

An Innovative Adaptive Noise Canceler Family for Cardiac Signal Filtering: Application to Wireless Body Sensor Networks

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In clinical scenario, during acquisition through a sensing system the cardiac signal (CS) encounters both physiological and non-physiological contaminations. These components mask the tiny features of the cardiac activity and affects diagnosis. To avoid gradient noise amplification problem in gaussian environment, we used normalization with higher order algorithm. This results in variants of least mean fourth (LMF) algorithms. The excess mean-square error of the LMS algorithm is depends only on the second order moment of the noise but excess mean-square error of the LMF algorithm depends on fourth moments of the noise that results in lower steady-state error as compared to the LMS algorithm. Based on normalization quantity, data and error normalized LMF algorithms facilitate adaptive noise cancellers (ANC) for CS de-noising. Finally, we tested the proposed implementations on original cardiac signals acquired from the MIT-BIH database and analyzed their performance with the basic LMF based ANC. The results show that the performances of the proposed normalized higher order algorithms are superior to the LMF counterparts in gaussian environment.

Keywords: Artifacts, Adaptive Noise Cancellers, Body Sensor Network, Cardiac Signal, LMF Algorithm, Noise Cancellation, Sensing Systems.

Introduction

Cardiovascular disease (CVD) refers to a large number of medical conditions relating to the heart's functionality. According to World Health Organization (WHO) every year millions of people in the world are victims due to CVDs because they are not treated timely¹. For this problem wireless body sensor network (WBSN) is a good remedy. When the patient is in remote location, using a wearable ECG sensor the cardiac activity in the monitor and sent for the doctor's response. The medical people suggests for immediate action. Such a two-way communication in critical condition is enabled by WBSN. An appreciable volume of research is undergoing in the field of WBSN^{2,3}. In ECG, QRS detection for body sensor networks in⁴, VLSI architecture is designed and implemented on nano-FPGA. Taihai Chen *et al* in⁵ presented an ultra low-power circuit implementation of the linear discriminate analysis classifier, and it is integrated with the ECG sensor node to enabling on-body normal and abnormal ECG classification. To reduce the data rate in ECG and

EMG wireless body sensors in⁶, the compressed sensing acquisition system is proposed. One of the major problems in ECG signal sensing is artifact removal. The artifacts of utmost importance that are encountered in the ECG signal include Power Line Noise, Baseline Wander (BW), Muscle Artifact (MA) and Electrode Motion artifact (EM). In addition to these, during transmission, channel noise also contaminates the features of the ECG signal. These artifacts strongly degrade the signal quality, cause improper diagnosis and lead to some ambiguities. Several methods have been reported in the literature which makes a point to address ECG enhancement using adaptive techniques as well as non-adaptive techniques. Verma *et al* presents⁷ improved morphological algorithm for elimination of ailments posed by impulse noise and baseline drift. Lay-Ekuakille *et.al* proposed⁸ a multidimensional approach with a combined use of decimated signal diagonalization, using this approach overcoming signal processing limitations encountered in quantitative EEG. For removing of acquisition noise and baseline drift Vikrant Bhateja *et.al* proposed⁹ combination of non linear morphological operators. Adaptive filters allow detection of time varying

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potentials and tracing of the dynamic variations of the signals. As in a survey¹⁰, the LMS algorithm yields the steady weight vector; but the adaptive estimates fail to meet Wiener solution for convergence analysis of steady state values. In practical applications like WBSN, the development of fast convergence and low complexity adaptive algorithms are needed. Recently, in¹¹ Rahman *et al.* proposed several computationally less complex adaptive algorithms in time domain. In different literature^{12,13,14}, it was reported that higher order adaptive algorithms performs better than conventional algorithms in gaussian environment.

In order to avoid gradient noise amplification problem, to increase convergence speed and to minimize instantaneous output error in conventional adaptive filters, normalization has to be applied¹⁵. In order to cope up with the complexity, simplified algorithms result lower computations¹⁶. In cardiac signal processing under critical conditions some of the samples in the ECG signal become zero i.e., the excitation is inadequate. At these samples the weights varies drastically. The fluctuations in weights is called weight drift problem. By introducing a small leakage factor we can overcome this problem¹⁷. Therefore, to ensure stability, by introducing a leakage factor the higher order LMF algorithm becomes Leaky LMF (LLMF). Later, by performing normalization on higher order algorithms and by combining these with simplified algorithms, new algorithms can be derived such as Data Normalized LLMF (DNLLMF) and Error Normalized LLMF (ENLLMF). By combining with simplified algorithms, the computational complexity of the normalized techniques is reduced to single multiplication. To check the performance of implemented ANC's the enhancement process is executed on contaminated cardiac signals, taken from MIT-BIH database. The simulated models show that the proposed hybrid ANC's score better than basic LLMF counterpart.

Low Complexity Algorithms for Noise Cancelation in Wireless Body Sensor Networks

Consider an LLMF based adaptive noise canceller with L taps. The input sequence to the adaptive filter is $d(n)$ based on which the filter coefficients should be adjusted and $x(n)$ is the reference noise signal. The weight update recursion is given by

$$w(n+1) = (1 - \mu\gamma)w(n) + \mu d(n)e(n)^3 \quad \dots (1)$$

where, $w(n) = [w_0(n)w_1(n) \dots w_{L-1}(n)]^T$ is the tap weight vector at the n th index; the input signal is $d(n) = [d(n)d(n-1) \dots d(n-L+1)]^T$. The error

signal is given as $e(n) = d(n) - w^T(n)x(n)$, and μ denotes the step-size parameter. In (1), the product $(\mu\gamma)$ is chosen as greater than but closer to 0. The weight update recursion for the SR (Sign Regressor) LLMF algorithm is obtained using (1) by replacing $d(n)$ with $\text{SGN}(d(n))$, where $\text{SGN}\{\cdot\}$, is the signum¹¹ function.

Normalization in weight update recursion of LLMF algorithm leads to data normalization and error normalization. Data Normalization results fast convergent adaptive algorithm, in which the step size parameter is normalized with respect to input data vector¹⁸ of noisy signal. This algorithm is Data Normalized LLMF (DNLLMF), its weight update recursion is as follows:

$$w(n+1) = (1 - \mu\gamma)w(n) + \left(\frac{\mu}{c+[d(n)]^T d(n)}\right) d(n)e(n)^3 \quad \dots (2)$$

where the variable step size parameter can be written as $\mu(n) = \left(\frac{\mu}{c+[d(n)]^T d(n)}\right)$. Here, μ is fixed step size as in LLMF filter. The parameter c is used to avoid the denominator becoming too small and so that the step size parameter too big. Instead of using instantaneous data vector for normalization, squared norm of the error vector can also be used. The resulting algorithm is called as Error Normalized LLMF (ENLLMF) algorithm. Error normalization provides significant improvements in decreasing Excess mean-squared error (EMSE) and consequently minimizing the signal distortion¹⁹. The weight update recursion of ENLLMF is given by,

$$w(n+1) = (1 - \mu\gamma)w(n) + \left(\frac{\mu}{c+[e(n)]^T e(n)}\right) d(n)e(n)^3 \quad \dots (3)$$

where the variable step size parameter can be written as $\mu_e(n) = \left(\frac{\mu}{c+[e(n)]^T e(n)}\right)$. The additional computations, required to compute $\mu(n)$ and $\mu_e(n)$, can be reduced by using block-based DNLLMF (BB-DNLLMF) and block-based ENLLMF (BB-ENLLMF) algorithms in which the input data is partitioned into blocks and the maximum magnitude within each block is used to compute variable step size. Further to reduce the computational complexity, BB-DNLLMF and BB-ENLLMF are combined with SR algorithm; which leads to BB-SRDNLLMF and BB-SRENLLMF algorithms respectively. The weight update equation for BB-DNLLMF is obtained by using (2) with $\mu(n) = \mu/d_{Li}^2$; and the weight update equation for BB-ENLLMF is obtained by using (3) with $\mu_e(n) =$

by performing the noise cancellation experiment for 10 times and averaging. For all noise cancellation figures, the number of samples is plotted on x-axis and amplitude is on y-axis, unless stated. Various adaptive filter structures are implemented using LLMF, DNLLMF, SRDNLLMF, BBDNLLMF, BBSRDNLLMF, ENLLMF, SRENLLMF, BBENLLMF and BBSRENLLMF algorithms.

Adaptive Baseline Wander Cancellation

For this experiment, we have collected first 4000 samples of the ECG signal corrupted with BW artifact. The contaminated ECG signal is applied as primary input to the adaptive filter. A typical BW with additive random noise from the noise generator is given as reference signal. Simulation results are

plotted in Fig. 1. Among all algorithms, BBENLLMF and BBDNLLMF gets highest SNR 5.8155dB and 5.7454dB respectively; where as its signed regressor versions gets 5.2215dB and 5.0434dB respectively. As multiplications in signed regressor versions are independent of the filter length, the computational complexity of the proposed ANC is less. Hence it is well suited for BSN applications.

Adaptive Muscle Artifact Cancellation

For cancellation of in-deterministic noise, we consider real MA removal from CS. Fig. 2 shows the removal of MA using several algorithms. This shows that the tracking capability of block based filters in presence of in-deterministic noise is better than their conventional implementations. Among all algorithms,

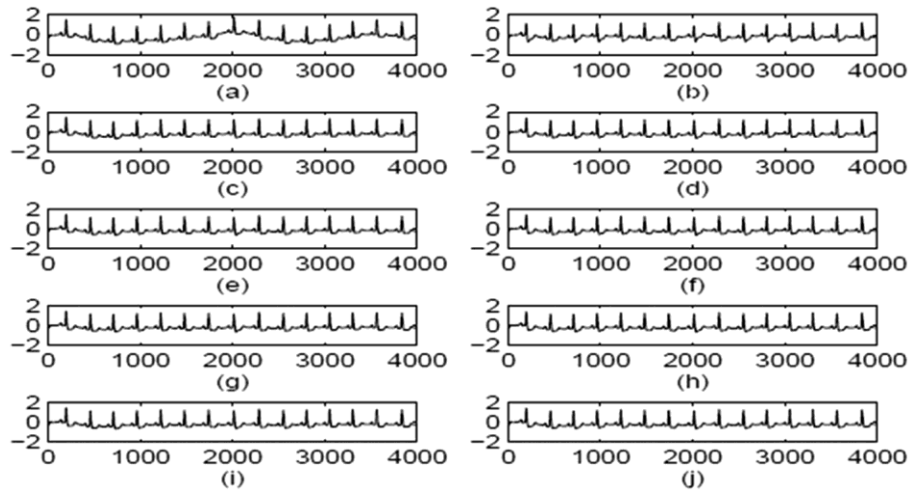


Fig. 1—Typical filtering results of BW Cancellation due to various ANCs (a). ECG with BW, (b). LLMF, (c). DNLLMF, (d). SRDNLLMF, (e). BBDNLLMF, (f). BBSRDNLLMF, (g). ENLLMF, (h). SRENLLMF, (i). BBENLLMF, (j). BBSRENLLMF.

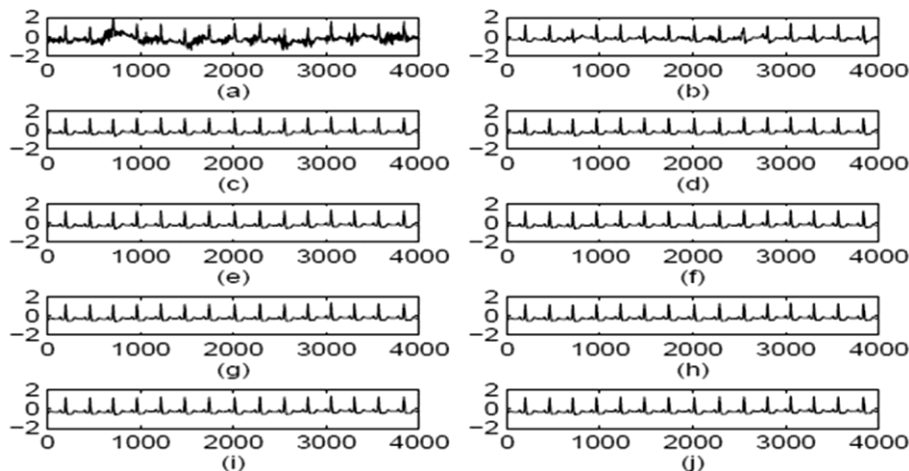


Fig. 2—Typical filtering results of MA Cancellation due to various ANCs (a). ECG with MA, (b). LLMF, (c). DNLLMF, (d). SRDNLLMF, (e). BBDNLLMF, (f). BBSRDNLLMF, (g). ENLLMF, (h). SRENLLMF, (i). BBENLLMF, (j). BBSRENLLMF.

block based sign regressor normalized algorithms seems better than the other implementations in terms of computational complexity and other performance measures like EMSE, MSD and SNR. Hence the proposed implementations are well suited for practical applications.

Conclusions

In this paper the process of artifact removal from ECG signals, corrupted by BW and MA noise, using leaky normalized higher order algorithms are presented. The various ANCs in their simplified form are developed for ECG noise cancelation. The suggested treatment exploits the modifications in the formula for weight update recursion and therefore pushes up the speed over the respective LMF based realizations. Various performance measures are determined and our experiments confirm that sign regressor and block based versions are better than their counter parts. Hence the proposed algorithms are well suited for wireless body sensor network applications in remote health care systems. We used block based approach for LLMF removing of MA and BW noise with reduced computational complexity. We can use further for removing of other noises which affects the ECG signal, and also for this Block based LMF techniques if we apply fast fouier transform and changing of step size may be give better result, with additional computational complexity.

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