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HYBRID MODEL FOR ADAPTIVE NOISE CANCELLERS IN ICG USING MODIFIED NON NEGATIVE ALGORITHMS

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ABSTRACT

In this paper, a new process of adaptive artifact elimination from Impedance Cardiography (ICG) signals is proposed. This is a composite model based on wavelet decomposition and adaptive filter. The prime feature of this type methodology is the realization of adaptive noise canceller (ANC) without any reference signal. The proposed model is able to generate a reference signal from the input signal itself with the help of wavelet transforms. In the real time medical environment during critical conditions due to heart rhythm disorders the filter coefficients may become negative. This makes the convergence unbalance, leads to low filtering capability. In order to solve this problem, we incorporate non-negative adaptive algorithms in the proposed ANC. To enhance the performance of ANC, error normalization is adapted to change filter coefficients automatically. Again, in order to minimize computational complexity and to avoid overlapping of data samples at the input stage of the filter a hybrid version of non-negative and sign based algorithms is considered for implementation. The resulting hybrid versions are error normalized nonnegative least mean square (EN^3LMS) algorithm, error normalized non negative sign regressor LMS (EN^3SRLMS) algorithm, error normalized non negative sign error LMS (EN^3SELMS) algorithm and error normalized non negative sign sign LMS (EN^3SSLMS) algorithm. Finally, various ANCs are developed using these algorithms, performance measures are computed and compared. All the implemented ANCs are tested on real impedance cardiogram signals.

Keywords: artifact canceller, cardiovascular diseases, impedance cardiogram, non-negative algorithm, remote health care.

1. INTRODUCTION

Cardiovascular diseases (CVD) refer to huge medical cases related to the function of the heart. In the 2015 annual report WHO states that nearly 50 % of all non-transmissible disease (NTD) deaths are due to CVDs [1]. Among these, most of the deaths are on the outside of the hospital; the reason is that the patient is not treated timely. Also AHA reported that greater than 1 out of 3 have greater than one type of CVD [1], CVD`s stands first globally for the major cause if deaths. In such a scenario WHO aimed to reduce the death rate by 25% due to NTDs globally by 2025[3].

Hence the investigation of cardiovascular health care technology becomes an intensive area. Impedance Cardiography (ICG) is one of the promising techniques among various methods of cardiac functionality study. ICG non invasive method measures the total electrical conductivity of the thorax and its variations in time to a number of cardio dynamic parameters such as stroke volume (SV), Heart Rate (HR) and cardiac output (CO) in medical scenario. ICG provides the impedance variations that occur at thorax due to high-frequency, low magnitude current flows through the thorax between two pairs of electrodes located outside the measured segment. The methodology and mathematical analysis to calculate ICG, SV, HR and CO are presented in [7]-[11]. To give treatment to a cardiac patient in critical conditions ICG signal analysis is a major task. However, during the extraction, the desired ICG signal meets with physiological and non-physiological noises known as Baseline Wander noise (BW), Electro Muscle noises (EM) and Impedance Mismatch noises (IM). These artifacts affect the signal shape and tiny features, which are the main parameters for diagnosis of disease. For efficient clinical investigations the ICG signals needed to be free from artifacts. As most of the biomedical artifacts are non stationary in their nature adaptive filtering techniques provides a better solution in this application. The Adaptive filter weights are updated automatically in accordance to the noise level of the input signal. Several researchers contributed their work to the analysis of ICG using signal processing techniques. In these contributions, mainly the adaptive filtering part focused on the least mean square (LMS) and recursive least square (RLS) algorithms. But in the critical conditions, these algorithms suffer with some drawbacks. The ICG signal amplitude levels vary significantly due to abnormal heart rhythms, this leads to filter weights become negative. Due to the negative filter weights the balanced convergence and effective filtering performance are not possible. This problem can be overcome by introducing a diagonal vector of input in the weight update equation of LMS algorithm. This algorithm is named as Non-Negative LMS (N^2LMS) algorithm; here the filter coefficients become non-negative. We normalize the step size with respect to error to improve the performance of the N^2LMS algorithm in terms of convergence and excess mean square error (EMSE). This leads to (EN^3LMS) algorithm. However, in conventional AAEs it is necessary to correlate the reference signal with a noise component to the noise affected signal. But, it is difficult to give a correlated reference signal in the medical environment. That means, there may be wide statistical differences could present between the reference signal given and actual contamination present in the recorded signal. Hence, an approach using discrete wavelet transform (DWT) is developed depending upon the contamination present in the desired signal it is used to generate a reference signal. This reference is used by the adaptive algorithm in the AAE to update the filter coefficients. Also, an important key factor in remote health monitoring systems is computational complexity. Therefore, in order to minimize computational complexity, for remote health monitoring systems the proposed AAE is more suitable. We combine the non negative algorithms with three simplified algorithms [22]. These simplified algorithms are based on LMS recursion known as sign regressor LMS (SRLMS), sign error LMS (SELMS) and sign sign LMS (SSLMS) algorithms. To make the proposed algorithms less computational complex, we combine the EN^3LMS algorithm with SRLMS, SELMS and SSLMS. This results, EN^3SRLMS, EN^3SELMS and EN^3SSLMS algorithms. In order to evaluate the performance of the above mentioned algorithms which are applicable to real time clinical scenario. DWT based AAEs are developed based on these algorithms and tested on real ICG signals. The performance measures considered are: convergence characteristics, signal to noise ratio (SNR), EMSE and misadjustment (MSD). The evaluation of the proposed algorithms and experimental results of the various implementations are shown later.

2. NEW ADAPTIVE ARTIFACT CANCELLER FOR ICG SIGNAL ANALYSIS

In conventional ICG which is applicable to remote health care monitoring system. Few physiological and non-physiological contaminations encounter with in the heart functionality graph, during signal acquisition and leads to unambiguous diagnosis and assessments. Along with these contaminations channel noise also one major problem. The channel noise may mask the tiny characteristics of the ICG signal. The main noises that encounter with the functioning of the heart is baseline wander noise (BW), electro muscle noise (EM) and impedance mismatch noise (IM). BW is the base line drift of the ICG signal due to the respiratory activity. EM is due to the muscle activity, IM is due to impedance mismatch between electrodes and skin, also due to mismatch of the electrodes.

Figure-1 illustrates the schematic block diagram of an AAE based on a wavelet technique for remote health monitoring systems.

The following equation represents the desired ICG signals contaminated with noises,

$ICG(k) = s(k) + n_1(k)$

Where, ICG (k) is ICG signal recorded;

$s(k)$ is the desired ICG signal of the heart functionality; n_1 (k) is the noise parameter. In a remote health care monitoring system the channel noise may also include in this parameter. The basic principle on which the proposed AAE operates is, the raw ICG signal recorded $ICG(k)$ which is the input to DWT decomposition section. By decomposing the input raw signal including the contamination present in it we generate a reference signal. This generated reference signal is given as a reference to the adaptive algorithm in order to update the filter weights automatically. In this approach the proposed AAE plays an important role in the realization of an intelligent remote health care monitoring system.

A. Reference signal extraction from noisy input

In our proposed method, for the decomposition of the signal wavelet transform is used. For, non stationary signals wavelet transform furnishes the temporal information. Wavelets are of two types
i. continuous wavelet transform (CWT) and
ii. discrete wavelet transforms (DWT).
The CWT for a signal $s(k)$ is given by

$$CWT(i,j) = \int_{-\infty}^{\infty} s(t)\frac{1}{\sqrt{i}}\varphi\left(\frac{t-j}{i}\right)dt \quad (1)$$

Where i and j are the scaling and shifting factors respectively, and $\varphi(.)$ is wavelet function. However, evaluating the scaling (i) and shifting (j) factors for every possible scale is computationally infeasible task. One possible way to solve the problem is to choose the i and j as a power of two, such analysis results DWT, is given by

$$DWT(l,m) = \frac{1}{\sqrt{2^l}}\int_{-\infty}^{\infty} s(t)\ \varphi\left(\frac{t-2^l m}{2^l}\right)dt \quad (2)$$

Where the scaling parameter is replaced by 2^l and shifting parameter is replaced by $m2^l$.

B. Algorithms for reference free AAEs

In the proposed AAE the raw ICG signal is taken as the input and it is contaminated with the noise, using the DWT decomposition method the reference signal is constructed. The AAE consists of an FIR filter of length L taps using weight update principle the coefficients are update in filters used. The basic LMS algorithm weighted equation is written as follows,

$$W(p+1) = W(p) + \eta\, a(n)\, e(n), \quad (3)$$

Where, $W(n+1)$ is the next weight coefficient,
$W(p)$ is the previous weight coefficient,
η is the step size,
$a(p)$ is the input signal to the adaptive filter, which is constructed from DWT decomposition, which is needed to be trained to remove noise from the raw $ICG(k)$ signal,
$e(p)$ is the error occurred, which is given as a feedback to the adaptive algorithm.

Due to the abnormalities in the ICG signal, because of drastic changes in the signal includes the weighting coefficients may become negative. This leads to poor performance in terms of convergence, stability and filtering capability of the adaptive algorithm. The Non-negative LMS (N^2LMS) algorithm overcomes these drawbacks.

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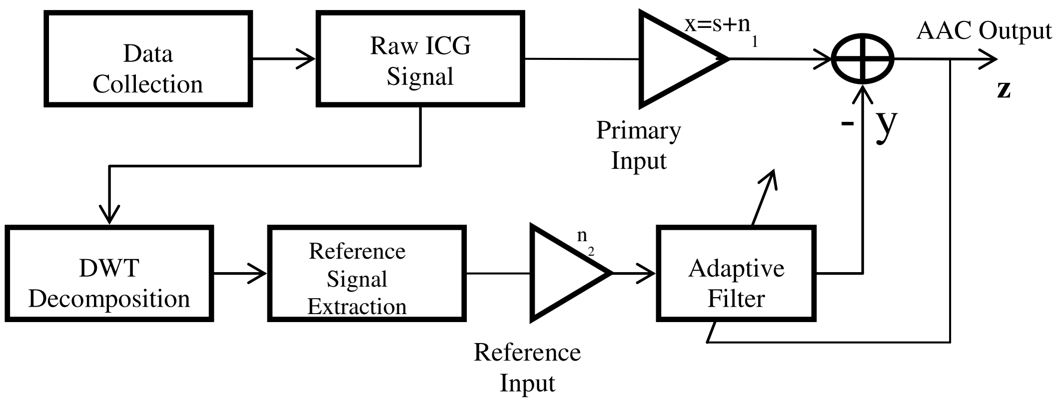

Figure-1. Structure of Adaptive Artifact Canceller for ICG signal enhancement using wavelet decomposition.

The weight update mechanism of N^2LMS is given by,

$$W(p+1)=W(p)+\eta D(p)a(p)e(p), \tag{4}$$

here, $D(p)$ is the diagonal matrix of the weight coefficients $W(p)$. From (4) each element of $W(p+1)$ is a variable step due to the combination of ηD(p). In N^2LMS algorithm when weighted coefficients tend to zero the convergence becomes unbalanced and the algorithm may diverge. This cause AAE becomes inactive for the removal of noise. To overcome the unbalanced state of convergence characteristics in abnormal situations and to improve the filter performance we propose EN^3LMS for ICG enhancement. In this algorithm the error normalization is used to improve convergence and performance of non-negative LMS algorithm [18], [31]. The weight update mechanism of EN^3LMS is given by,

$$W(p+1)=W(p)+\eta(p)D(p)a(p)e(p) \tag{5}$$

Where η(p) is variable step size in accordance with the reference input, and it is given by,

$$\eta(p) = \frac{\eta}{\alpha+e^t(p)e(p)} \tag{6}$$

Where α is a small constant to keep away the denominator become indefinite when the input sample becomes zero. In critical conditions, some input samples may become zero. In order to reduce the computational complexity of the algorithms mentioned above and therefore to be suitable for applications of remote health care. We combine the EN^3LMS algorithms with simplified algorithms elaborated in [30]. The weight update mechanism equations for these algorithms are written as follows:

a) The sign regressor variant of EN^3LMS algorithm has the weight update equation as follows,

$$W(p + 1) = W(p) + \eta(p)D(p)\, sign(a(p))\, e(p) \tag{7}$$

This algorithm is called as error normalized non negative signregressor LMS (EN^3SRLMS) algorithm.

b) The sign error variant of EN^3LMS algorithm has theweight update equation as follows,

$$W(p + 1) = W(p) + \eta(p)D(p)\, a(p)\, sign(e(p)) \tag{8}$$

This algorithm is called as error normalized non negative sign error LMS (EN^3SELMS) algorithm.

c) The sign sign variant of EN^3LMS algorithm has the weight update equation as follows,

$$W(p+1)= W(p) + \eta(p)D(p)\, sign(a(p))\, sign(e(p)) \tag{9}$$

This algorithm is called as sign sign error normalized non negative sign sign LMS (EN^3SSLMS) algorithm.

In equations (7)-(9), due to error normalization, in the denominator of $\eta(p)$ to compute $a^t(p)apn$) L multiplications are required. In order to minimize these multiplications we take only the highest value of $a(p)$ instead of taking all L values. Now the $\eta(p)$ is changed to $\eta_m(p)$ and it is given by,

$$\eta_m(p) = \frac{\eta}{\alpha+a_m^t a_m} \tag{10}$$

Where a_m s the maximum value of the $a(n)$ vector.

Now the new weight update mechanisms for EN^3LMS and its three signed variants respectively are written as follows:

$$W(p+1)=W(p)+\eta_m(p)D(p)a(p)e(p) \tag{11}$$

$$W(p+1)=W(p)+\eta_m(p)D(p)sign(a(p))e(p) \tag{12}$$

$$W(p+1)=W(p)+\eta_m(p)D(p)a(p)sign(e(p)) \tag{13}$$

$$W(p+1)=W(p)+\eta_m(p)D(p)sign(a(p))sign(e(p)) \tag{14}$$

These algorithms minimizes the computational complexity of the filtering process due the signum function involved [32]-[33].

Figure-3 shows the convergence curves of EN^3LMS algorithms and their SR, SE and SS variants. From these figures it is clear that between EN^3LMS and EN^3SRLMS algorithms, EN^3SRLMS is just a little bit inferior to EN^3LMS with lesser number of multiplications. So in real time applications EN^3SRLMS algorithm based AAE can be used because of highest convergence, good filtering capability and less computational complexity.

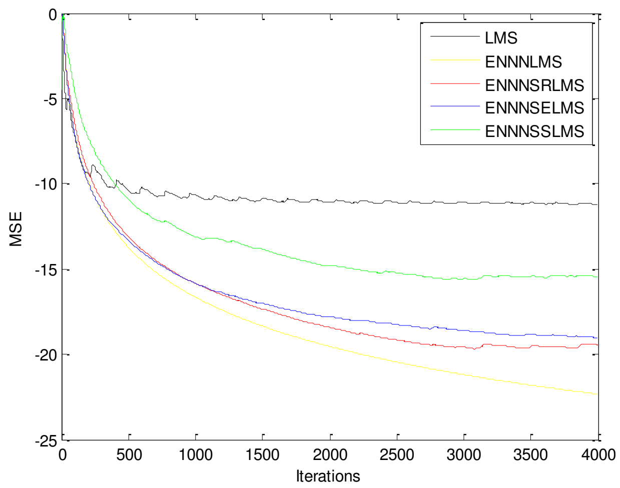

Figure-2. Typical convergence curves for ICG signal enhancement in Gaussian environment due to EN^3LMS and its sign based variants.

3. SIMULATION RESULTS

For the purpose of remote health monitoring systems we have introduced a new model for cancelation of noises in the ICG signals. In our works the ICG signals are extracted from VU-AMS ambulatory system [26]-[28]. We have used five ICG signals with 5000 samples, these ICG signals are named as Data1; Data2; Data3; Data4 and Data 5. In our experimental results we have shown only 2000 samples for better resolution. To assess the performance of various algorithms discussed in the previous section we have developed various AAEs using LMS, EN^3LMS, EN^3SRLMS, EN^3SELMS and EN^3SSLMS algorithms. As per our posited method, from the raw ICG signal using DWT decomposition we develop a reference signal and that is again given as a reference signal to the adaptive algorithm. The comparisons of SNR, EMSE and MSD due to various algorithms are tabulated in Tables 1, 2 and 3 respectively. Besides these measures we also calculated the weight coefficients for enhancing Data 1 during various artifacts cancelations to examine the non-negative constraint of the proposed AAEs, these are tabulated in Table IV. In our analysis the filter length is chosen as 10, the step size is considered as 0.1.

A. Removal of baseline wander artifact from ICG signals using new AAEs

This experiment illustrates the cancelation of baseline wander artifact from ICG signal. For this the raw ICG signal is given as input to DWT based AAE as shown in Figure-1. A reference signal is constructed by DWT decomposition. This reference signal in effective is used as a reference to the AAE, as shown in block diagram this is considered as n_2. By taking feedback from the output $z(n)$ the algorithm trains n_2 such that it is closely correlated with the contaminated component n_1 in the input ICG signal $x(n)$. To validate the performance of the DWT based AAE for BWA cancelation we considered SNR, EMSE and MSD as performance measures. Figure-4 shows the cancelation of BWA from the raw ICG signal. By observing this figure from Figure-4 (c and d) are clearer than the other AAEs. Among the algorithms considered EN^3SRLMS is better than EN^3LMS. This is due to the two normalization operations involved in the weight update recursion because of error normalization and data normalization in the signum function. The residual error component after filtering with various algorithms is shown in Figure-5. From Figure-5 (d) is it clear that the residual error in the case of EN^3SRLMS is less when compared to other algorithms. Finally, based on the experimental results, it can be concluded that EN^3SRLMS is better than the other algorithms and hence it can be used as adaptive algorithm in a practical health care monitoring system for remote applications.

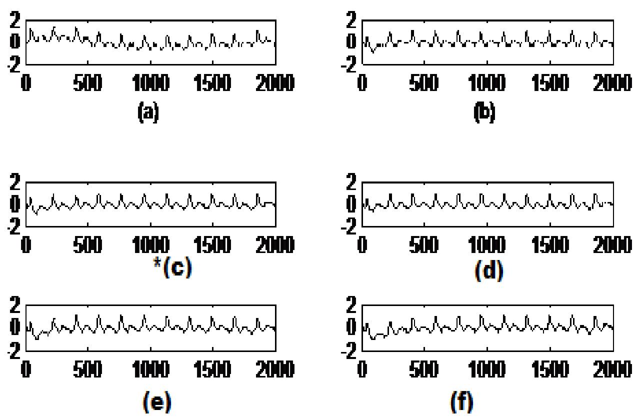

Figure-3. Filtering results of BWA due to various AAEs (a). ICG signal with BWA, (b). ICG filtering due to LMS updated AAE, (c). ICG filtering due to EN^3LMS updated AAE, (d). ICG filtering due to EN^3SRLMS updated AAE, (e). ICG filtering due to EN^3SELMS updated AAE, (f). ICG filtering due to EN^3SSLMS updated AAE (On x-axis number of samples and on y-axis signal amplitude in mV are shown).

VOL. 12, NO. 9, MAY 2017 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

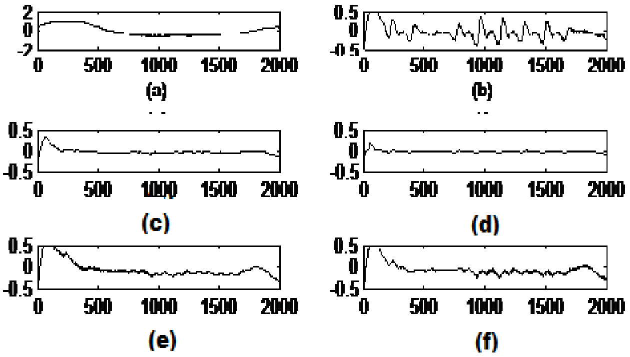

Figure-4. Comparison of residual noise after BWA filtering(a). Original artefact component, (b). Residual noise after LMS updated AAE, (c). Residual noise after EN^3LMS updated AAE, (d). Residual noise after EN^3SRLMS updated AAE, (e) Residual noise after EN^3SELMS updated AAE, (f). Residual noise after EN^3SSLMS updated AAE (On x-axis number of samples and on y-axis residual noise amplitude in mV are shown).

B. Electro muscle artifact removal from ICG signals using new AAEs

This experiment illustrates the cancelation of electro muscle artifacts from ICG signal. To validate the performance of the DWT based AAE for cancelation of EMA we considered SNR, EMSE and MSD as performance measures. Figure-6 shows the cancelation of EMA from the raw ICG signal. By observing this figure from Figure-6 (c and d) are more clear than the other AAEs. The residual error component after filtering with various algorithms is shown in Figure-7. From Figure-7 (d) is it clear that the residual error in the case of *EN^3SRLMS* is less when compared to other algorithms. This also confirmed from the Tables 1, 2 and 3. The average SNR for *EN^3LMS* and *EN^3SRLMS* are 9.7308dB and 10.2865dB respectively. The average EMSE for *EN^3LMS* and *EN^3SRLMS* are - 21.4392dB and -22.8350dB respectively. Similarly the average MSD for *EN^3LMS* and *EN^3SRLMS* are 0.0937 and 0.0883 respectively. Therefore, based on these performance measures it is clear that *EN^3SRLMS* is found to be better than other algorithms with respect to SNR, EMSE, MSD, convergence and computational complexity.

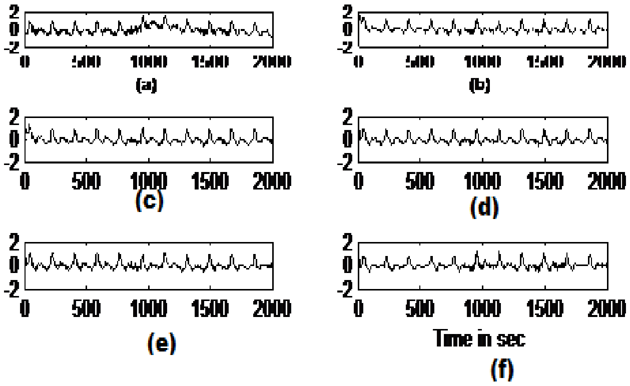

Figure-5. Filtering results of EMA due to various AAEs (a). ICG signal with EMA, (b). ICG filtering due to LMS updated AAE, (c). ICG filtering due to EN^3LMS updated AAE, (d). ICG filtering due to EN^3SRLMS updated AAE, (e). ICG filtering due to EN^3SELMS updated AAE, (f). ICG filtering due to EN^3SSLMS updated AAE (On x-axis number of samples and on y-axis signal amplitude in mV are shown).

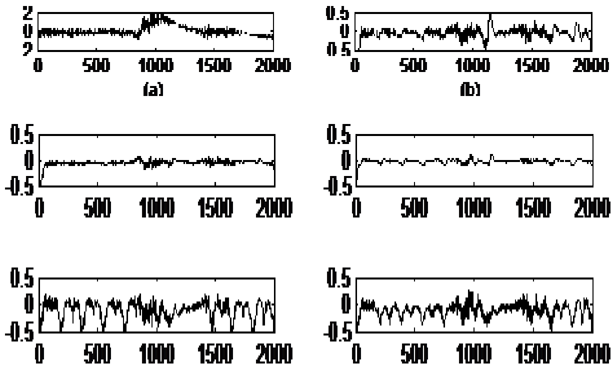

Figure-6. Comparison of residual noise after EMA filtering (a). Original artefact component, (b). Residual noise after LMS updated AAE, (c). Residual noise after EN^3LMS updated AAE, (d). Residual noise after EN^3SRLMS updated AAE, (e). Residual noise after EN^3SELMS updated AAE, (f). Residual noise after EN^3SSLMS updated AAE (On x-axis number of samples and on y-axis residual noise amplitude in mV are shown).

C. Impedance Mismatch Artifact (IMA) removal from ICG signals using new AAEs

This experiment illustrates the cancelation of impedance mismatch artifact from ICG signal. For this the raw ICG signal is given as input to DWT based AAE as shown in Figure-1. A reference signal is constructed by DWT decomposition. This reference signal in effective is used as a signal to the AAE, as shown in block diagram this is considered as n_2. By taking feedback from the output $z(n)$ the algorithm trains n_2 such that it is closely correlated with the contaminated component n_1 in the input ICG signal $x(n)$. To validate the performance of the DWT based AAE for IMA cancelation we considered SNR as the performance measure. Figure-8 shows the

VOL. 12, NO. 9, MAY 2017 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

cancelation of IMA from the raw ICG signal. By observing this figure from Figure-8 (c and d) are clearer than the other AAEs. The residual error component after filtering with various algorithms is shown in Figure-9. From Figure-9 (d) is it clear that the residual error in the case of *EN³SRLMS* is less when compared to other algorithms. This also confirmed from the Tables I, II and III. The average SNR for *EN³LMS* and *EN³SRLMS* are 9.6045dB and 10.2333dB respectively. The average EMSE for *EN³LMS* and *EN³SRLMS* are -19.8196dB and -20.6863dB respectively. Similarly the average MSD for *EN³LMS* and *EN³SRLMS* are 0.1270 and 0.0899 respectively. Therefore, based on these performance measures it is clear that *EN³SRLMS* is found to be better than other algorithms with respect to SNR, EMSE, MSD, convergence and computational complexity.

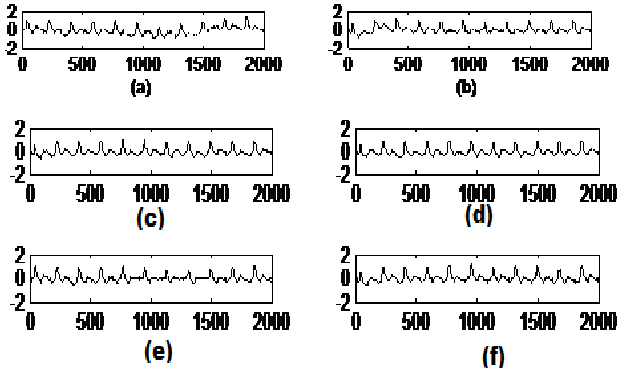

Figure-7. Filtering results of IMA due to various AAEs (a). ICG signal with IMA, (b). ICG filtering due to LMS updated AAE, (c). ICG filtering due to *EN³*LMS updated AAE, (d). ICG filtering due to *EN³*SRLMS updated AAE, (e). ICG filtering due to *EN³*SELMS updated AAE, (f). ICG filtering due to *EN³*SSLMS updated AAE (On x-axis number of samples and on y-axis signal amplitude in mV are shown).

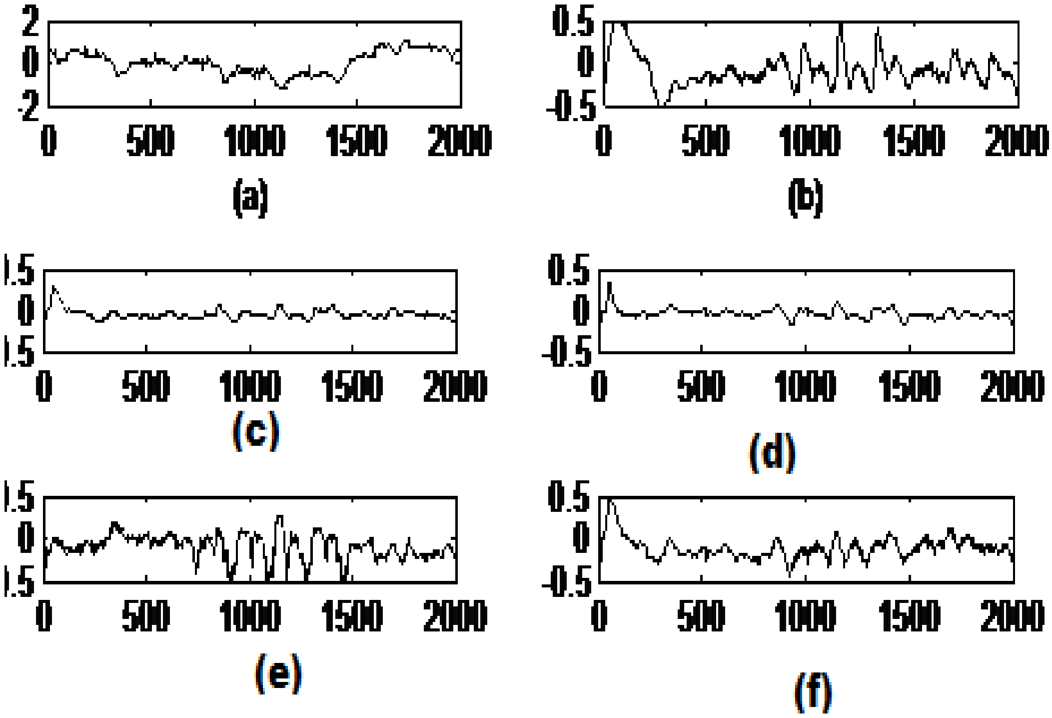

Figure-8. Comparison of residual noise after IMA filtering (a).Original artefact component, (b). Residual noise after LMS updated AAE, (c). Residual noise after *EN³*LMS updated AAE, (d). Residual noise after *EN³*SRLMS updated AAE, (e). Residual noise after *EN³*SELMS updated AAE, (f). Residual noise after *EN³*SSLMS updated AAE (On x-axis number of samples and on y-axis residual noise amplitude in mV are shown).

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Table-1. Comparison of SNR after ICG signal filtering due to various artifacts in dB.

Artifact type	Sample no.	LMS	E*N* 3 LMS	E*N* 3 SRLMS	E*N* 3 SELMSS	E*N* 3 SSLMS
BWA	Data 1	4.9815	10.0224	12.3887	9.5597	8.6621
	Data 2	4.9783	10.9098	12.3967	9.5476	8.7082
	Data 3	4.9876	10.9505	12.4706	9.4247	8.7186
	Data 4	4.9993	10.9112	12.3713	9.5015	8.5872
	Data 5	4.9782	10.9299	12.3780	9.4582	8.7035
	Average	4.9849	10.7447	12.4010	9.4983	8.6759
EMA	Data 1	4.3813	9.7503	10.4009	8.0288	7.3731
	Data 2	4.3905	9.7791	10.4472	8.4847	7.2409
	Data 3	4.3802	9.7154	10.4087	8.0743	7.4016
	Data 4	4.4016	9.7462	10.3864	8.0747	7.3077
	Data 5	4.3912	9.6594	10.3949	8.8145	7.2963
	Average	4.3889	9.7308	10.4076	8.2954	7.3239
IMA	Data 1	4.0359	9.0458	10.2865	8.5063	7.8741
	Data 2	4.0256	9.9142	10.1189	8.4337	7.9529
	Data 3	3.9916	9.1067	10.3249	8.4965	7.4232
	Data 4	3.9912	9.9909	10.2156	8.3643	7.1968
	Data 5	3.9939	9.9649	10.2206	8.4765	7.2253
	Average	4.0076	9.6045	10.2333	8.4554	7.5344

Table-2. Comparison of misadjustment.

Artifact type	Sample no.	LMS	E*N* 3 LMS	E*N* 3 SRLMS	E*N* 3 SELMSS	E*N* 3 SSLMS
BWA	Data 1	4.9815	10.0224	12.3887	9.5597	8.6621
	Data 2	4.9783	10.9098	12.3967	9.5476	8.7082
	Data 3	4.9876	10.9505	12.4706	9.4247	8.7186
	Data 4	4.9993	10.9112	12.3713	9.5015	8.5872
	Data 5	4.9782	10.9299	12.3780	9.4582	8.7035
	Average	4.9849	10.7447	12.4010	9.4983	8.6759
EMA	Data 1	4.3813	9.7503	10.4009	8.0288	7.3731
	Data 2	4.3905	9.7791	10.4472	8.4847	7.2409
	Data 3	4.3802	9.7154	10.4087	8.0743	7.4016
	Data 4	4.4016	9.7462	10.3864	8.0747	7.3077
	Data 5	4.3912	9.6594	10.3949	8.8145	7.2963
	Average	4.3889	9.7308	10.4076	8.2954	7.3239
IMA	Data 1	4.0359	9.0458	10.2865	8.5063	7.8741
	Data 2	4.0256	9.9142	10.1189	8.4337	7.9529
	Data 3	3.9916	9.1067	10.3249	8.4965	7.4232
	Data 4	3.9912	9.9909	10.2156	8.3643	7.1968
	Data 5	3.9939	9.9649	10.2206	8.4765	7.2253
	Average	4.0076	9.6045	10.2333	8.4554	7.5344

Table-3. Comparison of EMSE

Artifact type	Sample no.	LMS	E*N* 3 LMS	E*N* 3 SRLMS	E*N* 3 SELMS	E*N* 3 SSLMS
BWA	Data 1	-15.6161	-20.9294	-21.6141	-19.3120	-18.0165
	Data 2	-15.6155	-20.8971	-21.5883	-19.3521	-18.9065
	Data 3	-15.6312	-20.9067	-21.5539	-19.4433	-18.9678
	Data 4	-15.6089	-20.8209	-21.5806	-19.3459	-18.0760
	Data 5	-15.6361	-20.9243	-21.5378	-19.3897	-18.9699
	Average	-15.6215	-20.8956	-21.5794	-19.3686	-18.5873
EMA	Data 1	-15.6813	-21.0518	-22.7324	-19.5320	-18.2725
	Data 2	-15.6635	-21.5337	-22.9203	-19.9698	-18.7744
	Data 3	-15.6988	-21.5304	-22.8438	-19.0110	-18.8796
	Data 4	-15.6717	-21.5586	-22.8419	-19.9963	-18.9761
	Data 5	-15.6780	-21.5218	-22.8368	-19.9963	-18.9761
	Average	-15.6786	-21.4392	-22.8350	-19.7010	-18.7757
IMA	Data 1	-13.3694	-19.7849	-20.7161	-18.9384	-17.8268
	Data 2	-13.3844	-19.8624	-20.7151	-18.1661	-17.9233
	Data 3	-13.3632	-19.7973	-20.6582	-18.0964	-17.2163
	Data 4	-13.3873	-19.8394	-20.6915	-18.2422	-17.9594
	Data 5	-13.3551	-19.8142	-20.6508	-18.9877	-17.9541
	Average	-133718	-19.8196	-20.6863	-18.4861	-17.7759

4. CONCLUSIONS

In this works for the purpose of remote health monitoring application a new method was developed for enhancing the ICG signals. In this proposed method the adaptive artifact canceller does not require a reference signal externally it can construct the reference signal using DWT decomposition method. To update the filter weight coefficients in order to eliminate the noise the constructed reference signal is used. Due to the negative weights in order to avoid the divergence at the period of abnormal heart conditions we developed various non-negative LMS algorithms. Due to the negative weights occurred during the period of abnormal heart conditions to avoid divergence we have developed various non negative LMS algorithm. EN^3LMS, EN^3SRLMS, EN^3SELMS and EN^3SSLMS algorithms. Of all these algorithms sign regressor based algorithms need a less number of multiplications as well as achieving better convergence. The sign regressor version is little bit inferior than its unsigned version regarding its feature of convergence, from above all the inferences and results it is clear that EN^3SRLMS based AAE exhibits well than the other algorithms. For remote health monitoring systems in order to cancel the artifacts involved in the signal the DWT based AAE is well suited for such application.

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