Received May 17, 2018, accepted August 13, 2018, date of publication August 21, 2018, date of current version September 7, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2866303

Novel Logarithmic Reference Free Adaptive Signal Enhancers for ECG Analysis of Wireless Cardiac Care Monitoring Systems

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ABSTRACT In remote cardiac care monitoring applications, electrocardiogram (ECG) signals are contaminated by artifacts during data acquisition and transmission of signals. The removal of the artifacts is an important task for proper diagnosis. In this paper, an attempt has been made to remove the artifacts, especially baseline wander (BW), muscle artifacts (MA), power line interference (PLI), and electrode motion (EM) using a least mean logarithmic squares (LMLS) algorithm. Further to improve the filtering ability and speed up the convergence process, data normalization is applied. The above algorithm can be normalized with reference to maximum data normalization which leads to reduced computational complexity in the denominator. Based on the above algorithms, various adaptive signal enhancers (ASE's) are developed. To reduce the computational complexity of the signal enhancer, the proposed ASE's are combined with sign-based algorithms. The proposed ASE's are tested on real ECG signals obtained from the MIT-BIH database to compare the performance. The simulation results obtained illustrate that the block-based algorithms are better than LMLS in terms of the signal to noise ratio (SNR), excess mean square error, and computational complexity. Among the LMLS variants, the BB-SRNLMLS-based ASE's have better filtering ability with a reduced number of computations. The improvement of the SNR achieved in the process through the use of BB-SRNLMLS-based ASE's are calculated as 13.2945 dBs, 12.4589 dBs, 16.4289 dBs, and 13.6423 dBs, respectively, for BW, MA, PLI, and EM artifacts.

INDEX TERMS Adaptive signal enhancer, artifacts, computational complexity, electrocardiogram, remote health care.

I. INTRODUCTION

Based on World Health Organization (2016) report, it has been found that, Cardiovascular Diseases (CVD) are the major cause of death globally [1]. The number of victims of CVD's may be decreased if timely medical treatment is administered. In this context, remote cardio care systems play a vital role. However, in telecardiology applications, it is necessary to facilitate high resolution ECG signals to the doctors for proper diagnosis. In clinical scenario, during data acquisition, the ECG signals have been found to be contaminated with various artifacts like BW, PLI, EM and MA. BW is caused due to a sinusoidal component which has an approximate frequency of 0.5Hz, during the respiration of the patient. PLI artifact is generated inside the signal carrying cables. EM is due to impedance mismatch between skin and electrodes. MA is due to muscle contraction movement of the patient. As a result, artifact elimination process becomes an important task in remote cardiac care monitoring applications. In recent years, several researchers have presented innovative techniques to clean ECG signals to facilitate high-resolution cardiac activity at the time of diagnosis. Identification of ECG Artifacts and its removal techniques using artifacts filtering algorithms for continuous patient monitoring system is proposed [2]. Efficient cardiac signal Enhancement is done by variable step size algorithm [3]. Improved signal decomposition techniques are achieved by Bayesian framework for denoising and feature extraction [4]. Adaptive Spectrum Noise Cancellation (ASNC) algorithm is implemented for the removal of artifacts to obtain accurate Heart Rate (HR) [5]. It has been shown as an intelligent artifact eliminator, which not only tracks but also eliminates PLI without reference signal [6]. Li *et al.* [7] developed a real time lossless ECG compression technique. The Discrete Wavelet Transform (DWT) is used for the removal of noise in cardiac signals [8]. Lahmiri [9] developed ECG denoising architecture using Empirical Mode Decomposition (EMD) and Variation Mode Decomposition (VMD). The Hybrid denoising model is designed by combining EMD-DWT and VMD-DWT. Santosh *et al.* illustrated an improved model for denoising ECG signal using the non-local wavelet transform. The estimates are generated by the process of shrinkage, and the final estimate is calculated by averaging all the obtained estimates [10]. For continuous patient monitoring applications, a wearable device is developed [11] which coordinates with the smartphone. Jinseok et al. briefed about Motion and Noise (MN) detection. EMD is used to isolate the high frequency components, and then high pass filters are placed to remove randomness of the signal [12]. ECG denoising based on S-Transform (Stockwell transform) is proposed which increases the SNR. Mask window is applied to matrix for denoising ECG signal [13]. Removal of BW from the ECG is demonstrated, which has adaptive noise cancellers [14]. ECG signals are filtered by wavelet Wiener filter, which increases SNR [15]. Motion Artifact Beats (MAB) are identified automatically because of non-linear algorithm which has: clustering ECG signals, fuzzy logic and multi-parameter decision [16]. The Ensemble Empirical Mode Decomposition (EEMD) was used for the first time to improve the noise filtering performance [17]. Vullings *et al.* [18] demonstrated a method to enhance the ECG signal by dynamically increasing the SNR. This is achieved by Bayesian framework which constitutes of Kalman filter. PLI is removed by Notch filter and Adaptive filter [19]. Notch filter reduces the PLI by suppressing the predefined frequencies. An improved adaptive noise canceller reduces the PLI and Harmonics in ECG up to 4Hz. Efficient noise cancellers are proposed to enhance the ECG [20].

Among the techniques presented, it is found that less effort has been made to minimize the computational complexity of the ECG signal. In order to overcome these limitations, a hybrid realization is proposed by using sign-based algorithms [21], [22]. Although there are numerous filtering techniques, adaptive filtering is still considered an interesting approach for artifact removal from physiological quantities. It is because of the innate ability of filter coefficients which change depending upon the noise level of the input signal. One of the most significant adaptive algorithms called Least Mean Logarithmic Squares (LMLS) has been found to be better in such applications. The moderate approach of LMLS algorithm increases the convergence speed of adaptive algorithms by its relative cost function [23]. The performance of an adaptive algorithm can be increased further by applying data normalization [24].

Another major constraint in conventional adaptive noise cancellers is generation of reference signal. In practical applications, adaptive noise cancellers require a reference signal. But it is often not feasible to generate reference signal. Therefore, in our implementation we propose a hybrid version of ASE with DWT decomposition unit [25]. The DWT decomposition unit generates the reference signal from the obtained ECG signal. Hence, various ASE's are developed using LMLS variants with the DWT unit. These realizations are tested with real cardiac signals which are taken from the MIT-BIH arrhythmia database [26], and the performance measures are tabulated in the simulation results section.

II. LMLS BASED ADAPTIVE SIGNAL ENHANCEMENT OF ECG SIGNALS

The LMS is the most popular algorithm due to its simplicity. Due to stable and robust performance against different signal conditions it is very frequently used in real time health monitoring applications. In remote cardiac care scenario, artifacts and channel noise are non-stationary in nature. Conventional fixed coefficient filters cannot be used for filtering such artifacts. But an adaptive filtering strategy can be applied. A typical ASE structure is shown in Figure 1. The contaminated ECG is processed in the ASE unit. The main functional units of the proposed ASE are DWT decomposition unit and an adaptive algorithm to update FIR filter coefficients. The ECG signals gathered from the acquisition electrodes have an artifact component. Suppose c(n) is the recorded cardiac signal, it can be written as

$$\mathrm{c(n) = s(n) + a(n).}$$

Here, s(n) is heart activity, a(n) is artifact. c(n) undergoes DWT decomposition for generating a reference signal. This reference signal is fed to the FIR filter of length 'L', which is driven by an adaptive algorithm. The adaptive algorithm has the ability to change the filter coefficients of FIR filter. Suppose $a_1(n)$, correlates with the actual artifact component a(n). Based on feedback signal f(n), the adaptive algorithm changes the filter coefficients so that the convolution between the $a_1(n)$ and filter impulse response h(n) is brought closer to actual artifact component a(n) present in the cardiac signal c(n). Therefore, by using feedback signal, and changing filter coefficients, the reference changes to a(n). After some iterations, a(n) and $a_1(n)$ become approximately equal, thus nullifying the maximum components. This in turn makes the output of the ASE correlate s(n) with $s_1(n)$. However, at the output of the ASE, some residual noise will remain in the cardiac signal. The measurement of residual noise illustrates the performance of various algorithms used in the enhancement process.

The algorithm widely used in adaptive noise cancellation applications is the Least Mean Square (LMS). The technique of weights updation is mathematically written as,

$$\boldsymbol{m}\,(\boldsymbol{n}+\mathbf{1}) = \boldsymbol{m}\,(\boldsymbol{n}) + \mu \boldsymbol{c}\,(\boldsymbol{n}) f\,(n) \tag{1}$$

Where, m is the weight vector of the filter, n is the number of samples, μ is the step size of the adaptive algorithm.

Let us consider the length of FIR filter of LMLS as 'L'. The LMLS algorithm intrinsically combines the LMS and

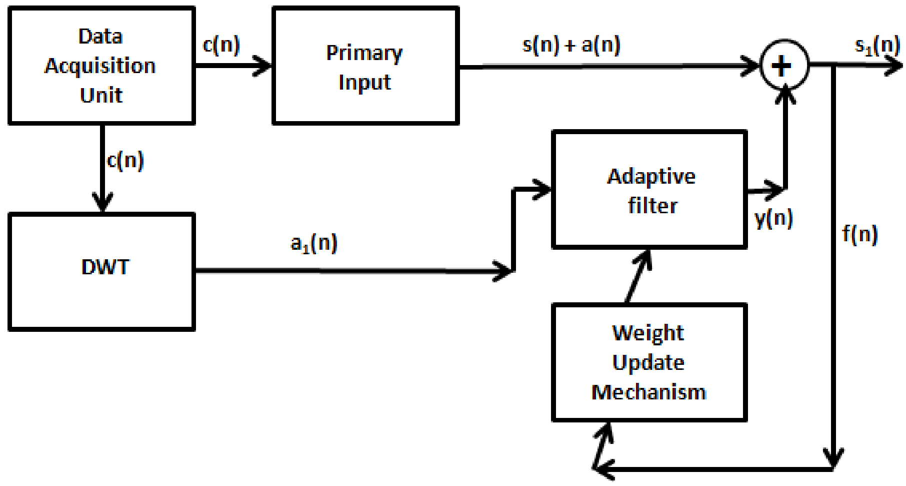

FIGURE 1. Structure of adaptive signal enhancer (ASE).

Least Mean Fourth (LMF) algorithms based on the error amount [23]. The mathematical recursion of LMLS algorithm is written as,

$$\boldsymbol{m}(\boldsymbol{n}+1) = \boldsymbol{m}(\boldsymbol{n}) + \mu \boldsymbol{c}(\boldsymbol{n}) f(n) \frac{\alpha f^2(n)}{1+\alpha f^2(n)} \tag{2}$$

$$= \boldsymbol{m}(\boldsymbol{n}) + \mu \frac{\alpha \boldsymbol{c}(\boldsymbol{n}) f^3(n)}{1+\alpha f^2(n)} \tag{3}$$

Where, c(n) is the cardiac signal, f(n) is the error quantity, α is the design parameter and is step size parameter.

In the proposed implementation, we are mainly focusing on two important features: the first is the generation of reference signal and the second is removal of artifacts from cardiac signal. DWT is generally used to decompose non-stationary biomedical signals. The blend of DWT and noise cancellers is discussed in order to remove the artifacts from the obtained EEG [25]. In the similar manner, we have integrated DWT and ASE to enhance ECG. Mallam *et al.* [21] discussed the L-level decomposition of an ECG signal using DWT.

There has been an extensive research done on the usage of DWT to eliminate artifacts from ECG. Researchers have found that, DWT systems can help in optimizing the refining of ECG. Therefore, we realize a hybrid model of DWT and LMLS based noise removal in the proposed ASE, as shown in Figure 1.

Figure 2, illustrates the decomposition of the cardiac signal c(n) into Low Frequency Component (LFC) and High Frequency Component (HFC). The approximation component is represented by "A", which is a LFC. The detailed component is represented by "D", which is a HFC [21]. Based on the nature of noise, "A" or "D" will be decomposed to generate reference signal. This reference signal is fed to FIR filter to perform multiplication operation with the filter coefficients. The output of FIR filter is connected to the adder. At the output of adder, the cardiac signal and artifacts are obtained. As the iterations continue, the adaptive algorithm adjusts the filter coefficients so that $a_1(n)$ is multiplied by filter coefficients and it changes to a(n). Since the statistical nature of the $a_1(n)$ and a(n) are equal, it results in "$a_1(n)$ - a(n)". Finally, the cardiac signal will be obtained at the output of the ASE with some residual noise.

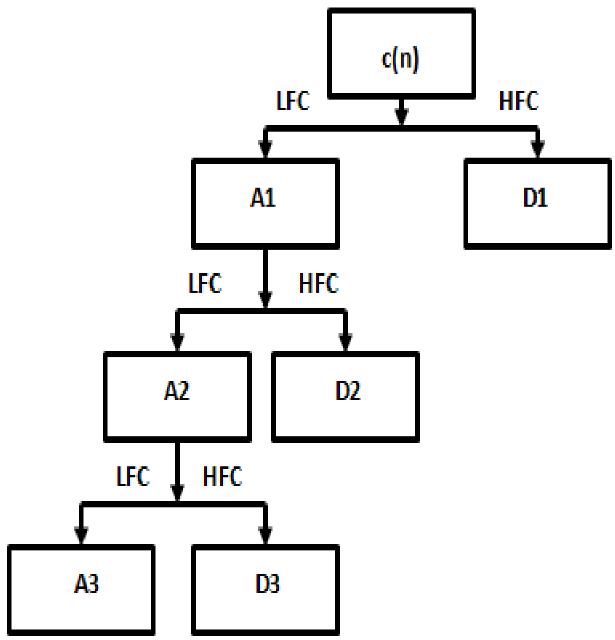

FIGURE 2. Decomposition of ECG signal using DWT.

A. HYBRID REALIZATION OF NORMALIZED LMLS (NLMLS) AND SIGN ALGORITHMS

Normalized LMS (NLMS) is another class of adaptive algorithm which updates the coefficients of the FIR filter. The mechanism of NLMS algorithm and LMS algorithm are similar, but step size is varied in accordance to the input data vector. Based on step size, the enhancement process reaches steady state.

TABLE 1. Computational complexity required for the generation of reference signal (where 'L' is filter length).

Type of Noise	Basic DWT Complexity		Level of Decomposition	Total Multiplications	Total Additions
	Multiplications	Additions			
PLI	L	L-1	2	2L	2L-2
BW	L	L-1	7	7L	7L-7
MA	L	L-1	3	3L	3L-3
EM	L	L-1	7	7L	7L-7

The weight updated equation for the NLMS algorithm is:

$$\boldsymbol{m}(\boldsymbol{n}+\mathbf{1}) = \boldsymbol{m}(\boldsymbol{n}) + \left[\frac{\mu}{p + \boldsymbol{c}^t(\boldsymbol{n})\,\boldsymbol{c}(\boldsymbol{n})}\right]\boldsymbol{c}(\boldsymbol{n})\,f(n) \tag{4}$$

Similarly, the normalized version of LMLS (NLMLS) can be realized to achieve better filtering, minimum steady state error and good convergence. Mathematically, NLMLS is written as,

$$\boldsymbol{m}(\boldsymbol{n}+\mathbf{1}) = \boldsymbol{m}(\boldsymbol{n}) + \mu\frac{\alpha\boldsymbol{c}(\boldsymbol{n})f^3(n)}{\|\boldsymbol{c}(\boldsymbol{n})\|^2\left(\|\boldsymbol{c}(\boldsymbol{n})\|^2 + \alpha f^2(n)\right)} \tag{5}$$

The sign algorithms are the key factors of hybrid realization to minimize the computational complexity in adaptive algorithm. The three types of sign algorithms are Sign Regressor Algorithm (SRA), Sign error Algorithm (SA) and Sign Sign Algorithm (SSA) [25]. The computational complexity of SRA is least among the sign algorithms. The number of multiplications required is only one and the multiplications are independent of filter length, as shown in Table 2.

In order to minimize the computational complexity, we combine NLMLS algorithm with Sign algorithms. The result is, Sign Regressor NLMLS (SRNLMLS), Sign NLMLS (SNLMLS) and Sign Sign NLMLS (SSNLMLS). These hybrid realizations achieve good filtering ability, fast convergence, less residual noise and low computational complexity. The weight update equations for these algorithms are mathematically written as,

$$\boldsymbol{m}(\boldsymbol{n}+\mathbf{1}) = \boldsymbol{m}(\boldsymbol{n}) + \mu sgn(\boldsymbol{c}(\boldsymbol{n})) \times \frac{\alpha f^3(n)}{\|\boldsymbol{c}(\boldsymbol{n})\|^2\left(\|\boldsymbol{c}(\boldsymbol{n})\|^2 + \alpha f^2(n)\right)} \tag{6}$$

$$\boldsymbol{m}(\boldsymbol{n}+\mathbf{1}) = \boldsymbol{m}(\boldsymbol{n}) + \mu sgn\left(f^3(n)\right) \times \frac{\alpha\boldsymbol{c}(\boldsymbol{n})}{\|\boldsymbol{c}(\boldsymbol{n})\|^2\left(\|\boldsymbol{c}(\boldsymbol{n})\|^2 + \alpha f^2(n)\right)} \tag{7}$$

$$\boldsymbol{m}(\boldsymbol{n}+\mathbf{1}) = \boldsymbol{m}(\boldsymbol{n}) + \mu sgn\left(f^3(n)\right) sgn(\boldsymbol{c}(\boldsymbol{n})) \times \frac{\alpha}{\|\boldsymbol{c}(\boldsymbol{n})\|^2\left(\|\boldsymbol{c}(\boldsymbol{n})\|^2 + \alpha f^2(n)\right)} \tag{8}$$

Where *sgn* is the signum function. The above equations are the updated versions of SRNLMLS, SNLMLS and SSNLMLS.

The computational complexity can be further diminished in equations (6)-(8) by using Block Based Normalization. In this approach, the step size is normalized by considering the maximum value of the input data sequence instead of entire data sequence. This reduces the number of multiplications by an amount "L-1" in the weight update mechanism and requires only one multiplication in the denominator. This version of NLMLS algorithm is called as a Block Based NLMLS (BBNLMLS) algorithm. The sign versions of the above algorithm result in: Block Based Sign Regressor NLMLS (BBSRNLMLS), Block Based Sign NLMLS (BBSNLMLS) and Block Based Sign Sign NLMLS (BBSSNLMLS). The mathematical expressions for these algorithms are expressed as,

$$\boldsymbol{m}(\boldsymbol{n}+\mathbf{1}) = \boldsymbol{m}(\boldsymbol{n}) + \frac{\mu}{\boldsymbol{c}_L^2} sgn(\boldsymbol{c}(\boldsymbol{n}))\frac{\alpha f^3(n)}{\left(\|\boldsymbol{c}(\boldsymbol{n})\|^2 + \alpha f^2(n)\right)} \tag{9}$$

$$\boldsymbol{m}(\boldsymbol{n}+\mathbf{1}) = \boldsymbol{m}(\boldsymbol{n}) + \frac{\mu}{\boldsymbol{c}_L^2} sgn\left(f^3(n)\right)\frac{\alpha\boldsymbol{c}(\boldsymbol{n})}{\left(\|\boldsymbol{c}(\boldsymbol{n})\|^2 + \alpha f^2(n)\right)} \tag{10}$$

$$\boldsymbol{m}(\boldsymbol{n}+\mathbf{1}) = \boldsymbol{m}(\boldsymbol{n}) + \frac{\mu}{\boldsymbol{c}_L^2} sgn\left(f^3(n)\right) sgn(\boldsymbol{c}(\boldsymbol{n})) \times \frac{\alpha}{\left(\|\boldsymbol{c}(\boldsymbol{n})\|^2 + \alpha f^2(n)\right)} \tag{11}$$

In view of the above algorithms, the DWT technique is used to build few ASE's and to extract artifacts from cardiac signals. The simulation results and its analysis are displayed in the segments that take after.

B. COMPUTATIONAL COMPLEXITY

The computational complexity of any signal conditioning technique is an important parameter in biomedical signal processing applications. In real-time operation of the medical telemetry, if the computational complexity is less, then lesser time will be required to carry out the computation. The data samples are delayed by an amount equal to the processing time due to large computational complexity. As a result, a large number of data samples are gathered at the input port. This leads to aliasing of the data samples. In remote cardiac care monitoring applications, computational complexity has to be minimized [24]. Hence, in the proposed ASE, hybrid versions of signum based algorithms are used to minimize the computational complexity.

The basic computational complexity mentioned in Table 1, indicates number of multiplications and additions required to compute DWT at various levels of decomposition.

TABLE 2. Computational complexity of various algorithms for the removal of artifacts (where 'L' is filter length).

Serial Number	Algorithm	Multiplications	Additions	Addition to Sign Check	Division
1	LMS	L+1	L+1	Nil	Nil
2	LMLS	L+7	L+2	Nil	1
3	NLMLS	2L+7	2L+2	Nil	1
4	SRNLMLS	L+7	L+2	Nil	1
5	SNLMLS	2L+5	2L+2	Nil	1
6	SSNLMLS	L+2	L+2	L+3	1
7	BB-NLMLS	L+7	L+2	Nil	1
8	BB-SRNLMLS	7	L+2	Nil	1
9	BB-SNLMLS	L+5	L+2	Nil	1
10	BB-SSNLMLS	2	2	L+3	1

Thus, from the Table 1, it can be stated that 'L' multiplications and 'L-1' additions are required to compute DWT [28]. The computational complexities of the LMLS variants are shown in Table 2. The overall computational complexity for the proposed algorithms is tabulated in Table 3. For example, in the PLI, there are two octaves, the total computational complexity will be the sum of the computational complexity of proposed LMLS variants plus the DWT complexity. Similarly, the computational complexity for a higher level of decomposition is dependent on the filter length 'L'.

From the Tables 3, it is found that, BBSRNLMLS requires less number of multiplications. ASE based algorithm is more useful in remote cardiac care monitoring systems. Further, due to clipping, a simple LMS combined with SRA needs only one multiplication. BBSRNLMLS requires seven multiplications to process the algorithm. In the case of BBSSNLMLS only two multiplications are sufficient. But, due to clipping of data vector and error, the signal quality will be degraded. So, BBSSNLMLS is not suitable for noise cancellation applications. Based on the above considerations it is confirmed that BBSRNLMLS can be a better algorithm in noise cancellation applications in cardiac care monitoring systems.

C. CONVERGENCE CURVES

The convergence characteristics of LMLS and NLMLS algorithms are shown in Figure 3 and Figure 4 respectively. From these characteristics, it is clear that normalization increases the convergence speed. However, by applying the signum function the convergence becomes slow. Also, from the illustrations, it is clear that the hybrid version of the Sign Regressor Algorithm (SRA) is inferior to the non-signum based algorithms. The convergence value should be optimal otherwise the system becomes unstable. So, from the convergence analysis, it is clear that SRA based normalized LMLS can be used in practical realizations due to good convergence and less computational complexity.

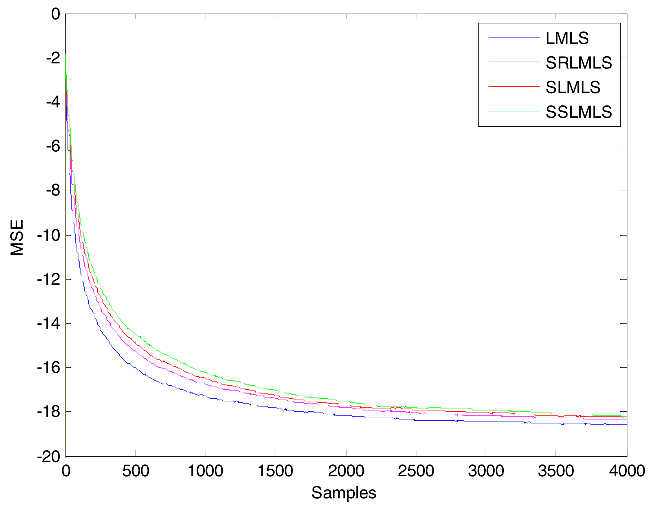

FIGURE 3. Convergence characteristics of various variants of LMLS algorithms.

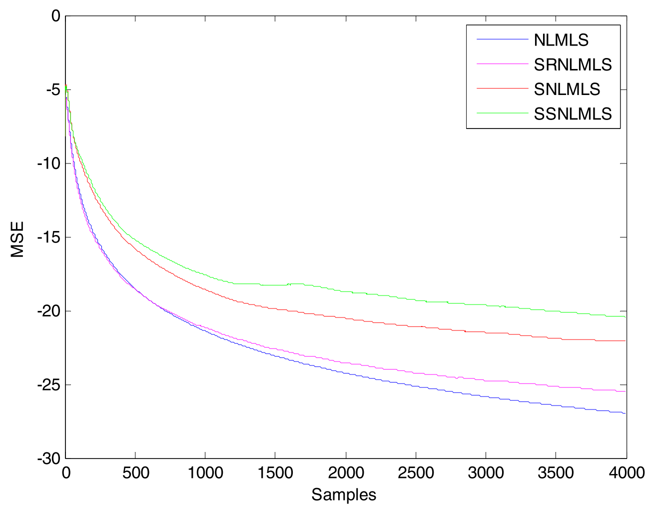

FIGURE 4. Convergence characteristics of various variants of NLMLS algorithms.

III. SIMULATION RESULTS

The implemented models are tested using the cardiac signals acquired from the MIT-BIH arrhythmia database [26]. The MIT−BIH Arrhythmia Database contains records of normal ECG signals. This provides an opportunity to test the robustness of QRS, P and T wave detection methods.

TABLE 3. Computational complexity of various adaptive signal enhancers (where 'L' is filter length).

Type of Noise	Algorithm	Multiplications	Additions	Addition with Sign Check	Division
PLI	LMS	3L+1	3L-1	Nil	Nil
	LMLS	3L+7	3L	Nil	1
	NLMLS	4L+7	4L	Nil	1
	SRNLMLS	3L+7	3L	Nil	1
	SNLMLS	4L+5	4L	Nil	1
	SSNLMLS	3L+2	3L	L+3	1
	BB-NLMLS	3L+7	3L	Nil	1
	BB-SRNLMLS	2L+7	3L	Nil	1
	BB-SNLMLS	3L+5	3L	Nil	1
	BB-SSNLMLS	2L+2	2L	L+3	1
BW	LMS	8L+1	8L-6	Nil	Nil
	LMLS	8L+7	8L-5	Nil	1
	NLMLS	9L+7	9L-5	Nil	1
	SRNLMLS	8L+7	8L-5	Nil	1
	SNLMLS	9L+5	9L-5	Nil	1
	SSNLMLS	8L+7	8L-5	L+3	1
	BB-NLMLS	8L+7	8L-5	Nil	1
	BB-SRNLMLS	7L+7	8L-5	Nil	1
	BB-SNLMLS	8L+5	8L-5	Nil	1
	BB-SSNLMLS	7L+2	7L-5	L+3	1
MA	LMS	4L+1	4L-2	Nil	Nil
	LMLS	4L+7	4L-1	Nil	1
	NLMLS	5L+7	5L	Nil	1
	SRNLMLS	4L+7	4L-1	Nil	1
	SNLMLS	5L+5	5L-1	Nil	1
	SSNLMLS	4L+2	4L-1	L+3	1
	BB-NLMLS	4L+7	4L-1	Nil	1
	BB-SRNLMLS	4L+7	4L-1	Nil	1
	BB-SNLMLS	4L+5	4L-1	Nil	1
	BB-SSNLMLS	4L+2	3L-1	L+3	1
EM	LMS	8L+1	8L-6	Nil	Nil
	LMLS	8L+7	8L-5	Nil	1
	NLMLS	9L+7	9L-5	Nil	1
	SRNLMLS	8L+7	8L-5	Nil	1
	SNLMLS	9L+5	9L-5	Nil	1
	SSNLMLS	8L+7	8L-5	L+3	1
	BB-NLMLS	8L+7	8L-5	Nil	1
	BB-SRNLMLS	7L+7	8L-5	Nil	1
	BB-SNLMLS	8L+5	8L-5	Nil	1

But in real time monitoring there are various sources to acquire the real ECG signal, depending on the application. For instance, if continuous patient monitoring is considered than the ECG signals are directly acquired from the patient to measure the performance and further to process it. Apart from the performance measures like convergence and computational complexity, the Signal to Noise Ratio (SNR) and Excess Mean Square Error (EMSE) are also considered as evaluation parameters in the filtering process. The results are tabulated in Tables 4, 5, 6 and the simulation results are shown in Figure 5 to Figure 12 respectively. For the experimentation purpose, first 4000 samples of the records were considered. We collected a set of five records from the MIT-BIH arrhythmia database with record numbers 101, 102, 103, 104 and 105. However, due to space constraints, the experimental results corresponding to data 105 are shown. In the implementation of ASE, we have used a FIR filter, of length 10. The adaptive algorithms have been tuned and converged to a step size of 0.01. A random noise with an intensity of 0.001 has been added to the artifact components to see its effect on free space in a practical telemetry system. The process of noise elimination is carried

TABLE 4. SNR computations of LMLS based ASE's obtained during artifact elimination process (all values in DB's).

Noise	Rec No	Before filtering	LMS		LMLS		NLMLS		SRNLMLS		SNLMLS		SSNLMLS	
			After filtering	SNR Improve	After filtering	SNR Improve	After filtering	SNR Improve	After filtering	SNR Improve	After filtering	SNR Improve	After filtering	SNR Improve
BW	101	1.5893	5.7878	4.1985	9.2438	7.6545	17.0567	15.4674	16.4692	14.8799	13.8314	12.2421	12.2582	10.6689
	102	1.5294	5.7892	4.2598	9.3139	7.7845	16.8758	15.3464	16.3283	14.7989	14.1867	12.6573	12.0638	10.5344
	103	1.5294	6.2976	4.7682	8.8871	7.3577	17.1726	15.6432	15.9851	14.4557	14.2947	12.7653	12.2052	10.6758
	104	1.5703	6.3978	4.8275	9.1382	7.5679	16.8048	15.2345	16.2279	14.6576	14.0349	12.4646	11.8018	10.2315
	105	1.5643	6.1767	4.6124	8.8536	7.2893	17.4868	15.9225	15.8701	14.3057	14.8193	12.4357	11.8237	10.2594
MA	101	1.2457	4.8872	3.6415	7.8102	6.5645	16.2244	14.9787	14.3692	13.1235	13.1433	11.8976	10.8465	9.6008
	102	1.2209	4.9814	3.7605	7.6785	6.4576	15.2977	14.0768	15.0108	13.7899	12.7996	11.5787	10.9852	9.7643
	103	1.2354	5.2006	3.9652	7.5788	6.3434	15.6702	14.4348	15.1144	13.879	12.9244	11.689	10.8032	9.5678
	104	1.2935	5.333	4.0395	7.7513	6.4578	15.5414	14.2479	15.1702	13.8767	12.6181	11.3246	10.6613	9.3678
	105	1.2179	5.2187	4.0008	8.0651	6.8472	16.1424	14.9245	14.3161	13.0982	12.6755	11.4576	11.0426	9.8247
PLI	101	0.6193	9.426	8.8067	9.7458	9.1265	19.0973	18.478	18.1986	17.5793	15.1882	14.5689	13.5149	12.8956
	102	0.6935	8.4698	7.7763	10.2628	9.5693	19.3029	18.6094	17.9332	17.2397	15.0391	14.3456	13.3174	12.6239
	103	0.6016	9.7894	9.1878	9.9484	9.3468	19.0584	18.4568	17.9483	17.3467	15.0595	14.4579	12.9515	12.3499
	104	0.6179	9.1263	8.5084	10.2982	9.6803	18.8535	18.2356	18.1865	17.5686	15.0746	14.4567	12.9649	12.347
	105	0.6473	9.6536	9.0063	10.5353	9.888	19.3352	18.6879	18.2618	17.6145	15.5758	14.9285	13.154	12.5067
EM	101	1.4983	5.9402	4.4419	8.8418	7.3435	16.7108	15.2125	15.7351	14.2368	13.7319	12.2336	11.8429	10.3446
	102	1.4874	6.1385	4.6511	9.0532	7.5658	16.9497	15.4623	15.8354	14.348	14.0354	12.548	12.3664	10.879
	103	1.4309	6.2747	4.8438	8.9077	7.4768	17.0103	15.5794	15.5186	14.0877	13.5207	12.0898	12.4065	10.9756
	104	1.4558	6.1175	4.6617	8.8905	7.4347	16.7826	15.3268	16.3645	14.9087	14.4334	12.9776	11.7984	10.3426
	105	1.4829	6.2611	4.7782	9.4076	7.9247	16.7174	15.2345	15.7726	14.2897	14.4074	12.9245	12.4172	10.9343

TABLE 5. SNR computations of block based ASE's obtained during artifact elimination process (all values in DB's).

Noise	Rec No	Before filtering	BBNLMLS		BBSRNLMLS		BBSNLMLS		BBSSNLMLS	
			After filtering	SNR Improve	After filtering	SNR Improve	After filtering	SNR Improve	After filtering	SNR Improve
BW	101	1.5874	16.3729	14.7855	14.9331	13.3457	13.4671	11.8797	10.9306	9.3432
	102	1.5249	16.2933	14.7684	15.0994	13.5745	13.1828	11.6579	11.1837	9.6588
	103	1.5183	15.8661	14.3478	15.2838	13.7655	12.9530	11.4347	10.8649	9.3466
	104	1.5093	15.7471	14.2378	14.9669	13.4576	12.8569	11.3476	11.0880	9.5787
	105	1.5643	16.1464	14.5821	14.8588	13.2945	13.4881	11.9238	11.3937	9.8294
MA	101	1.2589	14.9396	13.6807	13.4903	12.2314	11.5065	10.2476	9.3465	8.0876
	102	1.2209	14.8796	13.6587	13.5476	12.3267	11.9774	10.7565	10.0199	8.7990
	103	1.2093	14.6440	13.4347	14.1180	12.9087	11.8681	10.6588	10.1081	8.8988
	104	1.2193	14.5650	13.3457	14.2069	12.9876	11.9101	10.6908	9.5539	8.3346
	105	1.2179	14.4752	13.2573	13.6768	12.4589	12.1429	10.9250	9.4526	8.2347
PLI	101	0.6834	18.1202	17.4368	16.9179	16.2345	13.9202	13.2368	12.2628	11.5794
	102	0.6097	18.0674	17.4577	17.3781	16.7684	14.0664	13.4567	12.2976	11.6879
	103	0.6145	17.8493	17.2348	16.9613	16.3468	13.9619	13.3474	11.9613	11.3468
	104	0.6935	18.1634	17.4699	17.3803	16.6868	14.4258	13.7323	12.0393	11.3458
	105	0.6473	18.4720	17.8247	17.0762	16.4289	13.9041	13.2568	11.9005	11.2532
EM	101	1.4093	15.5317	14.1224	1.4093	13. 1357	12.6428	11.2335	11.3069	9.8976
	102	1.4154	15.6511	14.2357	15.1051	13.6897	13.2044	11.7890	10.8532	9.4378
	103	1.4399	16.0188	14.5789	15.0966	13.6567	13.2304	11.7905	10.8942	9.4543
	104	1.4578	16.3556	14.8978	15.2233	13.7655	12.9925	11.5347	11.0154	9.5576
	105	1.4829	16.4074	14.9245	15.1252	13.6423	13.0072	11.5243	10.7678	9.2849

using various ASE's based on LMLS variants. LMS, LMLS, NLMLS, SRNLMLS, SNLMLS, SSNLMLS, BBNLMLS, BBSRNLMLS, BBSNLMLS and BBSSNLMLS algorithms have been used for noise elimination respectively.

The original wavelet function is called as mother wavelet function which decomposes the signal into low frequency and high frequency coefficients. The main challenge in using discrete wavelet transform is to select the most optimum mother wavelet for the given tasks, as different mother wavelet applied on to the same signal may produces different results. The selection of mother wavelet is based on the accuracy of wavelet results. In this paper, we have used Daubechies 4 (db4) as mother wavelet. In biomedical signal analysis, db4 wavelet can be used since this function closely resembles the QRS complex of an ECG signal. In practical applications, Daubechies wavelets are usually adopted because they have no orthonormality. However, they have a finite time support (that eases the handling of border effects), and form a basis where the number of vanishing moments can be naturally increased.

The octave band tree is a special irregular tree structure which splits the signal into two equal bands. The number of levels of decomposition (Octaves) depends on the sampling frequency of the cardiac signal. In our work, we used a sampling frequency of 256Hz. The BW has a frequency approximately 0.5Hz, it has to undergo seven levels

TABLE 6. EMSE computations of various ASE's obtained during artifact elimination process (all value S in DB's).

S.No	Noise	Rec No	LMS	LMLS	NLMLS	SRNLMLS	SNLMLS	SSN LMLS	BB-N LMLS	BB-SRN LMLS	BB-S NLMLS	BB-SS NLMLS
1	BW	101	-11.1457	-15.7583	-29.9438	-27.3741	-25.3248	-23.4719	-28.3857	-26.2383	-24.4672	-22.4128
		102	-11.4418	-15.4579	-29.2323	-27.2323	-25.3438	-23.3480	-28.3348	-26.4590	-24.3454	-22.3466
		103	-11.4770	-15.3476	-29.4578	-27.3454	-25.5690	-23.1278	-28.2378	-26.1256	-24.2334	-22.4578
		104	-8.9635	-15.2366	-29.3232	-27.3343	-25.3485	-23.9863	-28.7890	-26.0973	-24.4343	-22.9076
		105	-12.6204	-15.3476	-29.4432	-27.9865	-25.2345	-23.6704	-28.1569	-26.3434	-24.2335	-22.2345
		Avg	**-11.1282**	**-15.4296**	**-29.4800**	**-27.4545**	**-25.3641**	**-23.5208**	**-28.3808**	**-26.2527**	**-24.3427**	**-22.4718**
2	MA	101	-12.1110	-16.4892	-30.0256	-28.4562	-26.3485	-24.7392	-29.6321	-27.4829	-25.1437	-23.7384
		102	-12.4097	-16.4566	-30.4556	-28.3434	-26.6885	-24.9978	-29.4323	-27.6780	-25.9764	-23.1223
		103	-11.7569	-16.4364	-30.4587	-28.4356	-26.4343	-24.6434	-29.4457	-27.5566	-25.2233	-23.9656
		104	-11.1118	-16.8790	-30.9098	-28.6589	-26.3213	-24.4346	-29.6545	-27.3345	-25.5344	-23.0865
		105	-13.8287	-16.9098	-30.7087	-28.9008	-26.1254	-24.5476	-29.6777	-27.3233	-25.6679	-23.4555
		Avg	**-12.2426**	**-16.6342**	**-30.5116**	**-28.5589**	**-26.3836**	**-24.6725**	**-29.5684**	**-27.4750**	**-25.5091**	**-23.4736**
3	PLI	101	-19.9894	-25.7472	-36.8462	-34.3921	-32.0933	-30.4483	-34.3848	-32.2103	-30.3842	-29.3947
		102	-21.8298	-25.4343	-36.2335	-34.4543	-32.6565	-30.3347	-34.8907	-32.4567	-30.6545	-29.3345
		103	-20.5036	-25.6689	-36.7808	-34.3478	-32.6589	-30.8890	-34.6567	-32.4543	-30.4579	-29.4346
		104	-21.5394	-25.4321	-36.5434	-34.7866	-32.9088	-30.7764	-34.6543	-32.4457	-30.9875	-29.4344
		105	-21.5227	-25.3468	-36.7343	-34.5676	-32.5436	-30.5689	-34.3214	-32.8909	-30.0754	-29.3479
		Avg	**-21.0769**	**-25.5258**	**-36.6276**	**-34.5096**	**-32.5722**	**-30.6034**	**-34.5815**	**-32.4915**	**-30.5119**	**-29.3892**
4	EM	101	-10.7955	-15.1247	-29.0353	-27.4183	-25.4853	-23.1947	-28.3019	-26.1468	-24.0345	-22.1495
		102	-10.7225	-15.4563	-29.4545	-27.3432	-25.3464	-23.9087	-28.1237	-26.2334	-24.3434	-22.5443
		103	-10.9025	-15.4366	-29.7790	-27.2134	-25.4346	-23.2314	-28.8907	-26.4457	-24.5856	-22.7890
		104	-8.2407	-15.7856	-29.8764	-27.1678	-25.4347	-23.1356	-28.6554	-26.7644	-24.4556	-22.6645
		105	-12.3952	-15.4545	-29.9875	-27.9876	-25.9087	-23.4677	-28.4567	-26.5467	-24.6578	-22.3334
		Avg	**-10.6112**	**-15.4515**	**-29.6265**	**-27.4260**	**-25.5219**	**-23.3876**	**-28.4856**	**-26.4274**	**-24.4153**	**-22.4961**

of decomposition. At the seventh level of decomposition the approximate coefficient function falls in the range of 0Hz to 1Hz. In the ECG signal, the frequency of MA is approximately ranged between 15-30Hz. For the said frequencies second level or third level decompositions are sufficient. Since, MA and ECG are having partially overlapping spectra, the MA activity can be reduced by allowing the patient to relax. This is suitable for short time monitoring. For long time monitoring, under an ambulatory condition, high frequency MA noise must be filtered using detailed components. The EM artifact has same type of pattern as that of BW. So, the same level of decomposition as that of BW is sufficient. The Power Line Interference (PLI) of 50/60Hz is the source of interference. Thus, for PLI, the second level decomposition is needed. In this paper we are considering the artifacts which are more recurring like BW, PLI, MA and EM. But there are artifacts which may occur occasionally like, loose lead artifact, Arterial pulse tapping artifact, Echo distortion artifact, Neuro modulation artifact, CPR compression artifact, Electromagnetic interference (EMI), Muscle tremor artifact.

A. ADAPTIVE ELIMINATION OF BW USING LMLS VARIANTS

The enhanced ECG after the removal of BW using various algorithms is shown in Figure 5. The residual noise after the noise elimination process is shown in Figure 6. The residual noise is less in the case of Figure 6 (c,d). The figure shows the residual noise is approaching a straight line, to indicate that much of the artifact is eliminated in the filtering action due to NLMLS and SRNLMLS algorithms. From the Figure 5 (a,j) we can observe the major reduction of noise in the ECG signals. In Figure 5(j), the ECG is clear and so is the computational complexity which is less and promises a great benefit in remote cardiac care applications. In this experiment, the performance of the DWT based ASE is measured using the SNR and EMSE, and the numerical values are noted in Table 4, Table 5 and Table 6 respectively. During the filtering process, Signal to Noise Ratio Improvement (SNRI) achieved by various techniques are, LMS achieves 4.6124dB, LMLS achieves 7.2893dB, NLMLS achieves 15.9225dB, SRNLMLS achieves 14.3057dB, SNLMLS achieves 12.4357dB, SSNLMLS achieves 10.2594dB, BBNLMLS achieves 14.5821dB BBSRNLMLS achieves 13.2945dB, BBSNLMLS achieves 11.9238dB and BBSSNLMLS achieves 9.8294dB. But, of all the algorithms BBSRNLMLS is found to be better in terms of filtering and computational complexity. The numerical values for EMSE are as follows, −12.6204dB for LMS, −15.3476dB for LMLS, −29.4432dB for NLMLS, −27.9865dB for SRNLMLS, −25.2345dB for SNLMLS, −23.6704dB for SSNLMLS, −28.1569dB for BBNLMLS, −26.3434dB for BBSRNLMLS, −24.2335dB for BBSNLMLS, and −22.2345dB for BBSSNLMLS. Among all the algorithms BBSRNLMLS are found to be the better considering the smaller number of multiplications with inferior filtering ability.

B. ADAPTIVE ELIMINATION OF PLI USING LMLS VARIANTS

In this section, removal of PLI is demonstrated. The received ECG is fed to DWT, which generates the reference signal. Using the feedback path, the algorithm trains the filter coefficients to relate closely to the artifact in the ECG. In this experiment the performance of the DWT based ASE were measured by SNR and EMSE which can be seen in Table 4,

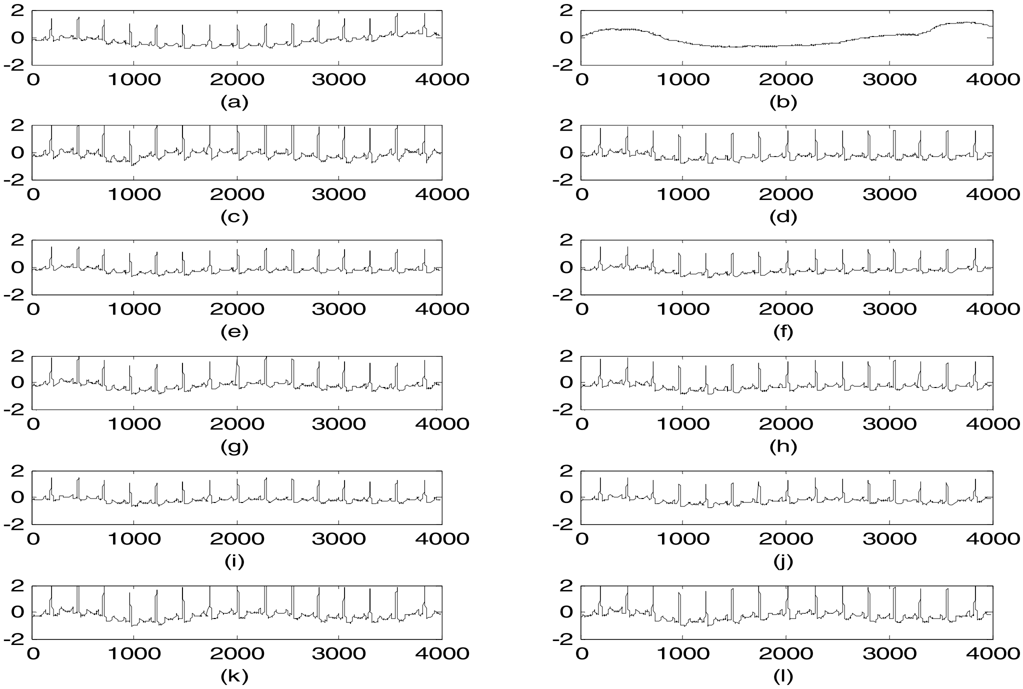

FIGURE 5. Enhanced ECG after BW elimination (a). ECG with BW (b). BW noise (c). Enhanced ECG after LMS (d). Enhanced ECG after LMLS (e). Enhanced ECG after NLMLS (f). Enhanced ECG after SRNLMLS (g). Enhanced ECG after SNLMLS (h). Enhanced ECG after SSNLMLS (I). Enhanced ECG after BBNLMLS (j). Enhanced ECG after BBSRNLMLS (k). Enhanced ECG after BBSNLMLS (l). Enhanced ECG after BBSSNLMLS (number of samples are taken on x-axis and amplitude on y-axis).

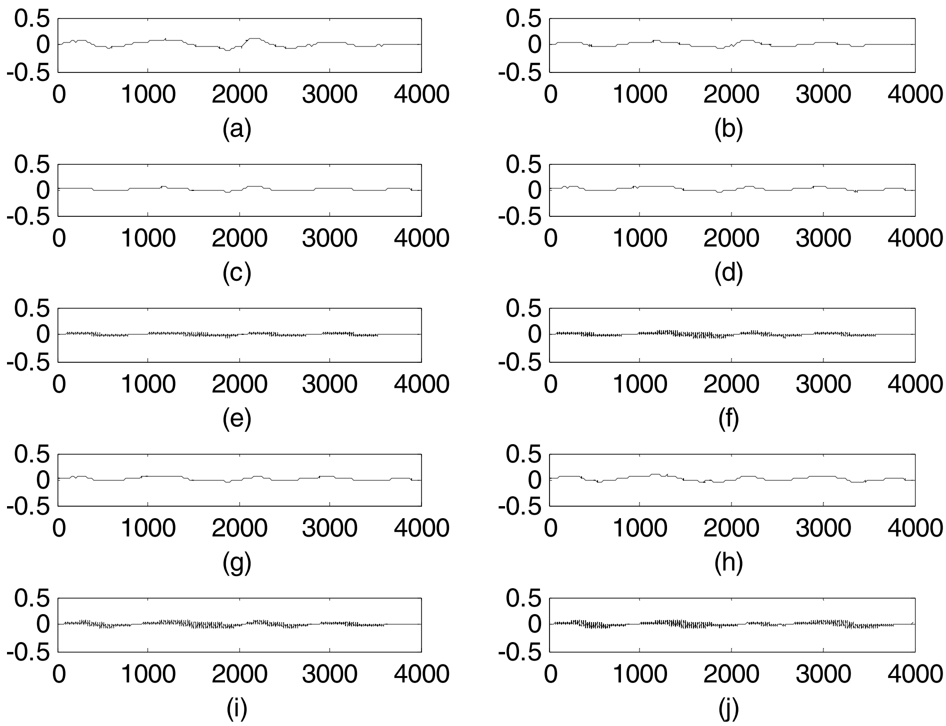

FIGURE 6. Residual noise in ECG signal after BW elimination, (a). after filtering with LMS (b). after filtering with LMLS (c). after filtering with NLMLS (d). after filtering with SRNLMLS (e). after filtering with SNLMLS (f). after filtering with SSNLMLS (g). after filtering with BBNLMLS (h). after filtering with BBSRNLMLS (i). after filtering with BBSNLMLS (j). after filtering with BBSSNLMLS (number of samples are taken on x-axis and amplitude on y-axis).

Table 5 and Table 6 respectively. The enhanced results of ECG after the removal of PLI using various algorithms are shown in the Figure 7. By comparing the Figure 7 (a) and Figure 7 (j), we can observe that the ECG is enhanced in Figure 7 (j) than the others. The residual noise after the noise elimination is shown in Figure 8, which is

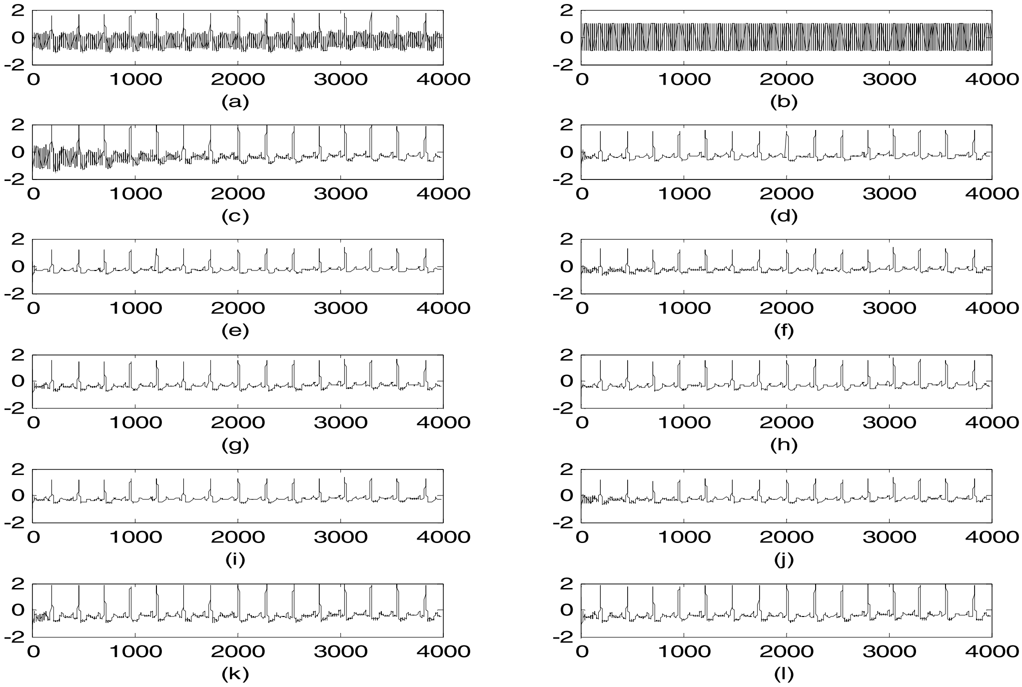

FIGURE 7. Enhanced ECG after PLI elimination (a). ECG with PLI (b). PLI noise (c). Enhanced ECG after LMS (d). Enhanced ECG after LMLS (e). Enhanced ECG after NLMLS (f). Enhanced ECG after SRNLMLS (g). Enhanced ECG after SNLMLS (h). Enhanced ECG after SSNLMLS (i). Enhanced ECG after BBNLMLS (j). Enhanced ECG after BBSRNLMLS (k). Enhanced ECG after BBSNLMLS (l). Enhanced ECG after BBSSNLMLS (number of samples are taken on x-axis and amplitude on y-axis).

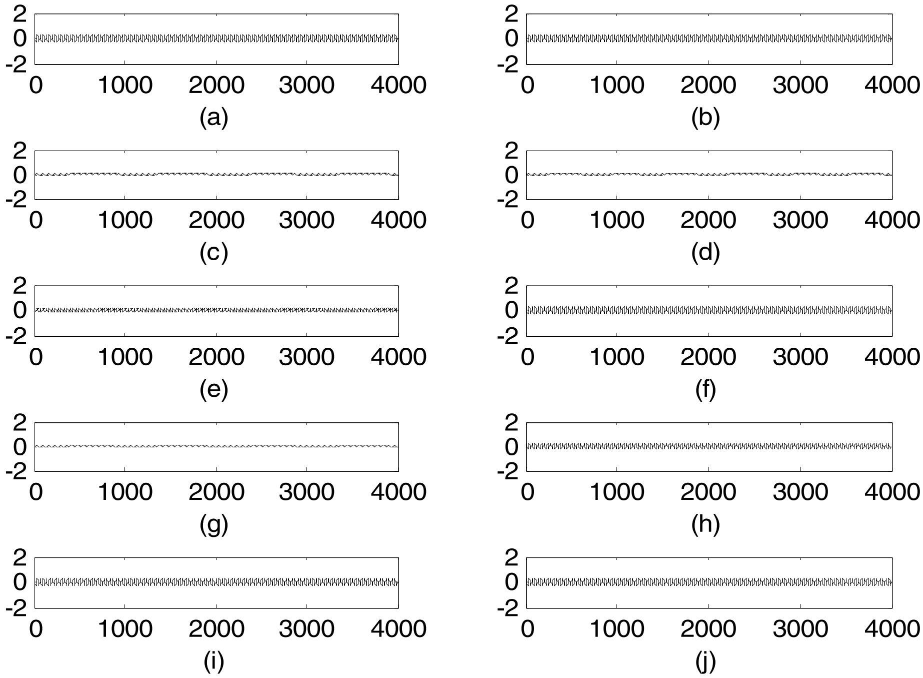

FIGURE 8. Residual noise in ECG signal after PLI elimination, (a). after filtering with LMS (b). after filtering with LMLS (c). after filtering with NLMLS (d). after filtering with SRNLMLS (e). after filtering with SNLMLS (f). after filtering with SSNLMLS (g). after filtering with BBNLMLS (h). after filtering with BBSRNLMLS (i). after filtering with BBSNLMLS (j). after filtering with BBSSNLMLS (number of samples are taken on x-axis and amplitude on y-axis).

even more reduced in Figure 8 (c, d). The SNR is also higher when compared with the other algorithms as shown in the Table 4, Table 5 and Table 6. During the filtering process the SNRI achieved by various techniques are, LMS achieves 8.0063dB, LMLS achieves 9.880dB, NLMLS achieves 18.2356dB, SRNLMLS achieves 17.6145dB, SNLMLS achieves 14.9285dB, SSNLMLS achieves 12.5067dB, BBNLMLS achieves 17.8247dB,

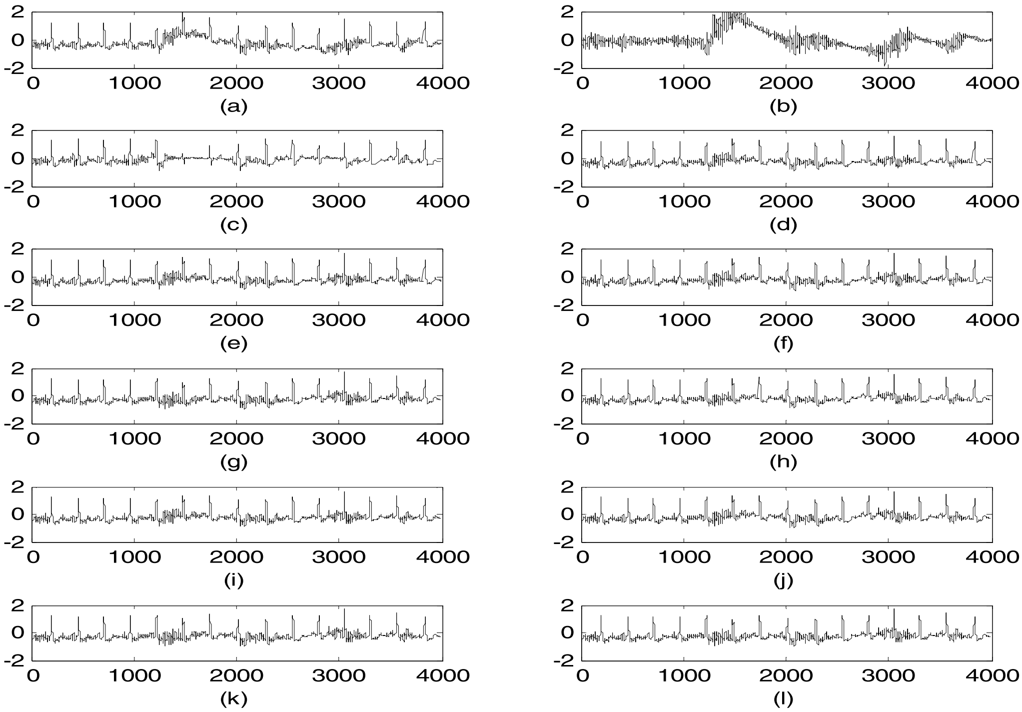

FIGURE 9. Enhanced ECG after MA elimination (a). ECG with MA (b). MA noise (c). Enhanced ECG after LMS (d). Enhanced ECG after LMLS (e). Enhanced ECG after NLMLS (f). Enhanced ECG after SRNLMLS (g). Enhanced ECG after SNLMLS (h). Enhanced ECG after SSNLMLS (i). Enhanced ECG after BBNLMLS (j). Enhanced ECG after BBSRNLMLS (k). Enhanced ECG after BBSNLMLS (l). Enhanced ECG after BBSSNLMLS (number of samples are taken on x-axis and amplitude on y-axis).

BBSRNLMLS achieves 16.4289dB, BBSNLMLS achieves 13.2568, and BBSSNLMLS achieves 11.2532. Similarly the numerical values for EMSE are, −21.5227dB for LMS, −25.3468dB for LMLS, −36.7343dB for NLMLS, −34.5676dB for SRNLMLS, −32.5436dB for SNLMLS, −30.5689dB for SSNLMLS, −34.3214dB for BBNLMLS, −32.8909dB for BBSRNLMLS, −30.0754dB for BBSNLMLS, and −29.3479dB for BBSSNLMLS. By considering less number of multiplications, BBSRNLMLS is found to be better, even though it is inferior to NLMLS, SRNLMLS, and BBNLMLS algorithms in terms of filtering ability.

C. ADAPTIVE ELIMINATION OF MA USING LMLS VARIANTS

The filtering results of various algorithms of MA are shown in the Figure 9. The MA is generated from the DWT, which is given as reference signal and the corrupted cardiac signal is given as the desired signal. In this experiment the performance of the DWT based ASE is measured using SNR and EMSE which are shown in Table 4, Table 5 and Table 6 respectively. The residual noise component after the noise elimination process is shown in Figure 10. The residual noise is less in the case of Figure 10 (c, d). During the filtering process the SNRI achieved by various techniques are, LMS achieves 3.0008dB, LMLS achieves 6.8472dB, NLMLS achieves 14.9245dB, SRNLMLS achieves 13.0982dB, SNLMLS achieves 11.4576dB, SSNLMLS achieves 9.8247dB, BBNLMLS achieves 13.2573dB, BB-SRNLMLS achieves 12.4589dB, BB-SNLMLS achieves 10.9250dB, and BBSSNLMLS achieves 8.2347dB. Similarly the numerical values of EMSE are as follows, −13.8287dB for LMS, −16.9098dB for LMLS, −30.7087dB for NLMLS, −28.9008dB for SRNLMLS, −26.1254dB for SNLMLS, −24.5476dB for SSNLMLS, −29.6777dB for BB-NLMLS, −27.3233dB for BBSRNLMLS, −25.6679dB for BB-SNLMLS and −23.4555dB for BBSSNLMLS. By considering less number of multiplications BBSRNLMLS is found to be better, even though it is inferior to NLMLS, SRNLMLS, and BBNLMLS algorithms in terms of filtering ability.

D. ADAPTIVE ELIMINATION OF EM USING LMLS VARIANTS

The filtering results of EM are shown in the Figure 11. In this experiment the performance of the DWT based ASE is measured using SNR and EMSE which are shown in Table 4, Table 5 and Table 6 respectively. The residual noise after the noise elimination process is shown in Figure 12. The residual noise is less in the case of Figure 12 (c, d). During the filtering process the SNRI achieved by various techniques are, LMS achieves 4.7782dB, LMLS achieves 7.9247dB, NLMLS achieves 15.2345dB, SRNLMLS achieves 14.2897dB, SNLMLS

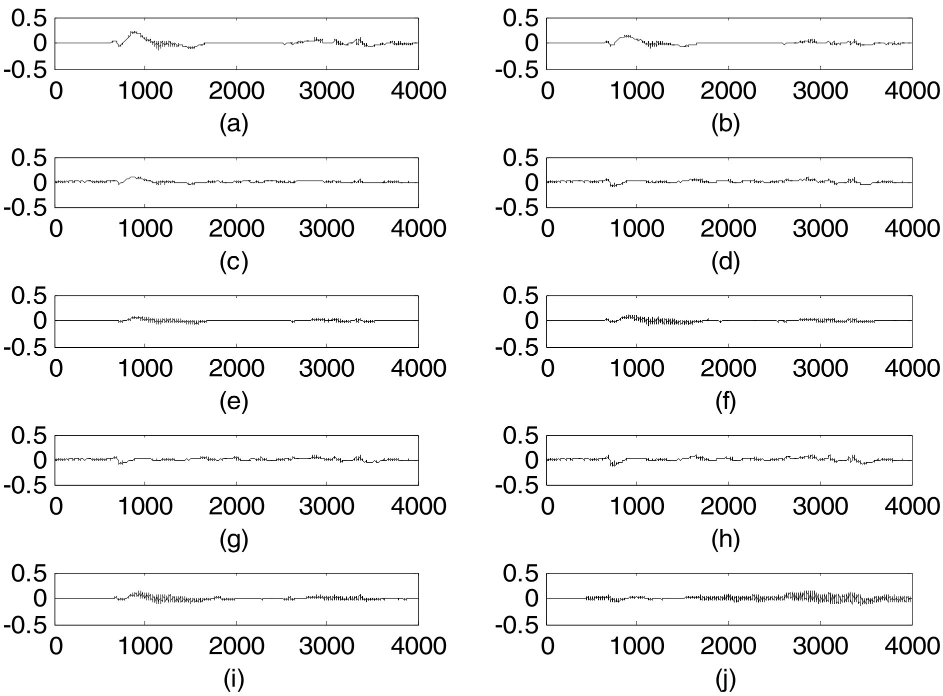

FIGURE 10. Residual noise in ECG signal after MA elimination, (a). after filtering with LMS (b). after filtering with LMLS (c). after filtering with NLMLS (d). after filtering with SRNLMLS (e). after filtering with SNLMLS (f). after filtering with SSNLMLS (g). after filtering with BBNLMLS (h). after filtering with BBSRNLMLS (i). after filtering with BBSNLMLS (j). after filtering with BBSSNLMLS (number of samples are taken on x-axis and amplitude on y-axis).

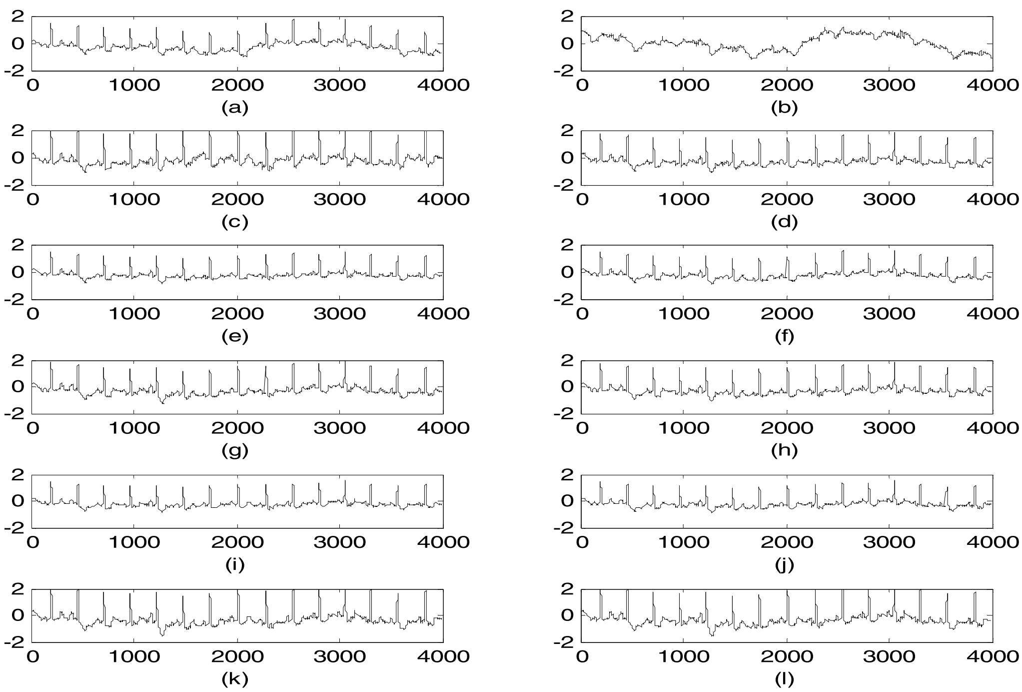

FIGURE 11. Enhanced ECG after EM elimination (a). ECG with EM (b). EM noise (c). Enhanced ECG after LMS (d). Enhanced ECG after LMLS (e). Enhanced ECG after NLMLS (f). Enhanced ECG after SRNLMLS (g). Enhanced ECG after SNLMLS (h). Enhanced ECG after SSNLMLS (i). Enhanced ECG after BBNLMLS (j). Enhanced ECG after BBSRNLMLS (k). Enhanced ECG after BBSNLMLS (l). Enhanced ECG after the BBSSNLMLS (number of samples are taken on x-axis and amplitude on y-axis).

achieves 12.9245dB, SSNLMLS achieves 10.9343dB, BBNLMLS achieves 14.9245dB, BBSRNLMLS achieves 13.6423dB, BBSNLMLS achieves 11.5243dB and BBSSNLMLS achieves 9.2849dB. Similarly the numerical values of EMSE are as follows, −12.3952dB for LMS, −15.4545dB for LMLS, −29.9875dB for

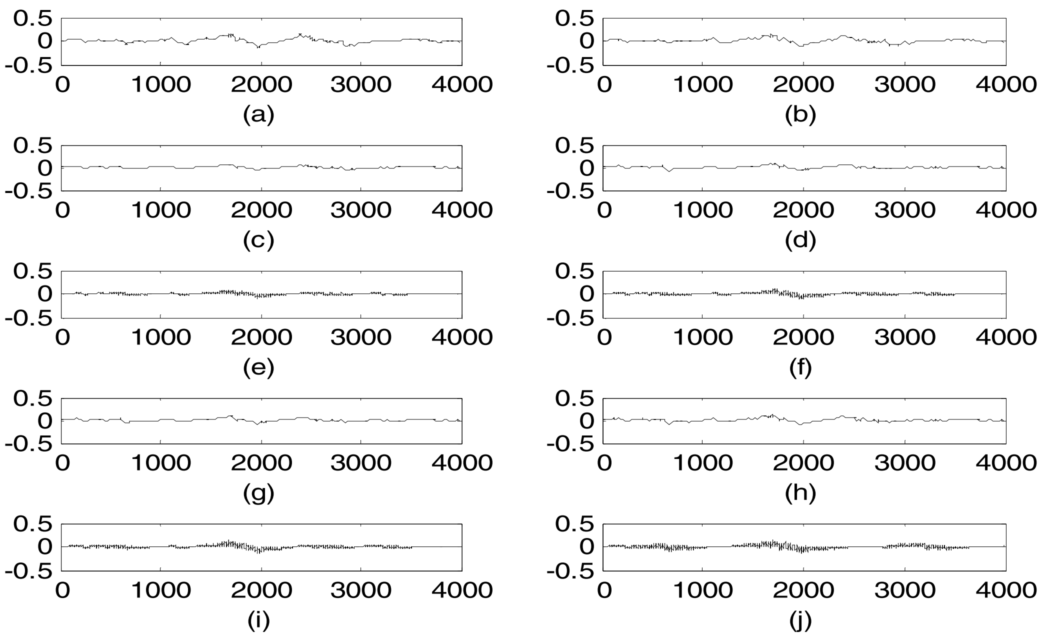

FIGURE 12. Residual noise in ECG signal after EM elimination, (a). after filtering with LMS (b). after filtering with LMLS (c). after filtering with NLMLS (d). after filtering with SRNLMLS (e). after filtering with SNLMLS (f). after filtering with SSNLMLS (g). after filtering with BBNLMLS (h). after filtering with BBSRNLMLS (i). after filtering with BBSNLMLS (j). after filtering with BBSSNLMLS (number of samples are taken on x-axis and amplitude on y-axis).

NLMLS, −27.9876dB for SRNLMLS, −25.9087dB for SNLMLS, −23.4677dB for SSNLMLS, −28.4567dB for BB-NLMLS, −26.5467dB for BBSRNLMLS, −24.6578dB for BB-SNLMLS and −22.3334dB for BB-SSNLMLS. By considering number of multiplications BBSRNLMLS is found to be better, even though it is inferior to NLMLS, SRNLMLS, and BBNLMLS algorithms in terms of filtering ability.

IV. CONCLUSION

In this paper, an attempt has been made to propose ASE-DWT based reference signal generation technique. The DWT unit generates the reference signal corresponding to the artifacts present in the cardiac signal. In proposed method LMLS based artifact cancellation is implemented. Simulation results have proved that by using LMLS based artifact cancellation, artifacts are removed from the cardiac signal. For comparison purpose various algorithms, namely, LMS, LMLS, NLMLS, SRNLMLS, SNLMLS, SSNLMLS, BBNLMLS, BBSRNLMLS, BBSNLMLS, and BBSSNLMLS are implemented for noise cancellation experiments.Among the considered algorithms BB-SRNLMLS achieves comparably better SNR and EMSE than the other algorithms. However, BB-SRNLMLS needs only '7' multiplications and greatly less than the other three algorithms NLMLS; SRNLMLS; BB-NLMLS. But the SNR and EMSE of BB-SRNLMLS is little bit inferior than the remaining algorithms. So, by considering the smaller number of computations required by BB-SRNLMLS, even though it is inferior in terms of SNR and EMSE it may be used for practical medical telemetry systems. The performance measures such as, SNR, EMSE, computational complexity, convergence characteristics are measured and shown in Tables 1, 2, 3, 4, 5, 6 and Figure 3, Figure 4 respectively. Thus, BBSRNLMLS based ASE is found to be better than other algorithms. Hence, this realization is suitable for real time remote cardiac care monitoring applications.

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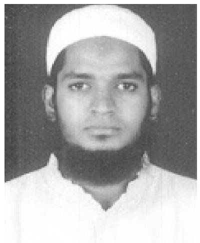

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