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ADAPTIVE NOISE CANCELLERS FOR CARDIAC SIGNAL ENHANCEMENT FOR IOT BASED HEALTH CARE SYSTEMS

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ABSTRACT

Cardiac Signals (CS) are affected with various artifacts during the acquisition and transmission. So these artifacts must be removed before presenting it to a doctor. In the proposed paper Normalized Median Least Mean Square (NMLMS) algorithm is being introduced for elimination of Power Line Interference (PLI), Baseline Wander (BW), Muscle artifacts (MA) and Electrode Motion (EM) from CS. The NMLMS has many advantages over the other conventional algorithms, i.e., it tends to reject single occurrence of large spikes of noise which otherwise introduces impulsive errors. Computational complexity can be reduced by the combination of sign algorithms with the NMLMS algorithm, which results in three new different algorithms. Based on the above algorithms, various Adaptive Noise Cancellers (ANC's) have been developed to eliminate BW, MA and EM from the CS. The above mentioned algorithms have applied to real CS obtained from the MIT-BIH database. The simulation results confirm that the NSRMLMS algorithm is better than the conventional LMS algorithms in terms of Signal to Noise Ration Improvement (SNRI), Excessive Mean Square Error (EMSE) and Misadjustment (MSD). From the simulation results it is clear that NSRMLMS achieves the highest SNRI than the conventional LMS algorithms. The values are as follows: 11.2748dB, 9.4715dB, 10.6917dB and 10.7076 dB. These are the average values in terms of SNRI for PLI, BW, MA and EM respectively. Due to the reduced computational complexity these algorithms are usefull for Internt of Things (IOT) based remote health care monitoring systems.

Key Words: *Adaptive Algorithms, Adaptive Noise Cancellers, Artifacts, Cardiac Signal, health care systems.*

1. INTRODUCTION

Generally the CS is affected by various types of artifacts, the most common are PLI, BW, MA and EM. In telecardiology during the transmission, channel noise is also added to the CS. But such type of artifacts will affect the morphology of the signal. So to remove these artifacts is a very important task

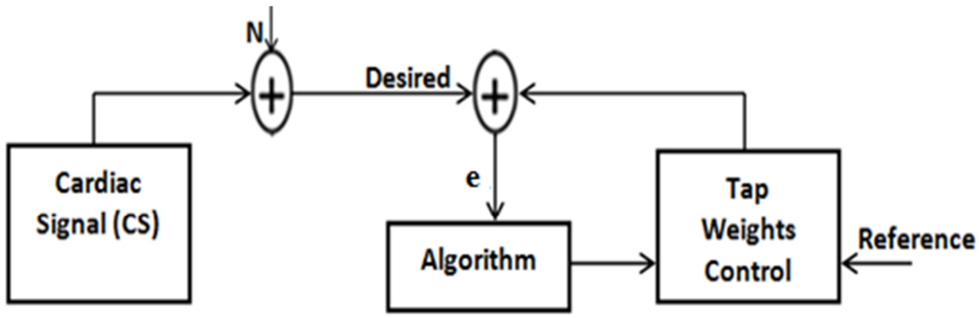

Figure 1: Cardiac Signal Enhancer.

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before it is presented to a doctor for diagnosis. Many artifact removal techniques are presented in the literature [1] - [10]. The adaptive form of filtering has found to be one of the best because of adjustable taps which in turn drives the EMSE towards zero. In the proposed paper, we are introducing a new ANC, which uses Normalized Median Least Mean Square (NMLMS) to filter CS. The main advantage of NMLMS it tends to reject single occurrence of large spikes of noise which otherwise introduces impulsive errors [11]. Furthermore to reduce the computational complexity, the sign algorithms are combined with NMLMS algorithm. Thus the Multiplication and Accumulation Multiplications and Accumulations (MAC) operations can be reduced. This results in Normalised Sign Regressor Median Least Mean Square algorithm (NSRMLMS), Normalized Sign Median Least Mean Square algorithm (NSMLMS) and Normalised Sign Sign Median Least Mean Square algorithm (NSSMLMS) respectively. A similar approach is used by Rahman et.al. in [12, 13] 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. These type of less computational complex algorithms and assosciated health care systems are more attractive in modern IOT based remote health care monitoring systems.

Adaptive Noise Cancellers (ANC's) are discussed in the second section and simulation results are discussed in the third section. In the third section the artifact cancellation techniques are presented using various algorihms. Finally we end up with the conlusion section. In the current work we have used adaptive algorithm based Adaptive Artifact Cancellers. The limitation of this proposed model is a reference signal is required.

2. ADAPTIVE NOISE CANCELLERS (ANC's)

Let m_L, e and μ be the terms representing the median function over a filter length of L, error signal, step size of an adaptive filter as shown in the Figure 1 and let N be the noise adding from the channel. If we consider N= [N1 N2 N3….NM]^T as the L length tap matrix and then the output of the filter would be N^Te. 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:

$$N_{n+1} = N_n + \mu . m_L \{e_n x_n\} \quad (1)$$

It is necessary to consider here the work of N.V. Thakor et.al in [14]. 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 gets adjusted, thus the signal gets alleviated by minimizing the noise. LMS is simpler to implement and computationally easy, but it diverges when the signal is at low SNRI. 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

$$N_{n+1} = N_n + \mu(n) m_L \{e_n x_n\} \quad (2)$$

The normalization is done with respect to the signal power and a small constant called leakage factor. It is used to avoid the stability problem if the signal power reaches null. Similarly proportionate normalized LMS (PNLMS) is analyzed in [15]. The idea behind the Median based type ANC is the performance of the LMS algorithm and its derivatives significantly. This gets degraded when subjected to input signals that are corrupted by impulsive noise, sometimes this leads to instability. Smoothing the noisy gradient components using a nonlinear filter is a good remedy for this problem. In order to minimize computational complexity, we combine this NMLMS with the three simplified sign algorithms.

The three sign algorithms are: Sign Regressor algorithm, Sign algorithm and Sign Sign algorithm. Therefore, with the combination of sign algorithms with NMLMS, we obtain a new set of algorithms: NSRMLMS, NSMLMS and NSSMLMS. Thus the weight update recurssions are given by the following equations.

$$N_{n+1} = N_n + \mu\, m_L \{e_n\, sgn\,(x_n)\} \quad (3)$$

$$N_{n+1} = N_n + \mu\, m_L \{sgn(e_n)\, x_n\} \quad (4)$$

$$N_{n+1} = N_n + \mu\, m_L \{sgn(e_n)\, sgn\,(x_n)\} \quad (5)$$

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3. SIMULATION RESULTS

To evaluate the performance of proposed ANCs we have used the real CS obtained from the MIT-BIH arrhythmia database [16]. The performance of the proposed ANC's is evaluated by using the following set of algorithms: LMS, MLMS, NMLMS, NSRMLMS, NSMLMS and NSSMLMS. The average values of SNRI, EMSE and MSD are calculated for the above mentioned algorithms. 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., PLI, BW, MA and EM are taken from the MIT-BIH database [17]. 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 added. In Figure 2, the simulation model is shown. CS is first recorded using a data acquistiotn unit. Then the CS is passed through adaptive filter with a reference signal. Finally the artifact free CS is presented on the display.

3.1 Power Line Interference (PLI) Cancellation:

As the name suggests, this noise is basically arisen because of the electric power. Generally CS is corrupted by PLI during the data acquisition. So cancellation of this artifact is the important task. In this paper PLI artifact is taken from the MIT-BIH database, which is given as a reference signal. The signal corrupted with the PLI artifact is given as the desired signal. The filtering performance of the various ANCs is presented in Figure 3. The simulation results corresponding to data 101 are shown in this section. Among the algorithms considered NSRMLMS gets 11.2356 dB with "L" number of reduced MACs due to sign regressor operation. Where as, conventional LMS achieves SNRI of 8.8067 dB only during artifact removal process. Similar order of performance is achieved with reference to EMSE and MSD.

3.2 Base Line Wander (BW) Cancellation:

The BW noise taken from the MIT-BIH database is given as the reference signal. The filtering performance of the various ANCs is presented in Figure 4. The simulation results corresponding to data 101 are shown in this section. Among the algorithms considered NSRMLMS gets 9.3572 dB with "L" number of reduced MACs due to sign regressor operation. Where, as conventional LMS achieves SNRI of 4.1985 dB only during artifact removal process. Similar order of performance is achieved with reference to EMSE and MSD.

3.3 Muscle Artifact (MA) Cancellation:

The MA artifact taken from the MIT-BIH database is given as a reference signal. The signal corrupted with the MA artifact is given as the desired signal. The filtering performance of the various ANCs is presented in Figure 5. The simulation results corresponding to data 101 are shown in this section. Among the algorithms considered NSRLMS gets 10.7631 dB with "L" number of reduced MACs due to sign regressor operation. Where, as conventional LMS achieves SNRI of 3.6415 dB only during artifact removal process. Similar order of performance is achieved with reference to EMSE and MSD.

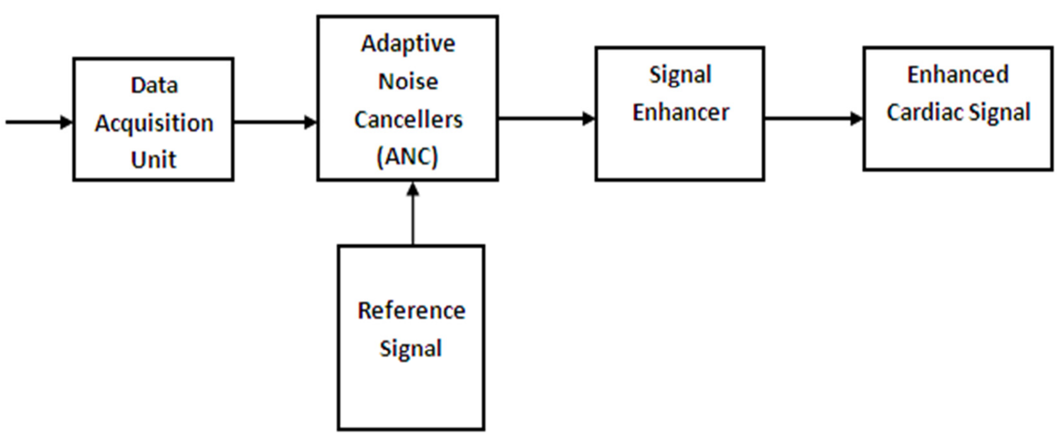

Figure 2: Experiemnta modal of proposed work

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3.4 Electrode Motion (EM) Cancellation:

In this experiment MA artifact taken from the MIT-BIH database is given as a reference signal. The signal corrupted with the MA artifact is given as the desired signal. The filtering performance of the various ANCs is presented in Figure 6. The simulation results corresponding to data 101 are shown in this section. Among the algorithms considered NSRMLMS gets 10.4778 dB with "L" number of reduced MACs due to sign regressor operation. Where as, conventional LMS achieves SNRI of 4.4419 dB only during artifact removal process. Thus the proposed NSRMLMS algorithm is better than the conventional algorithm in terms of the computational complexity. A similar order of performance is achieved with reference to EMSE and MSD.

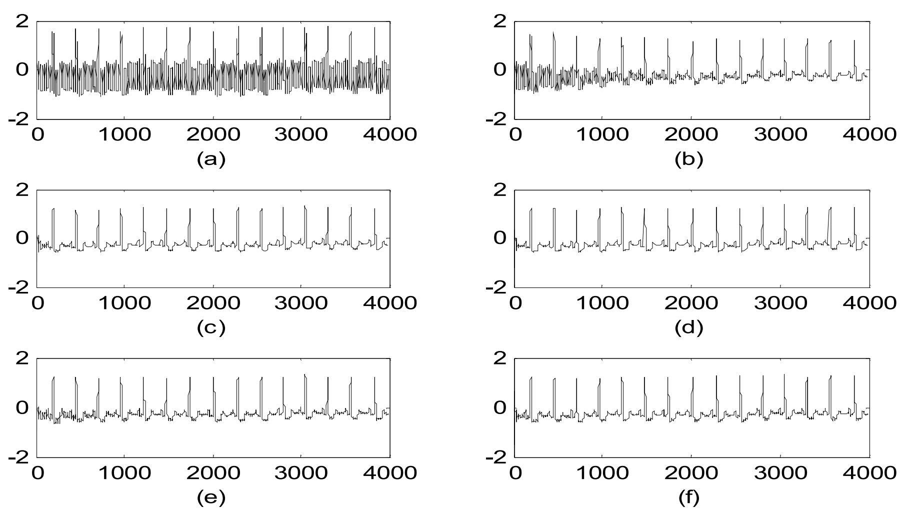

Figure 3: PLI Filtering results: a) Filtering with LMS, b) Filtering with MLMS, c) Filtering with NMLMS, d) Filtering with NSRMLMS, e) Filtering with NSMLMS, f) Filtering with NSSMLMS.

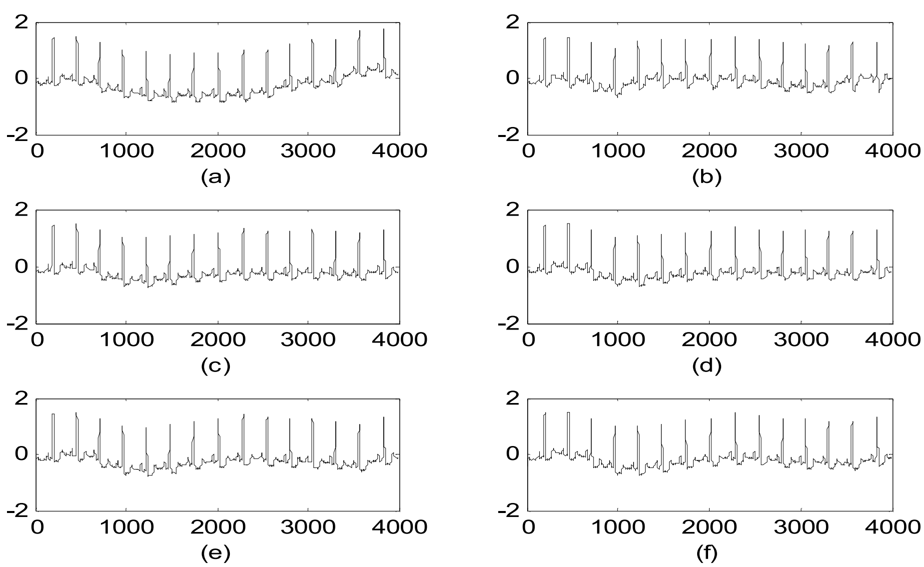

Figure 4: BW Filtering results: a) Filtering with LMS, b) Filtering with MLMS, c) Filtering with NMLMS, d) Filtering with NSRMLMS, e) Filtering with NSMLMS, f) Filtering with NSSMLMS.

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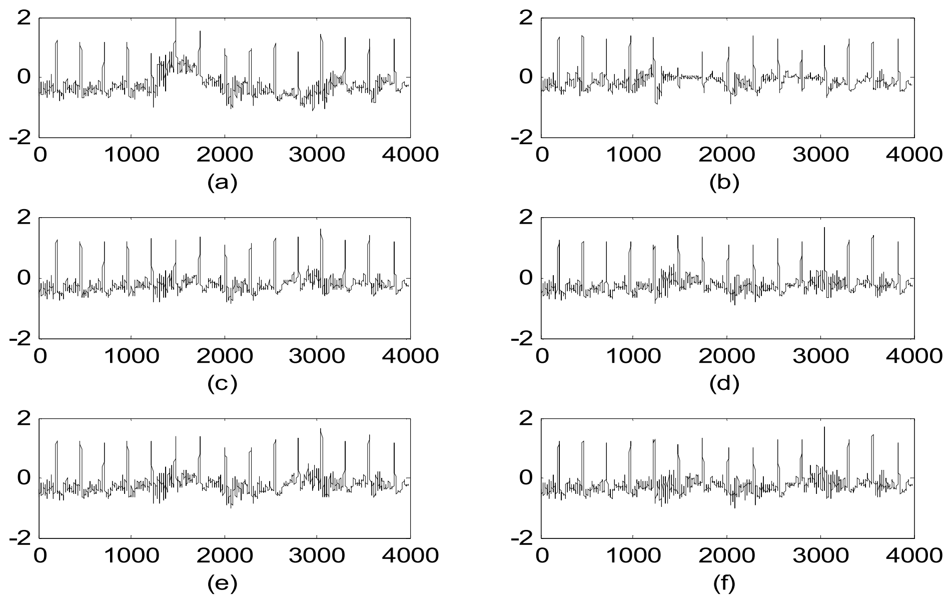

Figure 5: MA Filtering results: a) Filtering with LMS, b) Filtering with MLMS, c) Filtering with NMLMS, d) Filtering with NSRMLMS, e) Filtering with NSMLMS, f) Filtering with NSSMLMS.

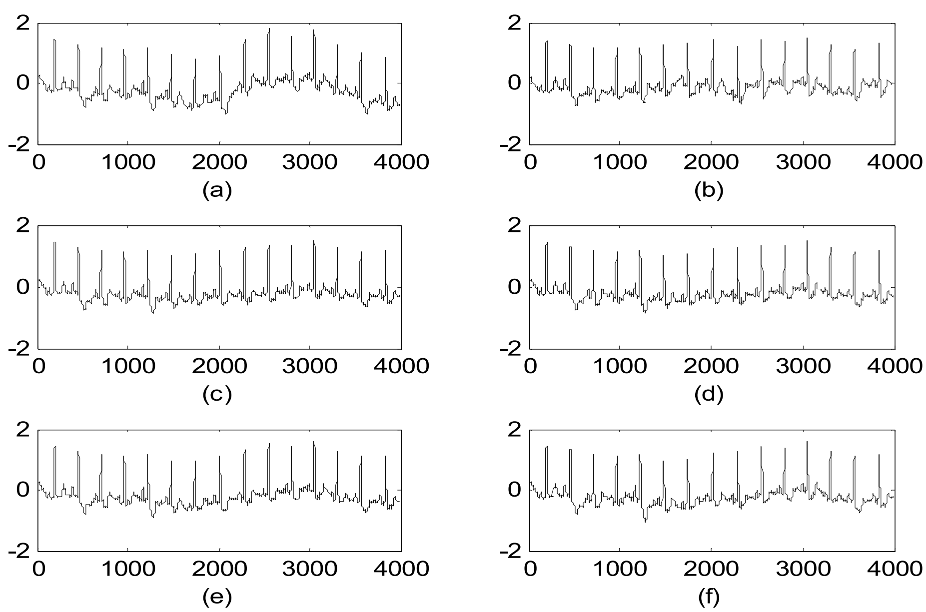

Figure 6: EM Filtering results: a) Filtering with LMS, b) Filtering with MLMS, c) Filtering with NMLMS, d) Filtering with NSRMLMS, e) Filtering with NSMLMS, f) Filtering with NSSMLMS.

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Table 1: Performance Contrast of Various Algorithms in Terms of SNRI for the Removal of Artifacts from Cardiac Signals (all values in dBs)

Noise	Data No	LMS	MLMS	NMLMS	NSRMLMS	NSMLMS	NSSMLMS
PLI	101	8.8067	9.3452	17.5534	11.2356	13.2567	15.6857
	102	7.7763	9.7754	17.9086	11.0945	13.3837	15.3534
	103	9.1878	9.5221	17.2367	11.1290	13.9403	15.4643
	104	8.5084	9.5577	17.0932	11.5693	13.4594	15.6709
	105	9.0063	9.0923	17.0154	11.3456	13.4535	15.2323
	Avg	**8.6571**	**9.4585**	**17.3614**	**11.2748**	**13.4987**	**15.4813**
BW	101	4.1985	2.3247	10.4673	9.3572	7.1180	5.3587
	102	4.2598	3.7849	10.1233	9.1299	7.9087	5.9821
	103	4.7682	2.7808	10.3344	9.5690	7.6754	5.0943
	104	4.8275	2.8411	10.7865	9.9695	7.9653	5.7839
	105	4.6124	3.5038	10.9908	9.3323	7.7183	5.0320
	Avg	**4.5332**	**3.0470**	**10.5404**	**9.4715**	**7.6771**	**5.4502**
MA	101	3.6415	3.4635	12.6754	10.7631	8.8657	6.7869
	102	3.7605	4.9736	12.4782	10.0956	8.8657	6.7657
	103	3.9652	3.4621	12.9087	10.6543	8.8659	6.4694
	104	4.0395	5.7719	12.4532	10.9786	8.8239	6.8558
	105	4.0008	4.8636	12.9763	10.9673	8.9785	6.9876
	Avg	**3.8815**	**4.5069**	**12.6983**	**10.6917**	**8.8799**	**6.7730**
EM	101	4.4419	4.3705	12.4546	10.4778	8.8928	6.5656
	102	4.6511	4.2589	12.6015	10.7564	8.5767	6.6545
	103	4.8438	3.3894	12.7687	10.6577	8.7553	6.6575
	104	4.6617	3.9291	12.3466	10.8675	8.6774	6.5645
	105	4.7782	3.8203	12.7889	10.7787	8.6574	6.7786
	Avg	**4.6753**	**3.9536**	**12.5920**	**10.7076**	**8.7119**	**6.6641**

Table 2: Performance Contrast of Various Algorithms in Terms of EMSE for the Removal of Artifacts from Cardiac Signals (all values in dBs)

Noise	Data No	LMS	MLMS	NMLMS	NSRMLMS	NSMLMS	NSSMLMS
PLI	101	-19.9894	-23.8923	-22.0933	-21.3347	-27.2322	-25.2323
	102	-21.8298	-23.3446	-22.2322	-21.3323	-27.5343	-25.2323
	103	-20.5036	-23.2323	-22.3434	-21.4568	-27.9033	-25.6686
	104	-21.5394	-23.2332	-22.3454	-21.5679	-27.3231	-25.5643
	105	-21.5227	-23.4234	-22.9332	-21.5654	-27.6789	-25.3249
	Avg	**-21.0769**	**-23.4251**	**-22.3895**	**-21.4514**	**-27.5343**	**-25.4044**
BW	101	-11.1457	-11.2754	-23.5745	-21.5676	-18.6789	-16.5678
	102	-11.4418	-11.5310	-23.7545	-21.3467	-18.1278	-16.3464
	103	-11.4770	-11.6089	-23.7564	-21.6454	-18.3478	-16.7687
	104	-8.9635	-9.0180	-23.3467	-21.4356	-18.4678	-16.3478
	105	-12.6204	-12.7328	-23.4655	-21.6454	-18.2355	-16.6768
	Avg	**-11.1282**	**-11.2332**	**-23.5795**	**-21.5281**	**-18.3715**	**-16.5415**
MA	101	-12.1110	-11.5792	-25.5779	-22.8697	-19.5476	-17.3457
	102	-12.4097	-12.2046	-25.3447	-22.7867	-19.3446	-17.5466
	103	-11.7569	-11.4107	-25.8675	-22.8767	-19.6454	-17.3265
	104	-11.1118	-10.8163	-25.6879	-22.4367	-19.6434	-17.2355
	105	-13.8287	-13.0058	-25.8798	-22.3465	-19.4364	-17.4557
	Avg	**-12.3426**	**-11.8033**	**-25.6715**	**-22.6632**	**-19.5234**	**-17.3820**
EM	101	-10.7955	-11.5703	-23.2344	-21.3457	-18.3578	-16.7564
	102	-10.7225	-11.7866	-23.3479	-21.8908	-18.6576	-16.3446
	103	-10.9025	-11.6255	-23.3448	-21.6678	-18.6879	-16.6575
	104	-8.2407	-9.1318	-23.3479	-21.3456	-18.4557	-16.3356
	105	-12.3952	-13.2715	-23.3456	-21.3456	-18.7889	-16.6787
	Avg	**-10.6112**	**-11.4771**	**-23.3241**	**-21.5191**	**-18.5895**	**-16.5545**

Table 3: Performance Contrast of Various Algorithms in Terms of MSD for the Removal of Artifacts from Cardiac Signals (all values in dBs)

Noise	Data No	LMS	MLMS	NMLMS	NSRMLMS	NSMLMS	NSSMLMS
PLI	101	0.0761	0.0573	0.1143	0.0105	0.0200	0.4161
	102	0.0460	0.0428	0.0821	0.0095	0.0187	0.2418
	103	0.0744	0.0455	0.056	0.0109	0.0197	0.3819
	104	0.0134	0.0161	0.0359	0.0092	0.0192	0.1124
	105	0.0725	0.0421	0.1204	0.0107	0.0207	0.4556
	Avg	**0.0564**	**0.04076**	**0.8174**	**0.0101**	**0.0196**	**0.3215**
BW	101	0.5829	0.5658	0.1385	0.2581	0.3294	0.3971
	102	0.5030	0.4928	0.1334	0.2525	0.3245	0.3911
	103	0.5960	0.5772	0.1345	0.2537	0.3266	0.3913
	104	0.4842	0.4782	0.1311	0.2533	0.3289	0.3995
	105	0.5630	0.5486	0.1399	0.2505	0.3250	0.3930
	Avg	**0.5458**	**0.5325**	**0.1354**	**0.2536**	**0.3268**	**0.3944**
MA	101	0.4667	0.5275	0.1583	0.2849	0.3202	0.3928
	102	0.4025	0.4220	0.1538	0.2823	0.3233	0.3930
	103	0.5579	0.5610	0.1577	0.2810	0.3220	0.3933
	104	0.8090	0.9305	0.1520	0.2805	0.3255	0.3996
	105	0.4262	0.6092	0.1501	0.2884	0.3242	0.3977
	Avg	**0.5324**	**0.6100**	**0.1543**	**0.2834**	**0.3230**	**0.3952**
EM	101	0.6319	0.5286	0.1493	0.2630	0.3368	0.3982
	102	0.5936	0.4946	0.1411	0.2621	0.3370	0.3979
	103	0.6792	0.5750	0.1424	0.2655	0.3395	0.3966
	104	0.5719	0.4683	0.1445	0.2667	0.3388	0.3949
	105	0.5929	0.4846	0.1488	0.2649	0.3316	0.3933
	Avg	**0.6139**	**0.5102**	**0.1452**	**0.2644**	**0.3376**	**0.3961**

In the above tables performance measeures of various algorithms in terms of SNRI, EMSE and MSD for the removal of artifacts are measured. MATLAB is the tool used to evaluate the experimentation results. The data sets 101 to 105 are considered as the input data samples. Based on the average values, the best algorithm can be identified. In Table 1, the performance of the LMS, MLMS, NMLMS and its sign variants are evalutated in terms of SNRI for the removal of artifacts from the CS. Similarly in Table 2 and Table 3 the performance of same algorithms are evaluated in terms of EMSE and MSD for the removal of artifacts from CS. Based on the simulation results and the tables it is found that the NSRMLMS algorithms is most suitable for IOT based remote healthcare applications.

4. CONCLUSION

In the proposed work, the removal of BW, MA and EM from CS is presented with the help of the median based type of adaptive algorithms. The normalization and sign based versions of MLMS are implemented to improve the suitability of the algorithm to use in real time. The MIT-BIH arrhythmia database is used to test the performance of the proposed noise cancellers. The SNRI, EMSE and MSD are considered as performance measures to evaluate the performance of the proposed implementations. Among various algorithms, NSRMLMS is found to be first in the list with reference to various performance measures. Next, the NSMLMS is found to be second in the list with reference to SNRI, EMSE, MSD and convergence, but it reduces “L” MACs in the normalization with respect to data vector. Finally, NSSMLMS is found to be third in the list with reference to SNRI, EMSE, MSD and convergence. But it reduces “L” MACs due to normalization and other “L” MACs due to sign operation. However, in practical health care monitoring devices NSRMLMS is well suited because of its reduced number of MACs even though it is slightly inferior than NSMLMS.

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