International Journal of Engineering & Technology, 7 (2.17) (2018) 74-78

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research Paper

Efficient adaptive noise cancellation techniques in an IOT Enabled Telecardiology System

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Abstract

An increasing number of elderly and disabled people urge the need for a health care monitoring system which has the capabilities for analyzing patient health care data to avoid preventable deaths. Medical Telemetry is becoming a key tool in assisting patients living remotely where a "Real-time Remote Critical Health Care Monitoring System" (RRCHCMS) can be utilized for the same. The RRCHCMS is capable of receiving and transmitting data from a remote location to a location that has the capability to diagnose the data and affect decision making and further providing assistance to the patient. During the cardiac analysis, several artifacts solidly affect the ST segment, humiliate the signal quality, frequency resolution, and results in large amplitude signals in ECG that simulate PQRST waveform and cover up the miniature features that are useful for clinical monitoring and diagnosis. In this paper, several leaky based adaptive filter structures for cardiac signal improvement are discussed. The Circular Leaky Least Mean Square (CLLMS) algorithm being the steepest drop strategy for dropping the mean squared error gives a better result in comparison with the Least Mean Square (LMS) algorithm. To enlarge the filtering ability some variants of LMS, Normalized Least Mean Square (NLMS), CLLMS, Variable Step Size CLLMS (VSS-CLLMS) algorithms are used in both time domain (TD) and frequency domain (FD). At last, we applied this algorithm on cardiac signals occurred due to MIT-BIH database. The performance of CLLMS algorithm is better compared to LLMS counterparts in conditions of Signal to Noise Ratio Improvement (SNRI), Excess Mean Square Error (EMSE) and Misadjustment (MSD). When compared to all other algorithms VSS-CLLMS gives superior SNRI. These values are 13.5616dB and 13.7592dB for Baseline Wander (BW) and Muscle Artifact (MA) removal.

Keywords: *Telecardiology, Artifact, Baseline wander,Muscle Artifact, ECG, IOT.*

1. Introduction

WHO report on global health scenario confirms that the major mortality rate is due to the reason that the patient is not timely treated. In [1-3] Suzzanna M. M. Martens, Mohammed Reza Meidani, Naumann Razzaq et al. discussed the suppression of the Power Line Interference (PLI) and harmonics added as noise to the High-Resolution ECG (HRECG). In [4] G. V. S. Karthik et al. presented several efficient and less complex signal conditioning algorithms for a brain signal enhancement in remote health care monitoring applications. In [5] H. Sharma et al. presented a technique that removes the baseline wander (BW) from electrocardiogram (ECG). In [6] Santhosh Kumar Yadav et al. described power line interference; baseline wander, muscle noise etc are due to the Adaptive White Gaussian Noise (AWGN). In [7] Rik Vullings et al. described that the ECG monitoring techniques are more necessary and less disruptive. In [8] Ebadollah Kheirati et al. described the paper that introduces an improved signal decomposition model based Bayesian Framework (EKS6). In [9] Rahman et al. presented an efficient and simplified nonlinear adaptive filters, having compound calculations such as multiplier, free weight update loops is used for termination of noise in ECG signals. In [10] Lukas smital et al. discussed about the adaptive wavelet wiener filtering of ECG signals mainly attentive on the diminition of broadband myopotentials (EMG) in ECG signals. In [11] Shintari Izumi et al. studies say that the Wearable Healthcare system must be with the exact size and weight constraints which enforce considerable restrictions on battery size and signal to noise ratio of biological signals. In [12] Muhammad Zia Ur Rahman, G. V. S. Karthik et al. proposed several block based leaky LMS algorithms for artefact removal from cardiac signal. In [13] Ke Li et al. discussed the lossless ECG with low-power wearable devices. In [14] Jinseok lee et al. described an automatic motion and noise artifacts which sometimes results in the disturbances in accuracy and performance of signals taken from the Holter monitor. In [15] Nassim Ravanshad et al. presented a level crossing QRS method says that an asynchronous analog is converted as information used for computing the RR intervals in ECG waves. In [16] Fatiha bouaziz et al. discussed an ECG signal gives a clinical procedure so as to evaluate a cardiac condition of a patient. In [17] E. Arrais Junior et al. discussed about ECG detection mechanism based on the Redundant Discrete Wavelet Transform (RDWT) analyzed with MIT-BIH arrhythmia database. In [18 -19] Gabriel Nallathambi, Jun Jhang et al. discussed about fire (IF) sampler and Body Area Networks (BAN). In [20] Jacquemet et al. discussed the drawing out and study of T-waves causing the atrial flutter in ECG. Several related biomedical signal processing techniques are presented in [21]-[48].

Considering health conditions of the person, a few very crucial steps in RRCHCMS are as following:

1. Signal attainment through IOT enabled sensor nodes.
2. Transferring the data through the cloud through gateways. Supressing the noises from the ECG wave gives the signal usable for correct diagnosis and usage of correct data transmission protocol reduces the power consumption and thus increased efficiency in wireless communication and also during the data analysis.
3. Data from the remote places will be sending to the doctor with the help of the web-mobile interface.

The core objective of this paper is to enhance the signal with the help of the Adaptive Noise Cancellers (ANC) applicable in real time.

2. Computationally Proficient Adaptive Filtering Techniques

2.1 Adaptive filter structure

Fig 1(a) shows a filter with a ECG signal g_1 as input by additive noise h_1 whereas the traditional input is artifact h_2 perhaps traced from one more noise producer h_2 that is correlated in a someway with h_1. If the filter output is z and the filter error is k = $(g_1 + h_1)$- r, then

$$k^2 = (g_1 + h_1)^2 - 2i(g_1 + h_1) + i^2$$
$$=(h_1 - i)^2 + g_1^2 + 2g_1h_1 - 2ig_1 \quad (1)$$

while wave and artifact are uncorrelated, the Mean-Squared Error (MSE) is

$$E[k^2] = E[(h_1 - i)^2] + E[g_1^2] \quad (2)$$

Reducing the MSE results in the finest least–squares approximation of the wave g_1.
Fig 1(b) represents one more condition, wherever the Electrocardiogram is traced from many conductor leads. The first input $g_1 + h_1$ is a wave from one of the leads. A traditional wave g_2 is gained from a second lead that is artifact less. Reducing the MSE leads to a filter output y that's the easiest least-squares guess of wave g_1. Using a system alike to (1) we are able to

$$E[k^2] = E[(g_1 - i)^2] + E[h_1^2] \quad (3)$$

2.2 Basic Least Mean Square Algorithm

The LMS technique is a repetitive method for reducing the MSE among the primary and the traditional inputs. The LMS algorithm can be represented as

$$l_{t+1} = l_t + 2\mu k_t B_t \quad (4)$$

Where $l_t = [l1_t l2_t \ldots\ldots lj_t \ldots\ldots ln_t]^T$ is a deposit of filter loads at time t. $B_t = [B1_t B2_t \ldots\ldots Bj_t \ldots\ldots Bn_t]^T$ is the input vector at time t of the models from the traditional signal, a_t is the wanted primary input from the ECG to be filtered, i_t is the filter output that is the best least squares estimate of a_t.

$$k_t = a_t - i_t \quad (5)$$

Parameter µ is empirically selected to produce convergence at a preferred rate; the larger its value, the earlier the convergence is and is equal to 1/(4µ€), where € is the largest eigenvalue of the autocorrelation matrix of the reference signal. This parameter causes excessive Misadjustment or instability, 1/€ > µ > 0.

3. Proposed Technique

The filtering and weight adaption of CLLMS technique with the numeral filter taps of M is written as

$$i(n)=\sum_{r=0}^{M-1} l_r(n-1)B(n-r) \quad (6)$$
$$k(n)=a(n)-i(n) \quad (7)$$
$$\delta_t(n) = \mu k(n) l(n)/(||p||^2 + \delta) \quad (8)$$

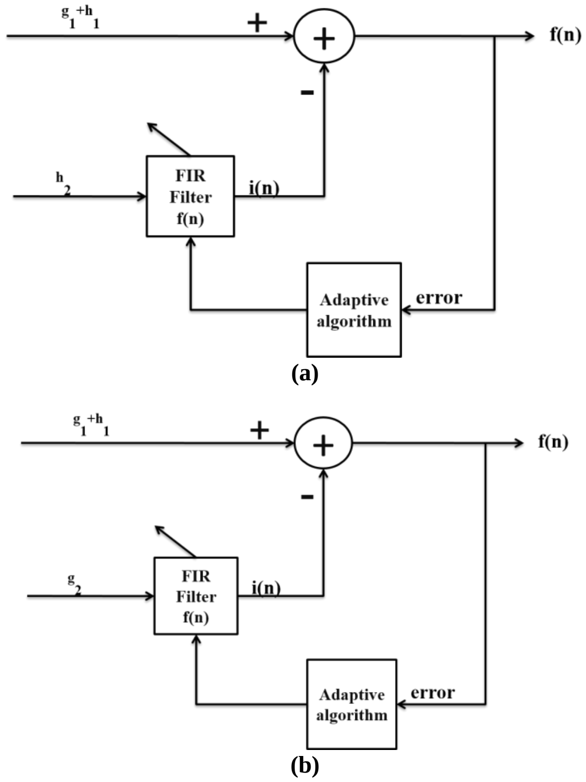

Fig. 1: Two adaptive filter structures. Type 1(a): the reference input is noise $\mathbf{h_2}$ correlated with noise $\mathbf{h_1}$: the desired signal appears at k (n). Type 1(b): The reference input is signal $\mathbf{g_2}$ correlated with signal $\mathbf{g_1}$: the desired signal appears at i(n).

Where $\delta_t(n)$ is adaption aspect of CLLMS technique and δ is very little positive constant meant for removing divide-by-zero fault

$$l_r(n+1) = l_r(n) + \delta_t(n)p(n-r) \quad (9)$$

The leakage factor is taken as base for only one of the weights following ordinary weight adaption of NLMS is completed through each model dispensation. The alternative of which load to be customized is made chronologically as given in equation (9). Although escape term is practical to only one load at a time, the process is recurring circularly.

$$l_t(n+1) = \delta_t(n)p(n-t) + l_t(n)\big(Q - \alpha_s l_t(n)k(n)k(n)\big) \quad (10)$$

Where $\alpha_s = \begin{cases} 0.00001 & \text{if } (|k(n-t)l_t(n)|) < \Omega \\ 0 & \text{otherwise} \end{cases}$, t= (t+1)

mod (M) and Ω is little positive constant and its rate is 0.00004. Later on, we discussed the proposed algorithm with changes to weight adaption factor $\delta_t(n)$ like, (i) the error wave k(n) is accepted during the variance limiter and the significant output is used in the coefficient–update equation. This is to discontinue the variance of the filter, which arises due to noise that appears in the ECG due to the reference signal y (n). Frequently a divergence limiter is a limiter and it doesn't allow the error to surpass in excess than the previous fault, (ii) Adaptive filter input power is predictable using long-term average of the de-correlated reference signals to enlarge the constancy, as well as to diminish the density precisely and (iii) and another advantage is to modify the permanent step size to changeable step size, which is oppositely proportional to long term average of the meeting reached. So, the changed equation for assessment of adaption feature$\delta_t(n)$ is exposed as

$$\delta_t(n) = \left(\frac{\mu_t(n)}{s_y(n)}\frac{s_{mod}(n)}{s_y(n)}y'^{(n)}\right) \tag{11}$$

Where, $\mu_t(n)$ is the changeable step size and is directly proportional to echo escape parameter Δ (n), $s_{mod}(n)$ is the customized error signal by variance limiter discussed in the following vice--section, $s_x(n)$ is the durable average of de-correlated faded noise wave and y'(n) is the reference signal. The static variables such as smoothened fixed previous error $s_s(n)$, durable average of error wave $s_u(n)$, durable average of adaptive filter input wave $s_y(n)$, and knowledge accelerate counter m(n) are memory factors used to pile up earlier states. The knowledge accelerate counter m(n) point out's the number of times loads are endlessly modified.

Divergence limiter:

This limiter suppresses the error when it is caused due to noise in the reference signal, visible at the output. The boundary equation is shown in equation (12) and the levelled absolute previous fault $s_s(n)$ is modernized as per the equation (13) for the next sample processing,

$$S_{mod}(n) = \text{sign}(k\,(n)) \min(\gamma_0\, s_s(n), |s(n)|) \tag{12}$$

$$l(y) = \begin{cases} s_s(n), & \text{if } (y'(n) = 1) \\ \gamma_2 s_s(n) + \gamma_1 |s(n)|, & \text{if } (\gamma_0 s_s(n) \le |s(n)|) \\ \gamma_3 s_s(n), & \text{elsewhere} \end{cases}$$

The block diagram for analyzing the adaption factor $\delta_t(n)$ unit with input as well as output terms is exposed in the figure (2).

The Estimation of Long-term averages:

The adaptive filter input power, $||p||^2$is expected as, by squaring and adding all the input models. This process requires additional complication with extra recollection for power level erratic. For the inferior order of filter taps, lofty difference in the reference power may reason damping. This may guide to in-security now and then. So, in our completion, (i) long-term average of de-correlated reference signal $s_y(n)$ is used to expect the input power of the adaptive filter and (ii) long-term average of fault $s_u(n)$ and input wave $s_a(n)$ are needed to find out the echo escape factor Δ(n). The averages are determined as given below

$$s_u(n) = s_u(n-1) + \gamma_4(|s(n)| - s_u(n-1)) \tag{13}$$

$$s_a(n) = s_a(n-1) + \gamma_4(|a(n)| - s_a(n-1)) \tag{14}$$

$$s_p(n) = s_p(n-1) + \gamma_4\left(|p(n)| - s_p(n-1)\right) \tag{15}$$

Where γ_4 is a constant and its assessment is equal to (1/(M+1)).

$$\Delta(\mathbf{n}) = \frac{\mathbf{s_u(n)}}{\mathbf{s_a(n)}} \tag{16}$$

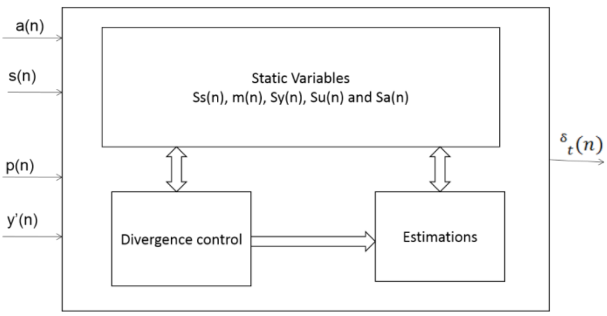

Fig. 2: Building block diagram of adaption factor $\delta_t(n)$ estimation unit.

LMS, NLMS, CLLMS and VSSCLLMS were compared and VSSCLLMS lead others. By utilizing presentation measures called SNRI, EMSE and MSD, we get ideal outcomes with the VSSCLLMS algorithm as observed in Table 1. So, the VSSCLLMS adaptive methods gives the improved results compared over the other adaptive techniques, verified from the Figure 4-5 and Table 1.

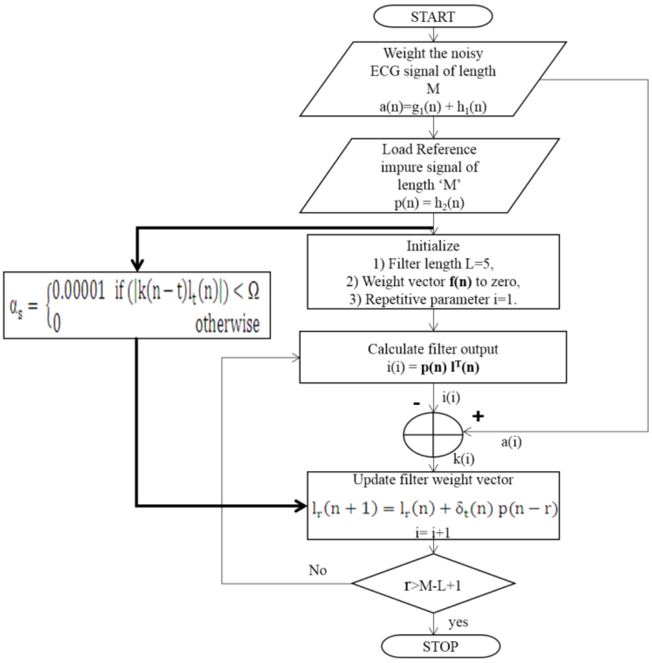

Fig. 3: Data Flow Chart of VSS-CLLMS

4. Results and Discussion

The focus in this paper is to supress non-physiological noices like BW and MA from ECG signal. This artefact cancellation is functional in 4 adaptive algorithms namely LMS, NLMS, CLLMS and VSS-CLLMS and those changes have been explained evidently in the Figure 4-5 where VSSCLLMS results more trustable outcome. The mathematical figures can be clearly seen from Table 1. The efficiency of algorithms are calculated using the SNRI, EMSE and MSD measures. Among data and error normalization, error normalized filters performs greatly due to broad range of error from the first iteration to the last iteration. The leaky filtering algorithms are finely suitable for wireless telecardiology applications in remote health care systems.

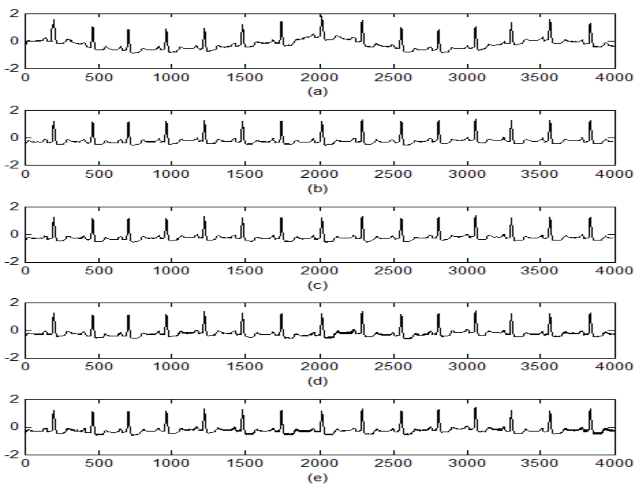

Fig. 4: Distinctive filtering outcome for BW cancellation by means of data normalization adaptive filtering techniques: (a) ECG signal with BW, (b) improved wave with LMS technique, (c) improved wave with NLMS technique, (d)improved wave with CLLMS technique, (e) improved wave with VSSCLLMS technique.

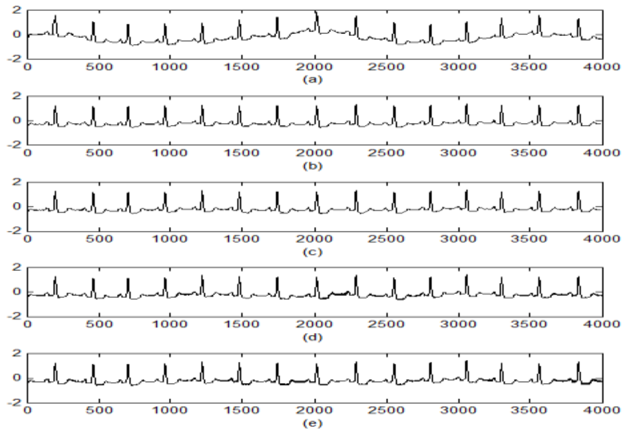

Fig. 5: Distinctive filtering outcome for MA cancellation by means of data normalization adaptive filtering techniques: (a) ECG signal with MA, (b) improved wave with LMS technique, (c) improved wave with NLMS technique, (d) improved wave with CLLMS technique, (e) improved wave with VSSCLLMS technique.

5. Conclusion

In this paper, the artifact reduction from ECG signals using Leaky standard adaptive algorithms in time and frequency area is researched. The numerous filter constructions based on LMS, NLMS, CLLMS and VSS-CLLMS techniques are enhanced for ECG noise cancellation. The presented action exploits the variations in the load modernize formula and thus drives up the speed over the own LLMS based realization. Yet, in time domain, leaky filtering procedure occurs due to averaging the amplitude of the filtered signal reduces but it superiorly smoothens the signal. Reduce in amplitude results in reduced SNRI. In both TD and FD, normalization improves convergence and filtering capability.

In our experiments, during BW elimination, VSSCLLMS achieves highest SNRI 13.56 dBs, that for MA elimination -22.85dBs.

Table 1: Adaptive algorithms vs Performance measure comparison table.

Artifact Type	Data No.	LMS			NLMS			CLLMS			VSS-CLLMS		
		SNRI	**EMSE**	**MSD**	**SNRI**	**EMSE**	**MSD**	**SNRI**	**EMSE**	**MSD**	**SNRI**	**EMSE**	**MSD**
BW	101	3.4563	-8.7653	0.318	5.4657	-11.098	0.296	9.5672	-17.653	0.199	13.7891	-20.891	0.092
	102	3.2459	-9.7651	0.414	6.2589	-11.909	0.292	10.2764	-19.815	0.114	12.2889	-21.37	0.08
	103	3.5612	-10.453	0.491	6.6784	-12.998	0.315	11.6789	-20.789	0.121	13.7864	-22.998	0.076
	104	3.3369	-11.167	0.5	7.456	-13.899	0.342	12.5123	-21.113	0.122	13.7064	-23.49	0.079
	105	3.408	-11.442	0.503	8.6536	-14.9	0.353	12.2375	-21.386	0.149	14.2375	-23.568	0.086
	Avg.	**3.4016**	**-10.319**	**0.445**	**6.9025**	**-12.961**	**0.319**	**11.2544**	**-20.151**	**0.141**	**13.5616**	**-22.463**	**0.083**
MA	101	3.8563	-9.1784	0.378	5.9657	-11.742	0.242	9.9672	-19.625	0.096	13.9891	-20.742	0.055
	102	3.9459	-10.987	0.385	6.4589	-12.494	0.258	10.8764	-20.985	0.104	12.1989	-20.997	0.06
	103	3.6612	-11.246	0.395	6.5784	-14.599	0.268	11.3789	-21.356	0.112	13.9987	-23.985	0.068
	104	3.9969	-12.349	0.413	7.456	-14.998	0.298	12.6123	-21.999	0.14	13.8712	-24.197	0.074
	105	-12.41	-12.41	0.403	-15.616	-15.616	0.289	-22.548	-22.548	0.138	-24.348	-24.348	0.078
	Avg.	**-11.234**	**-11.234**	**0.395**	**-13.89**	**-13.89**	**0.271**	**-21.302**	**-21.302**	**0.118**	**-22.854**	**-22.854**	**0.067**

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