Indian Journal of Science and Technology, *Vol 9(37), DOI: 10.17485/ijst/2016/v9i37/92836, October 2016*
ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

Efficient and Low Complexity Noise Cancellers for Cardiac Signal Enhancement using Proportionate Adaptive Algorithms

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Abstract

Objectives: To enhance the quality of Cardiac Signal for perfect diagnosis by the doctor. **Methods/Statistical Analysis:** We are introducing some adaptive filter structures for Cardiac Signal (CS) enhancement for the extraction of high resolution cardiac signals and these structures were based on the Proportionate Normalized Least Mean Square (PNLMS) algorithm. The main advantage of PNLMS over the conventional techniques is extraction of sparse coefficients, suitably weighing them and fast convergence. These ANCs are tested using MIT-BIH database to compare the performance. **Findings:** We consider Signal to Noise Ratio (SNR), Excess Mean Square Error (EMSE), Misadjustment (MSD), convergence curves and residual error plots as performance measures. Among the ANCs tested, PMNSRLMA based ANC is found to be better with reference to the considered performance measures and computational complexity. The average SNRI achieved by this ANC is 18.8856dBs for PLI elimination, 8.7580dBs for BW elimination, 8.5106dBs for MA elimination and 8.5012dBs for EM elimination. From the above results it is clear that in practical biotelemetry applications to minimize the computational complexity of the noise canceller we combine PNLMS with signature algorithms. Again, to reduce the complexity in the denominator of the normalized recursion, we use maximum normalized version of PNLMS. Finally, these variations result in seven algorithms in addition to PNLMS. Based on these algorithms, we develop various Adaptive Noise Cancellers (ANCs) to eliminate artifacts present in the CS and to present best quality signal to the doctor for diagnosis. **Application/ Improvement:** The standard of Cardiac Signal can be enhanced by improving data acquisition methods.

Keywords: Adaptive Algorithms, Adaptive Noise Cancellers, Artifacts, Cardiac Signals, Proportionate NLMS

1. Introduction

Monitoring at regular intervals and on a continuous basis is vital for the cardiac patients. With the greatest increase in the number of people facing the problem of Cardio Vascular Diseases (CVDs), the need for a timely and easy diagnosis is increasing. It is stated in the World Health Organization's (WHO) report on Non Communicable diseases that cardiac problems amount to 37% among the list[1]. However, many researchers (have worked to make a timely diagnosis and it is done in all forms right from the electrodes used in acquisition to identifying the arrhythmia[2–10]. One of the major advantages is that it is possible to track serious cardiac problems with the help of CS and Bardycardia. The Cardiac Signal obtained from an acquisition device basically represents heart's activity and it is composed of segments like P, Q, R, S and T waves. These components are of equal importance compared

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to the other in identifying the abnormalities in cardiac rhythm. However, they are commonly affected by the artifacts namely Power Line Interference (PLI), Base Line Wandering (BW), Muscle Artifact (MA), and Electrode Motion (EM) in the acquisition stage. The channel noise in addition to these artifacts will corrupt the CS during transmission in a tele cardiology system. The artifacts in general affect the morphology of the signal both in terms of amplitude and the shape too. But the deterioration of shape is not acceptable in the process of identifying abnormalities. So removing these artifacts is an important task before the diagnosis is made on it. Several noise removal techniques exist which involve and non-adaptive forms of filtering[11–21]. However, the adaptive forms have a considerable advantage over non adaptive in terms of the adjustable taps driving the EMSE towards zero.

In most of the ANCs for biomedical signal analysis Least Mean Square (LMS) algorithm is commonly accepted algorithm due to its less computational complexity and simplicity in implementation. However, the rate of convergence of LMS is slow when the eigenvalue spread is more, also the performance is a bit lower when the SNR is low. In order to overcome the stability issues various Normalized LMS (NLMS) algorithms are proposed[22–24]. The advantage of the normalized filters is that the step size is controlled here for better ESME performance and the algorithm does not depend on signal power. To cope up the issues associated with the conventional adaptive algorithm in CS enhancement, in the proposed paper we are introducing a new ANC. In the proposed ANC we use Proportionate Normalized LMS (PNLMS) to filter CS. The advantage lies in the extraction of sparse coefficients and suitably weighing them. This made it as one of the best alternatives among the various NLMS algorithms. Because it reduces the eigenvalue spread and thereby leads to fast convergence[25]. The PNLMS is similar to the NLMS proposed by26, in terms of normalization is performed. The only difference is in terms of the gain matrix. The gain matrix actually weighs the taps against their magnitude. Based on the analysis presented in [25,26] it is clear that the PNLMS not only enjoys stability similar to NLMS but also it increases the convergence rate by weighing the inactive taps with less weight.

Nowadays, because of the rapid developments in biotelemetry, it is needed that the computer algorithms used in the signal enhancement activity must have less computational complexity. This constraint is not properly optimized during the design of the ANC, at the input of the Cardiac Signal Enhancer (CSE) the input data vector elements overlap with each other and causes aliasing. This causes inaccurate diagnosis. Therefore, the proposed algorithms to be employed in CSE must have less computational complexity. This is also facilitated in the development of Lab On Chip (LOC), System On Chip (SOC) and nano devices for wearable health care devices. Hence, to achieve the full advantage of the PNLMS, we combine PNLMS with sign algorithms. This is because the PNLMS only weighs the taps, but it does not nullify the taps. On the contrary the Signum based techniques will make the taps to either zero or one depending on the condition. So using the PNLMS in conjunction with Signum will improve the rate of convergence, making them a good mix. This reduces the number of coefficients participating in the actual iteration process decreasing the complexity. This result three more algorithms, Proportionate Normalized Sign Regressor LMS (PNSRLMS), Proportionate Normalized Sign LMS (PNSLMS) and Proportionate Normalized Sign Sign LMS (PNSSLMS) algorithms. Again, to reduce the computational complexity in the denominator of the normalization process, we normalize the step size with reference to a maximum value of data vector. This reduces Multiplication and Accumulation (MAC) operations to one from filter length. This results another four algorithms, Proportionate Maximum Normalized LMS (PMNLMS), Proportionate Maximum Normalized Sign Regressor LMS (PMNSRLMS), Proportionate Maximum Normalized Sign LMS (PMNSLMS) and Proportionate Maximum Normalized Sign Sign LMS (PMNSSLMS) algorithms. A similar approach is used by [27,28] to increase the convergence rate. The applying Signum function also helps to mitigate the problem of increase in filter taps which arise in case of high data rate transmission. Some efficient ANC structures for biomedical signal analysis are presented in [29–31]. Finally, the proposed eight versions of proportionate algorithms are tested on real cardiac signals with different artifacts obtained from the MIT-BIH database. The performance of the developed ANCs is compared with conventional LMS based ANC. We have considered Signal to Noise Ratio (SNR), Excess Mean Square Error (EMSE), Misadjustment (MSD), convergence curves and residual error plots as performance measures.

2. Cardiac Signal Enhancement using Proportionate Adaptive Noise Cancellers

Let R, d, S, μ be the terms representing the reference signal, desired signal, error signal, step size of an adaptive filter as shown in the Figure1 and let v be the noise adding from the channel. If we consider $V=[V1\ V2\ V3....VM]^T$ as the m length tap matrix and then the output of the filter would be V^TR. Now the error signal generated by adding both the output of the filter and the desired signal upon minimization will result in tap update equation written as

$$V_{n+1} = V_n + \mu S(n) R_k \tag{1}$$

It is necessary to consider here the work of Thakor in [26]. Where the cardiac signal is filtered with LMS based ANC. The issues to be considered in selecting the reference were addressed in this work. It is possible to provide the reference as either signal or noise, but in our case we have chosen the noise as reference. It is considered to be correlated with the actual noise which is corrupting the signal. In the sequential iterations the taps get adjusted so that the signal gets alleviated from the noise by minimizing it. LMS is simpler to implement and computationally easy, but it diverges when the signal is at low SNR. Divergence is also a serious issue as it decides the suitableness of the algorithm in the real time environment and it depends on signal power. Normalization helps to minimize the limitations in the LMS algorithm. Many normalization algorithms exist in the literature. The fundamental equation for normalization can be taken as

$$V_{n+1} = V_n + \frac{\mu S(n) R_k}{\delta + R^2} \tag{2}$$

The normalization is done with respect to the signal power and a small constant called leakage factor is used to avoid the stability problem if the signal power reaches null. Similarly, Proportionate Normalized LMS (PNLMS) is analyzed in[32,33]. The idea behind the proportionate type filters is to exploit the sparsity existing in the data by properly selecting the taps and weighing them on an individual basis. The weighing is done by means of a gain matrix G. It assigns the taps to the taps based on their current estimated value. This significantly improves the convergence, but it will reduce when the taps are too small. Also, it helps to mitigate the problem of delay in communication, which is very critical in modern day health care applications where time of response is an important factor. The tap update equation of the PNLMS can be written as

$$V_{n+1} = V_n + \frac{\mu S G R_k}{\delta + {R_k}^T G R_k} \tag{3}$$

So from the above equation it is evident that the difference between the NLMS and PNLMS is observed in terms of the gain matrix in the numerator and the denominator.

Based on sign algorithms, it is possible to apply the Signum either to the signal or the error itself called as Signum versions. The mathematical expression for the Signum function can be given as

$$Sign(x) = \begin{cases} 1 : x > 0 \\ 0 : x = 0 \\ -1 : x < 0 \end{cases}$$

The signum function decides the coefficients that are used in filtering by reducing them to zero based on predefined criteria. However, reduction in performance as a result of this nullification is minimal. The signum function in addition to the sparseness is contributing to a great improvement in a reasonable performance. This is significant from the performance measure calculated. As mentioned earlier, it is possible to apply the signum for the regressor, error and both and by applying this to the equation (3). The equations of sign algorithms based PNLMS are given as,

$$V_{n+1} = V_n + \frac{\mu\, sign(S) G R_k}{\delta + {R_k}^T G R_k} \tag{4}$$

$$V_{n+1} = V_n + \frac{\mu S [G sign(R]_k)}{\delta + {R_k}^T G R_k} \tag{5}$$

$$V_{n+1} = V_n + \frac{\mu\, sign(S) sign(G R_k)}{\delta + {R_k}^T G R_k} \tag{6}$$

These are PNSRLMS, PNSLMS and PNSSLMS respectively.

Again in the above discussed algorithms, the computational complexity equal to "m" MACs in the denominator is reduced to only one MAC by normalizing the step size with a maximum value of input data vector. This results PMNLMS, PMNSRLMS, PMNSLMS and PMNSSLMS algorithms. A generalized flow diagram of these algorithms is shown in Figure 1.

Therefore, by applying maximum normalization, the weight update recursions are given by the following equations. Now equations (3)–(6) becomes,

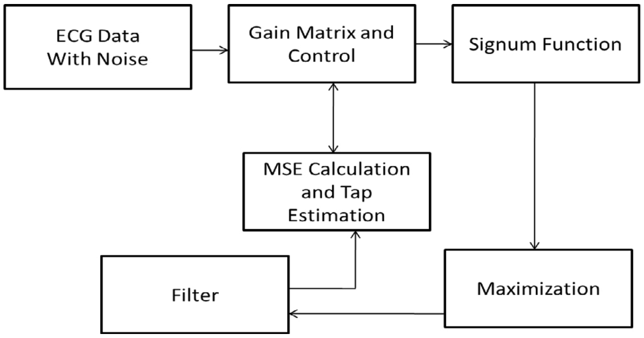

Figure 1. A generalized flow diagram of PMNLMS algorithm.

$$V_{n+1} = V_n + \frac{\mu SGR_k}{\delta + G\max(R_k)^2} \tag{7}$$

$$V_{n+1} = V_n + \frac{\mu sign(S)GR_k}{\delta + G\max(R_k)^2} \tag{8}$$

$$V_{n+1} = V_n + \frac{\mu sign(R_k)SGR_k}{\delta + Gmax(R_k)^2} \tag{9}$$

$$V_{n+1} = V_n + \frac{\mu sign(R_k)GSign(S)}{\delta + Gmax(R_k)^2} \tag{10}$$

These are PMNLMS, PMNSRLMS, PMNSLMS and PMNSSLMS respectively.

The convergence curves of PNLMS and its signum based versions are shown in Figure 2. From this figure, it is clear that PNSRLMS is slightly inferior to PNLMS. This is due to the normalization involved in the signum function applied to the data vector in addition to normalization performed over step size. The major advantage of PNSRLMS is, the multiplications in sign regressor operation are independent of filter length. Sign regressor operation needs only one multiplication. In this manner the performance of PNSRLMS is very close to PNLMS due to two normalizations performed and reduced number of multiplications by an amount "m". Whereas, the performance of PNSLMS and PNSSLMS is better than the conventional LMS algorithm due to the normalization operation, but inferior than PNLMS and PNSRLMS algorithms due to clipping the error quantity which is responsible for weight updation. Similarly, Figure 3 shows the convergence curves of PMNLMS and its sign variations. In these algorithms, as the step size normalization is performed with only one element in the performance of PMNLMS and its sign variants are little bit inferior than PNLMS and its sign variants. The remaining aspects of PNLMS are valid to PMNLMS and its variants.

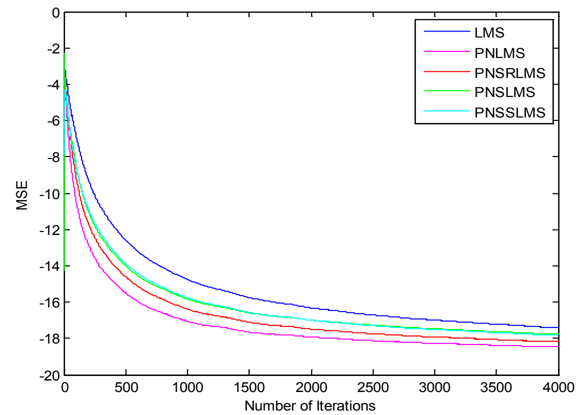

Figure 2. Convergence curves of PNLMS and its sign variations.

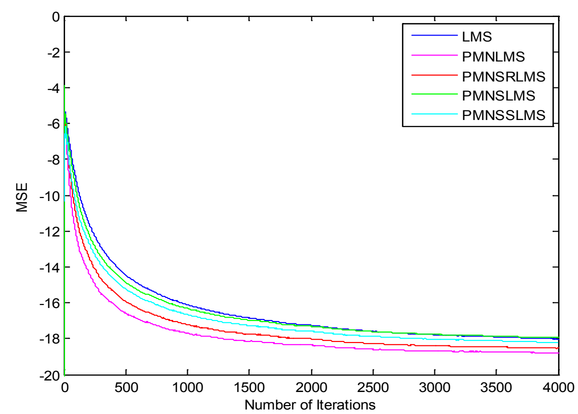

Figure 3. Convergence curves of PMNLMS and its sign variations.

3. Simulation Results

To evaluate the performance of proposed ANCs we have used the real cardiac signals obtained from the MIT-BIH arrhythmia database[34]. Records from data 101 - data105 are used for this purpose and are 10mv in amplitude. These artifacts were obtained from 47 subjects who were in the age between 23 and 89. The step size is fixed at 0.1 and the noise variance of 0.01 is taken. All the artifacts, i.e. Baseline Wander (BW), Muscle Artifact (MA) and Electrode Motion (EM) artifacts are taken from MIT database[35] and the Power Line Interference (PLI) is generated synthetically. The artifact database was generated with the help of eighteen test subjects who were healthy and have not shown any cardiac abnormalities. In addition, a random noise with a variance of 0.001 is also

Table 1. Performance contrast of various algorithms in terms of SNRI for the removal of artifacts from cardiac signals (all values in dBs)

Noise Type	Record Number	LMS	PNLMS	PNSR LMS	PNS LMS	PNSS LMS	PMN LMS	PMNSR LMS	PMNS LMS	PMNSS LMS
PLI	101	8.8067	21.9424	19.9272	12.6794	11.0263	18.9127	18.0693	10.8272	10.4053
	102	7.7763	19.8596	18.5959	14.6808	11.2682	18.4364	17.5972	9.5894	9.1745
	103	9.1878	22.1636	21.8145	20.2974	16.0675	21.6445	20.3978	12.6016	11.9881
	104	8.5084	20.5594	19.5193	18.8803	13.6205	18.9968	17.8104	13.5205	12.7405
	105	9.0063	22.0817	21.5112	17.3124	13.1450	21.6912	20.5534	12.6852	11.8273
	Average	**8.6571**	**21.3213**	**20.2736**	**16.7700**	**13.0255**	**19.9363**	**18.8856**	**11.8447**	**11.2271**
BW	101	4.1985	10.7289	9.7820	7.8641	6.4349	9.7382	8.8720	6.4298	5.4769
	102	4.2598	10.6345	9.7589	7.5936	6.5423	9.6931	8.8945	6.6351	5.3842
	103	4.7682	10.1037	9.4683	7.4910	6.6345	9.7573	8.7839	6.1894	5.5473
	104	4.8275	10.8794	9.7280	7.9838	6.2609	9.8621	8.8195	6.5692	5.7481
	105	4.6124	10.8849	9.2474	7.1285	6.4581	9.5391	8.4205	6.4562	5.6475
	Average	**4.5332**	**10.6462**	**9.5969**	**7.6122**	**6.4661**	**9.7179**	**8.7580**	**6.4559**	**5.5068**
MA	101	3.6415	10.2738	9.6948	7.8493	6.3587	9.7282	8.3482	6.3833	5.4893
	102	3.7605	10.5382	9.7969	7.1783	6.2654	9.2374	8.3089	6.8573	5.9458
	103	3.9652	10.5683	9.7647	7.3681	6.2573	9.8239	8.6499	6.8493	5.5891
	104	4.0395	10.9273	9.4005	7.4916	6.5893	9.2374	8.8922	6.9453	5.6758
	105	4.0008	10.3682	9.0338	7.3985	6.2359	9.9283	8.3538	6.9812	5.9231
	Average	**3.8815**	**10.5351**	**9.5381**	**7.4571**	**6.3413**	**9.5910**	**8.5106**	**6.8032**	**5.7246**
EM	101	4.4419	10.9872	9.8200	7.8668	6.6165	9.2869	8.9416	6.3333	5.6090
	102	4.6511	10.8975	9.2121	7.9552	6.0493	9.9843	8.2849	6.8379	5.8032
	103	4.8438	10.1567	9.7172	7.6646	6.8205	9.4761	8.0243	6.0553	5.5755
	104	4.6617	10.2148	9.5363	7.9293	6.3478	9.9875	8.6493	6.7010	5.9975
	105	4.7782	10.5675	9.7255	7.9868	6.5365	9.9531	8.6063	6.7485	5.2828
	Average	**4.6753**	**10.5647**	**9.6022**	**7.8805**	**6.4741**	**9.7375**	**8.5012**	**6.5352**	**5.6536**

Table 2. Performance contrast of various algorithms in terms of EMSE for the removal of artifacts from cardiac signals (all values in dBs)

Noise Type	Record Number	LMS	PNLMS	PNSR LMS	PNS LMS	PNSS LMS	PMN LMS	PMNSR-LMS	PMNS LMS	PMNSS - LMS
PLI	101	-19.9894	-28.3485	-25.8937	-22.9485	-21.0426	-24.5849	-23.8085	-22.6174	-21.3809
	102	-21.8298	-28.2394	-25.9384	-22.9573	-21.4403	-24.5900	-23.6457	-22.5399	-21.9632
	103	-20.5036	-28.9439	-25.9838	-22.8465	-21.3312	-24.7732	-23.2020	-22.3219	-21.0330
	104	-21.5394	-28.4940	-25.2883	-22.9126	-21.9606	-24.2273	-23.0210	-22.3475	-21.8814
	105	-21.5227	-28.2394	-25.9414	-22.8692	-21.9323	-24.7644	-23.8872	-22.4669	-21.7324
	Average	-21.0769	-28.4530	-25.8091	-22.9068	-21.5414	-24.5879	**-23.5128**	**-22.4587**	**-21.5981**
BW	101	-11.1457	-15.2413	-14.4933	-12.8937	-11.4152	-13.5762	-12.6424	-12.0876	-11.2732
	102	-11.4418	-15.2384	-14.2390	-12.9638	-11.9859	-13.4319	-12.8133	-12.4681	-11.9405
	103	-11.4770	-15.5833	-14.4995	-12.9536	-11.5217	-13.4857	-12.6770	-12.1874	-11.5730
	104	-8.9635	-15.3486	-14.3450	-12.7483	-11.0235	-13.3589	-12.4570	-12.0665	-11.5823
	105	-12.6204	-15.8493	-14.2952	-12.8625	-11.3252	-13.3894	-12.7836	-12.6854	-12.6255
	Average	**-11.1282**	**-15.4521**	**-14.3744**	**-12.8843**	**-11.454**	**-13.463**	**-12.675**	**-12.299**	**-11.799**

MA	101	-12.1110	-15.9035	-14.9834	-13.8597	-12.8371	-14.1028	-13.7597	-12.3046	-12.1944
	102	-12.4097	-15.9295	-14.9735	-13.8929	-12.7836	-14.1616	-13.8460	-12.5778	-12.3898
	103	-11.7569	-15.2830	-14.9184	-13.8419	-12.8472	-14.3329	-13.2722	-12.6010	-12.3823
	104	-11.1118	-15.2395	-14.8934	-13.8346	-12.6495	-14.4652	-13.7898	-12.5110	-12.2307
	105	-13.8287	-15.3450	-14.8674	-14.1462	-13.9798	-14.3728	-13.9585	-13.8730	-13.8459
	Average	**-12.244**	**-15.5401**	**-14.9272**	**-13.9150**	**-13.0194**	**-14.2870**	**-13.7252**	**-12.7734**	**-12.6086**
EM	101	-10.7955	-16.3290	-15.8548	-12.8107	-11.7429	-14.9675	-13.3399	-12.4484	-11.2794
	102	-10.7225	-16.2397	-15.5767	-12.5551	-11.8736	-14.1557	-13.3940	-12.5321	-11.8689
	103	-10.9025	-16.2390	-15.4745	-12.2360	-11.8239	-14.0457	-13.2951	-12.8610	-11.3711
	104	-8.2407	-16.2095	-15.5763	-12.1075	-11.9125	-14.7166	-13.6287	-12.4345	-11.6213
	105	-12.3952	-16.3905	-15.5128	-13.8622	-12.9831	-14.7103	-13.6962	-12.8369	-12.5703
	Average	**-10.6112**	-16.2815	-15.5990	-12.7143	-12.0672	-14.5191	-13.4707	-12.6225	-11.7422

Table 3. Performance contrast of various algorithms in terms of MSD for the removal of artifacts from cardiac signals (all values in dBs)

Noise Type	Record Number	LMS	PN LMS	PNSR LMS	PNS LMS	PNSS LMS	PMN LMS	PMNSR LMS	PMNS LMS	PMNSS LMS
PLI	101	0.0761	0.0397	0.0425	0.0456	0.0493	0.0427	0.0435	0.0486	0.0539
	102	0.0460	0.0221	0.0262	0.0287	0.0341	0.0289	0.0297	0.0327	0.0375
	103	0.0744	0.0364	0.0387	0.0421	0.0463	0.0394	0.0397	0.0483	0.0526
	104	0.0134	0.0075	0.0078	0.0082	0.0089	0.0077	0.0080	0.0097	0.0117
	105	0.0725	0.0383	0.0395	0.0456	0.0483	0.0391	0.0418	0.0497	0.0526
	Average	**0.0564**	**0.0288**	**0.0309**	**0.0340**	**0.0373**	**0.0315**	**0.0325**	**0.0378**	**0.0416**
BW	101	0.5829	0.3409	0.4388	0.4979	0.5198	0.3536	0.4703	0.5250	0.5487
	102	0.5030	0.3527	0.4144	0.4694	0.4922	0.3929	0.4600	0.5013	0.5009
	103	0.5960	0.3741	0.4766	0.4972	0.5761	0.3944	0.4961	0.5859	0.5963
	104	0.4842	0.3185	0.4354	0.4579	0.4644	0.3623	0.4656	0.4758	0.4821
	105	0.5630	0.3152	0.4427	0.4796	0.5392	0.3341	0.4887	0.5429	0.5574
	Average	**0.5458**	**0.3402**	**0.4415**	**0.4804**	**0.5183**	**0.3674**	**0.4761**	**0.5261**	**0.5370**
MA	101	0.4667	0.2866	0.3250	0.3739	0.4148	0.2956	0.3558	0.4017	0.4507
	102	0.4025	0.2881	0.3384	0.3448	0.3726	0.2995	0.3796	0.3665	0.3935
	103	0.5579	0.3231	0.3663	0.3886	0.4258	0.3462	0.3822	0.4176	0.5460
	104	0.8090	0.3633	0.3845	0.3953	0.6036	0.3837	0.4043	0.4270	0.6495
	105	0.4262	0.2848	0.3782	0.3812	0.3869	0.2955	0.3951	0.4064	0.4188
	Average	**0.5324**	**0.3091**	**0.3584**	**0.3767**	**0.4407**	**0.3241**	**0.3834**	**0.4038**	**0.4197**
EM	101	0.6319	0.3790	0.3915	0.4043	0.4481	0.3833	0.4030	0.4256	0.4974
	102	0.5936	0.3268	0.3465	0.3751	0.4224	0.3326	0.3681	0.3833	0.4724
	103	0.6792	0.3859	0.3909	0.4114	0.4720	0.3923	0.4166	0.4730	0.5484
	104	0.5719	0.3003	0.3230	0.3332	0.4472	0.3212	0.3450	0.3523	0.5386
	105	0.5929	0.3247	0.3328	0.3562	0.4536	0.3308	0.3549	0.3647	0.5665
	Average	**0.6139**	**0.3433**	**0.3569**	**0.3760**	**0.4486**	**0.35204**	**0.37752**	**0.3997**	**0.5246**

added. The impact of all the noise on the CS care shown in Figure 4. The performance measurements for all the four noises is calculated and tabulated as shown in the Tables 1–3. Figures 6–13 shows the performance of various ANCs during the noise cancellation process. In these figures the x-axis represents the samples and the y-axis represents the magnitude. The simulation results of data 101 are shown in this paper. However, the performance measures in terms of SNR, EMSE and MSD for all five records are tabulated in Tables 1–3.

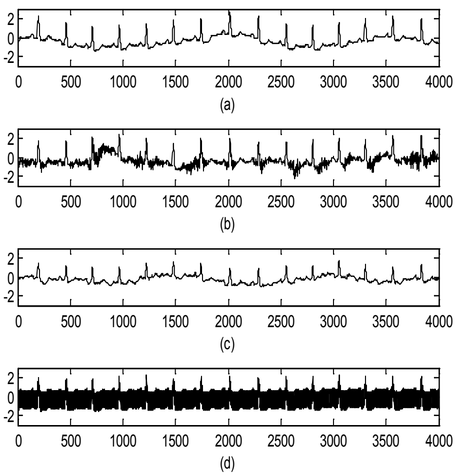

Figure 4. Cardiac signal with various artifacts. a)BW b)MA c)EM d) PLI.

3.1 Power Line Interference (PLI) Cancellation

The PLI noise generated from the generator is given as primary input and noisy CS as the desired signal to the filter structure shown in Figure 5. The noise affected CS is shown in Figure 4. It is 1mV in amplitude with 60Hz frequency and is sampled at 200Hz. The results of PLI filtering for the filters are presented in Figure 6 and Figure 7. In Figure 6 shows the cardiac signal after filtering with various ANCs. Figure 6 shows CS contaminated with PLI, 6(b) shows filtering results after LMS based ANC. Figure 6 shows filtered signal after PNLMS filtering, 6(d) shows CS after PNSRLMS filtering, 6(e) shows CS after PNSLMS filtering, 6(f) shows CS after PNSSLMS filtering. Figure 6 shows CS after PMNLMS filtering, 6(h) shows CS after PMNSRLMS filtering, 6(i) shows CS after PMNSLMS filtering and 6(j) shows CS after PMNSSLMS filtering. Figure7 shows the residual noise after filtering with various ANCs. The description of various subplots in Figure 7 are as, original PLI, 7(b) residual noise after LMS filtering, 7(c) after PNLMS, 7(d) after PNSRLMS, 7(e) after PNSLMS, 7(f) after PNSSLMS. Similarly, 7(g) shows residual noise after PMNLMS filtering, 7(h) after PMNSRLMS, 7(i) after PMNSLMS, 7(j) residual noise after PMNSSLMS filtering.

The signal morphology was recovered relatively greatly over its counterparts by PNSRLMS as shown in the Figure 7. The performance measurements in terms of SNRI, EMSE and MSD for PLI cancellation are shown in Tables 1–3. For these calculations, the PLI cancellation experiments are performed for ten times on each data and the average values are tabulated. The simulation results corresponding to data 101 are shown in this section. Among the algorithms considered PNLMS achieves highest SNR of 21.9424 dB, but PNSRLMS gets 19.9272 dB with "m" number of reduced MACs. In maximum normalized category PMNLMS gets 18.9127 dB with "m" number of reduced MACs in the denominator and PMSRLMS achieves 18.0693 dB with "m" number of reduced MACs in the denominator as well as in numerator due to sign regressor operation. Where, as conventional LMS achieves SNR of 8.8067 dB only during artifact removal process. A similar order of performance is achieved with reference to EMSE and MSD.

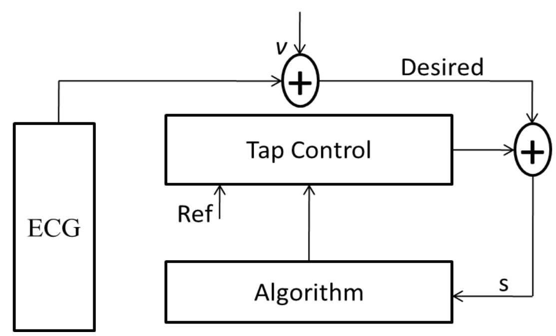

Figure 5. Cardiac signal enhancer.

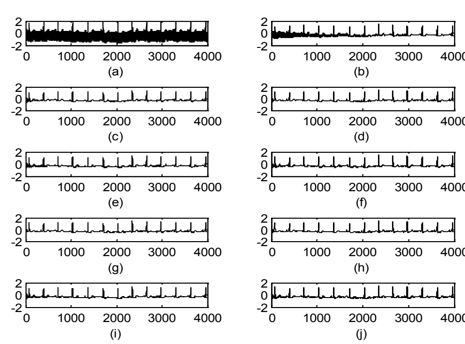

Figure 6. PLI Filtering results using various ANCs.

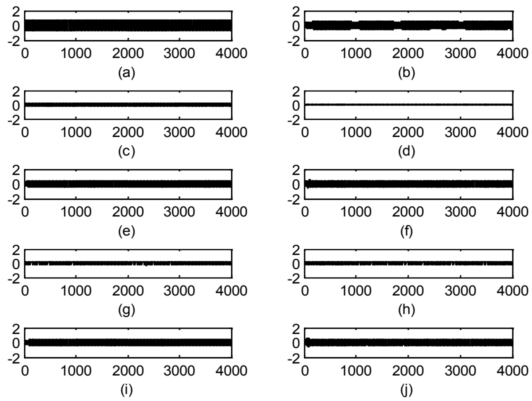

Figure 7. Residual noise after PLI filtering using various ANCs.

3.2 Base Line Wander (BW) Cancellation

Here the BW noise taken from the MIT-BIH database is given as the reference signal and the BW corrupted arrhythmia data was given as the desired signal is shown in the Figure 4 The filtering performance of the various ANCs is presented in Figure 8 and Figure 9. Figure 8 shows CS contaminated with BW, 8(b) shows filtering results after LMS based ANC. Figure 8 shows filtered signal after PNLMS processing, 8(d) shows CS after PNSRLMS filtering, 8(e) shows CS after PNSLMS filtering, 8(f) shows CS after PNSSLMS filtering. Figure 8 shows CS after PMNLMS, 8(h) shows CS after PMNSRLMS filtering, 8(i) shows CS after PMNSLMS filtering and 8(j) shows CS after PMNSSLMS filtering. Figure 9 shows the residual noise after filtering with various ANCs. The description of various subplots in Figure 9 are as, 9(a) original BW, 9(b) residual noise after LMS filtering, 9(c) after PNLMS, 9(d) after PNSRLMS, 9(e) after PNSLMS, 9(f) after PNSSLMS. Similarly, 9(g) shows residual noise after PMNLMS filtering, 9(h) after PMNSRLMS, 9(i) after PMNSLMS, 9(j) residual noise after PMNSSLMS filtering.

The simulation results corresponding to data 101 are shown in this section. Among the algorithms considered PNLMS achieves highest SNR of 10.7289 dB, but PNSRLMS gets 9.7820 dB with "m" number of reduced MACs. In maximum normalized category PMNLMS gets 9.7382 dB with "m" number of reduced MACs in the denominator and PMSRLMS achieves 8.8720 dB with "m" number of reduced MACs in the denominator as well as in numerator due to sign regressor operation. Whereas, conventional LMS achieves SNR of 4.1985 db only during artifact removal process. A similar order of performance is achieved with reference to EMSE and MSD.

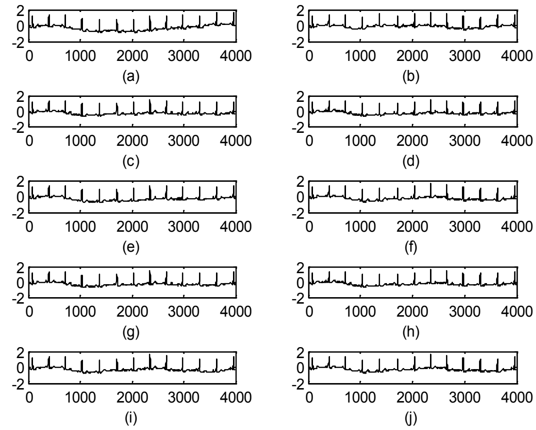

Figure 8. BW filtering results using various ANCs.

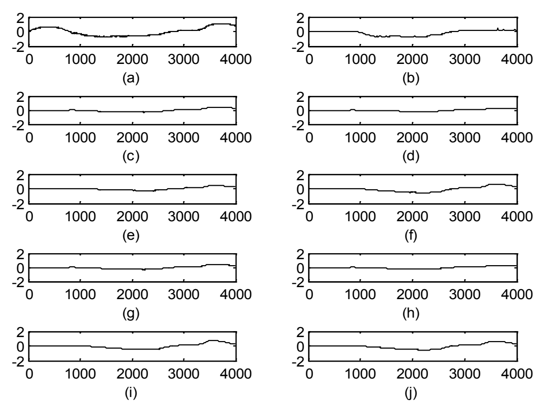

Figure 9. Residual noise after BW filtering using various ANCs.

3.3 Muscle Artifact (MA) Cancellation

Here the MA artifact taken from the MIT-BIH database is given as reference and the signal corrupted with the MA artifact is given as the desired signal. CS affected with MA artifact is shown in Figure. The filtering results and residual noise components after various ANCs are shown in Figure 10 and Figure 11. Figure 10 shows CS contaminated with MA, 10(b) shows filtering results after LMS based ANC. Figure 10shows filtered signal after PNLMS processing, 10(d) shows CS after PNSRLMS filtering, 10(e) shows CS after PNSLMS filtering, 10(f) shows CS after PNSSLMS filtering. Figure 5 shows CS after PMNLMS filtering, 10(h) shows CS after PMNSRLMS filtering, 10(i) shows CS after PMNSLMS filtering and 10(j) shows CS after PMNSSLMS filtering. Figure 11 shows the residual noise after filtering with various ANCs. The description of various subplots in Figure 11 are as, original MA, 11(b) residual noise after LMS filtering, 11(c) after PNLMS, 11(d) after PNSRLMS filtering, 11(e) after PNSLMS filtering, 11(f) after PNSSLMS filtering. Similarly, 11(g) shows residual noise after PMNLMS filtering, 11(h) after PMNSRLMS filtering, 11(i) after PMNSLMS filtering, 11(j) residual noise after PMNSSLMS filtering.

The simulation results corresponding to data 101 are shown in this section. Among the algorithms considered PNLMS achieves highest SNR of 10.2738 dB, but PNSRLMS gets 9.6948 dB with "m" number of reduced MACs. In maximum normalized category PMNLMS gets 9.7282 dB with "m" number of reduced MACs in the denominator and PMSRLMS achieves 8.3482 dB with "m" number of reduced MACs in the denominator as well as in numerator due to sign regressor operation. Where, as conventional LMS achieves SNR of 3.6415 dB only during artifact removal process. A similar order of performance is achieved with reference to EMSE and MSD.

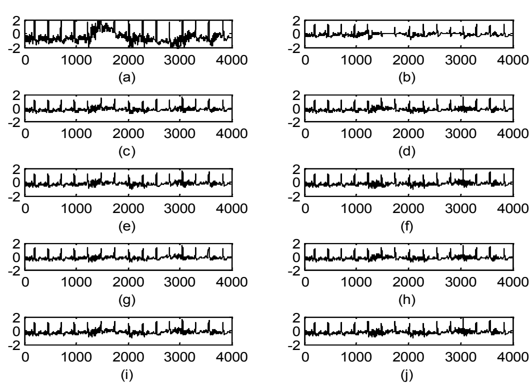

Figure 10. MA filtering results using various ANCs.

3.4 Electrode Motion (EM) Artifact

Like other noises the artifact is taken as reference and the corrupted signal is taken as the desired signal. The CS signal corrupted with EM artifact can be seen in Figure 4 The results of the filtering are shown in Figure 12 and Figure 13. Figure 12 shows CS contaminated with EM, 12(b) shows filtering results after LMS based ANC. Figure 12 shows filtered signal after PNLMS processing, 12(d) shows CS after PNSRLMS, 12(e) shows CS after PNSLMS, 12(f) shows CS after PNSSLMS filtering. Figure 5 shows CS after PMNLMS, 12(h) shows CS after PMNSRLMS, 12(i) shows CS after PMNSLMS and 12(j) shows CS after PMNSSLMS filtering. Figure 13 shows the residual noise after filtering with various ANCs. The description of various subplots in Figure 13 are as, 13(a) original EM, 13(b) residual noise after LMS filtering, 13(c) after PNLMS, 13(d) after PNSRLMS, 13(e) after PNSLMS, 13(f) after PNSSLMS. Similarly, 13(g) shows residual noise after PMNLMS filtering, 13(h) after PMNSRLMS, 13(i) after PMNSLMS, 13(j) residual noise after PMNSSLMS filtering.

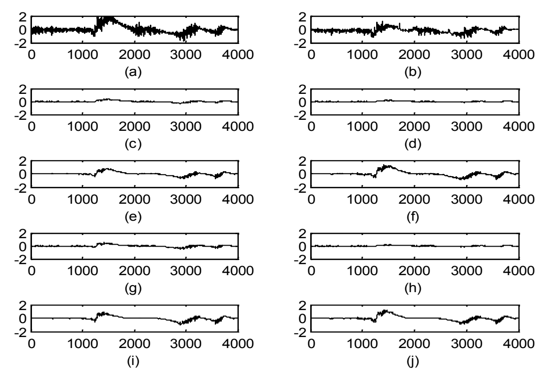

Figure 11. Residual noise after MA filtering using various ANCs.

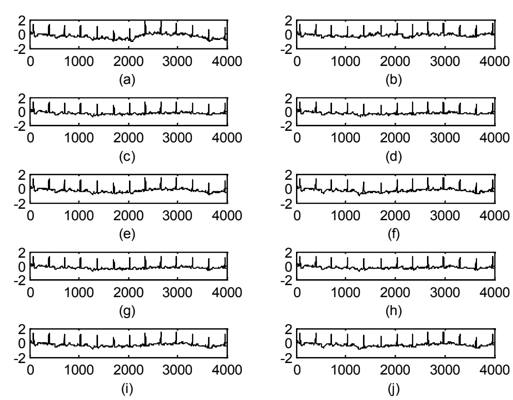

Figure 12. EM filtering results using various ANCs.

The simulation results corresponding to data 101 are shown in this section. Among the algorithms considered PNLMS achieves highest SNR of 10.9872 dB, but PNSRLMS gets 9.8200 dB with "m" number of reduced MACs. In maximum normalized category PMNLMS gets 9.2869 dB with "m" number of reduced MACs in the denominator and PMSRLMS achieves 8.9416 dB with "m" number of reduced MACs in the denominator as well as in numerator due to sign regressor operation. Whereas, conventional LMS achieves SNR of 4.4419 dB only during artifact removal process. A similar order of performance is achieved with reference to EMSE and MSD.

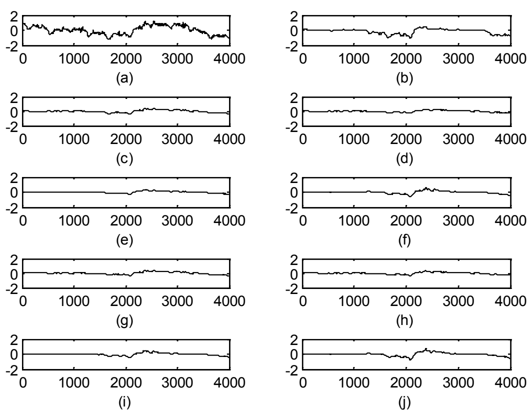

Figure 13. Residual noise after EM filtering using various ANCs.

4. Conclusion

In the proposed work, the removal of artifacts from cardiac signals is presented with the help of the proportionate type adaptive algorithms. The maximum normalization and sign based versions of PNLMS are implemented to improve the suitability of the algorithm to use in real time. MIT-BIH arrhythmia database is used to test the performance of the proposed noise cancellers. SNR, EMSE and MSD are considered as measures to evaluate the performance of the proposed implementations. Among various algorithms, PNLMS is found to be first in the list with reference to various performance measures. The PNSRLMS is found to be second in the list. PNSRLMS is little bit inferior to PNLMS with respect to SNR, EMSE, MSD and convergence, but reduces "m" MACs due to the sign regressor operation. Next, the PMNLMS is found to be third in the list with reference to SNR, EMSE, MSD and convergence, but it reduces "m" MACs in the denominator because of normalization with respect to maximum of data vector. Finally, PMNSRLMS is found to be fourth in the list with reference to SNR, EMSE, MSD and convergence. But it reduces "m" MACs in the denominator due to maximum normalization and other "m" MACs due to sign regressor operation. However, in practical health care monitoring devices PMNSRLMS is well suited because of its reduced number of MACs even though it is slightly inferior than PNLMS.

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