^2 = (s+n)^2 - 2(s+n)XW^T + WX^TXW^T. \tag{2}$$

The adaptive filter extracts the ECG signal by minimizing the mean square error (MSE). The MSE is defined as:

$$E[e^2] = E[(s+n)^2] + 2E[(s+n)X]W^T + WE[X^TX]W^T. \tag{3}$$

The least-mean-squares (LMS) algorithm is used to minimize Eq (3). According to this method, the next weight vector W_{t+1} is equal to the present weight vector W_t plus the change proportional to the negative gradient:

$$W_{t+1} = W_t - \alpha\Delta_t, \tag{4}$$

where the parameter α is a factor which controls the rate of LMS convergence. The gradient is defined as:

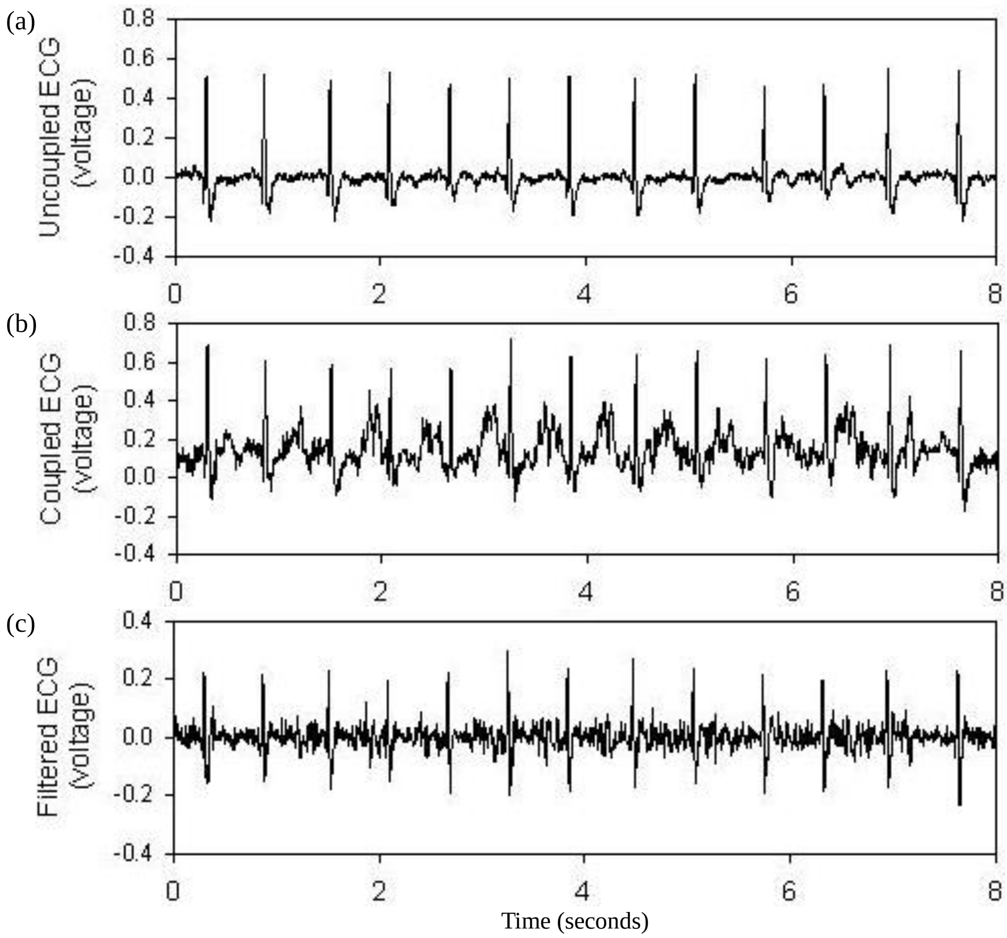

Figure 3. The synthetic experiments, (a) the uncoupled ECG, (b) the coupled ECG, (c) the filtered ECG.

$$\nabla_t = \left\{ \begin{array}{c} \dfrac{\partial E[e^2]}{\partial w_0} \\ \vdots \\ \dfrac{\partial E[e^2]}{\partial w_3} \end{array} \right\}_{W=W_t} . \quad (5)$$

Therefore the estimated gradient is defined as:

$$\hat{\nabla}_t = \left\{ \begin{array}{c} \dfrac{\partial [e^2]}{\partial w_0} \\ \vdots \\ \dfrac{\partial [e^2]}{\partial w_3} \end{array} \right\}_{W=W_t} = 2e \left\{ \begin{array}{c} \dfrac{\partial e}{\partial w_0} \\ \vdots \\ \dfrac{\partial e}{\partial w_3} \end{array} \right\}_{W=W_t} = -2eX . \quad (6)$$

Using this estimated gradient in place of the true gradient in Eq. (4) yields the Widrow-Hoff LMS algorithm [5]:

$$W_{t+1} = W_t + 2\alpha eX . \quad (7)$$

3. Results

Starting with an arbitrary initial weight vector, the LMS algorithm converges the weight values to the mean and remains stable when the parameter, α, is 0.01. In a portable recorder system, the number of iterations in the adaptive filter would be the main load of the MCU, with more iterations resulting in a lower MSE. In order to understand the performance of the adaptive filter, the uncoupled ECG was added to the different levels of motion artifact (2.2 to 10.2 dB, SNR). The uncoupled ECG signal was measured from the subject who stood and did not move his trunk. The synthetic motion artifact was obtained from the resultant signal of the accelerometer that was placed on the same subject. Figure 3 shows the uncoupled ECG, the coupled ECG, and the filtered ECG. The SNR of the coupled ECG is 2.2 dB. After 20 iterations, the filtered ECG is shown in Fig. 3(c). The adaptive filter with the differing numbers of iterations was used to reduce the noise of the coupled ECG. Figure 4 shows that the MSE between the uncoupled ECG and the filtered ECG increases as the power of the motion artifact increases, holding the number of iterations constant. When the number of iterations reached 60 times, the MSE would begin to converge to a stable value for any noise level.

In this experiment, the real-time recorded Lead II ECG, shown in Fig. 5(a), was taken when the subject was walking. Three electrodes were placed around the heart, and the accelerometer was closely placed at the side of the left leg electrode. The triaxial signals of the accelerometer are shown in Figs. 5(c)-(e), where the Y-axis signal represents crabwise motions, the X-axis signal represents forward and backward

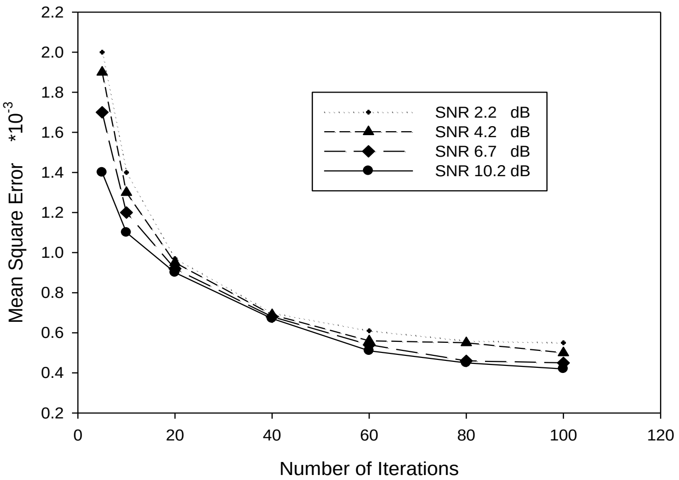

Figure 4. The performance comparison between the different levels of motion artifact being added to the uncoupled ECG for the different iteration numbers.

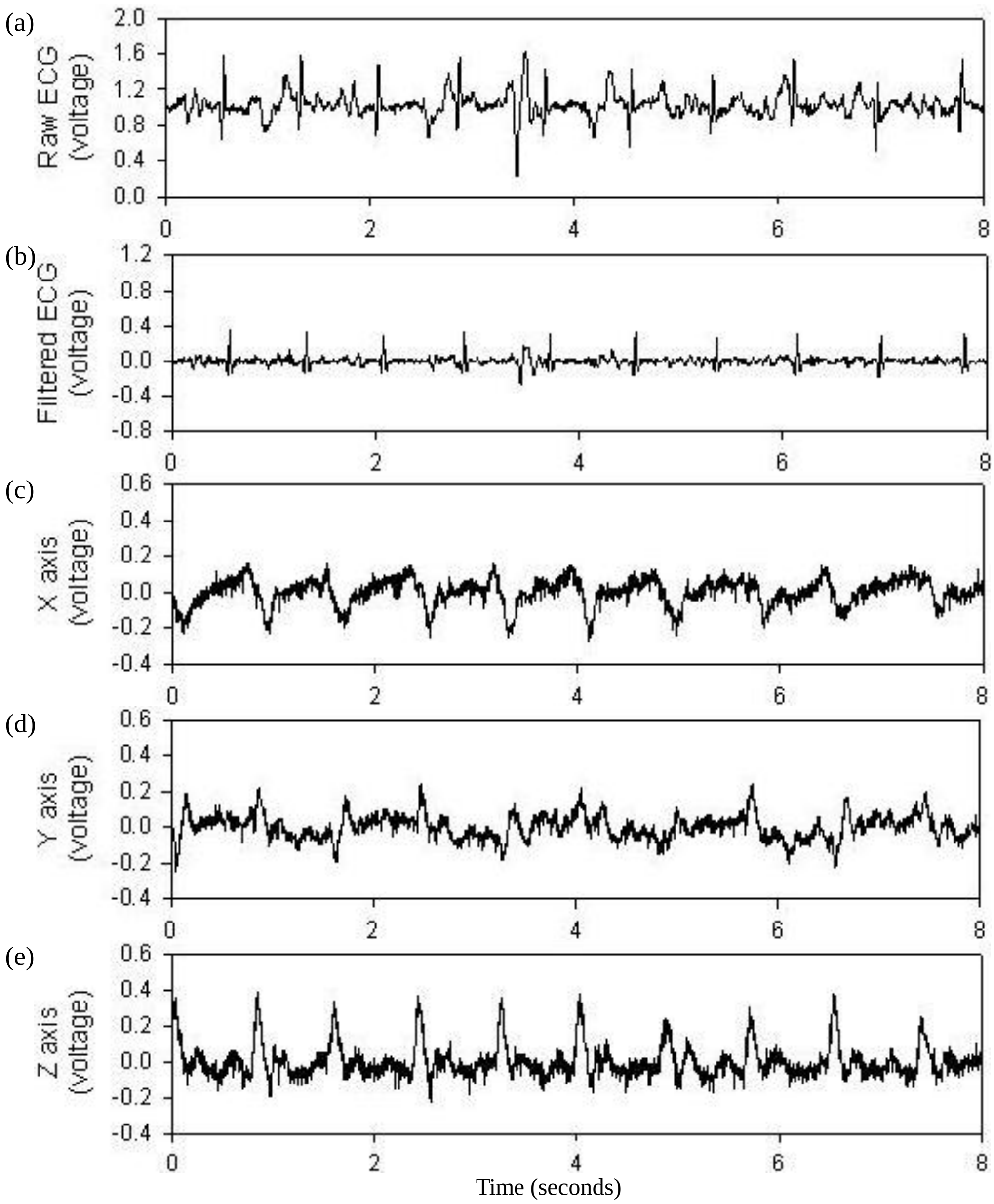

Figure 5. The performance of the adaptive filter under movement, (a) the real recorded ECG, (b) the filtered ECG, (c) the X-axis signal of the accelerometer, (d) the Y-axis signal of the accelerometer, and (e) the Z-axis signal of the accelerometer.

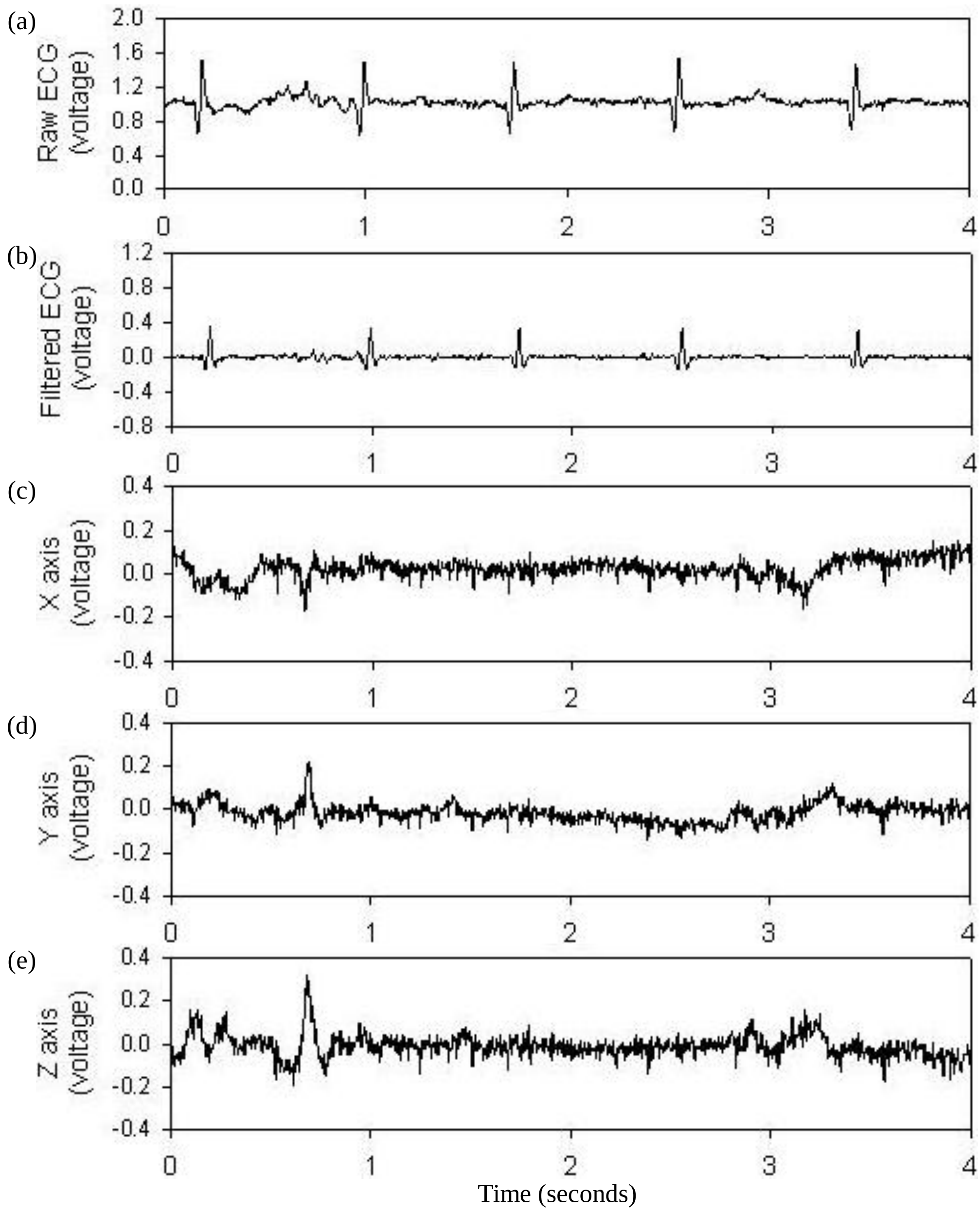

Figure 6. The performance of the adaptive filter under no movement, (a) the real recorded ECG, (b) the filtered ECG, (c) the X-axis signal of the accelerometer, (d) the Y-axis signal of the accelerometer, and (e) the Z-axis signal of the accelerometer.

motions and the Z-axis signal represents up and down motions. Figure 5(b) shows the filtered ECG. We found that some peaks of motion artifacts were larger than the R-wave in the real-time recorded ECG. However, as shown in Fig. 5(b), the adaptive filter could effectively reduce the power of the motion artifacts. Therefore, the R-waves of the filtered ECG were all larger than the maximum peak of the motion artifact. Moreover, the adaptive filter will be a high-pass filter at zero frequency when the reference input is constant. Thus, the baseline of the filtered ECG is zero.

Figure 6 shows the performance of the adaptive filter under movement-free condition. The filtered ECG signal, as shown in Fig. 6(b), has better quality than that of Fig. 6(b). Moreover, the acceleration signal had an instantaneous change at 0.8 second. The raw ECG also had a slow baseline change at the same time. The adaptive filter could reduce this motion artifact. But the body movement must not affect the baseline of the ECG. We could find that the acceleration signal also had an instantaneous change at 3.1 second. The raw ECG did not have any baseline change at the same time.

4. Discussion

An adaptive filter always needs references to filter the redundant signals that do not belong to the blind signal process. If the reference inputs and redundant signal had a higher correlation, the performance of the filter would be better. Motion artifacts belong to the transient baseline change caused by a change in the electrode-skin impedance with electrode motion. Therefore, the accelerometer must be placed very close to the electrode. However, in our measurements, paste-on column electrodes were used to measure the ECG. When the

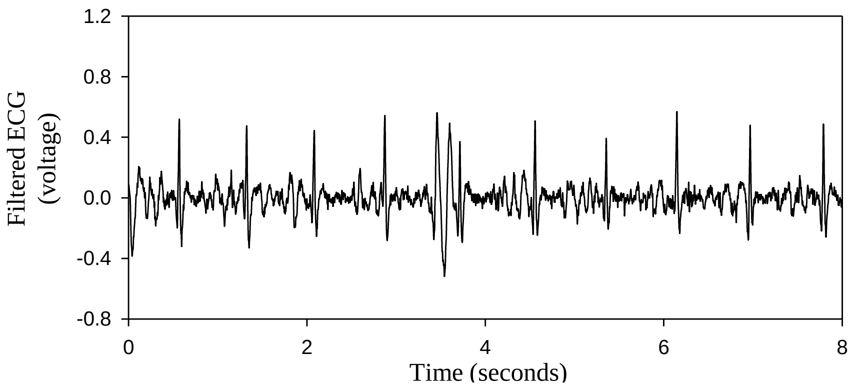

Figure 7. The performance of the Butterworth filter for the raw ECG of Fig. 6(a).

trunk was vibrating, the electrode-skin impedance may not have been changing. We found that the motion artifacts periodically did not occur, as shown in Fig. 5(a). Moreover, the band-pass filter also makes up the phase lag of the signal. The adaptive filter is a nonlinear-phase high-pass filter when the reference input is a constant. These reasons explain why the adaptive filter did not remove all motion artifacts from the measured ECG, as shown in Fig. 5(b).

Because the adaptive filter is a nonlinear phase filter, the filtered ECG signal will have some distortion at P-wave and T-wave. However, in telemetric health care, the ECG signal usually is used to detect the heart rate in real time [4,11]. These analysis algorithms all detect the QRS complex, and then calculate the R-R interval as the heart rate. Therefore, if the ratio of the amplitude of the R-wave and the noise is too small, the detection of fault heart rate will increase. In Fig. 5(a), we can find that some P-waves, T-waves or baseline wandering would be larger than the QRS complex. The adaptive filter could reduce these artifacts, and the QRS complex is clearly appeared in Fig. 5(b). Because the adaptive filter used the LMS algorithm to adjust the coefficients of the filter for minimizing Eq. (3), the amplitude of the filtered ECG must become small. But, the SNR of the filtered ECG signal could be raised.

In a previous study, Tong et al. proposed an adaptive filter using the recursive least square algorithm to reduce the motion artifact of ECG with an accelerometer [9]. We could find that the filtered ECG also had a large baseline noise. Therefore, as shown in Fig. 7, a high-pass Butterworth filter was used to filter the ECG signal of Fig. 5(a) which had order of four and cutoff frequency of 5 Hz, as suggested by [4]. The raw ECG signal has some peaks of motion artifacts larger than the R-wave. In Fig. 5(b), we can observe that the adaptive filter could effectively decrease the amplitude of the motion artifacts. However, the high-pass Butterworth filter could not reduce the peak of the motion artifact at 3.4 seconds.

5. Conclusion

In this paper, we proposed an algorithm to reduce the motion artifacts of the ECG which used an accelerometer to measure the signal of the vibrations or movement of the trunk as the reference inputs. The optimal weight of the adaptive filter could be adjusted by an LMS algorithm. Experiments show that the MSE between the uncoupled ECG and the filtered ECG would begin to converge to a stable value after 60 iterations. In the motion ECG signal, the algorithm could also effectively enhance the QRS complex.

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