An Unbiased Linear Artificial Neural Network with Normalized Adaptive Coefficients for Filtering Noisy ECG Signals

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***Abstract*—The electrocardiogram (ECG) is the most commonly used signal for diagnostic purposes in medicine. The adaptive filtering technique is suited for filtering ECG signals, which are inherently nonstationary. In this paper, we propose a novel neural-network-based adaptive filter to eliminate high-frequency random noise in ECG signals. We make use of a linear artificial neural network (ANN) with delayed values of the ECG time series as the filter inputs. The ANN does not contain a bias in its summation unit, and the coefficients are normalized. During the learning process, the normalized coefficients are used in the steepest-descent algorithm in order to achieve efficient online filtering of noisy ECG signals.**

Keywords—Artificial neural networks; Adaptive filters; ECG

I. INTRODUCTION

Computerized electrocardiography is a well-established practice. However, surface recording of the electrocardiogram (ECG) by placing electrodes on the subject's skin is susceptible to several different types of artifacts and noise. Commonly encountered artifacts include physiological signals generated by other organs or muscles of the body, and external interference from electronic medical devices, lights, or machines. Effective noise cancellation in the ECG is essential before further processing in applications such as beat classification, fetal ECG signal extraction from the maternal abdominal ECG, and the detection of cardiovascular abnormalities [1], [2].

The fundamental principles of adaptive filtering have been described by Widrow *et al.* [3]. The literature shows that many adaptive filtering methods have been effectively applied in diverse practical applications. Xue *et al.* [4] developed adaptive whitening and matched filters based on artificial neural networks (ANNs) to detect QRS complexes in ECG signals. Thakor and Zhu [5] proposed an adaptive recurrent filter to acquire the impulse response of the normal QRS complex, and applied it for arrhythmia detection in ambulatory ECG. Hamilton [6] compared adaptive and nonadaptive 60 *Hz* notch filters for reduction of power-line noise and ECG data compression. Sameni *et al.* [7] utilized an extended Kalman filter to extract the ECG from corrupted signals.

Although several filter structures have been proposed in the literature, many are inconvenient to use by physicians or engineers in practical applications, due to the requirement to set various parameters at appropriate values. The aim of this paper is to propose a normalized adaptive filter based upon an Unbiased Linear Artificial Neural Network (ULANN) to reduce high-frequency random noise in ECG signals.

The remaining parts of this paper are organized as follows. Section II presents the structure of the ULANN, together with the algorithm for updating the normalized filter coefficients. Section III provides a description of the signal preprocessing steps and the signal template model. Section IV presents the results of the ULANN filter in relation to those provided by the popular least-mean-square (LMS) and recursive-least-squares (RLS) filters [8]. Section V concludes the paper with discussion and directions for future work.

II. UNBIASED LINEAR ARTIFICIAL NEURAL NETWORK (ULANN) WITH NORMALIZED FILTER COEFFICIENTS

The structure of the ULANN filter is illustrated in Fig. 1. The ULANN filter is a transversal, linear, finite impulse response (FIR) filter, whose output is the convolution of the input signal $x(n)$ with the filter coefficients $w_m(n)$:

$$s(n) = \sum_{m=1}^{M} w_m(n)x(n-m+1) , \tag{1}$$

where $s(n)$ is an estimate of the reference signal $d(n)$ that is available from the template model. The primary difference compared with the LMS filter is that the ULANN filter does not contain a constant bias and the corresponding coefficient assigned for the same. The filter transfer function is given according to the time-domain input-output relationship as

$$H(z) = \sum_{m=1}^{M} w_m z^{-m+1} . \tag{2}$$

In order to obtain unit gain at DC, the FIR filter coefficients should meet the requirement given by

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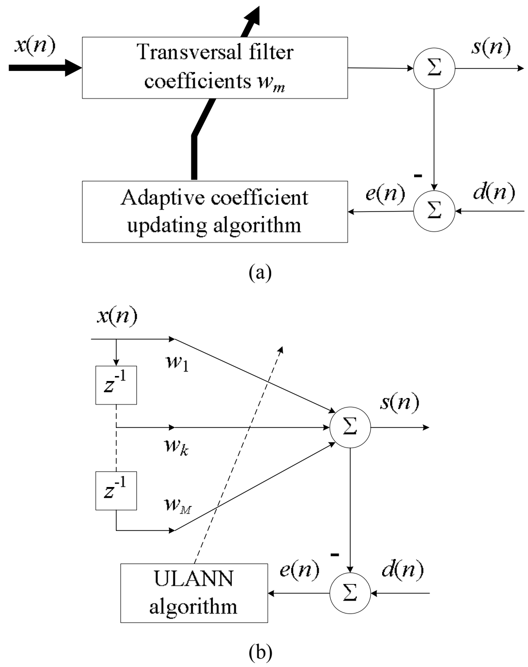

Figure 1. (a) Block diagram of the adaptive transversal filter. (b) Detailed structure of the ULANN adaptive filter.

$$\sum_{m=1}^{M} w_m = 1 . \tag{3}$$

By comparing the estimated signal with the reference input, we can produce the instantaneous error $e(n)$, i.e.,

$$e(n) = d(n) - s(n) = d(n) - \sum_{m=1}^{M} w_m(n)x(n-m+1) . \tag{4}$$

The ULANN filter is optimized by using the steepest-descent algorithm, which is considered to be a deterministic search method in the multidimensional filter-coefficient space. The convergence of the squared instantaneous error follows a distinct path provided by the corresponding negative gradient with respect to the filter coefficients, i.e.,

$$\begin{aligned} -\nabla_{w_m} e^2(n) &= -\frac{\partial}{\partial w_m}\left[d(n) - \sum_{m=1}^{M} w_m(n)x(n-m+1)\right]^2 \\ &= 2x(n-m+1)\left[d(n) - \sum_{m=1}^{M} w_k(n)x(n-k+1)\right]. \end{aligned} \tag{5}$$

By substituting (3) and (5) into the steepest-descent adaptation rule [8], we have the ULANN filter coefficients updated as

$$\begin{aligned} \hat{w}_m(n+1) &= \hat{w}_m(n) + \mu\left[\nabla_{w_m} e^2(n)\right] \\ &= \hat{w}_m(n) + 2\mu x(n-m+1)\left[d(n) - \sum_{k=1}^{M} \hat{w}_k(n)x(n-k+1)\right] \\ &= \hat{w}_m(n) + 2\mu x(n-m+1)\sum_{k=1}^{M} \hat{w}_k(n)\left[d(n) - x(n-k+1)\right], \end{aligned} \tag{6}$$

where μ represents the learning rate (typically $0 < \mu < 1$) that indicates the search magnitude in the negative gradient direction.

In each iteration of updating the filter coefficients, the filter coefficients should be modified so as to follow the requirement of (3), with the normalization

$$w_m(n+1) = \frac{\hat{w}_m(n+1)}{\sum_{m=1}^{M} \hat{w}_m(n+1)}, \tag{7}$$

where $\hat{w}_m(n+1)$ is the estimated coefficient value after the coefficient adaptation process.

III. Implementation of Signal Preprocessing and Adaptive Filtering Procedures

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* [9]. Fig. 2 (a) gives an example of an original signal. The complete implementation of the filtering procedures contains a signal preprocessing procedure which prepares the original signals for the appropriate inputs and templates for adaptive filtering. The procedures are presented, step-by-step, in the following subsections.

A. Derivative-based Highpass Filter

The first-order difference operator is used in the form of an infinite impulse response (IIR) filter to eliminate low-frequency baseline wander in the ECG signal, with the transfer function

$$H_1(z) = f_s\left[\frac{1-z^{-1}}{1-0.995z^{-1}}\right] \tag{8}$$

where f_s denotes the sampling frequency [1]. The zero at $z = 1$ is to reject the DC component. A pole is set at $z = 0.995$ so as to make the gain of the filter increase rapidly after DC. The magnitude response is commonly normalized so as to provide unit gain for frequencies greater than about 1 *Hz*. In our experiment, this highpass filter was used to remove baseline drift with no significant distortion of the QRS complexes in the ECG signals.

B. Comb Filter

Undesired components at 60 *Hz* and its harmonics are usually present in ECG signals as periodic artifacts due to power-line interference. In order to attenuate such periodic interference, we applied a comb filter with the transfer function [1]

$$\begin{aligned} H_2(z) &= 0.6312(1-1.8596z^{-1}+z^{-2})(1-0.8516z^{-1}+z^{-2}) \\ &\quad \times(1+0.6180z^{-1}+z^{-2})(1+1.7526z^{-1}+z^{-2}) \\ &= 0.6312 - 0.2150z^{-1} + 0.1512z^{-2} - 0.1288z^{-3} + 0.1228z^{-4} \\ &\quad -0.1288z^{-5} + 0.1512z^{-6} - 0.2150z^{-7} + 0.6312z^{-8}. \end{aligned} \tag{9}$$

The filter has zeros at 60, 180, 300, and 420 *Hz*, with the sampling rate at 1000 *Hz*. The coefficients were multiplied by the factor 0.6312 so that the filter has unit gain at DC.

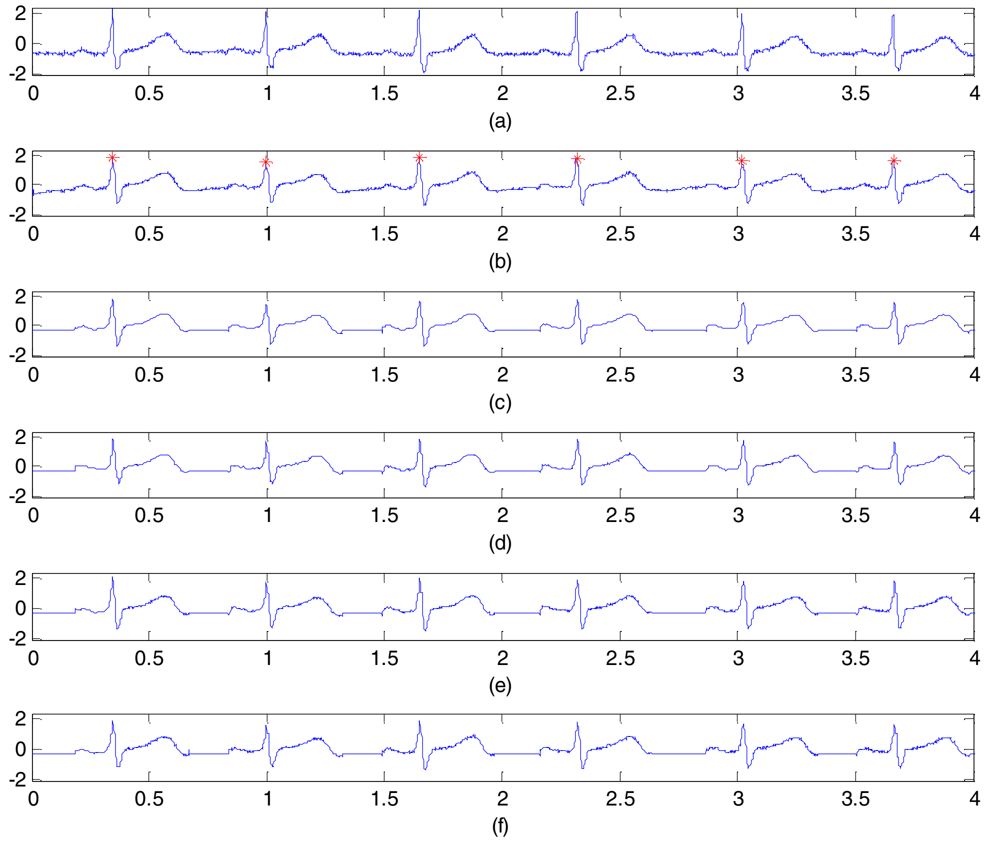

Figure 2. Illustration of the filtering steps with an ECG (No. 23 from the database). (a) Original signal. (b) Output of the combination of the first-order derivative-based and comb filters (with the detected locations of QRS complexes marked). (c) Rebuilt template signal. (d) Rebuilt output of the LMS filter. (e) Rebuilt output of the RLS filter. (f) Rebuilt output of the ULANN filter. The abscissa is marked in seconds.

C. *QRS Detection*

The QRS complex provides pivotal information for the analysis of ECG signals [10], and is frequently used as a real-time trigger for multichannel physiological signal processing [11]. After each QRS complex in a given ECG signal has been identified, the heart rate may be calculated, the ST segment may be examined for evidence of ischemia or infarction, or the ECG waveform may be classified as normal or abnormal. For the detection of QRS complexes, we applied the method of Murthy and Rangaraj [12], which includes the squared first-derivative operator, a moving-average filter, a threshold operator, and a simple peak-searching procedure.

In our experiments, the QRS complex is used as a reference for the segmentation of cardiac-cycle-to-cycle P-QRS-T waves and the building of the signal in the filter and output channels.

D. *Template Establishment*

The signal template used as the reference input for the adaptive filters is different from one cardiac cycle to another. First, segments of the ECG signal starting with the P wave and ending with the T wave from all cardiac cycles in the given signal are identified. Then, the P-T segment of the current cardiac cycle is smoothed with a Butterworth lowpass filter (-3 dB cutoff at 75 *Hz*), and used as the reference input of the current cardiac cycle for the adaptive filters.

E. *Adaptive Filters*

For the purpose of comparison, we also implemented the popular LMS and RLS adaptive filters [8]. The signal inputs for each adaptive filter are time series of cardiac P-T segments one followed by another, because the signal samples between successive cardiac cycles do not offer much information in most ECG signals. The reference input for the filters is the template signal for each cardiac cycle. By following the adaptation rule for each filter, the optimal parameters of each filter (listed in Table I) may be obtained. It is worth noting that the ULANN filter is the most sensitive of the filters used, because the active range of the filter parameter is much wider than that of the LMS or RLS filter.

F. *Rebuilding Channel Signals*

Cardiologists and physicians would prefer to read the whole ECG signal instead of cardiac-cycle-to-cycle segments. For this reason, we have to rebuild the channel outputs for the filters, together with the template signals.

In order to rebuild the channel signal, the isoelectric line was set to be the mean value of the difference between the preprocessed signals and the template signals. The smoothed template signal was placed upon the isoelectric line at every position where the corresponding QRS complex was detected in the original signal to form a template channel of the same duration as the original signal. For the channel output of a filter, the rebuilding procedure is similar, with the only difference being that the filter output signal is utilized instead of the template signal.

TABLE I. PARAMETERS OF ADAPTIVE FILTERS

ECG (No.)*	Filter Parameters Step Size (LMS)	Forgetting Factor (RLS)	Learning Rate (ULANN)
1	0.03	0.9	0.007
2	0.05	0.8	0.00005
3	0.04	0.9	0.001
4	0.04	0.7	0.01
5	0.02	1.0	0.0009
6	0.03	1.0	0.0005
8	0.001	0.9	0.001
9	0.014	0.8	0.001
10	0.03	0.6	0.0008
11	0.03	1.0	0.001
12	0.06	0.9	0.01
13	0.005	0.8	0.0005
14	0.04	0.9	0.0001
15	0.02	1.0	0.05
16	0.001	1.0	0.0001
17	0.02	0.8	0.003
18	0.02	0.9	0.1
19	0.05	0.7	0.01
20	0.04	0.5	0.01
21	0.001	0.8	0.0005
22	0.002	1.0	0.0005
23	0.04	1.0	0.2

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

IV. RESULTS

The rebuilt channel outputs of the three filters studied are shown in Fig. 2 (d)-(f), with the reference input in (c). The root-mean-squared error (RMSE) for the LMS, RLS, and ULANN adaptive filters, computed between the filter output and the corresponding template and averaged over the 22 ECG signals processed, are 0.0404 ± 0.0159 (mean ± standard deviation), 0.0391 ± 0.0075, and 0.0333 ± 0.0102, respectively. The filtered signals were also compared with the templates derived from each ECG signal using a measure of normalized correlation coefficient, and the nature of the noise removed by each filter was characterized by Shannon's entropy; the details of these measures are described in a companion paper [13].

V. CONCLUSION AND FUTURE WORK

Results obtained with 22 ECG signals indicate that the proposed ULANN adaptive filter can achieve lower average error with respect to a template derived from each ECG signal. Future work would include a study of the convergence characteristics of the filter coefficients on the squared-error performance surface, in accordance with the learning rate. The performance of the ULANN method needs to be tested with ECG signals including ectopic beats and abnormal waveforms. Furthermore, a noise reference channel could also be derived from the original signal to facilitate improved adaptive filtering.

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