Bat-LMS based Adaptive Filtering and Stock-well Transform Based Characteristics Point Extraction for Impedance Cardiography

Dr. Madhavi Mallam[1], Dr. A Guruva Reddy[2]

[1]Associate Professor, Department of ECE, PES Institute of Technology & Management, Shivamogga, India

[2]Professor, Department of ECE, PES Institute of Technology & Management, Shivamogga, India

Abstract: ***The automatic extraction of characteristic points in an Impedance Cardiography (ICG) signal is the critical step in any programmed ICG signal investigation and if the ICG signal is taken from the humans additionally contains some noise like signals, for example, motion artifacts. Extraction of ICG signals characteristic points and investigating the cardiac disorders of the human is a demanding task, since one single device is utilized and it gets a blend of different heart beats. In order to resolve such problems we propose a Bat-LMS based Adaptive filtering method with Stockwell Transform in this paper. The adaptive filter coefficients calculated by combining Bat algorithm with LMS algorithm. In this setup, error signal obtained from the filter is given to Bat algorithm which decides the proper step size with less error. Then the optimized step size value is given to LMS gives where it updates the coefficients of filter simultaneously. Finally, an automatic extraction of the characteristic points by utilizing S-Transform to detect start point (B), peak point (Z) and end point (X) of left ventricular ejection time accurately. The experimental results of ICG signal analysis shows the importance of our proposed adaptive filtering method.***

Keywords: Adaptive Filtering, Least Mean Square Estimation, BAT Algorithm, Impedance Cardiography signal, Characteristic points Extraction, Stockwell Transform

1. Introduction

Chronic heart failure patients have periodic episodes of clinical decomposition which doesn't impair only the life quality, utilize health care services like costs of hospitalization [1]. In order to minimize the severity and frequency of clinical events heart failure management programs is developed, but their efficacy might be restricted due to the physician in recognizing patients at imminent risk [2]. Dependable estimate of such events avoids clinicians to intervene violently and may reduce potentially the hospitalization necessity [3]. It has been speculated that the check of values of hemodynamic variable might recognize critical patients. Frequent assessment and parameter utilization is restricted due to the inappropriateness of the most accurate investigation techniques [4].

Nowadays, the introduction of Impedance Cardiography (ICG) has overcome these limitations. Because of its noninvasive, long term suitability, easy utilization and continuous monitoring of hemodynamic function it has been widely accepted [5]. ICG is a straightforward, economical and noninvasive strategy to screen electrical impedance change of thorax which is created by occasional change of blood volume in aorta [6]. A proper thorax model can be utilized for assessing Stroke Volume (SV), Cardiac Output (CO) and other hemodynamic parameters [7]. The ICG signal is impacted for the most part by movement artifact and respiratory artifact. Respiratory artifact is fundamentally brought about by changes of thoracic volume amid breathing, while movement artifact is generally created by body developments and muscle contraction [8]. The frequency range of respiratory and movement artifacts incompletely cover with frequency range of the ICG signal, so it is basic to evacuate every one of the artifacts [9]. The electrical impedance change brought on by blood volume change in aorta commonly represents 2-4% of the base impedance (for the most part around 20ohm), while the electrical impedance change created by the respiratory artifact and movement artifact might be 30% or considerably more [10].Consequently the movement and respiratory artifacts might prompt a considerable baseline drift in the ICG signal, In turn results errors in characteristic point's extraction and computation of the hemodynamic parameters. In order to suppress the artifacts from the ICG signal various techniques have been proposed [11-13]. In [14] the LMS algorithm study we consider the weights which aresed to estimate the coefficients of the discrete Fourier transform (DFT) of a signal under impact of lowfrequencies. In [15] used an adaptive filed, with the help of a thermistor based airflow sensor kept near the nostrils is taken as the reference input in order to cancel the respiratory artifact from ICG signal using LMS-based adaptive cancelation. As the respiratory sensor cannot be used in higher frequencies, this method is not efficient in suppressing higher spectral components of the respiratory artifact.

In this paper, we present a novel Bat – LMS based adaptive filtering technique for suppression of artifacts in ICG signal with Stock well (S-Transform) based Characteristic point extraction technique.The rest of the paper are arranged as follows. In Section 2, we describe our Bat-LMS based adaptive filtering method In Section 3, the parametric matrices analysis and experimental results of Proposed scheme is given. Finally, Section 4 explains the conclusion part of this paper.

2. Bat-LMS based Adaptive Filtering and Stock-well Transform Based Characteristics Point Extraction

Impedance Cardiography (ICG) is a noninvasive method for checking stroke volume, cardiac output and other hemodynamic parameters, which depends on detecting the change of thoracic electrical impedance brought on by blood volume change in aorta amid the cardiac cycle. Movement artifact and respiratory artifact can prompt baseline drift in ICG signal, especially within or after activity, which can bring about blunders while computing hemodynamic parameters.

In existing research works, Least Mean Square (LMS) based adaptive filtering methods were developed to suppress the artifacts by evaluating a reference ICG signal in synchronism with the respiratory stages distinguished from the output of the breath sensor. The constraints in LMS algorithm is that it is hard to choose step size variable. Another constraint is the estimation of stroke volume andother few cardiovascular indices utilizing ICG requires error free location of the characteristic points in the impedance cardiogram. In the most of the existing works, wavelet transform is utilized to concentrate characteristics points of ICG signal, however wavelet transform has a few drawbacks. Wavelet transform is time-scale investigation, and the scale as indicated by wavelet function is not corresponding to the frequency, and the transformation procedure is unpredictable, the result is inadequate and simple to be influenced by noises. In this work, we proposed a novel Bat – LMS based adaptive filtering technique to suppress the artifacts in ICG signal with Stock well (S-Transform) based Characteristic point extraction technique. Figure1 illustrate the flow diagram for proposed adaptive filtering method for ICG signals.

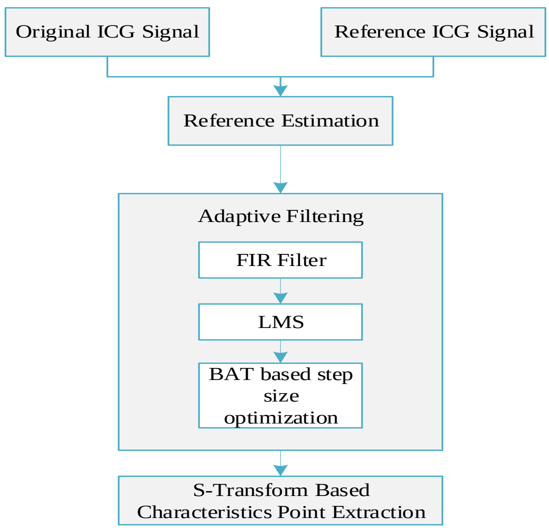

Figure 1: Flow diagram for proposed adaptive filtering method

In proposed scheme to calculate the adaptive filter coefficients by combining Bat algorithm with LMS algorithm. In this setup, error signal obtained from the filter is given to Bat algorithm which decides the proper step size with less error. Then the optimized step size value is given to LMS gives where it updates the coefficients of filter simultaneously. Then finally approximation of hemodynamic parameters needs error-free automatic extraction of the characteristic points. In this proposed method we introduce new technique called S-Transform which is better than wavelet transform for extracting characteristic points which include its start point (B), peak point (Z) and end point (X) of left ventricular ejection time. The proposed method will be implemented on Matlab working platform and the experimental results will be compared with existing techniques.

2.1 Design of an adaptive filter with step size optimization

The adaptive filter design is based on stable FIR filters, the fundamental adaptive The fundamental parameter in figure 2 adaptive filter is increasing the convergence factor through adaptive variation of the filter coefficients. Random change of the coefficients alter the filter characteristic due to the shift in the poles and shift in zeroes respectively.

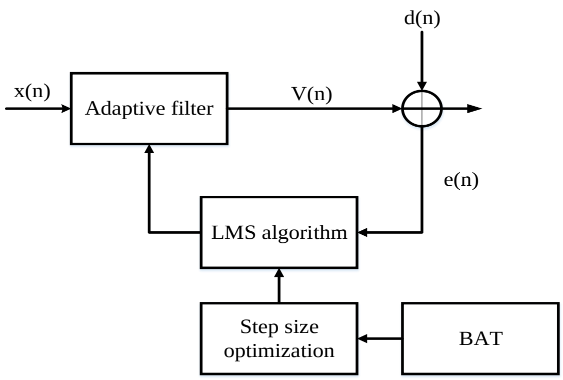

Figure 2: Proposed adaptive filter design for ICG signal

The two artifacts involved in an ICG signal are respiratory and movement artifacts, these can be characterized by an FIR filter, the FIR filter improves the parameter known as convergence speed.

The signal is usually modelled by a FIR filter using the following transfer function:

$$H(z)=\sum_{i=0}^{n_h-1} h_i z^{-i} \qquad (1)$$

Where *hi* is the signal impulse response. In time domain the input output relationship of FIR filter is represented as

$$y[n]=\sum_{k=0}^{N} h[k]x[n-k] \qquad (2)$$

The difference between the actual output and desired output can be minimized by varying the coefficients of the filter. If the gradient vector and step size are not chosen exactly, the weighted vector gets updated to the incoming data. This fetch the use of LMS algorithm in combination with our proposed filter design.

2.2 BAT Algorithm for step size optimization.

In our paper we utilize Bat Algorithm to solve the step size problem for LMS estimation algorithm parameters related to increase the convergence speed as shown in figure 3. All formulated problem conform to some constraints in the solution. First we should also consider the stability condition of step size.

$$0 < \mu_k(i) < \frac{2}{\lambda_{\max}\left(\sum_{l=1}^{N} c_{l,k} R_{u,l}\right)} \qquad (3)$$

Where $\lambda_{\max}(A)$ is the maximum eigenvalue of matrix A and $R_{u,l}$ is the covariance matrix of $u_{l,i}$.

Second we establish the upper bound for the step-size as

$$\mu_{k,\max}(i) = \frac{2}{\max_{l \in N_k} \|\hat{u}_{l,i}\|^2}, \qquad (4)$$

To prevent the situation for which the step-size is larger than $\frac{2}{\lambda_{\max}\left(\sum_{l=1}^{N} c_{l,k} R_{u,l}\right)}$. This upper bound can satisfy the stability condition.

$$\lambda_{\max}\left(\sum_{l=1}^{N} c_{l,k} R_{u,l}\right) \le \max_{l \in N_k} \lambda_{\max}(R_{u,l}) \le \max_{l \in N_k} E\|u_{l,i}\|^2 . \qquad (5)$$

Input powers $E\|u_{l,i}\|^2$ for $l = 1, \ldots\ldots, N$ are unknown in general. Therefore, the upper bound for the step-size is set to

$$\mu_{k,\max}(i) = \frac{2}{\max_{l \in N_k} \|\hat{u}_{l,i}\|^2} \qquad (14)$$

As a result, the variable step-size is expressed as

$$\mu_k(i) = \min\left[\frac{\sum_{l=1}^{N} c_{l,k}\left(\hat{\sigma}^2_{e_{l,k}}(i) - \hat{\sigma}^2_{v_{l,k}}(i)\right)}{\sum_{l=1}^{N} c^2_{l,k} \|\hat{u}_{l,i}\|^2\, \hat{\sigma}^2_{e_{l,k}}(i) + \delta}, \mu_{k,\max}(i)\right] \qquad (15)$$

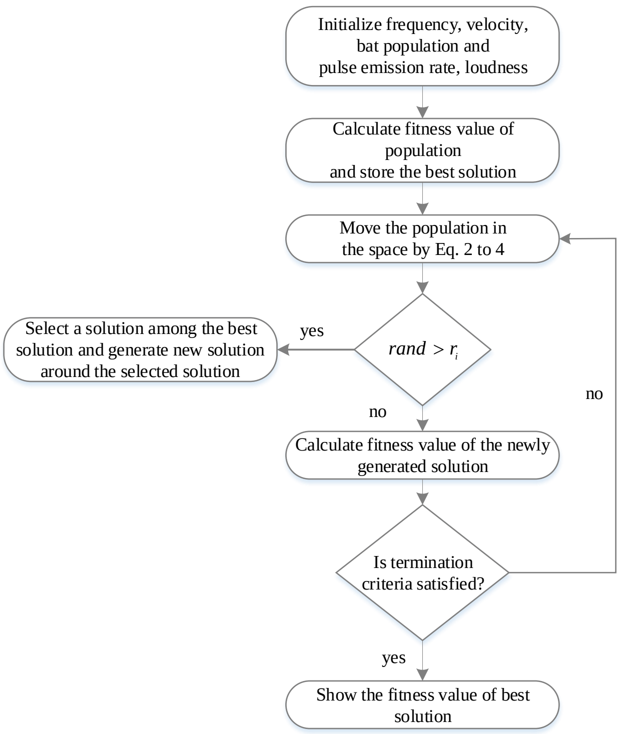

Figure 3: Flow chart for BAT algorithm

3. Results and Discussion

3.1 Experimental results

The initial and major concern in this research is the Characteristics Point Extraction for Impedance Cardiography. Figure 4 shows the original ICG signal acquired from a patient using 3 lead ICG and sent to bio kit Physiograph at a sampling rate of 1000 samples per second.

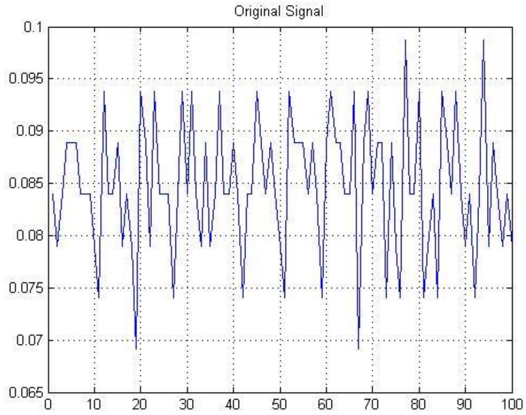

Figure 4: Input Original ICG signal

Adaptive filtering requires one or more additional reference signals that are independent of the ICG signal but correlated with the artifact.

The error signal obtained from the adaptive filter is given to Bat algorithm which decides the proper step size with less error. Then, the estimated signal is subtracted from the original ICG signal. After that, the resulting error signal is shown in figure 5.

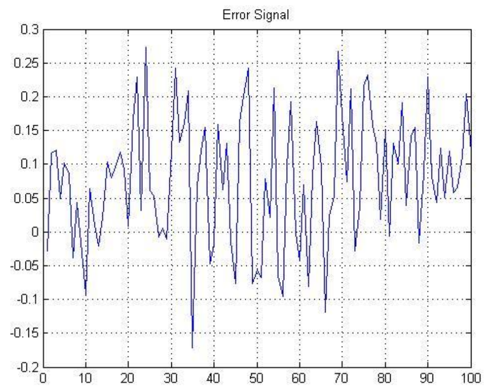

Figure 5: Error signal obtained from adaptive filter

Three main steps that target, respectively, the detection of the B, Z and the X points of the signal form the proposed transform technique for ICG characteristic point detection. The filtered and peak detected signal is shown in figure 6.

International Journal of Science and Research (IJSR)
ISSN: 2319-7064
ResearchGate Impact Factor (2018): 0.28 | SJIF (2019): 7.583

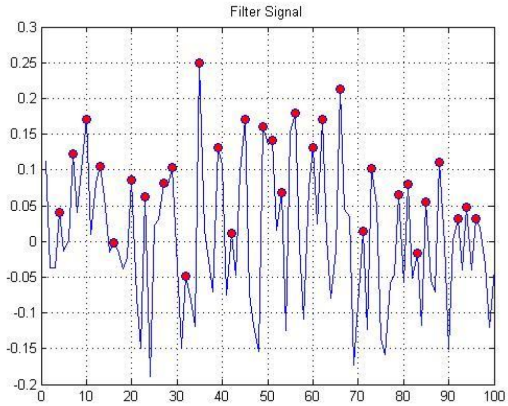

Figure 6: ICG filter and peak detected signal output

The peaks and valleys (especially B, Z and X points) become more distinct after this analysis. After extracting the feature of characteristic point detection, we can analyze the feature with others methods. For example, we can perform left ventricular ejection time form the characteristic point extraction based on the hemodynamic parameter estimation. Then finally approximation of hemodynamic parameters needs error-free automatic extraction of the characteristic points.

3.2 Proposed method validation and Comparisons

The ICG signals may be analyzed and detected using several techniques such as image processing, signal processing etc. in such techniques the characteristic point detection is done with the help of filters and classifiers. Our proposed filtering method uses S-transform to detect the characteristic points which include its start point (B), peak point (Z) and end point (X) of left ventricular ejection time from the ICG signal.

The performance of the proposed adaptive filtering method is evaluated by comparing its results with traditional LMS estimator. The Fig. 7 represents the comparison graph of the statistical measure results of proposed filtering method with the LMS estimator. TheSignal to Noise Ratio (SNR) graph concludes that, the resultant value is higher than comparison technique for all ICG signal. Also the graph concludes Mean Square Error (MSE) of the proposed adaptive filter is less than the LMS based technique.

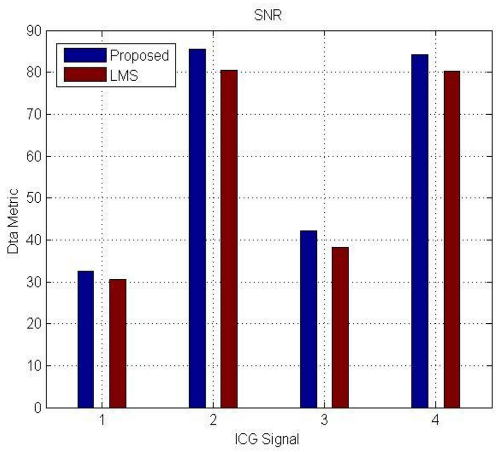

Figure 7: Signal to Noise Ratio (SNR)

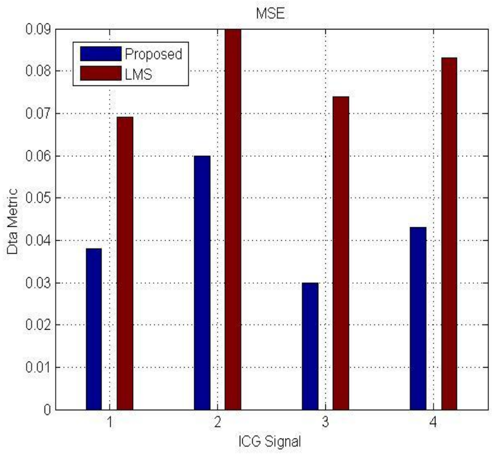

Figure 8: Mean Square Error (MSE)

The SNR is calculated at the filtered output which produces a noise free signal. The SNR and MSE comparison between our proposed methods with some other filtering techniques is shown in figure 9 and 10.

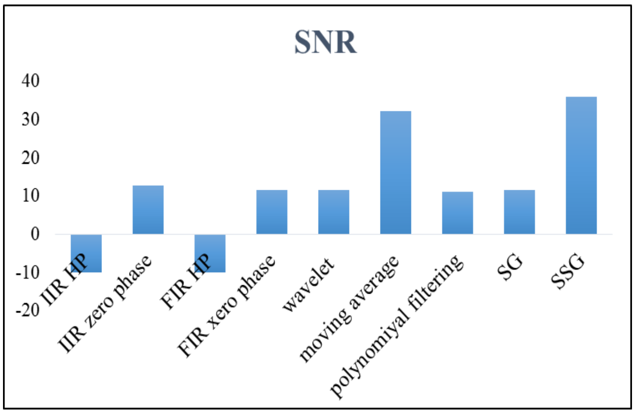

Figure 9: SNR comparison between different Filtering techniques with our proposed filter

The MSE comparison of our proposed method with some other existing denoising techniques is given in figure 10.

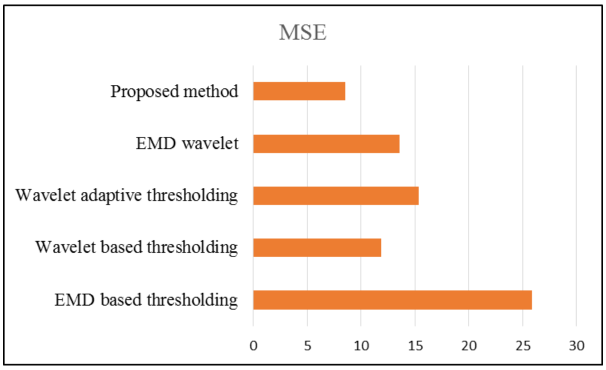

Figure 14: MSE comparison between ourProposed methods with other existing filtering techniques

The proposed method results were described and represented in precise. The ICG signal analysis were done in presence of high frequency noises and various artifacts were removed from the ICG signal We note also that the Z peaks beats are detected using the initial thresholdvalue. Moreover, statistical parameters are used in order to evaluate and compare existing algorithms.

4. Conclusion

In this paper, BAT-LMS based adaptive filtering and Stock-well transform is presented to remove respiratory and motion artifact and extract characteristic points from ICG signal respectively. Advantage of adaptive filtering is that it does not require any breath control, especially during or after exercise, when breath and cardiac activity is rapidly varying. We apply stock-well transform to detect characteristic points. The ST shows significantly great performance with a high sensitivity and a low detection error. It still needs to be further evaluated by applying it to record in a clinical setting for estimating the stroke volume, cardiac output and other hemodynamic parameters. In this work, we presented the usage of S-Transform in order to access the frequency content of the obtained characteristics points. Further, we have illustrated the detection of Z peak positions on some selected ICG segments with complicated patterns.

References

[1] Abraham W. T, Adamson P. B, Bourge R. C, Aaron M. F, Costanzo M. R, Stevenson L. W, ... and Weiner S, "Wireless pulmonary artery haemodynamic monitoring in chronic heart failure: a randomised controlled trial", The Lancet, Vol. 377, No. 9766, pp. 658-666, 2011.

[2] Giordano A, Scalvini S, Zanelli E, Corrà U, Longobardi G. L, Ricci V. A ... and Glisenti F, "Multicenter randomised trial on home-based telemanagement to prevent hospital readmission of patients with chronic heart failure", International journal of cardiology, Vol. 131, No. 2, pp. 192-199, 2009.

[3] Georgieva I, Mulder C. L, and Noorthoorn E, "Reducing seclusion through involuntary medication: a randomized clinical trial", Psychiatry research, Vol. 205, No. 1, pp. 48-53, 2013.

[4] Packer M, Abraham W. T, Mehra M. R, Yancy C. W, Lawless C. E, Mitchell J. E, ... and Pina I. L, "Utility of impedance cardiography for the identification of short-term risk of clinical decompensation in stable patients with chronic heart failure", Journal of the American College of Cardiology, Vol. 47, No. 11, pp. 2245-2252, 2006.

[5] Bour J, and Kellett J, "Impedance cardiography—A rapid and cost-effective screening tool for cardiac disease", European journal of internal medicine, Vol. 19, No. 6, pp. 399-405, 2008.

[6] Kieback A. G, Borges A. C, Schink T, Baumann G, and Laule M, "Impedance cardiography versus invasive measurements of stroke volume index in patients with chronic heart failure", International journal of cardiology, Vol. 143, No. 2, pp. 211-213, 2010.

[7] Fortin J, Habenbacher W, Heller A, Hacker A, Grüllenberger R, Innerhofer J, ... and PacherR,"Non-invasive beat-to-beat cardiac output monitoring by an improved method of transthoracic bioimpedance measurement", Computers in biology and medicine, Vol. 36, No. 11, pp. 1185-1203, 2006.

[8] Choudhari P. C, and Panse M. S,"Intelligent System Based on Impedance Cardiography for Non-invasive Measurement and Diagnosis", In Intelligent Systems Technologies and Applications, Springer International Publishing, pp. 69-78, 2016.

[9] Balachandran J. S, Bakker J. P, Rahangdale S, Yim-Yeh S, Mietus J. E, Goldberger A. L, and Malhotra A, "Effect of mild, asymptomatic obstructive sleep apnea on daytime heart rate variability and impedance cardiography measurements", The American journal of cardiology, Vol. 109, No. 1, pp. 140-145, 2012.

[10] Houtveen J. H, Groot P. F, and de Geus E. J, "Validation of the thoracic impedance derived respiratory signal using multilevel analysis", International Journal of Psychophysiology, Vol. 59, No. 2, pp. 97-106, 2006.

[11] Zhang, Hongjun, and John KJ Li, "Noninvasive monitoring of transient cardiac changes with impedance cardiography", Cardiovascular Engineering, Vol. 8, No. 4, pp. 225-231, 2008.

[12] Krivoshei A, Kukk V, and Min M, "Decomposition method of an electrical bio-impedance signal into cardiac and respiratory components", Physiological measurement, Vol. 29, No. 6, 2008.

[13] Ishiguro T, Umezu A, Yasuda Y, Horihata S, and Barros A. K, "Modified scaled Fourier linear combiner in thoracic impedance cardiography", Computers in biology and medicine, Vol. 36, No. 9, pp. 997-1013, 2006.

[14] Brito, D. S, Aguiar E, Lucena F, Freire R. C. S, Yasuda Y, and Barros A. K,"Influence of low frequency noise in adaptive estimation using the LMS algorithm", Signal Processing, Vol. 89, No. 5, pp. 933-940,2009.

[15] Pandey V. K, Pandey P. C, Burkule N. J, and Subramanyan L. R, "Adaptive filtering for suppression of respiratory artifact in impedance cardiography", In Engineering in Medicine and Biology Society, pp. 7932-7936, 2011.

[16] Tomsin K, Mesens T, Molenberghs G, Peeters L, and Gyselaers W, "Characteristics of heart, arteries, and veins in low and high cardiac output preeclampsia", European Journal of Obstetrics & Gynecology and Reproductive Biology, Vol. 169, No. 2, pp. 218-222, 2013.

[17] Yazdanian H, Mahnam A, Edrisi M, and AbdarEsfahani M, "Design and Implementation of a Portable Impedance Cardiograph System for Non-Invasive Stroke Volume Monitoring", Journal of Medical Signals and Sensors, Vol. 6, No. 1, 2016.

[18] Bernstein D. P, Henry I. C, Lemmens H. J, Chaltas J. L, DeMaria A. N, Moon J. B, and Kahn A. M, "Validation of stroke volume and cardiac output by electrical interrogation of the brachial artery in normals: assessment of strengths, limitations, and sources of error", Journal of clinical monitoring and computing, Vol. 29, No. 6, pp. 789-800, 2015.

[19] Ulbrich M, Muhlsteff J, Teichmann D, Leonhardt S, and Walter M, "A Thorax Simulator for Complex Dynamic Bioimpedance Measurements with Textile Electrodes", IEEE Transactions on Biomedical Circuits and Systems, Vol. 9, No. 3, pp. 412-420, 2015.