International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-7 Issue-4s2, December 2018

Motion Artifact Cancellation from ECG Signals using NLMS based Adaptive Filters

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Abstract: ***in the research, the normalized LMS adaptive filters is improved and proposed to reduce the motion artifact (MA) noise from ECG signals. The simulation result gives by the improved versions of adaptive filter (NLMS, PNLMS and IPNLMS) show superior performance when compared to other technique such as wavelet and empirical mode decomposition. Among adaptive filter, the PNLMS adaptive filter give the best performance among NLMS and IPNLMS adaptive filters.***

Index Terms: ***ECG Signal, Adaptive Filter, Proportionate, Improved Proportionate, µ-law,***

I. INTRODUCTION

Baseline Wander (BW), Powerline Interference (PLI), Electromyogram (EMG) and motion artifact (MA) are the most common sources of noise in ECG signal. Baseline wander noise taken from respiration system and skin electrodes [1]. The powerline interference, the 50 or 60 Hz frequency from power supply may prevents a clean ECG signals reading [2]. Electrical activity in muscles at rest and contraction known as EMG. The noise need to be removed since EMG noise may result an incorrect prediction of cardiac activities [3]. Motion artifact is contaminating in ECG signal resulting from body movement when the electrodes which are placed on the skin. It will have produced large amplitude signals in the ECG, misinterpreted and misdiagnosed might be occurred [4]. Therefore, noise filtration process must be implemented as the first stage in ECG signal processing. Different from MA, the BW, PLI and EMG noises are uncorrelated to the ECG signal and ease to be removed while the MA whose noise spectrum is correlated to the ECG signal, thus making it the most difficult type of noise to remove [2].

Numbers of adaptive filtering techniques used in noise cancellation process have been reported. Adaptive filters are widely used in acoustic echo cancellation [5]. Deng et al in their study shows the adaptive filters are capable of identifying sparse impulse response [6]. In the other hand, Otha el al reported a controllable step-size parameter in the multiple communication event and echo direction changes occur simultaneously. In the research, the optimal step-size parameter is employed from the output of the sub-adaptive filter and the echo path change detector which is controlled via the multiple communication detector. In the study, the Proportionate Normalised Least Mean Square (PNLMS) is set with a different step size for different coefficients based on the optimum magnitudes. Normally, the step-size parameter of adaptive filters changes depends on situations where a multiple communication and an echo direction change occur.

Beside widely used in communication field, adaptive filters were also used in stock market prediction [7]. The hybrid adaptive filters capable to estimate values of the five largest stock markets, namely, BSE100, NASDAQ, NIKKEI225, S&P NIFTY, and FTSE100. In medical applications, Thakor & Zhu [2] used least mean square (LMS) adaptive filter algorithms to reduce the EMG and MA effects in ECG signal. Next, adaptive filters have also been used to filter the ocular and facial muscles artifact in order to produce a clean electroencephalogram (EEG) signal [8-9].

In this paper, we put an effort to reduce the motion artifact in ECG signals. A number of adaptive LMS-based filters, such as Normalised Least Mean Square (NLMS), Proportionate NLMS (PNLMS), Improved PNLMS (IPNLMS) and µ-PNLMS (MPNLMS), are used in order to reduce the motion artifact noise from the ambulatory ECG signal. The signals were recorded using a 3-lead Holter monitor and were: augmented vector foot (aVf), augmented vector left (aVl) and augmented vector right (aVr), and attached to a human body [10]. In order to reduce the motion artifact noise, the signal either at the aVr, aVl or aVf lead is used as a primary input while an accelerometer put at the chest become the input reference [11]. The ECG signals used in this research are taken from the MIT-BIH library from subject with normal and Atrial Fibrillation (AF) conditions which were corrupted with motion artifact noise.

II. PROPOSED METHOD

Figure 1 shows a length L based adaptive filter structure with an input sequence $x(n)$ and with weights updated according to:

Manuscript published on 30 December 2018.
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$$w(n+1) = w(n) + \mu\, x(n)e(n) \quad (1)$$

The desired signal, $d(n)$ is a combination of a signal $s(n)$ which is corrupted with a noise signal, and applied to the adaptive filter shown in Figure 1.

The filter error shows as

$$e(n) = x(n) - d(n) \qquad (2)$$

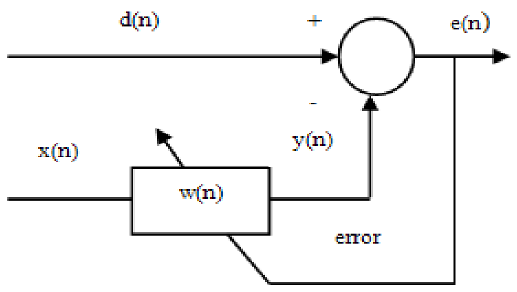

Figure 1. Adaptive filter structure.

The normalization of step size parameter of the normalised LMS (NLMS) algorithm, improve the stability and convergence rate of the filter output compared to the basic LMS adaptive filter [12]. The updated weight related to the NLMS algorithm is given by:

$$w(n+1) = w(n) + \frac{\mu\, x(n)e(n)}{x^T(n)x(n)} \quad (3)$$

Where the $x^T(n)x(n)$ is the normalized signal input while μ is a fixed convergence factor to control maladjustment.

The proportionate normalized least-mean-square (PNLMS) algorithm capable to converge faster than the normalized least mean squares (NLMS) algorithm [13]. The gain of the PNLMS algorithm has been adapted to the filter at each tap position. The gain is approximately proportional at each position to the current tap weight. The PNLMS algorithm of the weight updated with additional step-size update $G(n+1)$ is [13]:

$$w(n+1) = w(n) + \frac{\mu\, x(n)e(n)G(n+1)}{x^T G(n+1)x(n)} \quad (4)$$

and the diagonal matrix of the gain is [13]:

$$G(n+1) = diag[g_1(n+1), \cdots + g_L(n+1)] \quad (5)$$

The gain can be estimated as [13]:

$$g_l(n+1) = \frac{\gamma_l(n+1)}{\frac{1}{L}\sum_{i+1}^{L}\gamma_l(n+1)}, \quad with\ l = 1, \ldots, L \quad (6)$$

With the current impulse response as [13]:

$$\gamma_l(n+1) = max\left[\gamma_{min}(n+1), |\hat{w}_l(n)|\right] \quad (7)$$

and

$$\gamma_{min}(n+1) = \rho[\delta_p, |\hat{w}_1(n)|, |\hat{w}_L(n)|] \quad (8)$$

Where parameters ρ and δ_p have typical values of 5/L and 0.01, respectively. δ_p is a small positive number used to control the impulse response become overflow. The constant δ_p become crucial at the moment all coefficients are 0 (at the beginning) and, together with ρ to avoid the very small coefficient to be extinct. The initial convergence become slow down when ρ and δ_p is too large.

The performance of the PNLMS algorithm becomes inferior to the NLMS algorithm when the current impulse response is scattered. An improved on PNMLS (IPNMLS) algorithm proposed by Benesty and Gay [14], to overcome the disadvantages inherent in the PNLMS algorithm. The IPNLMS algorithm employs a combination of proportionate (PNLMS) and non-proportionate (NLMS) updating technique. The weight updating algorithm and diagonal matrix which related for IPNLMS is same as (4) and (5), respectively. However, the estimated gain for IPNLMS given by [13] is

$$g_l(n+1) = \frac{1-\alpha}{2L} + (1+\alpha)\frac{|w_l(n)|}{2|\sum_l^0 w_l(n)|} \quad (9)$$

The updating algorithm in (9) is controlled by a factor of α. It is noted that when $\alpha = -1$ the second term in (9) becomes zero and thus behaves as a NLMS algorithm. However, while the α is unity, the first term in (9) goes to zero and as a result it behaves as PNLMS.

III. Experimental Results

Normal, LVE and AF signals taken from the MIT-BIH database were extracted and corrupted by EMG noise as shown in Figure 3 four different adaptive filters (NLMS, PNLMS and IPNLMS) were used to filter the EMG noise contaminated ECG signals. In the experiments the SNR is varied to assess the relative performance of the various adaptive filters. The SNR is measured only after the signals reached the settling time stage. In this study, the SNR readings for all the adaptive filters are taken from samples 1001 to 3000 to ensure the signal in the steady- state.

Table 1. Signal to Noise Ratio (SNR, Db) Of Motion Artifact Noise Removal from ECG Signal with Normal (N) and Atrial Fibrillation (AF) Conditions.

	SNR Reading, (DB)	
	N	AF
Corrupted Signal	-8.36	0.97
Filtering Technique	N	AF
NLMS	3.06	5.34
PNLMS	5.93	8.60

Published By:
Blue Eyes Intelligence Engineering
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IPNLMS	-2.26	9.61

Table 1 shows the average of the signal performance of each filter for each of the given conditions. The best overall performance in reducing motion artifact noise was obtained by using the PNLMS algorithm as the adaptive filter.

Table 1 also shows that all de-noising techniques (NLMS, PNLMS and IPNLMS) yield better results compared to the corrupted signals.

It is shown that the PNLMS yields superior results compared to others adaptive filters in reducing motion artifact noise from the two subjects, normal and AF conditions.

The ability and capability of the three different adaptive filters to reduce the effects of motion artifact noise has been tested. The addition of proportional gain (PNLMS) is sufficient to obtain the optimum results. The merger of PNLMS and NLMS, producing IPNLMS is capable of improving the filter performance, however, no better than PNLMS performance.

IV. CONCLUSION

The modified NLMS-based adaptive filters are able to produce superior results in removing motion artifact noise from the ECG signals of subjects with normal and AF conditions compared to the conventional NLMS adaptive filter. Compared to the other filters, in this work the PNLMS is able to produce the best overall results. The outputs show the ability and capability of the proposed method to reduce the effect of motion artifact noise and leave behind the important information from the original signal. However, the use of time domain filtering unable to remove the motion artifact entirely since many information can be remove along with motion artifact noise. Time frequency domain filtering (wavelet decomposition) capable to give better performance since the technique it is doing the filtration process on both time and frequency domain.

ACKNOWLEDGEMENTS

This research work is supported by the research grant (RAGS/1/2014/TK03 /UPNM/2).

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