Proceedings of the 29th Annual International
Conference of the IEEE EMBS
Cité Internationale, Lyon, France
August 23-26, 2007.

Cancellation of Artifacts in ECG Signals Using a Normalized Adaptive Neural Filter

Yunfeng Wu, Rangaraj M. Rangayyan, and Sin-Chun Ng

Abstract—**Denoising electrocardiographic (ECG) signals is an essential procedure prior to their analysis. In this paper, we present a normalized adaptive neural filter (NANF) for cancellation of artifacts in ECG signals. The normalized filter coefficients are updated by the steepest-descent algorithm; the adaptation process is designed to minimize the difference between second-order estimated output values and the desired artifact-free ECG signals. Empirical results with benchmark data show that the adaptive artifact canceller that includes the NANF can effectively remove muscle-contraction artifacts and high-frequency noise in ambulatory ECG recordings, leading to a high signal-to-noise ratio. Moreover, the performance of the NANF in terms of the root-mean-squared error, normalized correlation coefficient, and filtered artifact entropy is significantly better than that of the popular least-mean-square (LMS) filter.**

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 clinical applications [1], [2]. However, in clinical practice, the surface recording of the ECG by placing electrodes on the subject's skin is susceptible to different types of artifacts. The predominant artifacts present in the ECG include:

1) Baseline Wander: The drift of the baseline is usually caused by respiration or movement of the patient.

2) Physiological Artifacts: This type of artifacts is mainly generated by other organs of the body or induced by muscular contractions related to breathing. Electrode-motion artifact is generally considered to be the most troublesome, since it can mimic the appearance of ectopic beats and cannot be removed easily by simple filters, as can noise of other types.

3) High-frequency Noise: This type of random noise could be due to the thermal effect in electrodes, the instrumentation amplifiers, the recording system, and pickup of ambient electromagnetic signals by cables [1]. In real-time clinical monitoring systems in surgery, electrosurgical noise is a significant obstacle to be overcome.

4) External Interference: Examples of environmental interference are those caused by 50 or 60 *Hz* power-supply lines, electrode motion, radiation from lights, and radio-frequency emissions from nearby medical devices.

The removal of artifacts is crucial in basic ECG monitoring systems, and also fundamental for many other applications, e.g., beat classification [3], [4], QRS detection 0, [6], analysis of asymptomatic arrhythmia [7], fetal ECG signal extraction from the maternal abdominal ECG [8], [9], classification of myocardial ischemia [10], ECG signal data compression [11], and the detection of cardiovascular diseases or abnormalities [1].

Adaptive filters are effective and popular for the filtering and analysis of ECG signals. The fundamental principles of adaptive filtering for noise cancellation have been described by Widrow *et al.* [12]. The literature shows that many adaptive filtering methods have been effectively applied in a number of practical applications [13]. Xue *et al.* [14] developed adaptive whitening and matched filters based on artificial neural networks to detect QRS complexes in ECG signals. Thakor and Zhu [15] proposed an adaptive recurrent filter to acquire the impulse response of the normal QRS complexes, and then applied it for arrhythmia detection in ambulatory ECG. Hamilton [16] compared adaptive and nonadaptive 60-*Hz* notch filters for the reduction of power-line noise and ECG data compression. Recently, Brouse *et al.* [17] used a wavelet technique to eliminate electrocautery noise in surgical monitoring systems.

Although the advantages of adaptive filters for ECG analysis are widely accepted, many such algorithms require detailed study of the components of a given ECG signal, e.g., segmentation of P-T waves [18], windowing of QRS complexes, delineation of artifacts [19], or filter-band reconstruction [20]. These methods consume a significant amount of time for modeling, and are not flexible for applications from one patient to another. In this paper, we present a new normalized adaptive neural filter (NANF) for cancellation of muscle artifact and high-frequency noise in ECG signals.

The remaining parts of this paper are structured as follows. Section 0 provides a description of the adaptive artifact cancellation system and the adaptation algorithm of NANF. Section III presents the empirical results obtained with the ECG records from the MIT-BIH Arrhythmia Database [21] using the proposed NANF method, and compares them with those of the commonly used least-mean-square (LMS) filter. Section IV concludes our study and presents possible directions for future work.

Yunfeng Wu is with the School of Information Engineering, Beijing University of Posts and Telecommunications, No. 10 Xi Tu Cheng Road, Haidian District, Beijing 100876, China (e-mail: y.wu@ieee.org).

Dr. R. M. Rangayyan is with the Department of Electrical and Computer Engineering, Schulich School of Engineering, University of Calgary, 2500 University Drive N.W., Calgary, AB, T2N 1N4, Canada (e-mail: ranga@ucalgary.ca).

Dr. S. C. Ng is with the School of Science and Technology, The Open University of Hong Kong, 30 Good Shepherd Street, Homantin, Kowloon, Hong Kong (e-mail: scng@ouhk.edu.hk)..

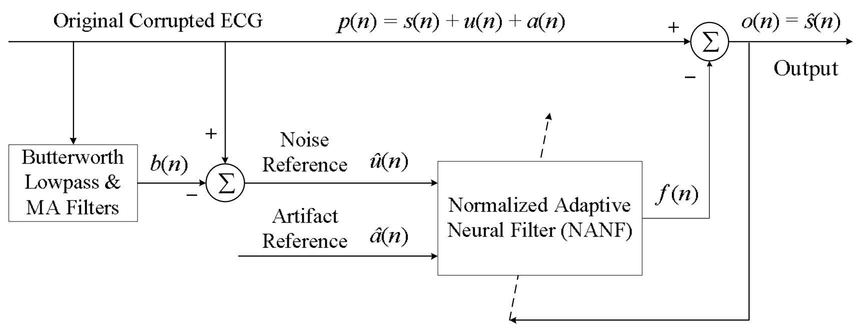

Fig. 1. Illustration of the adaptive artifact cancellation system for ECG signals.

II. Adaptive Cancellation System for the Removal of Artifacts from ECG Signals

A. System Description

An illustration of the adaptive artifact canceller is shown in Fig. 1. The original ECG signals are corrupted by muscle artifact and high-frequency noise. The purpose of the combination of the 12th-order Butterworth lowpass filter (-3 dB cutoff at 55 *Hz*) and the 15th-order moving-average (MA) lowpass filter (shown in Fig. 1) is to remove the 60 *Hz* power-line interference and smooth the ECG wave shape. The input to the NANF contains the muscle artifact reference and a noise reference.

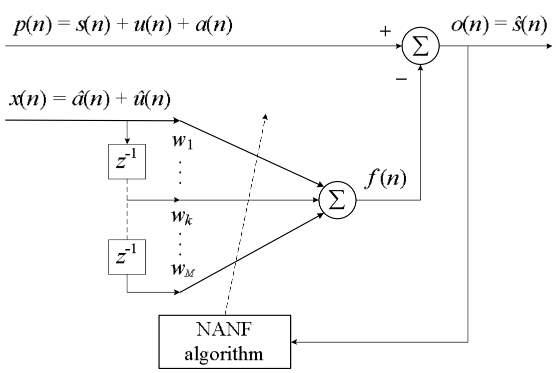

Fig. 2. The detailed structure of the NANF.

B. Adaptation Algorithm for the Normalized Adaptive Neural Filter

The NANF of order *M* is a transversal, linear, and finite impulse response (FIR) filter (see Fig. 2). The response of the filter $f(n)$ at each time instant *n* can be expressed as the convolution of the reference input $x(n)$ with the coefficients, i.e.,

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

In order to provide unit gain at DC, the filter coefficients $w_m(n)$ are normalized such that

$$\sum_{m=1}^{M} w_m(n) = 1. \tag{2}$$

The function of NANF is to modify the coefficients that get convolved with the reference input in order to estimate the artifacts present in the given signal. The output unit of the adaptive artifact canceller then subtracts the NANF response $f(n)$ from the primary input $p(n)$ to estimate the desired ECG signals as

$$o(n) = \hat{s}(n) = p(n) - f(n), \tag{3}$$

where the primary input includes the artifact-free (desired) ECG, muscle artifact, and high-frequency noise, i.e.,

$$p(n) = s(n) + u(n) + a(n). \tag{4}$$

Squaring both sides of (3) yields

$$\begin{aligned} \hat{s}^2(n) &= p^2(n) + f^2(n) - 2p(n)f(n) \\ &= \left[s(n)+u(n)+a(n)\right]^2 + f^2(n) \\ &\quad -2\left[s(n)+u(n)+a(n)\right]f(n) \\ &= s^2(n) + 2s(n)\left[u(n)+a(n)\right] + \left[u(n)+a(n)\right]^2 \\ &\quad + f^2(n) - 2\left[s(n)+u(n)+a(n)\right]f(n). \end{aligned} \tag{5}$$

By moving the term $s^2(n)$ to the left-hand side of (5), and then taking the expectation, we obtain

$$\begin{aligned} E\left[\hat{s}^2(n) - s^2(n)\right] = E\Big\{&\left[u(n)+a(n)\right]^2 + 2s(n)\left[u(n)+a(n)\right] \\ &+ f^2(n) - 2\left[s(n)+u(n)+a(n)\right]f(n)\Big\}. \end{aligned} \tag{6}$$

The aim of the adaptive artifact canceller is to minimize $E\left[\hat{s}^2(n) - s^2(n)\right]$ to a value as close to zero as possible. Such a goal can be achieved by optimizing the NANF coefficients according to the steepest-descent algorithm [22]. The process of convergence in the multidimensional coefficient space follows a deterministic searching path provided by the negative gradient direction as

$$\begin{aligned} &-\nabla_{w_k}\left[\hat{s}^2(n) - s^2(n)\right] \\ &= -\frac{\partial f^2(n)}{\partial w_k} + 2\frac{\partial\left[s(n)+u(n)+a(n)\right]f(n)}{\partial w_k} \\ &= -2x(n-k+1)\sum_{m=1}^{M} w_m(n)x(n-m+1) - 2p(n)x(n-k+1) \\ &= -2x(n-k+1)\left[\sum_{m=1}^{M} w_m(n)x(n-m+1) - p(n)\right]. \end{aligned} \tag{7}$$

By substituting (2) and (7) into the steepest-descent algorithm [22], we may rewrite the adaptation rule as

$$
\begin{aligned}
\hat{w}_k(n+1) &= \hat{w}_k(n) - \mu \nabla_{w_k}\left[\hat{s}^2(n) - s^2(n)\right] \\
&= \hat{w}_k(n) - 2\mu\, x(n-k+1)\left[\sum_{m=1}^{M} w_m(n)x(n-m+1) - p(n)\right] \quad (8)\\
&= \hat{w}_k(n) + 2\mu\, x(n-k+1)\sum_{m=1}^{M} w_m(n)\left[p(n) - x(n-m+1)\right],
\end{aligned}
$$

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

Before each time instant n+1, the filter coefficients should be normalized so as to meet the requirement of (2), i.e.,

$$
w_k(n+1) = \frac{\hat{w}_k(n+1)}{\sum_{k=1}^{M} \hat{w}_k(n+1)}. \quad (9)
$$

III. Empirical Results

The seven ECG signals studied are selected from the MIT-BIH Arrhythmia Database [21]. Each ambulatory ECG recording contains 21,600 samples that were digitized at 360 *Hz* with 11-bit resolution over a 10 *m*V range. The corresponding ECG tape numbers are given in Table I. The real muscle artifact reference is available from the MIT-BIH Noise Stress Test Database [21] (in the record 'ma'). For the purpose of comparison, we also applied the widely used LMS filter [13] in place of the NANF in the artifact cancellation system. The coefficient order and learning rate of each filter were set to be the same, as $M = 10$ and $\mu = 0.5$.

The results of artifact cancellation for the first 30 s of the ECG in Tape No. 101 are shown in Fig. 3. The primary input in the first trace is the original arrhythmia ECG recording contaminated by muscle artifact. The response $b(n)$ of the combination of the Butterworth lowpass and the MA filters (Fig. 1) is illustrated in the third trace. It can be observed that the adaptive canceller with the NANF is more effective than that with the LMS filter.

For numerical evaluation of the results of filtering, we measured the root-mean-squared error (*RMSE*) and normalized correlation coefficient (*NCC*) [23] between $o(n)$ and $b(n)$, as

$$
RMSE = \sqrt{\tfrac{1}{N_S}\sum_{n=1}^{N_S}[o(n) - b(n)]^2}, \quad (10)
$$

$$
NCC = \frac{\sum_{n=1}^{N_S} o(n)b(n)}{\sqrt{\sum_{n=1}^{N_S} o^2(n)\sum_{n=1}^{N_S} b^2(n)}}, \quad (11)
$$

where N_S denotes the sample numbers in the ECG signals.

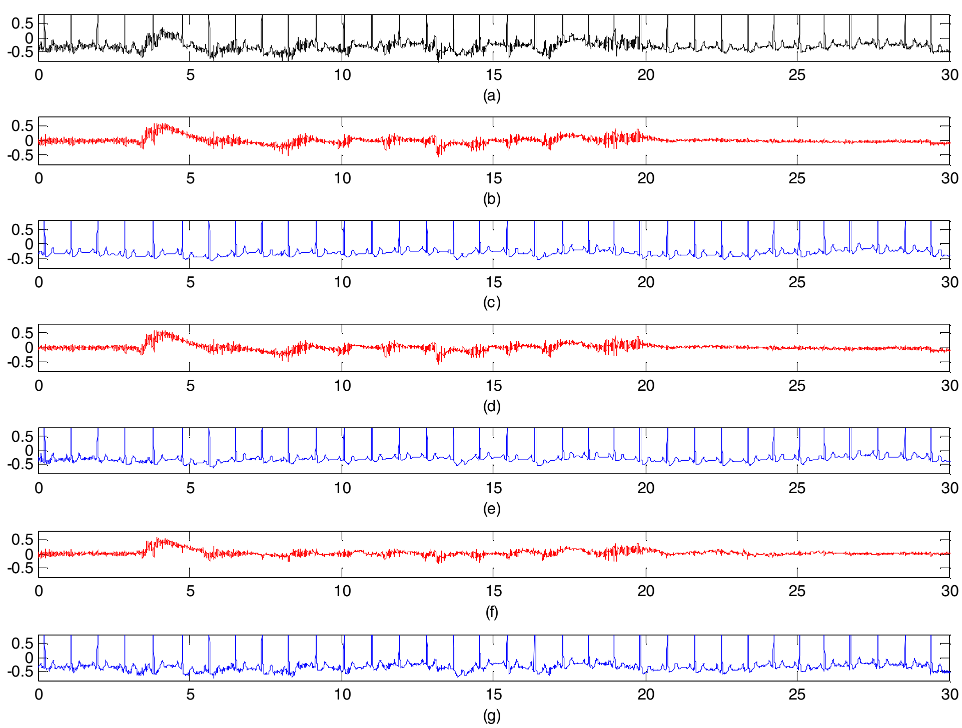

Fig. 3. Experimental results for the contaminated ECG Tape No. 101 from the MIT-BIH Arrhythmia Database. (a) ECG corrupted by the muscle artifact as primary input. (b) Reference input contains artifact and noise components. (c) Filtered ECG $b(n)$ obtained by the combination of the Butterworth lowpass and the MA filters. (d) Response of the NANF. (e) Output of the adaptive artifact canceller that involves the NANF. (f) Reponse of the least-mean-square (LMS) filter. (g) Output of the adaptive artifact canceller that involves the LMS filter. The abscissa is marked in seconds, and the ordinate is not calibrated.

The merit factor of artifact cancellation was measured in terms of the signal-to-noise ratio (*SNR*) and filtered-artifact entropy (*FAE*), with the latter defined as

$$FAE = -\sum_{\text{for all } bins} P_{bin} \log_2 P_{bin}\,, \tag{12}$$

where P_{bin} denotes the frequencies of occurrence for various bins (20 bins used in our experiments) for estimating the probability density function of the artifact removed.

The results of evaluation are listed in Table I, from which we can see that the NANF consistently outperforms the LMS filter with statistical significance. Regarding *RMSE*, the value achieved with the NANF is one seventh of that obtained with the LMS filter. The NANF also maintains better fidelity of ECG wave shape, as indicated by the larger *NCC* value obtained. In terms of *SNR*, the NANF achieved an average of 35.53 dB, which is about 19.23 dB higher than the corresponding result with the LMS filter.

IV. Conclusion and Future Work

The empirical results obtained demonstrate the tangible advantages of the proposed NANF method for adaptive cancellation of artifacts in ECG signals. The adaptive filtering procedure is much more effective, and also simpler to implement, as compared with several popular and conventional approaches, many of which require modeling of the ECG signals. The development of better neural-based adaptive filters that can also perform the function of the Butterworth lowpass and moving-average filters would be a part of our future work.

References

[1] R. M. Rangayyan, *Biomedical Signal Analysis: A Case-Study Approach*, New York, NY: Wiley, 2002.

[2] W. J. Tompkins, *Biomedical Digital Signal Processing: C Language Examples and Laboratory Experiments for the IBM PC*, Englewood Cliffs, NJ: Prentice Hall PTR, 1993.

[3] V. X. Afonso, W. J. Tompkins, T. Q. Nguyen, and S. Luo, “ECG beat detection using filter banks,” *IEEE Trans. Biomedical Engineering*, vol. 46, no. 2, pp. 192-202, 1999.

[4] Y. H. Hu, S. Palreddy, and W. J. Tompkins, “A patient-adaptable ECG beat classifier using a mixture of experts approach,” *IEEE Trans. Biomedical Engineering*, vol. 44, no. 9, pp. 891-900, 1997.

[5] C. Meyer, J. F. Gavela, and M. Harris, “Combining algorithms in automatic detection of QRS complexes in ECG signals,” *IEEE Trans. Information Tech. in Biomedicine*, vol. 10, no. 3, pp. 468-475, 2006.

[6] Y. H. Hu, W. J. Tompkins, J. L. Urrusti, and V. X. Afonso, “Applications of artificial neural networks for ECG signal detection and classification,” *Journal of Electrocardiology*, vol. 26 supplement, pp. 66–73, 1993.

[7] N. V. Thakor and Y. S. Zhu, “Applications of adaptive filtering to ECG analysis: Noise cancellation and arrhythmia detection,” *IEEE Trans. Biomedical Engineering*. vol. 38, no. 8, pp. 785–794, Aug. 1991.

[8] A. Khamene and S. Negahdaripour, “A new method for the extraction of fetal ECG from the composite abdominal signal,” *IEEE Trans. Biomedical Engineering*, vol. 47, no. 4, pp. 507-516, 2000.

[9] P. P. Kanjilal, S. Palit, and G. Saha, “Fetal ECG extraction from single-channel maternal ECG using singular value decomposition,” *IEEE Trans. Biomedical Engineering*, vol. 44, no. 1, pp. 51-59, 1997.

[10] R. Silipo and C. Marchesi, “Artificial neural networks for automatic ECG analysis,” *IEEE Trans. Sig. Proc.*, vol. 46, no. 5, pp. 1417–1425, 1998.

[11] Y. Zigel, A. Cohen, and A. Katz, “ECG signal compression using analysis by synthesis coding,” *IEEE Trans. Biomedical Engineering*, vol. 47, no. 10, 1308-1316, 2000.

[12] B. Widrow, J. R. Glover, J. M. McCool, J. Kaunitz, C. S. Williams, R. H. Hearn, and J. R. Zeidler, “Adaptive noise cancelling: Principles and applications,” *Proc. of IEEE*, vol. 63, no. 12, pp. 1692-1716, 1975.

[13] S. Haykin, *Adaptive Filter Theory, 4th ed.*, Englewood Cliffs, NJ: Prentice Hall PTR, 2002.

[14] Q. Xue, Y. H. Hu, and W. J. Tompkins, “Neural-network-based adaptive matched filtering for QRS detection,” *IEEE Trans. Biomedical Engineering*, vol. 39, no. 4, pp. 317-329, 1992.

[15] N. V. Thakor and Y. S. Zhu, “Applications of adaptive filtering to ECG analysis: Noise cancellation and arrhythmia detection,” *IEEE Trans. Biomedical Engineering*, vol. 38, no. 8, pp. 785-794, 1991.

[16] P. S. Hamilton, “A comparison of adaptive and nonadaptive filters for reduction of power line interference in the ECG,” *IEEE Transactions on Biomedical Engineering*, vol. 43, no. 1, pp. 105-109, 1996.

[17] C. Brouse, G. A. Bumont, F. J. Herrmann, and J. M. Ansermino, “A wavelet approach to detecting electrocautery noise in the ECG,” *IEEE Eng. Med. and Biol. Mag.*, vol. 25, no. 4, pp. 76-82, 2006.

[18] Y. F. Wu and R. M. Rangayyan, “An unbiased linear artificial neural network with normalized adaptive coefficients for filtering noisy ECG signals,” in *Proc. 20th Canadian Conf. Electrical and Computer Engineering (CCECE’07)*, Vancouver, BC, Canada, Apr. 2007.

[19] M. Blanco-Velasco, B. Weng, and K. E. Barner, “A new ECG enhancement algorithm for stress ECG tests,” in *Proc. 2006 Computers in Cardiology (CINC’06)*, Valencia, Spain, 2006, pp. 917-920.

[20] V. X. Afonso, W. J. Tompkins, T. Q. Nguyen, K. Michler, and S. Luo, “Comparing stress ECG enhancement algorithms,” *IEEE Eng. Med. and Biol. Mag.*, vol. 15, pp. 37-44, 1996.

[21] G. B. Moody, R. G. Mark, and A. L. Goldberger, “PhysioNet: A web-based resource for the study of physiologic signals,” *IEEE Eng. Med. and Biol. Mag.*, vol. 20, no. 3, pp. 70-75, 2001.

[22] S. Haykin, *Neural Networks: A Comprehensive Foundation, 2nd ed.*, Englewood Cliffs, NJ: Prentice Hall PTR, 1998.

[23] Y. F. Wu and R. M. Rangayyan, “An algorithm for evaluating the performance of adaptive filters for the removal of artifacts in ECG signals,” in *Proc. 20th Canadian Conf. Electrical and Computer Engineering (CCECE’07)*, Vancouver, BC, Canada, Apr. 2007.

TABLE I Results of Adaptive ECG Artifact Cancellation.

Tape No.	*RMSE*		*NCC* (%)		*SNR* (dB)		*FAE* (bit)	
	LMS	NANF	LMS	NANF	LMS	NANF	LMS	NANF
101	0.07	0.01	99.03	99.98	15.11	33.81	2.72	2.87
103	0.07	0.01	98.79	99.97	15.09	32.84	2.56	2.94
106	0.12	0.01	96.43	99.98	10.55	33.16	2.41	2.98
116	0.06	0.01	99.92	99.99	25.40	48.55	2.87	2.97
123	0.07	0.01	99.85	99.99	21.97	40.56	2.87	2.84
202	0.07	0.01	98.05	99.96	12.75	30.66	2.86	2.92
232	0.06	0.01	98.44	99.94	13.26	29.10	2.84	2.90
mean	0.07	0.01	98.64	99.97	16.30	35.53	2.73	2.92
standard deviation	0.02	0.00	1.19	0.02	5.37	6.78	0.18	0.05