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An Efficient Kalman Noise Canceller for Cardiac Signal Analysis in Modern Telecardiology Systems

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ABSTRACT The monitoring of electrocardiography (ECG) in ambulatory conditions is an important task for achieving success in remote healthcare monitoring. In this paper, Kalman-based adaptive artifact cancellation structures, which are the hybrid versions of least-mean-square (LMS) algorithm variants, are proposed for the high-resolution enhancement of an ECG signal. The main advantage of the Kalman-based adaptive filter structure lies in the extraction of the ECG signal at a low signal-to-noise ratio (SNR). This property helps the Kalman noise canceller (KNC) to achieve greater monitoring accuracy. The hybrid version of this Kalman algorithm makes the noise canceller independent of the step-size parameter, whereas the performance of conventional adaptive filters depends on the step-size parameter. In the proposed KNCs, we use discrete wavelet transform to generate a reference component from the contaminated ECG signal itself. In addition to these constraints, in remote health care monitoring, it is necessary to lower the computational burden and increase the convergence rate of the noise canceller. In a practical remote health care monitoring system if the computational burden of the signal conditioning unit is more, then it takes a much greater amount of time to process samples in the filter. This leads to waiting of incoming samples at the input port of the filter. This causes overlapping of samples at the input port and causes ambiguity in the diagnosis process. To achieve the feature of low computational complexity, we combine Kalman-based LMS (KLMS) with sign algorithms. In addition, data normalization is introduced to improve convergence characteristics. Finally, to test the performance of the proposed implementations, real ECG signals from the MIT-BIH database is used. The measured parameters, namely, SNR, excess mean square error, and mis-adjustment are calculated in the enhancement process to judge the ability of various algorithms. Experimental results confirm that the proposed Kalman-based adaptive algorithms are better than the LMS-based algorithms. Among the implemented techniques sign regressor-based KNC performs better in terms of various considered measures.

INDEX TERMS Adaptive noise cancellers, artifacts, convergence, electrocardiography, Kalman filter, telecardiology.

I. INTRODUCTION

This storage modern day healthcare and advancements in technology is able to reach and service a large group of people in all parts of the world where conventional health care systems face limitations. Advanced technologies are increasingly needed to meet the challenges posed by increased health issues. One of the most commonly known problems is heart health. With the diversities in lifestyles across the globe, this problem matters. In the WHO's report on non-communicable diseases, it was reported that approximately 33% of people face heart problems [1]. However, it is possible to identify cardiac health via analysis. Arrhythmia, which is indicative of heart problems, can be identified by analyzing ECG signals. It is done by monitoring the signal morphology over a time period. The components P, Q, R, S and T are the elements that are observed in an ECG signal, and these elements help in identifying the arrhythmia. However, the ECG signal can be severely affected by noise during extraction and transmission. Noise affects the shape and amplitude of the elements of ECG signals. As a result, identifying the arrhythmia when the ECG signal is masked by physiological and non-physiological artifacts and channel noise is an important task in health care technology. Therefore, filtering is needed to eliminate artifacts and clutter to provide high-resolution signals for accurate diagnosis. Several filtering approaches involving both adaptive and non-adaptive techniques have been reported in the literature. In [2] power-line interference cancellation based on various parameters, updating of a sine wave according to the least-mean-squares (LMS) algorithm is described. In [3] S-median thresholding technique is proposed for denoising the ECG signals. A non-local wavelet transform for removal of additive white Gaussian noise in ECG signals is described in [4]. In [5] power-line noise cancellation technique is described based on a new discrete Fourier transform scheme. A less computational complexity algorithm for the fiducially point tracking from the electrocardiogram (ECG) is presented in [6]. Adaptive tunable notch filter algorithm is proposed in [7] for the suppression of power line noise and muscle noise from cardiac activity. An ECG enhancement technique based on Stock well transform is proposed in [8]. In [9], data compression of multiplied electrocardiogram (MECG) using singular value decomposition in multi-resolution domain is proposed. In [10] fractal modeling and empirical mode decomposition methods are used for the cancellation of respiration artifact and power line noise from ECG signals. In [11], a new method based spatially selective artifact removal method for fetal ECG extraction is proposed. In [12] novel fractional zero-phase enhancement method is proposed for cancellation of noise in ECG signals.

Because noise in an ECG is random in nature, it will be helpful to use filters that have an innate ability to adjust the coefficients automatically. Such filters result in optimum solutions with minimum residual error. The removal of noise helps to appropriately identify segments for the detection of arrhythmia and other abnormalities. Non-adaptive techniques include basic Fourier, DFT-based [5], EMD-based [10], and wavelet-based denoising. Adaptive techniques include Least Mean Squares (LMS), least squares, and adaptive wavelet filtering. Many researchers have contributed to improving processing accuracy by trying to minimize noise and artifacts with the help of sophisticated electrodes and filtering techniques for suppression, by implementing techniques for compression, and by segment identification. A new biotelemetry system for monitoring cardiac activity is presented in [17]. An entropy measure-based algorithm for the detection of complex features of cardiac signal is proposed in [18] which use the calculation of the time dependent entropy. In [19] low-power analog IC based telecardiology system is presented. In [13] the empirical-mode decomposition (EMD) based technique is proposed to separate the useful information about the ST–T complex from artifacts. In [14] a new compression method based on weighted diagnostic distortion is proposed. Time domain Block Least Mean Square (TDBLMS) algorithm is proposed in [15] for EEG signal enhancement. In [16] discrete wavelet transforms based adaptive filtering approach and artificial neural network is proposed for cancellation of noise in ECG signal. A large set of adaptive algorithms was presented to enhance ECG signals, of which the LMS algorithm [21] is familiar due to its simplicity. In [22] block based adaptive filter structures for enhancement of cardiac signal is presented which estimate the deterministic components of the cardiac signal and eliminate the noise component. In [23] sign based nonlinear adaptive artifact elimination method is presented, and error nonlinearity-based adaptive filters are proposed, which is superior with reference to computational burden. The results obtained were quite encouraging for the use of the LMS algorithm in real-time applications. However, a serious drawback of LMS is slow convergence and its unstable nature. The recursive least squares (RLS) present a substantial computational burden [34]. Adaptive wavelet filtering decomposes the signal to perform enhancement [36], which in turn increases the computational complexity of the signal enhancement process. Slow convergence can be accelerated by data normalization and variable step size. In [24] a new adaptive algorithm is derived by the Euclidean norm of the tap-input. Bias compensated normalized least-mean-square (BC-NLMS) algorithm is proposed in [25] for noisy inputs which is based on the estimated input noise variance in the elimination process of the bias caused by noisy inputs. In [26] a variable step-size adaptive filter is proposed by correlation matrix analysis. Normalization helps to reduce the biased form of estimation by incorporating the squared vector of the signal. As a result, convergence and stability are accelerated. However, the normalized version alone still suffers from instability as it depends on noise.

In such a scenario, a Kalman filter is the best form of linear estimation technique. It involves estimating the state of the system, comparing it with actual measurements, finding the error and updating the coefficients. In this process, uncertainties exist. The noise signal statistics are fed as input; appropriate noise statistics reduce the estimation error. However, in real-time scenarios, feeding the system with the actual statistics beforehand may not be possible. As a result, initial errors are large as iterations are going on error reduces. The Kalman filter works better when the noise covariance is known. Provided with the appropriate initial conditions, the Kalman filter reaches the solution quickly, and it is immune to noise. Therefore, the drawbacks of the conventional LMS algorithm are suppressed by combining the data normalized by the LMS and the Kalman filter. This framework is presented in [27], and the resulting algorithm is the Kalman LMS (KLMS) algorithm. The KLMS algorithm assumes the LMS as a noisy observation system and tries to update the coefficients. Here, the Kalman state vector is a counterpart to the weight vector of the LMS algorithm. This process produces the advantages of reduced EMSE and increased filtering capability. The combination of Kalman and data-normalized LMS results in a better noise canceller, called the Kalman Noise Canceller (KNC), for ECG signal enhancement. The hybrid version of KNC is independent of step size [27]. This combination achieves good convergence, better filtering capability and sufficient stability in operation. On the other hand, in the artifact removal process, a reference signal is required. In a practical scenario, it is always not possible to give the exact reference signal. This causes ambiguity and degrades the high resolution of filtered signal. Hence, in our proposed KNCs, we generate the reference signal from the contaminated ECG signal itself by using DWT decomposition. In this way the proposed implementations become reference free realizations.

However, in real-time applications, such as remote health care monitoring systems, the computational complexity of the adaptive noise canceller (ANC) is an important factor. It plays a vital role in the implementation of a lab on a chip (LOC), a system on a chip (SOC), wearable devices and VLSI architectures for health care systems. The importance of biomedical signal analysis and processing in remote health care monitoring is elaborated in [39] and [40]. The computational complexity of KLMS can be minimized by combining it with simplified algorithms [23]. By combining KLMS with simplified sign-based algorithms, the resulting algorithms have lower computational complexity for the computation of weight update recursion. The three sign-based simplified algorithms greatly reduce the computational complexity of the weight update recursion of the corresponding technique. The sign regressor algorithm needs only one multiplication; the number of multiplications in this algorithm is independent of filter length [33]. This feature is very important in real-time implementations. This result minimizes computational complexity, which leads to the avoidance of inter-symbol interference at the input of the filter. We combine three familiar simplified algorithms with KLMS, resulting in the Kalman sign regressor LMS (KSRLMS), Kalman sign LMS (KSLMS) and Kalman sign sign LMS (KSSLMS) algorithms. The data normalization involved in KLMS causes the number of multiplications to be equal to the length of the filter in the denominator of normalization factor. This can be avoided by using the maximum data value of the data vector for the normalization operation. As a result, only one multiplication is needed in the denominator. We applied this strategy to KLMS and its sign variants. This results in the maximum normalized KLMS (MKLMS), maximum normalized Kalman sign regressor LMS (MKSRLMS), maximum normalized Kalman sign LMS (MKSLMS) and maximum normalized Kalman sign sign LMS (MKSSLMS) algorithms. Using these algorithms, we develop various KNCs, and performance analysis is conducted. For standardization, we also implement an LMS-based ANC for comparison. These implementations are tested on real cardiac activity components taken from the MIT-BIH arrhythmia database [29]–[32].

II. KALMAN BASED HYBRID ADAPTIVE NOISE CANCELLERS IN ARTIFACT CANCELLATION

Artifacts in a biomedical signal are mainly classified as two types. One is physiological noise and the other is non-physiological noise. Baseline Wander (BW) (0.5-Hz sinusoidal signal) and Muscle Artifact (MA) (5-500Hz) is physiological noises, whereas Power Line Interference (PLI) (60-Hz sinusoidal signal) and Electrode Motion (EM) (1-10Hz) is non-physiological noises [37]. The major aim is to remove these artifacts and thus eliminate the channel noise. To eliminate these artifacts, adaptive filtering is a promising technique. This is because of the ability of an adaptive filter to vary its tap weights depending on the acquired physiological signal characteristics. The basic filter used in the development of an adaptive filter is an FIR filter associated with an adaptive algorithm. The adaptive algorithm has the innate ability to change the filter coefficients automatically based on the feedback component taken from the output of the filter. A typical framework of ECG enhancement based on the LMS algorithm is presented in [28]. However, the major drawback of a typical adaptive noise canceller is the prior information about the noise is needed in the form of a reference signal. In practical situations it is difficult to predict the exact nature of the artifact contained in the ECG signal. To overcome this problem a wavelet-based decomposition is employed to generate the reference signal from the contaminated ECG signal. DWT decomposition-based reference signal generation implemented based on the framework presented in [36].

In our work we developed novel noise cancellers to eliminate artifacts from ECG signals and facilitates high resolution signals to the doctor for diagnosis. In our work we are using a Kalman algorithm in the development of proposed Kalman Noise Canceller (KNC) because by combining Kalman algorithm the adaptive algorithm becomes independent of step size. Whereas, the conventional adaptive algorithms are dependent on step size [27]. By using a normalized algorithm in the proposed KNC, SNR could be significantly improved [23], [34], and [35]. Again, by combining sign algorithms the computational complexity of the proposed KNC significantly reduced [33]. In this manner the hybrid realization of proposed KNC is well suited for remote health care monitoring systems.

Let us consider the adaptive filter shown in Figure 1. Let ‘x’ be a noisy ECG signal, i.e., $x = ecg + a + c$, where ‘ecg’ is the actual cardiac activity representation, ‘a’ is the artifact contaminate cardiac activity, ‘c’ is the channel noise, r is reference signal generated by DWT based decomposition of a noisy ECG signal, c is the channel noise during transmission, V is the coefficient matrix, and M is the filter length. Our goal is to minimize the noise in the contaminated ECG signal by training a reference signal. The generated reference signal in the decomposition process is correlated with the actual artifact component presented in the recorded cardiac component. By following the same framework presented in [28], we develop ANC by combining the Kalman and data normalized LMS algorithms. The output of the filter for the given input will be rV^T. The error can be taken as, $e = x - rV^T$. By minimizing the error, the output will become noise-free. Initially, we consider an LMS weight update recursion.

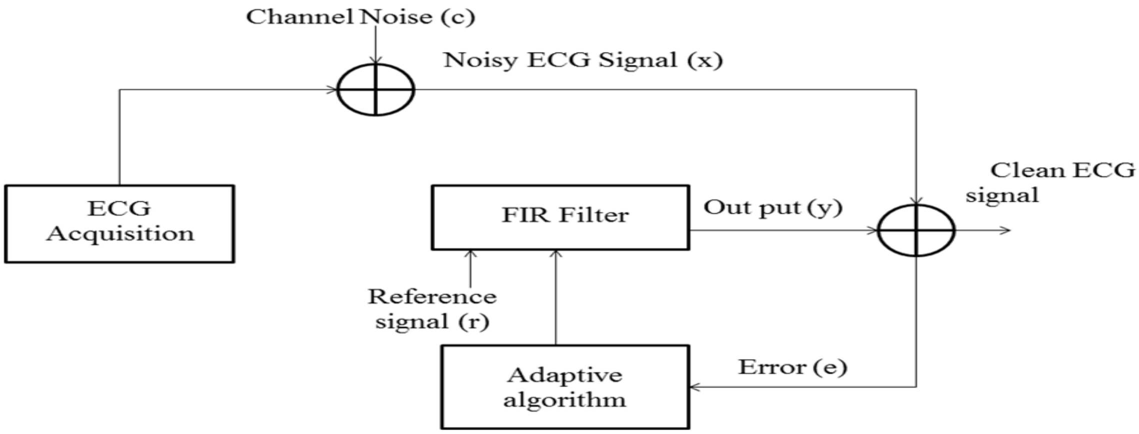

FIGURE 1. A typical Adaptive Noise Canceller for ECG signal enhancement.

The update equation for the LMS filter is given as,

$$V_{n+1} = V_n + \mu e(n) r(n) \tag{1}$$

where μ is the step size (in our simulations, μ is taken as 0.01), V_{n+1} is the filter weight coefficient of the next iteration, V_n is the present weight coefficient.

As mentioned earlier, the LMS algorithm has poor convergence and stability. Hence, to improve these qualities, data normalization is applied. This makes the step size a variable rather than a constant and increases the convergence and filtering capability. This modified algorithm is called the normalized LMS (NLMS) algorithm.

The weight update recursion after data normalization can be written as follows: -

$$V_{n+1} = V_n + \frac{\mu e(n) r(n)}{\delta + r(n)^2} \tag{2}$$

where δ is a constant; this avoids filter, coefficients becoming indefinite when the data value becomes zero. Here, the square term in the denominator will minimize the impact of the signal power of the filter response. However, as stated in [24], the signal is not immune to noise. This is one of the drawbacks of the NLMS algorithm.

Another drawback associated with this is the weight drift problem [25]. The Kalman filter (KF) is a better linear estimator. By giving the correct initial values, the Kalman filter is able to predict and correct the coefficients, reducing the residual noise in the enhancement process. The major concern in Kalman is that the process should be linear and noise should follow the Gaussian statistics.

The equations that govern the Kalman filtering are,

$$X(k+1) = F(k).x(k) + N(k) \tag{3}$$

$$Z(k) = H^T(k)x(k) + v(k) \tag{4}$$

where X and Z denote the state vector and measure vector; F and H denote the transition matrix and observation matrix; and N and v denote the state noise and measurement noise, respectively. Satisfying the conditions of linearity and noise statistics results in signal enhancement. However, the contamination associated with ECG component is non-linear; as a result, KF itself is not able to eliminate such artifact component. This can be avoided by combining KF with an NLMS algorithm. The resultant hybrid algorithm is called the Kalman LMS (KLMS) algorithm.

The mathematical recursion of KLMS algorithms is expressed as-

$$V_{n+1} = V_n + \frac{r(n)e(n)}{r(n)^2 + q_{v(n)}/\sigma_w^2} \tag{5}$$

where, σ_w^2 denotes the variance of coefficients and $q_{v(n)}$ denotes the variance of the measured noise and is the difference between the filter output and noisy input signal. Here, we calculate the second term of denominator as a separate function. The key feature of KLMS is that it is independent of the step size parameter, whereas the step size is a key parameter in conventional adaptive noise cancellers.

Computational complexity is another important factor that has to be considered, along with filtering capability, convergence speed and stability. If the mathematical complexity of the algorithm is huge, overlapping of data in the input of the filter occurs. This key feature must be considered while designing the filtering unit of a health care system to overcome the problem of data overlapping and ambiguities in diagnosis. Computational complexity can be minimized using familiar simplified algorithms. These algorithms apply a signum function to the data vector or error or both. This results in the Sign Regressor Algorithm (SRA), Sign Algorithm (SA) and Sign Sign Algorithm (SSA). The advantage of SRA is that it requires only one multiplication in computing the new weight coefficient. In addition, in SRA, the number of multiplications is independent of the filter length. The signum helps to reduce the complexity of encoding the vector to be either zero or one. This will make the filter reach the steady state quickly.

The basic mathematical equation of the signum function is represented as,

$$\text{sign}(r) = \begin{Bmatrix} 1, & r > 0 \\ 0, & r = 0 \\ -1, & r < 0 \end{Bmatrix} \tag{6}$$

By combining KLMS with SRA, SA and SSA, three sign-based KLMS algorithms can be derived. These are KSRLMS, KSLMS and KSSLMS. The weight update recursions for these new algorithms are written as follows, respectively.

$$V_{n+1} = V_n + \frac{\text{sign}(r(n))s(n)}{r(n)^2 + q_{v(n)}/\sigma_w^2} \tag{7}$$

$$V_{n+1} = V_n + \frac{r(n)\text{sign}(s(n))}{r(n)^2 + q_{v(n)}/\sigma_w^2} \tag{8}$$

$$V_{n+1} = V_n + \frac{\text{sign}\,(r\,(n))\ \text{sign}(s(n))}{r(n)^2 + q_{v(n)}/\sigma_w^2} \tag{9}$$

In the above three equations, the denominator contains $r(n)^2$. This indicates that the data vector of dimension $1 \times M$ is multiplied by its transverse matrix of dimension $M \times 1$. Thus, "M" multiplication and accumulation (MAC) operations need to be performed in the denominator of (7), (8) and (9). Furthermore, this can be minimized by performing the data normalization using the maximum value of the vector "r" rather than the entire vector. After applying this maximum data normalization operation, KLMS becomes a maximum data normalized KLMS (MKLMS). Its weight update recursion is written as,

$$V_{n+1} = V_n + \frac{\text{sign}(r(n))e(n)}{\max(r(n))^2 + q_{v(n)}/\sigma_w^2} \tag{10}$$

$$V_{n+1} = V_n + \frac{r(n)\text{sign}(e(n))}{\max(r(n))^2 + q_{v(n)}/\sigma_w^2} \tag{11}$$

$$V_{n+1} = V_n + \frac{\text{sign}\,(r\,(n))\ \text{sign}(e(n))}{\max(r(n))^2 + q_{v(n)}/\sigma_w^2} \tag{12}$$

Based on these Kalman-based algorithms, we develop various KNCs to eliminate artifacts from the ECG signals. The performance of these KNCs tests on real cardiac electrical activity components taken from the MIT-BIH database and performance metrics are compared. Figure 2 illustrates the flow of the ECG enhancement process using the KLMS algorithm. In our work we are concentrating on a novel signal processing technique which is suitable at the receiving end of a remote health care monitoring system (i.e., at hospital end) to eliminate all the artifacts and noises before the biomedical signals are presented to the doctor to facilitate high resolution signals.

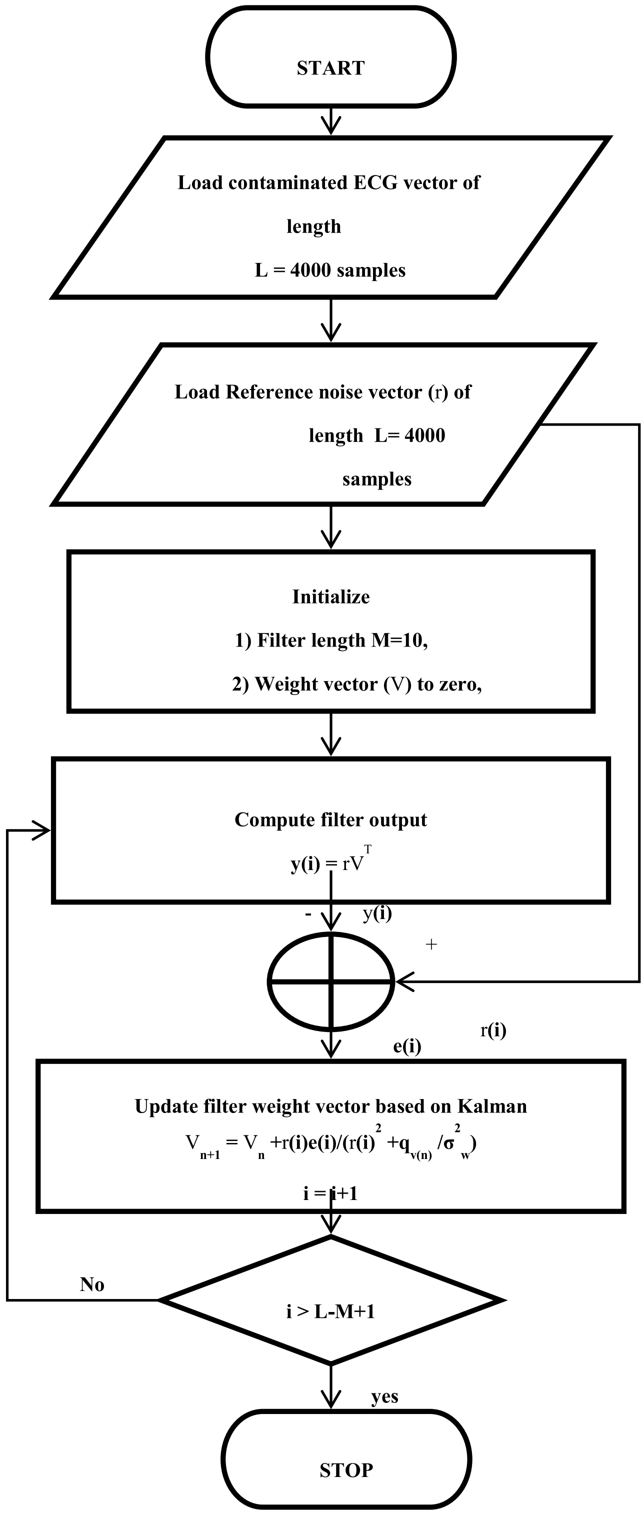

FIGURE 2. Flow chart of KLMS based adaptive noise canceller.

III. COMPUTATIONAL COMPLEXITY OF THE PROPOSED ALGORITHMS

The computational complexity of any signal conditioning technique is one of the important parameters in biomedical signal processing applications. As the computational complexity is large the data samples are delayed by an amount equal to the processing time of the technique. As a result, a large number of samples are gathered at the input port. This leads to aliasing of the data samples. Hence, in biotelemetry applications, computational complexity has to be minimized [24]. In the proposed KNCs, the hybrid

TABLE 1. Computational complexity of various algorithms in terms of filter length 'M'.

Serial Number	Algorithm	Multiplications	Additions	Addition with Sign Check	Division
1	LMS	M+1	M	Nil	Nil
2	KLMS	2M+1	2M	Nil	1
3	KSRLMS	M+1	2M	Nil	1
4	KSLMS	2M+1	2M	Nil	1
5	KSSLMS	1	M	M+1	1
6	MKLMS	M+1	M	Nil	1
7	MKSRLMS	2	M+1	Nil	1
8	MKSLMS	M+1	M+1	Nil	1
9	MKSSLMS	1	Nil	M+1	1

versions of signum based algorithms are used for enhancing the contaminated signal. The computational complexity of these algorithms is shown in Table 1. From the calculated number of computations, it is clear that among the algorithms MKSRLMS requires less number of multiplications. Hence, KNC based on this algorithm may be more useful in clinical remote health care monitoring systems. Due to clipping, a simple LMS combined with SRA needs only one multiplication. So, MKSRLMS requires only two multiplications to process the algorithm. In the case of MKSSLMS only single multiplications are sufficient. But, due to clipping the data vector and error the signal quality will be degraded. So, MKSSLMS could not be a better candidate in noise cancellation applications. Based on these considerations and number of computations for various algorithms, clipping mechanism, it is confirmed that MKSRLMS could be a better algorithm in noise cancellation applications in the context of health care monitoring scenario.

IV. EXPERIMENTAL ANALYSIS AND RESULTS

To analyze the ability of the developed implementations, we performed several experiments to remove artifacts from the ECG signals. To conduct these experiments, we developed nine KNCs using the LMS, KLMS, KSRLMS, KSLMS, KSSLMS, MKLMS, MKSRLMS, MKSLMS and MKSSLMS algorithms. The test, ECG records are taken from the familiar physiological signal database known as the MIT-BIH Arrhythmia Database [29], [30]. This database contains 48 two-channel ECG samples recorded from 47 patients [31], [32]. To evaluate the proposed algorithms, we took ten data samples from this database. These signals are as follows: record 100, record 101, record 102, record 103, record 104, record 105, record 106, record 107, record 108 and record 109. The enhancement results for record 105 are presented in this section. In our demonstration, we use the first 4000 data values of the considered records.

The enhancement experiments were repeated for 10 times, the averaged performance measures are recorded. The tap size of the adaptively driven FIR filter (M) is chosen as 10, and a Gaussian component of variance 0.001 is synthesized to resemble the free space propagation distortion. To prove the enhancement in the capability of developed KNCs, we consider the signal-to-noise ratio improvement (SNRI) in decibels (dBs.), EMSE, MSD and convergence characteristics as metrics. These values are tabulated to compare the performance. The convergence curves of the algorithms used in various KNCs are presented in Figure 3. Combining sign algorithms with LMS results in Sign Regressor LMS (SRLMS), Sign LMS (SLMS) and Sign Sign LMS (SSLMS). The convergence characteristics of LMS and its sign-based variants confirm that SRLMS is slightly inferior to LMS convergence. However, SRLMS is computationally less complex. SRLMS needs only one multiplication irrespective of filter length. Thus, by comparing the fewer number of multiplications, the inferior convergence can be tolerated in SRLMS [33], [34].

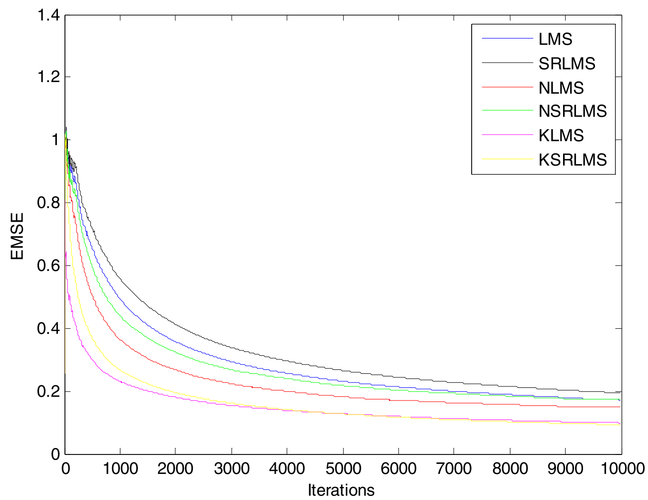

FIGURE 3. Convergence curves of LMS variants used in KNCs.

The data normalization involved in the signum function of SRLMS accelerates the convergence. Similarly, the sign regressor version of normalized LMS results in NSRLMS. This NSRLMS is also inferior in the convergence of the NLMS algorithm [35]. The combinational filter of NLMS and the Kalman filter (KLMS) converge better than the conventional data normalized algorithm [27]. Its sign regressor version (KSRLMS) is slightly inferior to KLMS with reduced computational complexity. Therefore, among the various algorithms, KSRLMS is found to have better convergence characteristics in the ECG enhancement process.

TABLE 2. Comparison of signal to noise ratio improvement using various techniques in artifact elimination process (all values in DBS).

Noise	Record	LMS	KLMS	KSRLMS	KSLMS	KSSLMS	MKLMS	MKSR LMS	MKS LMS	MKSS LMS
PLI	100	8.8067	35.1131	34.5969	18.4883	16.8064	34.9156	33.8324	17.4852	16.5083
	101	7.7763	35.0863	32.726	24.2205	18.6972	34.3788	30.5528	22.3745	17.9026
	102	9.1878	37.7453	35.4528	30.3539	25.4079	37.3046	34.7339	28.3374	24.0374
	103	8.5084	36.5171	34.5901	32.6849	25.7885	35.6344	33.1576	31.7058	22.5179
	104	9.0063	35.4189	34.5607	22.1021	20.3318	35.0864	33.5941	21.6486	18.5946
	105	7.3824	34.3246	33.2621	17.9363	15.3689	33.6463	32.4258	16.4732	15.0643
	106	6.9373	32.6382	31.6354	15.5821	13.6489	30.9345	28.7432	13.8532	12.9076
	107	8.0437	35.9056	33.6343	30.5421	24.8395	33.9538	32.4839	30.6487	21.6784
	108	9.7482	40.0592	37.6353	32.9953	26.7840	38.5639	36.2836	29.9954	26.0863
	109	7.0522	33.9052	32.5024	16.4143	14.3351	32.1335	31.7049	16.0634	14.8502
	Average	**8.2449**	**35.6713**	**34.0596**	**24.1319**	**20.2008**	**34.6551**	**32.7512**	**22.8585**	**19.0147**
BW	100	4.1985	10.7438	10.1639	9.0375	7.7482	10.3683	9.8524	8.7732	7.2738
	101	4.2598	11.7389	11.3846	10.1749	8.6392	11.4629	10.9493	9.8461	8.4863
	102	4.7682	12.8274	12.4295	11.3854	9.5985	12.6294	11.8375	10.7181	9.5737
	103	4.8275	13.6328	13.0386	12.7427	10.6972	13.2865	12.4819	11.8303	10.3854
	104	4.6124	11.8235	11.0115	10.1668	8.6035	11.4758	10.4885	9.2191	8.2994
	105	4.4523	11.7553	11.1346	10.2644	8.8432	11.5328	11.0143	9.9054	8.5532
	106	4.7002	12.7943	12.0754	11.0054	9.1435	12.4765	11.6593	10.4387	9.2156
	107	5.0318	13.9002	13.5839	13.1593	10.9843	13.7482	12.8952	12.163	10.7328
	108	3.9496	10.3853	9.6943	8.7194	7.3375	10.0037	9.2594	8.3291	6.8332
	109	5.3864	14.1737	13.8567	13.5374	11.2701	13.9803	13.0382	12.5837	11.0142
	Average	**4.6186**	**12.3775**	**11.8373**	**11.0193**	**9.2865**	**12.0964**	**11.3476**	**10.3806**	**9.0367**
MA	100	3.6415	9.7238	8.8373	6.7329	5.6854	9.3948	8.4822	6.2316	5.2954
	101	3.7605	10.5842	9.7502	7.3955	6.5748	10.0435	9.1743	6.8658	6.1487
	102	3.9652	10.9643	10.1749	7.6784	6.9273	10.6843	9.6489	7.1245	5.9956
	103	4.0395	11.9964	11.6948	7.9741	7.4903	11.7493	10.9485	7.4065	6.6949
	104	4.0008	11.5368	10.8812	9.6335	8.3614	11.4919	10.5382	9.1993	8.0227
	105	4.0137	11.7353	11.4839	7.7431	7.0463	11.5284	10.7301	7.0032	6.3954
	106	3.8326	10.7254	9.9415	7.4329	7.1839	10.3394	9.4821	6.9851	6.0525
	107	4.0528	12.0362	11.9373	8.0332	7.6382	11.9263	11.1739	9.4832	6.8103
	108	4.0947	12.6343	12.1705	8.3017	7.7728	11.9853	11.3721	9.5838	6.9041
	109	3.3724	9.3826	8.3523	6.5232	5.2956	9.0632	8.1934	6.0363	5.0961
	Average	**3.8773**	**11.1319**	**10.5223**	**7.7448**	**6.9976**	**10.8206**	**9.9743**	**7.5919**	**6.3415**
EM	100	4.4419	12.8734	12.4392	9.6836	7.8859	12.4043	11.8649	9.1868	6.9648
	101	4.6511	13.3836	12.8644	9.8848	8.9567	12.8535	12.4479	9.0439	8.3307
	102	4.8438	14.7856	13.8353	10.7354	9.4968	13.9465	12.6445	10.0438	8.9065
	103	4.6617	13.8857	12.9873	10.8665	6.8979	13.0849	12.3375	9.6053	6.7759
	104	4.7782	14.3462	13.5073	11.6725	7.6681	13.1311	12.6402	10.8627	7.4895
	105	4.8083	14.7392	13.8201	10.7291	9.4392	13.9291	12.6293	10.0051	8.9162
	106	3.9847	11.5921	11.2822	8.6254	6.4726	11.7542	10.5327	8.5256	5.9421
	107	4.1363	11.9373	11.3262	8.8242	6.8369	11.9353	10.7935	8.6903	6.0036
	108	4.3272	12.6589	12.2851	9.5631	7.6085	12.2593	1.6473	9.0464	6.6504
	109	5.1648	14.9535	13.974	10.9505	9.8362	13.9973	12.8402	10.2794	9.2015
	Average	**4.5798**	**13.5155**	**12.8321**	**10.1535**	**8.1098**	**12.9295**	**11.037**	**9.5289**	**7.5181**

In our implementation, KLMS is a hybrid of the Kalman filter and the NLMS algorithm. NLMS converges faster than the LMS algorithm [34]. Therefore, the combination of the Kalman and NLMS algorithms results in faster convergence. In general, the NLMS algorithm is a Markov process. It has current-state information, but otherwise does not preserve the data from the past scenario. The Kalman filter uses the new measurement with all the tracked history that is packed in the previous estimate. Hence, the proposed Kalman-based NLMS algorithm uses the past and present information. In this manner, KLMS achieves a higher convergence rate than the NLMS algorithm [38].

A. PLI REMOVAL USING HYBRID KALMAN NOISE CANCELLERS

In this section, we demonstrate the performance of the developed KNCs based on various Kalman-based adaptive noise cancellers to eliminate PLI. The contaminated cardiac activity with Gaussian component is fed at the input port of the KNC, as shown in Figure 1. The signal obtained after DWT decomposing is fed as the artifact reference. The artifact removal process is performed by using the techniques elaborated in Section 2. For comparison, we also implement LMS-based ANC. The artifact removal processed is employed on the ten records. The property of SRA confirms

TABLE 3. Comparison of performance in terms of emse due to various techniques in artifact elimination process (all values in DBS).

Noise	Record	LMS	KLMS	KSRLMS	KSLMS	KSSLMS	MKLMS	MKSR LMS	MKS LMS	MKSS LMS
PLI	100	-19.9894	-32.9973	-31.5135	-22.0271	-21.1271	-30.0069	-28.9675	-21.3471	-20.2162
	101	-21.8298	-37.4574	-36.2634	-29.2634	-28.4706	-35.5497	-34.6334	-26.5775	-24.4575
	102	-20.5036	-33.1259	-32.6097	-22.3048	-21.3048	-29.0031	-29.5943	-21.4507	-20.9180
	103	-21.5394	-35.3848	-34.8686	-28.6785	-27.7954	-34.9689	-32.8988	-26.7568	-25.6560
	104	-21.5227	-35.1846	-33.5983	-27.7841	-25.7409	-34.8294	-32.1953	-26.4261	-23.9846
	105	-19.5486	-32.5564	-31.3225	-22.0091	-21.0927	-29.9942	-28.6753	-21.0842	-20.1942
	106	-21.6764	-37.1902	-31.9774	-29.1741	-28.2432	-35.3487	-34.4923	-26.4783	-24.2052
	107	-20.3242	-33.0364	-32.3759	-22.1932	-21.1356	-28.9876	-29.3091	-21.1792	-20.7869
	108	-21.4692	-35.2762	-34.6329	-28.4097	-27.5845	-34.7974	-32.6291	-26.5721	-25.4357
	109	-21.4529	-35.0731	-33.3129	-27.5932	-25.6662	-34.6653	-32.0795	-26.2832	-23.7562
	Average	**-20.9856**	**-34.7282**	**-33.2475**	**-25.9437**	**-24.8161**	**-32.8151**	**-31.5475**	**-24.4155**	**-22.9611**
BW	100	-11.1457	-25.7864	-24.9907	-15.4578	-14.5432	-23.5345	-22.7834	-14.2365	-13.6545
	101	-11.4418	-28.8692	-27.0012	-16.7843	-15.8375	-26.9624	-24.1103	-15.4475	-14.9246
	102	-11.4770	-29.8604	-28.0212	-17.9345	-15.9990	-27.9958	-24.5672	-15.8843	-14.0601
	103	-8.9635	-20.2408	-18.4809	-11.9945	-10.5362	-18.5476	-17.5673	-9.4352	-8.3304
	104	-12.6204	-22.8493	-20.2952	-18.8625	-16.3252	-21.3894	-19.7836	-17.6854	-15.6255
	105	-10.9847	-24.9849	-23.9098	-14.7478	-13.5492	-22.5342	-21.8734	-13.7632	-12.7685
	106	-10.5999	-24.4959	-23.2869	-14.4978	-13.1495	-22.4675	-21.4867	-13.3954	-12.5398
	107	-11.8769	-28.9725	-28.2465	-17.9779	-16.0005	-27.0021	-24.2873	-16.0089	-14.5432
	108	-9.7465	-21.7682	-19.9874	-12.9786	-11.5673	-19.7698	-19.7994	-17.1067	-9.8767
	109	-12.8976	-22.5478	-20.1290	-19.3425	-16.7653	-22.4768	-19.5986	-17.9465	-15.9987
	Average	**-11.1787**	**-25.1766**	**-23.3287**	**-16.1245**	**-14.4144**	**-23.3717**	**-21.5415**	**-15.1859**	**-13.1853**
MA	100	-12.1110	-19.2274	-18.1104	-15.5640	-14.5762	-18.2002	-17.5506	-14.5473	-13.0135
	101	-12.4097	-20.1242	-18.8101	-16.6532	-15.6054	-19.4321	-18.7854	-15.6321	-14.0232
	102	-11.7569	-18.9392	-17.5235	-14.9965	-12.9999	-17.9979	-16.7593	-13.9954	-12.3245
	103	-11.1118	-16.7795	-15.9987	-13.7635	-11.5545	-14.6356	-13.8953	-12.4677	-11.7647
	104	-13.8287	-21.3458	-20.8675	-17.1469	-15.9797	-20.3723	-19.9582	-16.8734	-14.8457
	105	-12.0091	-19.1174	-18.6247	-15.3456	-14.4342	-18.0976	-18.5792	-14.3476	-13.0078
	106	-10.9974	-16.6742	-15.6874	-13.5497	-11.3762	-14.4576	-13.6539	-12.2986	-11.5769
	107	-10.5749	-16.4891	-15.2689	-13.1439	-10.9989	-14.0576	-13.2739	-11.9969	-11.1965
	108	-13.4397	-20.9987	-20.4386	-16.9969	-15.7583	-19.9795	-19.5638	-16.4783	-14.4475
	109	-14.0021	-21.6759	-21.0075	-17.3495	-16.1457	-20.7594	-20.1684	-17.0734	-15.0457
	Average	**-12.2241**	**-19.1371**	**-18.2337**	**-15.4510**	**-13.9429**	**-17.7990**	**-17.2188**	**-14.5711**	**-13.1246**
EM	100	-10.7955	-17.6987	-16.8876	-12.6524	-11.4434	-16.5245	-15.7842	-11.3566	-10.6536
	101	-10.7225	-16.6862	-15.8543	-11.6424	-10.4322	-15.5042	-14.7521	-10.3276	-8.8039
	102	-10.9025	-18.7562	-17.9734	-12.8434	-11.5342	-17.7054	-16.8634	-11.5289	-10.7140
	103	-8.2407	-14.0617	-13.2404	-9.7420	-8.3142	-12.3475	-11.3564	-8.2352	-7.0304
	104	-12.3952	-22.3905	-20.5128	-17.8622	-15.9831	-21.7103	-19.6962	-16.8369	-14.5703
	105	-9.1354	-15.2431	-14.5642	-10.6781	-9.8749	-13.4484	-12.5641	-9.2861	-7.9968
	106	-9.9437	-16.2314	-15.3567	-11.4657	10.6754	-14.2438	-13.3568	-10.0249	-8.7864
	107	-11.1352	-18.9572	-18.1482	-13.0434	-11.7345	-17.9234	-17.0672	-11.7302	-10.9243
	108	-11.5784	-19.4562	-19.1653	-15.6712	-13.6372	-19.3429	-18.3241	-14.4562	-11.7892
	109	-12.6763	-22.6982	-20.8924	-18.1239	-16.2387	-22.0029	-19.9735	-17.1293	-14.8739
	Average	**-10.7525**	**-18.2179**	**-17.2595**	**-13.3725**	**-9.8517**	**-17.0753**	**-15.9738**	**-12.0912**	**-10.6143**

that among the three signum based algorithms, SRA is less complex with reference to the multiplication operations needed. Hence, among the various hybrid algorithms in association with signum algorithms, SRA-based ANC / KNC is computationally less complex. This is one of the important performance measure parameters. For the performance

TABLE 4. Comparison of performance in terms of misadjustment due to various techniques in artifact elimination process (all values in DBS).

Noise	Record	LMS	KLMS	KSRLMS	KSLMS	KSS LMS	MK LMS	MKSR LMS	MKS LMS	MKSS LMS
PLI	100	0.0761	0.0437	0.0524	0.0525	0.0579	0.0528	0.0595	0.0638	0.0689
	101	0.0460	0.0078	0.0114	0.0152	0.0184	0.0146	0.0174	0.0204	0.0295
	102	0.0744	0.0402	0.0458	0.0482	0.0503	0.0446	0.0483	0.0511	0.0598
	103	0.0134	0.0032	0.0053	0.0065	0.0086	0.0048	0.0061	0.0073	0.0094
	104	0.0725	0.0389	0.0409	0.0440	0.0473	0.0415	0.0425	0.0478	0.0516
	105	0.0671	0.0339	0.0463	0.0464	0.0499	0.0467	0.0510	0.0569	0.0599
	106	0.0560	0.0246	0.0357	0.0358	0.0378	0.0362	0.0398	0.0412	0.0436
	107	0.0340	0.0065	0.0105	0.0145	0.0164	0.0137	0.0168	0.0202	0.0275
	108	0.0340	0.0055	0.0098	0.0103	0.0125	0.0118	0.0129	0.0158	0.0195
	109	0.0816	0.0567	0.0653	0.0654	0.0690	0.0659	0.0696	0.0732	0.0758
	Average	**0.0555**	**0.0261**	**0.0323**	**0.0338**	**0.0368**	**0.0332**	**0.0363**	**0.0397**	**0.0445**
BW	100	0.5829	0.3748	0.4864	0.5031	0.5527	0.3918	0.5012	0.5237	0.5672
	101	0.5030	0.2854	0.4629	0.4993	0.5417	0.3845	0.4844	0.5032	0.5552
	102	0.5960	0.4572	0.5015	0.5284	0.5730	0.4153	0.5302	0.5496	0.5658
	103	0.4842	0.1936	0.2457	0.2864	0.3045	0.2138	0.2948	0.3752	0.4453
	104	0.5630	0.3552	0.4427	0.4796	0.5392	0.3841	0.4587	0.5429	0.5574
	105	0.4953	0.2047	0.2568	0.2975	0.3156	0.2249	0.2988	0.3863	0.4564
	106	0.4521	0.1615	0.2136	0.2543	0.3024	0.2017	0.2627	0.3431	0.4243
	107	0.6070	0.4682	0.5125	0.5394	0.5840	0.4263	0.5412	0.5606	0.5768
	108	0.6380	0.4992	0.5435	0.5704	0.6140	0.4573	0.5722	0.5916	0.6078
	109	0.3998	0.1304	0.1825	0.2232	0.2713	0.1706	0.2316	0.3120	0.3932
	Average	**0.5321**	**0.3130**	**0.3848**	**0.4181**	**0.4598**	**0.3270**	**0.4175**	**0.4688**	**0.5149**
MA	100	0.4667	0.3042	0.3462	0.3524	0.3566	0.3143	0.3584	0.3955	0.4169
	101	0.4025	0.2482	0.3467	0.3509	0.3557	0.2575	0.3622	0.3754	0.3993
	102	0.5579	0.3973	0.4027	0.4435	0.4766	0.4084	0.4544	0.4761	0.5036
	103	0.8090	0.5935	0.6183	0.6524	0.6674	0.6138	0.6755	0.7149	0.7632
	104	0.4262	0.2848	0.3782	0.3812	0.3869	0.2955	0.3951	0.4064	0.4188
	105	0.5014	0.3443	0.3863	0.3987	0.4231	0.3543	0.4487	0.4678	0.4997
	106	0.6123	0.4096	0.4243	0.4558	0.4889	0.4207	0.4667	0.4884	0.5159
	107	0.6523	0.4496	0.4745	0.4957	0.5276	0.4537	0.5087	0.5284	0.5459
	108	0.7042	0.4978	0.5042	0.5467	0.5749	0.5032	0.5842	0.6124	0.6537
	109	0.7990	0.5835	0.6083	0.6424	0.6574	0.6038	0.6645	0.7049	0.7532
	Average	**0.5931**	**0.4112**	**0.4489**	**0.4719**	**0.4915**	**0.4225**	**0.4918**	**0.5170**	**0.5470**
EM	100	0.6319	0.4062	0.4133	0.4325	0.4472	0.4152	0.4563	0.5382	0.5972
	101	0.5936	0.3318	0.3482	0.3474	0.4463	0.3427	0.3583	0.3947	0.4628
	102	0.6792	0.4264	0.4376	0.4493	0.4562	0.4317	0.4688	0.5421	0.6037
	103	0.5719	0.2826	0.2893	0.3046	0.4134	0.3044	0.3204	0.3628	0.4962
	104	0.5929	0.3247	0.3328	0.3562	0.4536	0.3308	0.3549	0.3647	0.5665
	105	0.4998	0.2016	0.2083	0.2836	0.3324	0.2234	0.2394	0.2818	0.4152
	106	0.4577	0.1595	0.1662	0.2415	0.2903	0.1813	0.2351	0.2397	0.3731
	107	0.7192	0.4664	0.4776	0.4893	0.4962	0.4717	0.5088	0.5821	0.6437
	108	0.7582	0.5054	0.5166	0.5283	0.5352	0.5107	0.5478	0.6211	0.6827
	109	0.8093	0.5563	0.5678	0.5795	0.5861	0.5618	0.5987	0.6723	0.7336
	Average	**0.6314**	**0.3661**	**0.3757**	**0.4012**	**0.4456**	**0.3773**	**0.4088**	**0.4599**	**0.5574**

evaluation, we calculated SNRI, EMSE, and MSD and are compared. These results are presented in Tables 2, 3 and 4. Figure 4 show the filtering results of PLI using various algorithms.

Additionally, Figure 5 illustrates the residual artifact remains in the cardiac signal component after processing by various artifact cancellation techniques. From Figure 5, it is clear that KLMS, KSRLMS, MKLMS and MKSRLMS perform better than the other algorithms, as the residual noises after filtering using these algorithms are DC responses. Again, among these four algorithms, the performance is judged by comparing SNRI, EMSE and MSD. The simulation results of record 105 are shown in Figure 4, Figure 5, Figure 6 and Figure 12 show a comparison of various performance measure parameters during the PLI removal experiments. As shown in Tables 2, 3 and 4, among these algorithms, KLMS achieves the maximum SNRI of 35.4189 dBs., whereas its sign regressor version achieves 34.5607 dBs. with reduced multiplication operations.

Again, by reducing the number of multiplications in the denominator, MKLMS achieves 35.0864dBs; its sign regressor version achieves 33.5941dBs.

Therefore, by comparing these four algorithms, it is clear that MKSRLMS is better in the considered KNCs. MKSRLMS attempts to reduce the multiplication actions by an amount equal to the filter tap length in the denominator part of the normalization function, as well as in the weight update recursion. Considering the reduced number of

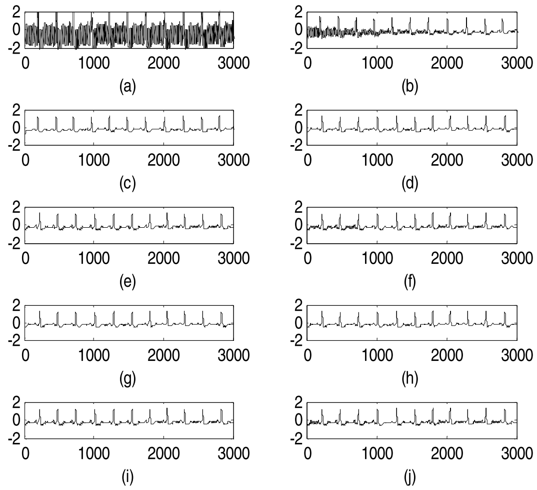

FIGURE 4. PLI Enhancement results: a) ECG with PLI, b) enhancement using the LMS, c) enhancement using KLMS, d) enhancement using KSRLMS, e) enhancement using KSLMS, f) enhancement using KSSLMS, g) enhancement using MKLMS, h) enhancement using MKSRLMS, i) enhancement using MKSLMS, and j) enhancement using MKSSLMS.

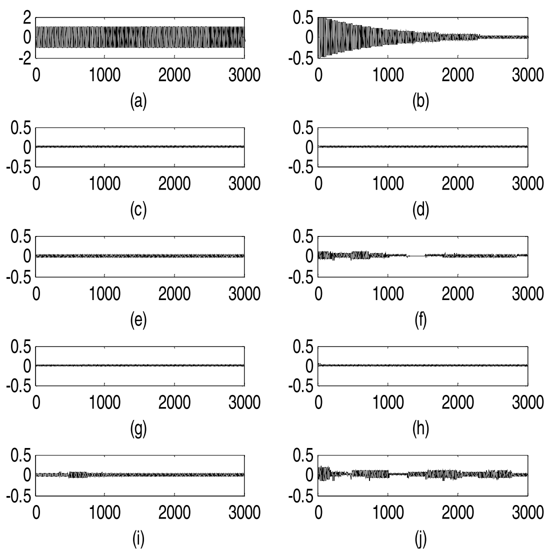

FIGURE 5. Residual Noise after PLI Filtering: a) Power Line Interference, b) noise component remains after LMS filtering, c) noise component remains after KLMS filtering, d) noise component remains after KSRLMS filtering, e) noise component remains after KSLMS filtering, f) noise component remains after KSSLMS filtering, g) noise component remains after MKLMS filtering, h) noise component remains after MKSRLMS filtering, i) noise component remains after MKSLMS filtering, and j) noise component remains after MKSSLMS filtering.

multiplications, the difference in SNRI between KLMS and MKSRLMS can be tolerated, which is only 1.8248 dB. The other versions of sign-based KNCs are worse than KLMS and its sign regressor version. The conventional LMS-based ANC only achieves an SNRI of 9.0063 dBs.

A similar type of behavior is observed among the KNCs / ANCs with reference to EMSE and MSD. The EMSE achieved by KLMS, KSRLMS, KSLMS, KSSLMS, MKLMS, MKSRLMS, MKSLMS, MKSSLMS and LMS are −35.1846, −33.5983, −27.7841, −25.7409, −34.8294, −32.1953, −26.4261, −23.9846 and −21.5227, respectively. From these calculations, it is clear that MKSRLMS and KLMS differ by a value of −2.9893 with a reduced number of multiplications. The MSD achieved by KLMS, KSRLMS, KSLMS, KSSLMS, MKLMS, MKSRLMS, MKSLMS, MKSSLMS and LMS are 0.0389, 0.0409, 0.0440, 0.0473, 0.0415, 0.0425, 0.0478, 0.0516 and 0.0725, respectively. From these calculations, it is clear that MKSRLMS and KLMS differ by a value of 0.0036 with a reduced number of multiplications.

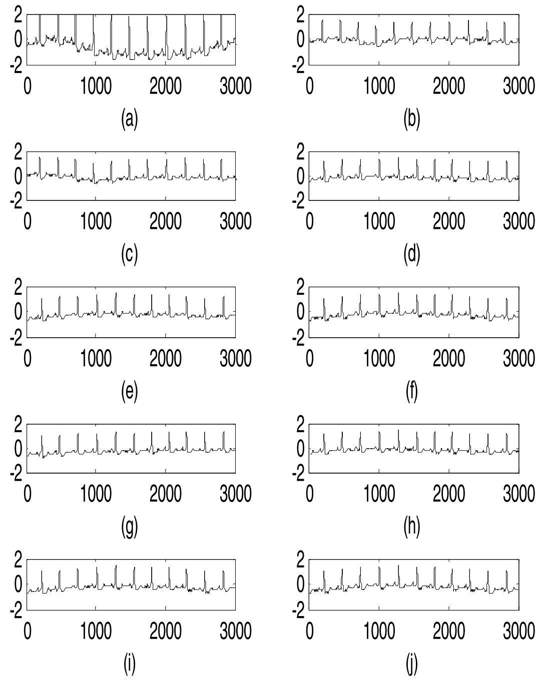

FIGURE 6. BW Enhancement results: a) ECG with BW, b) enhancement using the LMS, c) enhancement using KLMS, d) enhancement using KSRLMS, e) enhancement using KSLMS, f) enhancement using KSSLMS, g) enhancement using MKLMS, h) enhancement using MKSRLMS, i) enhancement using MKSLMS, and j) enhancement using MKSSLMS.

B. BW REMOVAL USING HYBRID KALMAN NOISE CANCELLERS

In this experiment, we attempted to eliminate BW from the ECG signals. Real ECG signals with BW are taken from the MIT-BIH sinus arrhythmia database and fed at the input port, as illustrated in Figure 1. The component obtained after DWT decomposition is taken as the reference signal. Filtering experiments are performed on the considered database ten times, and average values are tabulated. The performance metrics SNRI, EMSE and MSD are tabulated in Tables 2, 3 and 4. Figure 6 show the filtering results of BW using various algorithms. Additionally, Figure 7 illustrates the remaining noise after enhancement process by various KNCs. From Figure 7, it is clear that KLMS, KSRLMS, MKLMS and MKSRLMS perform better than the other algorithms, as the residual noise after filtering

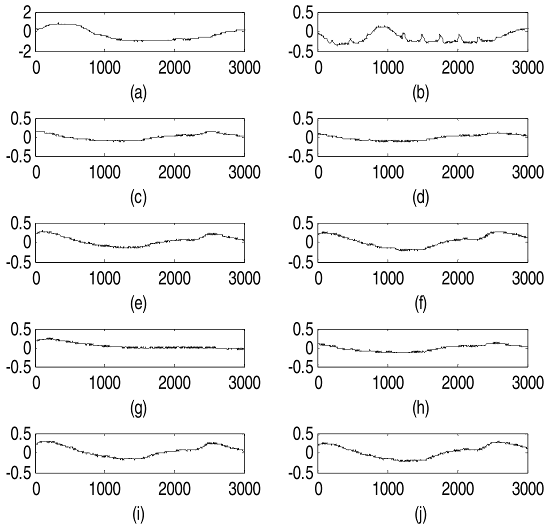

FIGURE 7. Residual Noise after BW Filtering: a) Baseline wander, b) noise component remains after LMS filtering, c) noise component remains after KLMS filtering, d) noise component remains after KSRLMS filtering, e) noise component remains after KSLMS filtering, f) noise component remains after KSSLMS filtering, g) noise component remains after MKLMS filtering, h) noise component remains after MKSRLMS filtering, i) noise component remains after MKSLMS filtering, and j) noise component remains after MKSSLMS filtering.

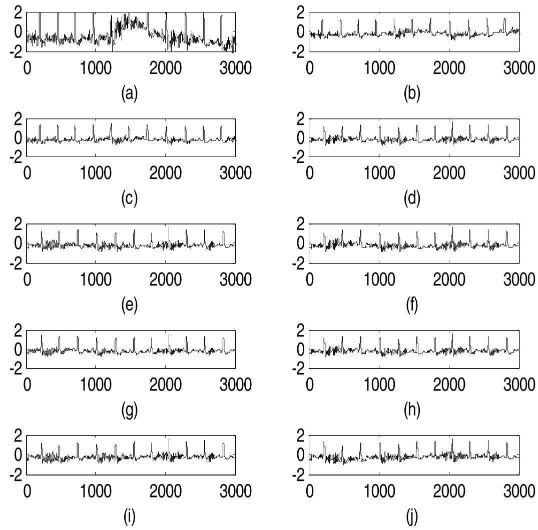

FIGURE 8. MA Enhancement results: a) ECG with MA, b) enhancement using LMS, c) enhancement using KLMS, d) enhancement using KSRLMS, e) enhancement using KSLMS, f) enhancement using KSSLMS, g) enhancement using MKLMS, h) enhancement using MKSRLMS, i) enhancement using MKSLMS, and j) enhancement using MKSSLMS.

using these algorithms is lessened. Again, among these four algorithms, the performance is judged by comparing SNRI, EMSE and MSD. The simulation results of data105 are illustrated in Figure 6, Figure 7 and Figure 12 illustrates various performance measure parameters during the BW removal experiments.

As tabulated in Tables 2, 3 and 4, among various algorithms, KLMS achieves the maximum SNRI of 11.8235 dBs., whereas its sign regressor version achieves 11.0115 dBs. with reduced multiplication operations. Again, by reducing the number of multiplications in the denominator, MKLMS achieves 11.4758 dBs.; its sign regressor version achieves 10.4885 dBs. Therefore, by comparing these four algorithms, it is clear that MKSRLMS is better in the considered KNCs. MKSRLMS attempts to reduce the number of multiplication actions by the tap length in the denominator part of the normalization function as well as in the weight update recursion. By considering the reduced number of multiplications, the difference in SNRI between KLMS and MKSRLMS can be tolerated, which is only 1.3350 dB. The other versions of sign-based KNCs perform worse than KLMS and its sign regressor version.

The conventional LMS-based ANC achieves an SNRI of only 4.6124 dB. A similar type of behavior is observed among the KNCs / ANCs with reference to EMSE and MSD. The EMSE achieved by KLMS, KSRLMS, KSLMS, KSSLMS, MKLMS, MKSRLMS, MKSLMS, MKSSLMS and LMS are -22.8493, -20.2952, -18.8625, -16.3252, -21.3894, -19.7836, -17.6854, $-15.6255$and -12.6204, respectively. From these calculations, it is clear that MKSRLMS and KLMS differ by a value of -3.0657 with the reduced number of multiplications. The MSD achieved by KLMS, KSRLMS, KSLMS, KSSLMS, MKLMS, MKSRLMS, MKSLMS, MKSSLMS and LMS are 0.3552, 0.4427, 0.4796, 0.5392, 0.3841, 0.4587, 0.5429, 0.5574 and 0.5630, respectively. From these calculations, it is clear that MKSRLMS and KLMS differ by a value of 0.1035 with the reduced number of multiplications.

C. MA REMOVAL USING HYBRID KALMAN NOISE CANCELLERS

In this experiment, we attempted to eliminate MA from the ECG signals. Real ECG signals with an MA are taken from the MIT-BIH sinus arrhythmia database and are given at the input port, as shown in Fig.1.The reference muscle artifact component is generated using DWT decomposition of a contaminated ECG signal. Filtering experiments are performed on the considered database ten times, and the average values are tabulated. The performance metrics SNRI, EMSE and MSD are presented in Tables 2, 3 and 4. Figure 8 show the filtering results of MA using various algorithms. Additionally, Figure 9 illustrates the remaining noise component after enhancement process. From Figure 9, it is clear that KLMS, KSRLMS, MKLMS and MKSRLMS perform better than the other algorithms, as the residual noise after filtering using these algorithms is lessened. Again, among these four algorithms, the performance is judged by comparing SNRI, EMSE and MSD. The simulation results of data105 are shown in Figure 8, Figure 9 and Figure 12 shows a comparison of various performance measure parameters during MA removal experiments.

As tabulated in Tables 2, 3 and 4, among the algorithms, KLMS achieves the maximum SNRI of 11.5368 dBs., whereas its sign regressor version achieves 10.8812 dBs.

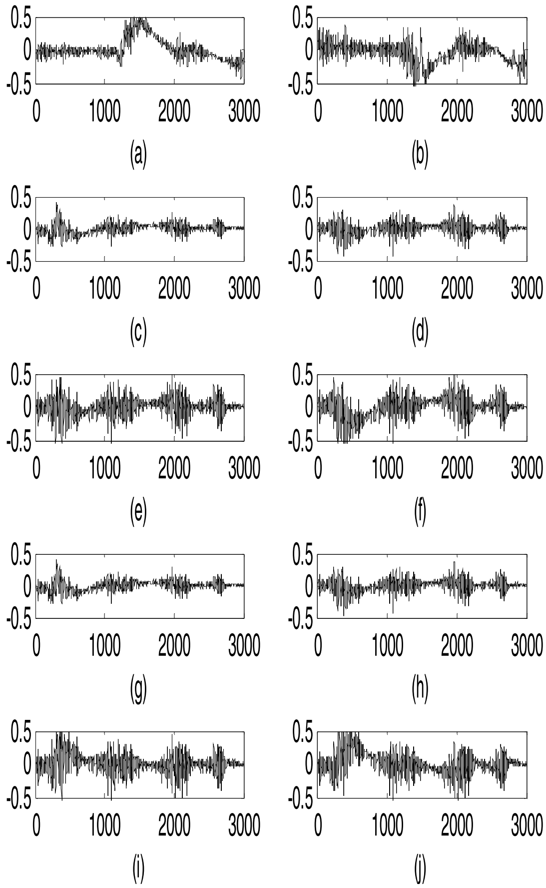

FIGURE 9. Residual Noise after MA filtering a)Muscle artifacts, b) noise component remains after LMS filtering, c) noise component remains after KLMS filtering, d) noise component remains after KSRLMS filtering, e) noise component remains after KSLMS filtering, f) noise component remains after KSSLMS filtering, g) noise component remains after MKLMS filtering, h) noise component remains after MKSRLMS filtering, i) noise component remains after MKSLMS filtering, and j) noise component remains after MKSSLMS filtering.

with the reduced multiplication operations. Again, by reducing the number of multiplications in the denominator, MKLMS achieves 11.4919 dBs.; its sign regressor version achieves 10.5382 dBs. Therefore, by comparing these four algorithms, it is clear that MKSRLMS is better in the considered KNCs. MKSRLMS attempts to reduce the number of multiplication action equal to the tap length in the denominator part of the normalization function as well as in the weight update recursion. By considering the reduced number of multiplications, the difference in SNRI between KLMS and MKSRLMS can be tolerated, which is only 0.9986 dB. The other versions of sign-based KNCs perform worse than KLMS and its sign regressor version. The conventional LMS-based ANC achieves an SNRI of only 4.0008 dB.

A similar type of behavior is observed among the KNCs / ANCs with reference to EMSE and MSD. The EMSE achieved by KLMS, KSRLMS, KSLMS, KSSLMS, MKLMS, MKSRLMS, MKSLMS, MKSSLMS and LMS are −21.3458, −20.8675, −17.1469, −15.9797, −20.3723, −19.9582, −16.8734, −14.8457 and −13.8287, respectively.

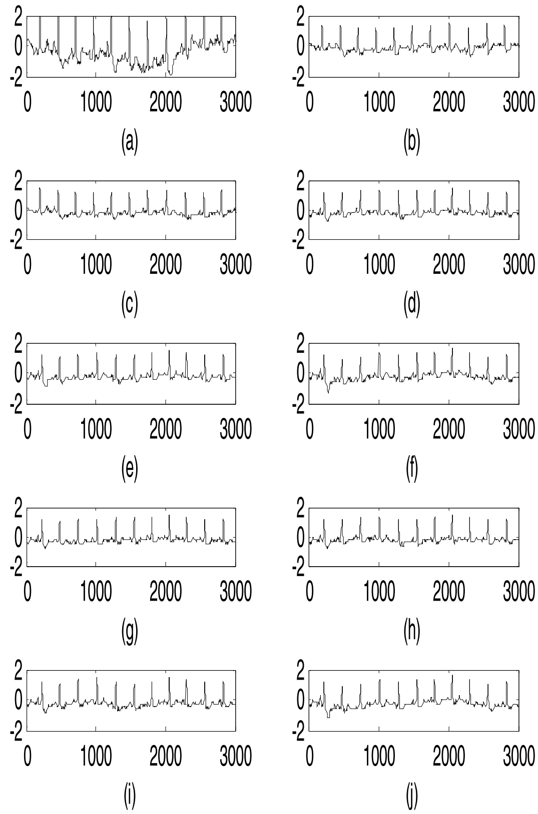

FIGURE 10. EM Enhancement results: a) ECG with EM, b) enhancement using the LMS, c) enhancement using KLMS, d) enhancement using KSRLMS, e) enhancement using KSLMS, f) enhancement using KSSLMS, g) enhancement using MKLMS, h) enhancement using MKSRLMS, i) enhancement using MKSLMS, and j) enhancement using MKSSLMS.

From these calculations, it is clear that MKSRLMS and KLMS differ by a value of −1.3876 with the reduced number of multiplications. The MSD achieved by KLMS, KSRLMS, KSLMS, KSSLMS, MKLMS, MKSRLMS, MKSLMS, MKSSLMS and LMS are 0.2848, 0.3782, 0.3812, 0.3869, 0.2955, 0.3951, 0.4064, 0.4188 and 0.4262, respectively. From these calculations, it is clear that MKSRLMS and KLMS differ by a value of 0.1103 with the reduced number of multiplications.

D. EM REMOVAL USING HYBRID KALMAN NOISE CANCELLERS

In this experiment, we attempted to eliminate EM from ECG signals. Real ECG signals with EM are taken from the MIT-BIH sinus arrhythmia database and are given at the input port, as shown in Fig.1. The reference electrode motion artifact component is generated using DWT decomposition of a contaminated ECG signal. Filtering experiments are performed on the considered database ten times, and the average values are tabulated. The performance metrics SNRI, EMSE and MSD are tabulated in Tables 2, 3 and 4. Fig. 10 shows the filtering results of EM using various algorithms.

Additionally, Fig.11 illustrates the remaining noise component after enhancement due to various techniques. From Fig.11, it is clear that KLMS, KSRLMS, MKLMS and

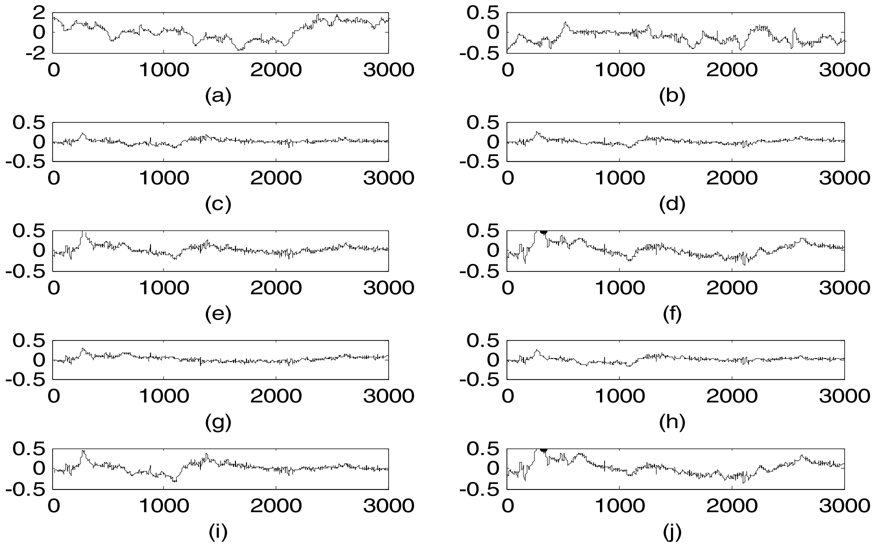

FIGURE 11. Residual Noise after EM filtering a) Electrode motion artifact, b) noise component remains after LMS filtering, c) noise component remains after KLMS filtering, d) noise component remains after KSRLMS filtering, e) noise component remains after KSLMS filtering, f) noise component remains after KSSLMS filtering, g) noise component remains after MKLMS filtering, h) noise component remains after MKSRLMS filtering, i) noise component remains after MKSLMS filtering, and j) noise component remains after MKSSLMS filtering.

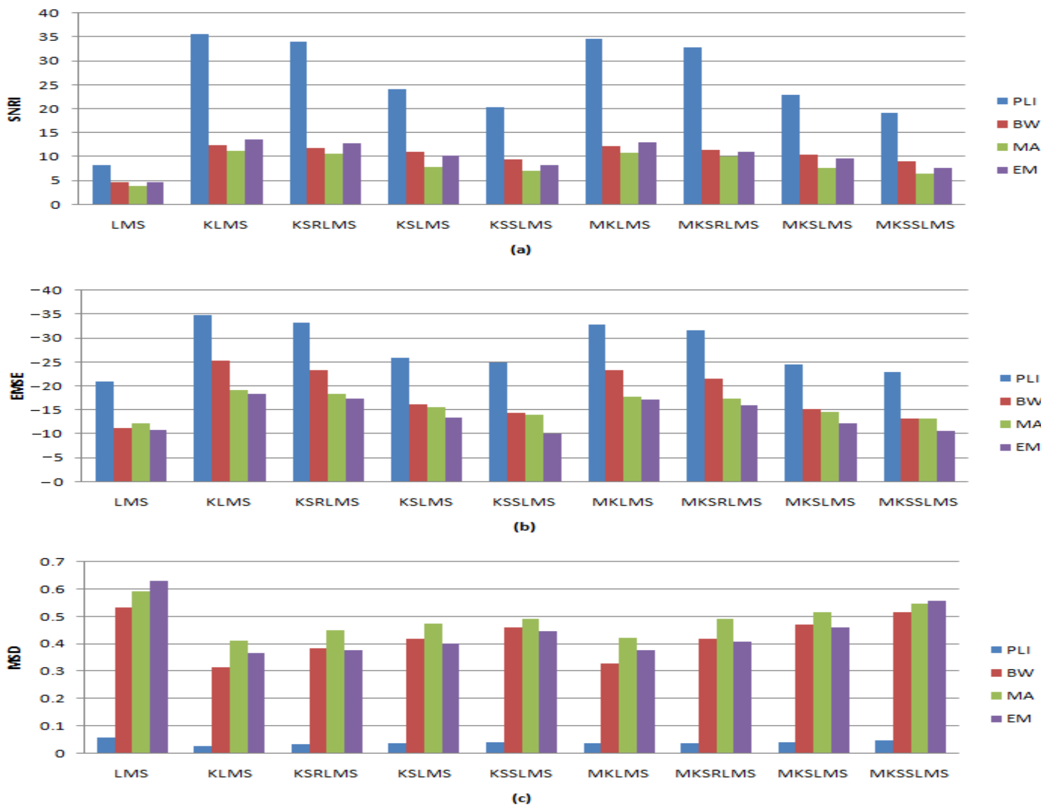

FIGURE 12. Comparison of performance measures during artifact elimination using various KNC.

MKSRLMS perform better than the other algorithms, as the residual noise after filtering using these algorithms is lessened.

Again, among these four algorithms, the performance is judged by comparing SNRI, EMSE and MSD. The simulation results of data105 are shown in Fig. 10, Fig. 11 and Fig. 12 shows a comparison of various performance measure parameters during the EM removal experiments. As shown in Tables 2, 3 and 4, among the algorithms, KLMS achieves the maximum SNRI of 14.3462 dBs., whereas its sign regressor version achieves 13.5073 dBs. with the reduced multiplication operations. Again, by reducing the number of multiplications in the denominator, MKLMS achieves 13.1311 dBs.; its sign regressor version achieves 12.6402 dBs. Therefore, by comparing these four algorithms, it is clear that MKSRLMS is better in the considered KNCs. MKSRLMS attempts to reduce the multiplication operations by an amount equal to the tap size in the denominator part of normalization function as well as in the weight update recursion. By considering the reduced number of multiplications, the difference in SNRI between KLMS and MKSRLMS can be tolerated, which is only 1.7060 dB. The other versions of sign-based KNCs perform worse than KLMS and its sign regressor version.

The conventional LMS-based ANC achieves an SNRI of only 4.7782 dB. A similar type of behavior is observed among the KNCs / ANCs with reference to EMSE and MSD. The EMSE achieved by KLMS, KSRLMS, KSLMS, KSSLMS, MKLMS, MKSRLMS, MKSLMS, MKSSLMS and LMS are −22.3905, −20.5128, −17.8622, −15.9831, −21.7103, −19.6962, −16.8369, −14.5703 and −12.3952, respectively. From these calculations, it is clear that MKSRLMS and KLMS differ by a value of −2.6943 with the reduced number of multiplications. The MSD achieved by KLMS, KSRLMS, KSLMS, KSSLMS, MKLMS, MKSRLMS, MKSLMS, MKSSLMS and LMS are 0.3247, 0.3328, 0.3562, 0.4536, 0.3308, 0.3549, 0.3647, 0.5665and 0.5929, respectively. From these calculations, it is clear that MKSRLMS and KLMS differ by a value of 0.0302 with the reduced number of multiplications.

V. CONCLUSION

In this paper, we present novel noise cancellers for ECG signal enhancement based on the Kalman filter. This proposed methodology is a reference free implementation because of DWT based decomposing the contaminated signal and is independent of step size due to the hybrid version of Kalman algorithm. These two features make the proposed KNC as a novel implementation in the context of ECG enhancement. To achieve better performance, we apply data normalization and signum algorithms with the proposed hybrid algorithm. The resultant KLMS and its variants exhibit superior performance than the conventional LMS-based ANC. These performance measures are presented in Tables 2, 3 and 4. The developed KNCs are demonstrated on real ECG components obtained from the MIT-BIH database. In noise cancellation experiments, KLMS, KSRLMS, MKLMS and MKSRLMS performed better than the other sign algorithm combinations. By considering convergence, computational complexity, SNRI, EMSE and MSD, it is finally concluded that MKSRLMS is well suited for remote health care applications. The key factor that enables the use of this algorithm in real-time implementations is its lower computational complexity.

Consent to Publish

The consent to publish has been obtained from the participant to report individual's data.

Ethics approval
Not applicable

Availability of data and materials

Not applicable

Competing Interests

The authors declare that they have no competing interests.

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