A novel fixed-point leaky sign regressor algorithm based adaptive noise canceller for PLI cancellation in ECG signals

Faiz, Mohammed Mujahid Ulla and Kale, Izzet

This is a copy of the author's accepted version of a paper subsequently published in the proceedings of the 2022 IEEE 7th Forum on Research and Technologies for Society and Industry Innovation (RTSI). Paris, France, 24 - 26 Aug, 2022.

The final published version will be available online at:

https://doi.org/10.1109/rtsi55261.2022.9905081

A novel fixed-point leaky sign regressor algorithm based adaptive noise canceller for PLI cancellation in ECG signals

Mohammed Mujahid Ulla Faiz*† and Izzet Kale*
*Applied DSP and VLSI Research Group
*Department of Computer Science and Engineering
*University of Westminster
*London, W1W 6UW, United Kingdom
†ECE Department
†Presidency University
†Bengaluru, 560064, India
E-mail: w1805470@my.westminster.ac.uk, kalei@westminster.ac.uk

***Abstract*—In this paper, a novel fixed-point Leaky Sign Regressor Algorithm (LSRA) based adaptive noise canceller has been employed for the cancellation of 60 Hz Power Line Interference (PLI) from the ElectroCardioGram (ECG) signal. A sufficient condition for the convergence in the mean of the LSRA algorithm is also derived. The fixed-point LSRA-based adaptive noise canceller employed in this work is fully quantized using an in-house quantize function. The most effective number of quantization bits required for the various parameters are found to be 6-bits and are determined through rigorous simulations. The filtered ECG signal free from 60 Hz PLI is successfully recovered using a novel 6-bit fixed-point LSRA-based adaptive noise canceller.**

Keywords*—*Artifacts, ECG, fixed-point, LSRA, PLI.

I. Introduction

Adaptive noise cancellers employed for the cancellation of various types of artifacts present in the ElectroCardioGram (ECG) signals have been mostly implemented to work with floating-point arithmetic operations. For efficient hardware implementation in terms of performance, power, and space requirements, an adaptive noise canceller must work with fixed-point arithmetic operations with the lowest number of quantization bits. This has been the motivation for carrying out this work.

Over the years many adaptive and non-adaptive (fixed) methods have been proposed for the cancellation of Power Line Interference (PLI) from ECG signals. An efficient Finite Impulse Response (FIR) filter, with a reduced number of filter coefficients, proposed for the removal of baseline wander and 50 Hz PLI from the ECG signal showed good performance [1]. The line interference subtraction filter was successfully used for the removal of 50 Hz PLI from the signal-averaged ECG systems in [2]. Digital Infinite Impulse Response notch filters were used for the removal of 60 Hz PLI from the ECG signals in [3]. The relative performance of an adaptive and non-adaptive 60 Hz notch filter was investigated for the reduction of PLI from the ECG signal in [4]. A nonlinear adaptive method for the elimination of PLI from the ECG signal was proposed in [5]. The proposed method offered a robust structure and was shown to have a high degree of immunity with respect to external noise [5]. An improved adaptive noise canceller for the reduction of the fundamental PLI component and its harmonics from the ECG signal was proposed in [6].

The Field Programmable Gate Array (FPGA) based implementation of an adaptive noise canceller for the removal of 50 Hz PLI from the ECG signal was shown in [7]. This article does not tell whether the FPGA-based implementation of the adaptive noise canceller was fixed-point or floating-point and does not give details of how many bits. An efficient Recursive Least Squares (RLS) adaptive notch filter for the suppression of PLI in ECG signals was developed in [8]. A PLI detector was also proposed in [8] that employed an optimal linear discriminant analysis algorithm for the detection of PLI in ECG signals. An efficient PLI removal algorithm was proposed based on a sliding discrete Fourier transform phase locking scheme and was implemented on an FPGA [9]. Again this article does not mention whether the hardware implementation of the adaptive noise canceller was fixed-point or floating-point and does not provide any word length information.

The work in [10] analyzes basic and advanced PLI filtering techniques and evaluates them in a wearable real-time processing scenario, assessing their performance on ECG signals. The work in [11] implements a state space RLS filter for tracking and elimination of PLI and its harmonics from a high resolution ECG signal. A fixed-lag Kalman smoother was proposed in [12] to filter out PLI from ECG recordings with minimal distortion of the ECG waveform. An adaptive notch filter of sharp resolution was proposed in [13] to filter out PLI from ECG signals. A 34-bit fixed-point Normalized Least Mean Square (NLMS) and a 34-bit fixed-point Improved Proportional Normalized Least Mean Square (IPNLMS) based VLSI architectures were proposed for accurate Fetal Electro-CardioGram (FECG) and Fetal Heart Rate (FHR) processing in [14]. In [15], it was shown that the extended Kalman filter-based adaptive noise canceller system outperforms the state-space recursive least squares filter-based adaptive noise canceller system and effectively eliminates PLI from ECG signals. Moreover, the performance evaluation of both single stage and multistage adaptive noise cancellers using various adaptive algorithms was compared for the removal of 60 Hz PLI and other artifacts from the ECG signal in [16].

The application of novel leaky adaptive algorithms for ECG denoising is an interesting topic that is unexplored. The Mean Square Error (MSE) performance of the Leaky Least Mean Square (LLMS) algorithm was analyzed in [17], [18]. In addition, stability bounds on the step-size of the LLMS algorithm were also determined in [17], [18].

In this paper, a novel fully quantized fixed-point Leaky Sign Regressor Algorithm (LSRA) based adaptive noise canceller has been implemented for the cancellation of 60 Hz PLI from ECG signals wherein all the input signals, output signals, step-size, leakage factor, and filter coefficients are quantized using various loss of precision schemes. In addition, stability bound on the step-size of the LSRA algorithm is also derived.

II. Fixed-Point Adaptive Noise Canceller

The fixed-point adaptive noise canceller for the cancellation of 60 Hz PLI from ECG signals as shown in Figure 1 is fully quantized. As can be seen from this figure, d_i forms the quantized primary input of the noise canceller, in our case d_i contains the ECG signal with 60 Hz PLI, $\mathbf{u}_i$ forms the quantized reference input of the noise canceller, in our case $\mathbf{u}_i$ contains the reference 60 Hz PLI that is correlated only with the 60 Hz PLI present in the corrupted ECG signal d_i, $\mathbf{w}_i$ are the quantized filter coefficients, and y_i is the quantized filter output.

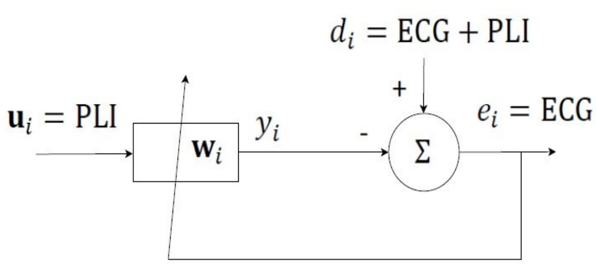

Fig. 1. **Fixed-point adaptive noise canceller [16], [19].**

The newly proposed LSRA algorithm has been employed in the fixed-point adaptive noise canceller shown in Figure 1. The weight update equation of the LSRA algorithm is given by:

$$\mathbf{w}_i = (1-\mu\alpha)\mathbf{w}_{i-1} + \mu \,\mathrm{sgn}[\mathbf{u}_i]^{\mathrm{T}} e_i, \tag{1}$$

where μ is the step-size and α is the leakage factor. Both these quantities are quantized as discussed in Section IV. The quantized filtered ECG signal e_i is free from 60 Hz PLI. An in-house quantize function developed was used and invoked by the following statement:

$$z = Quantize('type', x, 2^n); \tag{2}$$

where x is the unquantized input, $type$ is one of the four types of quantization methods, namely truncate, round, round-to-zero, and convergent round, n is the number of quantization bits, and z is the quantized output.

III. Convergence Analysis

By subtracting both sides of (1) from the optimal weight vector $\mathbf{w}^{\mathrm{o}}$ we get

$$\widetilde{\mathbf{w}}_i = (1-\mu\alpha)\widetilde{\mathbf{w}}_{i-1} - \mu \,\mathrm{sgn}[\mathbf{u}_i]^{\mathrm{T}} e_i + \mu\alpha\mathbf{w}^{\mathrm{o}}, \tag{3}$$

where the weight error vector $\widetilde{\mathbf{w}}_i$ is given by

$$\widetilde{\mathbf{w}}_i = \mathbf{w}^{\mathrm{o}} - \mathbf{w}_i. \tag{4}$$

Taking the expectation of both sides of (3) we obtain

$$\mathrm{E}[\widetilde{\mathbf{w}}_i] = (1-\mu\alpha)\mathrm{E}[\widetilde{\mathbf{w}}_{i-1}] - \mu\mathrm{E}\left[\mathrm{sgn}[\mathbf{u}_i]^{\mathrm{T}} e_i\right] + \mu\alpha\mathbf{w}^{o}. \tag{5}$$

From [20], we have

$$\mathrm{E}\left[\mathrm{sgn}[\mathbf{u}_i]^{\mathrm{T}} e_i\right] = \sqrt{\frac{2}{\pi\sigma_u^2}}\mathbf{R}\mathrm{E}[\widetilde{\mathbf{w}}_{i-1}], \tag{6}$$

where σ_u^2 is the regressor variance and $\mathbf{R} = \mathrm{E}[\mathbf{u}_i^{\mathrm{T}}\mathbf{u}_i]$ is the regressor covariance matrix. Upon substituting (6) into (5), we have

$$\mathrm{E}[\widetilde{\mathbf{w}}_i] = \left[\mathrm{I} - \mu\alpha - \mu\sqrt{\frac{2}{\pi\sigma_u^2}}\mathbf{R}\right]\mathrm{E}[\widetilde{\mathbf{w}}_{i-1}] + \mu\alpha\mathbf{w}^{o}. \tag{7}$$

From (7), it is easy to show that the mean behavior of the weight error vector, that is $\mathrm{E}[\widetilde{\mathbf{w}}_i]$, converges to the zero vector if the step-size μ is bounded by:

$$0 < \mu < \frac{2\sqrt{\pi\sigma_u^2}}{\alpha\sqrt{\pi\sigma_u^2} + \sqrt{2}\lambda_{\max}}. \tag{8}$$

where $\lambda_{\max}$ is the maximum eigenvalue of $\mathbf{R}$.

IV. Simulation Results

In the results below, 3600 samples of the clean ECG signal were taken from the MIT-BIH Arrhythmia Database Record: 105 [21], and they were later added with 3600 samples of synthetic PLI with amplitude 100 mv, frequency 60 Hz, sampled at 360 Hz. The sampling frequency of the synthetic PLI has been chosen to be the same as that of the ECG signal used in our experiments. The FIR filter length is fixed at $M = 5$, the number of iterations are fixed at $L = 10$, the step-size is fixed at $\mu = 0.01$, and the leakage factor is fixed at $\alpha = 0.002$.

The selection of the most effective number of quantization bits was done by first fixing the number of quantization bits used for the filter coefficients to a particular value ranging from 1 to 16 and then by varying the number of quantization bits used for the primary input, reference input, step-size, leakage factor, filter output, and filtered ECG signal of the fixed-point LSRA-based adaptive noise canceller from 1 to 16 for a given type of quantization method.

Five different experiments are conducted, namely unquantized full-precision, truncate, round, round-to-zero, and convergent round adaptive filtering methods employing the LSRA algorithm. In the latter four experiments, for example the round adaptive filtering operated with the same type of quantization method, namely round was used for the primary input, reference input, step-size, leakage factor, filter coefficients, filter output, and filtered ECG signal of the fixed-point LSRA-based adaptive noise canceller.

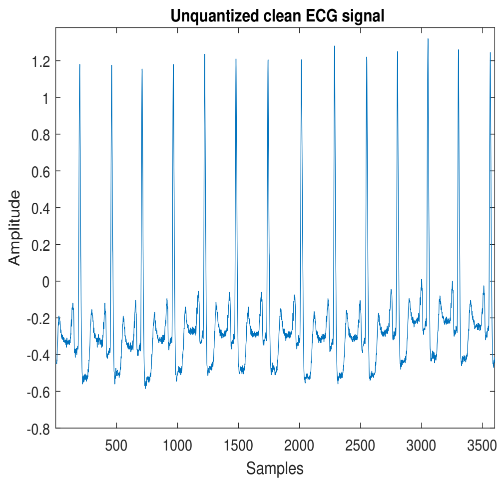

Fig. 2. **MIT-BIH Arrhythmia Database Record: 105.**

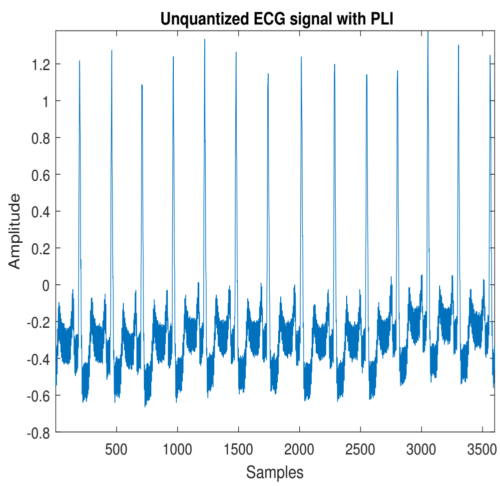

Fig. 3. **MIT-BIH Arrhythmia Database Record: 105 + 60 Hz PLI.**

The unquantized clean ECG signal free from artifacts is shown in Figure 2, the unquantized ECG signal with additive 60 Hz PLI is shown in Figure 3, and the filtered ECG signal recovered from the unquantized full-precision adaptive filtering method employing the LSRA algorithm is shown in Figure 4. As can be seen from Figure 4, the unquantized full-precision adaptive filtering method employing the LSRA algorithm successfully recovers the clean ECG signal.

The quantized filtered ECG signals recovered from truncate, round, round-to-zero, and convergent round adaptive filtering methods employing the LSRA algorithm are shown in Figures 5, 6, 7, and 8, respectively. As can be seen from Figures 5 and 7, the truncate and round-to-zero adaptive filtering methods employing the LSRA algorithm failed to recover the clean ECG signal, respectively. As can be seen from Figures 6 and 8, the quantized filtered ECG signals recovered from round and convergent round adaptive filtering methods employing the LSRA algorithm are found to be similar and are close to the filtered ECG signal recovered from the unquantized full-precision adaptive filtering method employing the LSRA algorithm as shown in Figure 4.

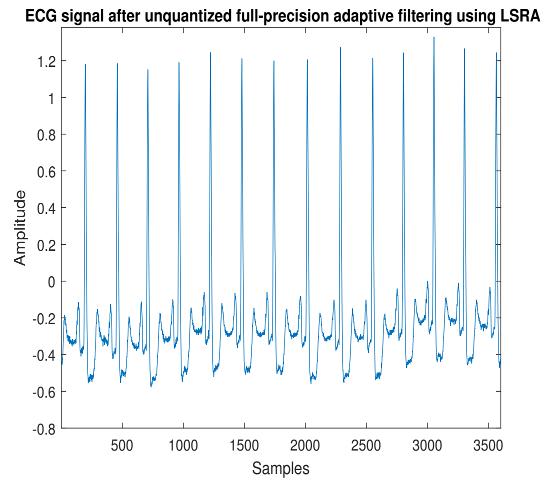

Fig. 4. **Recovered MIT-BIH Arrhythmia Database Record: 105 after unquantized full-precision adaptive filtering using LSRA.**

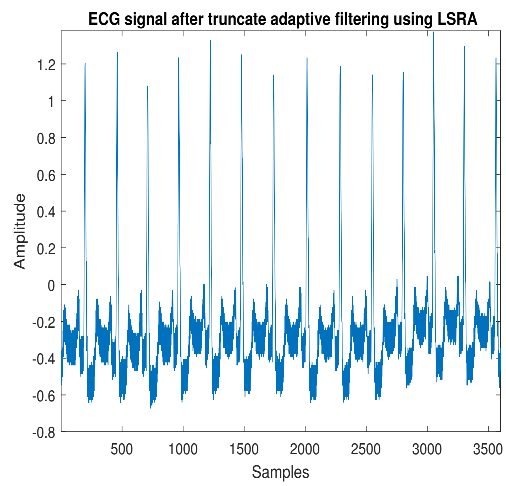

Fig. 5. **Recovered MIT-BIH Arrhythmia Database Record: 105 after truncate adaptive filtering using LSRA.**

As can be seen from Figures 10 and 12, the MSE performance of truncate and round-to-zero adaptive filtering methods employing the LSRA algorithm, respectively, is found to be similar to each other and is poor. This similarity of poor performance can also be observed from the quantized filtered ECG signals recovered from these two methods as shown in Figures 5 and 7, respectively. The MSE performance of the unquantized full-precision, round, and convergent round adaptive filtering methods employing the LSRA algorithm is found to be similar to each other as shown in Figures 9, 11, and 13, which can also be observed from the filtered ECG signals recovered from these three methods as shown in Figures 4, 6, and 8, respectively.

V. Conclusions

The most cost/performance effective number of quantization bits necessary for the primary input, reference input, step-size, leakage factor, filter coefficients, filter output, and filtered ECG signal of the fixed-point LSRA-based adaptive noise canceller were found to be 6-bits for the round and convergent

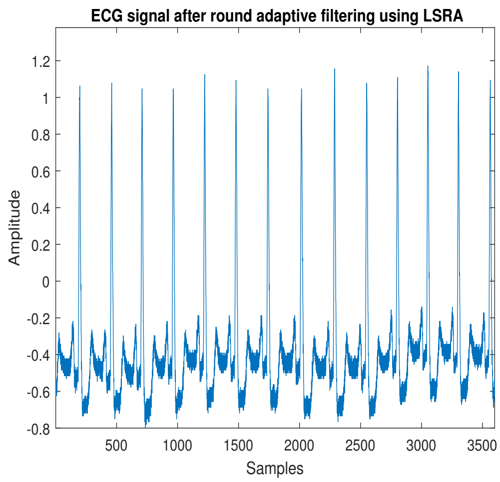

Fig. 6. **Recovered MIT-BIH Arrhythmia Database Record: 105 after round adaptive filtering using LSRA.**

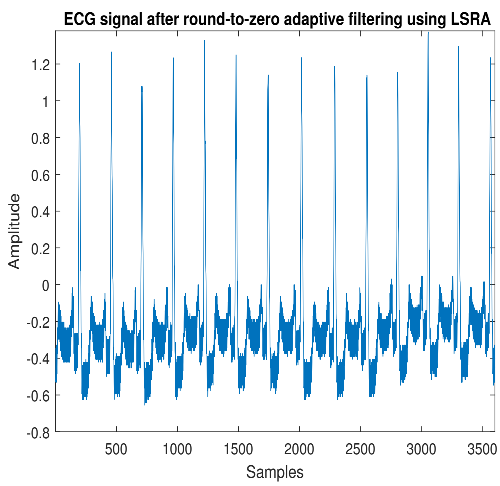

Fig. 7. **Recovered MIT-BIH Arrhythmia Database Record: 105 after round-to-zero adaptive filtering using LSRA.**

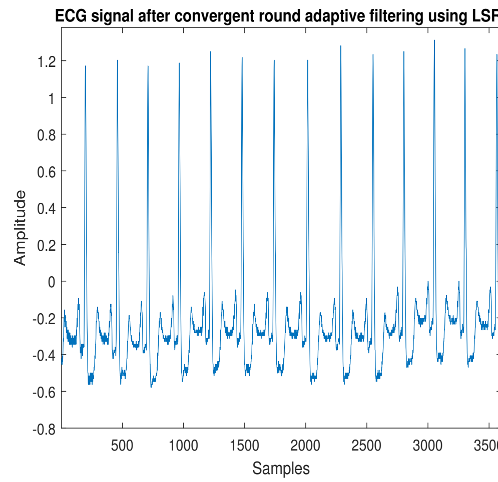

Fig. 8. **Recovered MIT-BIH Arrhythmia Database Record: 105 after convergent round adaptive filtering using LSRA.**

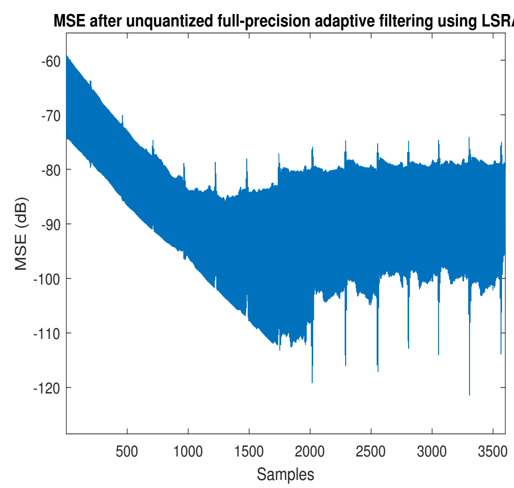

Fig. 9. **Mean square error after unquantized full-precision adaptive filtering using LSRA.**

round adaptive filtering methods. Thus, it is shown that in the presence of a well-correlated reference signal it is possible to successfully recover the filtered ECG signal free from 60 Hz PLI with 6-bits quantization for both the filter coefficients as well as the data paths for the round and convergent round adaptive filtering methods using the fixed-point LSRA-based adaptive noise canceller for a reduced complexity integrated implementation. Finally, the upper bound on the step-size of the LSRA algorithm is shown to be depending on the leakage factor.

Acknowledgment

The authors gratefully acknowledge the support provided by the University of Westminster and the Presidency University.

References

[1] J. A. V. Alsté and T. S. Schilder, "Removal of base-line wander and power-line interference from the ECG by an efficient FIR filter with a reduced number of taps," *IEEE Trans. Biomedical Eng.*, vol. BME-32, no. 12, pp. 1052–1060, Dec. 1985.

[2] Y. Z. İder, M. C. Şaki, and H. A. Güçer, "Removal of power line interference in signal-averaged electrocardiography systems," *IEEE Trans. Biomedical Eng.*, vol. 42, no. 7, pp. 731–735, July 1995.

[3] S.-C. Pei and C.-C. Tseng, "Elimination of AC interference in electrocardiogram using IIR notch filter with transient suppression," *IEEE Trans. Biomedical Eng.*, vol. 42, no. 11, pp. 1128–1132, Nov. 1995.

[4] P. S. Hamilton, "A comparison of adaptive and nonadaptive filters for reduction of power line interference in the ECG," *IEEE Trans. Biomedical Eng.*, vol. 43, no. 1, pp. 105–109, Jan. 1996.

[5] A. K. Ziarani and A. Konrad, "A nonlinear adaptive method of elimination of power line interference in ECG signals," *IEEE Trans. Biomedical Eng.*, vol. 49, no. 6, pp. 540–547, June 2002.

[6] S. M. M. Martens, M. Mischi, S. G. Oei, and J. W. M. Bergmans, "An improved adaptive power line interference canceller for electrocardiography," *IEEE Trans. Biomedical Eng.*, vol. 53, no. 11, pp. 2220–2231, Nov. 2006.

[7] R. Ramos, A. Mànuel-Làzaro, J. D. Río, and G. Olivar, "FPGA-based implementation of an adaptive canceller for 50/60-Hz interference in electrocardiography," *IEEE Trans. Instrum. Meas.*, vol. 56, no. 6, pp. 2633–2640, Dec. 2007.

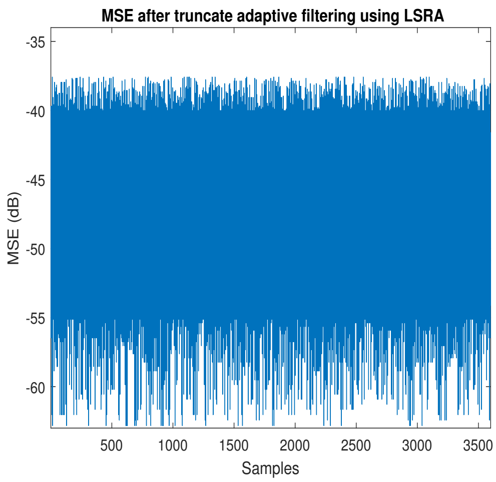

Fig. 10. **Mean square error after truncate adaptive filtering using LSRA.**

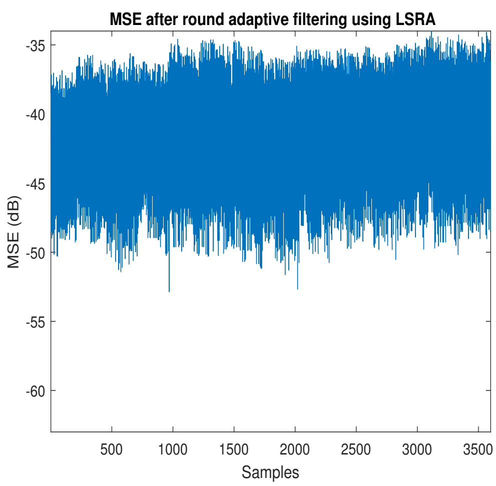

Fig. 11. **Mean square error after round adaptive filtering using LSRA.**

[8] Y.-D. Lin and Y. H. Hu, "Power-line interference detection and suppression in ECG signal processing," *IEEE Trans. Biomedical Eng.*, vol. 55, no. 1, pp. 354–357, Jan. 2008.

[9] S. Mishra, D. Das, R. Kumar, and P. Sumathi, "A power-line interference canceler based on sliding DFT phase locking scheme for ECG signals," *IEEE Trans. Instrum. Meas.*, vol. 64, no. 1, pp. 132–142, Jan. 2015.

[10] M. Tomasini, S. Benatti, B. Milosevic, E. Farella, and L. Benini, "Power line interference removal for high quality continuous bio-signal monitoring with low-power wearable devices," *IEEE Sensors Journal*, vol. 16, no. 10, pp. 3887–3895, Mar. 2016.

[11] N. Razzaq, S.-A. A. Sheikh, M. Salman, and T. Zaidi, "An intelligent adaptive filter for elimination of power line interference from high resolution electrocardiogram," *IEEE Access*, vol. 4, pp. 1676–1688, May 2016.

[12] G. J. J. Warmerdam, R. Vullings, L. Schmitt, J. O. E. H. V. Laar, and J. W. M. Bergmans, "A fixed-lag Kalman smoother to filter power line interference in electrocardiogram recordings," *IEEE Trans. Biomedical Eng.*, vol. 64, no. 8, pp. 1852–1861, Aug. 2017.

[13] B. Chen, Y. Li, X. Cao, W. Sun, and W. He, "Removal of power line interference from ECG signals using adaptive notch filters of sharp resolution," *IEEE Access*, vol. 7, pp. 150667–150676, Oct. 2019.

[14] P. U. da Costa, G. Paim, L. M. G. Rocha, E. D. C. da Costa, S. J. M. de Almeida, and S. Bampi, "Fixed-point NLMS and IPNLMS VLSI architectures for accurate FECG and FHR processing," *IEEE Trans. Biomedical Circuits and Syst.*, vol. 15, no. 5, pp. 898–911, Oct. 2021.

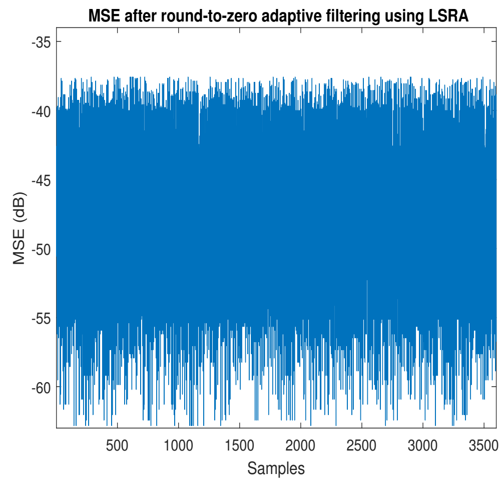

Fig. 12. **Mean square error after round-to-zero adaptive filtering using LSRA.**

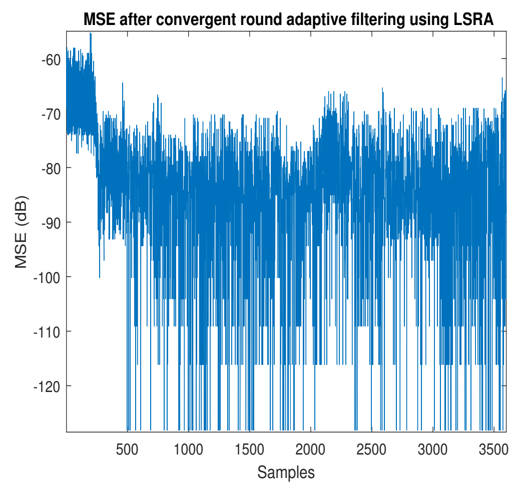

Fig. 13. **Mean square error after convergent round adaptive filtering using LSRA.**

[15] S. Tahir, M. M. Raja, N. Razzaq, A. Mirza, W. Z. Khan, S. W. Kim, and Y. B. Zikria, "Extended Kalman filter-based power line interference canceller for electrocardiogram signal," *Big Data*, vol. 10, no. 1, pp. 34–53, Feb. 2022.

[16] M. M. U. Faiz and I. Kale, "Removal of multiple artifacts from ECG signal using cascaded multistage adaptive noise cancellers," *Array*, vol. 14, Art. no. 100133, pp. 1–9, July 2022.

[17] K. Mayyas and T. Aboulnasr, "Leaky LMS: A detailed analysis," *in Proc. of the 1995 IEEE Int. Symp. on Circuits and Syst. (ISCAS 1995)*, Seattle, WA, USA, pp. 1255–1258, Apr. 1995.

[18] K. Mayyas and T. Aboulnasr, "Leaky LMS algorithm: MSE analysis for Gaussian data," *IEEE Trans. Signal Process.*, vol. 45, no. 4, pp. 927–934, Apr. 1997.

[19] A. H. Sayed, "Adaptive filters," *Wiley-IEEE Press*, 1^{st} Ed., Apr. 2008.

[20] M. M. U. Faiz, A. Zerguine, and A. Zidouri, "Analysis of the sign regressor least mean fourth adaptive algorithm," *EURASIP Jour. on Advances in Signal Process.*, vol. 2011, Art. no. 373205, pp. 1–12, Jan. 2011.

[21] PhysioBank ATM, Available: https://archive.physionet.org/cgi-bin/atm/ATM, Accessed on: 2 Apr. 2022.