Using an Adaptive Filter to Remove ECG Motion Artifact Interference

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***Abstract*— Motion artifact removal is one of the most important issues in portable ECG（electrocardiogram）monitoring. Motion artifacts are usually accompanied by significant baseline drift. Adaptive filtering has been used to filter motion artifacts and baseline drift. The 3-axis acceleration signal is selected as the noise reference signal. Results show that motion artifacts and baseline drift have been removed in filtered ECG, and the QRS complex of the filtered ECG has clearly appeared.**

INTRODUCTION

Different kinds of wearable ECG monitoring devices have been recently developed. These wearable devices usually have the advantage of low power and thus are suitable for long-term monitoring. Various wireless transmission skills have been applied to ECG monitoring. Using wireless transmission technologies increases the portability of this equipment and allows ECG measurement in daily life [1]-[3].

Compared with ambulatory ECG monitoring, portable ECG monitoring has encountered some problems. High quality signals are easily obtained in ambulatory ECG monitoring. By contrast, the motion during portable ECG monitoring results in large baseline drifts and motion artifacts.

Several methods have been proposed to reduce motion artifact. Blind source separation (BSS) has been proposed to separate ECG and noise [4] because these signals are uncorrelated. However, the BSS method needs multichannel ECG and complex processing, which reduces its portability. Adaptive filtering is also used to filter motion artifacts. A reference signal that is well correlated with the noise must be available for adaptive filtering. Skin electrode impedance and acceleration are relevant to motion artifact [5].

In this work, the 3-axis acceleration is selected as the noise reference signal, and the use of two LMS algorithms in adaptive filtering (ADF) is investigated.

ADAPTIVE FILTERING

ADF has time-varying coefficient, which is suitable for processing non-stationary random signal. ADF has been used to separate fetal ECG from pregnant ECG [6] and remove power supply noise. The adaptive filtering system used to reduce motion artifacts is shown in Fig.1.

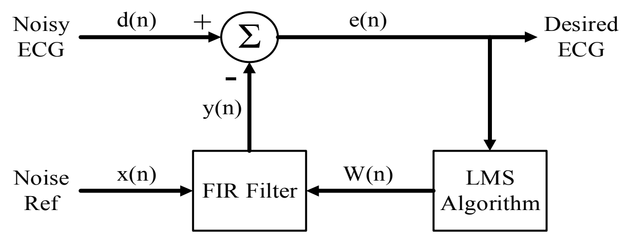

Fig.1 Adaptive filtering system

The system contains two input signals and one output signal. One input signal is the noisy ECG signal (d(n)), and the other one is the noise reference signal (x(n)).W(n) is the time-varying coefficient of the filter and is controlled by the LMS algorithm. y(n) is the filtered noise reference signal. The output filtered signal e(n) can be calculated from the follow equation (1):

$$e(n) = d(n) - W(n)x(n)^T \qquad (1)$$

The next filter coefficients W(n+1) can be calculated from the last coefficient W(n), which can be expressed as equation (2):

$$W(n+1) = W(n) + 2\mu e(n)x(n) \qquad (2)$$

μ is the step size. Different LMS algorithms can be obtained by changing the iterative formula of filter coefficients. By using sign function to reduce computational complexity, we can obtain two new LMS methods. Equation (3) is called LMS sign-error algorithm, and equation (4) is called LMS sign-data algorithm [7]. In this work, LMS sign-error and sign-data algorithms are used to reduce motion artifacts.

$$W(n+1) = W(n) + 2\mu sign(e(n))x(n) \qquad (3)$$

$$W(n+1) = W(n) + 2\mu e(n) sign(x(n)) \qquad (4)$$

EXPERIMENT AND RESULTS

Two electrodes are placed on the chest of the subject to measure the ECG signal. ADS129X is used to acquire and convert the ECG signal. The accelerometer is fixed on the chest and measures the acceleration while monitoring the ECG. ADXL345 is selected as the accelerometer because it direct outputs the digital value of acceleration and supports the IIC protocol. ADXL345 and ADS129X are controlled by the MCU (MSP430X). CC254X is used to send data to mobile phone through bluetooth. The subject is required to run slowly for 10 minutes, and the data are encoded into Matlab for further analysis.

Fig.2 shows an example of the collected data. Fig.2 (a) shows the ECG signal with motion artifacts. The ECG signal contains significant baseline drift. Fig.2 (b) shows the 3-axis acceleration collected at the same time. The acceleration changes with the body movement. The static offset of acceleration has not been handled because it does not influence adaptive filtering.

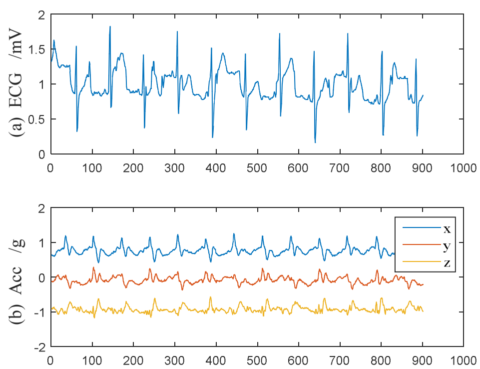

Fig.2 Collected data, (a) ECG with motion artifacts, (b) 3-axis acceleration

The filtering results are shown in Fig.3. Fig. 3 (a) shows the noisy ECG before filtering. The filtered ECG is shown in Figs.3 (b) and (c). The step size of the filter is set to 0.01.

Compared with Fig. 3 (a), (b) and (c) both show clean ECG. The baseline drift caused by motion has been removed, and the QRS wave is well preserved. However, the T wave was largely distorted both in LMS sign-error algorithm and sign-data algorithm. The filtering results can be used for HRV analysis. Compared with those from LMS sign-data algorithm, the results of LMS sign-error algorithm contain less noise during the S–T wave interval.

CONCLUSION

This work uses adaptive filtering to remove motion artifacts and filter out the noise caused by motion in portable ECG monitoring. The acceleration was easily obtained in this experiment as compared with that in the skin–electrode impedance. Hence, the 3-axis acceleration is selected as the noise reference signal of the adaptive filter. Two kinds of LMS algorithms, namely, LMS sign-error and LMS sign-data, are studied. In the experiment, LMS sign-error shows better performance than LMS sign-data. However, the two filtering methods both significantly distorted the T waves. The filtering results can be used for HRV analysis but hardly in other ECG diagnoses.

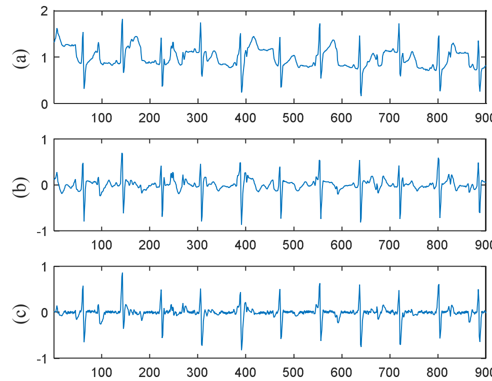

Fig.3 Experimental result, (a) ECG with motion artifacts, (b) filtered ECG using LMS sign-data, and (c) filtered ECG using LMS sign-error

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