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An Artifact Elimination in Cardiac Signal using Circular Leaky Normalized LMS Adaptive Algorithm through Iot

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ABSTRACT: In distant cardiac care observing purposes, Electrocardiogram (ECG) waves are infected by artifacts while gaining data and broadcast of signals. The elimination of the noise is a predominant mission for accurate analysis. In this paper, an effort has been made to eliminate the artifacts, mainly baseline wander (BW), muscle artifacts (MA), power line interface (PLI), and Electrode motion (EM) using a Normalized Least mean square error (NLMS) algorithm. Later on to recover the filtering capacity and speed up the convergence process, data normalization is used. The above algorithm is normalized with reference to maximum data normalization which results in lessened computational difficulty in the denominator. Based on the above algorithms, a variety of adaptive signal enhancers (ASE's) are improved. To decrease the computational difficulty of the signal enhancer, the designed ASE's are united with sign-based algorithms. The designed ASE's are analyzed on original ECG signals gained from the MIT-BIH database to evaluate the performance. The reproduction outcomes gained demonstrates that the block based algorithms are finer than NLMS in terms of the signal to noise ratio (SNR), excess mean square error and computational difficulty. Among the NLMS alternatives, the VSS-CLNLMS (Variable Stepsize Circular Leaky Normalized Least Mean Square error) based ASE's have fine filtering capacity with a lessened number of computations. The development of the SNR obtained in the progression with the use of VSS-CLNLMS-based ASE's are calculated as 13.2945 dBs, 12.4589 dBs, 15.6179 dBs and 14.0881 dBs respectively for BW, MA, PLI and EM artifacts.

Keyword: Electrocardiogram VSS-CLNLMS computations.

I. INTRODUCTION

ECG looks like the image representation of the heart actions. If any disorders arise in the heart it will lead to the infirmity of the body. In [1]-[4] world health organization details that they gave the definition of myocardial infarction which has a key outcome on physical and psychological health.

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Also in MONICA project they presented the data on the relation among coronary heart disease (CHD) morbidity and mortality. With the evolution of acute reperfusion therapy, the theory ST-elevation/ non ST-elevation has restored the established separation into Q-wave /non-Q wave in the categorization of acute coronary syndrome.
Scientists progressed the first E-Tattoo which measures both electrocardiograph (ECG) and seismocardiograph (SCG) readings. In [5]-[11] for artifact reduction they found four processing steps with best outcomes for QRS, P and T wave peaks. In later paper they went for a new method to find the motion artifact (MA) corrupted Photoplethysmographic (PPG) beats and to correct the beat morphology with the help of artificial neural network (ANN) and brought some improvement. Also they used adaptive-filtering Technique to remove MA in capacitive ECG recordings and the reference signal is taken from the power-line interference (PLI) which got better results. They used the baseline estimation and denoising with sparsity (BEADS) filter algorithm for rooting out the motion artifact and found its efficiency. Diverse artifacts can be eliminated efficiently with the combination of singular spectrum analysis (SSA) and second-order blind identification (SOBI) technique. Cardiopulmonary resuscitation (CPR) artifact can effectively be removed with the improved adaptive filtering technique. To suppress artifact in capacitive ECG wave closed-loop control of humidification is used in signal having poor quality. The real-time detection and caution of left anterior hemi block (LAHB) can be done in movable surroundings with weighted feature-based disease categorization algorithm having exactness of 95.3%. An effective lossy compression algorithm is used to reduce the energy utilization needed for wireless devices. Also stationary wavelet transform can be used to reduce MA overlaid on ECG signal which can be used wireless. The adaptive signal enhancers (ASE's) combined with sign-based algorithm are used to analyze ECG signals and achieved improved results. The modified ensemble empirical mode decomposition (CEEMD) followed by a decision rule-based algorithm is applied to find out the noise and is done with an accuracy of 98.90%. A fully ear-worn long-term blood pressure (BP) and heart rate (HR) monitor in addition to an unsupervised learning algorithm is utilized to remove artifacts and is done on wireless wearable devices from [12]-[17]. Deep neural network (DNN) method is used to find ECG irregularities and can easily be detected in less time using 12-leads with successful results. For HR features they found a synchronized gaining of capacitively coupled ECG (ccECG) with Radar signal brought improved results.

The invent of ECG chip which offers non-contact ECG signals with an input-impedance of 400 GΩ. A synthetic signal is applied to robust denoising algorithm for ECG analysis. Also marginalized particle-extended kalman filter (MP-EKF) algorithm is applied for ECG denoising along with particle filter with an automatic particle weighting approach. During simulated driving after cardiac effect ECG monitoring is done using ccECG in comparison with a galvanic reference ECG (rECG) for better results from [18]-[23] including [9],[10],[11]. Here piston driven device was used for monitoring exactly the rhythm when compressions occurred in the chest with enhanced results. A dictionary learning (DL)-based sparse illustration method is used for ECG signal improvement in [24]-[25] with computational efficiency. In [26] they found a technique on wavelet entropy measurements of heart rate variability (HRV) wave which gave better performance. In [27]-[28] an extended internet of things (IOT) technology was used for monitoring ECG signals in rural areas with low power and cost effective.

II. ADAPTIVE NOISE ELIMINATORS FOR CARDIAC IMPROVEMENT

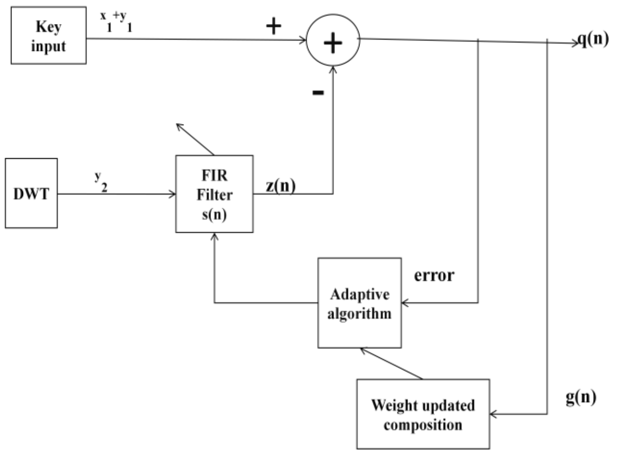
Fig 1(a) visualizes a filter that is a ECG signal with a key input x_1 with additional noise y_1 where the reference input is noise y_2 which is taken from the discrete wavelet transform (DWT) as a y_2 which is in correlation with y_1. The filter finally results as p and filter error as $q=(x_1+y_1)$ -z, then the equation can be viewed as

$$q^2 = (x_1+y_1)^2 - 2z(x_1+y_1)+z^2 \; (y_1-z)^2 + x_1^2+2x_1y_1-2zx_1 \qquad (1)$$

We know that the signal and noise are not correlated with each other then, the mean –squared error (MSE) can be written as

$$E\,[q^2] = E[(y_1-z)^2] + E[x_1^2] \qquad (2)$$

By reducing the Mean Square Error (MSE), results that the best least-squares will be ejected in the form as signal x_1. The adaptive filter will shows that either the signal or the noise will be extracted, and the process is repeated in circular manner to obtain the required result, accordingly the MSE is also reduced with the help of key and reference inputs.



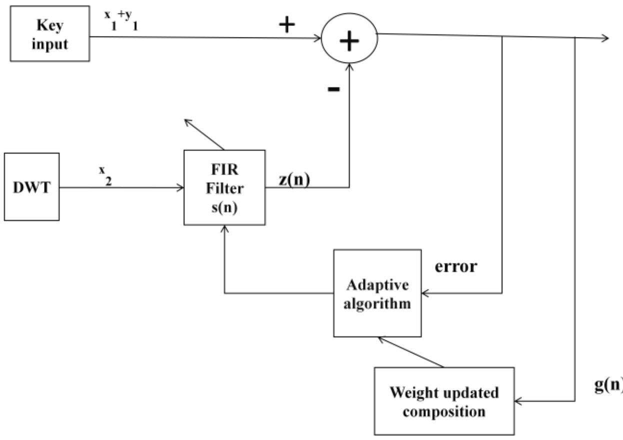


Fig. 1: Implemented composition of the adaptive noise eliminator (a) the reference input is noise y_2 correlated with noise y_1; the required signal occurs at q(n), (b) The reference input is signal x_2 correlated with x_1 signal the required signal occurs at z(n).

Fig 1(b) represents another way of explanation that the cardiogram signal is taken from many points that is from different positions of the body. The first key x_1+y_1 is a signal taken from one of the ECG leads and second lead as a reference signal $x_2$which is a noise free signal.

The signal $x_1$can be taken by the MSE from first lead and the reference inputs. Using the composition that is equation (1) we can write it as

$$E\,[q^2] = E[(x_1-z)^2] + E[y_1^2] \qquad (3)$$

Reducing the MSE will raises the filter output p which is the easiest least-square estimate of signal x1.

The LMS algorithm is the basic and simplest one to explain and to execute. This introduces a repetitive way to reduce the MSE from the key and reference inputs. Actually, a transversal filter composition is involved and the filter coefficients or weights are taken by using the LMS algorithm. The LMS algorithm can be expressed as

$$S_{t+1} = s_t + 2\mu\, q_t G_t \qquad (4)$$

Where, $s_t = [s1_{t,}\ s2_{t,} \ldots\ldots sj_{t,} \ldots\ldots sn_t]^T$ is a composition of filter weights at time t, $G_t = [G1_t, G2_{t,} \ldots\ldots Gj_{t,} \ldots\ldots Gn_t]^T$ is the key vector set at time t, and the reference signal, c_t is the required key input taken from the ECG to be purified, Z_t is the filter output which is a best least square approximation of $c_{t.}$

$$q_t = c_t - z_t \qquad (5)$$

The step size parameter μ is taken to take out the convergence at the required rate, the higher is the value, the speediest is the convergence that is 1/4μ€ where € is the highest eigen value of the autocorrelation matrix of the reference signal. This parameter should not be so high value, if it is high it gives the misadjustment and the signal is not a stable one, 1/€> μ >0

III. IMPLEMENTED TECHNIQUE

The introduced technique in this paper is the normalized least mean square (NLMS).Because of having the infinite weight approximations the NLMS leads to the occurrence of noise or if the permanent weights are maintained it leads to overflow and the least performance is observed,

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then they implemented another algorithm called leaky NLMS which is proportional to the leakage parameter which can restricts the weight and the weight overflow problem, but due to high cost in leaky NLMS, then we again linked the LNLMS with a error free circular LNLMS, such that there is a reduction in computations differentiated with the VSSNLMS.

The process is repeated until there is a reduction in computation so that it is named as circular NLMS for implementation. The VSSCLNLMS technique is implemented in addition with the stepsize gives the better result. The characteristics such as convergence rate, misadjustment or noise elimination and the stability, are delivered by the stepsize constraint μ, to lead the required contents and also the stepsize constraint have to be maintained in sense. The filtering and weight flexibility of CLNLMS related adaptive filter technique with the number of filter weights with N is given by: $Z(n)= \sum_{i=0}^{N-1} s_i(n-1)\, g(n-i)$ (6)

$$q(n)= c(n) – z(n) \qquad (7)$$

$$\delta_t(n) = \mu\frac{q(n)k(n)}{(|(|b|)|^2+\delta)} \qquad (8)$$

where, $\delta_t(n)$ is the adaption factor of CLNLMS technique and δis very negligible positive constant utilized for eradicating the divide by zero error.

$$S_i(n+1) = s_i(n) + \delta_t(n)\, b(n-i) \qquad (9)$$

The leakage parameter is undertaken for only one of the weights of NLMS is worked out by sampling procedure. The weights are being changed repetitively given in equation (9). Although the leakage constraint is injected for only one weight at that instant of time t and the procedure is iteratively done in a spherical manner so that it is named as Circular Leaky Normalized Least Mean Square Algorithm (CLNLMS).

$$S_t(n+1) = s_t(n)\, b(n-t)+ \delta_t(n)(D-\Omega_s s_t(n)q(n)\, q(n))$$

$$\text{Where, } \Omega_s = \begin{cases} 0.00001, & if\ (|q(n-t)s_t(n)|) \\ 0, & otherwise \end{cases} \qquad (10)$$

Where, Ɣ is small positive constant and its value is 0.00004. The introduced algorithm is explained with the help of the flowchart as visualized below:

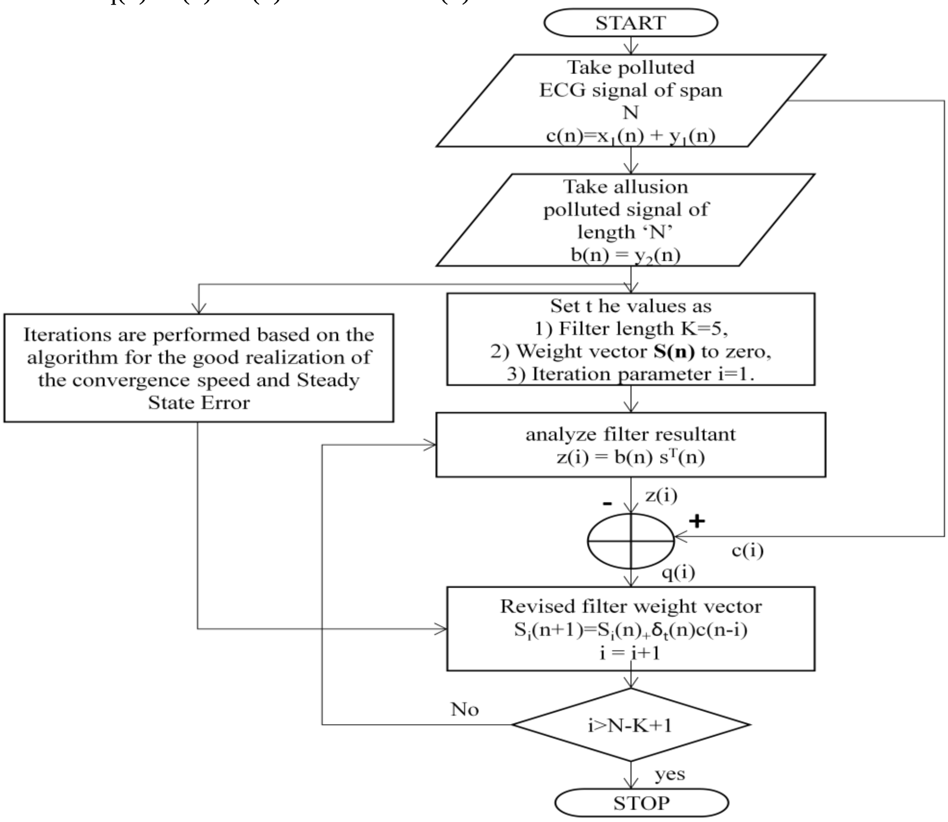

Fig. 2: Representation of VSS-CLNLMS adaptive noise elimination in the form of Workflow.

Then after, we moved out to the introduced algorithms which have some changes in accordance to weight flexibility factor as $\delta_t(n)$are, (a) the error signal q(n) is pipelined into the divergence regulator and the obtained result is utilized for the filter weight future coefficient equation. This is to object the divergence of the filter, which occurs due to the noise ejected in the cardiograph signal because of the reference signal g(n) resultation. Actually a divergence regulator is a regulator and it is used to object the error not to get more than the past error.(b) Adaptive filter key power is approximated utilizing the long term mean of the de-correlated reference signals to increment the stability, as well as to minimize the difficulty in mathematical computations and in addition to memory availability and (c) the other advantages to move the state of stepsize from fixed to variable, which is indirectly in relation with the long-term mean of the convergence achieved. Then the changed equation approximation of adaption parameter $\delta_t(n)$ is visualized as:

$$\delta_t(n) = \left[\frac{\mu_t(n)}{x_{x(n)}}\frac{x_{mod}(n)}{x_x(n)}g'(n)\right] \qquad (11)$$

In the above equation (10), $\mu_t(n)$ is the variable step size and it is proportional to echo leakage constraint η(n), $x_{mod}(n)$ is the changeable error signal by divergence ejector explained in the subsequent sub-section, $x_x(n)$ is the long term mean of de-correlated far end noise signal and $g'(n)$ is the referencesignal.

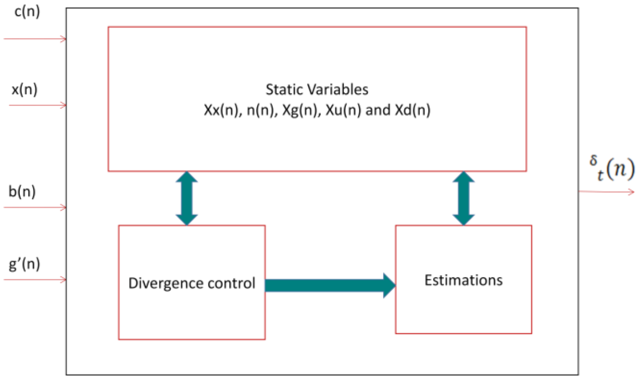

Fig. 3: Structural representation of adaption factor δt(n) approximation unit.

The above diagram for approximating the set over factor δt(n) unit with key and resultant parameter is shown in figure (3). The standing changeable parameters such as error free signal from past error $x_p(n)$, long term mean of error signal $x_u(n)$, long term mean of adaptive filter key signal $x_x(n)$, a learning speed of counter n(n) are memory terms utilized to store past states. The learning speedup incremented n(n) represents the number of times the weights are incremented sequentially are very flexible and make the eligibility of the reference signal.

Divergence Regulator:

The working of this one is to regulate the error and not to beat the error than the past error. This reduces the error that occurs due to noise in the reference signal which result at the output. The regulator equation is given by equation (12) and the, cleared and purified past error $x_p(n)$ is future as per the equation (13) for the subsequent sampling procedure.

$X_{mod}(n)$ = sign(q(n)) min (p_0 $x_p(n)$,|x(n)| (12)

$$S(x) = \begin{cases} x_p(n) if\ (g'(n) = 1) \\ \Omega_2 x_p((n) + \Omega_1 |x(n)|,\ if\ (\Omega_0 x_p(n) \le |x(n)| \\ \Omega_3 x_p(n), \quad elsewhere \end{cases}$$

The analysis of long term mean: Consider that the adaptive filter key power, $||b||^2$ is analyzed as, by squaring all the key samples and adding them. This process needs more difficulty .So we approached anotherprocess that is enabling the power parameter and summing the difference between the power of current de-correlated reference signal and the past sample of it. This process requires less computations with more memory element for raising the power constraint. For lower order filter weight there is a big difference in the reference power will cause the diffusion. This causes the procedure to be not stable. So in our practices, (i) Long-term mean of de-correlated reference signal $x_x(n)$ is used to give the input as power to the adaptive filter and (ii) Long-term mean of error $x_u(n)$ and key signal $p_b(n)$ are utilized to approximate the echo leakage parameter ɳ(n). The mean will be approximated and written as:

$$x_u(n) = x_u(n-1) + \Omega_4(|x(n)| - x_u(n-1))(13)$$
$$x_c(n) = x_c(n-1) + \Omega_4(|x(n)| - x_c(n-1))(14)$$
$$x_a(n) = x_a(n-1) + \Omega_4(|x(n)| - x_a(n-1))(15)$$

Where Ω_4 is a constant and its value is represented as (1/(N+1)). The convergence of noise elimination of adaptive technique is obtained by leakage parameter ɳ(n) and it is represented as given,

$$ɳ(n) = \frac{x_u(n)}{x_c(n)}(16)$$

IV. RESULTS AND DISCUSSIONS

In this session, we explained about the PLI removal, EM Removal occurred in cardiograph signal. The PLI removal is done by using the four adaptive techniques those are LMs, NLMS,CLNLMS and VSS-CLNLMS And those changes are visualized in the figure(4)-(6). The obtained resultant are related to the data 105 which is explained in the literature So, from the figure (4)-(6) we got the result perfectly in the algorithm VSS-CLNLMS. By viewing all the above figures the noise gets minimized highly in VSS-CLNLMS and also the pure signal occurred in the same table (1)-(3) represents the characterization of these techniques in value of SNRI, EMSE and MSD. From our practices and computed characteristic valuations it is perfect that the preferred algorithms as VSS-CLNLMS related Adaptive Noise Eliminators (ANE) shows the better performance while eliminating the artifacts.

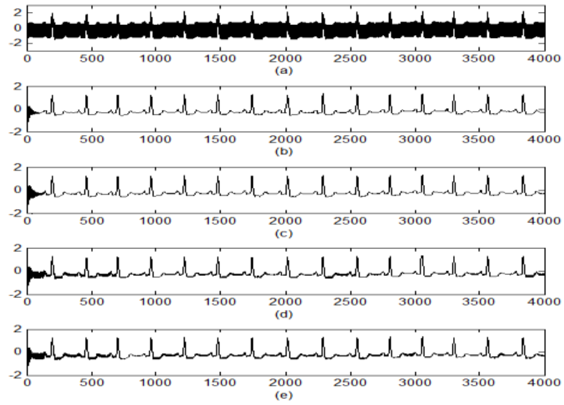

Fig. (4): Filtered outcomes of PLI removal by data normalized adaptive filtering techniques: (a) cardiac signal having PLI, (b) obtained signal by LMS algorithm (c) obtained signal by NLMS algorithm (d) obtained signal by CLNLMS algorithm (e) obtained signal by VSS-CLNLMS algorithm.

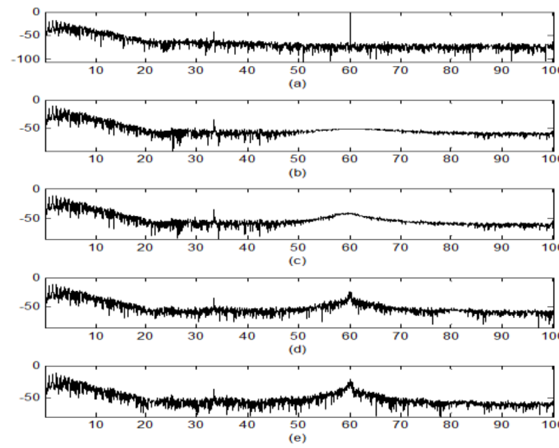

Fig. (5): Characteristic representation of frequency spectrums for PLI removal by data normalized adaptive filtering techniques: (a) cardiac signal having PLI, (b) obtained signal by LMS algorithm (c) obtained signal by NLMS algorithm (d) obtained signal by CLNLMS algorithm (e) obtained signal by VSS-CLNLMS algorithm.

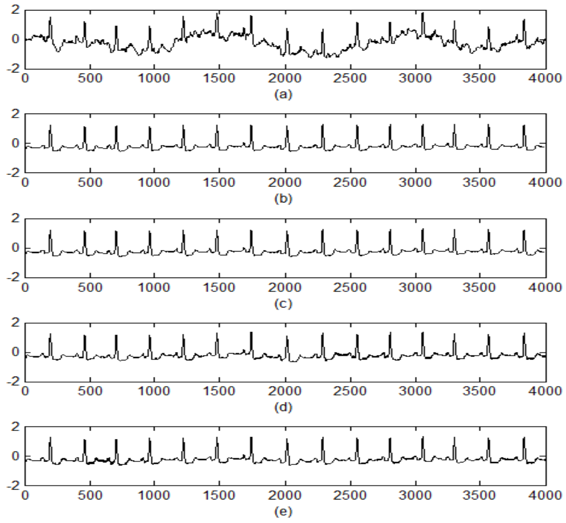

Figure (6): Filtered outcomes of EM removal by data normalized adaptive filtering techniques: (a) cardiac signal having PLI, (b) obtained signal by LMS algorithm (c) obtained signal by NLMS algorithm (d) obtained signal by CLNLMS algorithm (e) obtained signal by VSS-CLNLMS algorithm.

Table 1 SNRI differentiation with different algorithms in cardiac signal improvement procedure (In dBs)

Artifact Type	Data Number	LMS	NLMS	CLNLMS	VSSCLNLMS
PLI	101	7.6252	9.5821	13.5869	15.5921
	102	7.9011	7.9126	11.9244	14.96662
	103	7.9901	11.9927	12.9947	16.9996
	104	7.6901	9.691	10.6971	13.7102
	105	7.761	11.6792	14.351	16.8211
	Average	**7.7935**	**10.1715**	**12.7108**	**15.6179**
EM	101	3.7751	7.8521	9.812	13.991
	102	3.574	8.6141	10.3126	14.1612
	103	3.7651	8.912	11.5682	13.2146
	104	3.912	9.8962	12.812	13.6619
	105	3.9509	9.9019	13.8212	15.412
	Average	**3.79542**	**9.03526**	**11.6652**	**14.0881**

Table 2 EMSE differentiation with different algorithms in cardiac signal improvement procedure (In dBs)

Artifact Type	Data Number	LMS	NLMS	CLNLMS	VSSCLNLMS
PLI	101	-18.8921	-36.6125	-39.0724	-40.9776
	102	-17.4217	-35.6214	-38.6024	-39.7765
	103	-18.9921	-37.792	-39.7027	-41.031
	104	-20.9612	-37.896	-40.9247	-42.8921
	105	-21.7217	-38.112	-41.3679	-43.4699
	Average	**-19.5977**	**-37.2067**	**-39.934**	**-41.6294**
EM	101	-8.4727	-10.9317	-19.4682	-20.4489
	102	-9.8498	-12.4821	-20.1998	-20.8439
	103	-10.1199	-13.242	-21.4612	-23.1319
	104	-10.4496	-13.4827	-21.3698	-23.1891
	105	-10.7025	-13.4959	-21.6878	-23.4921
	Average	**-9.9189**	**-12.7268**	**-20.8373**	**-22.2211**

Table 3 MSD differentiation with different algorithms in cardiac signal improvement procedure (In dBs)

Artifact Type	Data Number	LMS	NLMS	CLNLMS	VSSCLNLMS
PLI	101	0.0339	0.0284	0.0259	0.0196
	102	0.0419	0.0387	0.0269	0.0118
	103	0.0478	0.0302	0.0239	0.0137
	104	0.0462	0.0327	0.0202	0.0116
	105	0.0458	0.0217	0.0179	0.0103
	Average	**0.0431**	**0.0303**	**0.0229**	**0.0134**
EM	101	0.4877	0.2972	0.0912	0.0699
	102	0.6118	0.3457	0.1682	0.0792
	103	0.6453	0.2997	0.1532	0.0762
	104	0.5792	0.3142	0.1042	0.0791
	105	0.5935	0.3029	0.1501	0.0798
	Average	**0.5835**	**0.3119**	**0.1333**	**0.0768**

V. CONCLUSION

In this literature, the process of artifact reduction from cardiac signal related to LMS, NLMS, CLNLMS and VSSCLNLMS techniques are raised to remove the artifact in ECG. And also in this we have goaled the fast convergence rate by relating with the normalization. The SNRI, EMSE and MSD results are visualized in table (1)-(3). And from the figure (4)-(6), it outputs that the PLI and EM noises are cancelled perfectly due to VSS-CLNLMS when differentiated this algorithm with the LMS hierarchy algorithms. In our practices, the VSS-CLNLMS algorithm from PLI goes to high SNRI of 15.6179 dBs, and the EM goals to 14.0881 dBs.

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