Design of an Adaptive Filter with a Dynamic Structure for ECG Signal Processing

Ju-Won Lee and Gun-Ki Lee

Abstract: Biomedical signals such as ECG, EMG, and EEG are extremely important in the diagnosis of patients. It is difficult to filter noise from these signals, and errors resulting from filtering can distort a biomedical signal. Existing systems have shown poor performance when complicated noise appears. Adaptive filtering is selected to contend with these defects. Existing adaptive filters can adjust the filter coefficient with the given filter order, but they can produce an unsuitable order in different environments. In order to solve this problem, an optimal adaptive filter with a dynamic structure was designed. Positive experimental results were obtained.

Keywords: Dymanic structure LMS adaptive filter, biomedical signal, electrocardiogram.

1. INTRODUCTION

The most vital informative signals used to diagnose patients are the electrocardiogram (ECG), which is generated from heart activity; the electromyogram (EMG), which is generated from electrical activity in the muscles; and the electroencephalogram (EEG), which is generated from the brain. The ECG signal, measured with an electrocardiograph, is a biomedical electrical signal occurring on the surface of the body due to the contraction and relaxation of the heart. This signal represents an extremely important measure for doctors, as it provides vital information about a patient's cardiac condition and general health [1,2]. Generally, the frequency band of the ECG signal is 0.05 to 100Hz, and the ECG signal includes 60Hz power line noise, baseline wander due to respiration, and muscle artifacts resulting from the movement of electrodes during measurement. 60Hz power line noise can affect the Q- and P-waves of the ECG signal, generating errors during the diagnosis of arrhythmia or myocardial infarction. Power line noise can cause errors by distorting the ECG signal during the measurement of the QRS complex interval or the QT interval, which are important parameters in diagnosis. In order to remove 60Hz power line noise, an LMS adaptive filter can be applied by setting the notch filter of the 60Hz band or the 60Hz-component as a reference signal, so as to adjust the filter coefficient until the error is minimized from the input signal where the 60Hz-component is included [3-6]. The baseline wander—the low-frequency noise (below 1Hz) resulting from respiration—has the same frequency band as the ST segment of the ECG signal. It is used as a diagnostic parameter for myocardial infarction. The effective removal of the baseline wander is recommended in order to measure the ST segment with precision. Since muscle artifacts are distributed in a wide frequency band, they can generate distortions in the ECG signal when noises are removed. As it includes diverse noises as well as changes in time, analysis is difficult. Since this noise can be affected by the patient's physical condition and the environment, signal processing should be adapted to the environment. The noise can be the temperature variance of the electric system, static electricity, the patient's potential variance, the patient's movement, power line noise (60Hz), high-frequency noise, and so on. Among these factors, the patient's movement can result in the poor performance of the ECG instrument. These biomedical signals vary in time and are non-linear, so the least mean square (LMS) adaptive filter is mainly used. The LMS adaptive filter, however, removes noise or obtains the desired signal features by adapting the filter coefficients according to a given filter order; as a result, from time to time, the output error of the filter cannot be minimized in a noisy environment. The filter order should be adapted, as noise mixing depends on the environment. In addition, excessive filter ordering can cause distortions of the biomedical signal [2,6]. A new LMS adaptive filter algorithm was proposed to adapt the filter order and the filter coefficients simultaneously, thus improving

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the performance of existing LMS adaptive filters in processing biomedical signals. The new filter was applied to ECG signal processing to verify its performance.

2. LMS ADAPTIVE FILTER

The general LMS adaptive filter removes noise or obtains a desired signal by adapting the filter coefficient with the least-mean-square algorithm based on a given filter order [7,8]. The output of the LMS adaptive filter can be expressed as

$$\hat{S}(n) = S(n) + N(n) - \hat{N}(n), \tag{1}$$

$$\hat{N}(n) = \sum_{i=0}^{L} W_i N_R(n-i), \tag{2}$$

$$W_i(n+1) = W_i(n) + 2\mu S(n) N_R(n-i), \tag{3}$$

where $i: 0,1,2,...,L$, μ: convergence constant, L: filter order, $S(n)$: original ECG signal, $N(n)$: noise signal, $\hat{S}(n) = E(n)$: filtered ECG signal, $\hat{N}(n)$: the estimated noise signal, $W_i(n)$: the filter coefficient, and $N_R(n)$: the reference noise signal. The LMS adaptive filter adapts the filter coefficients in order to obtain the desired signal, thus converging the filter output error to minimize it. However, the desired solution range may not be reached during the convergence; instead, a local minimum may be reached, allowing no further convergence. In addition, the filter output error may not be further minimized if no proper filter order is set, resulting in poor performance. In order to solve these problems, we should increase the filter order with the trial error method or adjust the convergence constant and readapt it.

3. PROPOSED LMS ADAPTIVE FILTER WITH DYNAMIC STRUCTURE

In this study, a method of varying filter order to solve problems related to LMS adaptive filter performance and convergence was suggested. In the first step of the convergence, error drastically decreases. However, since the adaptation count increases, the error slowly decreases, as in a typical logarithmic function. Based on this characteristic, we adapted the filter order. Its structure is shown in Fig. 1. When the adaptation limit is reached, the convergence is

$$E(p) = \sum_{n=0}^{PR} \hat{S}(n)^2, \tag{4}$$

$$\Delta E = | E(p) - E(p-1) - E(p-2) + E(p-3) | \approx 0, \tag{5}$$

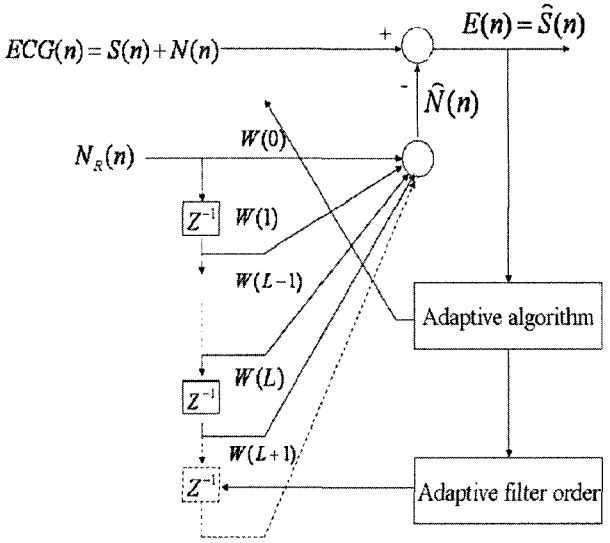


Fig. 1. LMS adaptive filter with dynamic structure.

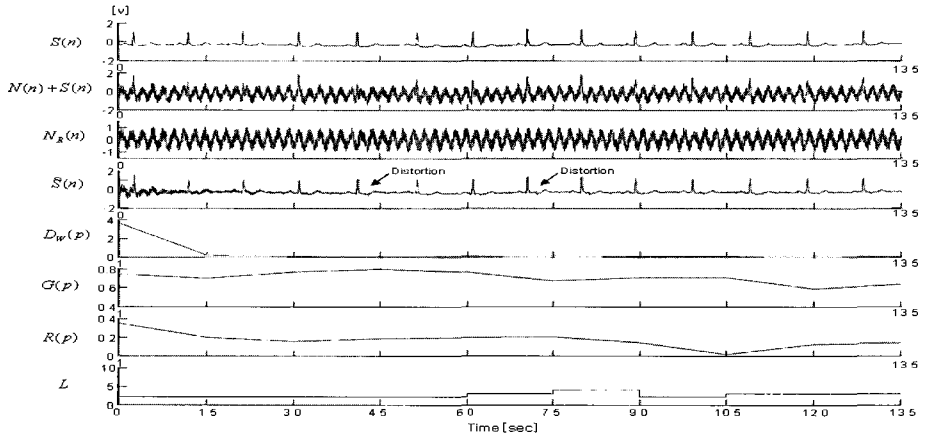
where p is the period of the ECG signal and ΔE is the difference between the error in the previous convergence and that in the current convergence.

If $\Delta E = 0$, instead of accessing to the desired signal, the performance of the LMS adaptive filter is not improved. If the coefficient of the LMS adaptive filter constantly and minutely changes, convergence is in progress. Therefore, the convergence of the LMS adaptive filter can be understood from the different $D_W(p)$ of filter coefficients and the change of the filter coefficients, as shown in (6).

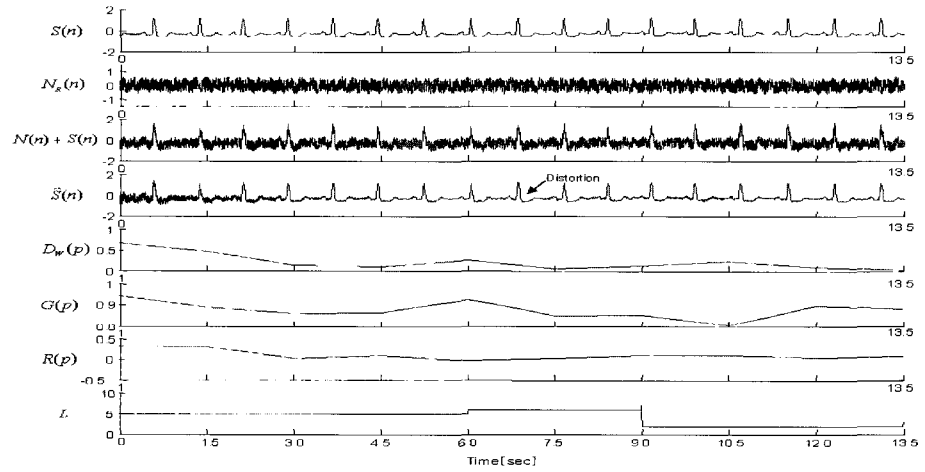
$$D_W(p) = \sum_{n=0}^{L} \left| W_p(n) - W_{p-1}(n) \right|, \tag{6}$$

where L is the order of the current filter and $W_p(n)$ and $W_{p-1}(n)$ are the current filter coefficients and the filter coefficients of one ECG signal period before, respectively. If the change of the filter coefficient is large, the filter order can be converged to a small order. If small, it cannot be converged to a small order, so the filter order should be largely increased. However, if the LMS adaptive filter produces satisfactory filter output, the change of the filter output error and the change of the filter coefficient access is 0. It should be determined whether the noise is included in the current filter output signal. Therefore, we obtained the relationship between the noise and the filter output, as shown in (8).

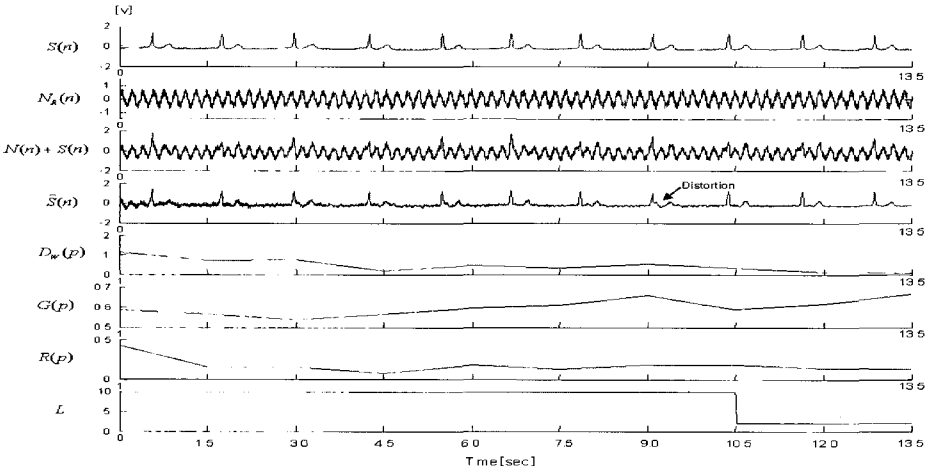
$$G(p) = \sum_{n=0}^{P} | \hat{S}(n) | / \sum_{n=0}^{P} | S(n) + N(n) |, \tag{7}$$



(a) The output of DSAF for MIT-BIH ECG signal 101 with noises.



(b) The output of DSAF for MIT-BIH ECG signal 105 with noises.



(c) The output of DSAF for MIT-BIH ECG signal 202 with noises.

Fig. 2. Outputs of the proposed DSAF for ECG signals of MIT-BIH's 101, 105 and 202; $S(n)$: original ECG signal, $S(n)+N(n)$: ECG signal with noises, $\hat{S}(n)$: Filtered ECG signal, $D_W(p)$: different of filter coefficients for p period, $G(p)$: estimated noise gain, $R(p)$: cross-correlation for $S(n)+N(n)$ and the estimate noise $\hat{N}(n)$, and L: filter order change of DSAF.

$$R(p)=\max\left(\sum_{k=0}^{P-k-1}\hat{S}(p,k)\{G(p)\hat{N}(p,k+l)\}\right), \quad l=0,1,2,.. \tag{8}$$

where $G(p)$: the noise gain for a p period and $R(p)$: the maximum value of cross-correlation. We decided to adjust the filter order under the following conditions:

$$if\left\{\begin{array}{c} D_W(p)\le\beta,\ R(p)\ge R_D \\ \{R(p)-R(p-1)\}>0,\ \{R(p-2)-R(p-3)\}>0 \end{array}\right\}$$
$$then\left\{\begin{array}{c} L=L+1 \\ L=L-1 \end{array}\right\}, \tag{9}$$

where β and R_D are the threshold value and are the sensitivity to adjust the order of the adaptive filter. (9) is to decrease the filter order because the filter order is bigger as the correlation value to the noise increases (the filter output signal is distorted by the current filter order). In other words, the algorithm (DSAF: dynamic structure adaptive filter) of the LMS adaptive filter with the dynamic structure, suggested collectively, allows the filter order and the filter coefficient to be adapted to the measurement environment.

4. EXPERIMENT AND RESULTS

To verify the algorithm suggested in this paper, we filtered the ECG signals and evaluated the overall error of the signal and the optimal filter order. In this experiment, we used MATLAB to estimate the performance of the proposed dynamic rescue filter, and we experimented with two kinds of ECG signals. The parameters of the implemented DSAF are as follows: the convergence constant is 0.01, the initial coefficients of filter are all 1, β is 0.01, R_D is 1, and the initial order of filter set as shown in table 1. The ECG signals used in experimentation are the MIT-BIH ECG signals (MIT-BIH 101, MIT-BIH 105, MIT-BIH 202) and the normal ECG signal generated from Kontron Medical's Arrhythmia Simulator 994. First, in our experiment on the MIT-BIH ECG signal, we added the artifact and 60Hz electric power line noise in these ECG signal and filtered these signals. The reference signal of the adaptive filter used these noise signals. The filtered results (the outputs of the adaptive filter) are shown in Fig. 2, where the filter order is converged to minimize the distortion of ECG signal. In the second experiment, ECG signal, artifacts, and power line noise were generated from Kontron Medical's Arrhythmia Simulator 994, and are the acquired signal by BioPac's MP100. The signal is a combination of the healthy person's ECG signal ($5V_{p\text{-}p}$), 60[Hz] noise ($1[V_{p\text{-}p}]$) and muscular artifacts which is random noise with $1[V_{p\text{-}p}]$, as shown in Fig. 3 and Fig. 4; the reference signal of the LMS adaptive filter is obtained from sampling the signal containing no P-QRS-T of the ECG signal as shown Fig. 4. The sampling frequency of the input and the reference signals is 200Hz; the resolution is 8bits. We simulated the proposed LMS adaptive filter and the general LMS adaptive filter. Figs. 5, 6, 7, and 8 show the experimental results. The LMS adaptive filter's filter order was set as 5-th; after convergence and filtering, the ECG signal was distorted. The output error of the LMS adaptive filter is shown in Fig. 5. The absolute average error

$$AAE=1/P\sum_{k=0}^{P}|S(P-k)-\hat{S}(P-k)|,$$

which is one of the output performances, of the general LMS adaptive filter was calculated as 0.0566[V] for one ECG period. Fig. 4 shows the distortion in the ST-segment. Figs. 6 and 7 show the output and the error signal of the LMS adaptive filter with a dynamic structure. The LMS adaptive filter's filter order was set as 5-th; after convergence and filtering, the ECG signal was distorted. The order is shown in Table 1. The absolute average error (which is one of the output performances) of the general LMS adaptive filter was calculated as 0.0566[V] for one ECG period.

Fig. 4 shows the distortion in the ST-segment. Figs. 6 and 7 show the output and the error signal of the LMS adaptive filter with a dynamic structure. Its

Table 1. Simulation results in vary ECG signal with the noises; GAF: General LMS adaptive filter, DSAF: the proposed LMS adaptive filter, AAE: Absolute average error, IO: initial filter order, and FO: final filter order of DSAF.

Filter	ECG signal	Noise [Vp-p]		AAE	Filter order	
		Artifacts	60 [Hz],		IO	FO
GAF	MIT-BIH 101	1	1	0.030	2	-
	MIT-BIH 105	1	0.2	0.025	5	-
	MIT-BIH 202	0.5	1	0.069	10	-
	AS994	1	1	0.056	5	-
DSAF	MIT-BIH 101	1	1	0.020	2	3
	MIT-BIH 105	1	0.2	0.009	5	4
	MIT-BIH 202	0.5	1	0.021	10	3
	AS994	1	1	0.014	5	2

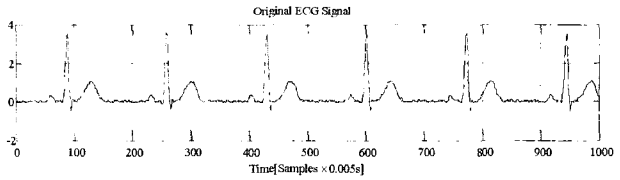


Fig. 3. Original ECG signal.

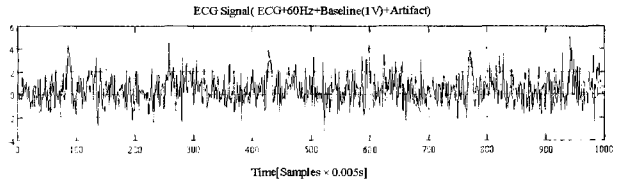


Fig. 4. Noise + ECG Signal.

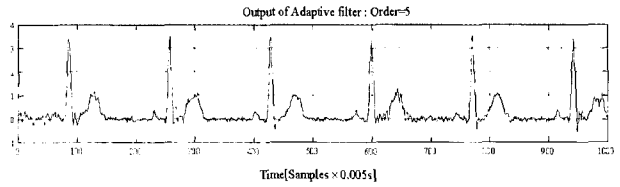


Fig. 5. Output of the general LMS adaptive filter.

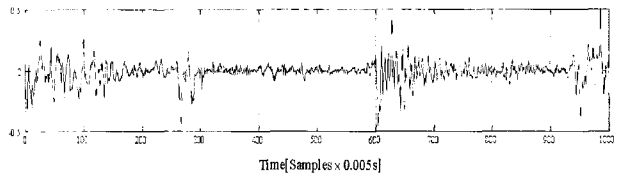


Fig. 6. Output error of the general LMS adaptive filter.

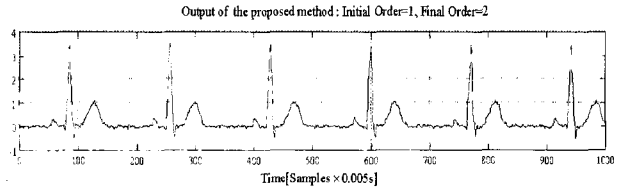


Fig. 7. Output of the proposed DSAF.

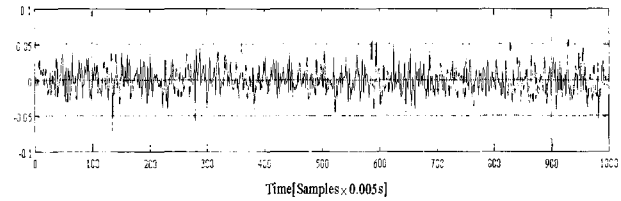


Fig. 8. Output error of the proposed DSAF.

absolute average error (0.0142[V]) is superior to that of the general LMS adaptive filter. The filter order was set as 1-st in the beginning, but it was 2-nd at convergence. The results of filtering the two kinds of ECG are shown in Table 1. As seen in Table 1, the proposed DSAF showed better performance in minimizing the distortion of the ECG signal than the general LMS adaptive filter did.

5. CONCLUSIONS

Biomedical signals play a crucial role in the diagnosis of patients. A new structure and algorithm for the LMS adaptive filter with a dynamic structure was suggested, as signal changes in time and can be variously mixed with noise depending on the environment and based on the patient's condition. Excessive filtering results in a distorted signal. To verify performance, we selected two kinds of ECG signal and evaluated the performance of the proposed DSAF for these signals. The LMS adaptive filter is widely used to filter the ECG signal, but the existing LMS adaptive filters adapt to the environment showing limitations in the given filter, so its convergence and performance cause distortions and even poor performance, depending on the environment and the patient's condition. In contrast, the proposed DSAF provided better performance in the experiment. Here, the optimal filter order with minimum distortion of the signal was obtained. Therefore, we can expect improved performance when the suggested LMS adaptive filter (DSAF) is applied to ECG signal processing.

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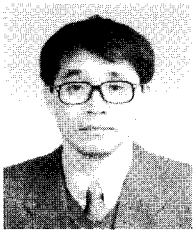

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