An Algorithm for Evaluating the Performance of Adaptive Filters for the Removal of Artifacts in ECG Signals

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***Abstract*—Filtering electrocardiogram (ECG) signals calls for a filter whose impulse response can be automatically adjusted according to the varying characteristics of the signal and artifacts. In order to eliminate effectively the artifacts in ECG signals, we propose the unbiased linear artificial neural network (ULANN) as a new type of adaptive filter. This paper compares the performance of the ULANN filter with the prevailing least-mean-squares (LMS) and recursive-least-squares (RLS) adaptive filters, for the removal of artifacts in noisy ECG signals. The measures of performance include the root-mean-squared error, a normalized correlation coefficient (*NCC*), and entropy. A template derived from each ECG signal is used as a reference to derive the measures. The *NCC* values for the ULANN, LMS, and RLS filter, averaged over 22 ECG signals, are 0.9956 ± 0.0022, 0.9948 ± 0.0020, and 0.9940 ± 0.0026, respectively. The results indicate that the ULANN filter provides filtered signals with the highest waveshape fidelity among the three filters studied.**

***Keywords*—Adaptive filters; ECG; Entropy; Correlation coefficient**

I. INTRODUCTION

The electrocardiogram (ECG) is the electrical manifestation of the contractile activity of the heart, and is the most commonly used biomedical signal for the detection of asymptomatic arrhythmia and diagnosis of cardiovascular diseases or abnormalities [1]. In clinical practice, ECG recordings commonly contain concomitant artifacts, including baseline drift, power-line interference, and high-frequency random noise. The stage of artifact removal is crucial in ECG monitoring systems, and fundamental for many other ECG processing applications [2]. Unfortunately, most conventional approaches suffer from drawbacks of unreliability in dealing with ambiguous patterns derived from noisy signals. Artificial neural networks (ANNs), with the properties of experience-based learning and fault tolerance, are considered to be promising for the analysis of ECG signals. Recently, ANN techniques have been exploited for the detection of QRS complexes [3] and classification of myocardial ischemia [4].

In a companion paper [5], we proposed an unbiased linear artificial neural network (ULANN) for the removal of artifacts in ECG signals. This paper evaluates the performance of the proposed adaptive filtering method. The results of the ULANN filter are compared with those of the least-mean-squares (LMS) and recursive-least-squares (RLS) adaptive filters [6].

The subsequent parts of this paper are structured as follows. Section II provides brief descriptions of the procedures of adaptive ECG filtering, along with details of the proposed quantitative measures of performance. Section III presents empirical results of evaluation the adaptive ECG filters.

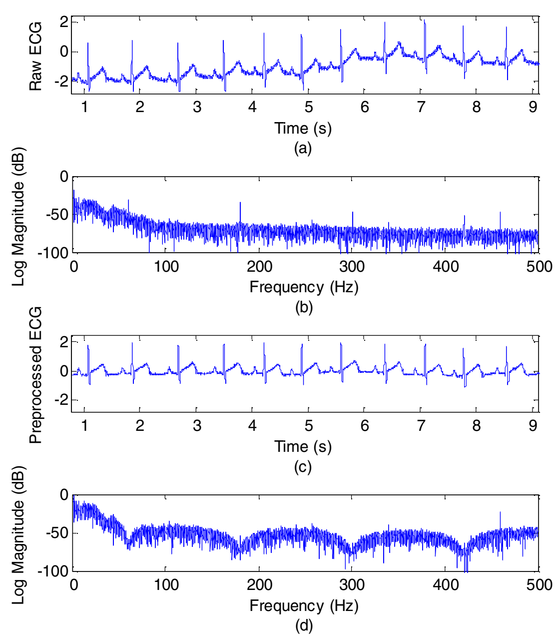

Figure 1. Illustration of the effect of combination of the derivative-based and comb filters with an ECG signal (No. 14 from the database). (a) Original signal. (b) Power spectrum of the signal. (c) Output of the combination of the derivative-based and comb filters. (d) Power spectrum of the output of the combination of the derivative-based and comb filters.

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Section IV provides a discussion on the limitations of signal templates for adaptive filtering of ECG signals, in relation to the scheme of adaptive noise cancellation. Section V concludes the paper with a summary of the merits of the proposed ULANN filter and comments on future work.

II. Implementation of Adaptive Filtering and Performance Evaluation Methods

The ECG data used in our experiments are 22 records of lead II noisy ECG signals recorded from a total of 11 subjects (seven females and four males, aged 4 to 29 years, including two normal subjects and nine patients with suspected cardiovascular abnormalities causing murmurs), sampled at 1000 *Hz* [7]. In the ECG signal preprocessing step before adaptive filtering, a first-order difference operator is applied to cancel baseline wander without distorting the QRS complexes in the ECG signal. A comb filter is used to eliminate the fundamental 60 *Hz* and higher-order harmonics (at 180, 300, and 420 *Hz*) present in artifacts due to power-line interference. The QRS complexes in the ECG signal are detected using a computationally efficient method designed by combining a smoothed derivative-based filter, a threshold operator, and a peak-searching approach. In order to set up a signal template, the P-T intervals (with the duration of 520 ms each) within the cardiac cycles of the ECG signal are segmented. The P-T segments are smoothed by using a Butterworth lowpass filter (-3 dB cutoff at 75 *Hz*), and used as the reference input for the corresponding cardiac cycles. The ULANN filter does not contain a bias in its summation unit, and the coefficients are normalized. During the learning process, the normalized coefficients are updated by the steepest-descent algorithm so as to achieve adaptive ECG filtering (see Wu and Rangayyan [5], Section II). To rebuild the output channel, the filtered cardiac signals are synchronously placed on the isoelectric line in accordance with their QRS location references.

A sample output of the combination of the derivative-based and comb filters for an ECG signal (No. 14), with baseline drift and power-line interference that are clearly visible, is shown in Fig. 1. It is clear that the baseline drift and power-line interference seen in Fig. 1 (a) and (b) have been effectively eliminated, as shown in Fig. 1 (c) and (d). The rebuilt filter outputs of an ECG signal (No. 4) are shown in Fig. 2 (d)-(f), along with the raw signal (a), preprocessed signal (b), and rebuilt template signal (c). For a quantitative study of the

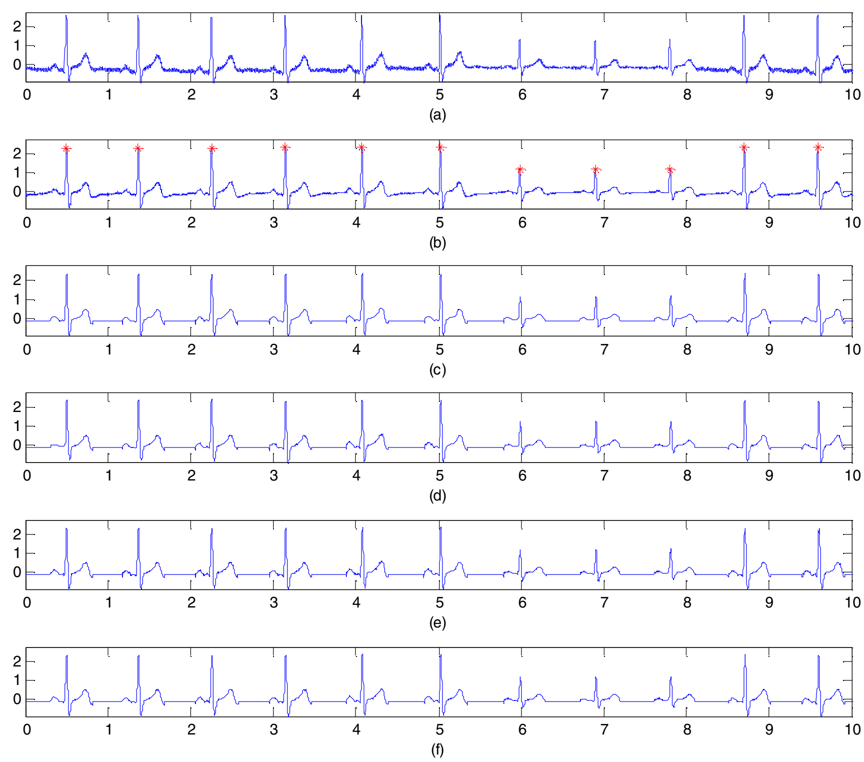

Figure 2. Illustration of the filtering steps with an ECG (No. 4 from the database). (a) Original signal. (b) Output of the combination of the first-order derivative-based and comb filters (with the detected locations of QRS complexes marked). (c) Rebuilt template signal. (d) Rebuilt output of the LMS filter. (e) Rebuilt output of the RLS filter. (f) Rebuilt output of the ULANN filter. The abscissa is marked in seconds, and the ordinate is not calibrated.

performance of the adaptive filters, the evaluation criteria utilized are as follows.

A. Root-Mean-Squared Error

The average magnitude of the noise remaining in the output of each filter is measured by the root-mean-squared error (*RMSE*) as

$$RMSE = \frac{1}{N_B}\sum\nolimits_{N_B}\sqrt{\frac{1}{N_S}\sum\nolimits_{n=1}^{N_S}[d(n)-s(n)]^2}\ , \tag{1}$$

where $s(n)$ is the filter output, $d(n)$ is the template, N_B denotes the number of cardiac cycles analyzed, and N_S represents the number of samples included in each P-T segment.

B. Normalized Correlation Coefficient

The normalized correlation coefficient (*NCC*) is the most popular measure of association in time-series prediction [8]. In our experiments, *NCC* is used to characterize the similarity between filtered signals and the corresponding templates, as

$$NCC = \frac{1}{N_B}\sum\nolimits_{N_B}\left[\frac{\sum\nolimits_{n=1}^{N_S}s(n)d(n)}{\sqrt{\sum\nolimits_{n=1}^{N_S}s^2(n)\sum\nolimits_{n=1}^{N_S}d^2(n)}}\right]. \tag{2}$$

C. Filtered Noise Entropy

Shannon's entropy [9] of the first-order difference residual signal (original cardiac beat signal subtracted from an average beat or template) was used by Hamilton and Tompkins [10] for ECG data compression. In our investigation, Shannon's entropy is used to characterize the nature of the noise $m(n)$ removed by the adaptive filter, i.e.,

$$m(n) = x(n) - s(n)\ , \tag{3}$$

where $x(n)$ represents the input signal. The probability density function of the noise removed can be estimated by calculating the frequencies of occurrence P_{bin} for various bins (20 bins used in our experiments). The entropy of the filtered noise (*FNE*) is then defined as

$$FNE = -\sum_{\text{for all } bins} P_{bin}\log_2 P_{bin}\ . \tag{4}$$

III. Results of Evaluation of the Filters

The empirical results of evaluation of the proposed ULANN filter, along with those for the LMS and RLS filters, are tabulated in Table I. It is worth noting that the ULANN filter produces a larger *RMSE* only for five of the 22 signals as compared with either the LMS or RLS filter. The ULANN filter provides the highest fidelity in terms of *NCC* for 17 signals, among the three filters studied. Concerning the noise removed, as indicated by *FNE*, the ULANN filter outperforms the LMS and RLS filters for 19 and 16 signals, respectively. Box plots of the *RMSE* and *NCC* measures are depicted in Fig. 3. It can be observed that the ULANN adaptive filter performs better, with respect to prediction accuracy and fidelity, than the LMS and RLS filters, with statistical significance. Similar statistical analysis of *FNE* is not appropriate, because the sources of noise are multifarious and not comparable.

TABLE I Results of Evaluation of the Adaptive Filters

ECG		Root-Mean-Squared Error (*RMSE*)			Normalized Correlation Coefficient (*NCC*)			Filtered Noise Entropy (*FNE*)		
No.*	**Cardiac beats analyzed**	**LMS**	**RLS**	**ULANN**	**LMS**	**RLS**	**ULANN**	**LMS**	**RLS**	**ULANN**
1	20	0.0269	0.0307	0.0278	0.9963	0.9951	0.9965	2.5932	2.5832	2.5856
2	17	0.0379	0.0317	0.0315	0.9951	0.9956	0.9966	2.5407	2.5924	2.5943
3	22	0.0391	0.0376	0.0340	0.9933	0.9932	0.9942	2.6958	2.6809	2.7177
4	21	0.0317	0.0365	0.0310	0.9943	0.9908	0.9941	2.3934	2.3835	2.4240
5	19	0.0322	0.0275	0.0282	0.9951	0.9960	0.9962	2.3102	2.2962	2.2338
6	24	0.0319	0.0303	0.0257	0.9952	0.9952	0.9966	2.0290	2.0461	2.0311
8	22	0.0353	0.0267	0.0225	0.9952	0.9965	0.9973	2.0888	2.0851	2.1013
9	21	0.0309	0.0478	0.0231	0.9969	0.9926	0.9982	2.3242	2.3559	2.3497
10	21	0.0316	0.0455	0.0274	0.9970	0.9938	0.9975	2.5296	2.5241	2.5111
11	21	0.0317	0.0333	0.0207	0.9965	0.9964	0.9985	2.3031	2.3420	2.3478
12	21	0.0395	0.0389	0.0529	0.9939	0.9937	0.9884	2.7794	2.7392	2.8521
13	17	0.0446	0.0469	0.0320	0.9890	0.9874	0.9941	2.8065	2.8076	2.8627
14	14	0.0294	0.0307	0.0410	0.9966	0.9967	0.9933	2.9917	2.9902	3.0243
15	33	0.0413	0.0517	0.0449	0.9969	0.9934	0.9957	2.6324	2.6330	2.6618
16	33	0.0502	0.0388	0.0398	0.9953	0.9969	0.9969	2.5408	2.5747	2.5978
17	24	0.0618	0.0492	0.0640	0.9945	0.9959	0.9930	2.7907	2.7755	2.7999
18	26	0.0339	0.0429	0.0306	0.9967	0.9944	0.9973	2.4622	2.4786	2.4218
19	24	0.0349	0.0439	0.0252	0.9912	0.9879	0.9955	2.1742	2.1531	2.1760
20	25	0.0336	0.0363	0.0250	0.9955	0.9942	0.9961	2.0926	2.0902	2.1210
21	18	0.0450	0.0389	0.0307	0.9936	0.9958	0.9965	2.6482	2.6483	2.6655
22	17	0.0392	0.0401	0.0316	0.9947	0.9935	0.9961	2.7671	2.7339	2.8174
23	5	0.0497	0.0493	0.0466	0.9934	0.9941	0.9942	3.4191	3.4242	3.4201

*. The No. 7 raw ECG signal does not exist in the database used.

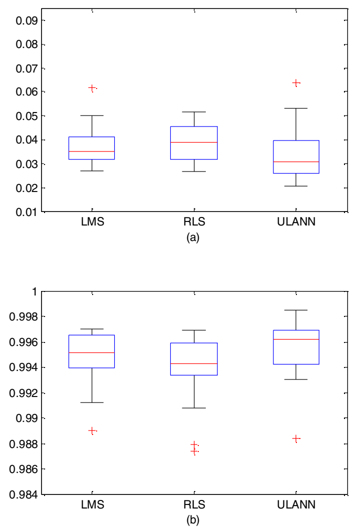

Figure 3. Box plots of (a) *RMSE* and (b) *NCC* for the three adaptive filters studied. The "+" signs indicate the outliers exceeding the range of the corresponding box by more than 1.5 times its inter-quartile range.

IV. Discussion

A. Fixed versus Variable Templates

One of the strategies to generate the reference input for adaptive filtering is to create an unaltered signal template that could be obtained by averaging several initial cardiac beat segments. Such a scheme is simple, and causes some pitfalls. First, the unaltered signal template being repeated from cardiac cycle to cycle would enhance the stationary characteristics of the reference input, which might cause the adaptive filter to behave somewhat similarly to a fixed filter. Second, the fixed signal template would be inappropriate if the ECG signal includes ectopic beats, e.g., premature ventricular contractions.

The use of a variable or adaptive signal template is one of a few possible solutions: the signal template is updated for each cardiac cycle, as implemented in our experiments. One possible strategy is to utilize the preceding filtered signal as the template for the upcoming heart beat. However, a normal cardiac beat template will not be suitable for ectopic beats. To overcome this limitation, we applied a Butterworth lowpass filter to generate a smoothed signal template, with the cost of a delay of one heart beat.

B. Signal Template or Noise Reference for Adaptive Filters

Although a variable signal template is able to increase the prediction accuracy of the adaptive filter, this scheme only deals with the current beat, rather than effectively acquiring statistical knowledge from the entire available history of the signal. One promising solution is to use noise as the reference input, and to convert the filter to be an adaptive noise canceller instead of a signal predictor. The principle behind such a filter is that the primary noise is not correlated with the signal of interest. Regardless of the changes in the ECG signal, the primary noise is commonly assumed to be a random variable with zero mean. Thus, the use of a noise reference input is more flexible than the approach of using a signal template. The primary noise estimated from the previous cardiac beat can be utilized to filter the upcoming beat, regardless of whether it is a normal or ectopic beat. An adaptive noise canceller may not need the procedures of QRS detection and P-T interval segmentation, because the source of the reference input is now shifted to the primary noise, not the ECG signal.

V. Conclusion

The proposed ULANN filter has improved prediction accuracy, resulting in high fidelity of waveshape, and the removal of random noise more effectively than the LMS and RLS filters. The strategy of a variable signal template has been successfully implemented in this investigation, although this approach requires a high level of computational complexity for QRS detection and P-T interval segmentation. Future work would be directed toward a study of adaptive noise cancellation based on the ULANN for both normal and arrhythmic ECGs.

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