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Full Length Research Paper

Removal of random noises for electrocardiogram (ECG) signals using adaptive noise canceller without reference input

Ching-Haur Chang*, Kang-Ming Chang and Hsien-Ju Ko

Department of Photonics and Communication Engineering, Asia University, Taiwan.

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The removal of random noises in electrocardiogram (ECG) using adaptive noise canceller (called single-input adaptive noise canceller) without reference input is presented in this paper. Common approaches for noise cancellation require reference input that must be well-correlated with the noise part of the primary input. However, the reference input may be limited in availability and hence, results in degradation of performance. ECG signals can be treated as quasi-periodic signals relative to their additive random noises. This paves the way for the possibility of using single-input adaptive noise canceller for the removal of random noises in ECG under limited availability of reference input. Computer simulation results verified that commonly used adaptive noise canceller cannot perform well for a poorly correlated reference input. Also, the results indicated that the single-input adaptive noise canceller with delays in the primary input performs almost the same as the commonly used adaptive noise canceller under a well-correlated reference input.

Key words: Adaptive noise canceller, electrocardiogram (ECG), mean-square error, reference input, single-input adaptive noise canceller.

INTRODUCTION

Adaptive filters are capable of separating interference components from the signal of interest, even under the case when interference components are overlapped to the signal in frequency. Furthermore, adaptive filters can process signals in real time and hence, provide good tools for time-critical applications. In this paper, the removal of random noises in ECG with a single-input adaptive noise canceller (SIANC) is addressed.

In the study of Widrow et al. (1975), they gave the basic principles and applications of adaptive filters. Lots of researches were carried out on the application of adaptive filters to the removal of artifacts for biomedical signals (Thakor and Zhu, 1991; Mehrkanoon et al., 2007; Kavitha et al., 2007; Sennels et al., 1997; Correa et al., 2007; Wu et al., 2009; Slim and Raoof, 2010; Chang et al., 2010; Rahman et al., 2011). For example, Wu et al. (2009) proposed an unbiased and normalized adaptive noise reduction system for suppressing random noises in ECG signals. Slim et al. (2010) developed an adaptive structure with an ECG reference signal carried out by wavelet decomposition. Rahman et al. (2011) compared several sign based normalized adaptive filters for removing artifacts in ECG and gave a suggestion on wireless biotelemetry. Correa et al. (2007) used adaptive filters in cascade for artifact removal from electroencephalogram (EEG) signals. Suresh and Puttamadappa (2008) proposed a combination of adaptive noise canceller (ANC) and adaptive signal enhancer in a multilayer recurrent neural network to remove the electromyography (EMG)/ECG artifacts as well as to enhance the EEG signals. Additionally, many non-adaptive schemes, such as those based on empirical mode decomposition (Weng et al., 2006), ensemble empirical mode decomposition (Chang, 2006) and on the evaluation of higher-order statistics at different wavelet bands (Sharma et al., 2010) can also be used for the same applications. However, they cannot achieve results in real time and will not be involved in this paper.

Commonly used ANCs basically require two inputs: primary input and reference input. For an ANC to be feasible, the reference input must be correlated with the

*Corresponding author. E-mail: chchnag@asia.edu.tw. Tel: +886 4 2332 3456 Ext: 20033. Fax: +886 4 2332 0718.

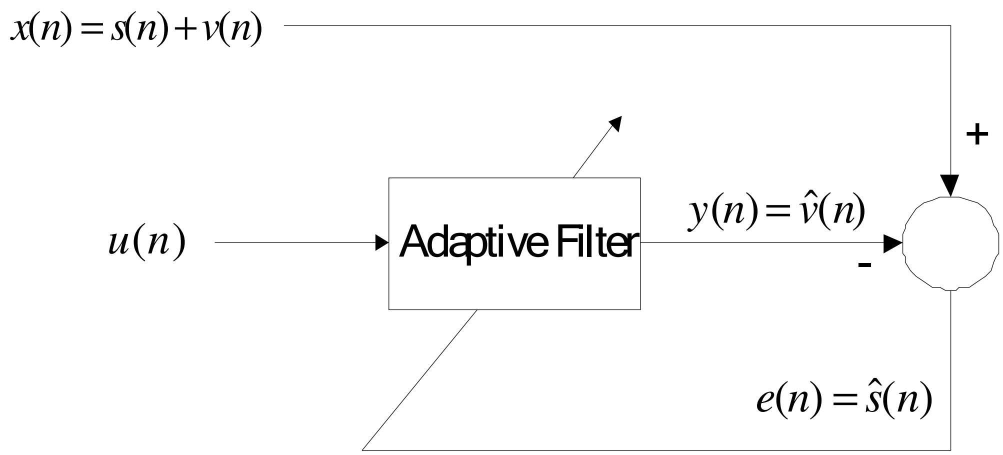

Figure 1. General model of ANC with reference input.

noise part of the primary input in order to cancel the noise therein. However, there are cases in which commonly used ANCs are limited in use. For example, if off-line processing of ECG recordings is required, the recordings themselves are the only data available for processing. Moreover, in the case when reference input cannot be well-correlated with the noise part of the primary input, ANC cannot perform well as the case with a well-correlated reference input. In such cases, alternative approaches other than an ANC must be pursued.

The aim of this paper is to provide a solution for the cases mentioned earlier. Random noises generally encountered in ECG recordings, include power-line interference, EMG noise and instrumentation noise. Due to the fact that ECG signals can be treated as quasi-periodic signals relative to the additive random noises, SIANC can be a useful alternative for removing the random noises under limited availability of reference input. Computer simulation results confirmed the assertion we made in this paper.

METHODOLOGY

Here, commonly used ANC is firstly introduced with an underscore of its possible issue on the availability of reference input and then, how and why the SIANC can be effective is described.

ANC with reference input

The commonly used ANC is as shown in Figure 1. Two inputs are required in this structure: the primary input and reference input, and the primary input is denoted the as:

$$x(n) = s(n) + v(n) \tag{1}$$

where $s(n)$ is the signal and $v(n)$ is the noise. In our case, $s(n)$ is the clean ECG signal and $v(n)$ is the random noise. Consequently, the adaptive filter has the task to estimate the noise, that is, $y(n) = \hat{v}(n)$. Under this condition, the error signal becomes:

$$e(n) = x(n) - y(n) = s(n) + v(n) - \hat{v}(n) \approx s(n) \tag{2}$$

That is, the clean ECG signals to be estimated.

Possible issue in ANC with reference input

Equation 2 works only when the reference input is well-correlated with the noise part of the primary input, that is, $v(n)$. To achieve this goal, a lead need to be placed somewhere from which the correlation in between is maximum. This could be a problem, because to have such a reference input may not be an easy task. The reason why this may happen is at least twofold. First, the component picked up by the lead for the reference input may correlate in some extent to the signal besides the noise. Second, the path connecting the component picked up by the sensor to the reference input may cause distortion. As such, in reality, it could be difficult to have a reference input that is well-correlated with the noise part, while the signal part remains uncorrelated. This tells that the ANC may degrade its performance under limited availability of the reference input. Figure 2 depicts the ANC with limited availability on the reference input represented by a filter denoted by $L(z)$. Hence, the input to the adaptive filter may not be well-correlated with the noise part of the primary input and hence, a good cancellation described by Equation 2 may not be possible.

Single-input adaptive noise canceller (SIANC)

For inputs comprising distinct components, an ANC can be configured as a SIANC with delays inserted in the path of reference input or in the path of primary input (Widrow et al., 1975). Figure 3 shows the two configurations of SIANC. The block is denoted as z^{-D}, with D being the number of delays in samples, making the random noises in $x(n)$ and $x(n-D)$ uncorrelated while their signal components remained correlated. The adaptive filter in Figure 3a tries to estimate the periodic components that existed in

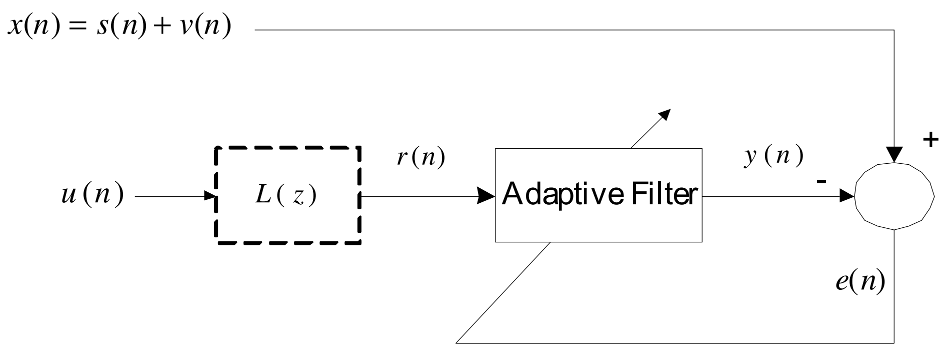

Figure 2. ANC with limited availability on the reference input.

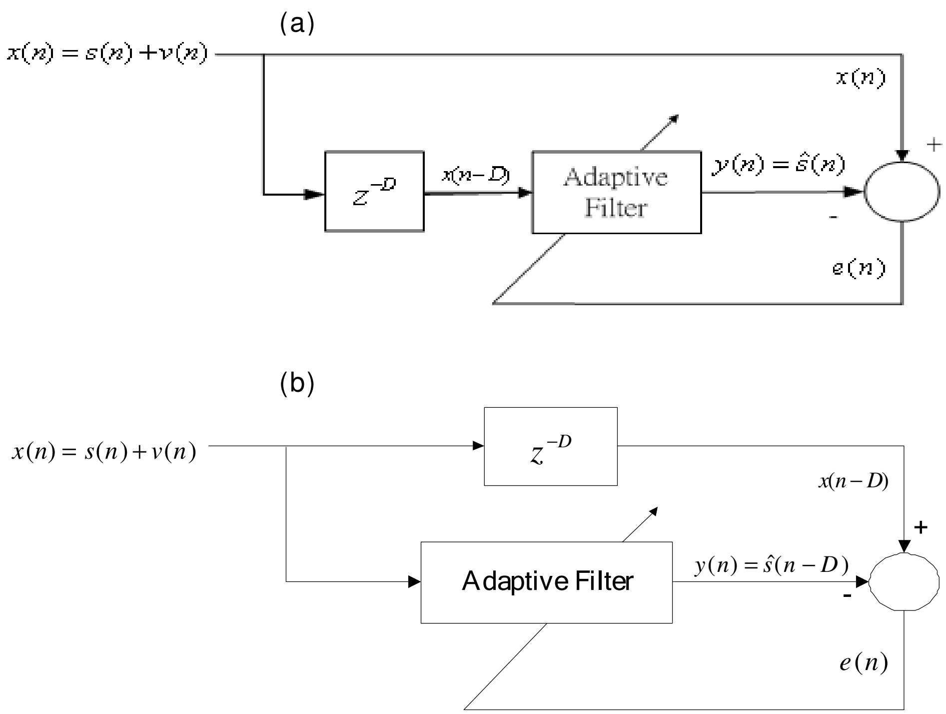

Figure 3. SIANC with delays inserted in the paths of (a) reference input and (b) primary input.

$x(n)$, that is, $s(n)$, while that in Figure 3b tries to estimate $x(n-D)$, that is, $s(n-D)$. Accordingly, the outputs from the adaptive filters will be the estimates of the clean ECG signals.

Care must be taken in using the two configurations shown in Figure 3. *M* is denoted as the length of the adaptive filters. The relations between *M* and *D* should be $M < D$ for Figure 3a, while $M > D$ for Figure 3b. Otherwise, the adaptive filters may cancel both components in the primary input (Widrow et al., 1975).

Learning algorithm

Typical least mean square (LMS) algorithm is employed for updating the tap-weights of the adaptive filters. For example, in Figure 3a, the adaptive filter output is of the form:

$$y(n) = \sum_{k=0}^{M-1} w_k(n)x(n-D-k) \tag{3}$$

where *M* is the number of taps of the adaptive filter. The error signal $e(n)$ is:

$$e(n) = x(n) - y(n) \tag{4}$$

The tap-weights of the adaptive filter is updated according to the rule:

$$w_k(n+1) = w_k(n) + \mu e(n)x(n-D-k), \quad k = 0, 1, \cdots, M-1 \tag{5}$$

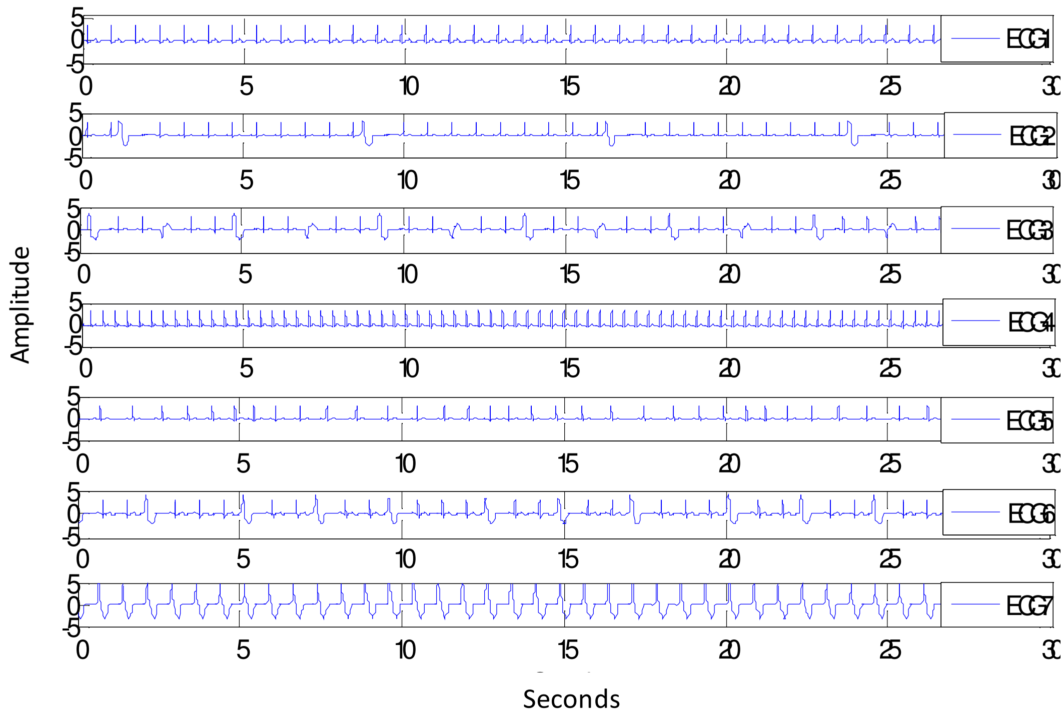

Figure 4. Seven ECG signals with ECG1: normal ECG and ECG2-ECG7: arrhythmia ECGs.

where μ is the step size controlling the speed of convergence. After completing the learning, the error signal becomes:

$$e(n) = x(n) - y(n) = s(n) + v(n) - \hat{s}(n) \approx v(n) \qquad (6)$$

That is, the random noises should be removed.

RESULTS

Simulated normal and arrhythmia ECGs derived from an ECG simulator (type number BC Biomedical PS-2210 Patient Simulator) with 60 s duration are used in this study. Figure 4 shows the seven ECGs with ECG1 being the normal one and from ECG2 to ECG7 being the six arrhythmia ones (Chang, 2010).

The EMG noise has the model of a random variable with normal distribution. The maximum noise level is predetermined as an amplitude ratio with respect to V_{pp}, the peak-to-peak voltage of the normal ECG. The maximum EMG noise level is then produced by scaling the random sequence with a predefined percentage and the multiplication to V_{pp} is a ratio of 1/8 (Chang, 2010). The clean ECGs shown in Figure 4 are obtained with a sampling rate of1,000 samples/s, which are then corrupted with a 50% EMG noise to produce the noisy ECGs. To have reference input with limited availability for the simulation of the ANC, the filter $L(z)$ as indicated in Figure 2 is chosen to be:

$$L(z) = \tfrac{1}{N}(1 + z^{-1} + \cdots + z^{-N+1}) \qquad (7)$$

where N is the length of the filter. The first-null bandwidth of the filter is f_s / N Hz with f_s being the sampling frequency of the signal. We define the mean-square error (MSE) between the clean ECG and the filtered ECG as follows:

$$\mathrm{MSE} = \frac{1}{m}\sum_{n=1}^{m}\{s(n) - e(n)\}^2 \quad \text{for ANC} \qquad (8)$$

$$\mathrm{MSE} = \frac{1}{m}\sum_{n=1}^{m}\{s(n) - y(n)\}^2 \quad \text{for SIANC with delays in the reference} \qquad (9)$$

and

$$\mathrm{MSE} = \frac{1}{m}\sum_{n=1+D}^{m+D}\{s(n-D) - y(n)\}^2 \quad \text{for SIANC with delays in the primary} \qquad (10)$$

where m is the number of samples within the segment where adaptive filters converged. Table 1 compares the MSE (in dB) achieved by two configurations of SIANCs

Table 1. Mean-square error (MSE) comparison for different ECG signals.

ECG	MSE (dB)				
	ANC with reference well-correlated with the noise in the primary input	ANC with reference distorted by a LPF with first-null bandwidth of 200 Hz	ANC with reference distorted by a LPF with first-null bandwidth of 100 Hz	SIANC with delays in primary input	SIANC with delays in reference input
ECG1	-28.30	-21.30	-21.06	-28.37	-16.57
ECG2	-27.81	-20.88	-21.09	-27.89	-15.42
ECG3	-26.53	-21.21	-20.26	-28.72	-10.16
ECG4	-28.05	-20.69	-21.06	-28.15	-14.23
ECG5	-31.03	-21.38	-21.15	-27.86	-14.22
ECG6	-26.83	-20.80	-20.35	-27.77	-9.60
ECG7	-29.05	-20.16	-18.83	-27.55	-14.29

Table 2. Mean-square error (MSE) comparison for different *M*'s.

M	MSE (dB)				
	Reference well-correlated with the noise in the primary input	Reference distorted by a LPF with first-null bandwidth at 200 Hz	Reference distorted by a LPF with first-null bandwidth at 100 Hz	SIANC with delays in primary input	SIANC with delays in reference input
20	-30.01	-22.08	-20.99	-22.60	-14.89
30	-30.18	-22.18	-20.80	-28.25	-14.99
40	-30.69	-22.35	-20.93	-28.19	-16.68
50	-29.60	-22.45	-20.96	-28.11	-22.77
60	-30.43	-22.08	-20.78	-28.53	-27.84
70	-29.84	-22.05	-20.78	-28.28	-27.88
80	-29.32	-21.75	-20.72	-28.37	-28.25

with the ANC with well-correlated reference input and those with reference inputs distorted by the filter represented by Equation 7 with different *N*s. One distorted reference input is produced by using $N=5$, which is the output of the filter with first-null bandwidth of $1{,}000/5=200$ Hz. The other is produced by using $N=10$, which is the output of the filter with first-null bandwidth of $1{,}000/10=100$ Hz. Other parameters chosen are: $M=40$ and $\mu=0.01$ for the ANC; $M=40$ and $\mu=0.00005$ for SIANC. In addition, $D=700$ is chosen for the SIANC with delays in the reference input, and $D=20$ is chosen for that with delays in the primary input. All of these parameters were obtained by trial and error. The results indicate that the SIANC with delays in the primary input performs quite the same as ANC with well-correlated reference input and equally well for all types of the ECGs. However, this is not the case for the SIANC with delays in the reference input. It is obviously seen that the performance of ANC is highly dependent on the availability of the reference input. The case using bandwidth of 100 Hz performs worse than that using 200 Hz. Table 2 extends similar comparison for all structures using different *M*s. Again, it is seen that the SIANC with delays in the primary input, performs closely to ANC with well-correlated reference input provided that *M* is large enough. The results show that the SIANC with delays in the primary input achieves almost the same result for $M \geq 30$. However, this is not the case for that with delays in the reference input. In this case, $M \geq 60$ is required under the delay chosen. Note that for the SIANC with delays in the primary input, the case of $M=20$ cannot perform well. This is because the value of *M* must be greater than *D* (Widrow et al., 1975). It is suggested that the one using SIANC with delays in the primary input performs better than that with delays in the reference input due to the fact that much shorter *M* is adequate for the former.

Figure 5 compares the filtered results using the ANC under different availability of reference inputs with that using the SIANC. Only SIANC with delays in the primary input is performed in this comparison. Figure 5a shows the clean ECG and Figure 5b is the noisy one. Figure 5c shows that the filtered ECG using the ANC with well-correlated reference input achieved a very good result in. Figure 5d shows the output for the ANC with a poorly correlated reference input. The reference input is

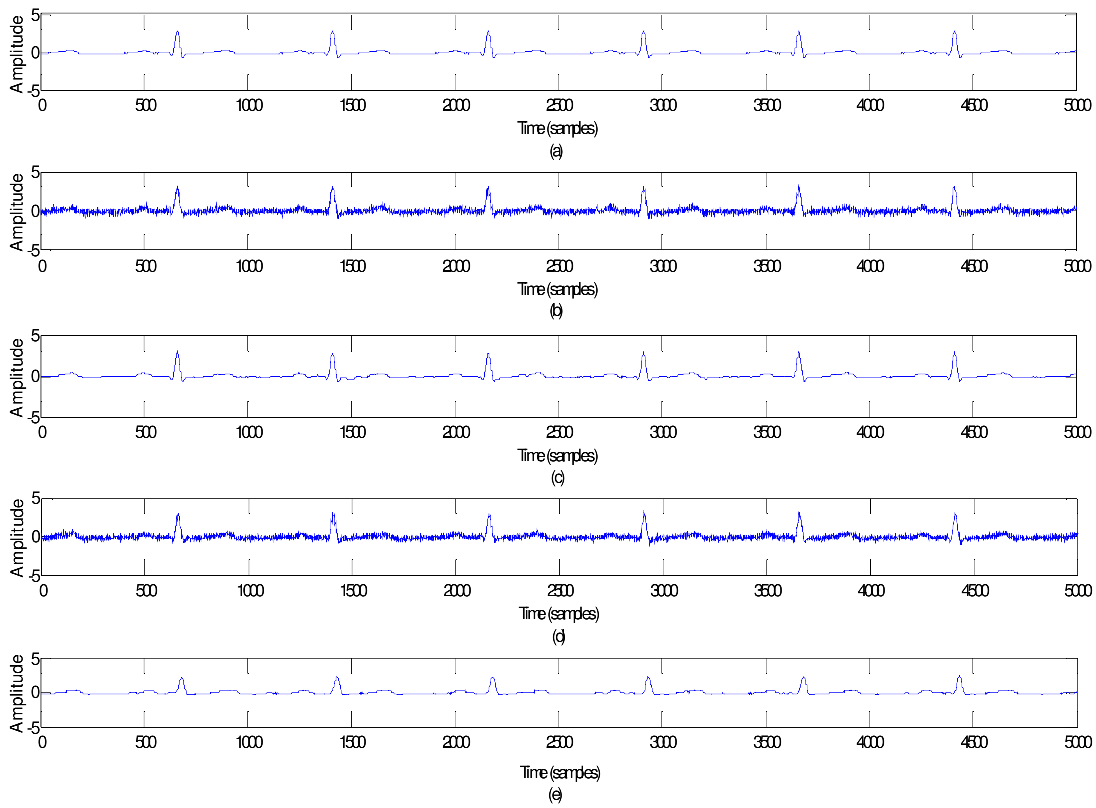

Figure 5. Comparison of ECG signals for (a) clean ECG, (b) ECG corrupted with 50% EMG noise, (c) filtered ECG by using ANC with well-correlated reference input, (d) filtered ECG by using ANC with poorly correlated reference input, and (e) filtered ECG by using SIANC.

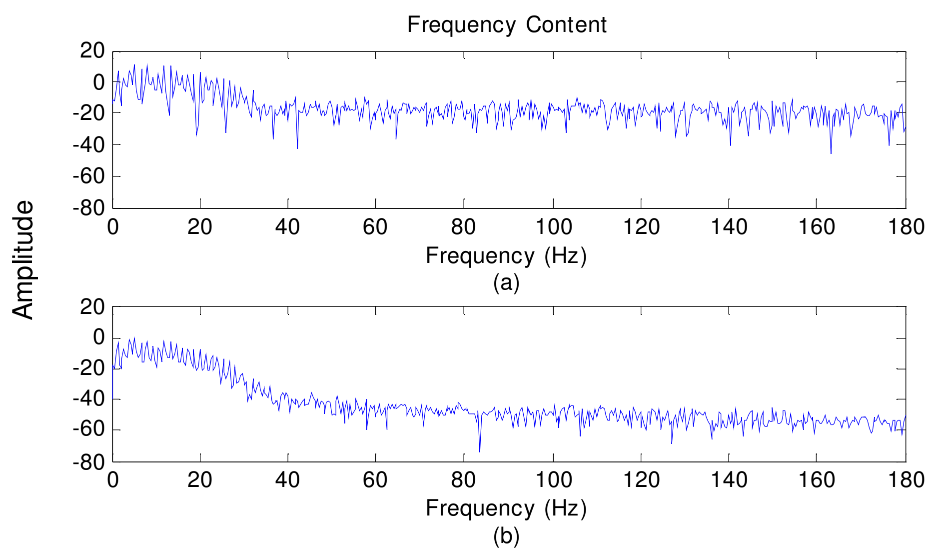

Figure 6. Power spectra for (a) an ECG with 50% EMG noise and (b) its corresponding filtered ECG.

produced by using Equation 7 with $N = 5$. It is obvious that the ANC cannot perform well in this case. Figure 5e shows the filtered ECG by using the SIANC. It is seen that the SIANC performs almost the same as that of the ANC with well-correlated reference input. Figure 6 shows the spectra for the noisy ECG and the filtered ECG.

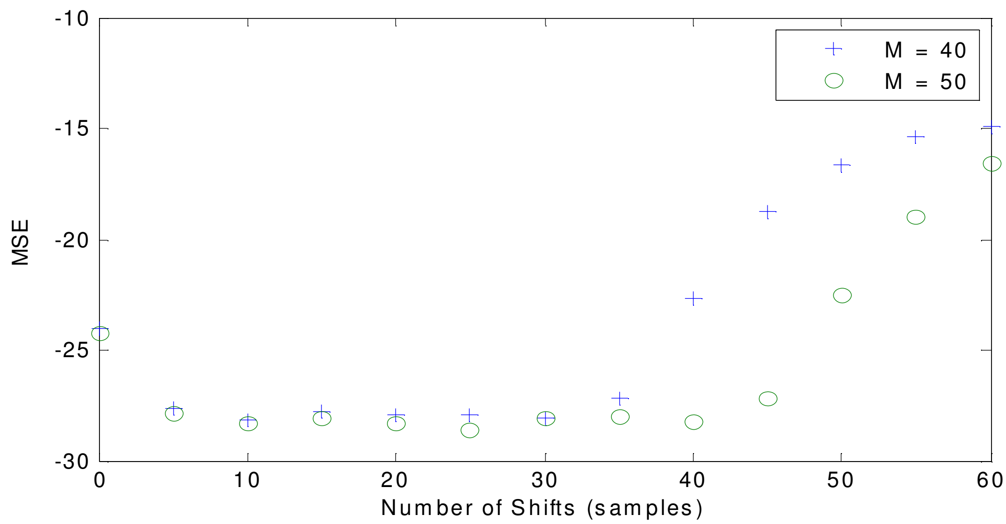

Figure 7. The effect of *D* on the MSE performance with different *M*'s.

Before processing, the difference of the power between low and high frequencies is about 14 dB as shown in Figure 6a. After processing, the difference increases to 33 dB as shown in Figure 6b. Finally, to see the effect of *D* on the MSE performance, two different values of *M*, $M = 40$ and $M = 50$, are chosen for comparison. It can be seen from Figure 7 that the performance becomes worse whenever $D > M$. Here, a simulated ECG corrupted with 50% EMG noise is used. The step size chosen is $\mu = 0.00005$.

Conclusion

The issue of using ANC with limited availability on the reference input is discussed and the use of SIANC is presented in this paper. Reference input not well-correlated with the noise part of the primary input may degrade the performance of the ANC. ECG signals can be treated as quasi-periodic signals as compared to the randomness nature of high-frequency noise. By shifting the noisy ECG signal in time, the noise component can become uncorrelated while the signal component still remains correlated. Thus, SIANC can be an alternative to ANC when the reference input is not available. Computer simulation results confirmed the effectiveness of the SIANC. Future works are needed to investigate the effect of the lack of availability on the commonly used ANCs for bioelectric signals other than ECG.

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