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Denoising Artifacts from Cardiac Signal Using Normalized Variable Step Size LMS Algorithm

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Abstract: In this paper, an efficient Error Data Normalized Variable Step Size Least Mean Square (EDNVSSLMS) adaptive algorithm is presented to enhance the quality of an Electrocardiogram (ECG) signal. Due to physiological and non-physiological effects, ECG signals usually undergo numerous artifacts such as Baseline Wander, Muscle artifact, Power Line Interference and Electrode Motion artifacts. The proposed EDNVSSLMS algorithm de-noise these artifacts with better Peak Signal to Noise Ratio, misadjustment and convergence rate compared to other LMS based algorithms, while preserving important clinical wave features morphologies. Also, based on o EDNVSSLMS algorithm, we implemented sign and block based EDNVSS algorithms. Finally we have applied these algorithms to ECG signals corrupted with noise. The performance results shows that Block Based EDNVSSLMS algorithm gives better elimination of noises in the ECG signal with less misadjustment and high peak to signal noise ratio. For less computational complexity and for fast communication of the signal is main, then we select Sign Regressor EDNVSS algorithm. *Copyright © 2015 IFSA Publishing, S. L.*

Keywords: Artifacts, Biotelemetry, Noise cancelation, Misadjustment, Signal to noise ratio.

1. Introduction

The accurate interpretation of biomedical signals is a critical and extraction of clinical parameters from this is a challenging process. In the clinical laboratory when we acquiring the ECG signal, the quality of the signal encounters various sources of artifacts, the predominate artifacts are Power Line Interference (PLI), Baseline Wander (BW), Electrode Motion (EM) artifact and Muscle Artifact (MA) etc. Some times the patient is at a far from the location where a cardiologist is not available, then using ECG wearable recorder, the cardiac condition can be monitored and the signal can be sent to a hospital for suggestions. The specialist doctor in hospital can send decision that has to be taken immediately to take correct decision and rescue the life. When transmitting of these signals from the far patient to cardiologist, the channel noise also added, which will further degrade the signal quality and which will mask the tiny features of the ST segment of the ECG signal. For removing these artifacts [1] and the accurate interpretation of ECG signal give the desired signal values, otherwise doctor may give wrong diagnosis to patient due to undesired artifacts.

There are several approaches used to enhance the quality of ECG signal in the literature using both fixed and adaptive filters [2-9]. Compared to Wiener filter an adaptive filter can give better results because of its alteration of filter weights according to the input signal. In [4] Brouse et al. proposed wavelet approach to detecting electrocautery noise in the ECG. A variable step size LMS algorithm for adaptive noise cancellation is introduced by Kwong [7], as step size increases or decreases, allowing the adaptive filter track the input signal and produces a small steady state error. For less computational complexity [8, 9] compared to LMS algorithm Sign-Regressor LMS, Sign LMS and Sign-Sign LMS are implemented. In [10] Kabir et al. and in [11] Blanco-Velasco et al. presented empirical mode decomposition and discrete wavelet transform for removing of noises in ECG signal, but it takes high computational complexity compared to mean square algorithms. There are several improved VSS algorithms [12-14] are developed for increasing quality of signal. In this paper we are presenting an efficient Error Data Normalization Variable Step Size (EDNVSS) LMS based algorithms to increase the signal to noise ratio (SNR) and better convergence rate with less misadjustment error. For less computational complexity we used sign regressor EDNVSS- LMS algorithm, which will give equivalent SNR as that of BBEDNVSS algorithm. For analysis of these algorithms we have taken the real ECG signal MIT-BIH database.

1.1. Least Mean Squares (LMS) Adaptive Algorithm

For many years, the adaptive filter has been a popular and effective tool for analyzing signals. The Fig. 1 shows the adaptive filter structure.

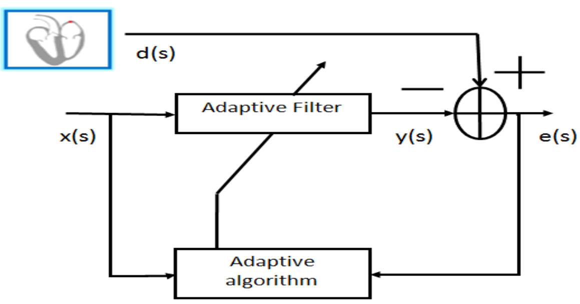

Fig. 1. Adaptive filter structure.

Consider LMS based adaptive filter algorithm of length M, which takes the input vector $x(s)$, the desired signal $d(s)$ (ECG-heart), then system generates adaptive filter output $y(s)$ as

$$y(s) = W^T(s)X(s). \tag{1}$$

The input signal vector representation is given by

$$X(s) = [x(s),\ x(s-1),\ ...,\ x(s-M+1)],$$
$$W(s) = [w(s),\ w(s-1),\ ...,\ w(s-M+1)]^T$$

is the tap weight vector at s^{th} index and $e(s)$ is the error signal, which is the difference between the desired signal $d(s)$ and the estimated signal $y(s)$.

The updated weight vector for LMS algorithm is given by the following equation.

$$W(s+1) = W(s) + \mu X(s)e(s)\ , \tag{2}$$

where μ is the step size which controls the convergence rate and expectation of mean square value. The value of to be chosen in such way that it reaches to minimum steepest decent value and in general the value to be smaller than $2/tr(R)$, where R is the auto correlation of input signal $X(s)$ and $tr[R]$ is the trace of R.

2. Proposed Efficient Error Data Normalized Variable Step Size LMS Adaptive Algorithm

In LMS algorithm, the step size is fixed so that we cannot increase the convergence speed and cannot reduce the misadjustment error. We can use Data Normalized LMS (DNLMS) algorithms [15] for better filtering capability, fast convergence and to reduce the misadjustment error. In [16] Aboulnasr et al. presented a robust VSSLMS algorithm for analysis and simulation. This algorithm has lower convergence rate due to early reducing step size value and the auto correlation between the error values. In LMS algorithm, we have large Excess Mean Square Error (EMSE) due to the fixed step size, which leads to signal distortion in the desired output signal. For better convergence and somehow decreased EMSE, we use Error Normalized (nonlinear) LMS (ENLMS) algorithms [17]. In these algorithms, the step size is normalized with error signal so that the desired signal distortion is reduced in the output.

In the DNLMS algorithm, the time-varying step-size is inversely proportional to squared norm of the data vector, whereas in ENLMS algorithm it is inversely proportional to squared norm of the error vector. Due this fact, EMSE is somehow less in ENLMS than NLMS algorithm. If we use both error and data normalization at a time then we can get good SNR and fast convergence rate. So we propose Error Data Normalized Variable Step Size (EDNVSS*)* LMS algorithm. In this algorithm, the step size is controlled by taking both error and data at a time. The weight update equation for EDNVSS LMS algorithm is as follows.

$$W(s+1) = W(s) + \mu(s)X(s)e(s), \tag{3}$$

where $\mu(s)$ is the variable step size.

The variable step size $\mu(s)$ for the ENLMS algorithm is given by

$$\mu(s) = \frac{\mu}{z + e^{T(s)} e(s)}; \tag{4}$$

The step size for EDNVSSLMS algorithm is

$$\mu(s) = \frac{\mu}{\beta(\|E(s)\|^2) + (1-\beta)(\|X(s)\|^2)}, \tag{5}$$

where β is the small constant and is less than one, which controls the step size $\mu(s)$. The value $\mu(s)$ is high for starting iterations which leads to fast convergence. When iterations increases $\mu(s)$ is gradually reduces which leads to low misadjustment ratio and low EMSE. To achieve this we have to choose the step size $\mu = 1 - (0.01)/s$. For eg., If the initial step size is 0.2, the value $\mu = 0.19$ for the iteration s=1; and the value $\mu = 0.185$ for the iteration s=2. Thus the step size is gradually reduce when iterations increase. Also,

$$E(s) = \sum_{k=0}^{N-1} |e(s-k)|, \tag{6}$$

where N is to be chosen such that N is less than the number of iterations.

Sign based algorithms [18] are used in order to reduce the computational complexity and for fast transmission of signals. These sign based algorithms are also used in hardware designs such as Field Programmable Gate Arrays and Application Specific Integrated Circuits.

The signum function is defined as following.

$$sign(y(s)) = \begin{cases} -1 & \text{if } y(s) < 0 \\ 0 & \text{if } y(s) = 0 \\ 1 & \text{if } y(s) > 0 \end{cases} \tag{7}$$

The signaum can be applied for error function or data function and also for both. We apply the sign function to the proposed EDNVSSLMS algorithm. When replacing the $X(s)$ by $SGN(X(s))$, i.e. data is clipped, in equation (3), the Sign Regressor or sign data EDNVSSLMS algorithm as follows.

$$W(s+1) = W(s) + \mu(s) SGN(X(s)) e(s) \tag{8}$$

When replacing the $e(s)$ by $SGN(e(s))$, i.e. error is clipped, in equation (3), we get the Sign Error or simply Sign EDNVSSLMS algorithm as follows.

$$W(s+1) = W(s) + \mu(s)(X(s)) SGNe(s) \tag{9}$$

To improve the convergence rate and to reduce the gradient noise amplification for EDNVSSLMS algorithm, we use Block Based approach to EDNVSSLMS algorithm. In this approach the incoming data is subdivided into blocks, from each block choose maximum magnitude and it can be used to compute variable step size parameter. The weight update relation for BB-EDNVSSLMS is as follows.

$$W(s+1) = W(s) + \frac{\mu(s)}{X_{Mj}^2 + \varepsilon} X(s) e(s), \tag{10}$$

where

$$X_{Mj} = \max\{|X_k|, k \in Z'_j\},$$

$$Z'_j = \{jM,\ jM+1, \ldots,\ jM+M-1\},\ j \in Z.$$

When $X_{Mj} \neq 0$ then choose $\varepsilon = 0$.

The convergence rate indicates that reducing the power of the error signal. The slow convergence rate means it takes the long time to calculate the filter coefficients and vice versa. The convergence characteristics are shown in Fig. 2, and are obtained for cancellation of PLI which is corrupted with ECG signal. From Fig. 2, we can observe that BBEDNVSSLMS algorithm and EDNVSS-LMS algorithm gives better elimination of PLI and less MSE than the other algorithms.

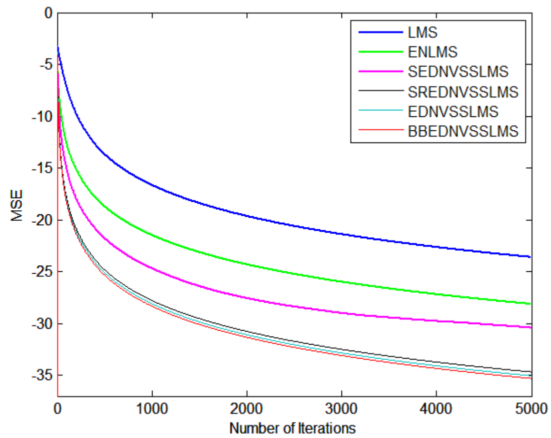

Fig. 2. Convergence characteristics of different adaptive algorithm.

3. Simulation Results

In order to test the ability of the elimination of artifacts and effectiveness of various characteristics of the proposed EDNVSS LMS algorithms, we have taken the several ECG recordings from bench mark, the Massachusetts Institute of Technology – Boston's Beth Israel Hospital (MIT-BIH) Arrhythmia Database, Physionet [19]. The recordings of ECG were digitized at 360 Hz per channel with a resolution of 11 bits over a 10 mV range. In the Arrhythmia laboratory Database total 47 subjects of ECG recordings collected from 22 women aged

32-89 years, and 25 men aged 23-89 years. For the simulation process, we have collected different ECG record subjects of 5000 samples from the database. Due to space constraints simulation results for record no. 230 are shone in this paper. Tabular values are presented for other collected ECG records. We have taken number of samples on X-axis and amplitude taken on Y-axis for all graphs except for the frequency spectrum graph. For better analysis, we have chosen the order of the filter as four, added the random variance as 0.0001 to the original noise. Also, we have chosen the step size as 0.01 for LMS, 0.05 for Normalized LMS and 0.2 for the remaining three algorithms.

The simulation results for PLI demonstrates that, the original ECG signal is corrupted with 60 Hz power line frequency, and it is sampled with a sampling frequency of 200 Hz's. As shown in Fig. 1 this corrupted ECG signal is applied at desired input and noisy signal is applied at reference input. Fig. 3 shows that the frequency spectrum for corrupted ECG signal with PLI, the PLI reduction using LMS and EDNVSS-LMS algorithms. From this frequency spectrum we can view the oval shape which indicates 60 Hz frequency better eliminated using BBEDNVSS algorithm compared to LMS algorithm.

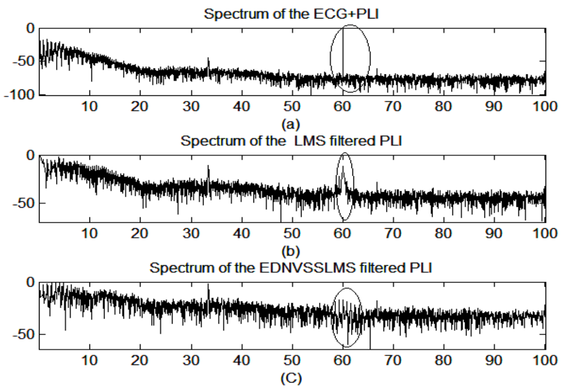

Fig. 3. (a) Frequency spectrum of ECG with 60 Hz power line noise (b) Frequency spectrum using LMS filtering (c) Frequency spectrum using EDNVSSLMS filtering.

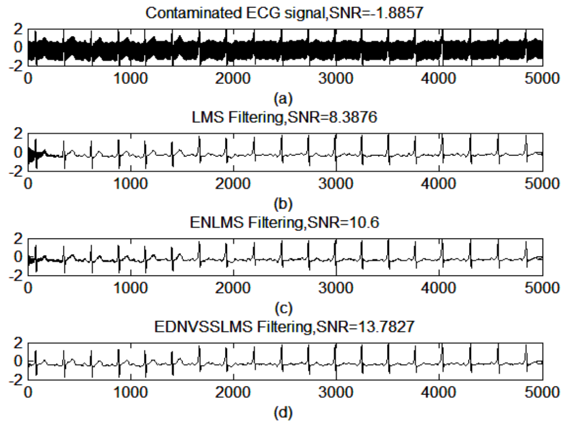

Fig. 4. (a) ECG, corrupted with PLI. Recovered ECG signal after elimination of PLI with (b) LMS (c) ENLMS (d) EDNVSSLMS algorithms.

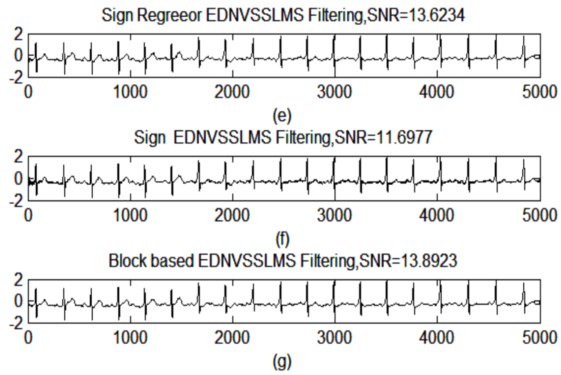

Fig. 5. Recovered ECG signal after elimination of PLI using (e) SREDNVSS LMS (f) SEDNVSS-LMS (g) BBEDNVSS-LMS algorithms.

By using different adaptive algorithms for different patient records we eliminated the PLN as shown in Fig. 4 and Fig. 5. From this graphs we can concluding that noise is more eliminated using EDNVSS algorithm compared to LMS algorithm. The SNR is calculated for the elimination of PLI and their values are presented in Table 1. From the SNR calculation it is shown that average SNR of EDNVSS-LMS gets 13.4489 dB and block based EDNVSS algorithm gets slightly higher value of 13.5706 dB where as LMS algorithms draw 8.0132 dB. As it is shown in Table 1, it is clear that the SREDNVSS algorithm gets SNR value 13.2873 dB, which is approximately equal to the SNR of EDNVSS-LMS algorithm.

The non stationary real noises such as BW, EM and MA are collected from MIT-BIH noise stress ECG arrhythmia database [20]. The noise stress database contains 12 half-hour ECG recordings and 3 half hour recordings of noise typical in ambulatory ECG recordings. When the electrodes were placed on the limbs locations and if these noises are present in the ECG signal then the PQRST are not clearly visible in the recorded signal.

Omid Sayadi et. al [21] analyzed that BW artifact is a low frequency signal. The BW artifact will appear, in general, due to moving subject, respiration or motion of the leads. The ECG signal corrupted with the BW artifact and is shown in Fig. 6 (a). This artifact is eliminated using various algorithms and are shown in Fig. 6 (b-e). We calculated SNR for different records using different algorithms. The average SNR for ENLMS we get 6.436 dB, EDNVSS-LMS gets 5.542 dB and Block based EDNVSS gets 5.716 dB. From the Table 2 – we can observe that the, using different adaptive algorithms reducing the baseline wander and calculated average SNR, for NLMS we get 6.4374 dB, EDNVSS-LMS gets 5.5431 dB and Block based EDNVSS gets 5.7173 dB.

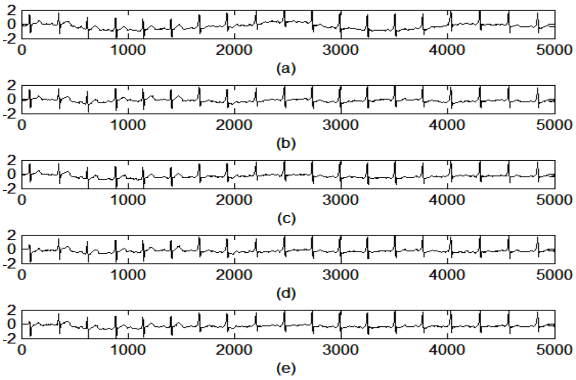

Fig. 6. (a) ECG corrupted with BW. Elimination of BW using (b) LMS (c) NLMS (d) DNVSS-LMS (e) BBEDNVSS-LMS algorithms.

The EM artifact sometimes called as non-physiological noise [22, 23] due to result of intermittent mechanical forces acting on the electrodes. Sometimes this artifact may cause due to the significant amount of BW and MA. In general, the motion artifact has a frequency range of 2-10Hz, but the real EM noise is sampled at 360Hz frequency. In order to match of the ECG frequency, EM noise is anti aliased and re-sampled with 200Hz frequency.

The ECG with EM artifact and elimination of EM using different algorithms are shown in Fig. 7. The performance of various algorithms for removal of EM are shown in Table 3. The average SNR for ENLMS is 5.558 dB, EDNVSS-LMS is 5.815 dB, and BB-EDNVSS algorithm is 6.455 dB. Among these the BBEDNVSS algorithm gets high elimination rate of EM when compared to remaining algorithms.

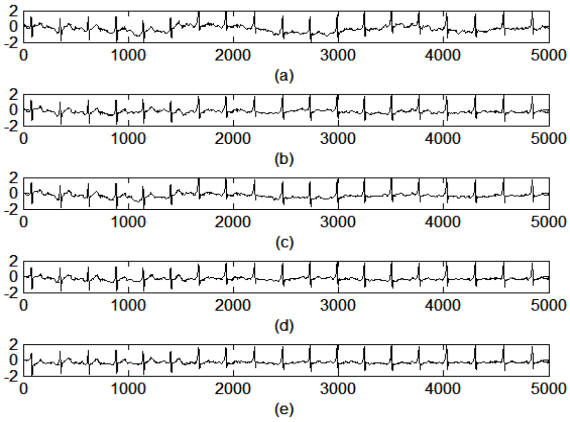

Fig. 7. (a) ECG corrupted with EM. Elimination of EM using (b) LMS (c) NLMS (d) EDNVSSLMS (e) BBEDNVSS-LMS algorithms.

Table 1. Performance comparision of various algorithms for cancellation of PLI artifact. (All values are in decibels)

Noise	Rec. No.	SNR Before Filtering	SNR After Filtering					
			LMS	EN-LMS	EDNV SSLMS	SREDN VSSLMS	SEDN VSSLMS	BBED NVSSLMS
PLI	101	-2.9522	7.2822	10.1076	12.2612	12.103	9.2871	12.345
	102	-3.8873	6.4098	10.0389	12.1284	11.917	9.0883	12.1877
	103	-2.4437	7.8306	10.691	13.2133	13.0623	10.3918	13.3107
	104	-3.2014	7.2014	10.5596	13.1297	12.8934	10.5473	13.2356
	105	-2.6491	7.6427	10.0973	13.0779	12.944	9.1734	13.2169
	113	-1.706	8.5419	10.1127	13.5867	13.4583	9.1701	13.7144
	203	-1,6849	8.5359	11.4853	13.5045	13.3599	11.4055	13.5714
	214	-1.6193	8.6723	12.0797	14.4299	14.2808	12.2594	14.4499
	217	-0.6692	9.6279	13.3658	15.3753	15.2313	12.0435	15.0269
	230	-1.8857	8.3876	10.5999	13.7826	13.6233	11.6984	13.8921
Average			8.0132	10.9138	13.4489	13.2873	10.5064	13.5706

Table 2. Baseline Wader artifact reduced using different adaptive algorithms, snr before filtering 1.25 dB.

Noise	Rec. No.	LMS	EN-LMS	EDNVSS-LMS	SR-EDN VSS-LMS	SEDN VSS-LMS	BBED NVSS-LMS
BW	101	3.426	4.634	4.2228	1.6082	1.5472	5.3515
	102	4.3654	6.1747	4.2143	1.7717	1.4654	4.5426
	103	4.3748	5.6306	5.7853	3.3921	2.6935	5.1465
	104	4.3242	5.4442	6.0829	2.2387	2.6338	7.1078
	105	4.1872	5.3046	5.5486	2.64	2.5582	4.5598
	113	4.1941	6.9927	5.5974	4.271	2.8007	5.2832
	203	4.2837	8.6719	5.3176	3.7121	3.3995	6.4515
	217	4.9031	10.5988	7.255	4.9362	5.386	7.3915
	230	3.7633	4.4853	5.8648	3.1255	2.7782	5.6214
Average		4.2024	6.4374	5.5431	3.0772	2.8069	5.7173

Table 3. Electrode Motion artifact reduced using different adaptive algorithms, snr before filtering 1.25 dB.

Noise	Rec No.	LMS	EN-LMS	EDN VSS-LMS	SR-EDN VSS-LMS	SEDN VSS-LMS	BBEDNVS SLMS
EM	101	3.536	3.230	4.726	2.1595	1.9891	5.081
	102	4.859	5.660	5.186	2.1211	2.9073	5.250
	103	4.635	3.455	5.927	3.7092	3.1257	7.244
	104	4.347	9.138	5.642	2.9105	3.2474	6.494
	105	4.613	3.736	5.955	3.5214	2.8495	6.349
	113	3.494	4.677	5.099	3.6903	3.6992	5.098
	203	4.912	8.820	5.887	3.8463	4.076	6.124
	217	4.859	7.712	7.699	5.9254	5.784	8.822
	230	4.285	3.602	6.22	4.1472	3.2348	7.640
Average		4.393	5.558	5.815	3.5589	3.4347	6.455

The MA is due to the muscular activity in the body and it produces a bio-potential signal, this signal fluctuates very faster than ECG signal wave. The MA frequency is very high, ranging from 5 to 500 Hz. Usually, MA is the most troublesome noise, which mainly affects the QRS complex of the ECG wave. The MA corrupted with real ECG signal and reducing of this artifact, using different adaptive filters as shown in Fig. 8. From Table 4, we can observe that the average SNR of EDNVSS-LMS algorithm is 6.097 dB, which is better elimination of muscular noise when compared with the other algorithms.

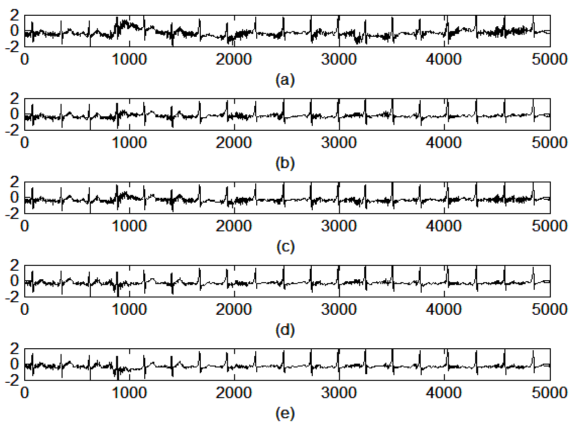

Fig. 8. (a) ECG corrupted with MA. Elimination of MA using (b) LMS (c) NLMS (d) EDNVSS-LMS (e) BBEDNVSS-LMS algorithms.

Some more parameters were analyzed for cancellation of PLI in ECG signal as shown in Table 5. The EMSE is due the deviation of weights from their optimal value. We can also find out this is the difference between the MSE produced by the adaptive algorithm at time '*s*' and the minimum mean square error produced by the Wiener filter [15]. The convergence characteristics of steady state EMSE as shown in Fig. (9), from this graph we can observe that EMSE is very less for BBEDNVSS LMS algorithm when compared with remaining algorithms. Minimum Mean Square Error (MMSE), it represents the portion of the primary signal that cannot be cancelled by the optimal weight. The misadjustment is a dimensionless parameter and gives the ratio of steady state EMSE to MMSE value. When this value is less then we can predict the signal correctly. Also we consider and calculated the Peak Signal to Noise Ratio (PSNR). When PSNR is higher value then the reconstructed signal quality is good.

The misadjustment value for BBEDNVSS LMS and EDNVSS LMS algorithms are 3.4004e-06 and 4.2668e-05 respectively, which are very less values. Also PSNR for these algorithms are 40.9588 dB and 40.7009 dB, which are higher values than the remaining algorithms. But when less computational complexity is the main criterion, compared to above two algorithms and approximate equal amount of misadjustment and PSNR required for fast transmission of the signal, then we can chose the SREDNVSSLMS algorithm.

Table 4. Muscle Artifact reduced using different adaptive algorithms, snr before filtering 1.25 dB.

Noise	Rec. No.	LMS	EN LMS	EDN VSS LMS	SR-EDN VSS-LMS	SEDN VSS-LMS	BBED NVSS LMS
MA	101	3.896	4.179	5.354	3.6387	2.6321	5.116
	102	4.326	4.225	5.597	3.1041	2.8789	5.627
	103	5.153	4.610	6.429	3.8467	2.3568	4.815
	104	4.497	3.818	6.061	4.7288	4.562	6.736
	105	4.958	4.263	6.253	4.4785	2.8843	5.261
	113	4.035	4.952	5.144	4.681	3.612	3.396
	203	4.959	4.516	6.418	5.6859	4.5446	7.981
	217	5.464	7.000	7.853	5.7386	5.7397	7.091
	230	4.74	4.491	5.764	4.042	3.0396	5.064
Average		4.669	4.672	6.097	4.4382	3.5833	5.676

Table 5. Comparison of parameters after elimination of PLI using various algorithms.

Algorithm	MSE	EMSEss (dB)	Misadjustment	PSNR(dB)
LMS	0.0044	-46.1727	1.1395e-04	29.2740
ENLM	0.0015	-36.7689	9.9329e-04	33.7950
EDNVSSLMS	3.1368e-04	-56.2881	1.1096e-05	40.7009
SREDNVSSLMS	3.4167e-04	-50.4387	4.2668e-05	40.3297
SEDNVSSLMS	9.0597e-04	-35.8234	0.0012	36.7950
BBEDNVSSLMS	2.9559e-04	-61.4244	3.4004e-06	40.9588

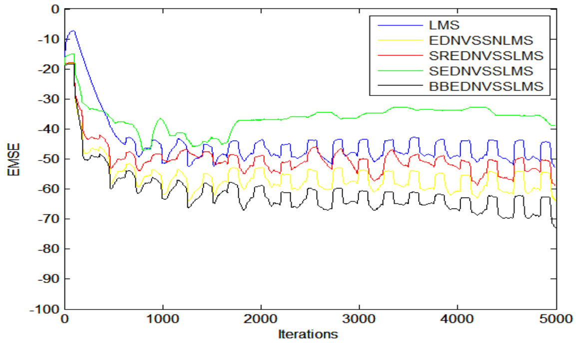

Fig. 9. Excess Mean Square Error Characteristics.

4. Conclusion

This paper shows that different Error Data normalized variable step size based algorithms, which are used to reducing the non-physiological, physiological artifacts and random noise present during acquisition of the ECG signal. In this attempt we have implemented EDNVSSLMS, Sign Regressor EDNVSSLMS, Block Based EDNVSSLMS algorithms and which are compared with basic LMS and ENLMS algorithms. The following parameters are calculated for the performance measure are SNR, EMSE, Misadjustment and PSNR. Using different ECG records and properly chosen desired signal and input signal in such way that we get better filter response. From the simulation result analysis the BBEDNVLSS algorithm gives better minimizing of PLI, BW, EM and MA with high PSNR and less misadjustment ratio compared to other algorithms. For fast evaluation of the signal we then choose SREDNVSSLMS algorithm which also gives equivalent performance as that of EDNVSSLMS with less computational that is number of additions, multiplications required to evaluate the weight update equation.

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