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Artifact Elimination in Impedance Cardiography using Gradient based Adaptive Signal Enhancement Techniques

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Abstract*: Impedance Cardiography (ICG) is a noninvasive method for indirect measurement of stroke volume, monitoring the cardiac output and observing the other hemodynamic parameters by the blood volume changes in the body. The blood volume changes inside a certain body segment due to a number of physiological processes are extracted in the form of the impedance variations of the body segment. The ICG analysis provides the heart stroke volume in sudden cardiac arrest. In the clinical environment desired ICG signals are influenced by several physiological and non-physiological artifacts.As these artifacts are not stationary in nature, we proposed adaptive filtering techniques to eliminate the artifacts. In this paper we used Least Mean Square (LMS), Least Mean Fourth (LMF), Median LMS (MLMS), Leaky LMS (LLMS), and Dead Zone (DZLMS) adaptive techniques to eliminate artifacts from the desired signals. Several adaptive signal enhancement units (ASEUs) are developed based on these adaptive techniques, and evaluated on the real ICG signal components. The ability of these algorithms is evaluated by performing the experiments to eliminate the various artifacts such as sinusoidal artifacts (SA), respiration artifacts (RA), muscle artifacts (MA) and electrode artifacts (EA). Among these techniques, the DZLMS based ASEU performs better in the filtering process. The signal to noise ratio improvement (SNRI) for this algorithm is calculated as 11.9140 dB, 7.3657 dB, 10.4060 dB and 10.5125 dB respectively for SA, RA, MA and EA. Hence, the DZLMS based ASEUs are well suitable for ICG filtering in the real time health care monitoring systems.

Index Terms*: Adaptive Filter, Artifacts, Impedance Cardiography, signal enhancement, stroke volume.

I. INTRODUCTION

According to the reports given by World Health Organization (WHO), ischemia Heart disease is the major cause of the death worldwide [1]. One of the popular methods to measure the cardiac activity is hemodynamics, in which the blood flow throughout the body is often measured. Impedance plethysmography methods that use electrical impedance changes on the body surface to measure tissue volume changes. Impedance Cardiography (ICG) is a simple, inexpensive and noninvasive technique to monitor the electrical impedance changes of thorax, which is caused by periodic changes in the volume of blood in aorta. Stroke Volume (SV), Cardiac Output (CO) and other hemodynamic parameters are estimated by using an appropriate thorax model [2]. The variations of thoracic impedance are identified by Electrical bio-impedance that uses electric current stimulation. The Cardiac output is continuously evaluated using electrodes by analyzing the variation of the signal that occurs with various mathematical models. The Research has been initiated in the ICG field with the fluids flow study in the cardiac area using Impedance Plethysmography methods[3]. In [6] the investigation of ICG is presented in subjects with heart diseases during the exercises. With the technology advancement, wearable devices are designed with ICG sensors to facilitate long term recordings and comfort to patients [7]. Theinception of ICG there has been an increase in the reliability and an improvement in the cardiac parameter's measurement [8–12]. During the ICG signal extraction, the desired signal components are influenced by undesired artifact components. The tiny features of the desired components are masked by artifacts, which causes ambiguities during diagnosis [6]. The major artifacts that are contaminated with desired components are Sinusoidal Artifacts (SA), Respiratory Artifacts (RA), Muscle Artifacts (MA) and Electrode Artifacts (EA). Hence, high resolution ICG signals are facilitated by eliminating the artifacts to estimate intensity of stroke volume.Theseartifacts are not stationery in the real-time situations and that's why conventional fixed weighted filters are not preferable for ICG filtering. Thus, adaptive filtering techniques are suitable for ICG filtering to change the filter weights in according to the error component [13]. Until now, several authors are proposed several adaptive signal enhancement techniques [14–17] to enhance the ICG signal. The major drawbacks of these methods are high steady state error, weight drift, round off error and impulsive noise. To overcome thesedrawbacksand to improve the performance of artifact cancelation we developed some hybrid techniques. With these hybrid techniques we can obtainless computation complexity.

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In [18-21] Rahman et al. developed some adaptive noise cancellers to enhance the cardiac signal and brain activity using various LMS variants. We considered the same framework for enhancing the ICG signal filtering. The ASEU performance for ICG signal analysis in a typical health care monitor system can be improved by various hybrid signal processing techniques. Signal enhancement capability, convergence rate, and computational complexity are the characteristics of interest in any typical health care monitor system. To achieve this, we developed various adaptive techniques. Least Mean Square (LMS) algorithm is the fundamental adaptive algorithm. Higher order filters can perform better than the estimation of mean square employed in the LMS algorithm. The minimization of the fourth moment of the output estimation error called as Least-Mean Fourth (LMF) algorithm. In this paper we developed hybrid algorithms with the combination of LMS algorithm, these algorithms are Median LMS (MLMS) algorithm, Leaky LMS (LLMS) algorithm and Dead Zone LMS (DZLMS) algorithm. The implementation of these algorithms is demonstrated in the next section. Based on the simulation results the DZLMS based ASEUs perform better than the remaining variants.

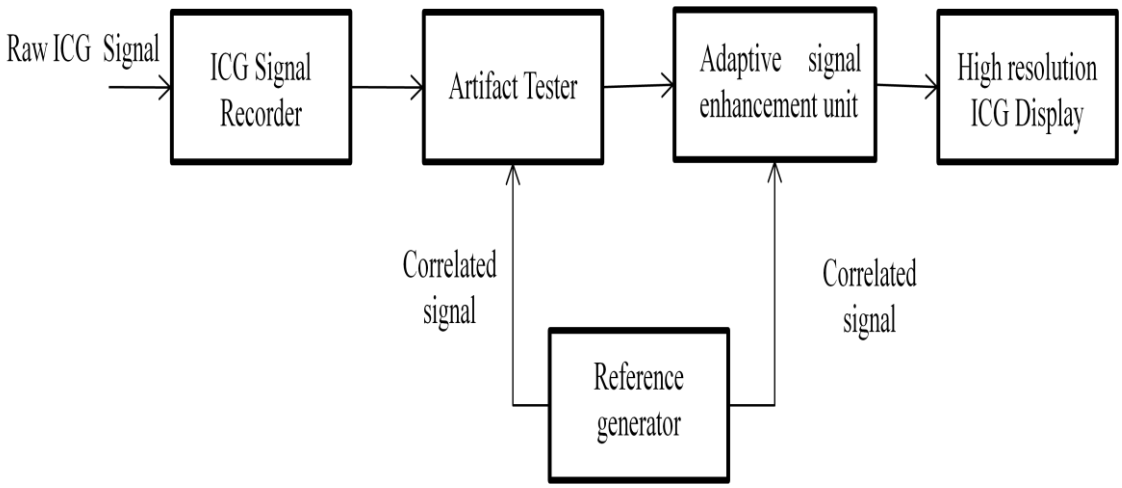

Fig. 1: Block diagram of proposed ICG signal analyzer.

II. ENHANCEMENT OF IMPEDANCE CARDIOGRAPHY SIGNALS USING HYBRID TECHNIQUES

In the clinical environment various artifacts are contaminated with the ICG signal and causes ambiguity in the diagnosis. Hence the artifacts should be removed in order to enhance the desired ICG signal. The physiological components of the artifacts are not stationary in nature. Hence, we have to apply adaptive filtering techniques to eliminate the clutter components in the noisy input ICG signal. Fig. 1 shows the block diagram of typical health care system for ICG analysis. The input to the system is noisy ICG signal recorded from the corresponding input electrodes. Thenoise type can be identified by the recorded quantities that are subjected to normalized power testing. For this, we have to use a reference generator that consists of several artifact samples. Once the type of artifact is identified the noisy ICG signal is fed as an input to ASEU. The correlated noise component signal is given as reference input to ASEU. Fig. 2 shows the internal structure of an ASEU. ASEU is the key block in the typical health care system. Therefore, this paper presents several signal processing techniques for developing ASEU.An ASEU consists of a FIR filter and an adaptive weight update mechanism. We developed several strategies for weight updating. For this, an LMS based adaptive filter is considered with tap length L.The input to the EU is x(n). This includes impedance component h(n) and artifact component N(n). η(n) is the correlated noise signal generated by the reference generator. Let q(n) is the FIR filter impulse response, z(n) is the output of FIR filter, ε(n) be the error signal.

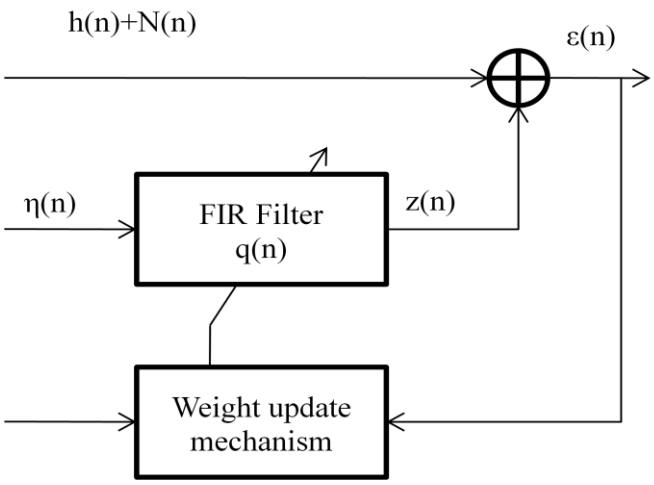

Fig. 2: A typical adaptive signal enhancement unit (ASEU).

The weight updating mechanism for an LMS based SEU can be mathematically written as,

$$q(n+1) = q(n)+\lambda x(n)\varepsilon(n) \quad (1)$$

Where, $q(n) = [q_0(n)\ q_1(n)\ \ldots\ q_{L-1}(n)]^t$ is the nth tap weight vector, $x(n) = [x(n)\ x(n-1)\ \ldots\ x(n-L+1]^t$ is input sequence, $\varepsilon(n) = x(n)-q^t(n)\eta(n)$ and 'λ' represents a step-size.

A. Least Mean Fourth algorithm

Adaptive filters with higher order can perform better than the LMS estimation in the particular scenarios. In order to observe this, we considered fourth order filter to eliminate artifacts from desired ICG signals. One such example is Least Mean Fourth algorithm [27], in this the fourth moment of the output estimation error is minimized. LMF algorithm tries to a higher power of the error signal, particularly the fourth order. The weight update mechanism for an LMS based SEU can be mathematically represented as,

$$\boldsymbol{q}(n+1) = \boldsymbol{q}(n) + \lambda \boldsymbol{x}(n)\varepsilon^3(n) \qquad (2)$$

In comparison with LMS algorithm, the LMF algorithm provides least steady state error (SSE). This is due to the fact that in the LMS algorithm the excess mean-square error depends only on the second order noise component. Whereas in LMF algorithm the excess mean-square error depends on fourth order moments of the noise component that consequence in lower SSE as compared to the conventional LMS algorithm. This provides good stability and fast convergence rate. The higher-order statistics require smaller step-size in the LMF algorithm to ensure stable adaptation [28]-[29].

2.2 Median LMS Algorithm (MLMS)

The performance of LMS and its derivatives is considerably degraded when it wasapplied to input signals that are corrupted by impulsive noise, sometimes this creates instability. In ICG signal processing this case happens when the amplitude of the wave increases. This problem can be reduced by using a nonlinear filter to smoothing the noisy gradient components. This modification leads to median LMS [22]. The calculation of the median size of the window L + 1, for each component of the gradient vector, will smoothout the impulsive noise [30] effect. If the input signal and reference signal are not corrupted by impulsive noise the MLMS performance is same as the conventional LMS, thus the extra computation cost of MLMS is not worth.

The weight update recursion is given by,

$$\boldsymbol{q}(n+1) = \boldsymbol{q}(n) + \lambda . med_L[\boldsymbol{x}(n)\varepsilon(n), \boldsymbol{x}(n-1)\varepsilon(n-1 \ldots\ldots \boldsymbol{x}n-L\varepsilon(n-L)] \qquad (3)$$

The median function is used to reject single occurrence of large spikes of noise. These spikes may affect the estimates of $\boldsymbol{q}(n)$ and introduce impulsive errors. This phenomenon can be effectively utilized in the situations, in which ICG signal is contaminated with the artifacts.

2.3 Leaky LMS algorithm

The LMS algorithm is widely used in many applications due to its simplicity. It is very sensitive to rounding errors and creates other perturbations, since the weight recursion equation is basically an integrator. For example, inadequate excitation in the input sequence may cause the unbounded constraint estimates. Since the un-damped modes become unstable [23], it is necessary that LMS algorithm stability causes these modes to zero. Such problems can be avoided by introducing a small leakage factor ξ into the weight vector. The effect of ξ is the un-damped modes are forced to zero if either $\varepsilon(n)$ or $x(n)$ is zero [24]. The parameter $\xi$is known as the leak and the algorithm is referred to as leaky LMS algorithm (LLMS).

The weight update recursion is given by,

$$\boldsymbol{q}(n+1) = (1-\lambda\xi)\boldsymbol{q}(n) + \lambda\varepsilon(n)\boldsymbol{x}(n) \qquad (4)$$

In (4) the product $\lambda\xi$ has been chosen in such a way that it should be greater than but close to zero. The LLMS is used to enhance the adaptive filter characteristics; which we exploit to efficiently cancel the artifacts from ICG signals, few are listed below.

1. It is useful to improve the convergence properties when the input correlation matrix is not well conditioned.
2. Algorithm that stops when the correction term is too small.
3. Over flow due to finite-precision arithmetic.

2.4 Dead Zone LMS algorithm

The smaller values of $\varepsilon(n)$ may stand for disturbances but may also result from numerical instability. In an ICG noise canceller the small and large errors may create additional filtering operations, leading to a delay in decision making. Under typical conditions the decision must be made instantaneously. These extra computations are avoided by setting a threshold value for the error. The Dead Zone LMS (DZ-LMS) is used in various signal processing applications to reduce the problems with rounding errors. The algorithm applies nonlinearity of the dead zone. If the error signal falls below the pre-defined threshold value then the algorithm stops uploading the tap-weight vector. We use this property of DZ-LMS in filtering the ICG signal. This Dead Zone nonlinearity is defined as

$$d\{m\} = \begin{Bmatrix} m-\alpha, m > \alpha > 0 \\ 0, -\alpha < m < \alpha \\ m+\alpha, m < -\alpha \end{Bmatrix} \qquad (5)$$

where $\alpha$is threshold.

The weight update recursion is given by,

$$\boldsymbol{q}(n+1) = \boldsymbol{q}(n) + \lambda\boldsymbol{x}(n)d\{\varepsilon(n)\} \qquad (6)$$

In this paper we developed several ASEUs and the performance of these ASEUs are tested with real time ICG signal components. Fig. 3 shows the convergence characteristics of proposed algorithms. From the convergence curves it is observed that DZLMS converges faster than other techniques.

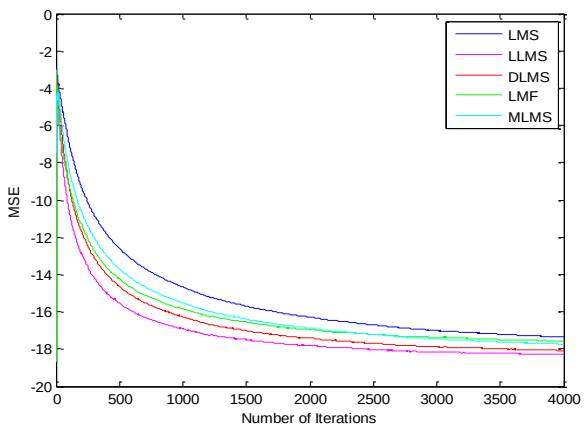

Fig. 3: Convergence characteristics of proposed algorithms.

III. SIMULATION RESULTS

To exhibit that the proposed techniques are actually efficient in clinical situations, various ICG signals are used to evaluate the proposed techniques. In the simulation experiments we have taken ICG signal samples from five distinct persons. The proposed techniques are evaluated by considering *Signal to Noise Ratio Improvement* (*SNRI*), *Excess Mean Square Error* (*EMSE*) and *Misadjustment*(*MSAD*) for the five experiments, averaged and compared with conventional LMS based ASEU. Tables 1-3 give the characteristics of proposed implementations. In the experiments five ICG samples record 1, record 2, record 3, record 4 and record 5 are used. These ICG records are contaminatedwith artifacts such as SA, RA, MA and EA. Various ASEUs for ICG enhancement is developed using the LMS, LMF, MLMS, LLMS, DZLMS algorithms. The signal analyzer consists of reference generator that generates four types of artifacts synthetically by using the real artifacts features taken from the MIT-BIH databases. The Artifact tester compares the power spectral density (PSD) of the input noisy signal and synthesized artifact obtained from the reference generator. By doing so, reference generator can identify the type of noise in the input signal. So that the similar type of correlated noise component is applied as reference signal to ASEU. This ASEU is influenced by an adaptive algorithm to update its filter weights based on input data. Based on these considerations, in our experiment, we have implemented five ASEUs using the algorithmsdiscussed in above section. These ASEUs are operated under four modules to remove the artifacts SA, RA, MA and EA respectively. The comparison of these techniques in ICG filtering for various artifacts is shown in Fig. 4. Due to space considerations, we have shown the experimental results for removal of two artifacts for record 1. Fig. 5 shows a typical ICG signal component contaminated with various types of artifacts.

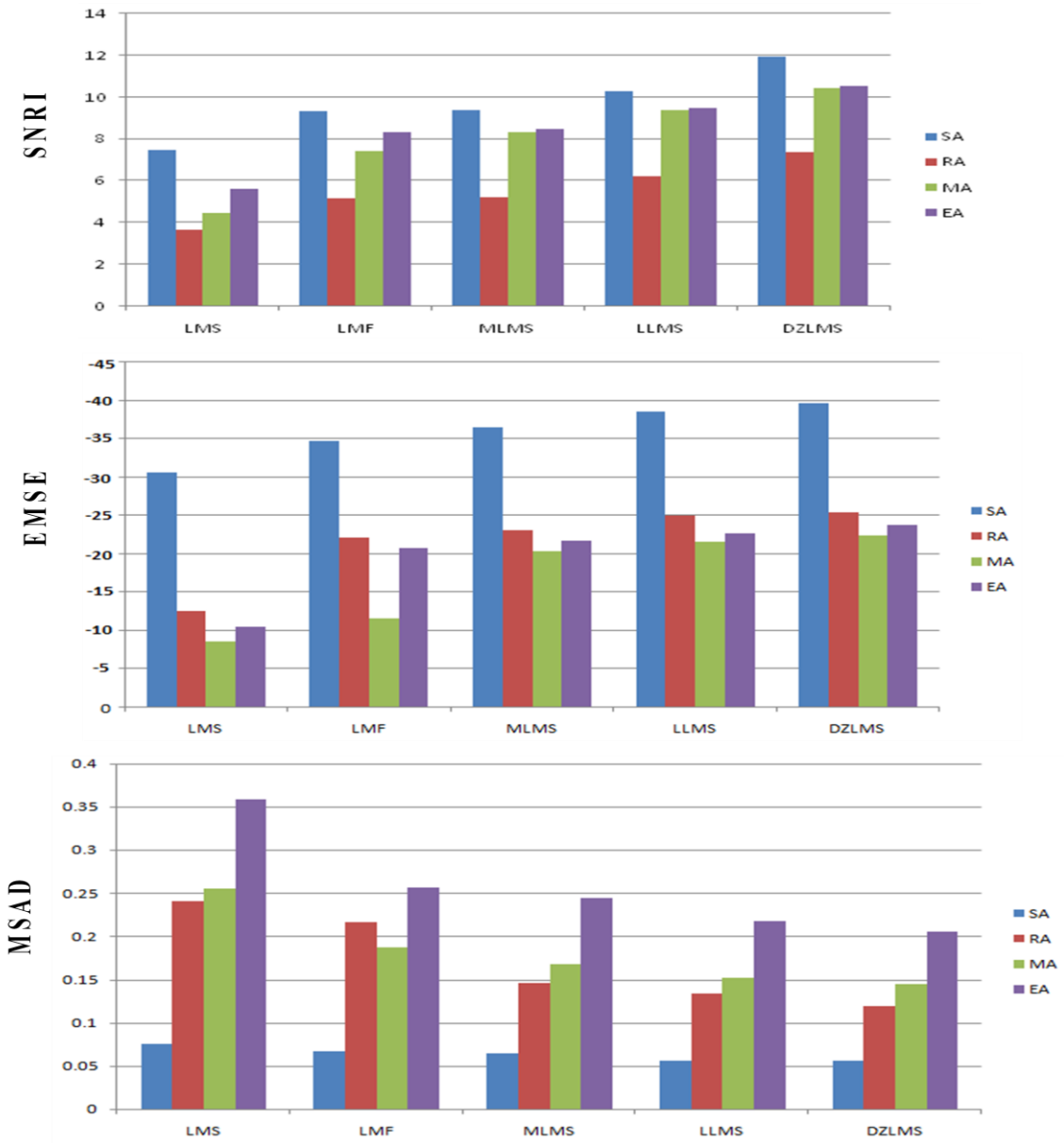

Fig. 4: Comparison of performance measures in ICG filtering due to various adaptive filters.

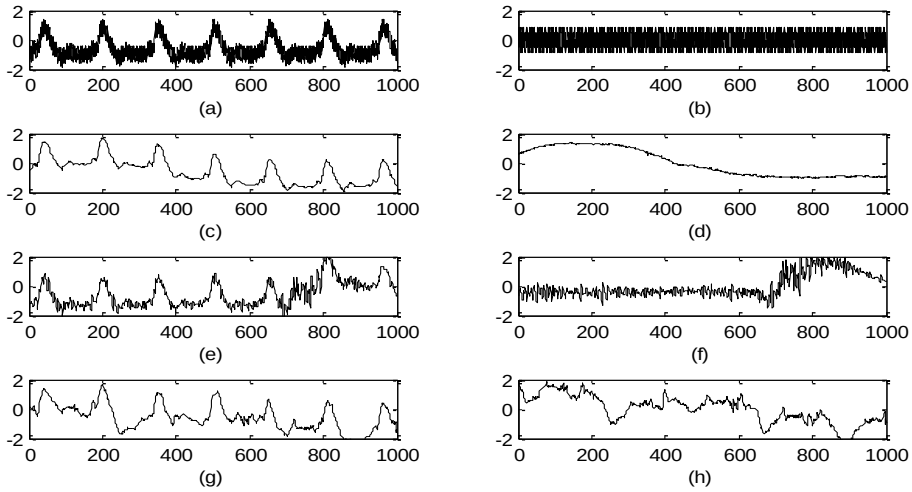

Fig. 5:A typical ICG component with various artifacts (a) ICG with SA, (b) SA component, (c) ICG with RA, (d) RA component, (e) ICG with MA, (f) MA component, (g) ICG with EA, (h) EA component. (Number of samples are taken x-axis, and amplitude in millivolts is taken on y -axis).

A. Filtering of Sinusoidal Artifacts (SA) Using Adaptive Algorithms

In this experiment removal of SA components from input signal is performed. The input to the ASEU is noisy ICG as shown in Fig. 5(a). This input signal contains desired ICG signal and SA components, and it is applied as the input to ASEU shown in Fig. 2. By comparing the input signal PSD components, artifact tester and reference generator generates a reference signal to the ASEU. The reference signal is correlated to artifact component present in the noisy input signal. The adaptive algorithm automatically updates the filter coefficients based on error components. For updating the filter coefficients, the algorithm constitutes the reference signal so that it correlated as much as possible with the actual noise component and cancels each other. The performances of these techniques are compared with SNRI, EMSE and MSAD. These are averaged for five experiments for each artifact and are tabulated in Tables 1–3. From the experimental results we can observed that DZLMS based ASEU filters the SA components from the input signal almost completely. This technique requires a smaller number of computations hence it could be preferred for real time applications. The filtering capability of the proposed ASEUs in terms of SNRI is calculated as **7.4758** dBs, **9.3221** dBs, **9.3460** dBs, **10.2499** dBs and 11.**9140**dBs for LMS, LMF, MLMS, LLMS and DZLMS respectively. DZLMS achieves EMSE, MSAD as **-39.5453** dBs and **0.0556** dBs respectively. Based on these performance measures it may be concluded that DZLMS based ASEU performs better in SA filtering of ICG signals. Hence, this technique is recommendable for the implementation in real time health care monitoring devices and wearable remote health care systems.

B. Filtering of Respiration Artifact (RA) using Adaptive Algorithms

This experiment shows the enhancement process of desired ICG component contaminated with RA. Here also the raw ICG is fed to ASEU as shown in Fig. 2. A correlated respiration activity, component obtained from a reference generator after PSD comparison analysis is given to ASEU. The ICG affected with RA is shown in Fig. 5(c). Fig. 6 shows the simulation results of our experiments. The performance measures for five samples are shown in Tables 1–3. The DZLMS based ASEU performs better among all algorithms. This enables DZLMS based artifact canceller is better than all other counterparts. The filtering capability of the proposed ASEUs in terms of SNRI is calculated as **3.6509** dBs, **5.1280** dBs, **5.1941** dBs, **6.1988** dBs and **7.3657** dBs for LMS, LMF, MLMS, LLMS and DZLMS respectively. DZLMS achieves EMSE, MSAD as **-25.2445** dBs and **0.1194** dBs respectively. By comparing the performance measures among all the algorithms, it seems as DZLMS based ASEU is better with reference to computational complexity, SNRI, EMSE and MSAD. Hence, these realizations are well suited for real time implementations.

C. Filtering of Muscle Artifact (MA) using Adaptive Algorithms

This experiment demonstrates the enhancement process of ICG component encountered with MA. The desired ICG signal is affected by muscle artifact is applied as the input signal to ASEU as shown in Fig. 2. A signal produced by muscle activity correlated with artifact present in the input noisy signal is given as reference signal to adaptive ASEU. The ICG affected with MA is shown in Fig. 5(e). Fig. 7 shows the simulation results for removal of MA. The performance measures for five samples are shown in Tables 1–3. The DZLMS based ASEU performs better among all algorithms. This enables DZLMS based artifact canceller is better than all other counterparts. The filtering capability of the proposed ASEUs in terms of SNRI is calculated as **4.4266** dBs, **7.4133** dBs, **8.3038** dBs, **9.3605** dBs and **10.4060** dBs for LMS, LMF, MLMS, LLMS and DZLMS respectively. DZLMS achieves EMSE, MSAD as **-22.2441** dBs and **0.1442** dBs respectively. By comparing the performance measures among all the algorithms, it seems as DZLMS based ASEU is better with reference to computational complexity, SNRI, EMSE and MSAD. Hence, these realizations are well suited for real time implementations.

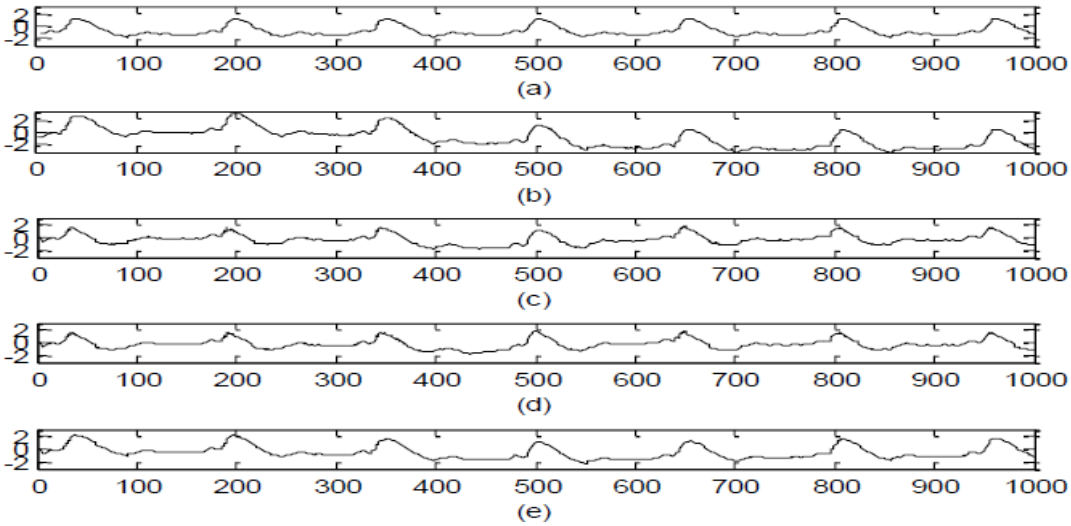

Fig. 6. Typical ICG enhancement results of RA cancelation (a) ICG filtered with LMS algorithm, (b) ICG filtered with LMF algorithm, (c) ICG filtered with MLMS algorithm, (d) ICG filtered with LLMS algorithm, (e) ICG filtered with DZLMS algorithm. (Number of samples are taken x-axis, and amplitude in millivolts is taken on y -axis).

D. Filtering of Electrode Artifact (EA) using Adaptive Algorithms

This experiment shows that the enhancement process of ICG component influenced by EA. The desired ICG signal is affected by electrode artifact is applied as an input to ASEU as shown in Fig. 2. A noise signal generated by electrode activity correlated with artifact present in the noisy input is applied as reference signal to ASEU. The ICG affected with EA is shown in Fig. 5(g). The performance measures for five samples are shown in Tables 1–3. The DZLMS based ASEU performs better among all algorithms. This enables DZLMS based artifact canceller is better than all other counterparts. The filtering capability of the proposed ASEUs in terms of SNRI is calculated as **5.5846** dBs, **8.2974** dBs, **8.4698**dBs, **9.4781**dBs and **10.5125**dBs for LMS, LMF, MLMS, LLMS and DZLMS respectively. DZLMS achieves EMSE, MSAD as **-23.6647** dBs and **0.2053**dBs respectively. By comparing the performance measures among all the algorithms, it seems as DZLMS based ASEU is better with reference to computational complexity, SNRI, EMSE and MSAD. Hence, these realizations are well suited for real time implementations.

IV. CONCLUSION

In this paper several efficient artifact filtering techniques are developed for ICG signal. In order to achieve fast convergence rate and enhancement capability we used various ASEUs based on LMS, LMF, MLMS, LLMS and DZLMS algorithms. These methods are tested in real time to eliminate artifacts like SA, RA, MA and EA from noisy input ICG signals. The convergence characteristics of proposed techniques are shown in fig. 3. The experimental results are shown in fig. 6-7. From the simulation results we can observe that DZLMS based ASEU performs better with reference to computational complexity, SNRI, EMSE and MSAD. Hence, these realizations are well suited for real time applications.

REFERENCES

1. World health statistics 2014—A wealth of information on global public health. *World Health Organization* (2014).
2. Shyu Liang-Yu, Chiang Chia-Yin, Liu Chun-Peng, Hu Wei-Chih. "Portable Impedance Cardiogra-phy System for Real-Time Noninvasive Cardiac Output Measurement"., Journal of Medical and Biological Engineering, 20(4), (2000), pp. 193-202.
3. G. D. Jindal et al, "Corrected formula for estimating peripheral blood flow by impedance plethysmography," Med. Biol. Eng. Comput., 32, (1994), pp. 625-628.
4. W. Nechwatal, P. Bier, A. Eversmann, and E. Knig, The noninvasive determination of cardiac output by means of impedance cardiography: Comparative evaluation with a thermal dilution technique. *Basic Research in Cardiology* 71, 542 (1976).
5. J. C. Denniston, J. T. Maher, J. T. Reeves, J. C. Cruz, A. Cymerman, and R. F. Grover, Measurement of cardiac output by electrical impedance at rest and during exercise. *Journal of Applied Physiology* 4, 140 (2011).
6. 6.Y. Zhang *et al*, "Cardiac output monitoring by impedance cardiography during treadmill exercise," *IEEE Trans. Biomed. Eng.*, vol. 33(11), pp. 1037-1041, Nov. 1986.
7. Marquez JC, Remp°er M, Seoane F and Lindecrantz K. Textrode-enabled transthoracic electrical bioimpedance measurements-towards wearable applications of impedance cardiography. Journal of Electrical Bioimpedance: Vol. 4; pp. 45-50; 2013.
8. A. Harley and J. C. Greenfield, Jr., Determination of cardiac output in man by means of impedance plethysmography. *Aerospace Medicine* 39, 248 (1968).
9. R. P. Patterson, Fundamentals of impedance cardiography. *IEEE Engineering in Medicine and Biology Mag.* 8, 35 (1989).
10. M. J. Major, World, Estimation of cardiac output by bioimpedance cardiography. *Journal of the Royal Army Medical Corps.* 136, 92 (1990).
11. Nancy M. Albert, Bioimpedance cardiography measurements of cardiac output and other cardiovascular parameters. *Critical Care Nursing Clinics of North America* 18, 195 (2002).
12. C. V. Parmar, Divyesh L. Prajapati, P. A. Gokhale, H. B. Mehta, and C. J. Shah, Study of cardiac output based on non-invasive impedance plethysmography in healthy volunteers. Innovative Journal of Medical and Health Science 2, 104 (2012).
13. A. N. Ali, Advanced Bio Signal Processing, Springer Verlag, Berlin, Germany (2009).
14. O. Dromer, O. Alata, and O. Bernard, Impedance cardiography filtering using scale fourier linear combiner based on RLS algorithm, *IEEE EMBS*, September (2009).

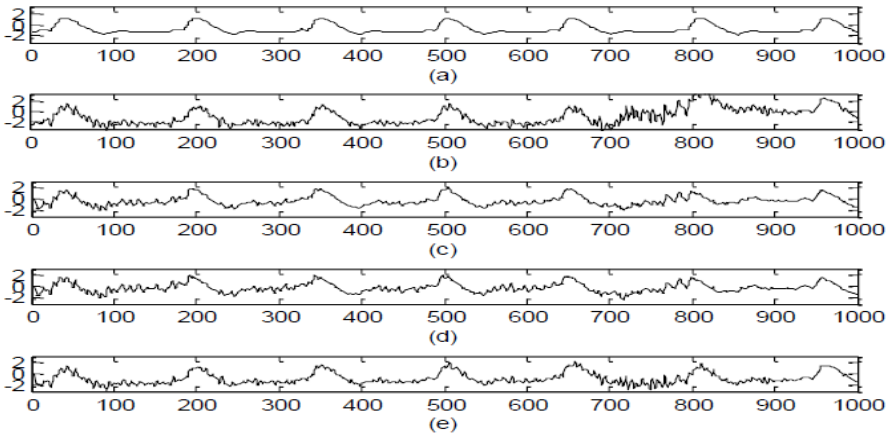

Fig. 7. Typical ICG enhancement results of MA cancelation (a) ICG filtered with LMS algorithm, (b) ICG filtered with LMF algorithm, (c) ICG filtered with MLMS algorithm, (d) ICG filtered with LLMS algorithm, (e) ICG filtered with DZLMS algorithm. (x-axis number of samples and y -axis amplitude in millivolts).

15. G. H. M. Willemsen, E. J. C. De Geus, C. H. A. M. Klaver, L. J. P. Van Doornen, and D. Carroll, Ambulatory monitoring of the impedance cardiogram, Psychophysiology, Cambridge University Press (1996), Vol. 33, pp. 184–193.
16. Vinod K. Pandey and Prem C. Pandey, Cancellation of respiratory artifact in impedance cardiography. *EMBS, IEEE* (2005).
17. Haykin, Adaptive Filter Theory, Eaglewood Clirs, Prentice-Hall, NJ (1991).
18. S. C. Douglas, A family of normalized LMS algorithms. IEEE Signal Processing Letters 1, 49 (1994).
19. J. J. Jeong, K. Koo, G. T. Choi, and S. W. Kim, A variable step size for normalized subband adaptive filters. IEEE Signal Processing Letters 19, 906 (2012).
20. H. C. Huang and J. Lee, A new variable step-size NLMS algorithm and its performance analysis. IEEE Transactions on Signal Processing 60, 2055 (2012).
21. K. Mayyas ; T. Aboulnasr, "Leaky LMS algorithm: MSE analysis for Gaussian data", IEEE Transactions on Signal Processing, vol.45, issue. 4, 1997, pp. 927-934.
22. K.F. Wan ; P.C. Ching, "A fast response split-path median LMS algorithm", EEE Transactions on Circuits and Systems II: Analog and Digital Signal Processing, Volume: 43 , Issue: 4,pp. 344 – 346, 1996.
23. K. Mayyas ; T. Aboulnasr, "Leaky LMS algorithm: MSE analysis for Gaussian data", IEEE Transactions on Signal Processing, vol.45, issue. 4, 1997, pp. 927-934.
24. Mohammad Shukri Salman ; Mohammad Naser SabetJahromi ; AykutHocanin ; Osman Kukrer, "A weighted zero-attracting Leaky LMS algorithm", SoftCOM 2012, 20th International Conference on Software, Telecommunications and Computer Networks, 2012, pp.1-3.

Table 1: SNRI computations for various filtering techniques during ICG enhancement (all the values are in dBs).

Noise Type	Record Number	LMS	LMF	MLMS	LLMS	DZLMS
SN	1	7.5735	9.3378	9.4283	10.2482	11.7073
	2	7.0427	8.7284	8.8463	9.1973	11.6556
	3	7.2253	9.2493	9.1369	10.3517	11.5277
	4	7.8312	9.8048	9.7829	10.7443	12.5782
	5	7.7061	9.4904	9.5356	10.7079	12.1012
	Avg.	**7.4758**	**9.3221**	**9.3460**	**10.2499**	**11.9140**
RN	1	3.8562	5.0599	5.7126	6.4512	7.2357
	2	3.9863	5.9103	6.2264	7.0063	8.7893
	3	3.1553	4.5137	4.1920	5.1426	6.7743
	4	3.4827	4.6741	4.4882	6.0185	6.9427
	5	3.7738	5.4821	5.3515	6.3754	7.0864
	Avg.	**3.6509**	**5.1280**	**5.1941**	**6.1988**	**7.3657**
MN	1	4.1067	7.2603	8.0473	9.3218	10.2673
	2	4.3682	7.4762	8.2854	9.4475	10.5641
	3	4.6382	7.6638	8.4428	9.6186	10.6588
	4	4.0552	6.8004	7.7493	8.7569	9.7906
	5	4.9649	7.8659	8.9943	9.6578	10.7493
	Avg.	**4.4266**	**7.4133**	**8.3038**	**9.3605**	**10.4060**
EN	1	5.4344	8.3233	8.4483	9.3658	10.4748
	2	5.0637	7.3453	7.7886	9.1484	9.7642
	3	5.9856	8.7382	8.8639	9.7839	10.9438
	4	5.8538	8.5953	8.6743	9.6174	10.7819
	5	5.5857	8.4847	8.5737	9.4748	10.5979
	Avg.	**5.5846**	**8.2974**	**8.4698**	**9.4781**	**10.5125**

Table 2: EMSE computations for various filtering techniques during ICG enhancement (all the values are in dBs).

Noise Type	Record Number	LMS	LMF	MLMS	LLMS	DZLMS
SN	1	-30.5369	-34.6285	-36.7729	-38.5094	-39.4206
	2	-30.9784	-35.3695	-36.9974	-38.8649	-39.9064
	3	-30.1202	-34.0032	-35.5783	-38.1004	-39.2177
	4	-30.3227	-34.1483	-35.6442	-38.3221	-39.4628
	5	-30.7375	-35.0674	-36.8023	-38.7036	-39.7188
	Avg.	**-30.5391**	**-34.6434**	**-36.3590**	**-38.5001**	**-39.5453**
RN	1	-12.2738	-21.3693	-22.5683	-24.4745	-25.7363
	2	-12.6742	-22.6352	-23.2539	-25.5373	-26.3621
	3	-12.3849	-21.8643	-22.9956	-24.6215	-25.9874
	4	-12.9735	-22.8937	-23.7548	-25.9659	-26.8527
	5	-12.0494	-21.0053	-22.1345	-24.1164	-21.2839
	Avg.	**-12.4712**	**-21.9536**	**-22.9414**	**-24.9431**	**-25.2445**
MN	1	-8.9736	-19.7362	-20.6483	-21.8541	-22.6353
	2	-8.4456	-19.4728	-20.3647	-21.5285	-22.4476
	3	-8.0687	-18.6389	-19.5546	-20.6382	-21.7603
	4	-8.7386	19.5862	-20.4829	-21.6279	-22.2397
	5	-8.1245	-19.2316	-20.2879	-21.3876	-22.1378
	Avg.	**-8.4702**	**-11.4987**	**-20.2677**	**-21.4073**	**-22.2441**
EN	1	-10.0543	-20.2653	-21.3169	-22.1124	-23.2697
	2	-10.8678	-20.9752	-21.8964	-22.7649	-23.9975
	3	-10.6685	-20.7594	-21.5429	-22.6428	-23.6753
	4	-10.1654	-20.3572	-21.4982	-22.3846	-23.5668
	5	-10.5279	-20.8518	-21.6638	-22.7002	-23.8144
	Avg.	**-10.4568**	**-20.6418**	**-21.5836**	**-22.5210**	**-23.6647**

Table 3: MSAD computations for various filtering techniques during ICG enhancement (all the values are in dBs).

Noise Type	Record Number	LMS	LMF	MLMS	LLMS	DZLMS
SN	1	0.0754	0.0692	0.0658	0.0578	0.0565
	2	0.0725	0.0646	0.0613	0.0545	0.0533
	3	0.0704	0.0612	0.0602	0.0514	0.0521
	4	0.0795	0.0698	0.0685	0.0593	0.0581
	5	0.0776	0.0674	0.0664	0.0587	0.0578
	Avg.	**0.0751**	**0.0664**	**0.0644**	**0.0563**	**0.0556**
RN	1	0.2651	0.2456	0.1683	0.1472	0.1194
	2	0.2537	0.2289	0.1527	0.1422	0.1332
	3	0.2602	0.2432	0.1626	0.1436	0.1167
	4	0.2256	0.2013	0.1273	0.1232	0.1153
	5	0.2014	0.1632	0.1182	0.1154	0.1125
	Avg.	**0.2412**	**0.2164**	**0.1458**	**0.1343**	**0.1194**
MN	1	0.2416	0.1853	0.1636	0.1543	0.1369
	2	0.2377	0.1746	0.1537	0.1474	0.1255
	3	0.2176	0.1547	0.1386	0.1279	0.1184
	4	0.2975	0.2172	0.1997	0.1687	0.1784
	5	0.2818	0.2044	0.1844	0.1637	0.1619
	Avg.	**0.2552**	**0.1872**	**0.1680**	**0.1524**	**0.1442**
EN	1	0.3712	0.2668	0.2536	0.2153	0.2039
	2	0.3579	0.2473	0.2316	0.2014	0.1954
	3	0.3006	0.2103	0.2087	0.1963	0.1873
	4	0.3952	0.2961	0.2775	0.2649	0.2392
	5	0.3704	0.2642	0.2516	0.2122	0.2005
	Avg.	**0.3591**	**0.2569**	**0.2446**	**0.2180**	**0.2053**

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