Process techniques for human thoracic electrical bio-impedance signal in remote healthcare systems

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Analysis of thoracic electrical bio-impedance (TEB) facilitates heart stroke volume in sudden cardiac arrest. This Letter proposes several efficient and computationally simplified adaptive algorithms to display high-resolution TEB component. In a clinical environment, TEB signal encounters with various physiological and non-physiological phenomenon, which masks the tiny features that are important in identifying the intensity of the stroke. Moreover, computational complexity is an important parameter in a modern wearable healthcare monitoring tool. Hence, in this Letter, the authors propose a new signal conditioning technique for TEB enhancement in remote healthcare systems. For this, the authors have chosen higher order adaptive filter as a basic element in the process of TEB. To improve filtering capability, convergence speed, to reduce computational complexity of the signal conditioning technique, the authors apply data normalisation and clipping the data regressor. The proposed implementations are tested on real TEB signals. Finally, simulation results confirm that proposed regressor clipped normalised higher order filter is suitable for a practical healthcare system.

1. Introduction: The World Health Organisation reports that ischaemic heart disease is a major cause of death worldwide [1]. Among the various methods of cardiac activity measurement, haemodynamics is a popular method in which blood flow across the body and forces affecting it are often measured. Impedance plethysmography techniques which use the changes in electrical impedance over body surface for measurement of changes in the tissue volumes can be used to study haemodynamics. Thoracic electrical bio-impedance (TEB) is a non-invasive and flexible method of calculating cardiac stroke volume. Research in the field of TEB started with the study of the flow of fluids in the body, especially in cardiac area using impedance plethysmography techniques since 1940s [2]. By early 1970s, using TEB the cardiac stroke volume was measured [3]. Several comparative studies were carried out in the field between non-invasive TEB and invasive methods like thermodilution which shown promising results in favour of TEB [4, 5]. In [6], analysis of TEB is carried on subjects with heart diseases while they were performing exercises. Results have shown that cardiac parameters measured during these tests are reliable and mostly accurate. Since the inception of TEB, there have been an increase in the reliability of the technique and improvement in measurement of cardiac parameters [7–14].

However, the recording of thoracic bio-impedance component encounters with several physiological and non-physiological artefacts. These artefacts mask the tiny features of the TEB signal and cause ambiguities in diagnosis [6]. The dominant artefacts are respiration noise (RN) and muscle noise (MN). Hence, to facilitate high-resolution thoracic impedance component for determining stroke volume and intensity, these artefacts have to be removed. In practical scenarios, these artefacts are non-stationary in nature and hence conventional fixed coefficient filters are not suitable for TEB enhancement. So that nonlinear adaptive signal processing techniques have to be applied, as adaptive filters have the innate ability to change their filter coefficients in accordance with the statistical nature of the signal and noise component.

So far, several researchers have made contributions to TEB enhancement using signal processing techniques [15–19]. In these papers, the authors used conventional least mean square (LMS) and recursive least square algorithm for signal enhancement. However, these algorithms suffer with problems like weight drift, low convergence, large step size and computational complexity

[20, 21]. In a typical biotelemetry scenario, the nature of the channel is Gaussian. Studies proved that higher order adaptive algorithms like least mean fourth (LMF) perform better in Gaussian environment. These algorithms have fast convergence and low steady-state error [22, 23]. Based on these considerations, in this Letter, we propose to develop some signal conditioning techniques using LMF algorithm. To improve filtering capability and minimise computational complexity, data normalisation and clipping data regressor with respect to LMF algorithm can be applied [24–28]. Hence, by combining these approaches, we propose mixed signal conditioning algorithms for the development of signal enhancement unit (SEU) for remote healthcare monitoring systems. These are data clipped LMF (DCLMF), data normalised LMF (DNLMF) and data normalised clipped LMF (DNCLMF) algorithms. The proposed techniques are well suited with TEB sensors in wearable healthcare systems. The theory and experimental results of these algorithms are presented in the next sections.

2. Higher order techniques for TEB enhancement: In a real-time clinical environment, RN and MN artefacts contaminate the TEB component and causes ambiguity in diagnosis. To ensure accurate interpretation of parameters associated with TEB, the artefacts have to be eliminated. Since the physiological quantities are non-stationary, here we use adaptive filtering to eliminate clutter components from the desired signals. The input to the system is thoracic electrical activity from corresponding electrodes. The acquisition system is a six lead system. The recordings are continuously re-sampled at 250 Hz by a 12-bit analogue to digital converter (ADC). The recorded quantity undergoes normalised power testing to identify which type of artefact is present. In this phenomenon, we calculate the power spectral density (PSD) of the input signal and compare the PSD with that of reference artefact. The artefact whose PSD is correlated with input signal PSD is given as a reference signal to SEU. For this purpose, we considered a reference generator, which consists of various samples of artefacts. After identifying particular type of artefact, the contaminated signal is given to SEU. The correlated noise component is given as reference to SEU. The internal structure of a typical SEU is shown in Fig. 1.

SEU consists of a finite impulse response (FIR) filter and a weight update mechanism. Here, we propose various strategies for updating weight coefficients. For this analysis, let us consider

Fig. 1 Typical SEU

a LMF-based adaptive filter with tap length M . The input signal to the SEU is $z(n)$. This consists of impedance component $I(n)$ and artefact component $A(n)$. Let $a(n)$ be the correlated reference signal taken from reference generator. Let $p(n)$ be the impulse response of the FIR filter, $q(n)$ be the output of the FIR filter, $r(n)$ be the error generated in the SEU. The weight update mechanism of the LMF algorithm can be written as

$$p(n+1) = p(n) + sz(n)r(n)^3, \quad (1)$$

where $p(n) = [p_0(n) \ p_1(n) \ \dots \ p_{M-1}(n)]^T$ is the tap weight vector at the n th index, $z(n) = [z(n) \ z(n-1) \ \dots \ z(n-M+1)]^T$ is the input sequence, $r(n) = z(n) - p(n)a(n)$ and s represents step size. Simplified adaptive algorithms make use of the clipping of input data [29, 30], combined which leads to the minimisation of computational complexity. The resultant algorithm is the DCLMF. The weight update relations for this algorithm can be written as

$$p(n+1) = p(n) + s\text{CLP}\{z(n)\}\{r(n)^3\}, \quad (2)$$

where $\text{CLP}\{\cdot\}$ is the well-known clipping function i.e.

$$\text{CLP}\{r(n)\} = \begin{cases} 1:r(n) > 0 \\ 0:r(n) = 0 \\ -1:r(n) < 0 \end{cases} \quad (3)$$

To improve convergence rate, filtering capability and to reduce computational complexity, we apply data normalisation with LMF and DCLMF algorithms. This results in DNLMF and DCNLMF algorithms. The weight update recursions are written as follows

$$p(n+1) = p(n) + s(n)z(n)r(n)^3, \quad (4)$$

$$p(n+1) = p(n) + s(n)\text{CLP}\{z(n)\}\{r(n)^3\}, \quad (5)$$

where $s(n)$ is the variable step size with respect to input data sequence iteratively, and it is given by

$$s(n) = \frac{s}{u + z^T(n)z(n)} \quad (6)$$

The parameter u is set to avoid denominator becoming too small and step size parameter too big.

The computational complexity of various algorithms is given in Table 1. As the sign-based algorithms are largely free from the multiplication and accumulation (MAC) operations, the proposed

Table 1 Computational complexity comparison table

Algorithm	Multiplications	Additions	Addition with Sign Check (ASC)
LMF	$M+3$	$M+1$	nil
DCLMF	3	$M+1$	nil
DNLMF	M	$M+1$	nil
DCNLMF	nil	nil	$M+3$

schemes provide an elegant means to remove noise from the TEB. The convergence characteristics of these algorithms are shown in Fig. 2. Among the algorithms, DNLMF converges faster. This is due to the variable step size involved in the weight update equation. DCNLMF is just inferior to DNLMF. This is because of clipping the data vector. However, the multiplications in the numerator of the DCNLMF weight update equation are independent of filter length. This is the chief advantage of this technique. Similarly, DCLMF is just inferior to LMF at the cost of reduced multiplications by an amount equal to filter length. In our work, we have considered data clipping to minimise the number of multiplications. In real-time applications, multiplications are complex and needed to be minimised, especially when designing very large scale integration (VLSI) architecture, lab on a chip or in a wearable device. By using data clipping in DCLMF, the number of multiplications are reduced to '3' from ' $M+3$ ' in LMF. This indicates DCLMF is independent of filter length. In practical applications, the filter length is excessively large; under such scenarios DCLMF becomes more advantageous. Similarly, DCNLMF completely eliminates multiplication operation and makes that algorithm more suitable in real-time systems.

3. Simulation results: To show that the proposed algorithms are really effective in clinical situations, the method has been validated using several TEB recordings with a wide variety of wave morphologies recorded using the VU University Ambulatory Monitoring System (VU-AMS) [9, 10]. For TEB recording, the system utilises Kendall ARBO H98SG electrocardiogram electrodes. In our simulation, we have recorded 10,000 samples of the TEB component from five different persons. However, due to space constraint, to facilitate good quality of signal in our experiments, we only processed first 1000 samples. In the evaluation process of the proposed implementation, we considered *signal-to-noise ratio improvement (SNRI)*, *mis-adjustment (MSD)* and *excess mean square error (EMSE)* in ten experiments, averaged and compared with conventional LMS-based SEU. SNRI is defined

Fig. 2 Convergence characteristics of LMF and its variants

as improvement in signal-to-noise ratio (SNR) before filtering to after filtering. SNR is the ratio of the power of a signal to the power of contaminating noise. A very high SNR is desirable in a biotelemetry system. EMSE is defined as the residual mean square error after convergence occurred. MSD is defined as the ratio of EMSE to minimum mean square error. These characteristics are tabulated in Tables 2–4, and all the values are expressed in dBs. To resemble the free space effect, a Gaussian noise of variance with 0.001 is added to TEB component used in a biotelemetry system. In our experiments, the acquired five records I, II, III, IV and V are used. These records are contaminated with artefacts like RN and MN. Various SEUs for TEB enhancement are developed using LMF, DCLMF, DNLMF and DNCLMF algorithms. Real reference

Table 2 SNRI contrast of various algorithms in SEU noise

Noise	Rec. No.	LMF	DCLMF	DNLMF	DNCLMF
RN	I	2.6223	2.2988	9.2835	8.8684
	II	3.4151	3.6222	9.9221	9.1670
	III	3.6636	3.5199	9.6706	8.4149
	IV	3.2347	3.6594	9.8762	8.6819
	V	3.2080	3.6516	9.5719	8.9086
	average	3.1562	3.3502	9.6648	8.8026
MN	I	3.6782	4.9526	9.2398	8.5324
	II	4.8424	4.5589	10.5530	9.1802
	III	4.8542	4.7658	10.5896	9.3226
	IV	3.9619	5.0389	9.9318	9.0462
	V	3.5273	3.6173	9.8561	8.7664
	average	4.1720	4.5867	10.0448	8.9695

Table 3 MSD contrast of various algorithms in SEU

Noise	Rec. No.	LMF	DCLMF	DNLMF	DNCLMF
RN	I	0.2689	0.2734	0.2458	0.2518
	II	0.0561	0.0876	0.0318	0.0476
	III	0.0508	0.0719	0.0362	0.0412
	IV	0.1408	0.2538	0.1058	0.1216
	V	0.1875	0.2046	0.1283	0.1592
	average	0.1408	0.1782	0.0864	0.1023
MN	I	0.4862	0.5652	0.3814	0.4375
	II	0.1268	0.1924	0.1028	0.1163
	III	0.1024	0.1523	0.0732	0.0924
	IV	0.2263	0.2857	0.1869	0.2019
	V	0.1834	0.2291	0.1238	0.1549
	average	0.2250	0.2849	0.1736	0.2006

Table 4 EMSE contrast of various algorithms in SEU

Noise	Rec. No.	LMF	DCLMF	DNLMF	DNCLMF
RN	I	−14.7143	−9.6724	−20.7042	−17.4955
	II	−15.1246	−10.8562	−22.1860	−18.2662
	III	−14.8554	−9.9248	−21.8249	−17.9715
	IV	−14.0268	−8.6675	−20.1692	−16.8249
	V	−16.0064	−12.4869	−23.1243	−20.8298
	average	−14.9455	−10.3215	−21.6017	−17.2775
MN	I	−12.6849	−7.5498	−16.4062	−14.1748
	II	−11.9854	−6.1493	−15.6023	−13.5023
	III	−10.8442	−5.4701	−14.4351	−12.7026
	IV	−11.7763	−6.0196	−15.2365	−12.9198
	V	−15.2062	−9.8066	−19.1989	−18.4337
	average	−12.4994	−6.9991	−16.1758	−14.3468

signals are taken from the MIT-BIH database. This SEU is driven by an adaptive algorithm to change its filter coefficients in accordance with the input data based on the algorithms discussed in Section 2. The performance of these SEUs is compared with reference to the above-mentioned performance measures. Due to space limitation, in this Letter, we have shown the experimental results of record II.

Adaptive cancellation of RN: This module works for the enhancement of TEB component contaminated with RN. The input signal is applied to the SEU as shown in Fig. 1. This input contains actual TEB component and RN. The reference signal is a noise component, which is somewhat correlated with the artefact present in the input quantity of the SEU. Based on error value the adaptive algorithm associated with the SEU automatically trains the coefficient of FIR filter. In this way, by updating the filter weights, the algorithm make up the reference signal such that it is maximally correlated with the actual noise component and get cancel with each other. These simulation results are shown in Fig. 3. The performance of these implementations is compared with reference to SNRI, MSD and EMSE. These averaged values of ten executions of various algorithms for RN removal are tabulated in Tables 2–4. With reference to SNRI and computational complexity, the performance of DNCLMF algorithm is found to be better than the other implementations. This algorithm achieves SNRI 24.1134 dB, which is little bit inferior to DNLMF-based SEU. However, because of data clipping this algorithm greatly reduces computational complexity in terms of number of multiplications required to compute the weight update recursion of the algorithm. In EMSE and MSD measurements, DNCLMF-based signal enhancement is found to be better than other implementations by considering low computational complexity due to the data clipping.

Fig. 3 Typical TEB enhancement results based on LMF and variants for RN cancellation

a Original TEB signal
b TEB signal with RN
c Filtered signal with LMF-based SEU
d Filtered signal with DCLMF-based SEU
e Filtered signal with DNLMF-based SEU
f Filtered signal with DNCLMF-based SEU (x-axis represents the number of samples and y-axis represents the amplitude of the signal in mV)

Fig. 4 Residual noise after RN removal
a Original RN component
b Residual noise after LMF filtering
c Residual noise after DCLMF filtering
d Residual noise after DNLMF
e Residual noise after DNCLMF

Fig. 4 shows the residual error after RN filtering using various algorithms. From this figure, it is evident that after LMF and DCLMF, the residual noise is more and considerable amount of

Fig. 5 Typical TEB enhancement results based on LMF and variants for MN cancellation
a Original TEB signal
b TEB signal with RN
c Filtered signal with LMF-based SEU
d Filtered signal with DCLMF-based SEU
e Filtered signal with DNLMF-based SEU
f Filtered signal with DNCLMF-based SEU (x-axis represents the number of samples and y-axis represents the amplitude of the signal in mV)

Fig. 6 Residual noise after MN removal
a Original RN component
b Residual noise after LMF filtering
c Residual noise after DCLMF filtering
d Residual noise after DNLMF
e Residual noise after DNCLMF

RN component is still present in the signal, whereas, the performance of the DNLMF and DNCLMF is found to be better. In the case of these two algorithms, the residual noise is almost like a direct current (DC) line. This indicates that the filtering capability of these algorithms is better than LMF and DCLMF algorithms. Therefore, based on the computational complexity shown in Table 1, convergence characteristics shown in Fig. 2, performance measures shown in Tables 2–4, it can be concluded that DNCLMF is a suitable candidate for noise removal from TEB signal.

Adaptive cancellation of MN: This module demonstrates the enhancement process of TEB component contaminated with MN. The TEB affected by MN is given as input to SEU as shown in Fig. 1. A signal generated by muscle activity correlated with artefact present in the input is given as reference to adaptive algorithm. The simulation results are shown in Fig. 5. The performance measures are calculated, averaged for ten times and shown in Tables 2–4. From these tables it is clear that among all the algorithms DNLMF-based SEU performs better, but its data, clipped version is just inferior with reference to SNRI, MSD and EMSE MSD with reduced number of multiplications. This enables DNCLMF-based noise canceller to be better than all other counterparts. The average SNRI for DNLMF and DNCLMF in the enhancement process is measured as 14.0418 and 12.5282 dB, respectively. Fig. 6 shows the residual noise component after MN removal due to various algorithms. Like RN filtering in the MN filtering process, the residual noise is less for DNLMF and DNCLMF algorithms. For these algorithms, the residual noise is almost DC except between samples 700 and 800, whereas the residual component for LMF and DCLMF has several ripples. Based on the residual noise, computational complexity and performance measures shown in Tables 2–4, it can be concluded that DNCLMF is better for practical implementations than the other algorithms.

4. Conclusion: In this Letter, some efficient SEUs for remote healthcare monitoring systems are proposed. To improve the ability of the proposed SEUs, we applied real TEB signals for enhancement. To ensure stability, convergence, filtering and less

computational complexity, we have combined the characteristics like higher order filtering and clipping data regressor. From the simulation results it is confirmed that DNCLMF performs better than their other counterparts. The major advantages of this version are fast convergence and good filtering capability due to variable step size and less computational burden due to clipping the data regressor. Hence, this technique is well suited for remote healthcare monitoring applications.

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