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Adaptive Artifact Elimination in Telecardiology Systems using Leaky LMS Variants

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Abstract: ***Evaluation of Electrocardiogram (ECG) facilitates the heart stroke volume in the sudden cardiac arrest. ECG is a noninvasive method for indirect analysis of stroke volume, monitoring the cardiac output and observing the hemodynamic parameters by changes in the blood volume of the body. Changes in the blood volume caused due to several physiological processes are extracted in the form of the impedance variations of the body segment. In the real time clinical environment ECG signals are contaminated with various artifacts. As these artifacts are not stationary in nature, we developed several hybrid adaptive filtering techniques to enhance the resolution of ECG signals. Least mean square (LMS) algorithm is the basic enhancement technique in the adaptive filtering. But, in the non-stationery environment the LMS algorithm suffers with low convergence rate and weight drift problems. In this paper we developed hybrid versions of LMS algorithm that is Normalized Leaky LMS (NLLMS) for ECG signal enhancement. More over to improve the rate of convergence, filtering capability and to minimize the computational complexity we also implement various sign versions of LLMS algorithms. The sign versions of NLLMS algorithms are sign regressor NLLMS (SRNLLMS), Sign NLLMS (SNLLMS), and Sign Sign NLLMS (SSNLLMS). Based on these adaptive algorithms, we developed several adaptive signal enhancement units (ASEUs) and performance is evaluated on the real ECG signal components obtained from MIT-BIT database. To ensure the ability of these algorithms, four experiments were performed to remove 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 SRNLLMS performs better in the artifacts removing process. The signal to noise ratio improvement (SNRI) for this algorithm is calculated as 18.3165 dBs, 8.0964 dBs, 6.7025 dBs and 8.0825 dBs respectively for SA, RA, MA and EA. Hence, the SRLLMS based ASEUs are more suitable in ECG signal filtering in real time health care sensing systems.***

Index Terms**:** ***adaptive filter, artifacts, electrocardiography, non-invasive, signal enhancement.***

I. INTRODUCTION

According to the statistic reports given by World Health Organization (WHO), the ischemia Heart disease is one of the leading causes of death worldwide [1]. One of the popular methods to measure cardiac activity is hemodynamics in which the flow of the blood across the body is measured. Impedance plethysmography techniques that use changes in electrical impedance on the surface of the body to measure hemodynamic parameters. Electrocardiography (ECG) is a simple, inexpensive and noninvasive method to observe the electrical impedance changes of thorax, which is caused due to the periodic changes in the volume of blood in aorta.To estimate Cardiac Output (CO), Stroke Volume (SV) and other hemodynamic parameters [2] an appropriate thorax model is used. To identify the variations of body impedance due to the periodic changes in the flow of blood caused by heartbeat. The Research has been stared in this field of ECG with particularly in cardiac area using Impedance Plethysmography techniques [3]. Several studies are accomplished in the field among noninvasive ECG and invasive methods [4, 5]. The evaluation of ECG is presented in [6] which subjects with heart diseases. The experimental results are most reliable and accurate. With the advancement in technology, wearable devices with ECG sensors are designed to facilitate long term recordings and provide comfort to patients [7]. Since the origin of ECG there has been an increase in the reliability of the technique and development in the cardiac parameter's measurement [8–11]. During the extraction of ECG signal the desired signal components are contaminated with artifacts. The tiny features of the desired signal components are masked by these artifacts and causes ambiguities during diagnosis [6]. The major artifacts are Sinusoidal Artifacts (SA), Respiratory Artifacts (RA), Muscle Artifacts (MA) and Electrode Artifacts (EA). These artifacts must be eliminated to provide high resolution ECG signal components for estimating stroke volume and intensity. These artifacts are not stationery and hence conventional filters with fixed coefficients are not preferable for ECG filtering. So that adaptive filtering techniques are suitable to change the filter weights in according to the statistical nature of error signal [12].Until now, several researchers have proposed various signal processing techniques to enhance the ECG signal [13-15]. In these papers, conventional Least Mean Square (LMS) and Recursive Least Square (RLS) algorithms are used to remove artifacts. But the drawbacks of these algorithms are weight drift, and less stable. To overcome these drawbacks and to enhance the performance of artifact cancelation we developed some hybrid algorithms. With these hybrid algorithms we can also achieve less computation complexity. In [16–19] Rahman et al. used some adaptive artifact cancellers to enhance the cardiac signal and brain activity using various versions of LMS.

We considered the same framework for the development of ECG signal enhancement. The performance of ASEUs for ECG analysis in a typical health care monitor system can be improved by various hybrid signalprocessing techniques.

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The characteristics of interest in any typical health care monitor system are signal enhancement capability, convergence rate, and computational complexity.

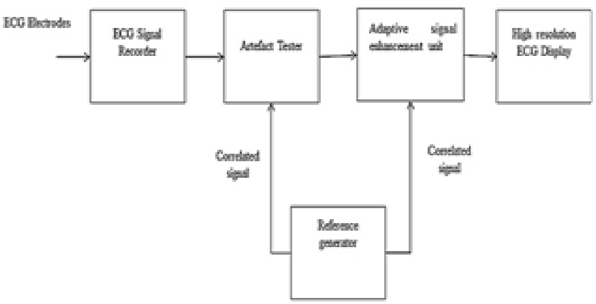

Figure 1: Block diagram of proposed ECG signal analyzer

To achieve these features, we developed various adaptive algorithms. The basic adaptive algorithm is Least Mean Square (LMS) algorithm. To avoid weight drift and to increase the stability Normalized Leaky LMS (NLLMS) algorithm has been developed. In this paper Further to improve the rate of convergence, filtering capability and to reduce computational complexity we implemented various sign versions of NLLMS algorithms. The variants of LLMS algorithms are Sign Regressor NLLMS (SRNLLMS) algorithm, Sign NLLMS (SNLLMS) algorithm and Sign SignNMS (SSNLLMS) algorithm. The implementation of these algorithms is discussed in the next section.

II. RELATED ENHANCEMENT OF ELECTROCARDIOGRAPHY SIGNALS USING HYBRID TECHNIQUES

In the real time clinical environment various artifacts encountered with the actual ECG signal and causes ambiguity in the diagnosis. Hence the artifacts should be removed in order to ensure exact interpretation of parameters related to ECG. Since the physiological quantities of artifacts are not stationary in nature, we have to use adaptive techniques to remove undesired components from the noisy input signal. Fig. 1 shows the block diagram of typical health care system for ECG analysis. The input to the health care system is raw ECG signal recorded from the corresponding electrodes. The noise type can be identified by the normalized power testing of the recorded quantity. For this, a reference generator is considered which comprises of several artifact samples. After identifying certain type of artifact, the corrupted signal is given as input to ASEU. The noise correlated signal is designated as reference signal to ASEU. Fig. 2 shows the internal structure of an ASEU. ASEU is the basic building block in the typical health care sensing system. Therefore, in this paper several signal processing techniques for developing ASEUs are presented.An ASEU consists of a FIR filter and a weight update system. Here we developed several techniques for weight coefficients. For this, here we consider an LMS based adaptive filter with input sample length K. y(n) is the input signal to ASEU. This comprises of impedance component J(n) and artifact component G(n). g(n) is the reference signal correlated to noise components generated from the reference generator. u(n) be the filter impulse response, o(n) is the FIR filter output, v(n) be the error signal produced in the ASEU. The weight updating mechanism for an LMS based SEU can be mathematically written as,

$$u(n+1) = u(n)+\delta y(n)v(n) \quad (1)$$

where, $u(n) = [u_0(n)\ u_1(n)\ \ldots\ u_{K-1}(n)]^t$ is the n^{th} weight coefficient vector, $y(n) = [y(n)\ y(n-1)\ \ldots\ y(n-K+1]^t$ is input vector, $v(n) = y(n)-u^t(n)g(n)$ and 'δ' indicates a step-size.

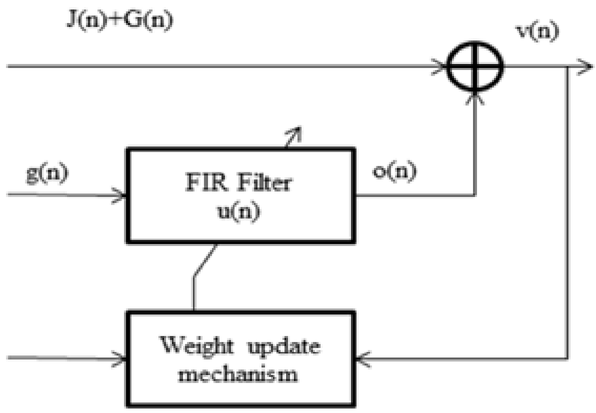

Figure2: A typical adaptive signal enhancement unit

A. NORMALIZED LEAKY LMS ALGORITHM

The conventional Least-Mean-Square algorithm is widely used in various biomedical applications due its simplicity and robustness. The LMS algorithm is sensitive to rounding errors and causes several perturbations, since the weight coefficient equation is generally an integrator. For example, inappropriate excitation in the input sequence leads to unbounded parameter [20-21] estimates. Since it is possible that these un-damped modes become unstable, it is necessary that the stability of the LMS algorithm causes these modes to zero [22]. Such drawbacks are overcome by introducing a leakage factor β into the weight vector. The purpose of the leakage factor β is that the tap weights are become zero if either v(n) or $y(n)$ is zero. The parameter $\beta$is known as the leak and the algorithm is referred to as leaky LMS algorithm (LLMS). The weight update recursion is given by,

$$u(n+1) = (1-\delta\beta)u(n) + \delta v(n)y(n) \quad (2)$$

In (2) the product $\delta\beta$ is selected in such a way that it should be greater than but closed to 0. The LLMS has been used to advance the adaptive filter characteristics.The mathematical expression for normalized leaky LMS (NLLMS) is written as follows,

$$u(n+1) = (1-\delta\beta)u(n) + \delta(n)v(n)y(n) \quad (3)$$

where $\delta(n)$ is the data normalized version of fixed step size.

B. SIGN VARIANTS OF NLLMS

The new variants that provided with the signum function of either the input signal components, the error signal components, or both, have been implemented from the various LLMS based adaptive algorithms discussed above for simple implementation. It allows significant reduction in computation time, mainly the time required for "multiply and accumulate" (MAC) operations. The sign-based techniques reduce the computational complexity of the adaptive filter and, therefore, it is preferable for

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biotelemetry applications. In this paper we apply the signum function [23] to LLMS algorithm and evaluate the performance in removing artifacts from ECG signals.

SIGN-REGRESSOR NLLMS (SRNLLMS) ALGORITHM

The sign-regressor variant is derived from the LLMS recursion by adjusting the input vector $\mathbf{y}(n)$ with Sign{$\mathbf{y}(n)$}, where the Signum function is applied to input $\mathbf{y}(n)$ on an element-by-element basis. The signed-regressor LLMS weight recursion is given by

$$\boldsymbol{u}(n+1) = (1-\delta\beta)\boldsymbol{u}(n) + \delta(n)v(n)Sign\{\boldsymbol{y}(n)\} \quad (4)$$

Where

$$Sign\{\boldsymbol{y}(n)\} = \left\{\begin{matrix} 1: \boldsymbol{y}(n) > 0 \\ 0: \boldsymbol{y}(n) = 0 \\ -1: \boldsymbol{y}(n) < 0 \end{matrix}\right\} \quad (5)$$

The kth coefficient in the sign of the data vector may be written as follows:

$$Sign\{\boldsymbol{y}(n-k)\} = \frac{y(n-k)}{|y(n-k)|} \quad (6)$$

Because of the signum function, as in (6) data normalization takes place. So, this algorithm enjoys the advantages good stability and better filtering, convergence.

SIGN NLLMS (SNLLMS) ALGORITHM

This SLLMS variant is obtained from the LLMS recursion by adjusting *v(n)* with its *sign(v(n))*. The weight recursion for SLLMS algorithm is given by:

$$\boldsymbol{u}(n+1) = (1-\delta\beta)\boldsymbol{u}(n) + \delta(n)Sign\{v(n)\}\boldsymbol{y}(n) \quad (7)$$

By using sign{v(n)}, the computation complexity for the implementation of recursion becomes reduce than the LLMS, particularly for high speed applications that require hardware implementation of the recursion. The simplification in the sign-error algorithm comes when the step size is chosen in power of 2, $\delta = 2^{-l}$, so that multiplications are not required for recursion implementation. A set of shift and add/subtract operation would enough for updating the filter weight recursion.

SIGN-SIGN NLLMS (SSNLLMS) ALGORITHM

The sign-sign algorithm combines the sign and sign-regressor recursions resulting in the following recursion:

$$u(n+1) = (1-\delta\beta)u(n) + \delta(n)Sign\{v(n)\}Sign\{y(n)\} \quad (8)$$

Here because of the signum function for both data and error, some residual noise remains in the filtering process. At the same time computational complexity mostly reduced .Among the three, SRNLLMS performs better because of the leakage term and data normalization involved because of the signum function. Moreover, its computational complexity is also reduced by using signum function.

III. SIMULATION RESULTS

To demonstrate that the proposed techniques are truly efficient in clinical situations, the methods have been evaluated using various ECG signal recordings in our experiment we have taken samples of the ECG signal components from five patients. The proposed techniques are evaluated by considering *Signal to Noise Ratio Improvement* (*SNRI)* in the experiment, averaged the five samples and compared with the conventional LMS based Adaptive Signal Enhancement Unit (ASEU). Tables I shows the SNRI contrast for various algorithms. In our experiment a Gaussian noise with variance of 0.001 is added to ECG signal component. Here we are using five ECG records i.e., record 101, record 102, record 103, record 104 and record 105. These records are influenced by artifacts like SA, RA, MA and EA. Several ASEUs are developed for ECG signal enhancement using the LMS, NLLMS, SRNLLMS, SNLLMS, SSNLLMS 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. By doing so, reference generator can identify the type of noise in the input signal. So that the similar type of correlated noise signal is applied as a reference signal to ASEU. The ASEU can update its filter coefficients using an adaptive algorithm in accordance with the error component. Based on these considerations, in our experiment, we have implemented five ASEUs using the algorithms discussed in Section 2.These ASEUs are operated under four modules to remove the artifacts SA, RA, MA and EA respectively. The comparison of these techniques in ECG filtering for various artifacts is shown in Fig. 4. Due to space limitation consideration we have shown the experimental results of record 105 only for eliminating artifacts. Fig.3 shows a typical ECG component contaminated with various types of artifacts.

A. FILTERING OF SINUSOIDAL ARTIFACTS (SA) USING ADAPTIVE ALGORITHMS

In this experiment SA components are removed from the input raw ECG signal. The input signal to the ASEU is raw ECG as shown in Figure 3(a). This input contains desired ECG component and sinusoidal artifacts, and is given as input to ASEUshown in Figure 2.By comparing the Power Spectral Density of the input noisy signal components, artifact tester and reference generator gives a reference signal to the ASEU. The reference signal is correlated to artifact component exist in the input signal ofthe ASEU.The ASEU can update its filter coefficients using an adaptive algorithm in accordance with the error component. In this manner, coefficients of FIR filter are updated, the algorithm constitutes the reference signal so that it correlated as much as possible with the actual noise component and cancels eachother. Fig. 3 shows the experimental results of SA removal from input signal. The performances of these adaptive techniques are compared with reference to SNRI. These are averaged for five experiments for each artifact and are tabulated in Table 1. From the experimental results it is confirmed that SRNLLMS is performing better than other algorithms in terms of filtering ability SNRI and computational complexity. Hence, this algorithm is well suited for practical implementation.

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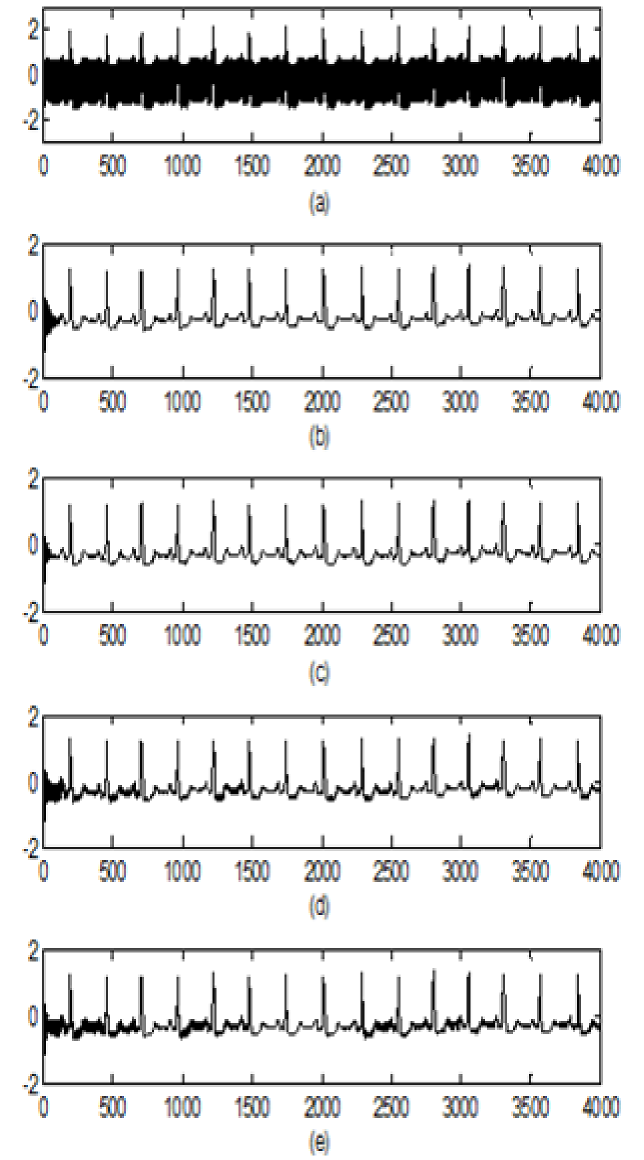

Figure 3: Typical ECG enhancement results of SA cancelation (a) ECG signal contaminated with SA, (b) ECG filtered with LMS algorithm, (c) ECG filtered with NLLMS algorithm, (d) ECG filtered with SRNLLMS algorithm, (e) ECG filtered with SNLLMS algorithm, (f) ECG filtered with SSNLLMS algorithm. (x-axis number of samples and y -axis amplitude in millivolts).

B. FILTERING OF RESPIRATION ARTIFACT (RA) USING ADAPTIVE ALGORITHMS

This experiment shows that the enhancement process of ECG signal influenced by RA. The desired ECG signal is affected by RA is applied as input to ASEU as shown in Figure 2. An undesired signal is generated due to the activity of electrodes, which is correlated to artifact present in the noisy input signal. This correlated signal is given as reference to adaptive mechanism. Figure 4 shows the experimental results for EA removal from input signal. Table Igives the performance measures of proposed techniques in terms of SNRI. From these measures we can observe that the SRNLLMS based ASEU performs better. This enables SRLLMS based artifact canceller is better than all other counterparts.

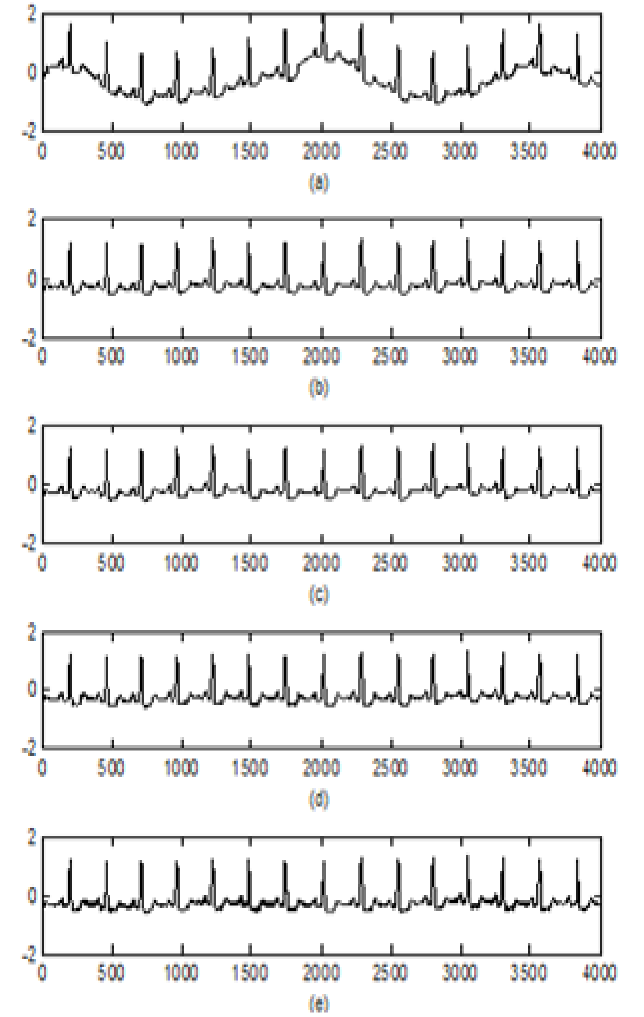

Figure 4: Typical ECG enhancement results of RA cancelation (a) ECG signal contaminated with RA, (b) ECG filtered with LMS algorithm, (c) ECG filtered with NLLMS algorithm, (d) ECG filtered with SRNLLMS algorithm, (e) ECG filtered with SNLLMS algorithm, (f) ECG filtered with SSNLLMS algorithm. (x-axis 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 given as input to ASEU as shown in Fig. 2. An undesired signal is generated due to the activity of muscles, which is correlated to artifact present in the noisy input signal. This correlated signal is given as reference signal to ASEU. Table I gives the performance measures of proposed techniques in terms of SNRI. The experimental results of MA elimination are shown in Figure 5. From the SNRI contrast it is clear that SRNLLMS is performing better than the other counterpart algorithms due to the sign regressor function and data normalization.

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 NLLMS algorithm, (d) ECG filtered with SRNLLMS algorithm, (e) ECG filtered with SNLLMS algorithm, (f)

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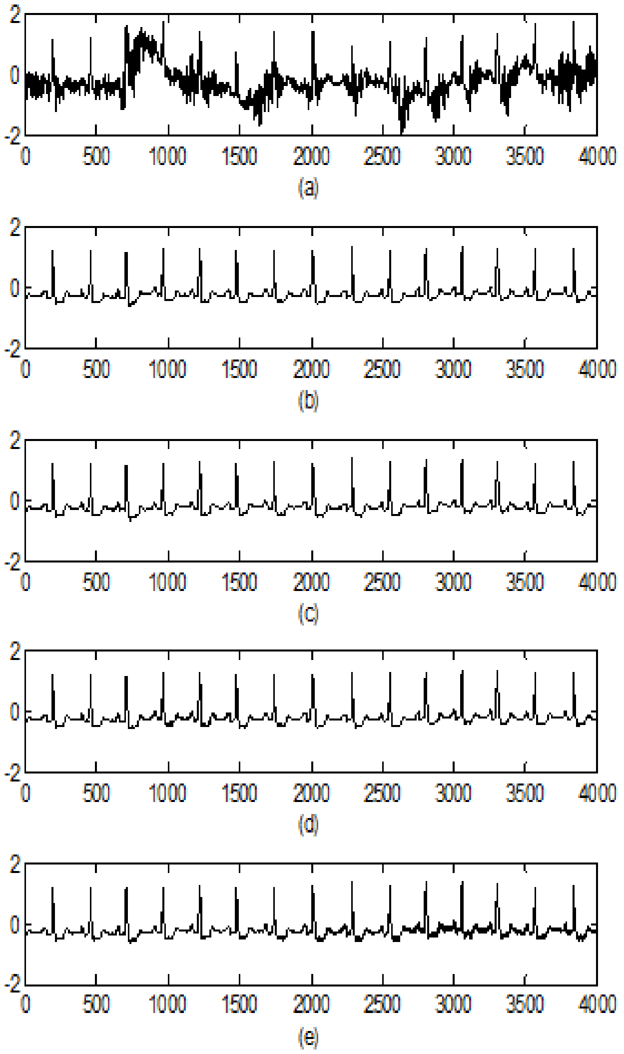

ECG filtered with SSNLLMS algorithm. (x-axis number of samples and y -axis amplitude in millivolts).

D. FILTERING OF ELECTRODE MOTION ARTIFACT (EA) 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. Table I gives the performance measures of proposed techniques in terms of SNRI. The filtering results are shown in Figure 6. From these measures we can observe that the SRNLLMS based ASEU performs better. This enables SRNLLMS based artifact canceller is better than all other counterparts.

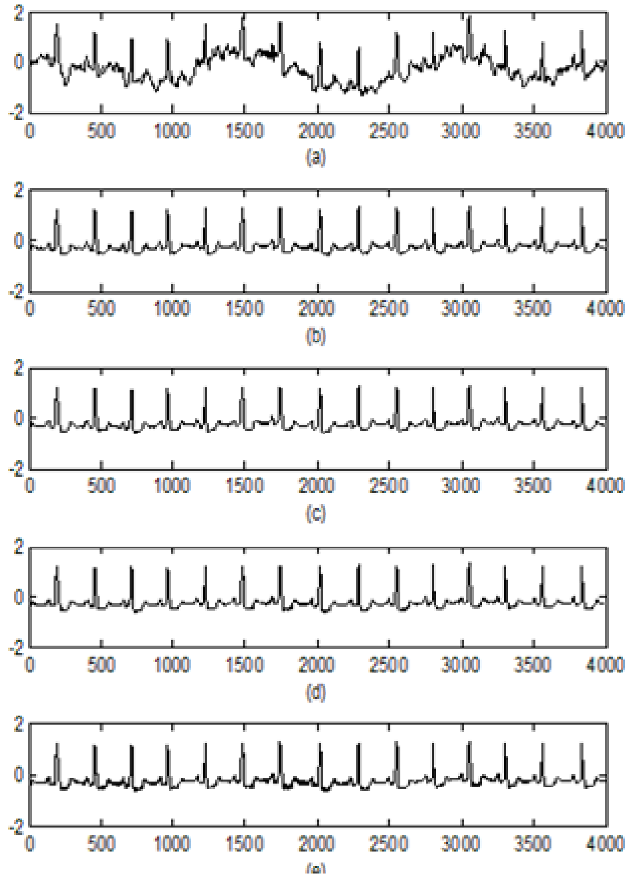

Figure 6: Typical ECG enhancement results of EA cancelation (a) ECG signal contaminated with EA, (b) ECG filtered with LMS algorithm, (c) ECG filtered with NLLMS algorithm, (d) ECG filtered with SRNLLMS algorithm, (e) ECG filtered with SNLLMS algorithm, (f) ECG filtered with SSNLLMS algorithm. (x-axis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

IV. CONCLUSIONS

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 LMS, NLLMS, SRNLLMS, SNLLMS and SSNLLMS algorithms. These techniques are tested in real time to eliminate artifacts like SA, RA, MA and EA from the desired ECG signals. The filtering experimental results are presented in Figures 3, 4, 5 and 6. The performance of all the proposed techniques is measured in terms of SNRI, tabulated in Table I. From the filtering results, SNRI computations and the appearance of sign regressor function the SRNLLMS is found to be better than the other algorithms discussed in the paper in terms ofconvergence, filtering, SNRI and computational complexity. Hence, SRNLLMS based ASEU is well suited for real time applications.

Table II. SNRI computations for various filtering techniques during ECG enhancement (all values in dBs).

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Noise	Rec. no	LMS	NLLMS	SRNLLMS	SNLLMS	SSNLLMS
SA	101	7.7763	20.6722	18.1474	16.3429	14.6284
	102	9.1878	21.8948	19.7464	17.8168	15.9846
	102	8.5084	21.4625	19.3468	17.3796	15.4685
	104	9.0063	21.9848	19.7954	17.8562	15.8957
	105	7.3824	20.2369	18.3165	16.3488	14.2684
	Avg.	8.3722	21.2502	19.0705	17.1488	15.2491
RA	101	4.2398	8.2395	7.8439	6.4575	5.3741
	102	4.7682	8.6946	8.2648	6.6458	5.6928
	102	4.8275	8.8185	8.4682	6.8726	5.8795
	104	4.6124	8.5624	8.1658	6.6187	5.5672
	105	4.4523	8.3984	8.0964	6.5984	5.4687
	Avg.	4.5840	8.5426	8.1678	6.6386	5.5964
MA	101	3.7605	7.2755	6.3934	5.4683	4.1327
	102	3.9652	7.7952	6.6975	5.6321	4.6258
	102	4.0395	7.8108	6.7782	5.7432	4.5485
	104	4.0008	7.7981	6.6325	5.6025	4.5123
	105	4.0137	7.8065	6.7025	5.6287	4.5268
	Avg.	3.9559	7.6972	6.6408	5.6149	4.4692
EA	101	4.6511	9.3731	7.8520	6.3184	5.3481
	102	4.8438	9.6582	8.0835	6.6282	5.6582
	102	4.6617	9.5215	7.9862	6.5619	5.6216
	104	4.7782	9.6842	8.0357	6.5726	5.6815
	105	4.8083	9.6723	8.0825	6.6139	5.7982
	Avg.	4.7486	9.5818	8.0039	6.539	5.6115

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 Electrocrdigraphy : 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 Electrocrdigraphyduring 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 Electrocrdigraphy . 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 Electrocrdigraphy . IEEE Engineering in Medicine and Biology Mag. 8, 35 (1989).
10. M. J. Major, World, Estimation of cardiac output by bioElectrocrdigraphy . Journal of the Royal Army Medical Corps. 136, 92 (1990).
11. Nancy M. Albert, BioElectrocrdigraphy measurements of cardiac output and other cardiovascular parameters. Critical Care Nursing Clinics of North America 18, 195 (2002).
12. A. N. Ali, Advanced Bio Signal Processing, Springer Verlag, Berlin, Germany (2009).
13. O. Dromer, O. Alata, and O. Bernard, Electrocrdigraphy filtering using scale fourier linear combiner based on RLS algorithm, IEEE EMBS, September (2009).
14. 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.
15. Vinod K. Pandey and Prem C. Pandey, Cancellation of respiratory artifact in Electrocrdigraphy . EMBS, IEEE (2005).
16. Haykin, Adaptive Filter Theory, Eaglewood Clirs, Prentice-Hall, NJ (1991).
17. S. C. Douglas, A family of normalized LMS algorithms. IEEE Signal Processing Letters 1, 49 (1994).
18. 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).
19. 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).
20. 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.
21. Teppei Washi ; Arata Kawamura ; YoujiIiguni, “Sinusoidal Noise Reduction Method Using Leaky LMS Algorithm”, 2006 International Symposium on Intelligent Signal Processing and Communications, 2007, pp. 303-306.
22. 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.
23. M. Z. U. Rahman, S. R. Ahamed, and D. V. R. K. Reddy, “Efficient sign based normalized adaptive filtering techniques for cancellation of artifacts in ECG signals: Application to wireless biotelemetry,” Signal Process., 91, (2011), pp. 225–239.

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