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# Adaptive Noise Cancellation Techniques for Impedance Cardiography Signal Analysis

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***Abstract*: Impedance Cardiography (ICG) evaluation facilitates the volume of heart stroke in the sudden cardiac arrest. It is a noninvasive method for measurement of stroke volume, cardiac output monitoring and observing the hemodynamic parameters by changes in the body blood volume. Bloodvolume changes caused due to various physiological processes is extracted in the form of the variations in the impedance of the body segment. In the real time clinical environment during the extraction the ICG signals are influenced with several artifacts.As these artifacts are not stationary in nature, we can't predict their characteristics. Hence,we developed several hybrid adaptive filtering mechanisms to improve the ICG signals resolution. Least mean square (LMS) algorithm is the basic enhancement technique in the adaptive filtering. However, in the non-stationery situation the LMS algorithm suffers with low rate of convergence and weight drift problems. In this paper we developed some hybrid variantsof LMS algorithm those are Leaky LMS (LLMS) for ICG signal enhancement. More over to progress the convergence rate, filtering capability and to reduce the computational complexity we also developed various sign versions of LLMS algorithms. The sign variants of LLMS algorithms are sign regressor LLMS (SRLLMS), Sign LLMS (SLLMS), and Sign Sign LLMS (SSLLMS). Severaladaptive signal enhancement units (ASEUs) are developed based on adaptive algorithms and performance is evaluated on the real ICG signal taken from MIT-BIT database. To ensure the efficiency 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 associated with SRLLMS performs better in the artifacts filtering process. The signal to noise ratio improvement (SNRI) for this algorithm is calculated as 9.3388 dBs, 5.7514 dBs, 8.4449 dBs and 8.7358 dBs respectively for SA, RA, MA and EA. Hence, the SRLLMS based ASEUs are more suitable in ICG signal filtering in real time health care sensing systems.***

***Index Terms*: Adaptive Filter, Artifacts, Impedance Cardiography, non-invasive, signal enhancement.***

## I. INTRODUCTION

According to the World Health Organization (WHO) statistic reports, the ischemia heart disease is one of the major leading causes of death worldwide [1]. Hemodynamics is one of the popular methods to determine cardiac activity in which the blood flow across the body is measured. Impedance plethysmographytechniques that use changes in electrical impedance on the surface of the body to measure hemodynamic parameters. Impedance Cardiography (ICG) is a simple, inexpensive and noninvasive method to evaluate the thorax electrical impedance changes, which is caused due to the periodic variations in the blood volume in aorta. Cardiac Output (CO), Stroke Volume (SV) and other hemodynamic parameters [2] are evaluated using an appropriate thorax model. To identify the impedance variations of the body due to the periodic changes in the flow of blood caused by heartbeat. The Research has been stared in this field of ICG with particularly in cardiac area using Impedance Plethysmography techniques [3]. A number of studies are accomplished in the field among noninvasive ICG and invasive methods [4, 5]. The ICG signal evaluation is presented in [6] which subjects with heart diseases. The experimental results are most consistent and exact. With the improvement in the technology, wearable devices with ICG sensors are intended to facilitate long term recordings and provide comfort to patients [7]. Since the origin of ICG there has been an increase in the reliability of the technique and development in the cardiac parameter's measurement [8–11]. During the ICG signal extraction the desired signal components are corrupted by artifacts. The tiny features of the desired signal components are masked by these non-stationaryartifacts and creates ambiguities during diagnosis [6]. The most important artifacts are Sinusoidal Artifacts (SA), Respiratory Artifacts (RA), Muscle Artifacts (MA) and Electrode Artifacts (EA). So that adaptive filtering techniques are suitable to update the filter weights in according to the statistical nature of error signal [12].

In [13-15] various signal processing techniques are proposed to enhance the ICG signal. Least Mean Square (LMS) and Recursive Least Square (RLS) algorithms are used to remove artifacts. But weight drift and instability are the major drawbacks of these algorithms. We developed some hybrid algorithms to overcome these problems and to enhance the performance of artifactsfiltering.Lesscomputation complexity also achieved with these techniques. In [16–19] Rahman et al. used some adaptive artifact cancellers to remove artifacts from the cardiac signal and brain activity signals using various variants of LMS. Here also we considered the same framework for the development of ICG signal enhancement.

The performance of ASEUs can be improved by using various hybrid signal processing techniques for ICG signal analysis in a typical health care monitor system. Signal enhancement capability, convergence rate, and computational complexity are the characteristics of interest in any health care monitor system.

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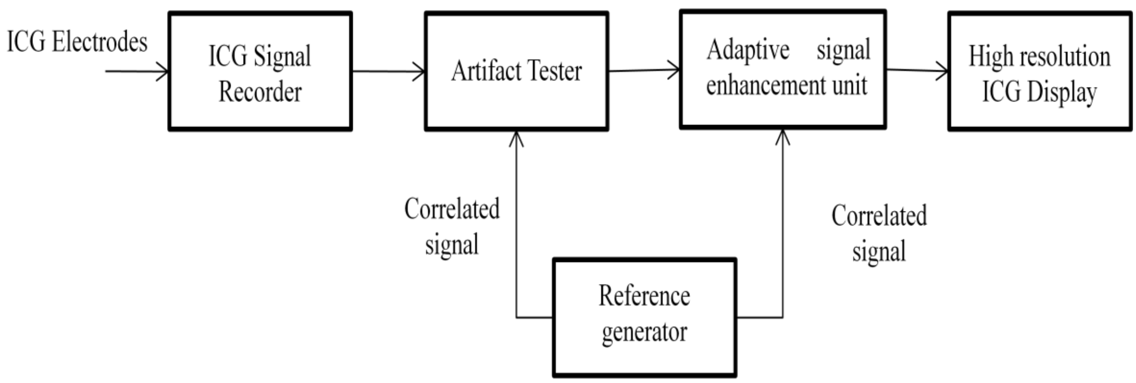


Fig. 1: Block diagram of proposed Adaptive Artifact Eliminator for Impedance Cardiography Signal.

To achieve these features, we developed a variety of adaptive algorithms. Least Mean Square (LMS) algorithm is the fundamental adaptive algorithm. To avoid weight drift and to increase the stability Leaky LMS (LLMS) algorithm has been developed. In this paper further to enhance the rate of convergence, filtering capability and to reduce computational complexity we combined LLMS algorithm with three sign variants. The three sign variants of LLMS algorithms are Sign Regressor LLMS (SRLLMS) algorithm, Sign LLMS (SLLMS) algorithm and Sign Sign LLMS (SSLLMS) algorithm. The implementation of these algorithms is discussed in the next section. Based on the simulation results the SSLLMS based ASEUs perform better than the remaining algorithms.

## II. ENHANCEMENT OF IMPEDANCE CARDIOGRAPHY SIGNALS USING HYBRID TECHNIQUES

In the clinical environment several artifacts contaminated with the desired ICG signal and create ambiguity in the diagnosis. Hence the artifacts should be removed in order to ensure exact interpretation of parameters related to ICG. Since the characteristics of artifacts are not stationary in nature, we have to use adaptive filtering techniques to eliminate undesired artifact components from the noisy input signal. Fig. 1 shows the block diagram of typical health care system for ICG analysis. The input to the health care system is noisy ICG signal recorded from the respective electrodes. The typeof noise can be identified by the normalized power testing of the recorded quantity. For this, a reference generator is used which consists of several artifact samples. After identifying certain type of noise, the noisy ICG 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 essential building block in the health care sensing system. Therefore, in this paper several signal processing techniques for developing ASEUs are presented.

An ASEU contains a FIR filter and a weight update mechanism. Here we used several techniques for updating 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,

$$u(n+1) = u(n)+\delta y(n)v(n) \tag{1}$$

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.

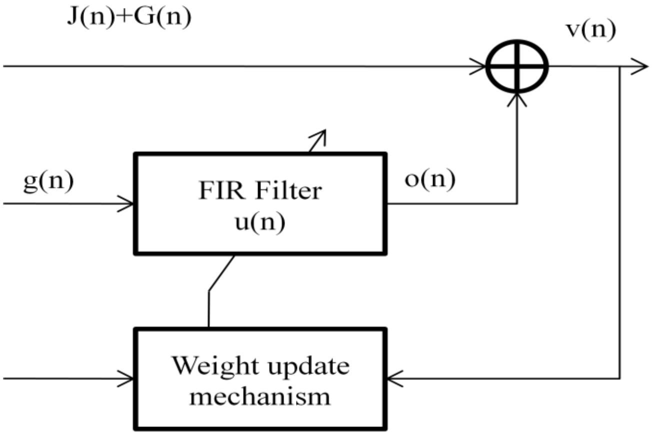


Fig. 2. A typical adaptive signal enhancement unit.

### A. Leaky LMS algorithm

The conventional Least-Mean-Square algorithm is usually used in several biomedical applications due its simplicity and robustness. It is very sensitive to rounding errors and creates 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 essential that the stability of the LMS algorithm causes these modes to zero [22]. Such problems are overcome by introducing a leakage factor $\beta$ into the weight vector. The purpose of the leakage factor $\beta$ 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).

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The weight update recursion is given by,

$$u(n+1) = (1-\delta\beta)u(n) + \delta v(n)y(n) \tag{2}$$

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.

**B. Sign variants of LLMS:**

The new versions that are provided with the signum function of either the input signal components, the error signal components, or both, have been implemented with the LLMS based adaptive algorithms discussed above for simple implementation. It provides significant reduction in computation time, mainly the time taken for "multiply and accumulate" (MAC) operations. The sign-based mechanisms reduce the computational complexity of the adaptive filter and, therefore, it is suitable for biotelemetry applications. In this paper we apply the signum function [23] to LLMS algorithm and evaluate the performance in removing artifacts from ICG signals.

***Sign-Regressor LLMS algorithm***

The sign-regressor technique is developed from the LLMS recursion by modifying the input vector **y**(n) with Sign{**y**(n)}, where the Signum function is applied to **y**(n) on an element-by-element basis. The signed-regressor LLMS weight recursion is given by

$$\boldsymbol{u}(n+1) = (1-\delta\beta)\boldsymbol{u}(n) + \delta v(n) Sign\{\boldsymbol{y}(n)\} \tag{3}$$

Where

$$Sign\{\boldsymbol{y}(n)\} = \begin{Bmatrix} 1: \boldsymbol{y}(n) > 0 \\ 0: \boldsymbol{y}(n) = 0 \\ -1: \boldsymbol{y}(n) < 0 \end{Bmatrix} \tag{4}$$

The *k*th coefficient in the sign of the data vector may be written as follows:

$$Sign\{\boldsymbol{y}(n-k)\} = \frac{y(n-k)}{|y(n-k)|} \tag{5}$$

In(5) the data normalization takes place due to the presence of signum function. So, this algorithm provides good stability, better filtering capability, and convergence.

***Sign Error or Sign LLMS (SLLMS) algorithm***

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

$$\boldsymbol{u}(n+1) = (1-\delta\beta)\boldsymbol{u}(n) + \delta Sign\{v(n)\}\boldsymbol{y}(n) \tag{6}$$

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

***Sign-Sign LLMS (SSLLMS) algorithm***

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

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

Here because of the signum function is applied for both data and error, some residual noise still remains in the filtering process. At the same time computational complexity almost reduced.

Among the three models, SRLLMS performs well because of the leakage factor and normalization of data involved with signum function. Moreover, its computational complexity is also reduced by using signum function.

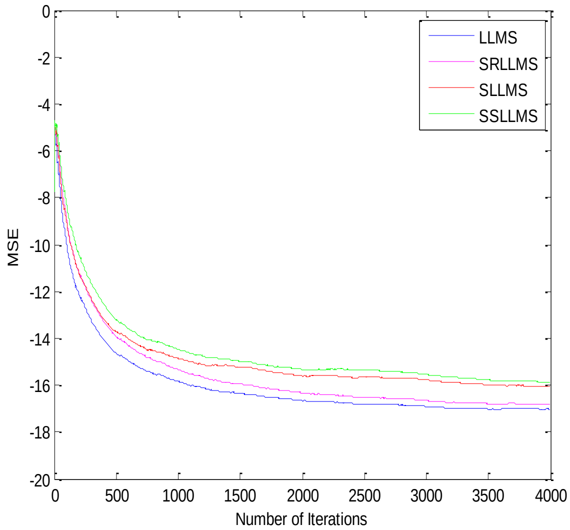


Fig. 3: Convergence characteristics of proposed algorithms.

## III. SIMULATION RESULTS

To show that the proposed models are accurately efficient in clinical situations, the techniques have been evaluated using various ICG signal recordings. In our simulation experiments we have taken ICG signal samples from five patients. The proposed models are evaluated by considering *Signal to Noise Ratio Improvement* (*SNRI*), *Excess Mean Square Error* (*EMSE*) and *Misadjustment* (*MSAD*) in the experiments, averaged the five samples and compared with the conventional LMS based Adaptive Signal Enhancement Unit (ASEU). Tables I–III give the characteristics of proposed implementations. In our experiment a Gaussian noise with variance of 0.001 is added to ICG signal component. Here we are using five ICG records i.e., record 1, record 2, record 3, record 4 and record 5. These records are influenced by artifacts like SA, RA, MA and EA. Several ASEUs are developed for ICG signal enhancement using the LMS, LLMS, SRLLMS, SLLMS, SSLLMS 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 contaminated 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 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.

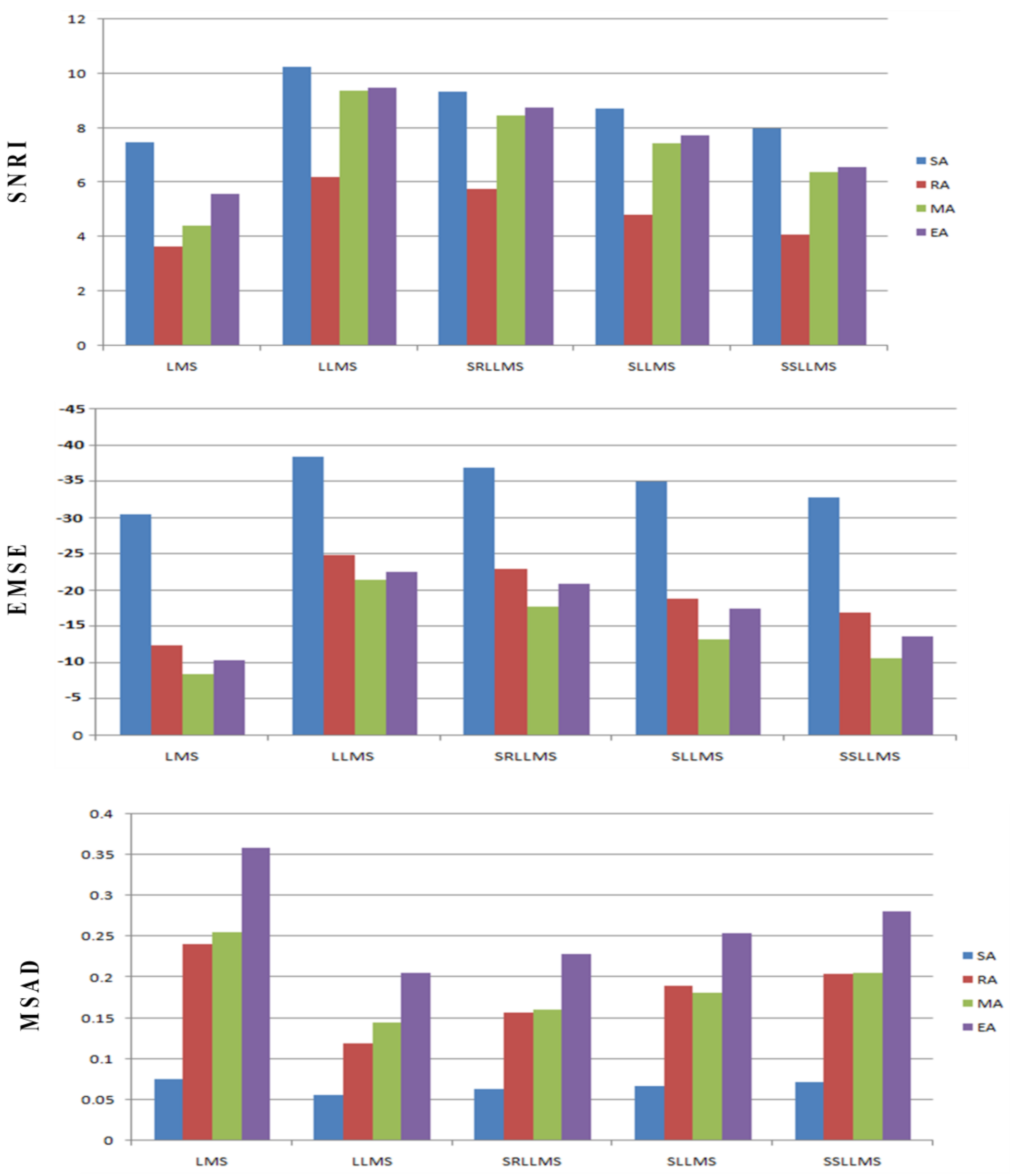


Fig 4:Comparison of performance measures in ICG filtering due to various adaptive filters.

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 limitation consideration we have shown the experimental results of record I only for eliminating two artifacts. Fig. 5 shows a typical ICG component contaminated with various types of artifacts. Due to space

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

In this experiment SA components are removed from the input raw ICG signal. The input signal to the ASEU is raw ICG as shown in Figure 5(a). This input contains desired ICG component and sinusoidal artifacts, and is given as input to ASEU shown 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 of the 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 each other. Fig. 6 shows the simulation results of SA removal from input signal. The performances of these adaptive techniques are compared with reference to SNRI, EMSE and MSAD. These are averaged for five experiments for each artifact and are tabulated in Tables 1–3.

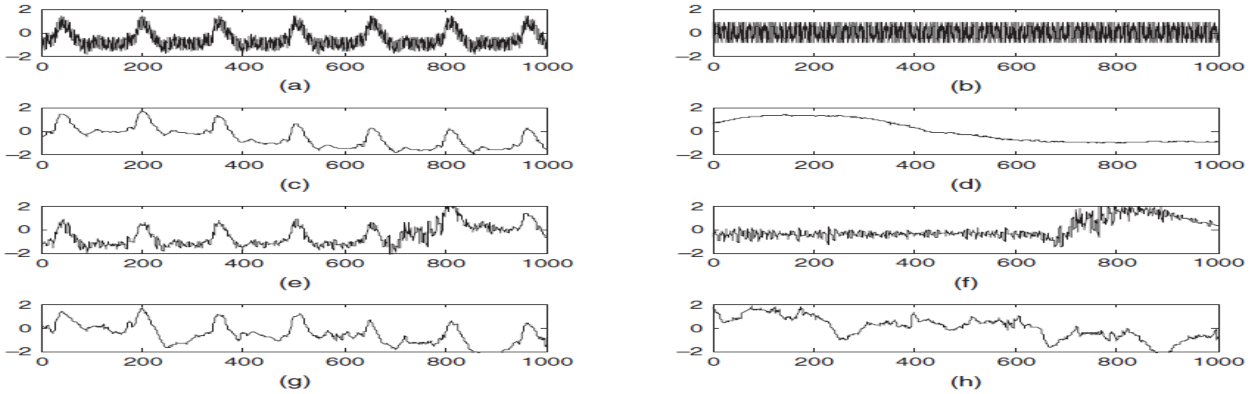


Fig. 5: A typical ICG component with various artifacts (a) ICG with SA, (b) SA component, (c) ICG with RA, (d) RA component, (e) ICG with MA, (f) MA component, (g) ICG with EA, (h) EA component. (x-axis number of samples and y -axis amplitude in millivolts).

From the experimental results it is observed that SRLLMS based ASEU performs better in the filtering of SA from the input signal almost completely. This could be preferred for real time applications due to its smaller number of multiplications. The filtering capability of the proposed ASEUs in terms of SNRI is calculated as **7.4758**dBs, **10.2499**dBs, **9.3388**dBs, **8.7173**dBs and **7.9852**dBs for LMS, LLMS, SRLLMS, SLLMS and SSLLMS respectively. SRLLMS achieves EMSE, MSAD as **-36.9503** dBs and **0.0638** dBs respectively. Based on these performance measures it may be concluded that SRLLMS 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 Electrode Artifact (EA) using Adaptive Algorithms

This experiment shows that the enhancement process of ICG signal influenced by EA. The desired ICG signal is affectedby electrode artifact 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. The ICG affected with EA is shown in Figure 5(d). Figure 7 shows the experimental results for EA removal from input signal. Tables I–III gives the performance measures of proposed techniques. From these measures we can observe that the SRLLMS based ASEU performs better. This enables SRLLMS 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, **9.4781** dBs, **8.7358**dBs, **7.7497** dBs and **6.5519**dBs for LMS, LLMS, SRLLMS, SLLMS and SSLLMS respectively. SRLLMS achieves EMSE, MSAD as **-20.9569** dBs and **0.2283** dBs respectively. By comparing the performance measures among all the algorithms, it seems as SSLLMS based ASEU is better with reference to computational complexity, SNRI, EMSE and MSAD. Hence, these realizations are suitable for real time implementations.

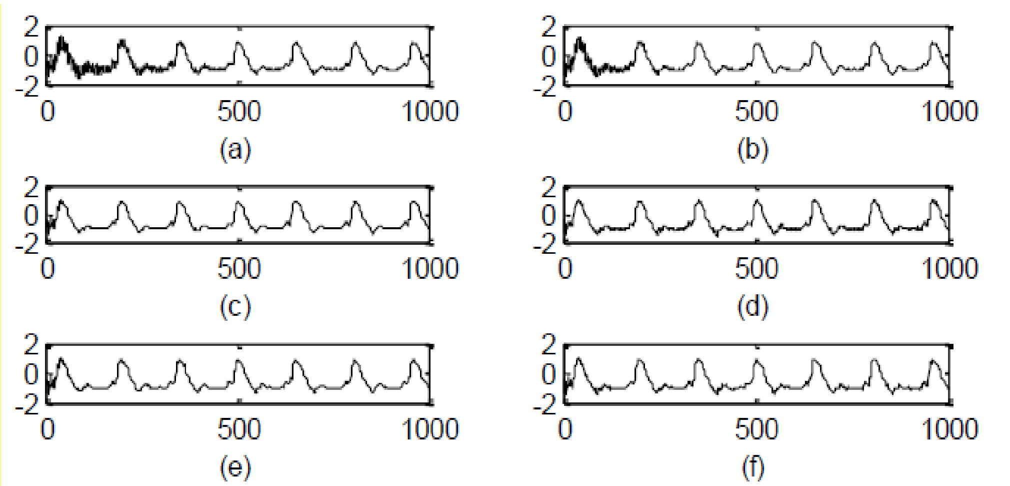


Fig. 6. Typical ICG enhancement results of SA cancelation (a) ICG signal contaminated with SA, (b) ICG filtered with LMS algorithm, (c) ICG filtered with LLMS algorithm, (d) ICG filtered with SRLLMS algorithm, (e) ICG filtered with SLLMS algorithm, (f) ICG filtered with SSLLMS algorithm. (x-axis number of samples and y -axis amplitude in millivolts).

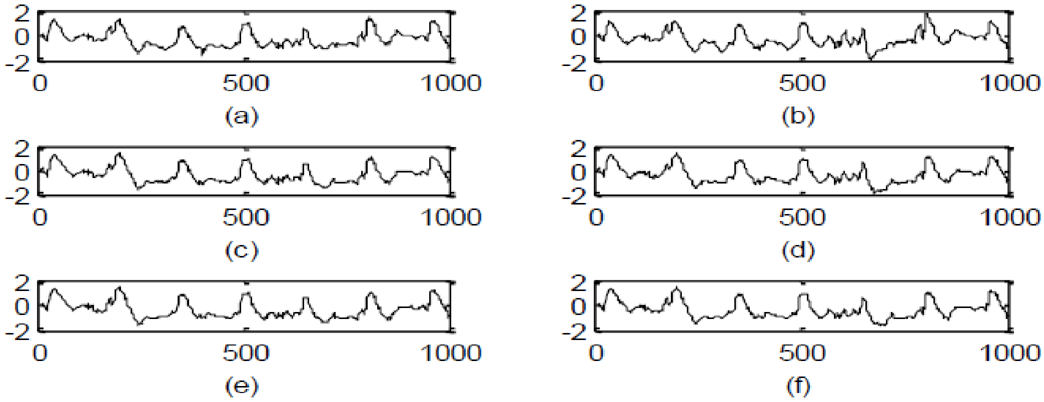


Fig. 7. Typical ICG enhancement results of EA cancelation (a) ICG signal contaminated with EA, (b) ICG filtered with LMS algorithm, (c) ICG filtered with LLMS algorithm, (d) ICG filtered with SRLLMS algorithm, (e) ICG filtered with SLLMS algorithm, (f) ICG filtered with SSLLMS algorithm. (x-axis number of samples and y -axis amplitude in millivolts).

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

This experiment demonstrates the enhancement process of ICG component encountered with MA. The desired ICG 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. Tables 1–3 gives the performance measures of proposed techniques. From these measures we can observe that the SSLLMS based ASEU performs better. The filtering capability of the proposed ASEUs in terms of SNRI is calculated as **4.4266** dBs, **9.3605**dBs, **8.4449**dBs, **7.4533** dBs and **6.3692** dBs for LMS, LLMS, SRLLMS, SLLMS and SRLLMS respectively. SSLLMS achieves EMSE, MSAD as **-17.7707** dBs and **0.1605** dBs respectively. By comparing the performance measures among all the algorithms, it seems as SRLLMS based ASEU is better with reference to computational complexity, SNRI, EMSE and MSAD. Hence, these realizations are suitable for real time implementations.

### D. 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. Tables 1–3 gives the performance measures of proposed techniques. From these measures we can observe that the SSLLMS based ASEU performs better. This enables SRLLMS 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, **6.1988** dBs, **5.7514**dBs, **4.8031** dBs and **4.0980**dBs for LMS, LLMS, SRLLMS, SLLMS and SSLLMS respectively. SRLLMS achieves EMSE, MSAD as **-23.0325** dBs and **0.1574** dBs respectively. By comparing the performance measures among all the algorithms it seems as SRLLMS 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 signal enhancement techniques are developed for ICG signal. In order to achieve convergence speed and enhancement capability we have used various ASEUs based on LMS, LLMS, SRLLMS, SLLMS and SSLLMS algorithms. These techniques are tested in real time to eliminate artifacts like SA, RA, MA and EA from the desired ICG signals. The convergence characteristics of proposed techniques are shown in figure 3. The experimental results are shown in figure 6&7. From the experimental results we can conclude that SRLLMS based ASEU is better with reference to computational complexity, SNRI, EMSE and MSAD. Hence, these adaptive realizations are suitable for real time applications.

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

| Noise | Rec. no | LMS | LLMS | SRLLMS | SLLMS | SSLLMS |
|---|---|---|---|---|---|---|
| SN | I | 7.5735 | 10.2482 | 9.3782 | 8.6373 | 7.8856 |
| | II | 7.0427 | 9.1973 | 9.0146 | 8.8559 | 8.4432 |
| | III | 7.2253 | 10.3517 | 9.1762 | 8.2714 | 7.6986 |
| | IV | 7.8312 | 10.7443 | 9.6867 | 8.9669 | 8.1328 |
| | V | 7.7061 | 10.7079 | 9.4381 | 8.8549 | 7.7657 |
| | **Avg.** | **7.4758** | **10.2499** | **9.3388** | **8.7173** | **7.9852** |
| RN | I | 3.8562 | 6.4512 | 5.8633 | 4.9356 | 4.3256 |
| | II | 3.9863 | 7.0063 | 6.7156 | 5.6478 | 4.5508 |
| | III | 3.1553 | 5.1426 | 4.8769 | 4.2905 | 3.7512 |
| | IV | 3.4827 | 6.0185 | 5.5375 | 4.4269 | 3.8747 |
| | V | 3.7738 | 6.3754 | 5.7636 | 4.7146 | 3.9875 |
| | **Avg.** | **3.6509** | **6.1988** | **5.7514** | **4.8031** | **4.0980** |
| MN | I | 4.1067 | 9.3218 | 8.3895 | 7.3278 | 6.1273 |
| | II | 4.3682 | 9.4475 | 8.5836 | 7.5853 | 6.4851 |
| | III | 4.6382 | 9.6186 | 8.8654 | 7.7995 | 6.7792 |
| | IV | 4.0552 | 8.7569 | 7.4536 | 6.5879 | 5.5546 |
| | V | 4.9649 | 9.6578 | 8.9325 | 7.9658 | 6.8996 |
| | **Avg.** | **4.4266** | **9.3605** | **8.4449** | **7.4533** | **6.3692** |
| EN | I | 5.4344 | 9.3658 | 8.6404 | 7.6351 | 6.4325 |
| | II | 5.0637 | 9.1484 | 8.3167 | 7.5475 | 6.1403 |
| | III | 5.9856 | 9.7839 | 9.0437 | 7.8542 | 6.9056 |
| | IV | 5.8538 | 9.6174 | 8.9643 | 7.9432 | 6.7581 |
| | V | 5.5857 | 9.4748 | 8.7137 | 7.7686 | 6.5228 |
| | **Avg.** | **5.5846** | **9.4781** | **8.7358** | **7.7497** | **6.5519** |

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

| Noise | Rec. no | LMS | LLMS | SRLLMS | SLLMS | SSLLMS |
|---|---|---|---|---|---|---|
| SN | I | -30.5369 | -38.5094 | -36.4185 | -34.3267 | -32.4632 |
| | II | -30.9784 | -38.8649 | -36.7831 | -34.6782 | -32.6805 |
| | III | -30.1202 | -38.1004 | -37.2457 | -35.3528 | -33.0342 |
| | IV | -30.3227 | -38.3221 | -37.6936 | -35.7964 | -33.4587 |
| | V | -30.7375 | -38.7036 | -36.6106 | -34.5877 | -32.5594 |
| | Avg. | **-30.5391** | **-38.5001** | **-36.9503** | **-34.9484** | **-32.8392** |
| RN | I | -12.2738 | -24.4745 | -22.3945 | -18.2568 | -16.4227 |
| | II | -12.6742 | -25.5373 | -23.7326 | -19.7331 | -17.7953 |
| | III | -12.3849 | -24.6215 | -22.6489 | -18.7367 | -16.8956 |
| | IV | -12.9735 | -25.9659 | -24.8397 | -20.0736 | -18.1748 |
| | V | -12.0494 | -24.1164 | -21.5467 | -17.4475 | -15.2469 |
| | Avg. | **-12.4712** | **-24.9431** | **-23.0325** | **-18.8495** | **-16.9071** |
| MN | I | -8.9736 | -21.8541 | -18.7863 | -14.5536 | -11.8463 |
| | II | -8.4456 | -21.5285 | -17.5134 | -13.9374 | -10.3837 |
| | III | -8.0687 | -20.6382 | -16.7839 | -11.6354 | -9.8936 |
| | IV | -8.7386 | -21.6279 | -18.5342 | -14.0373 | -11.2691 |
| | V | -8.1245 | -21.3876 | -17.2357 | -12.4921 | -10.0524 |
| | Avg. | **-8.4702** | **-21.4073** | **-17.7707** | **-13.3312** | **-10.6890** |
| EN | I | -10.0543 | -22.1124 | -20.4728 | -16.8532 | -13.1473 |
| | II | -10.8678 | -22.7649 | -21.7363 | -18.0348 | -14.2532 |
| | III | -10.6685 | -22.6428 | -21.0272 | -17.8651 | -13.8739 |
| | IV | -10.1654 | -22.3846 | -20.6818 | -17.0182 | -13.3951 |
| | V | -10.5279 | -22.7002 | -20.8665 | -17.5635 | -13.5895 |
| | Avg. | **-10.4568** | **-22.5210** | **-20.9569** | **-17.4670** | **-13.6518** |

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

| Noise | Rec. no | LMS | LLMS | SRLLMS | SLLMS | SSLMS |
|---|---|---|---|---|---|---|
| SN | I | 0.0754 | 0.0565 | 0.0646 | 0.0694 | 0.0712 |
| | II | 0.0725 | 0.0533 | 0.0637 | 0.0678 | 0.0704 |
| | III | 0.0704 | 0.0521 | 0.0614 | 0.0645 | 0.0695 |
| | IV | 0.0795 | 0.0581 | 0.0653 | 0.0707 | 0.0750 |
| | V | 0.0776 | 0.0578 | 0.0640 | 0.0664 | 0.0734 |
| | Avg. | **0.0751** | **0.0556** | **0.0638** | **0.0678** | **0.0719** |
| RN | I | 0.2651 | 0.1194 | 0.1892 | 0.2005 | 0.2125 |
| | II | 0.2537 | 0.1332 | 0.1573 | 0.1895 | 0.2016 |
| | III | 0.2602 | 0.1167 | 0.1644 | 0.1976 | 0.2098 |
| | IV | 0.2256 | 0.1153 | 0.1426 | 0.1863 | 0.1995 |
| | V | 0.2014 | 0.1125 | 0.1334 | 0.1732 | 0.1962 |
| | Avg. | **0.2412** | **0.1194** | **0.1574** | **0.1894** | **0.2039** |
| MN | I | 0.2416 | 0.1369 | 0.1575 | 0.1717 | 0.1997 |
| | II | 0.2377 | 0.1255 | 0.1427 | 0.1673 | 0.1971 |
| | III | 0.2176 | 0.1184 | 0.1301 | 0.1592 | 0.1773 |
| | IV | 0.2975 | 0.1784 | 0.1937 | 0.2098 | 0.2452 |
| | V | 0.2818 | 0.1619 | 0.1783 | 0.1973 | 0.2053 |
| | Avg. | **0.2552** | **0.1442** | **0.1605** | **0.1811** | **0.2049** |
| EN | I | 0.3712 | 0.2039 | 0.2225 | 0.2464 | 0.2870 |
| | II | 0.3579 | 0.1954 | 0.2134 | 0.2321 | 0.2515 |
| | III | 0.3006 | 0.1873 | 0.2015 | 0.2216 | 0.2426 |
| | IV | 0.3952 | 0.2392 | 0.2578 | 0.2798 | 0.3253 |
| | V | 0.3704 | 0.2005 | 0.2465 | 0.2905 | 0.3004 |
| | Avg. | **0.3591** | **0.2053** | **0.2283** | **0.2541** | **0.2814** |

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