International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958, Volume-8 Issue-5, June 2019

Artifacts Elimination in Impedance Cardiography Signals using Median Adaptive Algorithms

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Abstract*: *In the recent years, elimination of the artifact from Impedance Cardiography (ICG) signals is an active area. For monitoring the cardiac output, stroke volume and other hemodynamic parameters are assessed by using ICG which is non-invasive method. While acquiring the ICG signal this method affected by various non-stationary artifacts such as respiration artifacts (RA), muscle artifacts (MA), electrode artifacts (EA) and sinusoidal artifacts (SA) leads to difficulty in diagnosis. Hence for accurate diagnosis we proposed several hybrid adaptive filtering techniques having hybrid variants like Median LMS (MLMS), Sign Regressor MLMS(SRMLMS), Sign MLMS (SMLMS), Sign Sign MLMS (SSMLMS). Based on these hybrid algorithms we developed the adaptive signal enhancement units (ASEUs) and evaluated the performance of ICG signal components obtained from MIT-BIT database. Among these algorithms ASEU performance by the SRMLMS gives the better filtering technique. The parameter of signal to noise ratio improvement (SNRI) for SA, RA, MA and EA are measured as 8.6926 dBs, 4.6278 dBs, 7.4453 dBs and 7.8061 dBs respectively. Hence for ICG signal filtering in real time health care sensing systems SRMLMS based ASEUs are more suitable for better performance.

Index Terms*: *Adaptive Filter, Impedance Cardiography, Hemodynamic parameters, stroke volume, signal enhancement

I. INTRODUCTION

The periodic changes of blood volume in aorta creates the changes of electrical impedance in thorax. Impedance Cardiography (ICG) is a simple, inexpensive and noninvasive method to measure those to monitor those changes. An appropriate thorax model can be used to measure hemodynamic parameters [1]-[3], Stroke Volume (SV) and Cardiac Output (CO). In favor of ICG [4]-[5]several comparative results are carried out in the field among invasive ICG and noninvasive methods like thermo dilution. With comfort of the patients [6] several wearable devices with ICG sensors are designed to facilitate recordings. Since the initiation of ICG there has been an increased in the improvement cardiac parameters [7]-[9] and of technique reliability. In the extraction process ICG signals are contaminated by physiological and non-physiological artifacts. These cause ambiguities during diagnosis of signal due to masking of artifacts.The major artifacts contaminated with the desired ICG components are Muscle Artifacts (MA), Sinusoidal Artifacts (SA), Respiratory Artifacts (RA), and Electrode Artifacts (EA). It is necessary to eliminate artifacts to obtain high resolution ICG signal for estimating stroke volume and intensity. It is difficult predict the characteristics of artifacts when these artifacts are not stationery in nature. So, it is preferred adaptive filtering techniques based on adaptive variable weights according to statistical variations of signal and noise [10].To enhance the ICG signal resolution several algorithms are used like Recursive Least Square (RLS) andconventional Least Mean Square (LMS) [11]-[12].But these gives high steady state error and impulsive noise.To resolve these problems and to enhance the performancewe developed several Adaptive signal enhancement units (ASEUs) based on some hybrid variants of LMS. In addition, it is necessary to consider the low complexity algorithm.In [13]-[15] Rahman et al. proposed some adaptive noise cancellers to enhance the cardiac signal and brain activity using several variants of LMS. Hence for the development of ICG signal filtering techniques in this paper we fallow the same frame work to decrease the complexity. The Signal enhancement capability, convergence rate, and computational complexity are effectively improved by implementing theASEUs for ICG by using the hybrid techniques.High steady state error and impulsive noise are the main problem in LMS algorithm.To overcome these drawbacks, we proposed Median LMS (MLMS) algorithm.In this paper further improvement has made in convergence rate, filtering capability and computational complexity wise by various variants of MLMS algorithm, Sign Regressor MLMS (SRMLMS) algorithm, Sign MLMS (SMLMS) algorithm and Sign Sign MLMS (SSMLMS) algorithm. The hybrid implementation of SRMLMS based ASEUs and performance results are discussed in next section.

II. ENHANCEMENT OF IMPEDANCE CARDIOGRAPH SIGNALS USING HYBRID TECHNIQUES

During the extraction, the ICG signal is influenced by several artifacts that cause ambiguity in the diagnosis. Hence the artifacts should be eliminated in order to estimate accurate hemodynamic parameters of ICG. Adaptive filtering techniques are used to remove the non-stationary artifacts. Figure 1 shows the typical block diagram ASEU. It consists of FIR filter and weight update mechanism. In this paper several signal processing techniques are proposed for developing various ASEUs.Here we developed several strategies for weight update mechanism. First consider a conventional LMS [11] based adaptive filter with tap length N. The input to the ASEU is raw ICG signal u(n), it contains desired signal Z(n) as well as noise components R(n).R(n) is reference signal correlated with R(n) generated by the reference generator is applied

Revised Manuscript Received on June 12, 2019.

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as input to the FIR filter. Let w(n) is the impulse response of the FIR filter, y(n) is the FIR filter output, d(n) is the error signal generated in the ASEU.

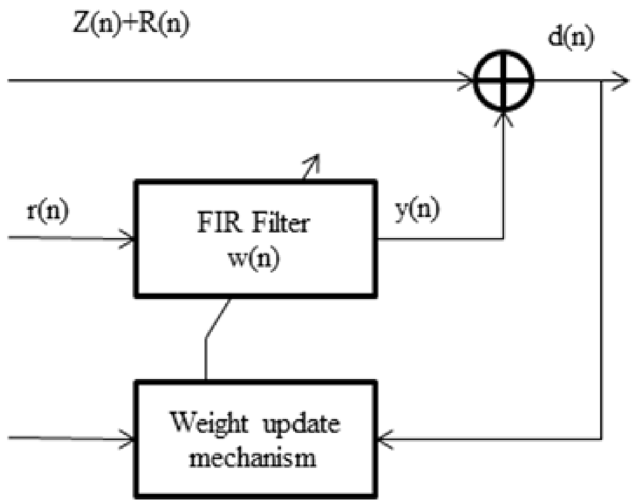


Figure 1: A typical adaptive signal enhancement unit (ASEU)

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

$$w(n+1) = w(n) + \alpha\, u(n) d(n) \quad (1)$$

where, w(n) = [w0(n) w1(n) … wN-1(n)]t is the nth tap weight vector, u(n) = [u(n) u(n−1) … u(n−N +1]t is input sequence, d(n) = u(n)-wt(n)r(n) and ‘α’ represents a step-size.

A. *Median LMS Algorithm (MLMS)*

The performance of the LMS algorithm and its derivatives is significantly degraded when it is subjected to input signals that are influenced by impulsive noise, sometimes this leads to instability. This problem can beovercome by using a nonlinear filter to smoothing the noisy gradient components. This modification leads to median LMS [16].

The weight updating mechanism for an MLMS based ASEU can be mathematically written as,

$$w(n+1) = w(n) + \alpha.\mathrm{med}_L[u(n)d(n), u(n-1)d(n-1) \ldots \ldots u(n-L)d(n-L)] (2)$$

B. *Sign variants of MLMS*

Here, we developed new algorithms that use signum [17] of either the error signal components, the input signal components, or both, have been derived from the various MLMS based adaptive algorithms for simple implementation. Hence, computation time will be reduced particularly the time required for "multiply and accumulate" (MAC) operations [17]. The sign-based techniques result in the reduction of the computational complexity of the filter and, therefore, is suitable for biotelemetry applications. In this paper we developed three sign variants of MLMS namely Sign Regressor MLMS (SRMLMS), Sign MLMS (SMLMS) and Sign Sign MLMS (SSMLMS). The weight updatingrecursion for these three variants is as,

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \alpha.med_L[d(n)Sign\{\boldsymbol{u}(n)\}, d(n-1)Sign\{\boldsymbol{u}(n-1)\} \ldots d(n-L)Sign\{\boldsymbol{u}(n-L)\}](3)$$

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \alpha.med_L[Sign\{d(n)\}\boldsymbol{u}(n), Sign\{d(n-1)\}\boldsymbol{u}(n-1) \ldots Sign\{d(n-L)\}\boldsymbol{u}(n-L)](4)$$

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \alpha.med_L[Sign\{d(n)\}Sign\{\boldsymbol{u}(n)\}, Sign\{d(n-1)\}Sign\{\boldsymbol{u}(n-1)\} \ldots Sign\{d(n-L)\}Sign\{\boldsymbol{u}(n-L)\}] \quad (5)$$

Where

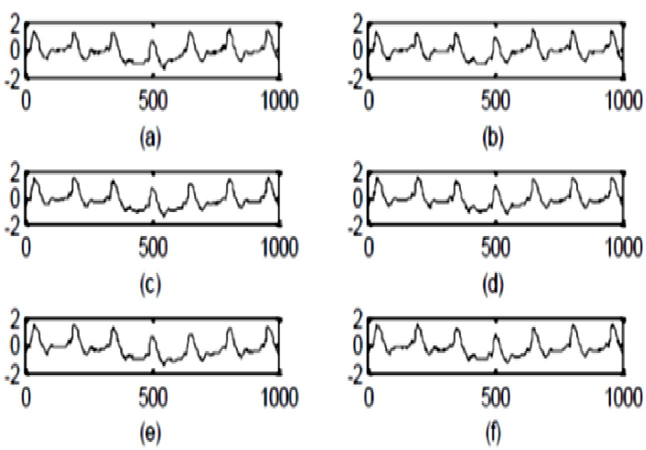
$$Sign\{\boldsymbol{u}(n)\} = \begin{cases} 1: \boldsymbol{u}(n) > 0 \\ 0: \boldsymbol{u}(n) = 0 \\ -1: \boldsymbol{u}(n) < 0 \end{cases} (6)$$

III. SIMULATION RESULTS

To demonstrate that the proposed algorithms are truly effective in clinical situations, the method has been validated using various ICG recordings taken from the MIT-BIH data base. In our simulation experiment we have taken four ICG recordings (1, 2, 3, and4) from four different people. These records are contaminated with SA, RA, MA and EA. Various SEUs for ICG enhancement is developed using the LMS, MLMS, SRMLMS, SMLMS, SSMLMS algorithms. In the evaluation procedure of the proposed techniques, we considered *Signal to Noise Ratio Improvement* (*SNRI*), *Excess Mean Square Error* (*EMSE*) and *Misadjustment*(*MSAD*) for four experiments; averaged and compared with conventional LMS based Adaptive Signal Enhancement Unit (ASEU). Tables 1–3 give the characteristics of proposed implementations.Due to space limitation we have shown the experimental results only for two artifacts. Figure 2 & Figure 3 show the filtering results for RA & MA respectively.

A. *Filtering of Respiratory Artifact (RA) Using Adaptive Algorithms*

In this experiment RA components are removed from input raw ICG. This is given as input to ASEU shown in Figure 1. The reference signal is generated from the reference generator which is correlated to RA.



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International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958, Volume-8 Issue-5, June 2019

Figure 2: Typical ICG enhancement results of RA cancelation (a) ICG signal contaminated with RA (b) ICG filtered with LMS algorithm, (c) ICG filtered with MLMS algorithm, (d) ICG filtered with SRMLMS algorithm, (e) ICG filtered with SMLMS algorithm, (f) ICG filtered with SSMLMS algorithm Based on error value the adaptive algorithm associated with the ASEU automatically updates the of FIR filter coefficients. Figure 2 shows the simulation results for removal of RA. The performances of these implementations are compared with reference to SNRI, EMSE and MSAD and tabulated in Tables 1-3. By comparing the performance measures among all the algorithms, it seems as SRMLMS based ASEU is better with reference to computational complexity, SNRI, EMSE and MSAD. Hence, these realizations are well suited for real time implementations.

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

In this experiment MA components are removed from input raw ICG. This is given as input to ASEU shown in Figure 1. The reference signal is generated from the reference generator which is correlated to MA. Based on error value the adaptive algorithm associated with the ASEU automatically updates the of FIR filter coefficients. Figure 3 shows the simulation results for removal of MA. The performances of these implementations are compared with reference to SNRI, EMSE and MSAD and tabulated in Tables 1-3. By comparing the performance measures among all the algorithms, it seems as SRMLMS based ASEU is better with reference to computational complexity, SNRI, EMSE and MSAD. Hence, these realizations are well suited for real time implementations.

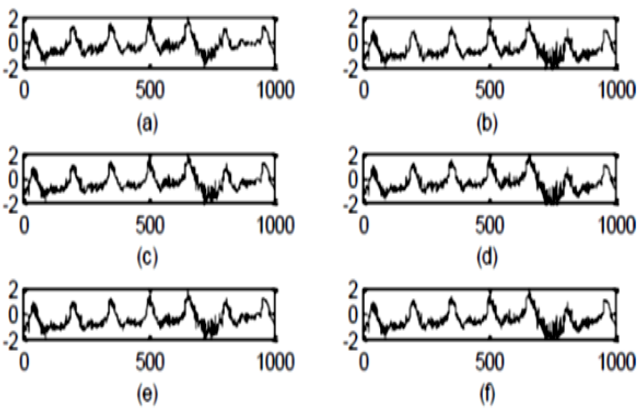

Figure 3: Typical ICG enhancement results of MA cancelation (a) ICG signal contaminated with MA (b) ICG filtered with LMS algorithm, (c) ICG filtered with MLMS algorithm, (d) ICG filtered with SRMLMS algorithm, (e) ICG filtered with SMLMS algorithm, (f) ICG filtered with SSMLMS algorithm.

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

In this experiment SA components are removed from input raw ICG. This is given as input to ASEU shown in Figure 1. The reference signal is generated from the reference generator which is correlated to SA. Based on error value the adaptive algorithm associated with the ASEU automatically updates the of FIR filter coefficients. The performances of these implementations are compared with reference to SNRI, EMSE and MSAD. These are averaged for four experiments for each artifact and are tabulated in Tables 1-3. Based on these performance measures it may be concluded that SRMLMS 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.

D. *Filtering of Electrode Artifacts (EA) Using Adaptive Algorithms*

In this experiment EA components are removed from input raw ICG. This is given as input to ASEU shown in Figure 1. The reference signal is generated from the reference generator which is correlated to EA. Based on error value the adaptive algorithm associated with the ASEU automatically updates the of FIR filter coefficients. The performances of these implementations are compared with reference to SNRI, EMSE and MSAD. These are averaged for four experiments for each artifact and are tabulated in Tables 1-3. By comparing the performance measures among all the algorithms, it seems as SRMLMS based ASEU is better with reference to computational complexity, SNRI, EMSE and MSAD. Hence, these realizations are well suited for real time implementations.

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

Noise	Rec. no	LMS	MLMS	SRMLMS	SMLMS	SSMLMS
SN	1	7.5735	9.4283	8.9637	8.3882	7.9915
	2	7.0427	8.8463	8.2753	7.8315	7.2658
	3	7.2253	9.1369	8.3272	7.9961	7.6847
	4	7.8312	9.7829	9.2043	8.8072	8.5516
	Avg.	**7.4182**	**9.2986**	**8.6926**	**8.2558**	**7.8734**
RN	1	3.8562	5.7126	5.0273	4.5737	3.1638
	2	3.9863	6.2264	5.8839	4.9980	3.3785
	3	3.1553	4.1920	3.7826	3.5362	3.3386
	4	3.4827	4.4882	3.8172	3.6638	3.5729
	Avg.	**3.6201**	**5.1548**	**4.6278**	**4.1929**	**3.3635**
MN	1	4.1067	8.0473	7.2678	6.5789	5.8791
	2	4.3682	8.2854	7.5287	6.9858	6.1041
	3	4.6382	8.4428	7.8014	7.3264	6.6673
	4	4.0552	7.7493	7.1833	6.2653	5.4672
	Avg.	**4.2921**	**8.1312**	**7.4453**	**6.7891**	**6.0294**
EN	1	5.4344	8.4483	7.6738	6.8972	6.2557
	2	5.0637	7.7886	7.0673	6.7363	6.0822
	3	5.9856	8.8639	8.3829	7.9247	7.0036
	4	5.8538	8.6743	8.1003	7.4782	6.8864
	Avg.	**5.5844**	**8.4438**	**7.8061**	**7.2591**	**6.5570**

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

Noise	Rec. no	LMS	MLMS	SRMLMS	SMLMS	SSMLMS
SN	1	-30.5369	-36.7729	-35.4435	-34.6294	-32.8935
	2	-30.9784	-36.9974	-35.9721	-34.8293	-33.8832
	3	-30.1202	-35.5783	-34.4713	-33.2479	-31.5583
	4	-30.3227	-35.6442	-34.9846	-33.8102	-32.0392
	Avg.	**-30.4896**	**-36.2482**	**-35.2179**	**-34.1292**	**-32.5936**
RN	1	-12.2738	-22.5683	-20.8104	-17.7959	-15.2518
	2	-12.6742	-23.2539	-22.0127	-19.7322	-16.3635
	3	-12.3849	-22.9956	-21.5739	-18.2160	-15.5895
	4	-12.9735	-23.7548	-22.7892	-20.1126	-16.8774
	Avg.	**-12.5766**	**-23.1432**	**-21.7966**	**-18.9642**	**-16.0206**
MN	1	-8.9736	-20.6483	-19.6633	-16.2652	-11.9026
	2	-8.4456	-20.3647	-18.2731	-15.2552	-11.0725
	3	-8.0687	-19.5546	-17.3293	-14.2721	-10.2542
	4	-8.7386	-20.4829	-18.8859	-15.6547	-11.5634
	Avg.	**-8.5566**	**-20.2626**	**-18.5379**	**-15.3618**	**-11.1982**

EN	1	-10.0543	-21.3169	-18.2536	-15.2618	-11.3177
	2	-10.8678	-21.8964	-20.5218	-16.8673	-12.7173
	3	-10.6685	-21.5429	-19.9736	-16.2794	-12.4084
	4	-10.1654	-21.4982	-18.5683	-15.6211	-11.7728
	Avg.	**-10.439**	**-21.5636**	**-19.3293**	**-16.0074**	**-12.0541**

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

Noise	Rec. no	LMS	MLMS	SRMLMS	SMLMS	SSMLMS
SN	1	0.0754	0.0658	0.0661	0.0698	0.0724
	2	0.0725	0.0613	0.0642	0.0685	0.0712
	3	0.0704	0.0602	0.0637	0.0672	0.0698
	4	0.0795	0.0685	0.0699	0.0734	0.0767
	Avg.	**0.0745**	**0.0640**	**0.0660**	**0.0697**	**0.0725**
RN	1	0.2651	0.1683	0.1763	0.1987	0.2055
	2	0.2537	0.1527	0.1678	0.1962	0.2024
	3	0.2602	0.1626	0.1945	0.2013	0.2261
	4	0.2256	0.1273	0.1456	0.1752	0.1889
	Avg.	**0.2512**	**0.1527**	**0.1711**	**0.1929**	**0.2057**
MN	1	0.2416	0.1636	0.1927	0.2004	0.2123
	2	0.2377	0.1537	0.1782	0.1975	0.2012
	3	0.2176	0.1386	0.1528	0.1718	0.1978
	4	0.2975	0.1997	0.2176	0.2215	0.2486
	Avg.	**0.2486**	**0.1639**	**0.1853**	**0.1978**	**0.2150**
EN	1	0.3712	0.2536	0.2979	0.3126	0.3326
	2	0.3579	0.2316	0.2781	0.2996	0.3016
	3	0.3006	0.2087	0.2517	0.2792	0.2973
	4	0.3952	0.2775	0.3002	0.3261	0.3397
	Avg.	**0.3562**	**0.2429**	**0.2820**	**0.3044**	**0.3178**

IV. CONCLUSION

In this paper several hybrid techniques are implemented for enhance the ICG signal performance. In order to improve the convergence speed and enhancement capability we used various ASEUs based on LMS, MLMS, SMLMS, SRMLMS, and SSMLMS algorithms. These techniques are simulated and tested in real time to eliminate artifacts like RA, SA, EA and MA from desired ICG signals. The experimental results are shown in Figures 2-3. We can conclude from the experimental results that the performance of SRMLMS based ASEU gives better markwith reference to computational complexity, SNRI, EMSE and MSAD. Hence, these realizations are well preferred for real time applications.

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