Artifact Cancellation from Cardiac Signals in Health Care Systems using a Zoned Adaptive Algorithm

Asiya Sulthana, Zia Ur Rahman

Abstract: ***Electrocardiogram (ECG) is a noninvasive technique for indirect evaluation of volume of stroke, output related to cardiac is monitoredalsoobservation ofaddedparameters that are hemodynamic thru changes related to blood volume is done within the body. Changes taking place in the blood volume inside a certain body segment due to several physiological processes are extracted in the form of the impedance variations of the body segment. The Analysis of ECG facilitates the heart stroke volume in sudden cardiac arrest. In the clinical environment ECG signals are affected by various physiological and non-physiological artifacts.As these artifacts are not stationary, we propose adaptive filtering techniques to improve ECG signals. In this paper we used normalized version of Dead Zone Least Mean Square (NDZLMS) adaptive techniques to remove artifacts in ECG signals. So as to minimize the computational complexity, this DZLMS is combined with sign algorithms and results Sign Regressor NDZLMS (SRNDZLMS), Sign NDZLMD (SNDZLMS), Sign Sign NDZLMS (SSNDZLMS) algorithms. Based on these algorithms, several adaptive signal enhancement units (ASEUs) are developed and validated on the real ECG signal components.To ensure the ability of these algorithms, four experiments were performed to eliminate the various artifacts such as sinusoidal artifacts (SA), respiration artifacts (RA), muscle artifacts (MA) and electrode artifacts (EA). Among these techniques, the ASEU based on SRNDZLMS performs better with respect to process of filtering. The signal to noise ratio improvement (SNRI) for this algorithm is calculated as 21.8684 dB, 8.4544 dB, 8.6966 dB and 8.7101 dB respectively for SA, RA, MA and EA. Hence, the SRNDZLMS based ASEUs are more suitable for filtering ECG signal in real health care monitoring systems.***

Index Terms: ***adaptive filter, artifacts, electrocardiogram, signal enhancement, stroke volume***

I. INTRODUCTION

Ischemia Heart disease remains one of the leading causes of death worldwide based on World Health Organization (WHO) reports[1]. Hemodynamics is a popular method to measure the cardiac activity, in which the flow of the blood throughout the body is often measured. Impedance plethysmography methods that use electrical impedance changes on the body surface to measure tissue volume changes. Electrocardiogram (ECG) is a simple, inexpensive and noninvasive method to monitor electrical impedance changes for thorax, which is initiatedthru periodic changes in the volume of blood in aorta. An appropriate thorax model can be used to estimate Cardiac Output (CO), Stroke Volume (SV), alsoadditionalfactors that are hemodynamic [2]. Bio-impedance in electrical form identifies the variations related to thoracic impedance using electric current stimulation. The output related to Cardiac standsconstantly evaluated by means of electrodes by analyzing the variation of the signal that occurs with various mathematical models. The Research has been stared within area of ECG thru study related to fluids flow within cardiac area with the use of methods for Impedance Plethysmography[3]. In [6] the investigation of ECG is presented in subjects with heart diseases during the exercises. With the advancement in technology, wearable devices with ECG sensors are designed to facilitate recordings of long termalsorelieffor patients [7]. Fromorigin ofECG,an increase within reliability alsoenhancementrelated to cardiac parameter's measurement is presented [8–12].

While extracting the ECG signal, the desired signal components are contaminated with undesired artifacts. Minute features related to desired signal are masked by artifacts, which causes ambiguities during diagnosis [6]. The leading artifacts are Sinusoidal Artifacts (SA), Respiratory Artifacts (RA), Muscle Artifacts (MA) and Electrode Artifacts (EA). Hence, to facilitate high resolution ECG signal for estimating intensity of stroke volume these artifacts need to be eliminated. In the real-time situations, these artifacts are not stationery and that's why conventional fixed weighted filters are not appropriate for ECG filtering. Thus, adaptive filtering techniques are suitable to change the filter weights in according to the error component [13]. Until now, several authors are proposed techniques to enhance the ECG signal using several adaptive signal enhancement techniques [14–17]. The drawbacks of these techniques are high steady state error, weight drift, round off error and impulsive noise. To overcome these drawbacks and to enhance the performance of artifact cancelation we developed some hybrid algorithms. With these hybrid algorithms we can achieve less computation complexity also. 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 the development of ECG signal filtering techniques.The performance of ASEUs for ECG analysis in a typical health care monitor systemcan be improved by various hybrid signal processing techniques. The characteristics of interest in any typical health care monitor system are signal enhancement capability, convergence rate, and computational complexity. Toachieve these

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features, we developed various adaptive algorithms. The basic adaptive algorithm is Least Mean Square (LMS) algorithm. In some critical situations, zoning the signal conditioning with the help of some threshold is needed. In that aspect we developed ASEU based on NDZLMS and its signum variants.

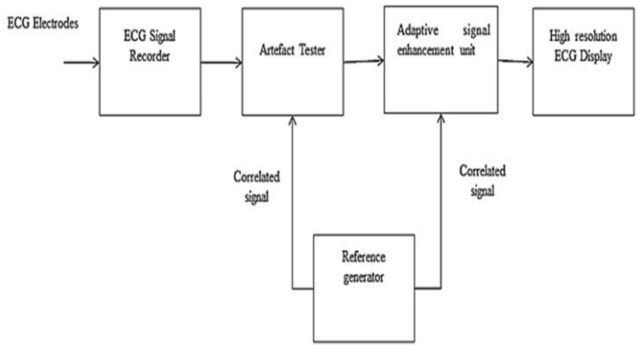

Figure 1: Block diagram of proposed ECG signal analyzer

II. ENHANCEMENT OF ELECTROCARDIOGRAM SIGNALS USING HYBRID VERSIONS OF DZLMS ALGORITHM

In the real time clinical environment various artifacts encountered with the ECG signal and causes ambiguity in the diagnosis. Hence the artifacts should be eliminated in order to enhance the desired ECG signal. The physiological components are not stationary in nature we have to apply adaptive filtering techniques to suppress the clutter components in the noisy input signal. Fig. 1 shows the block diagram of typical health care system for ECG analysis. System input remains as raw signal of ECGrecorded from the corresponding electrodes. To identify the noise, type the recorded quantities are subjected to normalized power testing. For this, a reference generator is considered that consists of several artifact samples. Once the artifact is identified the noisy signal is fed as an input to ASEU. The correlated signal of noise componentstandsto be provided as inputreference 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.

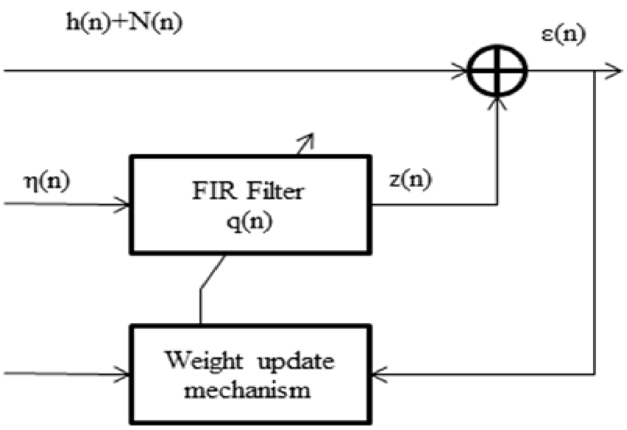

Figure 2: A typical adaptive signal enhancement unit (ASEU).

An ASEU consists of a FIR filter also an adaptive mechanism for updating the weights.Several adaptivetechniques are developed. Thus,an LMS adaptive filter remains considered using length of the tap L. Input given for the EU remains 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 output for FIR filter, ε(n) as error signal.

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

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

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

Within clinical environment the smaller values of $\varepsilon(n)$ may stand for disturbances but may also result from numerical instability. In an ECG 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 ECG signal. This Dead Zone nonlinearity is defined as,

$$d\{m\} = \begin{Bmatrix} m-\alpha, m > \alpha > 0 \\ 0, -\alpha < m < \alpha \\ m+\alpha, m < -\alpha \end{Bmatrix} \qquad (2)$$

where $\alpha$is threshold.

The weight update recursion is given by,

$$\mathbf{q}(n+1) = \mathbf{q}(n) + \lambda\mathbf{x}(n)d\{\varepsilon(n)\} \qquad (3)$$

The data normalization version DZLMS is nothing but Normalized Dead Zone LMS (NDZLMS), whose weight update relationremains given by,

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

Now the SRNDZLMS, SNDZLMD, SSNDZLMS algorithms are given respectively as follows,

$$q(n+1) = q(n) + \lambda(n)\ sign\{x(n)\}d\{\varepsilon(n)\} \qquad (5)$$

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

$$q(n+1) = q(n) + \lambda(n)\ sign\ \{x(n)\}\ sign\ \{d\{\varepsilon(n)\}\} \qquad (7)$$

Based on these mathematical recursions several ASEUs are developed alsoverifiedwithactual ECG signals takenas of MIT-BIH data bank. The experimental results are presented in the next section.

III. SIMULATION RESULTS

Towards demonstrating that projectedtechniquesstand truly efficient within clinical applications,techniquesare evaluated with various ECG signals. In the simulation experiments we have samples related to ECG signal takenas of five distinct persons. Proposed techniques are verifiedthru considering *Signal to Noise Ratio Improvement* (*SNRI)* for fivetrials, averaged alsorelatedthruASEU developed based on conventional LMS. Table I give the SNRI calculations in the process of signal enhancement. In the experiments five ECG samples record 101, record 102, record 103, record 104 and record 105 are used. These ECG records are influenced by artifacts such as SA, RA, MA and EA. Various ASEUs for ECG enhancement is developed using the NDZLMS, its three sign variants alsorelated with LMS technique. Signal analyzer consists of reference generator that generates four types of artifacts synthetically by using the real artifacts features of MIT-BIH databases. Artifact tester compares power spectral density (PSD) for contaminated noisy input signal also 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 component of noiseremains applied as reference signal for ASEU. This ASEU is influenced for updating the weights of the filter thru adaptive techniques based on input data. Based on theseconsiderations, 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. Due to spaceconsiderations, we have shown the experimental results for removal of all the artifacts for record 105 only. These experimental outputs are shown in Figures 3 to 6 respectively for SA, RA, MA and EA.

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

In this experiment SA components are removed from input signal. The input signal to the ASEU is raw ECG from Fig.3(a). Desired component of ECG alsosinusoidal artifacts are present in the input, and are given as input to ASEU shown in Fig. 2. By comparing the input signal PSD components, artifact tester and reference generator gives a reference signal to the ASEU. The reference signal is correlated to artifact component present in the ASEU input. Adaptive technique based ASEU inevitably updates coefficients of filter based on error components. Adaptivetechnique involves reference signal so that it correlated as much as possible with noise component and cancels each other, to update coefficients of filter. The performances of techniques remain compared with respect to SNRI. These are averaged for five experiments for each artifact and are tabulated in Table I. From the experimental results we can observed that SRNDZLMS based ASEU filters the SA from desired ECG signal almost completely. This could be preferred for real time applications due to its smaller number of multiplications due to the presence of SR function. Based on these performance measures it may be concluded that DZLMS based ASEU performs better in SA filtering of ECG signals. Hence, this technique is recommendable for the implementation in real time health care monitoring devices and wearable remote health care systems.

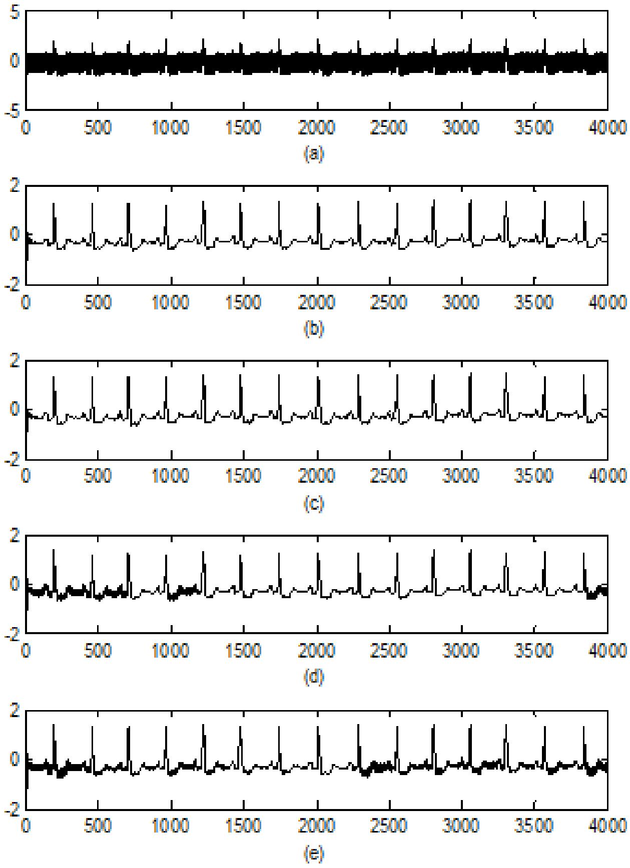

Figure 3: Typical ECG enhancement results for SA cancelation (a) ECG signal contaminated with SA, (b) ECG filtered with LMS algorithm, (c) ECG filtered with NDZLMS algorithm, (d) ECG filtered with SRNDZLMS algorithm, (e) ECG filtered with SNDZLMS algorithm, (f) ECG filtered with SSNDZLMS algorithm. (x-axis number of samples also y -axis amplitude in millivolts).

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

This experiment shows the enhancement process of desired ECG component contaminated with RA. Here also the raw ECG 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 ECG affected with RA remains depicted in Fig.4(a). Fig.4depicts simulation results for our experiments. Performance measures for five samples based on SNRI are presented in Table I. The SRNDZLMS based ASEU performs better among all algorithms. This enables SRNDZLMS related artifact canceller is better than all other counterparts. By comparing the performance measures among all the

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algorithms, it seems as SRNDZLMS based ASEU is better with reference to computational complexity, SNRI, convergence and filtering ability. Hence, this realizationis well suited for real time implementations.

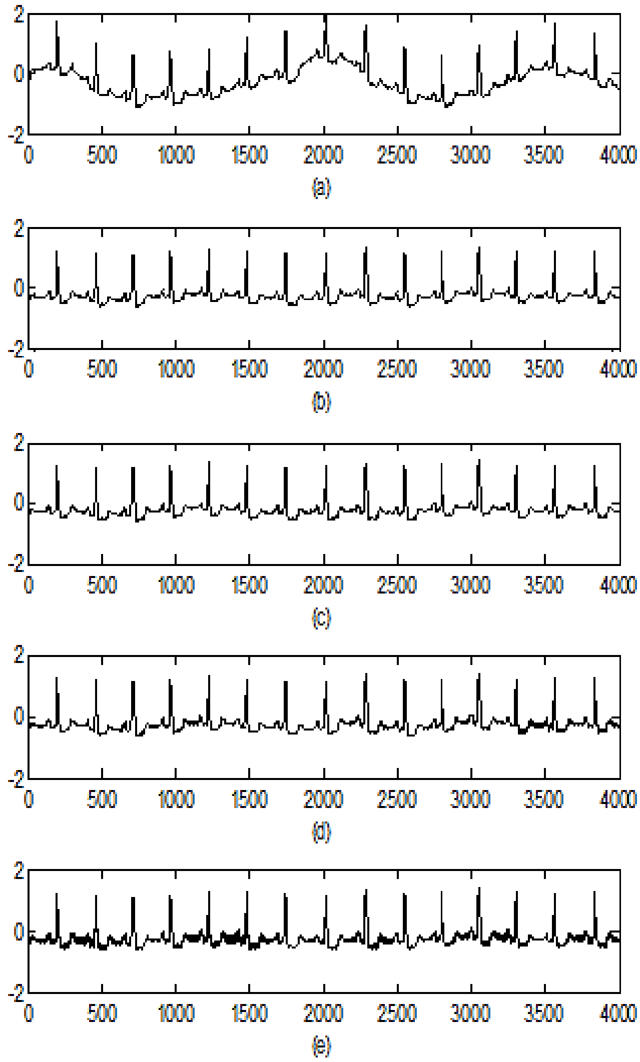

Figure 4: Typical ECG enhancement results of RA cancelation (a) ECG signal contaminated with RA, (b) ECG filtered with LMS algorithm, (c) ECG filtered with NDZLMS algorithm, (d) ECG filtered with SRNDZLMS algorithm, (e) ECG filtered with SNDZLMS algorithm, (f) ECG filtered with SSNDZLMS algorithm. (x-axis number of samples and y -axis amplitude in millivolts).

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

This experiment demonstrates the enhancement process of ECG component encountered with MA. The desired ECG signal is affected by muscle artifact is applied as the input signal to ASEU is depicted from Fig. 2. In correlationthru artifact present within noisy input signal, a signal produced thru muscle activityremains provided as reference signal to adaptive ASEU.ECG affected with MA remains presented in Fig.5(a). Fig.5depicts simulation results for removal of MA. The performance measures for five samples based on SNRI are depicted from Table I. The SRNDZLMS dependent ASEU performs better among all algorithms. By comparing the performance measures among all the algorithms, it seems that the above said algorithm based ASEU is better with reference to computational complexity, SNRI, convergence and filtering ability. Hence, this realization is well suited for real time implementations.

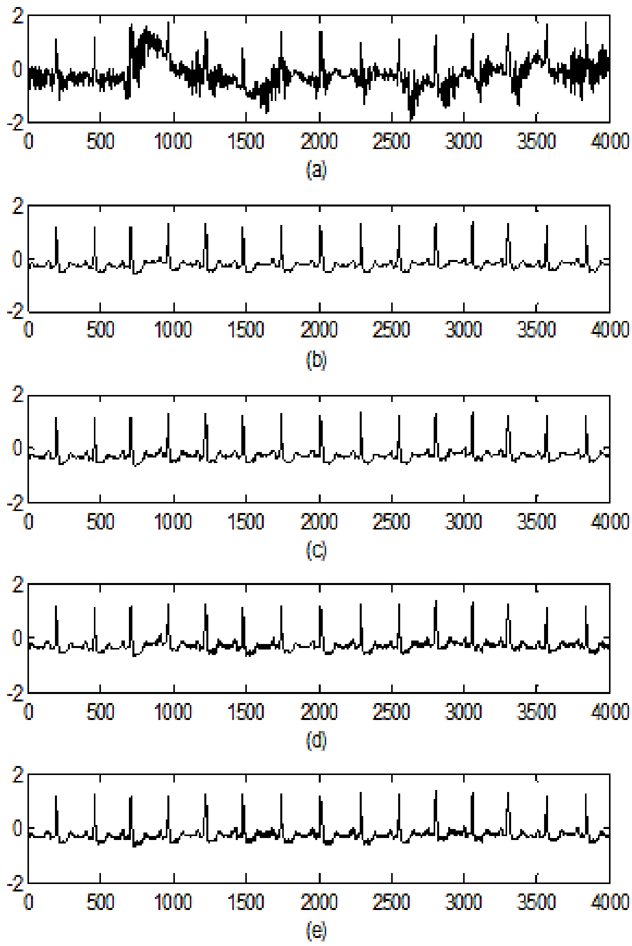

Figure 5: Typical ECG enhancement results of MA cancelation (a) ECG signal contaminated with MA, (b) ECG filtered with LMS algorithm, (c) ECG filtered with NDZLMS algorithm, (d) ECG filtered with SRNDZLMS algorithm, (e) ECG filtered with SNDZLMS algorithm, (f) ECG filtered with SSNDZLMS algorithm. (x-axis number of samples and y -axis amplitude in millivolts).

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

This experiment shows that the enhancement process of ECG component influenced by EA. The desired ECG signal is affected by electrode artifact is applied as an input for ASEU is presented from Fig. 2.

Noise signalremainsproducedthru electrode activity in correlation artifact available within noisy input stands applied to be reference signal to ASEU. ECG affected with EAremainsdepicted from Fig.6(a). Performance metrics derivedusing five samples based on SNRI is presented in Table I.

The NDZLMS related ASEU performs better among all algorithms. This enables NDZLMS based artifact canceller is better than all other counterparts. But, due to less computational complexity SRNDZLMS is found to be

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better as this algorithm is independent of tap length of the filter. Hence, this realization is well suited for real time implementations.

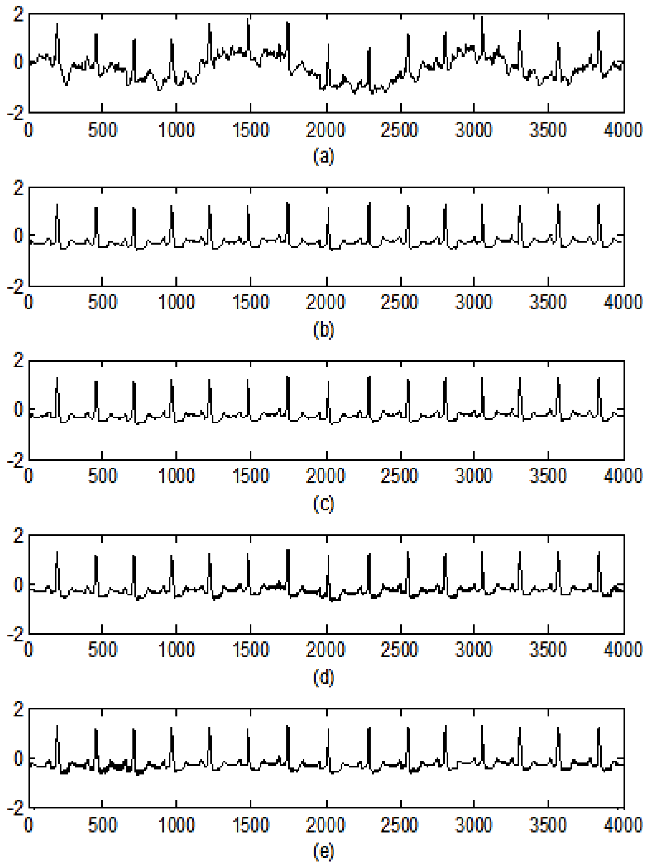

Figure 6: Typical ECG enhancement results of EA cancelation (a) ECG signal contaminated with EA, (b) ECG filtered with LMS algorithm, (c) ECG filtered with NDZLMS algorithm, (d) ECG filtered with SRNDZLMS algorithm, (e) ECG filtered with SNDZLMS algorithm, (f) ECG filtered with SSNDZLMS algorithm. (x-axis number of samples and y -axis amplitude in millivolts).

Noise Type	Rec. No.	LMS	NDZLMS	SR NDZLMS	S NDZLMS	SS NDZLMS
SA	101	25.3474	23.9454	21.7196	20.8471	25.3474
	102	25.6859	24.2785	21.9875	21.1987	25.6859
	102	25.5785	24.1658	21.9523	21.0984	25.5785
	104	25.6326	24.2464	21.9758	21.0867	25.6326
	105	25.1325	23.6585	21.7068	20.6785	25.1325
	Avg.	**25.4753**	**24.0589**	**21.8684**	**20.9818**	**25.4753**
RA	101	10.7392	9.4697	8.2498	6.2539	10.7392
	102	10.8455	9.6625	8.5682	6.6575	10.8455
	102	10.9257	9.6872	8.5985	6.6837	10.9257
	104	10.8135	9.6584	8.4682	6.6348	10.8135
	105	10.7859	9.6128	8.3876	6.2868	10.7859
	Avg.	**10.8219**	**9.6181**	**8.4544**	**6.5033**	**10.8219**
MA	101	10.6348	9.6485	8.2749	6.5849	10.6348
	102	10.8575	9.8575	8.6582	6.8982	10.8575
	102	10.8862	9.8792	8.8754	6.8476	10.8862
	104	10.8797	9.8628	8.8282	6.8265	10.8797
	105	10.8326	9.8687	8.8467	6.8576	10.8326
	Avg.	**10.8181**	**9.8233**	**8.6966**	**6.8029**	**10.8181**
EA	101	10.4728	9.5869	8.7398	7.5397	10.4728
	102	10.7286	9.7937	8.9825	7.8675	10.7286
	102	10.4982	9.6875	8.5682	7.5864	10.4982
	104	10.7068	9.7628	8.6286	7.7895	10.7068
	105	10.7168	9.7465	8.6316	7.8614	10.7168
	Avg.	**10.6246**	**9.7154**	**8.7101**	**7.7289**	**10.6246**

IV. CONCLUSION

In this paper several efficient signal enhancement techniques are developed for ECG signal. In order to achieve convergence speed and enhancement capability we have used various ASEUs based on NDZLMS and its sign algorithms. These techniques are tested in real time to eliminate artifacts like SA, RA, MA and EA from desired ECG signals. The filtering results are shown in Figures 3-6. The performance measures in terms of SNRI for the removal of various artifacts are shown in Table I. From the experimental results it is found that SRNDZLMS based ASEU is better with respect to SNRI, convergence, filtering ability and computational complexity. Hence, this realization is 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. Y. Zhang et al, “Cardiac output monitoring by Electrocardiogram 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, BioElectrocardiogram 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, Electrocardiogram filtering using scale fourier linear combiner based on RLS algorithm, IEEE EMBS, September (2009).
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 Sabet Jahromi ; Aykut Hocanin ; Osman Kukrer, "A weighted zero-attracting Leaky LMS algorithm", SoftCOM 2012, 20th International Conference on Software, Telecommunications and Computer Networks, 2012, pp.1-3.

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