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# ECG Signal Enhancement using Circular Leaky Adaptive Algorithm in an IOT Enabled Sensor System

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***Abstract:*** Increasing number of elderly and disabled people, urges the need for a health care monitoring system which has the capabilities for analyzing patient's healthcare data to avoid preventable deaths. Medical Telemetry which is becoming a key tool in assisting patients living remotely and a "Real-time Remote Critical Health Care Monitoring System" (RRCHCMS) can be utilized for the same. So the removal of artifacts, to facilitate high-resolution cardiac signals from recordings is a main issue to examine. In this paper, several leaky based adaptive filter structures for cardiac signal improvement are discussed. These filters will recognize the mechanism of cardiac signal and eliminates the noise factor. The Circular Leaky Least Mean Square (CLLMS) algorithm gives a better result. To increase the filtering ability some variants of LMS, Normalized Least Mean Square (NLMS), Circular Leaky Least Mean Square (CLLMS), Variable Step Size CLLMS (VSS-CLLMS) algorithms used in both time domain (TD) and frequency domain (FD). At last, we applied this algorithms on cardiac signals occurred due to MIT-BIH database and compared over the predictable LLMS algorithm. The result gives the performance of CLLMS algorithm which is better compared to LLMS counterparts in conditions of Signal to Noise Ratio Improvement (SNRI), Excess Mean Square Error (EMSE) and Misadjustment (MSD). Compared to all other algorithms VSSCLLMS gives higher SNRI than all supplementary algorithms. These values are 15.6016dB and 14.0789dB for Power line Interference (PLI) and Electrode Motion artifacts (EM) removal.

***Keywords:*** Adaptive filtering, artifacts, ECG signal, medical telemetry, leaky algorithms.

## 1. INTRODUCTION

WHO celebrates a world health day on 7th April 2016 and make a report based on heart deceises. This is the first global report on cardio vascular deceises which highlights the prevention and treatment of that disease. In [1] Suzzanna M.M. Martens et. al., presented how to remove the Power Line Interference (PLI) and harmonics contains in ECG. So to overcome this PLI and harmonics the notch filters and adaptive cancellers are come into account. In [2] Mohammedreza Meidani discussed that new algorithms are introduced to eliminate the PLI from ECG by using the FIR filter which is with less hardware. In [3] Naumann Razzaq et. al., described the improved adaptive filter i.e. noise rejection filter for termination of PLI and harmonics from High-Resolution ECG (HRECG). In [4] G. V. S. Karthik et. al., Presented several efficient and less complex signal conditioning algorithms for 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) using the Hilbert Vibration Decomposition (HVD). In [6] Santhosh Kumar Yadav et. al., described regarding ECG signals are usually degraded by power line interference, baseline wander, muscle noise etc are due to the Adaptive White Gaussian Noise (AWGN). In this, the noise free can be achieved by contraction of its two-dimensional discrete wavelet transforms coefficient. In [7] Rik Vullings et. al., described that the ECG monitoring techniques are more necessary and less disruptive become outflow of less signal quality (SQ). To improve SQ and signal to noise ratio (SNR) repeated ECG waves are to be averaged so that they can retrieve the lost signal data with the help of a bayesion framework. In [8] Ebadollah Kheirati et. al., described the paper that introduces an improved signal decomposition model based Bayesian Framework (EKS6). EKS6 is more compatible; separate the ECG components efficiently when compared with the new EKS4. In this paper, we check out for T/QRS ratio. In [9] Rahman et. al., presented an efficient and simplified nonlinearity based adaptive filters, which are having compound calculations such as multiplier free weight update loops are used for termination of noise in ECG signals. In [10] Lukas smital et. al., obtainable about the adaptive wavelet wiener filtering of ECG signals mainly attentive on the diminution of broadband myopotentials (EMG) in ECG signals. In [11] Shintari Izumi et. al., studies says 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 which is with low-power wearable devices. The ECG waveform is split into four waveforms according to its deviations and the most suitable method will aim from various linear prediction methods for different regions. In [14] Jinseok lee et. al., described an automatic motion and noise artifacts which sometimes causes the disturbances in accuracy and performance of signals taken from the Holter monitor. In [15] Nassim Ravanshad et. al., presented a Level crossing based QRS algorithm says that an asynchronous analog is converted as information for measuring the RR intervals in ECG signals.In [16] Fatihabouaziz et. al., discussed an ECG signal gives a clinical practice in order to evaluate a cardiac condition of a patient. An improved QRS algorithm is designed with multi-resolution and this wholly analyzed with the help of arrhythmia database. In [17] E. Arrais Junior et. al., obtainable about the ECG signal i.e. detection based on the Redundant Discrete Wavelet Transform (RDWT) analyzed with MIT-BIH arrhythmia database. In [18] Gabriel Nallathambi et. al., presented the continuous monitoring of ECG data they introduced a method to convert an analog input into pulses at very low power with the help of fire (IF) sampler. In [19] Jun Jhang et. al., explained that the low energy consumption is the main role in Body Area Networks (BAN) because of to pass a large amount of data, causes additional energy consumption. To minimize the additional amount of energy and efficiently compressed sensing (CS) based approach is used. In [20] Jacquemet et. al., discussed the extraction and analysis of T-waves causing the atrial flutter in ECG. We consider mainly T, for diagnosis and continuous monitoring of patients so that, the flicker waves superposed on the T-wave this causes the missing of the data. At the end, the T-wave precision and healthiness have risen as compared to the present. In [21] Eric Y. Chow et. al., discussed that at past to use the RF technology in the biomedical application is a big task but now they make it as useful with the help of RF technology but problem is occurred due to the Electro-Magnetic (EM) effect in the body at higher frequencies, at last, with the help of RF devices the communication and speed is achieved in medical telemetry.In [22] Md. Shahidul Islam et. al., presented that the conversion of a wireless system to an implantable device so that the antenna detuning and biocompatibility are giving the similar result such that an RFID designed such that it will not change for any physical parameters. In [23] Ya Li Zheng et. al., described for every hour the blood pressure (BP) observation with the cuff electrode is done, but these are not suitable at night time. So the author introduced Pulse Transit Time (PTT) without cuff to remove transients. In [24] Johan Wannenberg et. al., described a signal that is efficient to give a result on remote mobile health monitoring system. In [25] Basem M. Badr et. al., described that assembling of small animals in biological research, for that a Wireless Power Transfer (WPT) plan is suitable. Because of the animals, movement coupling loss occurs such that arranged ferrite rods used COMSOL software is used. Medium Ferrite angled (4MFA) configuration is better compared to the other ferrite collection. In [26] Shuenn–Yuh Lee et. al., discussed a low power biosignal attainment and a categorization of body sensor networks. In [27] Hanjun Jiang et. al., discussed a 10Mbps OQPSK transceiver working in the certain frequency range in medical telemetry as wireless communication with high data rate and low power consumption. In [28] Yu-Ting Li et. al., presented that the electrical simulation is used to study about nerve regeneration in bio-microsystem which is used to repair nerve and the nerve impedance in Sciatic Nerve Injury Rat Model for the observation of 42 days. In [29] Trung Q. Le et. al., described the sleeplessness in people. In the medical field to find out the disease of Obstructive Sleep Apnea at first they introduced Continuous Positive Airway Pressure (CPAP)even this method have some discrepancies they introduced Dirichlet Process based Mixture Gaussian Process (DPMG). In[30] Sebastian Thelen et. al., discussed that the telemedicine purpose in case of emergency conditions and they are using off the shelf devices to maintain the telemedicine in emergency conditions. In [31] Jayant Charthad et. al., presented about a mm sized implantable device using ultrasonic power transfer for good performance inside the body and efficiency of the implant.

Taking inputs from the references discussed above, The RRCHCMS's data flow can be briefed as

1. Signal Acquisition through IOT enabled sensor nodes.
2. Acquired biomedical data, post enhancement and processing, is wirelessly transferred through intermediate gateways to cloud. Signal enhancement and processing, includes Adaptive Artifact Cancellation, Encryption and Decryption in order to ensure safety and security, Modulation as per low power and efficient Wireless Communication Standards and Data Analytics.
3. Information from cloud is made available to the doctor for remote diagnosis through web/mobile application interface.

The scope of this paper is to develop the Signal Enhancement Unit with various Adaptive Noise Canceller algorithms and to validate their suitability in real time. Whereas, the other components of the RRCHCMS can be dealt in future.

## 2. ADAPTIVE NOISE CANCELLORS IN ECG ENHANCEMENT

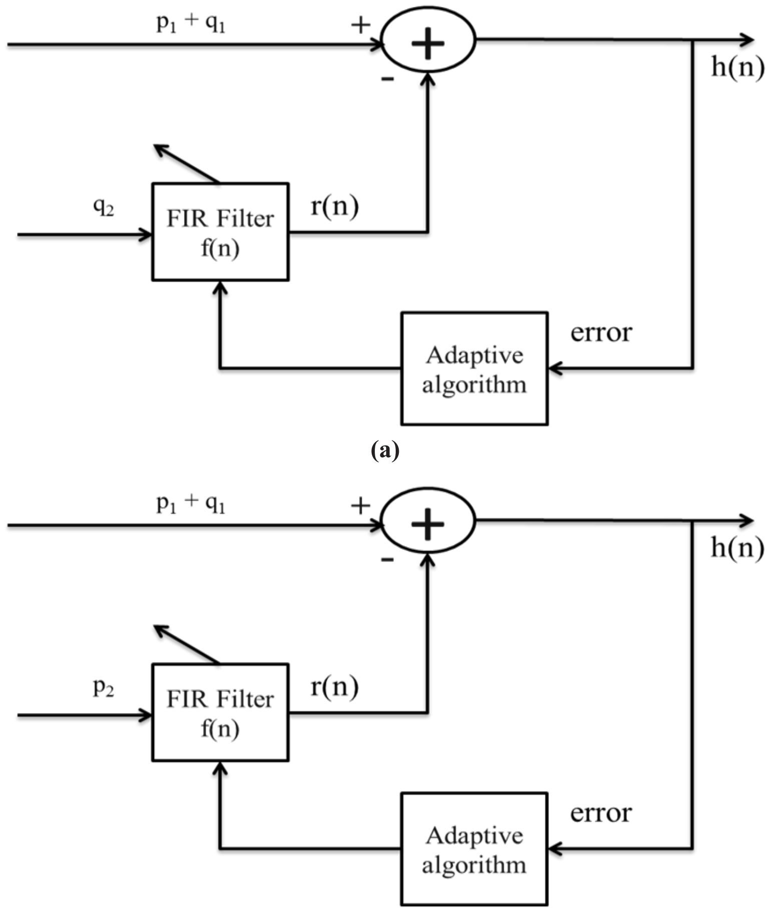
Figure 1(a) shows a filter with a primary input that is an ECG signal $p_1$ with additive noise $q_1$ while the reference input is noise $q_2$ possibly recorded from another generator of noise $q_2$ that is correlated in some way with $q_1$. If the filter output is y and the filter error is $h = (p_1 + q_1) - r$, then

$$\begin{aligned} h^2 &= (p_1 + q_1)^2 - 2r(p_1 + q_1) + r^2 \\ &= (q_1 - r)^2 + p_1^2 + 2p_1q_1 - 2rp_1 \end{aligned} \tag{1}$$

Since signal and noise are uncorrelated, the mean -squared mistakes (MSE) is

$$\mathrm{E}[h^2] = \mathrm{E}[(q_1 - r)^2] + \mathrm{E}[p_1^2] \tag{2}$$

Minimizing the MSE outcomes in a filter error output that is the best least – squares estimate of the signal $p_1$.The adaptive filter out extracts the signal, or removes noise, by way of iteratively minimizing the MSE among the primary and reference inputs.




**(b)**

**Figure 1: Basic adaptive noise canceller structure, (a) The reference input is noise $q_2$ correlated with noise $q_1$; the desired signal appears at $h(n)$, ($b$): The reference input is signal $p_2$ correlated with $p_1$ signal the desired signal appears at $r(n)$**

Figure 1(b) illustrates another state of affairs wherever the cardiogram is recorded from many conductor leads. The first input $p_1 + q_1$ is a signal from one of the leads. A reference signal $p_2$ is obtained from a second lead that is noise free. The signal $p_1$ can be extracted by the MSE among the number one and the reference inputs. Using a system similar to (1) we are able to

$$\mathrm{E}[h^2] = \mathrm{E}[(p_1 - r)^2] + \mathrm{E}[q_1^2] \tag{3}$$

Minimizing the MSE leads to a filter output y that's the simplest least-squares estimate of signal $p_1$.

The LMS algorithm is considered to be the fundamental adaptive algorithm. LMS algorithm involves an iterative technique for minimizing the MSE among the primary and the reference inputs. Usually, a transversal filter structure is engaged and the filter coefficients or weights are obtained using the LMS algorithm. The LMS algorithm is written as

$$f_{t+1} = f_t + 2\mu h_t \mathrm{A}_t \tag{4}$$

where, $f_t = [f1_t f2_t, \ldots, fj_t, \ldots, fn_t]^{\mathrm{T}}$ is a set of filter weight sattimet, $\mathrm{A}_t = [\mathrm{A}1_t\mathrm{A}2_t, \ldots, \mathrm{A}j_t, \ldots, \mathrm{A}n_t]^{\mathrm{T}}$ is the input vector at time $t$ of the samples from the reference signal, $b_t$ is the desired primary input from the ECG to be filtered, $r_t$ is the filter output that is the best least squares estimate of $b_t$

$$h_t = b_t - r_t. \tag{5}$$

parameter μ is empirically selected to produce convergence at a desired rate; the larger its value, the faster the convergence is = 1/(4μ€) where € is the largest eigenvalue of the autocorrelation matrix of the reference signal. This parameter may not be so large that it causes excessive Misadjustment or instability, 1/€ > μ > 0.

## 3. PROPOSED TECHNIQUE

In this, we used the adaptive filter techniques such as Normalized Least Mean Square (NLMS) algorithm. The option of boundless weight estimates may occur in NLMS in the presence of noise or in fixed word length implementations, interests overflow, and degraded performance so that we came to leaky NLMS algorithm which depends on leakage factor at which this stabilizes the weight and also weight drift problem and due to hardware cost in leaky NLMS we came to a bias-free circular leaky LMS and due to its low additional complexity requirement compared to other VSSNLMS. So CLLMS algorithm is selected for analysis. The VSSCLLMS algorithm is introduced along with the parameter step size this is the most important parameter plays a key role. The performance metrics such as convergence rate, Misadjustment or noise cancellation and stability, are observed by the step size parameter μ, to meet the preferred requirements, the step size parameter must be controlled.

The filtering and weight adaption of CLLMS based adaptive filter algorithm with the number of filter taps of M is given by

$$r(n) = \sum_{i=0}^{M-1} f_i(n-1)\mathrm{A}(n-i) \tag{6}$$

$$h(n) = b(n) - r(n) \tag{7}$$

$$\delta_t(n) = \mu h(n) l(n)/(|(|a|)|^2 + \delta) \tag{8}$$

where, $\delta_t(n)$ is called adaption factor of CLLMS algorithm and δ is very small positive constant used for avoiding divide-by-zero error.

$$f_i(n+1) = f_i(n) + \delta_t(n)\, a(n-i) \tag{9}$$

The leakage factor is introduced for only one of the weights after regular weight adaption of NLMS is done through each sample processing. The choice of which weight to be modified is done sequentially as given in equation (9). Even though leakage term is applied to only one weight at a time, the process is repeated circularly.

$$f_t(n+1) = \delta_t(n)\, a(n-t) + f_t(n)(\mathrm{I} - \alpha_s f_t(n) h(n) h(n))$$

where,

$$\alpha_s = \begin{cases} 0.00001, \text{ if } (|h(n-t) f_t(n)|) < \Omega \\ 0, \text{ otherwise} \end{cases} \tag{10}$$

$$t = (t+1) \bmod (\mathrm{M})$$

where, Ω is small positive constant and its value is 0.00004.

The proposed algorithm is applied using a flowchart as shown below:

Later on, we discussed the proposed algorithm have some modifications to weight adaption factor $\delta_t(n)$ are, (i) the error signal $h(n)$ is passed through the divergence limiter and the consequential output is used in the coefficient –update equation. This is to stop the divergence of the filter, which arises due to noise occurred in the ECG due to the reference signal $x(n)$ occurs at an output. Usually a divergence limiter is a limiter and it does not allow the error to exceed too much than the previous error, (ii) Adaptive filter input power is estimated using long-term average of the de-correlated reference signals to increase the stability, as well as to reduce the complexity mathematically and also the memory requirement and (iii) and another advantage is to change the fixed step size to variable step size, which is inversely proportional to long term average of the convergence achieved. So, the modified equation for estimation of adaption factor $\delta_t(n)$ is shown as:

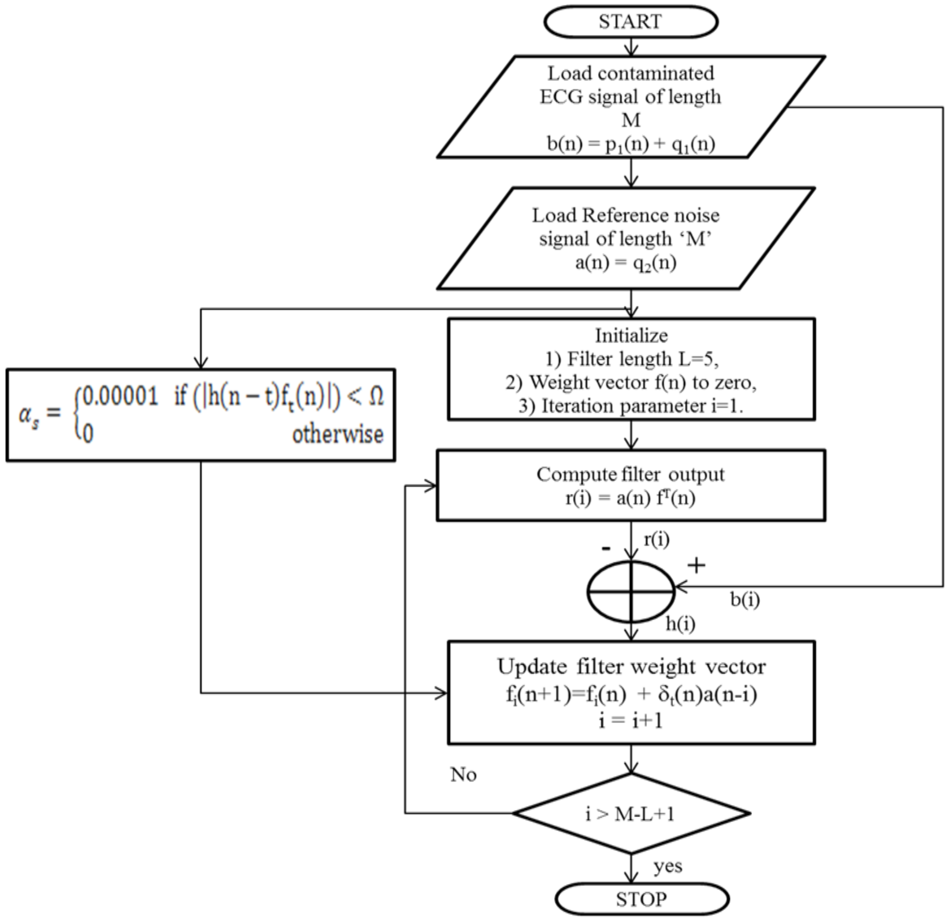



**Figure 2: Flow Chart of VSSCLLMS based adaptive noise canceller**

$$\delta_t(n) = \left( \frac{\mu_t(n)}{p_x(n)} \frac{p_{\text{mod}}(n)}{p_x(n)} x'(n) \right) \tag{11}$$

In the above equation (10), $\mu_t(n)$ is the variable step size and is directly proportional to echo leakage parameter $\Delta(n)$ , $p_{\text{mod}}(n)$ is the modified error signal by divergence limiter described in the subsequent sub-section, $p_x(n)$ is the long-term average of de-correlated farend noise signal and $x'(n)$ is the reference signal.

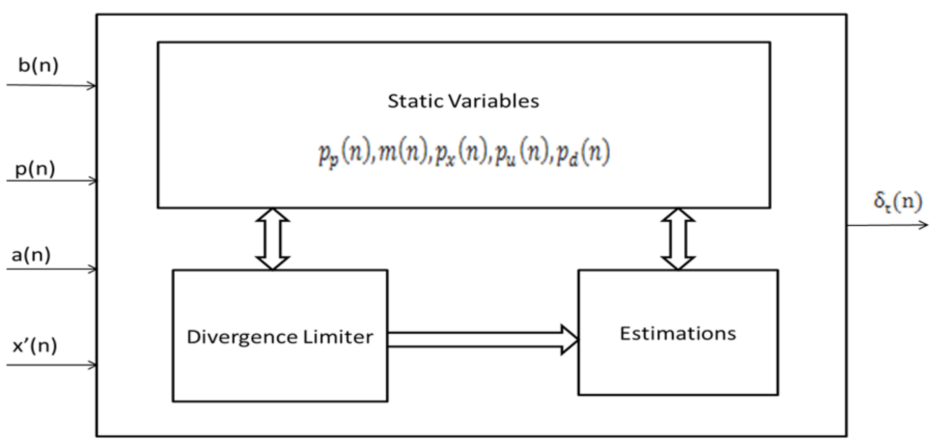



**Figure 3: Block diagram of adaption factor $\delta_t(n)$ Estimation unit**

The block diagram for estimating the adaption factor $\delta_t(n)$ unit with input and output terms is shown in the Figure 3.

The static variables such as smoothened absolute previous error $p_p(n)$, long term average of error signal $p_u(n)$, long-term average of adaptive filter input signal $p_x(n)$, and learning speed up counter $m(n)$ are memory elements used to store previous states. The learning speed up counter $m(n)$ indicates the number of times weights are continuously adapted recently after the silence or reference signal presence.

**Divergence limiter:** This as it works like a limiter at which used for not to raise the error than the previous error. It shortens the error when it rises due to noise in the reference signal which occurs at the output. The limiter equation is given by equation (12) and the smoothened absolute previous error $p_p(n)$ is updated as per the equation (13) for the next sample processing,

$$P_{\text{mod}}(n) = \text{sign}(h(n)) \min(Y_0 p_p(n), |p(n)|) \tag{12}$$

$$f(x) = \begin{cases} p_p(n), & \text{if } (x'(n) = 1) \\ \gamma_2 p_p(n) + \gamma_1 |p(n)|, & \text{if } (\gamma_0 p_p(n) \le |p(n)|) \\ \gamma_3 p_p(n), & \text{elsewhere} \end{cases}$$

**The Expectation of Long-term averages:** Actually, the adaptive filter input power, $\|a\|^2$ is expected as, by squaring all the input samples and summing up them. This procedure will require more complexity. So we went for the other method i.e. maintaining the power variable and adding the difference between the power of current de-correlated reference signal and very oldest sample to it. This procedure requires low additional complexity with additional memory for power level variable. For the lower order of filter taps, high variation in the reference power may cause damping. This may lead to instability now and then. So, in our implementation, (i) long-term average of de-correlated reference signal $p_x(n)$ is used to expect the input power of the adaptive filter and (ii) long-term average of error $p_u(n)$ and input signal $p_b(n)$ are used to estimate the echo leakage factor $\Delta(n)$. The averages are estimated as given below:

$$p_u(n) = p_u(n-1) + \gamma_4(|p(n)| - p_u(n-1)) \tag{13}$$

$$p_b(n) = p_b(n-1) + \gamma_4(|b(n)| - p_b(n-1)) \tag{14}$$

$$p_a(n) = p_a(n-1) + \gamma_4(|a(n)| - p_a(n-1)) \tag{15}$$

where, $Y_4$ is a constant and its value equal to (1/(M + 1)). The convergence of the noise cancellation of adaptive algorithm is observed by leakage parameter $\Delta(n)$ and it is written as given below,

$$\Delta(n) = \frac{p_u(n)}{p_b(n)} \tag{16}$$

## 4. RESULTS AND DISCUSSIONS

In this section they studied on the PLI cancellation, EM cancellation caused in ECG signal, This PLI cancellation is applied in 4 adaptive algorithms they are LMS, NLMS, CLLMS and VSS-CLLMS and those variations have been shown clearly in the Figure 4-6. The simulation results corresponding to data 105 are shown in this paper.

However, from the Figure 4-6 we obtain the ideal result, in the adaptive technique called VSSCLLMS.

By observing all the above Figures the noise get reduced more in the VSSCLLMS adaptive algorithm and we get the noise free ECG signal at VSSCLLMS. Table 1-3 shows the performance of these algorithms in terms of SNRI, EMSE and MSD. From our experiments and calculated performance measures it is clear that among the considered algoritms VSSCLLMS based ANC performance better in the artefact removal process.

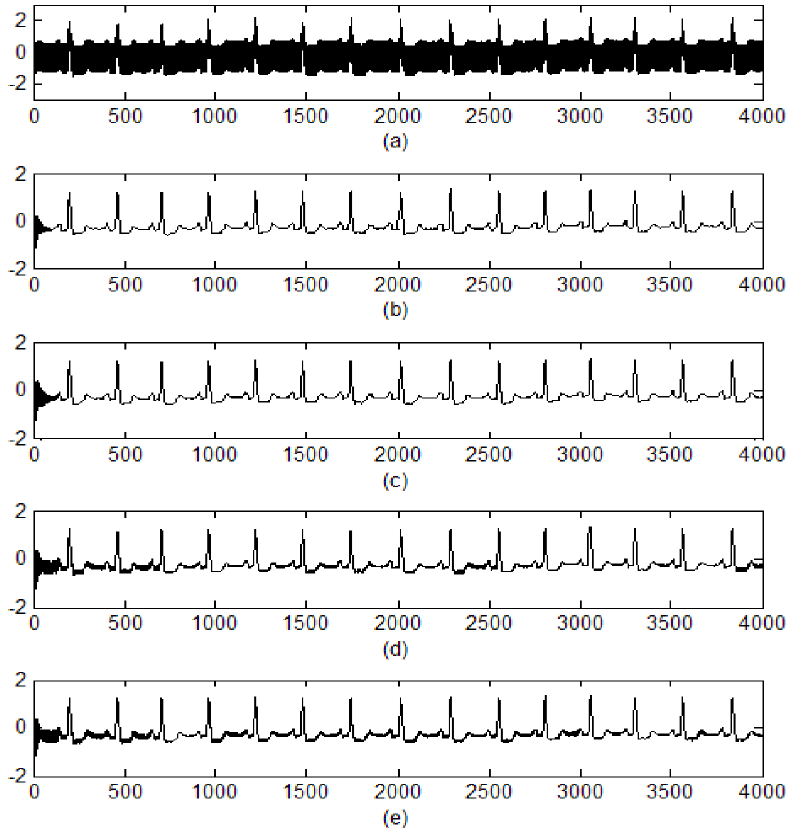
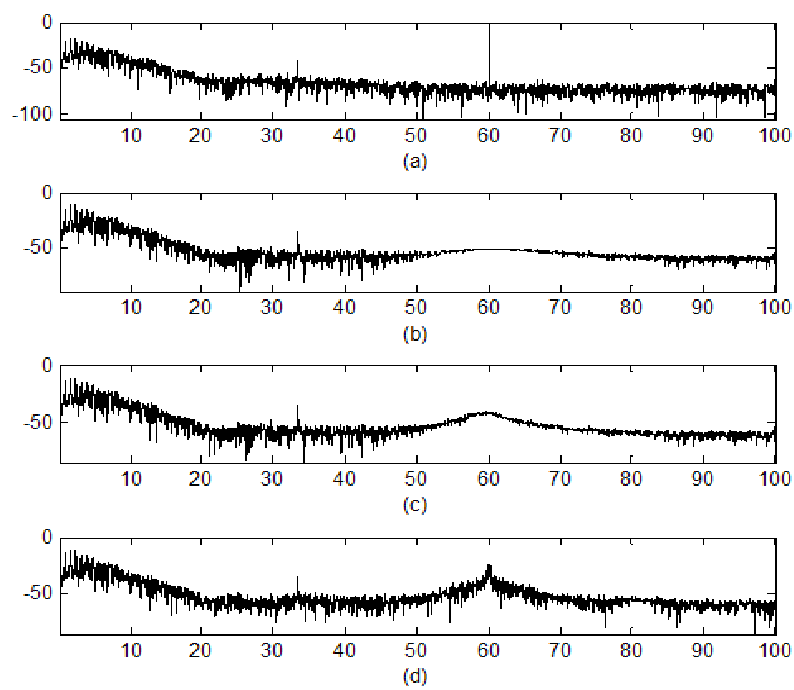



**Figure 4: Typical filtering results for PLI cancellation using data normalized adaptive filtering techniques: (a) ECG signal with PLI, (b) recovered signal using LMS algorithm, (c) recovered signal using NLMS algorithm, (d) recovered signal using CLLMS algorithm, (e) recovered signal using VSSCLLMS algorithm**



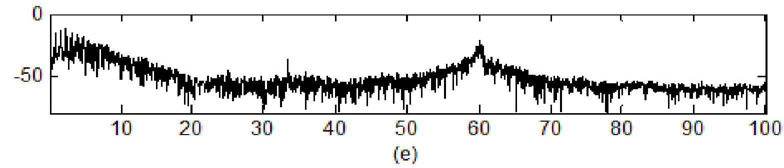



**Figure 5: Typical frequency spectrums for PLI cancellation using data normalization adaptive filtering techniques: (a) ECG signal with PLI, (b) recovered signal using LMS algorithm, (c) recovered signal using NLMS algorithm, (d) recovered signal using CLLMS algorithm, (e) recovered signal using VSSCLLMS algorithm**

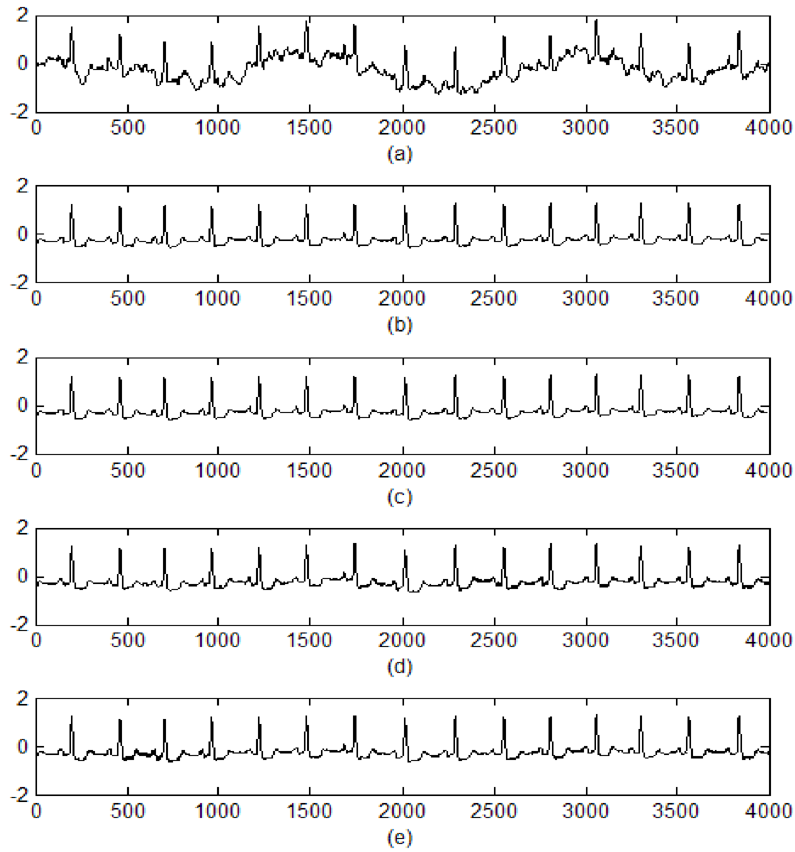



**Figure 6: Typical filtering results for EM cancellation using data normalization adaptive filtering techniques: (a) ECG signal with EM, (b) recovered signal using LMS algorithm, (c) recovered signal using NLMS algorithm, (d) recovered signal using CLLMS algorithm, (e) recovered signal using VSSCLLMS algorithm**

**Table 1**
**SNRI comparisoin of various algorithms in ECG signal enhancement process (In dBs)**

| *Artifact Type* | *Data Number* | *LMS* | *NLMS* | *CLLMS* | *VSSCLLMS* |
|---|---|---|---|---|---|
| PLI | 101 | 7.5768 | 9.5776 | 13.5867 | 15.5897 |
| | 102 | 7.8907 | 10.9086 | 11.9234 | 14.9654 |
| | 103 | 7.9865 | 11.9876 | 12.9945 | 16.9986 |
| | 104 | 7.6894 | 9.6899 | 10.6913 | 13.6956 |
| | 105 | 7.7567 | 11.6712 | 14.3427 | 16.7590 |
| | Average | 7.7800 | 10.7669 | 12.7077 | 15.6016 |

| *Artifact Type* | *Data Number* | *LMS* | *NLMS* | *CLLMS* | *VSSCLLMS* |
|---|---|---|---|---|---|
| EM | 101 | 3.7632 | 7.8431 | 9.7865 | 13.9891 |
| | 102 | 3.5639 | 8.5643 | 10.2341 | 14.1587 |
| | 103 | 3.7643 | 8.8907 | 11.4587 | 13.2049 |
| | 104 | 3.8720 | 9.8765 | 12.7830 | 13.6589 |
| | 105 | 3.9484 | 9.8975 | 13.7543 | 15.3829 |
| | Average | 3.7823 | 9.0144 | 11.6033 | 14.0789 |

**Table 2**
**EMSE comparisoin of various algorithms in ECG signal enhancement process (In dBs)**

| *Artifact Type* | *Data Number* | *LMS* | *NLMS* | *CLLMS* | *VSSCLLMS* |
|---|---|---|---|---|---|
| PLI | 101 | –18.9076 | –36.7895 | –39.0923 | –40.9876 |
| | 102 | –17.4532 | –35.8214 | –38.7063 | –39.8765 |
| | 103 | –19.8765 | –37.8965 | –39.8076 | –41.1360 |
| | 104 | –20.9987 | –37.9987 | –40.9876 | –42.9721 |
| | 105 | –21.8298 | –38.1297 | –41.4684 | –43.5685 |
| | Average | –19.8132 | –37.3272 | –40.0124 | –41.7081 |
| EM | 101 | –8.5884 | –10.9416 | –19.4783 | –20.4578 |
| | 102 | –9..9412 | –12.4937 | –20.2149 | –20.8521 |
| | 103 | –10.2148 | –13.1598 | –21.4721 | –23.1478 |
| | 104 | –10.4596 | –13.4984 | –21.4785 | –23.2987 |
| | 105 | –10.7225 | –13.5054 | –21.6935 | –23.5628 |
| | Average | –9.99633 | –12.7198 | –20.8675 | –22.2638 |

**Table 3**
**MSD comparisoin of various algorithms in ECG signal enhancement process**

| *Artifact Type* | *Data Number* | *LMS* | *NLMS* | *CLLMS* | *VSSCLLMS* |
|---|---|---|---|---|---|
| PLI | 101 | 0.0341 | 0.0297 | 0.0264 | 0.0197 |
| | 102 | 0.0421 | 0.0398 | 0.0276 | 0.0121 |
| | 103 | 0.0497 | 0.0301 | 0.0247 | 0.0146 |
| | 104 | 0.0454 | 0.0340 | 0.0197 | 0.0120 |
| | 105 | 0.0460 | 0.0221 | 0.0184 | 0.0105 |
| | Average | 0.0434 | 0.0311 | 0.0233 | 0.0137 |
| EM | 101 | 0.4879 | 0.2987 | 0.0915 | 0.0746 |
| | 102 | 0.6123 | 0.3564 | 0.1689 | 0.0796 |
| | 103 | 0.6458 | 0.3182 | 0.1548 | 0.0755 |
| | 104 | 0.5794 | 0.3146 | 0.1149 | 0.0792 |
| | 105 | 0.5936 | 0.3068 | 0.1458 | 0.0834 |
| | Average | 0.5838 | 0.3189 | 0.1351 | 0.0784 |

## 5. CONCLUSION

In this paper, the procedure of artifact elimination from ECG signals using Leaky based adaptive algorithms in time and frequency domain is discussed. The several filter structures based on LMS, NLMS, CLLMS and VSSCLLMS techniques are improved for ECG noise cancellation. We achieved fast convergence by applying normalization. The SNRI, EMSE and MSD outcomes are shown in Table1-3. From the Figure 4-6, it results that the PLI and EM artifacts are removed effectively due to VSSCLLMS compared to LMS counter parts. In our experiments, during PLI eleimation VSSCLLMS achieves highest SNRI 16.7590dBs, that for EM elimination 15.3829dBs.

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