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Artifact Elimination in Thoracic electrical bioimpedance signals using new Normalized Adaptive Filters

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ABSTRACT

Thoracic electrical bioimpedance (TEB) used for facilitating stroke volume from sudden cardiac arrest signals. It is a non -invasive method used monitoring cardiac outputs, measuring stroke volumes and to observe changes in hemodynamic parameters of volume of blood. While measuring volume of blood, TEB signal is contaminated with physiological and non-physiological signal artifacts. For avoiding these artifacts in this paper proposed an adaptive filter method for enhancing TEB Signals. Least Mean Square (LMS) algorithm is a basic adaptive method, but it is non stationary in nature and it has low convergence rate problems. Hence, Bias compensated Normalized Least Mean Square (BC NLMS) algorithm is proposed, then it check initially for stability in terms of mean deviation analysis and mean square deviation analysis. Depending in this analysis, noisy input variance estimation and variable step size are taken into consideration for better performance in terms of reduced steady error rate, good stability and convergence improvement. In this paper we present various adaptive noise cancellers (ANCs) for the elimination of artifacts from TEB signals. Also, in simulation results, artifacts are eliminated from noisy input signal and it performs well when compared to exiting methods.

Key words: Adaptive filtering, Cardiac output, Noisy input, Hemodynamics, Thoracic Electrical Bioimpedance, Variable step size.

1. INTRODUCTION

Hemodynamics is one of the parameters used generally to calculate cardiac activity, using this parameter blood flow across the body is measured. To study hemodynamics impedance Plethysmography technique is used, then measurement changes in tissue volumes can be calculated with help of electrical impedance changes over the body. Thoracic electrical bioimpedance (TEB) is a non-invasive method used for monitoring impedance changes in thorax. Generally invasive method [1], [2] like thermodilution Pulmonary Artery Catheter (PAC) is used for measuring changes in blood flow, but this method is critical for sick patients, it requires qualified staff. To avoid these limitations non- invasive methods are used. In non-invasive methods also Doppler echocardiography and the Magnetic Resonance Imaging (MRI) are still complicated and expansive techniques and they are not used in real time monitoring. For avoiding all limitations, impedance cardiography is used. It is a non-invasive, simple and cost-effective tool, then hemodynamic parameters like stoke volume (SV) and cardiac output (CO) are calculated. It is fast response technique and it can be easily used in ambulatory monitoring also. Periodic changes in blood volume of aorta can create changes in electrical impedance of thorax, then identified changes of body due to the change in blood flow of heart, according to changes parameters are measured. Mathematically cardiac output is a product of stroke volume and heart rate and their units are L/min. Cardiac output is generally calculated who are suffering with cardiovascular diseases especially with coronary artery problems. This TEB method is considered as diagnosing technique used for measuring the electrical changes in biological tissues of thorax. It is generally calculated as constant and small current passed thorough outer electrodes and then we acquired changes in electrical voltage by inner electrodes. Basically [3]-[5], thorax means the part between the neck and abdomen of body, so that two electrodes are placed across the neck and other two electrodes are placed above the abdomen, then current is injected and their corresponding voltages are calculated. Then the acquire voltage is proportional to impedance variations of thorax region. Impedance (Z) is defined by ohm's law and it is the ratio of acquired voltage (V) to injected current (I). If we know the current strength, then impedance can be easily calculated. Then the impedance cardiography can be recorded as dZ/dt.

By using wireless telemetry, who are suffering with chronic diseases is monitored in remote areas. Particularly Congestive heart failure patients, telemetry services are used. By using monitoring devices in home environment, detected the early signs of patient health, wearable electrode devices are used for monitoring, then checked the changes in heart rate, respiration rate of chronic patient is monitored. Daily monitoring of patient is done using PPG finger clip to know heart rate. Where as in ambulatory setup, by expansion of chest acquired the respiratory signals, but is done by using elastic belts which are not so easy to use for elderly patients. In [6], to extract electrocardiographic (ECG) signals from bioimpedance spectroscopy (BIS) is used without any sensors rather than a trans-thoracic bioimpedance monitor (BIM) electrodes. Respiration is common artifacts occurred from

TEB measurements. By using BIM, thoracic fluid status is accessed, it connects to vest includes with chest belts and they are integrated with electrodes. By using microwave communication telemetry, it enabled the interface of control device and user, then by ejecting current corresponding voltage is measured. Thoracic bioimpedance is obtained over time by measuring impedance in anatomy and fluid stat of thorax region. Bioimpedance values are inaccurate in some intensive care units (ICU) due to some significant noises and body motions of patients and also due to sensitive of placing of electrodes varies according size of patient body, physical factors then it will affect the electrical conductivity of skin and electrodes due to humidity and temperature changes. So, in [7] proposed a bioreactance based noninvasive method is used for measuring cardiac output. It is calculated based on phase shift analysis of oscillating current that occur along with thoracic cavity depends on amplitude of signal, but is has so much electrical noise, so theoretical improvement is not possible. Various adaptive filter techniques are studied in [8]-[13] for removing artifacts from signals. Electrical impedance spectroscopy (EIS) system is used to apply constant amplitude by changing current between two electrodes of thorax, then the voltage across them is calculated. For better characterization, present system has to use wide frequency range [14]-[16], then calculated impedance values and there are some artifacts are present due to the polarization, movement, probe controlments etc., and this parasite effects are avoided by using impedance spectra measurements. While measuring stroke volume and cardiac output using TEB it has some advantages and disadvantages. Advantages of using non-invasive TEB include low risk to patient, cost effective and easy to implement whereas the disadvantages are in electrode displacement mistakes, movement artifacts. To avoid these artifacts proposed artificial network with long short-term memory (LSTM) is used for filtering and reconstruction of signal and it gives better outputs when compared to Scaled Fourier Linear Combiner (SFLC). While measuring impedance cardiography using TEB, respiratory artifacts are occurred. By notifying the physiological and non-physiological artifacts from wireless telemetry measurements, they are reduced by using adaptive algorithm along with TEB module, also studied various signal analyzing techniques in [17]-[29]. There are mathematical difficulties are also there while measuring stroke volume in remote health care monitoring systems. So, in this paper for improvement of TEB, proposed a Bias Compensated Normalized LMS algorithm for removing artifacts. From respiratory artifacts, noise is removed by using data normalization to artifacts. Convergence is also improved when compared to LMS algorithm because normalization factor is considered here to weight update equation of proposed algorithm. Hence there is an improvement in terms of stability, convergence rate and steady state error rate with the existed techniques.

2. BIAS COMPENSATED NLMS FOR NOISY ARTIFACTS

Stroke volume is calculated based on impedance cardiography recordings; it is the volume of blood pumped to left ventricle during one contraction of cycle it is denoted in ml. Cardiac output is product of stroke volume and heart rate. Heart rate is measured in bpm. Then cardiac output units are represented as L/min. The most used equation for calculating stroke volume is represented as follows:

$$S_V = \sigma \frac{d^2}{r^2} \left(\frac{dr}{dt}\right)_{max} . LV_{ET}$$

Here S_V is stroke volume, σ is blood resistivity, its value is considered as constant during cardiac cycle, d is distance between electrodes, r is the impedance measured between inner electrodes, LV_{ET} is left ventricular ejection time it is represented in 's'.

2.1 Least Mean Square Algorithm

Consider a system model with finite impulse response (FIR) vector as shown in figure. Desired signal at particular time is represented as

$$d_t = v_t^T f^0 + O_t \tag{1}$$

$v_t = [v_t, v_{t-1}, \dots v_{t-K+1}]^T$ is noise free input, v_t is input with zero mean white gaussian noise, O_t is noise at output filter. Input and output with variance σ_t^2. FIR filter is corrupted by noise, at 't' iteration noise input vector is given as

$$\bar{v_t} = v_t + n_t \tag{2}$$

Where $n_t = [n_t, n_{t-1}, n_{t-K+1}]^T$ is noise vector input with gaussian noise σ_t^2. Input vector v_t , input noise n_t and output noise O_t are independent mutually. Then priori error is expressed as

$$\begin{aligned} \bar{e_t} &= d_t - \bar{v}_t^T f_t \\ &= d_t - \bar{v}_t^T f_t - n_t^T f_t \\ &= e_t - n_t^T f_t \end{aligned} \tag{3}$$

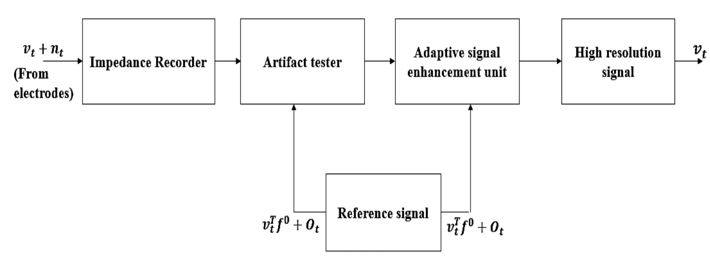

Figure 1: Artifact cancellation block diagram for impedance cardiography signal

Here f_t is weight update filter with $f_t \in \mathcal{R}^{K\,x\,1}$

Output Posterior error ε_t for noise free input is expressed as

$$\begin{aligned} \bar{\varepsilon_t} &= d_t - \bar{v}_t^T f_{t+1} \\ &= d_t - v_t^T f_{t+1} n_t^T f_{t+1} \\ &= \varepsilon_t - n_t^T f_{t+1} \end{aligned} \tag{4}$$

Then the updated LMS weight equation is expressed as

$$f_{t+1} = f_t + \eta\, \bar{\varepsilon}_t O_t \quad (5)$$

2.2 Normalized LMS algorithm & Bias Compensated NLMS algorithm

Basic normalized LMS [30] equation for noise free input is expressed as

$$f_{t+1} = f_t + \eta \frac{v_t\, e_t}{v_t^T v_t} \quad (6)$$

Where η is step size parameter.

If the input vector is noisy, instead of v_t and e_t noise measurements $\bar{v_t}$ and $\bar{e_t}$ are available. For this weight update equation of (6), to get noise free output of TEB output needs a biased estimate. For handling bias problems, caused due to noise inputs bias compensation 'c_t' vector is added to NLMS weight equation.

$$f_{t+1} = f_t + \eta \frac{\bar{v_t}\, \bar{e_t}}{\bar{v}_t^T v_t} + c_t \quad (7)$$

Error weight vector is represented as $\tilde{f_t} \cong f^o - f_t$, then equation (7) is expressed in terms of $\tilde{f_t}$

$$f_{t+1} = f_t - \eta \frac{\bar{v_t}\, \bar{e_t}}{\bar{v}_t^T v_t} - c_t \quad (8)$$

Bias compensation vector c_t have to derive for satisfying the unbiasedness criterions for a set of given data $\tilde{v_t} = \{\bar{v_i} | 1 \le i \le t\}$ as

$$E(\tilde{f}_{t+1}|\tilde{v_t}) = 0 \text{ when } E(\tilde{f_t}|\tilde{v_t}) = 0 \quad (9)$$

Then by solving unbiasedness criterion from [31], then vector is obtained as

$$c_t = \eta \frac{\sigma_t^2 f_t}{\bar{v}_t^T \bar{v}_t} \quad (10)$$

By substituting equation (10) in equation (7), we get the Bias Compensated NLMS algorithm as

$$f_{t+1} = f_t + \eta \frac{\bar{v_t}\, \bar{e_t} + \sigma_t^2 f_t}{\bar{v}_t^T \bar{v}_t} \quad (11)$$

For noisy inputs off unknown system, Bias Compensated NLMS algorithm (BC NLMS) provides unbiased estimates. Input variance σ_t^2 is estimated if we want to use in BC NLMS algorithm, because it is not practically available. Then practically, BC NLMS is calculated as

$$f_{t+1} = f_t + \eta \frac{\bar{v_t}\, \bar{e_t} + \hat{\sigma}_{n,t}^2 f_t}{\bar{v}_t^T \bar{v}_t} \quad (12)$$

Where $\hat{\sigma}_{t,t}^2$ is input noise, variance estimate σ_t^2at particular iteration of t.

Mean deviation and Mean square deviation is calculated in BC NLMS algorithm for stabilizing the unbiased conditions of input noise signals. By considering step size is variable also Mean square deviation value is minimized then performance of proposed algorithm is better in terms of convergence rate and reduces steady state error rate.

A. Analysis of Mean Deviation

Stabilization of BC NLMS is done by analyzing the convergence curve of mean deviation between unknown vector f^o and their estimation vector f_n for the data set $\tilde{v}_t$ is expressed as

$$\lim_{t\to\infty} E\left(\tilde{f_t}|\tilde{v}_t\right) = 0 \quad (13)$$

$E(\tilde{f_t}|\tilde{v}_t)$ is mean deviation of bias compensated NLMS algorithm. Then equation (12) can be written as

$$\tilde{f}_{t+1} = \tilde{f_t} - \eta \frac{\bar{v_t}\, \bar{e_t}}{\bar{v}_t^T \bar{v}_t} - \eta \frac{\hat{\sigma}_{n,t}^2 f_t}{\bar{v}_t^T \bar{v}_t} \quad (14)$$

For this mean deviation, posterior error is expressed in terms of $\bar{v_t}$ as

$$\begin{aligned} \bar{e_t} &= \bar{v}_t^T \tilde{f_t} + O_t - n_t^T f^0 \\ &= \bar{v}_t^T \tilde{f_t} + O_t - n_t^T (\tilde{f_t} + f_t) \end{aligned} \quad (15)$$

Equation (15) is substituted in (14), it leads to dynamic equation of $\tilde{f_t}$ as

$$\tilde{f}_{t+1} = \tilde{f_t} - \eta \frac{\bar{v_t}}{\bar{v}_t^T \bar{v}_t}\left(\bar{v}_t^T \tilde{f_t} + O_t - n_t^T f^0\right) + \eta \frac{\hat{\sigma}_{t,t}^2}{\bar{v}_t^T \bar{v}_t}\left((\tilde{f_t} - f^0\right)$$

$$= \left(I - \eta \frac{\bar{v_t}\,\bar{v}_t^T}{\bar{v}_t^T \bar{v}_t} - \eta \frac{\hat{\sigma}_{n,t}^2}{\bar{v}_t^T \bar{v}_t} I\right)\tilde{f_t} - \eta \frac{\bar{v_t}\, O_t - \bar{v_t} n_t^T f^0 + \sigma_t^2 f^0}{\bar{v}_t^T \bar{v}_t} \quad (16)$$

B. Mean Square Deviation Analysis

Mean square deviation dynamic equation is analyzed based on the propagation behavior of MSD for proposed BC NLMS algorithm. Convergence curve is associated with dynamic equation of MSD and it is derived.

For given set $\bar{v_t}$, conditional covariance matrix $\tilde{v}_t$ defined as

$$P_t \cong E\left(\tilde{f_t}\tilde{f}_t^T|\tilde{v}_t\right) \quad (17)$$

Then mean square deviation of proposed algorithm is represented as

$$p_t \cong E\left(\tilde{f_t}\tilde{f}_t^T|\tilde{v}_t\right) = Tr(P_t) \quad (18)$$

Dynamic equation of above MSD can be derived as below: Let us consider dependencies n_t, f_t and $\tilde{f_t}$, then if they are neglected then the recursive dynamic equation is represented as

$$P_{t+1} \le \left(1 - \frac{2\eta - \eta^2}{\beta K} + \frac{(2\eta - \eta^2)\sigma_t^2}{\bar{v}_t^T \bar{v}_t}\right) p_t + \frac{\eta^2}{\bar{v}_t^T \bar{v}_t}\left(\sigma_t^2 \sigma_f^2 + \frac{K(\hat{\sigma}_{t,t}^4 - 2\hat{\sigma}_{n,t}^2)\sigma_t^2}{\bar{v}_t^T \bar{v}_t} + \sigma_n\right) \quad (19)$$

Post multiplying transpose of (14) is taken to self, then taken the conditional expectation is taken for set $\tilde{f_t}$gives

$$P_{t+1} = P_t + \frac{\eta^2\sigma_e^2}{(\bar{v}_t^T\bar{v}_t)^2}\bar{v}_t^T\bar{v}_t + \frac{\eta^2\hat{\sigma}_{t,t}^4}{(\bar{v}_t^T\bar{v}_t)^2}E(\bar{v}_t^T\bar{v}_t|\tilde{v}_t) - \frac{2\eta\hat{\sigma}_{t,t}^2}{\bar{v}_t^T\bar{v}_t}E\left(\tilde{v}_t\bar{e}_t\bar{v}_t^T\middle|\bar{\nabla}_t\right) + \frac{2\eta^2\hat{\sigma}_{t,t}^2}{(\bar{v}_t^T\bar{v}_t)^2}E\left(\tilde{v}_t\bar{e}_t\bar{v}_t^T\middle|\bar{\nabla}_t\right) \tag{20}$$

$E(\bar{v}_t^T, v_t)$ is neglected based on orthogonality principle because there is a relative scale between $E(\bar{v}_t^T, v_t)$ and $E(\bar{v}_t^T, \bar{v}_t)$. Then in equations (20), last three terms are represented in terms of n_t on f_t and $\tilde{f}_t$ as

$$E\left(f_t f_t^T\middle|\bar{\nabla}_t\right) = 0 \tag{21}$$

$$E\left(\bar{v}_t\bar{e}_t f_t^T\middle|\bar{\nabla}_t\right) = E\left(\bar{v}_t(\bar{v}_t^T\tilde{f}_t + O_t - n_t^T f^0)f_t^T\middle|\bar{\nabla}_t\right)$$
$$= E\left(\bar{v}_t\left(\bar{v}_t^T\tilde{f}_t + O_t - n_t^T(\tilde{f}_t + f_t)\right)f_t^T\middle|\bar{\nabla}_t\right)$$

$$= \bar{v}_t^T\bar{v}_t P_t - \sigma_t^2 P_t \tag{22}$$

$$E\left(\bar{v}_t\bar{e}_t f_t^T\middle|\bar{\nabla}_t\right)$$
$$= E\left(\bar{v}_t(\bar{v}_t^T\tilde{f}_t + O_t - n_t^T f^0)\right)\left(f_t^T\middle|\bar{\nabla}_t\right)$$

$$= E\left(\bar{v}_t\left(\bar{v}_t^T\tilde{f}_t + O_t - n_t^T(\tilde{f}_t + f_t)\right)\right)\left(f_t^T\middle|\bar{\nabla}_t\right)$$

$$= -E\left(n_t n_t^T f_t f_t^T\middle|\bar{\nabla}_t\right)$$

$$= -\sigma_t^2\sigma_e^2 I \tag{23}$$

Then we get

$$P_{t+1} = P_t - \frac{2\eta}{\bar{v}_t^T\bar{v}_t}\bar{v}_t^T\bar{v}_t P_t + \frac{2\eta\sigma_t^2}{\bar{v}_t^T\bar{v}_t}P_t + \frac{\eta^2\hat{\sigma}_{t,t}^4}{(\bar{v}_t^T\bar{v}_t)^2}\bar{v}_t^T\bar{v}_t - \frac{2\eta^2\hat{\sigma}_{t,t}^2\sigma_t^2\sigma_f^2}{(\bar{v}_t^T\bar{v}_t)^2}I \tag{24}$$

For the above equation, trace can be taken on both sides, then by using below relation:

$$Tr\left(E\left(f_t f_t^T\middle|\bar{\nabla}_t\right)\right) = E\left(f_t^T f_t\middle|\bar{\nabla}_t\right)$$
$$= K\sigma_f^2 \tag{25}$$

Then MSD dynamic equation is derived as

$$P_{t+1} = P_t - \frac{2\eta}{\bar{v}_t^T\bar{v}_t}Tr(\bar{v}_t^T\bar{v}_t P_t) + \frac{2\eta\sigma_t^2}{\bar{v}_t^T\bar{v}_t}P_t + \frac{\eta^2\sigma_e^2}{\bar{v}_t^T\bar{v}_t} + \frac{K\eta^2(\hat{\sigma}_{t,t}^4 - 2\hat{\sigma}_{t,t}^2\sigma_t^2\sigma_f^2)}{(\bar{v}_t^T\bar{v}_t)^2} \tag{26}$$

By using trace properties, inequalities for $Tr(\bar{v}_t\bar{v}_t^T P_t)$ in (26) is obtained as

$$Tr(\bar{v}_t\bar{v}_t^T)\lambda_{min}(P_t)$$
$$\leq Tr(\bar{v}_t\bar{v}_t^T P_t)$$
$$\leq Tr(\bar{v}_t\bar{v}_t^T)\lambda_{max}(P_t) \tag{27}$$

Then by substituting (27) into (26) gives

$$P_{t+1} \leq P_t - 2\eta\lambda_{min}(P_t) + \frac{2\eta\sigma_t^2}{\bar{v}_t^T\bar{v}_t}P_t + \frac{\eta^2\sigma_e^2}{\bar{v}_t^T\bar{v}_t} + \frac{K\eta^2(\hat{\sigma}_{n,t}^4 - 2\hat{\sigma}_{n,t}^2\sigma_t^2\sigma_f^2}{(\bar{v}_t^T\bar{v}_t)^2} \tag{28}$$

It has to satisfy that $K\lambda_{min}(P_t) \leq Tr(P_t)$, it exits as positive constant $\alpha \geq 1$so that

$$\lambda_{min}(P_t) \approx \frac{Tr(P_t)}{\alpha K} \tag{29}$$

Value of α is set to one because input noise covariance matrix is conditioned well for white Gaussian input noise vector, so equation (29) for MSD is shown as

$$P_{t+1} \leq \left(1 - \frac{2\eta}{\alpha K} + \frac{2\eta_t\sigma_t^2}{\bar{v}_t^T\bar{v}_t}\right)P_t + \frac{\eta^2\sigma_e^2}{\bar{v}_t^T\bar{v}_t} + \frac{K\eta^2(\hat{\sigma}_{n,t}^4 - 2\hat{\sigma}_{n,t}^2\sigma_t^2\sigma_f^2}{(\bar{v}_t^T\bar{v}_t)^2} \tag{30}$$

Then by substituting equation (15) results with conditional variance we get the above equation. After substituting (31) into (30), MSD dynamic equations is represented as equation (19).

$$= \bar{v}_t^T\bar{v}_t E\left(f_t f_t^T\middle|\bar{\nabla}_t\right) - E\left(n_t^T v_t f_t f_t^T\middle|\bar{\nabla}_t\right) - E\left(n_t v_t f_t f_t^T\middle|\bar{\nabla}_t\right)$$

$$\sigma_e^2 = \left(\frac{\bar{v}_t^T\bar{v}_t}{\alpha K} - \sigma_t^2\right)P_t + \sigma_t^2\sigma_f^2 + \sigma_o^2 \tag{31}$$

2.3 Bias Compensated NLMS Algorithm for Stability

For proposed algorithm, new estimation is proposed for stability guarantee in input noise variance, then a variable step size [32] is considered for obtaining better convergence in MSD dynamic equation.

Input noise variance estimation method

$\bar{e}_t, \hat{e}_t$ *and* f_t are conditional variances for the conventional noisy inputs for set $\bar{\nabla}_t$ is

$$\sigma_e^2 \cong E\left(\bar{e}_t^2\middle|\bar{\nabla}_t\right) \tag{32}$$

$$\sigma_{\hat{e}}^2 \cong E\left(\hat{e}_t^2\middle|\bar{\nabla}_t\right) \tag{33}$$

$$\sigma_f^2 \cong \frac{1}{K}E\left(f_t^T f_t\middle|\bar{\nabla}_t\right) \tag{34}$$

Where $\hat{e}_t = sign(\bar{e}_t)max\left(|\bar{e}_t| - \sqrt{\sigma_o^2}, 0\right)$

Then stochastic variances $\sigma_e^2, \sigma_{\hat{e}}^2$ and $\sigma_f^2$are estimated using time averaging at 't' instant as $\sigma_{e,t}^2\, \sigma_{\hat{e},t}^2$ and $\sigma_{f,t}^2$ .Then computed above estimates as

$$\sigma_{e,t}^2 = \partial\sigma_{e,t-1}^2 + (1 - \partial)\bar{e}_t^2 \tag{35}$$

$$\sigma^2_{\hat{e},t} = \partial \sigma^2_{\hat{e},t-1} + (1-\partial)\hat{e}^2_t \tag{36}$$

$$\sigma^2_{\hat{f},t} = \partial \sigma^2_{\hat{f},t-1} + (1-\partial)\frac{1}{K} f_t^T f_t \tag{37}$$

Here ∂ is a forgetting factor.

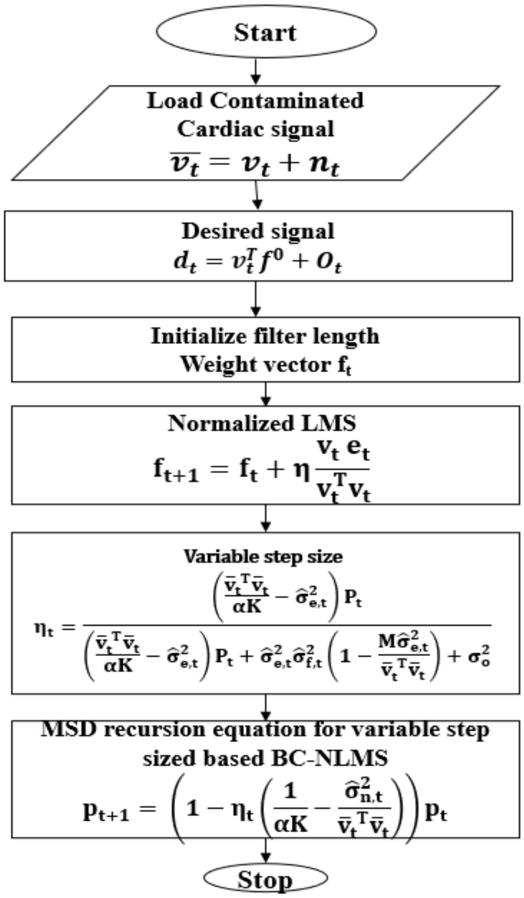

Figure 2: Flowchart of BC NLMS for artifact cancellation

In this paper, new estimation method σ_t^2 is considered to satisfy stability conditions. Noisy input variance is estimated at any particular iteration t such that

$$\hat{\sigma}^2_{n,t} = \begin{cases} \varphi_t , & if \;\; \varphi_t < \frac{\bar{v}_t^T \bar{v}_t}{\alpha K} \\ \hat{\sigma}^2_{n,t} , & Otherwise \end{cases} \tag{38}$$

Where,

$$\varphi_t = \frac{\hat{\sigma}^2_{e,t}}{K\hat{\sigma}^2_{f,t} + \tau} \tag{39}$$

For reducing steady state error rate and to get better convergence of proposed method, variable step size is considered. In this paper Step size η is replace9999999999999999999999999999d by variable step size. Flow chart of proposed algorithm for removing artifacts from cardiac signals shown in figure 2. There is a large reduce in MSD corresponding to variable step size η_t, then at particular iteration 't' step size is given by

$$\eta_t = \frac{\left(\frac{\bar{v}_t^T \bar{v}_t}{\alpha K} - \hat{\sigma}^2_{e,t}\right) P_t}{\left(\frac{\bar{v}_t^T \bar{v}_t}{\alpha K} - \hat{\sigma}^2_{e,t}\right) P_t + \hat{\sigma}^2_{e,t}\hat{\sigma}^2_{f,t}\left(1 - \frac{M\hat{\sigma}^2_{e,t}}{\bar{v}_t^T \bar{v}_t}\right) + \sigma_o^2} \tag{40}$$

Variable step size adjusts optimally then steady state error is reduced by decreasing MSD. This variable step size has regularization effects, then its performance is good even for badly excited inputs also. Then by substituting (40) into (12) gives the proposed algorithm

$$f_{t+1} = f_t + \eta_t \frac{\bar{v}_t \bar{e}_t + \hat{\sigma}^2_{n,t} f_t}{\bar{v}_t^T \bar{v}_t}$$

$$= f_t + \left\{ \frac{\left(\frac{\bar{v}_t^T \bar{v}_t}{\alpha K} - \hat{\sigma}^2_{e,t}\right) P_t}{\left(\frac{\bar{v}_t^T \bar{v}_t}{\alpha K} - \hat{\sigma}^2_{e,t}\right) P_t + \hat{\sigma}^2_{e,t}\hat{\sigma}^2_{f,t}\left(1 - \frac{M\hat{\sigma}^2_{e,t}}{\bar{v}_t^T \bar{v}_t}\right) + \sigma_o^2} \right\}$$

$$\times \frac{(\bar{v}_t \bar{e}_t + \hat{\sigma}^2_{e,t} f_t}{\bar{v}_t^T \bar{v}_t}$$

$$= f_t + \frac{\left(\frac{\bar{v}_t^T \bar{v}_t}{\alpha K} - \hat{\sigma}^2_{e,t}\right)(\bar{v}_t \bar{e}_t + \hat{\sigma}^2_{n,t} f_t) P_t}{\left\{\left(\frac{\bar{v}_t^T \bar{v}_t}{\alpha K} - \hat{\sigma}^2_{e,t}\right) P_t + \hat{\sigma}^2_{e,t}\hat{\sigma}^2_{f,t} + \sigma_o^2\right\} \bar{v}_t^T \bar{v}_t + \vartheta_t} \tag{41}$$

Where $\vartheta_t = -K\hat{\sigma}^4_{n,t}\hat{\sigma}^2_{f,t}$. Since Variable step size has regularization term ϑ_t property and this proposed algorithm works well even in bad signals. Finally, the MSD recursion function for the variable step size is represented as

$$p_{t+1} = \left(1 - \eta_t\left(\frac{1}{\alpha K} - \frac{\hat{\sigma}^2_{n,t}}{\bar{v}_t^T \bar{v}_t}\right)\right) p_t \tag{42}$$

For stability of proposed bias compensated NLMS algorithm along with better convergence and variable step size we have to consider mean square deviation with stability guarantee is given as for variable step size, limit is considered as

$$0 < \eta_t < 1$$

Also, there is a monotonic decrease in MSD for stabilization guarantee so that $p_{t+1} - p_t < 0$ which gives better convergence for proposed algorithm.

3. RESULTS AND DISCUSSION

For evaluating performance of proposed bias compensated Normalized LMS (BC NLMS) algorithm conducted experiments with contaminated cardiac signals. Data is considered from the Massachusetts Institute of Technology and Boston's Beth Israel Hospital (MIT-BIH) arrhythmia database. It consists of 48 two channel ambulatory services and data is acquired from 47 patents with different age groups from 23 to 89 years. Then samples are considered from inpatients and outpatients of hospitals. Then these data are discretized with 360 PPS, with a range 10mv and in the resolution of 11 bits. By using two channel Holter recorders with help of Del Mar Avionics model 445 cardiac signal are recorded, then analog to digitization process id done using Mar Avionics model 660 unit. In one channel, 360 samples/ second digitization is selected for eliminating interferences using narrow band digital notch filter. These recorders are mixed with noises muscle artifacts, respiratory artifacts and electrode artifacts. For signal enhancement from these artifacts proposed a bias compensated normalized LMS (BC NLMS) algorithm. Reference generator is present ins signal analyzer, it generates synthetically various artifacts with help of real artifacts takes from MIT BIH database.

Power spectral density of noisy input signal compares artifact tester with synthesized input taken from reference generator. Then the reference generator identifies the type of noise signal present in input, then similar type of correlated signals is applied at reference generator at adaptive enhancement unit. Then this adaptive unit updates filter weight equations depending on input data. Depending on this consideration implemented an artifact cancellation based adaptive filter and is discussed in earlier section. By using this technique different artifacts are removed from contaminated cardiac signal. Contaminated artifact signals like muscle artifacts, respiratory artifacts and electrode artifacts are passed through adaptive signal enhancement unit, and their corresponding reference artifact is also generated from reference generator, it was done after power spectral density analysis comparison done at signal enhancement unit. After filtering noises are reduced by the proposed bias compensated normalized LMS algorithm. By the proposed algorithm it not only reduces the artifacts present in the contaminated signal, also it stabilizes the output signal because of using mean square deviation analysis in weight update equation of proposed algorithm, so convergence is improved when compared to LMS and NLMS algorithm, steady state error also reduced because of using variable step size parameter in weight update equation of NLMS algorithm. Without losing performance of proposed algorithm, steady state error is reduced.

Table 1: SNR computations for removal of RN using LMS and its normalized versions (all values in dBs)

Records	LMS	NLMS	BC NLMS
1	3.2869	6.6218	9.2362
2	3.1278	6.1521	9.4765
3	3.6823	6.4562	9.6829
4	3.4572	6.9892	9.8225
5	3.8692	6.2326	9.1254
Average	3.4846	6.4903	9.4687

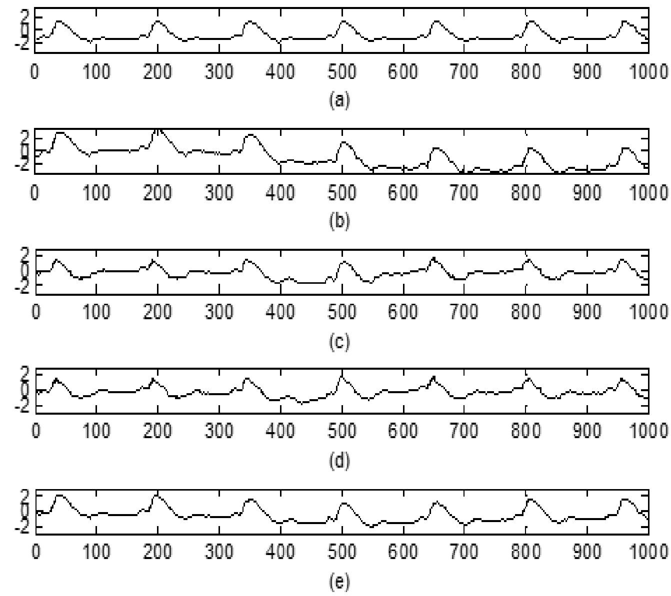

Figure 3: TEB enhancement results based for Cancelation of RN (a) TEB original signal, (b). TEB Signal with RN, (c). Filtered signal with LMS based ANC, (d) Filtered signal with NLMS based ANC and (e) Filtered signal with BC NLMS based ANC

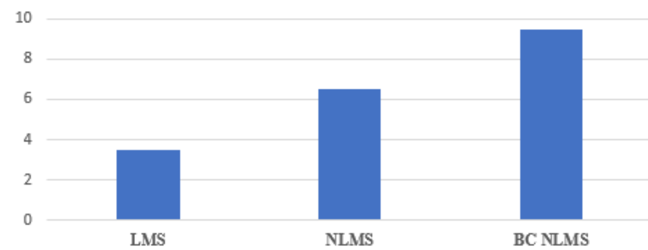

Figure 4: Comparison of RN cancellation for various ANCs

Table 2: SNR computations for removal of MN using LMS and its normalized versions (all values in dBs)

Records	LMS	NLMS	BC NLMS
1	4.2628	8.4723	10.2628
2	4.3697	8.1628	10.9875
3	4.1751	8.9258	10.0893
4	4.8527	8.4768	10.4982
5	4.6721	8.0156	10.6986
Average	4.4664	8.4106	10.5072

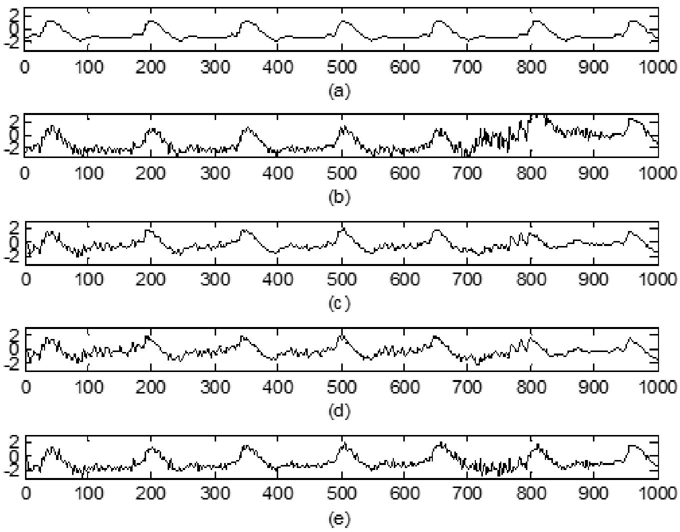

Figure 5: TEB enhancement signal results MN Cancelation (a) TEB original signal, (b) TEB Signal with RN, (c) Filtered signal with LMS based ANC, (d) Filtered signal with NLMS based ANC and (e) Filtered signal with BC NLMS based ANC

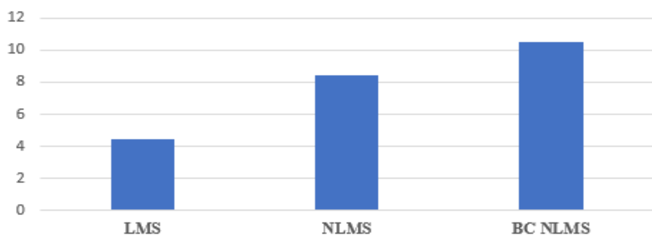

Figure 6: Comparison of MN cancellation for various ANCs

Artifacts are removed by this proposed method from the contaminated cardiac signal while measuring parameters using hemodynamics tool for signal enhancement. In simulations, considered 10,000 sample data of TEB from 5 different patients but for convenience processed first 1000 samples only, then evaluated the performance by using signal to noise (SNR) and then averaged the data of five patients. In this paper considered the respiration noise (RN) and muscle noise (MN) of TEB contaminated signal also observed the SNR values for LMS, NLMS and BC NLMS of implemented adaptive filter are shown. SNR computation tables for respiratory noise and muscle noise for 5 patients averaged data is shown in table 1 and table 2 respectively. Original TEB signal, then with noise artifacts and their LMS variants of proposed implementation results are shown in figure 3 and 5, their comparison graphs are shown in figure 4 and 6 respectively. It is clear that noise is reduced for BC NLMS when compared to LMS and NLMS.

4. CONCLUSION

In this paper, proposed a Bias compensated normalizes LMS algorithm for stability guarantee for artifact signals. In impedance cardiography signal, signal is contaminated with artifact signals. These artifact signals are enhanced by using adaptive filter method. For stability guarantee in noisy input signal, calculated dynamic equations for mean deviation analysis and mean square deviation analysis. For this stability guarantee and improvement in performance a variable step size is considered for in estimation of weight update equation of input signal. So, simulation results give better results in term of better convergence rate, reduced steady state error rate when compared to exited adaptive methods of LMS and NLMS. Further proposed method also reduces artifacts presents in contaminated cardiac signal of impedance cardiography signal. Hence artifacts like respiratory artifacts, muscle artifacts due to movement and electrode artifacts like position of electrodes in contact with skin interferences are reduced by the proposed algorithm.

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