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ARTIFACT REMOVAL IN ECG SIGNALS USING MODIFIED DATA NORMALIZATION BASED SIGNAL ENHANCEMENT UNITS FOR HEALTH CARE MONITORING SYSTEMS

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ABSTRACT

Low complexity noise cancellation structures are needed for reliable transmission of ECG signals at real time environments. These low complexity structures can be developed with the help of the partial update techniques for better convergence and complexity. In this paper the same idea is used to derive several structures which are good at convergence and complexity. Based on partial update mechanism of the coefficients of the adaptive filter, we upgraded the conventional normalized least mean square (NLMS) algorithm. This modified algorithm updates only some coefficients of the taps where the signal characteristics widely deviate from the previous iteration. The modified NLMS (MNLMS) based on partial update mechanism is combined with signum based algorithms to minimize number of multiplications during filtering process. Further, we proposed maximum value of data for normalizing the step size to decrease the number of multiplications in the denominator of the normalization function. These are suitable to operate at high data rate applications, and to test the working of these structures in real time conditions the MIT-BIH arrhythmia database was used. Here the signal to noise ratio, the miss adjustment error is used as performance measures and all the test data is tabulated. The structures have shown good performance over the standard LMS algorithm in terms of the filtering, complexity and convergence.
Keywords: *Adaptive Noise Canceller, Artifacts, Computational Complexity, Convergence, ECG Signal.*

1. INTRODUCTION

The cardiac signal obtained from an ECG device is an important source of information for identifying various heart abnormalities. It helps to prevent the death of large group of people who are facing the risk of sudden cardiac arrest and other heart related diseases. It is stated in [1] WHO report that 33% of people with non-communicable diseases are suffering with the cardiac problems. To overcome it the abnormalities in heart need to be identified quickly and accurately. But ECG suffers from artifacts which makes the identification of the abnormalities difficult and error prone. To overcome them filtering of the signal need to be done. The artifacts are of mainly four types and they mainly add to the signal due to the manmade and natural reasons. The power line interference which appears at the fundamental and harmonics of the power line frequency is an example of an artifact. The others are Base Line Wandering, Muscle artifact and motion artifact. The artifacts appear in the form of the spurious amplitudes and combine with the minor and vital parts of ECG signal. It will be difficult to differentiate the noise and signal amplitudes at this stage. This makes the identification error prone. Challenges arise when less time is available for the diagnosis and also accuracy is required.

All the segments of the signal are important in identifying different arrhythmia conditions. In [2] Y. Nagahama et.al has studied about the possible conclusions to be drawn from the PQ segment depression. It was concluded that the depression of PQ is an indicative measure for sudden cardiac deaths. In [3] J.M. Dekker have identified that the abnormalities in ST and T wave are also an indicative measure of the coronary heart disease and the change in repolarization intervals helps to identify the heart disease. In [4] A. Elhendy et.al has studied depression of Q wave to identify the myocardial infarction in the stress induced patients. In this way every component present in the ECG signal represents the functioning of heart and is important in decease diagnosis.

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The minimization of artifacts requires efficient removal techniques as well as accuracy in acquisition. To have the accuracy many proposals were made in the literature. They range from designing electrodes to developing the hardware. In [5] Nick Van Helleputte et.al proposed a motion artifact canceller at 345 µW technology. It uses the surface electrode – tissue impedance measurement for cancellation. The system has an onboard processing unit for artifact removal and other readouts. Base line wander occurs when the subject performs a physical activity. Generally the base line wander will add into the signal when the subject is breathing and its influence is seen in terms of the baseline drift in the signal. In case of continuous monitoring of activity the impact of base line wander will be more. Similarly in case of the ambulatory monitoring the risk of error will be more. Thomas N et.al in [6] implemented a tracking system for this purpose. Its purpose is to continuously track the drift and cancel it and prevent the saturation of the front end. An acquisition and classification system is seen in the work of [7] shuenn Yun Lee et.al. These days ECG was thought to be operated at all types of the everyday activities. As a result the above techniques can only limit the artifacts and it is necessary to cancel the artifacts beyond this limit. Filtering the signal is next to minimization methods for removing the artifacts. The well-known techniques like EMD, ICA, and DFT have been used for the non-adaptive filtering of the ECG signal. The ECG signal is composed of time varying potentials as a result the fixed co-efficient non-adaptive filters cannot be used. In addition to the signal the noise is also a random signal so using the adaptive filters helps to serve purpose. The adaptive and non-adaptive based proposals exist in the literature [8]–[13].The weights of an adaptive filter will adjust to the signal environment and as a result the noise removal will be high and the signal changes can be tracked easily and accurately.

The success of an adaptive filter depends on the weight vector initialization and how they are updated. Also the error depends on the method of step size adaption. The step size plays an important parameter in adaptive filtering. It controls the rate of convergence and the error. Good convergence rate requires large step size and the good error performance requires the low step size adaption. Noise cancellation of ECG with the help of the LMS algorithm is widely popular technique for adaptive filtering due to the less complexity involved. But as stated in [14] the LMS based estimation is biased towards the signal power. The stability to the changes in the signal to noise ratio will be poor for an LMS.

Transmission of the signal in a fast and reliable way is necessary in wireless transmission. In transmission of ECG the complexity plays a vital role because it depends on allowable time of transmission, power and other resources. To maintain it the data rate will be set high and for that purpose the filter length needs to be increased but this increases the complexity. In large length ECG data during signal conditioning a considerable amount of samples does not undergo wide statistical changes. Hence, processing of these samples and re-adjusting the weight coefficients causes additional computation burden to the signal conditioning unit. To avoid such unnecessary updation, an algorithm based on partial update mechanism is presented in [16]. Using this frame work, to ensure good convergence we propose a partial update based signal enhancement unit (SEU) for eliminating artifacts from ECG signals. By combining partial update mechanism and data normalization for step size we modified the conventional NLMS algorithm. The resultant algorithm is termed as modified NLMS (MNLMS) algorithm. Further in order to minimize the computational complexity of this algorithm it is combined with sign based algorithms. The resultant hybrid algorithms are sign regressor MNLMS (SRMNLMS), sign MNLMS (SMNLMS) and sign sign MNLMS (SSMNLMS). Again to minimize complexity associated with numerator component of normalization operation we considered to use maximum value of the input block and normalize with that value only instead of normalizing with entire input data vector. This approach yields to complete the denominator processing using one multiplication and accumulation (MAC) instead of MACs equal to filter length. After this block based approach MNLMS is re-termed as block based MNLMS (BBMNLMS). Using these algorithms we developed various SEUs for ECG signal enhancement units for a remote health care monitoring system. The developed models are tested using real ECG signals contaminated with several artifacts obtained from MIT-BIH data base. The performances of these SEUs are measured in terms of signal to noise ratio improvement (SNRI) and excess mean square error (EMSE). In section 2 we discuss various algorithms used in the work. Section 3 describes results and analysis of results. Here we considered four types of artifacts to test

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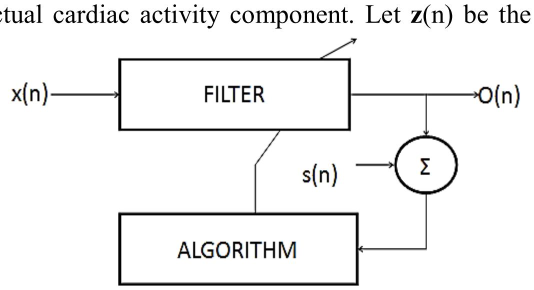
the performance of the proposed algorithms in ECG enhancement.

2. ALGORITHMS FOR ECG SIGNAL ENHANCEMENTUNIT IN A HEALTH CARE MONITORING SYSTEMS

In ECG signal enhancement the removal of artifacts is the key phenomenon. In this work we propose an adaptive filtering based signal enhancement unit (SEU) to eliminate various artifacts present in the ECG signals and to facilitate high resolution ECG signals for diagnosis. This SEU consists of a FIR filter of length "P", adaptive algorithm to update filter coefficients in accordance to the input non-stationery signal and a comparator. Let x(n) be the input ECG signal. In principle, this cardiac activity contaminated with artifacts like power line interference (PLI), baseline wander (BW), muscle artifact (MA) and electrode motion artifact (EM). These artifacts contaminate the tiny features of ECG signal which are crucial for diagnosis. The contaminated ECG signal to be filtered is applied to an adaptive filter structure. In this paper the fundamental algorithm upon which derivatives want to make is the LMS algorithm. The filter coefficients during the updating will reduce the error and tries to cancel the noise in the signal as per the framework of N.V. Thakoor et.al [15]. Let s(n) is a reference signal, which is somewhat correlated with the artifact component present in the recorded ECG signal. O(n) is the output signal after enhancement. A sample of this O(n) is taken and is given as a feedback signal to the algorithm in the SEU. Let it be e(n). The artifact component in the ECG signal is designated as a(n). Therefore, x(n)=c(n)+a(n). Here, c(n) is the actual cardiac activity component. Let **z**(n) be the



filter coefficients.

Fig.1. A Typical Signal Enhancement Unit

The structure of a typical SEU is shown in the Fig.1.

The weight update relation of the basic LMS algorithm can be written as,

$$z_{n+1} = z_n + \mu x(n) e(n) \tag{1}$$

The NLMS algorithm was a LMS variant with the step size normalized. The variant was introduced to control the miss adjustment error that occurs due to the bad step size, and signal power. The equation for NLMS is given as below

$$z_{n+1} = z_n + \frac{\mu x(n) e(n)}{\delta + (x(n))^2} \tag{2}$$

The denominator of the equation is made to control the convergence with the squared regressor term. This provides the algorithm stability against the signal power. The term δ is used to avoid the stability problems when the signal contains the zero valued coefficients. Also, this behaves as the variant form of LMS due to the scaling of the step size and this improves the convergence. The constant in the denominator is introduced to prevent the algorithm to become unstable when the squared term tends to become zero. The above algorithm gives the reduced error, but the squared term in the denominator will increase the number of MAC operations, this increase the complexity and time to converge will increase. To reduce the number of computations in [16] a partial update based methodology is proposed to update only required tap coefficients rather than all taps of the filter, this yields a modified NLMS (MNLMS) algorithm.

Now the MNLMS mathematically represented as,

$$z_{n+1} = z_n + \frac{q \mu x(n) e(n)}{\delta + (x(n))^2} \tag{3}$$

Where q = diag {Q} and Q = {1 if x > x_{max}}. The term q will be either zero or one based on the value of x. If the value of x is greater than the threshold then the q will be set to one otherwise it is set to zero thus reducing the entire numerator to zero and number of calculations reduces. The above procedure reduces the computations involved but not the complexity. To reduce the complexity in this paper the sign algorithms are introduced. These algorithms have less convergence compared to NLMS but the complexity reduces and the error will be little high. The signum function is successfully used in [17]-[19] by Rahman et.al for removing artifacts. The sign algorithms are of three types, namely sign regressor, sign and sign sign algorithms. Therefore, in order to minimize computational complexity of MNLMS algorithm, we combine MNLMS with sign based algorithms. The hybrid versions are named as, SRMNLMS,

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SMNLMS and SSMNLMS algorithms. The weight update equations are written as,

$$z_{n+1} = z_n + \frac{q\mu sign(x(n))e(n)}{\delta + (x(n))^2} \tag{4}$$

$$z_{n+1} = z_n + \frac{q\mu x(n) sign(e(n))}{\delta + (x(n))^2} \tag{5}$$

$$z_{n+1} = z_n + \frac{q\mu sign(x(n)) sign(e(n))}{\delta + (x(n))^2} \tag{6}$$

In the equations (3)-(6) the denominator of the normalization function requires "P" multiplications. When the filter length is large, the normalization function requires many multiplications. To avoid these excess multiplications we propose a normalization phenomenon, in which only the maximum value of input block is utilized for normalization. Using this block based approach only one multiplication is needed instead of "P" multiplications. This version is called as a block based MNLMS (BBMNLMS) algorithm. The hybrid versions of BBMNLMS with sign algorithms results SRBBMNLMS, SBBMNLMS and SSBBMNLMS algorithms. The weight update equations of these block based algorithms are given as,

$$z_{n+1} = z_n + \frac{q\mu sign(x(n))e(n)}{\delta + (\max(x(n)))^2} \tag{7}$$

$$z_{n+1} = z_n + \frac{q\mu x(n) sign(e(n))}{\delta + (\max(x(n)))^2} \tag{8}$$

$$z_{n+1} = z_n + \frac{q\mu sign(x(n)) sign(e(n))}{\delta + (\max(x(n)))^2} \tag{9}$$

Finally, using these algorithms several SEUs are developed and tested with real ECG signals obtained from MIT-BIH data base [20]-[21].

3. SIMULATION RESULTS

In a typical signal enhancement unit generally adaptive filters are used for artefact elimination. But, the drawback of conventional adaptive filters is, it need to update all the tabs. This increases the computational burden to the filter. In order to avoid this, we propose a modified NLMS algorithm which updates the tap coefficients when the corresponding data value changes more. Otherwise the particular coefficients are not updated. In this section several experiments are performed to test the developed ANCs in cardiac signal enhancement. The noisy cardiac signals are taken from MIT-BIH arrhythmia database [20]-[21]. The MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory CS recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory ages 23 years to 89 years. Twenty-three recordings were chosen at random from a set of 4000 24-hour ambulatory CS recordings collected from a mixed population of inpatients (about 60%) and outpatients (about 40%) at Boston's Beth Israel Hospital; the remaining 25 recordings were selected from the same set to include less common but clinically significant arrhythmias that would not be well-represented in a small random sample. The ECG recordings were made using Del Mar Avionics model 445 two-channel reel-to-reel Holter recorders, and the analog signals were recreated for digitization using a Del Mar Avionics model 660 playback unit [22]-[23]. In our experiments we have considered a dataset of five cardiac activity records: data101, data102, data103, data104 and data105 to ensure the consistency of results, the simulation results for data 101 are shown in this paper. In these experiments we have used first 4000 samples of the CS. All the experiments were performed for 10 times and average values are tabulated. The length of the adaptive filter is chosen as 10, a random noise of variance 0.001 is added to the signals, which resembles the channel noise. For evaluating the performance of the proposed ANC structures we have measured the signal-to-noise ratio improvement (SNRI) in decibels (dBs) and EMSE.

3.1. Performance of SEU in Power Line Interference Elimination from ECG Signal

In this experiment we prove the ability of the proposed ANCs in eliminating the PLI artifact. The noisy cardiac signal with PLI noise is given as input to the ANC as shown in the Fig. 1. A synthetic PLI with 60Hz frequency is given as reference signal. The noise cancellation experiments are performed using the algorithms discussed in the previous section. For comparison we also implement LMS based SEU. The experiments are performed on the dataset consists of five records. The enhancement results are shown in Fig. 2. Next, to evaluate the performance of the SEUs we measure SNRI and EMSE. These are tabulated in Table I and Table II. Fig. 6 provides the comparison of these performance measures. In our experiments, among the considered algorithms it is found that MNLMS algorithm achieves highest SNRI 17.6444dB. However, based on the

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application of sign regressor operation SRMNLMS needs less number of multiplications during the enhancement process. This algorithm achieves 14.9689dB SNRI. Further, using maximum data value normalization BBMNLMS and its sign regressor version needs reduced number of multiplications in the enhancement process than VNLMS and its sign regressor version. But , this technique needs a reference signal. This is the drawback of the proposed technique. Therefore, based on SNRI, EMSE and number of multiplications among all the considered algorithms SRBBMNLMS based SEU performs better with tolerable SNRI. Hence, this algorithm can be used in practical remote health care monitoring systems for cardiac signal enhancement.

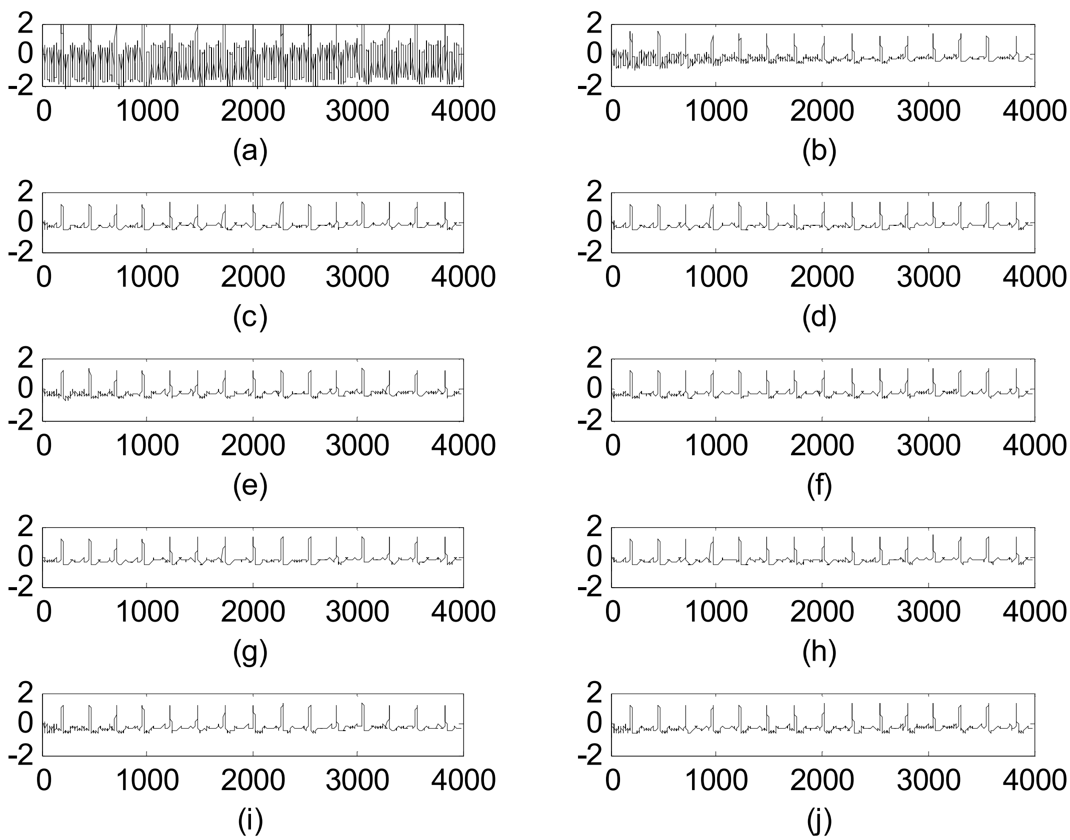

Fig.2. PLI Filtering results a) Cardiac Signal with Power Line Interference, b) Filtering with LMS, c) Filtering with MNLMS, d) Filtering with BBMNLMS, e) Filtering with SRMNLMS, f) Filtering with SRBBMNLMS, g) Filtering with SMNLMS, h) Filtering with SBBMNLMS, i) Filtering with SSMNLMS, j) Filtering with SSBBMNLMS.

3.2. Performance of SEU in Baseline Wander Elimination from ECG Signal

In this experiment we prove the ability of the proposed SEUs in eliminating the BW artifact. The noisy cardiac signal with BW noise is given as input to the SEU as shown in the Fig. 1.A real base line wander artifact is taken as reference obtained from MIT-BIH data base. The noise cancellation experiments are performed using the algorithms discussed in the previous section. For comparison we also implement LMS based SEU. The experiments are performed on the dataset consists of five records. The enhancement results are shown in Fig. 3. The parameters SNRI and EMSE are taken as measures of performance. These are tabulated in Table I and Table II. Fig. 6 shows the comparison of these performance measures. In our experiments, among the considered algorithms it is found that MNLMS algorithm achieves highest SNRI 8.6627dB. However, based on the application of sign regressor operation SRMNLMS needs less number of multiplications during the enhancement process. This algorithm achieves 7.6036 dB SNRI. Further, using maximum data

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value normalization BBMNLMS and its sign regressor version needs reduced number of multiplications in the enhancement process than MNLMS and its sign regressor version. Therefore, based on SNRI, EMSE and number of multiplications among all the considered algorithms SRBBMNLMS based SEU performs better with tolerable SNRI. Hence, this algorithm can be used in practical remote health care monitoring systems for cardiac signal enhancement.

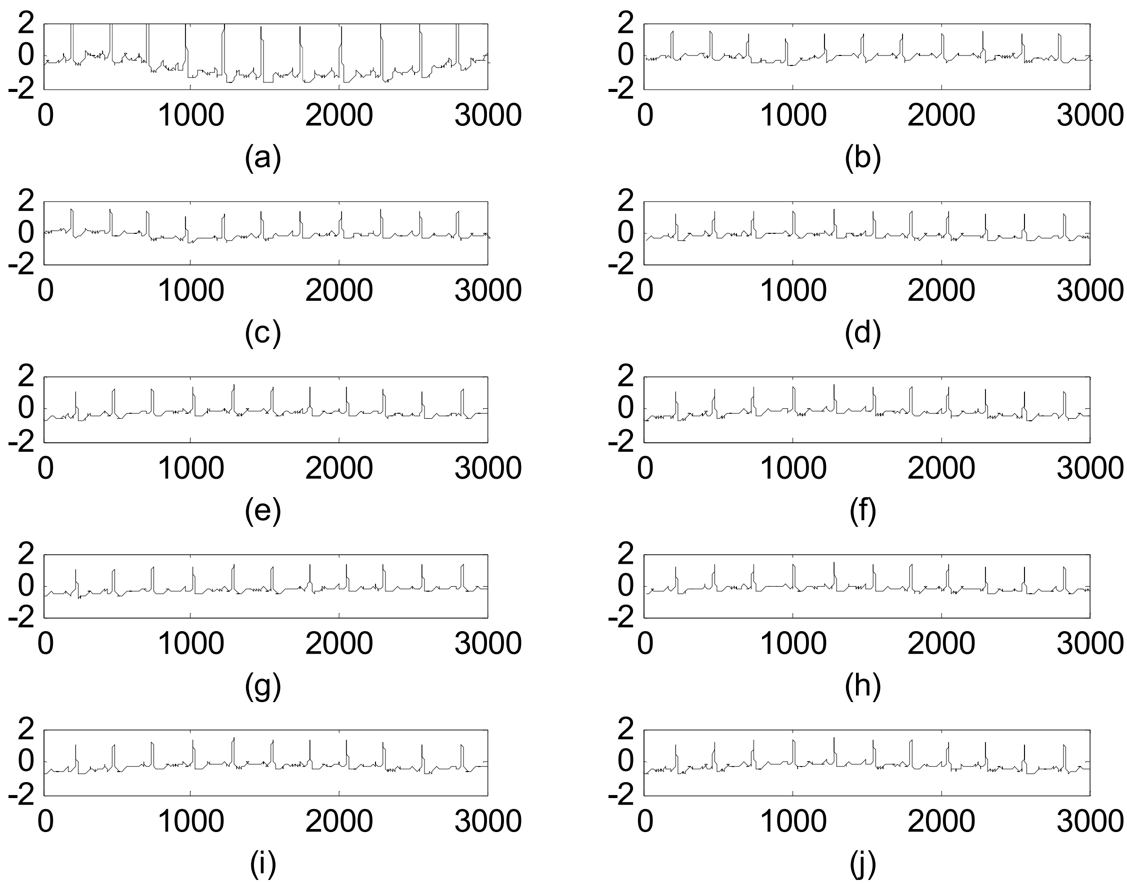

Fig.3. BW Filtering results a) Cardiac Signal with base line wander, b) Filtering with LMS, c) Filtering with MNLMS, d) Filtering with BBMNLMS, e) Filtering with SRMNLMS, f) Filtering with SRBBMNLMS, g) Filtering with SMNLMS, h) Filtering with SBBMNLMS, i) Filtering with SSMNLMS, j) Filtering with SSBBMNLMS.

3.3. Performance of SEU in Muscle Artifact Elimination from ECG Signal

In this experiment we prove the ability of the proposed SEUs in eliminating the muscle artifact (MA). The noisy cardiac signal with MA noise is given as input to the SEU as shown in the Fig. 1. A real MA is taken as reference obtained from MIT-BIH data base. The noise cancellation experiments are performed using the algorithms discussed in the previous section. For comparison we also implement LMS based SEU. The experiments are performed on the dataset consists of five records. The enhancement results are shown in Fig. 4. The parameters SNRI and EMSE are taken as measures of performance. These are tabulated in Table I and Table II. Fig. 6 shows the comparison of these performance measures. In our experiments, among the considered algorithms it is found that MNLMS algorithm achieves highest SNRI 7.6636dB. However, based on the application of sign regressor operation SRMNLMS needs less number of multiplications during the enhancement process. This algorithm achieves 6.8039 dB SNRI. Further, using maximum data

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value normalization BBMNLMS and its sign regressor version needs reduced number of multiplications in the enhancement process than MNLMS and its sign regressor version. Therefore, based on SNRI, EMSE and number of multiplications among all the considered algorithms SRBBMNLMS based SEU performs better with tolerable SNRI. Hence, this algorithm can be used in practical remote health care monitoring systems for cardiac signal enhancement.

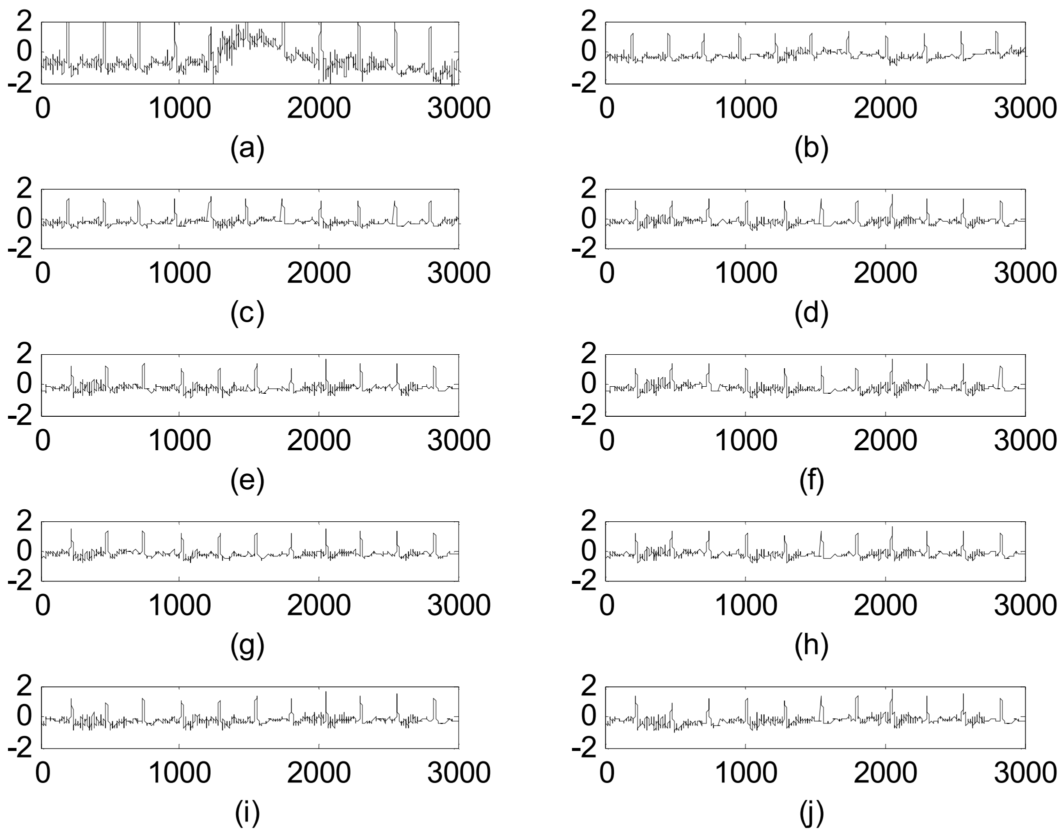

Fig.4. MA Filtering results a) Cardiac Signal with muscle artifacts, b) Filtering with LMS, c) Filtering with MNLMS, d) Filtering with BBMNLMS, e) Filtering with SRMNLMS, f) Filtering with SRBBMNLMS, g) Filtering with SMNLMS, h) Filtering with SBBMNLMS, i) Filtering with SSMNLMS, j) Filtering with SSBBMNLMS.

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3.4. Performance of SEU in Electrode Motion Artifact Elimination from ECG Signal

In this experiment we prove the ability of the proposed SEUs in eliminating the EM artifacts. The noisy cardiac signal with EM noise is given as input to the SEU as shown in the Fig. 1. A real EM is taken as reference obtained from MIT-BIH data base. The noise cancellation experiments are performed using the algorithms discussed in the previous section. For comparison we also implement LMS based SEU. The experiments are performed on the dataset consists of five records. The enhancement results are shown in Fig. 5. The parameters SNRI and EMSE are taken as measures of performance. These are tabulated in Table I and Table II. Fig. 6 shows the comparison of these performance measures. In our experiments, among the considered algorithms it is found that MNLMS algorithm achieves highest SNRI 8.3780dB. However, based on the application of sign regressor operation SRMNLMS needs less number of multiplications during the enhancement process. This algorithm achieves 7.4176dB SNRI. Further, using maximum data value normalization BBMNLMS and its sign regressor version needs reduced number of multiplications in the enhancement process than BBMNLMS and its sign regressor version. Therefore, based on SNRI, EMSE and number of multiplications among all the considered algorithms SRBBMNLMS based SEU performs better with tolerable SNRI. Hence, this algorithm can be used in practical remote health care monitoring systems for cardiac signal enhancement.

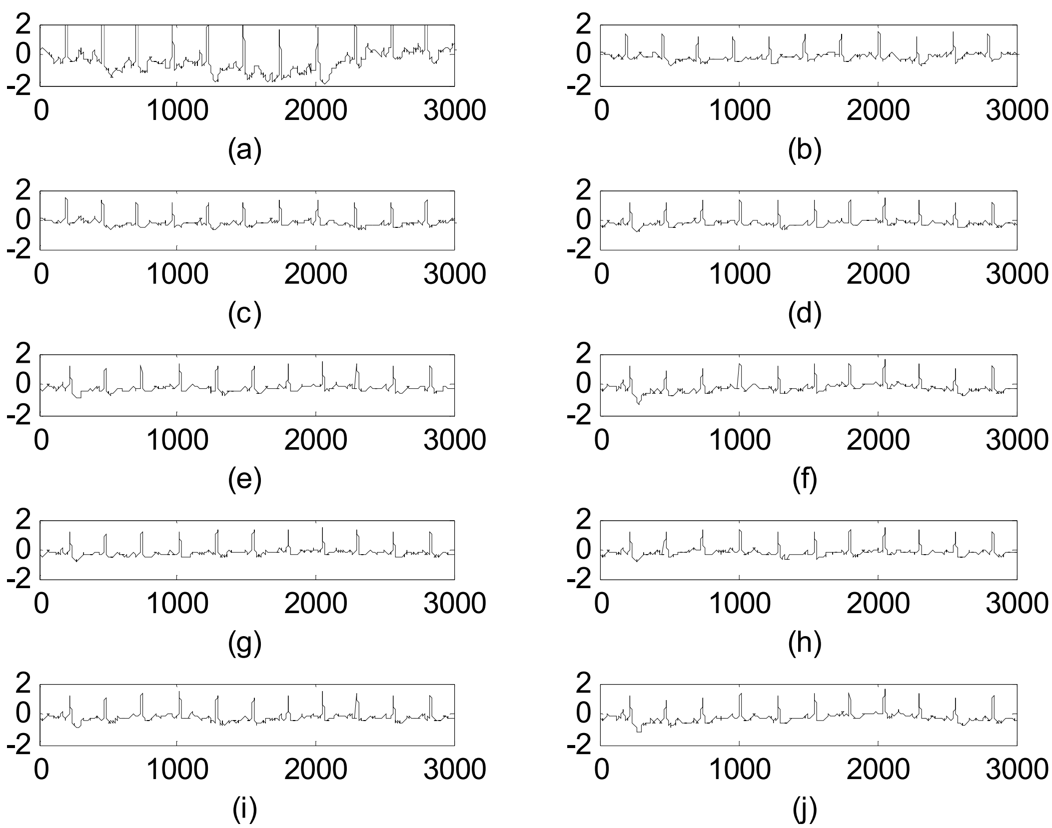

Fig.5. EM Filtering results a) Cardiac Signal with muscle artifacts, b) Filtering with LMS, c) Filtering with MNLMS, d) Filtering with BBMNLMS, e) Filtering with SRMNLMS, f) Filtering with SRBBMNLMS, g) Filtering with SMNLMS, h) Filtering with SBBMNLMS, i) Filtering with SSMNLMS, j) Filtering with SSBBMNLMS.

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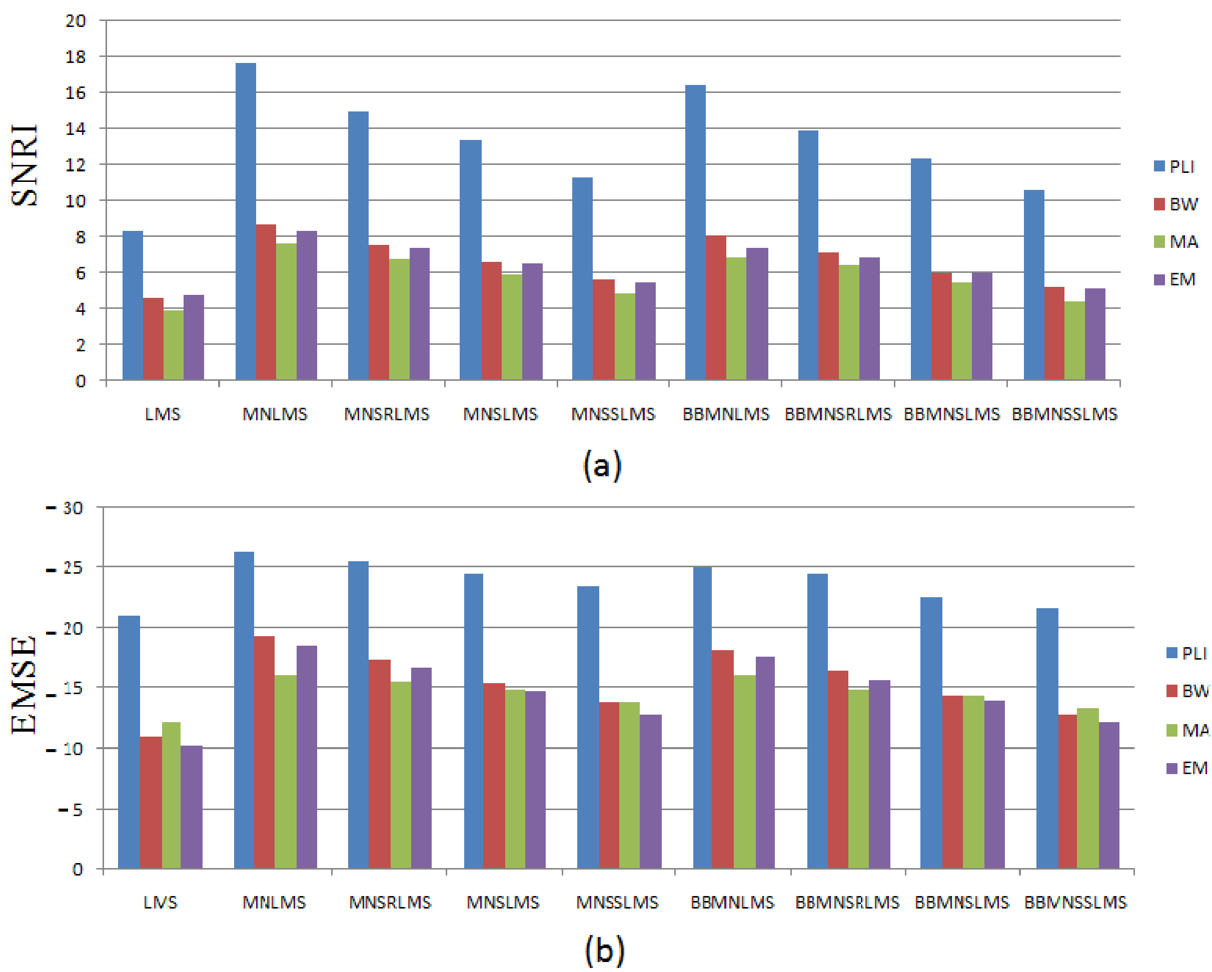

Fig. 6. a) Comparison of SNRI for various SEUs during artifact elimination.
b) Comparison of EMSE for various SEUs during artifact elimination.

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Table I: Performance Contrast Of Various Algorithms In Terms Of Snri For The Removal Of Artifacts From Ecg Signals (All Values In Dbs)

Noise Type	Record Number	LMS	MNLMS	SRMN LMS	SMN LMS	SSMN LMS	BBMN LMS	SRBBMN LMS	SBBMN LMS	SSBBMN LMS
PLI	101	7.7763	17.0363	14.7454	12.9026	10.8353	15.9874	13.5574	11.9974	10.2364
	102	9.1878	18.5674	15.6534	13.9878	11.9969	17.0373	14.8443	12.9774	11.1735
	103	8.5084	17.6272	14.9353	13.3638	11.1634	16.4347	13.8763	12.3634	10.5839
	104	9.0063	18.1543	15.2542	13.8487	11.8565	16.9456	14.2635	12.7452	10.9474
	105	7.3824	16.8371	14.2563	12.8564	10.5823	15.7183	13.0713	11.7284	9.9246
	Average	**8.3722**	**17.6444**	**14.9689**	**13.3918**	**11.2868**	**16.4246**	**13.9225**	**12.3623**	**10.5731**
BW	101	4.2598	7.8842	6.6754	5.8735	5.5735	7.5672	6.1931	5.2851	5.1738
	102	4.7682	8.9735	7.8352	6.7373	5.9324	8.4353	7.6452	6.2534	5.2746
	103	4.8275	8.7436	7.6843	6.9953	5.0272	8.2336	7.1664	6.3368	4.9842
	104	4.6124	8.9735	7.9983	6.8563	5.9362	8.1735	7.0933	6.2887	5.3232
	105	4.4523	8.7391	7.8248	6.6720	5.7358	8.2286	7.3785	6.0318	5.3653
	Average	**4.5841**	**8.6627**	**7.6036**	**6.6268**	**5.6411**	**8.1276**	**7.0953**	**6.0391**	**5.2242**
MA	101	3.7605	7.8635	6.8863	5.8472	4.6353	7.0026	6.5332	5.0832	4.2693
	102	3.9652	7.9163	7.0036	6.1735	5.8307	7.1279	6.8306	5.9639	5.1637
	103	4.0395	7.7854	6.6964	5.9334	4.7847	6.9876	6.2836	5.1742	4.1836
	104	4.0008	7.1635	6.9524	5.5735	4.7835	6.5357	6.0162	5.3836	4.4837
	105	4.0137	7.5893	6.4812	5.9562	4.4762	6.8543	6.3561	5.7462	4.1583
	Average	**3.9559**	**7.6636**	**6.8039**	**5.8967**	**4.9021**	**6.9016**	**6.4039**	**5.4702**	**4.4517**
EM	101	4.6511	8.0634	7.7853	6.2325	5.6358	7.6353	7.10363	5.6357	5.4359
	102	4.8438	8.8476	7.0648	6.5734	5.1836	7.0936	6.6452	6.1037	4.9856
	103	4.6617	8.1027	7.9663	6.3634	5.9376	7.7372	7.2735	5.9852	5.3552
	104	4.7782	8.3524	7.0253	6.5469	5.1052	7.1005	6.4332	6.1043	4.8633
	105	4.8083	8.5239	7.2463	6.8769	5.3783	7.3154	6.9281	6.3679	5.1284
	Average	**4.7486**	**8.3780**	**7.4176**	**6.5186**	**5.4481**	**7.3764**	**6.8767**	**6.0393**	**5.1536**

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Table Ii
Performance Contrast Of Various Algorithms In Terms Of Emse
For The Removal Of Artifacts From Ecg Signals
(All Values In Dbs)

Noise Type	Record Number	LMS	MNLMS	SRMN LMS	SMN LMS	SSMN LMS	BBMN LMS	SRBBMN LMS	SBBMN LMS	SSBBMN LMS
PLI	101	-21.8298	-24.8635	-24.0036	-23.5442	-22.0484	-24.0487	-23.4833	-21.9503	-20.7452
	102	-20.5036	-27.2528	-26.8562	-25.2693	-24.4384	-25.8639	-25.0163	-22.9984	-22.1845
	103	-21.5394	-25.8471	-25.0346	-24.0474	-23.1836	-24.4356	-24.0283	-22.1847	-21.1734
	104	-21.5227	-26.9846	-25.9974	-24.9374	-23.9104	-25.4746	-24.9208	-22.8963	-22.0062
	105	-19.5486	-26.9127	-25.9371	-24.8963	-23.8754	-25.1682	-24.8374	-22.7073	-21.9948
	Average	**-20.9888**	**-26.3721**	**-25.5657**	**-24.5389**	**-23.4912**	**-24.9982**	**-24.4572**	**-22.5474**	**-21.6208**
BW	101	-11.4418	-19.0648	-17.1537	-15.2536	-13.1056	-18.0158	-16.0126	-14.1739	-12.2174
	102	-11.4770	-19.5993	-17.4839	-15.4843	-13.6904	-18.5382	-16.3803	-14.3985	-12.4495
	103	-8.9635	-19.8643	-17.7947	-15.6944	-13.8862	-18.7836	-16.5586	-14.6903	-12.7748
	104	-12.6204	-17.7539	-15.8649	-13.8632	-13.6543	-16.3457	-15.6827	-13.3549	-13.5574
	105	-10.9847	-20.4825	-18.1247	-16.4328	-14.7485	-19.2739	-17.2418	-15.3491	-13.7624
	Average	**-11.0974**	**-19.3529**	**-17.2843**	**-15.3456**	**-13.8170**	**-18.1914**	**-16.3752**	**-14.3933**	**-12.9523**
MA	101	-12.4097	-16.4366	-15.3854	-14.6736	-13.2859	-16.2749	-15.1274	-14.3835	-13.0845
	102	-11.7569	-16.9746	-15.8463	-14.7844	-13.9846	-15.8064	-14.7563	-13.8465	-12.7483
	103	-11.1118	-13.7452	-12.8468	-12.4371	-11.8463	-13.3473	-12.1482	-12.0648	-11.8072
	104	-13.8287	-16.9735	-15.8608	-15.5937	-14.3752	-16.3774	-15.4276	-15.2554	-14.2375
	105	-12.0091	-15.8735	-17.9371	-16.8631	-15.6398	-18.3847	-17.1805	-16.0495	-14.3926
	Average	**-12.2232**	**-16.0006**	**-15.5752**	**-14.8703**	**-13.8263**	**-16.0381**	**-14.9280**	**-14.3199**	**-13.2541**
EM	101	-10.7225	-18.5745	-16.5835	-14.3895	-12.6453	-17.4829	-15.5538	-13.4862	-11.6839
	102	-10.9025	-18.2739	-16.1742	-14.1084	-12.0653	-17.1983	-15.2741	-13.2626	-11.2314
	103	-8.2407	-18.8496	-16.8893	-14.8759	-12.9483	-17.9764	-15.8493	-13.8996	-11.9869
	104	-12.3952	-16.7558	-14.8836	-13.9375	-12.9537	-15.8753	-14.1372	-13.7633	-12.7352
	105	-9.1354	-20.3278	-18.8293	-16.2834	-14.1289	-19.3772	-17.6178	-15.3492	-13.6739
	Average	**-10.2792**	**-18.5563**	**-16.6719**	**-14.7189**	**-12.948**	**-17.5821**	**-15.6864**	**-13.9521**	**-12.2622**

4. CONCLUSIONS

In this paper several signal enhancement units for health care monitoring systems are presented. These are based on partial update based normalized LMS algorithm and its variants. The variations are based on signed versions of MNLMS algorithm. Further, we reduce the computational complexity by using block based normalization with maximum value of data vector. This reduces the computational complexity of the denominator of the normalization operation. The hybrid version of MNLMS and sign regressor algorithm needs minimum number of computations among the considered algorithms. Therefore, based on our simulation results and computed performance measures, it is clear that among all the considered algorithms SRBBMNLMS based ANC performs better than the counter parts, even though it is just inferior to MNLMS, SRMNLMS and BBMNLMS due to reduced number of multiplications in the enhancement process. Hence, this implementation is well suited for remote health care monitoring systems in clinical environment.

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