ORIGINAL RESEARCH PAPER

Volume-8 | Issue-11 | November - 2019 | PRINT ISSN No. 2277 - 8179 | DOI : 10.36106/ijsr

INTERNATIONAL JOURNAL OF SCIENTIFIC RESEARCH

ADAPTIVE LINE ENHANCEMENT: AN ALTERNATIVE TO ADAPTIVE NOISE CANCELLATION FOR SUPPRESSION OF MOTION ARTEFACTS IN ELECTROCARDIOGRAPHY

Engineering

Aparna S. Lakhe*	Research Scholar, Bio-Medical Engineering Department, MGM's College of Engineering & Technology, Kamothe, Navi-Mumbai - 410209. *Corresponding Author
R. K. Jain	Scientific Officer, Bhabha Atomic Research Centre, Electronic division, Bhabha Atomic Research Centre, Trombay, Mumbai, Maharashtra - 400085
Vineet Sinha	Scientific Officer, Bhabha Atomic Research Centre, Electronic division, Bhabha Atomic Research Centre, Trombay, Mumbai, Maharashtra - 400085
T. S. Ananthakrishnan	(Ex) Head, Electronics Division, Bhabha Atomic Research Centre, Mumbai - 400085.
Preeti P. Athavale	Assistant Professor, Bio-Medical Engineering Department, MGM's College of Engineering & Technology, Kamothe, Navi-Mumbai - 410209.
Sushma N. Bhat	Senior Research Fellow, Bhabha Atomic Research Centre, Electronic division, Bhabha Atomic Research Centre, Trombay, Mumbai, Maharashtra - 400085
G. D. Jindal	Professor, Bio-Medical Engineering Department, MGM's College of Engineering & Technology, Kamothe, Navi-Mumbai - 410209.

ABSTRACT

Adaptive filtering is the method of choice to remove motion artefacts in the bioelectric signals. This technique adaptively removes the embedded noise, in relation to correlated noise fed to the reference input of the filter. To generate reference noise, accelerometer is attached to electrode/sensor, which becomes cumbersome for the user. This paper introduces a method of suppressing motion artefacts in electrocardiography signal using Adaptive Line Enhancement which does not require reference noise and obviates need of extra noise sensor. In this method the original signal is directly fed to the signal input of the adaptive filter and same is delayed and fed to the reference input. The quantum of delay is optimized to remove the motion artefact embedded in the signal; observed to be 0.3 seconds in the present case. Thirty-five ECG data files with superimposed artefact have been subjected to adaptive filtering as well as adaptive line enhancement with root mean square error of 25.95±20.12 and 31.00±16.27, input-output correlation of 0.87±0.11 and 0.78±0.16 and signal to noise ratio of 6.15±6.43 and 1.59±5.16 respectively. These observations suggest adaptive line enhancement as an alternative to adaptive noise cancellation in situations where recording of reference noise is not practically feasible.

KEYWORDS

adaptive filtering; adaptive line enhancement; electrocardiography; motion artefact

1. INTRODUCTION

ECG is usually corrupted with electrical line interference, motion artefacts and electrocardiogram (EMG) artefacts. Motion artefacts are generated due to change in electrical properties between skin electrode interfaces. During recording of electrocardiography, whenever there is movement of electrode or subject, electrical properties between skin electrode interfaces changes, which leads to introduction of these motion artefacts in the recorded ECG. Since the frequencies of motion artefact overlaps with those of ECG, usage of fixed filtering leads to loss of physiological information. Moreover, the artefacts specification is unknown and dynamic, which calls for adaptive filtering[1].

Though adaptive filters were introduced in 1957 for various applications, Widrow et al[2] were probably the first to use adaptive noise cancellation for removing 60Hz line interference from ECG signal. Following this, many researchers have been using adaptive filtering for varied application with satisfactory results. Figure 1 illustrates the basic operating principle of adaptive filter. The filter requires two inputs; signal 'S' corrupted with noise 'N' and reference noise 'N_c', correlated with N. Error 'ε' is the difference between the filter output 'Y' and input signal (S+N). The adaptation algorithm updates the filter coefficients depending upon the error to match filter output 'Y' with the reference signal 'N_c'. Different types of adaptation algorithm are used for updating filter coefficients among which commonly used are least mean square (LMS), normalised least mean square (NLMS), recursive least squares (RLS) etc. After iterative convergence the error gives the enhanced version of input signal 'S'[3].

The motion artefacts in ECG are being removed using this popular technique called as adaptive noise cancellation (ANC). The reference signal required by the filter is generated using additional sensor usually accelerometer, coupled to the electrode, to capture the movement signal. Many researchers [4-8] have implemented this technique with satisfactory results.

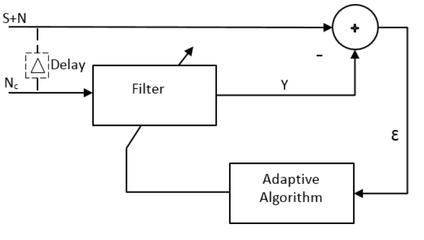

Figure 1: *shows schematic diagram of adaptive filtering. If comprises three blocks, namely summation, filter and adaptive algorithm. Noise corrupted signal (S+N) goes as input to summation, the reference noise (Nc) is connected to filter input. The filter output (Y) goes as negative input to summation. The summation output ε, which is also the adaptive filter output, is given as error input to adaptive algorithm to converge the same to minimum value. For adaptive line enhancement, the corrupted signal is delayed in time and given to filter in place of the reference noise, shown as dotted line in the figure.*

As a variant of adaptive filtering, adaptive predictor is used to separate broadband and narrowband frequency components in the signal by introducing delayed signal at the reference input of the adaptive filter (shown in Figure 1 by dashed line) in place of reference noise. The delay is introduced such that the broadband components becomes de-correlated and gets separated out at the error output of adaptive filter. This technique, also called as adaptive line enhancement (ALE), is widely used in communication system, speech signal processing and biomedical signal processing [9,10]. Basak et al[11] and Tsalaile et al[12] have used this technique for separating heart sound from the lung sound. Sanei et al[13] have used new approach of ALE based on singular spectral analysis for separating ECG and EMG. ALE has a wide spectrum of its application such as 60Hz noise removal, heart sound denoising [14] etc. In view of above, adaptive line enhancement has been used to supress motion artefacts as an alternative to ANC, which is described in this paper.

PRINT ISSN No. 2277 - 8179 | DOI : 10.36106/ijsr

2. MATERIALS AND METHOD

Adaptive noise cancellation and adaptive line enhancement have been implemented in matlab. The evaluation parameters were chosen as root mean square error (RMSE), correlation coefficient (CC) and signal to noise ratio (SNR), which have been computed from uncorrupted input signal (resting ECG) and the adaptive filter output. The implemented algorithms are tested on total 35 pre-recorded resting ECG data files using Tele-ECG unit developed by Electronic Division (ED), Bhabha Atomic Research Centre (BARC) with sampling rate of 500 samples per second. To corrupt the signal with motion artefacts, the noise N_c is generated independently from an ambulatory subject for superimposing on the resting ECG signal to make it noisy with motion artefacts. This has been given as input signal S+N and N_c is connected as correlated noise for adaptive noise cancellation.

Least mean square (LMS) adaptive algorithm is chosen due to its simplicity and satisfactory performance [15]. The learning rate (or step size) was initially taken as per the recommendations of Steven Tang [16]; i.e. fraction of the minimum resolution of the input signal. Since the signal varies from -2.4 to +2.4 Volts with 24-bit resolution, the signal resolution is 0.286 microvolts. Starting from initial learning rate of 0.0715 microvolts (one fourth of the signal resolution) with the help of RMSE, it was optimised at 0.9 nano-volts.

For adaptive line enhancement, the input signal to the adaptive filter is delayed and fed to reference input of the filter. Considering ECG as broadband signal (0.05-150 Hz) the delay is computed to be 3.33 samples (rounded to 3). Similarly motion artefact, a narrow band (<2Hz), yields a delay of 250 samples. Since the broadband components are not correlated to its previous samples unlike narrow band, introducing the delay will de-correlate the broadband components that appear as error. The correlated narrowband i.e. motion artefacts gets separated in the output 'Y' of adaptive filter [17]. For the present study the delay is optimised between 3 and 250 samples as follows.

In the manner similar to optimisation of learning rate, the delay has been varied in steps of 10 from 40 to 250 samples and values of RMSE have been observed for one of the data files (Sr. no.11). Figure 2 shows graph of RMSE values versus delay suggesting optimum delay to be 150 samples.

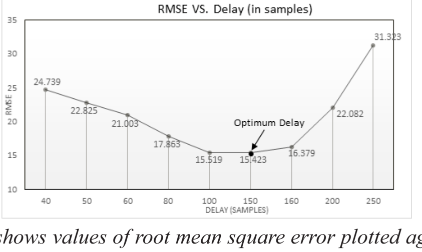

Figure 2 *shows values of root mean square error plotted against the delay (in terms of sample numbers). A minima is observed at delay of 150 samples, suggesting it to be optimum delay for adaptive line enhancement.*

In ALE another approach had been implemented. The input signal is low pass filtered (1Hz 3dB) and then connected to reference input with optimum delay. This approach has been named as adaptive line enhancement filtered (ALE_f). Thus, the filtered signal correlates with the noise in the corrupted ECG signal. Delay in this case has been optimised to be 270 samples in the manner similar to that of ALE described above.

Performance indicators, namely RMSE, CC and SNR, are calculated from resting ECG (S_i) and adaptive filter output ECG (ε_i) using the following formulae [18].

3. RESULTS

Table 1 gives central tendency and dispersion values of RMSE, CC and SNR observed in 35 data files processed for ANC, ALE and ALEf. Figure 3 shows plot of RMSE for all the 35 subjects (values arranged in descending order for ANC). The plots of CC and SNR have also shown similar trend (not shown here). As can be seen from the table and the figure, performance indicators for ALE and ALEf are in the same range and essentially show no significant difference. Therefore, the main comparison is between ANC and ALE. The mean and median values of RMSE are little higher for ALE than that of ANC. In contrast, similar values for CC and SNR are little lower for ALE than that of ANC. Higher values of RMSE and lower values of CC and SNR for ALE in comparison to ANC suggest performance of the later is superior to that of the former. However smaller range of ALE for RMSE and SNR in comparison to that of ANC suggests superiority of ALE. These contradictory observations call for detailed analysis.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[S(i) - \varepsilon(i)]^2}$$

$$CC = \frac{N[\sum_{i=1}^{N} S(i) * \varepsilon(i) - \sum_{i=1}^{N} S(i) \sum_{i=1}^{N} \varepsilon(i)]}{\sqrt{\left\{N \sum_{i=1}^{N} S(i)^2 - \left[\sum_{i=1}^{N} S(i)\right]^2\right\}\left\{N \sum_{i=1}^{N} \varepsilon(i)^2 - \left[\sum_{i=1}^{N} \varepsilon(i)\right]^2\right\}}}$$

$$SNR = 10\,log\{\frac{\sum_{i=1}^{N} \varepsilon(i)^2}{\sum_{i=1}^{N}[S(i) - \varepsilon(i)]^2}\}$$

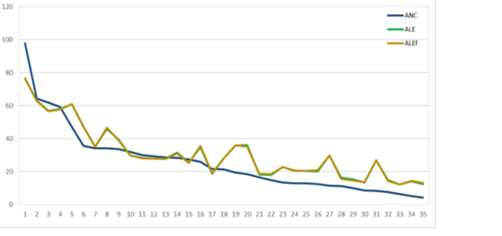

Figure 3 shows the RMSE values for ANC, ALE and ALE_f. Values are arranged in descending order for ANC for visual comparison. Values are nearly overlapping for ALE and ALE_f but little higher than that of ANC.

Figures 4 and 5 show the output of ANC, ALE and ALE_f in two subjects (Sr. nos. 1 and 33 respectively). Resting ECG in Figure 4 shows no baseline wander. In this case the values of performance indicators (RMSE) are 12.43 and 4.33, (CC) are 0.93 and 0.99 and (SNR) are 8.62 and 17.75 for ALE and ANC respectively. All these values consistently show little superior performance of ANC. In contrast, resting ECG of another subject (Sr. no. 33) is having little baseline wander as shown in Figure 5. Corresponding performance indicators in this case are (RMSE) 35.46 and 19.54, (CC) 0.48 and 0.84 and (SNR) -3.74 and 5.42 respectively. These values suggest ANC is far superior as compared to ALE or ALE_f. Apparently the performance of ANC is observed to be superior to that of ALE. However it is observed that baseline wander of resting ECG in Figure 5 is unaffected in ANC filtered ECG but it gets suppressed in the ALE filtered ECG. Thus in reality ALE suppresses the reference noise (which is superimposed on resting ECG) as well as noise present in the resting ECG. From this view point, ALE performs better than ANC, though it is not evidenced by performance indicators.

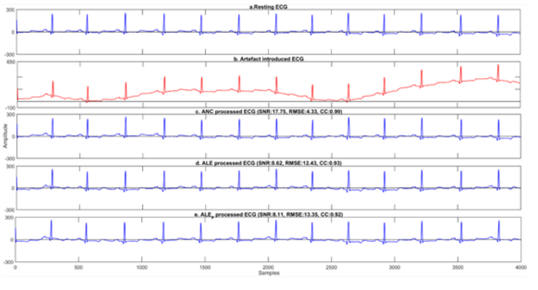

Figure 4 shows (a) resting ECG without baseline wander, (b) ECG with superimposed motion artefact, and filtered outputs of ANC (c) ALE (d) and ALEf (e). Similarity in (c), (d) and (e) is evident from morphology of the output signal and SNR, RMSE, and CC values.

Table 1: Statistical measurements

Methods	RMSE			CC			SNR		
	Mean	Median	Range	Mean	Median	Range	Mean	Median	Range
ANC	25.95±20.12	21.38	4.33:97.75	0.87±0.11	0.88	0.64:1.00	6.15±6.43	3.46	-1.72:21.52
ALE	31.00±16.27	28.03	12.28:76.61	0.78±0.16	0.77	0.48:0.97	1.59±5.16	0.07	-5.51:12.74
ALE_F	30.97±16.22	27.86	12.18:76.27	0.78±0.16	0.78	0.46:0.97	1.73±5.20	0.11	-5.37:12.82

PRINT ISSN No. 2277 - 8179 | DOI : 10.36106/ijsr

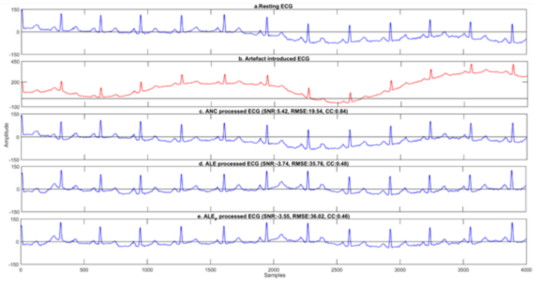

Figure 5 shows data similar to that of Figure 4 in a subject having baseline wander in resting ECG. As seen outputs in (d) and (e) have not only suppressed motion artefacts but also baseline wander as compared to that of (c). SNR, RMSE and CC values appear to be better for (c), since it is very close to (a).

4. DISCUSSION

Adaptive noise cancellation has been successfully used in the past for suppressing noise as well as motion artefacts in the signal by majority of the investigators [5-9]. The necessity of correlated noise/artefact at the reference noise input of the filter has limited its application in clinical medicine, as it calls for another transducer to be used along with signal sensing probes simultaneously. There has always been a need for an alternative method to ANC which does not necessitate simultaneous recording of correlated noise. With this in view, adaptive line enhancement has been investigated and compared with ANC in the present study. The advantage of ALE is that it does not require correlated noise as reference noise input to the filter, in place the same corrupted signal is delayed with respect to time and fed to the reference noise input. As a variant of ALE, the corrupted signal is low pass filtered for removing high frequency ECG signal and retaining low frequency noise at the reference noise input. A comparison has been made in the performance of ANC, ALE and ALE_f in the present study.

As described in preceding section, performance indicators have shown that ANC outstands in performance of all the three methods, though visual impression is otherwise. Among ALE and ALE_f, later does not add to any additional benefit in comparison to ALE, rather it adds complexity of using additional LPF. Therefore, the main comparison is between ANC and ALE.

As illustrated by Figures 4 and 5, ANC suppresses only the correlated noise from the corrupted signal and leaves inherent noise of the signal unfiltered at the output. In contrast, ALE suppresses the correlated noise as well as the inherent noise. But the performance indicators (RMSE, CC and SNR), which are dependent on the difference between the resting ECG and filtered ECG, show otherwise. This discrepancy can be attributed to inherent noise in the resting ECG, which is suppressed by ALE resulting into large error at the filter output. Since inherent noise is not processed by ANC, the filter output is almost like resting ECG resulting into lesser error in comparison to ALE. Therefore, a clean resting ECG is ideally required for comparison of performance indicators. Thus, the performance indicators RMSE, CC and SNR are not truly suitable in studies involving resting ECG with inherent noise.

On the basis of this study, it can be said that ALE offers two advantages: 1) It does not require additional sensor for noise and 2) It filters not only correlated noise but also inherent noise in the resting ECG. Thus, ALE offers an effective alternative to ANC for suppressing motion artefacts.

Acknowledgement

The authors are grateful to Board of Research in Nuclear Sciences (BRNS), Department of Atomic Energy, Government of India for supporting this research. The authors are thankful to Mrs. Anita Behere, Head, Electronics Division, Bhabha Atomic Research Centre, Mumbai (BARC); Dr. S. K. Narayankhedkar, Principal, MGMCET; Prof. K. Venkat Raman, Head, Biomedical Engineering Department, MGMCET; and Dr. Bhai Mangesh Naik, Asso. Prof., Department of Medicine, MGMIHS for their valuable contribution and support. The authors take this opportunity to acknowledge help from Ms. Jyoti Jethe and Ms. Paridhi Jain throughout this work. The authors are also thankful to Mr. Nazim Momin, Mr. Suryapal Prajapati and Mr. B.V. Gaikwad for giving a helping hand and encouragement during the work.

REFERENCES

1. Honig M., Messerschmitt D., Kirsteins Ivars, Quazi Azizul. (1987). Adaptive Filters: Structures, Algorithms, and Applications. The Journal of the Acoustical Society of America, 81(2), 578.
2. Widrow B., Glover J.R., Mccool John M., Kaunitz John, Williams Charles S., Hean Robert H., ….. Goodlin Robert C. (1975). Adaptive Noise Cancelling: Principles and Applications. Proceedings of the IEEE, 63(12), 1692-1716.
3. Diniz P. (2008). Adaptive Filtering: Algorithms and Practical Implementation. New York: Springer.
4. Liu S. (2011). Motion Artifact Reduction in Electrocardiogram Using Adaptive Filter. Journal of Medical and Biological Engineering, 31(1), 67–72.
5. Raya M. A. D. and Sison LG. (2002). Adaptive noise cancelling of motion artifact in stress ECG signals using accelerometer. Proceedings of the Second Joint EMBS/BMES Conference, 2, 1756-1757.
6. Yoon SW., Min SD., Yun YH., Lee Seungpyo, Lee Myoungho. (2008). Adaptive motion artifacts reduction using 3-axis accelerometer in e-textile ECG measurement system. Journal of Medical Systems, 32(2), 101–106.
7. Kim Hyejung, Kim Sunyoung, Helleputte Nick, Berset Torfinn, Penders Julien, Hoof CV, and Yazicioglu RF. (2013). Motion Artifact Removal using Cascade Adaptive Filtering for Ambulatory ECG Monitoring System. IEEE Biomedical Circuits and Systems Conference, 160-163.
8. Thakor NV. and Zhu YS. (1991). Applications of adaptive filtering to ECG analysis: Noise cancellation and arrhythmia detection. IEEE Transactions on Biomedical Engineering, 38(8), 785–794.
9. Ramli R, Noor A, Samad S. (2012). A Review of Adaptive Line Enhancers for Noise Cancellation. Australian Journal of Basic and Applied Sciences, 6(6), 337–352.
10. Treichler J. (1979). Transient and convergent behaviour of the adaptive line enhancer. IEEE Transactions on Acoustics, Speech, and Signal Processing, 27(1), 53–63.
11. Basak K., Mandal S., Manjunatha M., Chatterjee J., Ray A. K. (2010). Phonocardiogram Signal Analysis Using Adaptive Line Enhancer Methods on Mixed Signal Processor. International Conference on Signal Processing and Communications (SPCOM), 1-5.
12. Tsalaile T. and Sanei S. (2007). Separation of heart sound signal from lung sound signal by adaptive line enhancer. 15th European Signal Processing Conference, 1231-1235.
13. Sanei S., Lee T. K. M., and Abolghasemi V. (2012). A new adaptive line enhancer based on singular spectrum analysis. IEEE Transactions on Biomedical Engineering, 59(2), 428–432.
14. Lakhe A, Sodhi I, Warrier J, et al. (2016). Development of digital stethoscope for telemedicine. Journal of Medical Engineering & Technology, 40(1), 20–24.
15. Widrow B. and Kamenetsky M. (2003). Statistical Efficiency of Adaptive Algorithms. Neural Networks, 16(5-6), 735-744.
16. Steven Tang. (2000). Adaptive Filters. In Tompkins WJ (Ed.), Biomedical Digital Signal Processing: C-Language Examples and Laboratory Experiments for the IBM PC, (pp. 174–183). New Jersy: Prentice Hall.
17. Douglas SC. (1999). Introduction to Adaptive Filters. In Vijay K. Madisetti and Douglas B. Williams (Ed.). Digital Signal Processing Handbook. Chapter 18, Boca Raton, CRC Press LLC.
18. Liu Z., Mi Y., Mao Y. (2014). An improved real-time denoising method based on lifting wavelet transform. Measurement Science Review, 14(3), 152–159.