Array 14 (2022) 100133

Contents lists available at ScienceDirect

Array

journal homepage: www.elsevier.com/locate/array

Removal of multiple artifacts from ECG signal using cascaded multistage adaptive noise cancellers

Mohammed Mujahid Ulla Faiz *, Izzet Kale

Applied DSP and VLSI Research Group, Department of Computer Science and Engineering, University of Westminster, London, W1W 6UW, United Kingdom

ARTICLE INFO

Keywords:
ECG
LMS
LMF
LMMN
PLI

ABSTRACT

Although cascaded multistage adaptive noise cancellers have been employed before by researchers for multiple artifact removal from the ElectroCardioGram (ECG) signal, they all used the same adaptive algorithm in all the cascaded multi-stages for adjusting the adaptive filter weights. In this paper, we propose a cascaded 4-stage adaptive noise canceller for the removal of four artifacts present in the ECG signal, viz. baseline wander, motion artifacts, muscle artifacts, and 60 Hz Power Line Interference (PLI). We have investigated the performance of eight adaptive algorithms, viz. Least Mean Square (LMS), Least Mean Fourth (LMF), Least Mean Mixed-Norm (LMMN), Sign Regressor Least Mean Square (SRLMS), Sign Error Least Mean Square (SELMS), Sign-Sign Least Mean Square (SSLMS), Sign Regressor Least Mean Fourth (SRLMF), and Sign Regressor Least Mean Mixed-Norm (SRLMMN) in terms of Signal-to-Noise Ratio (SNR) improvement for removing the aforementioned four artifacts from the ECG signal. We employed the LMMN, LMF, LMMN, LMF algorithms in the proposed cascaded 4-stage adaptive noise canceller to remove the respective ECG artifacts as mentioned above. We succeeded in achieving an SNR improvement of 12.7319 dBs. The proposed cascaded 4-stage adaptive noise canceller employing the LMMN, LMF, LMMN, LMF algorithms outperforms those that employ the same algorithm in the four stages. One unique and powerful feature of our proposed cascaded 4-stage adaptive noise canceller is that it employs only those adaptive algorithms in the four stages, which are shown to be effective in removing the respective ECG artifacts as mentioned above. Such a scheme has not been investigated before in the literature.

1. Introduction

Adaptive noise cancellation is a method of estimating signals, which are corrupted by additive noise or interference. This method employs a primary input, which is the corrupted signal, and a secondary or reference input, which is the noise correlated with the noise present in the primary input. The reference input is adaptively filtered and subtracted from the primary input in order to obtain the signal estimate. The adaptive noise cancellation method can be employed whenever an appropriate reference input is available [1,2].

Thakor and Zhu [3] proposed several adaptive filter structures for noise cancellation and arrhythmia detection in ECG signals. The diverse forms of noise like baseline wander, 60 Hz PLI, muscle artifacts, and motion artifacts were eliminated from the ECG signal [3]. Hamilton [4] investigated the relative performance of an adaptive and nonadaptive 60-Hz notch filters for the reduction of PLI in the ECG signal. Ziarani and Konrad [5] proposed a nonlinear adaptive method of elimination of PLI from the ECG signal. The proposed method offered a robust structure and is shown to have a high degree of immunity with respect to external noise [5]. Raya and Sison [6] proposed an adaptive noise cancellation method to remove motion artifacts in stress ECG signals by using an accelerometer. The adaptive noise cancellers in [6] are implemented using the two of the most widely employed adaptive filtering algorithms, viz. LMS and Recursive Least Squares (RLS). Martens et al. [7] proposed an improved adaptive noise canceller for the reduction of the fundamental PLI component and harmonics in the ECG signal. Behbahani [8] simulated and tested an adaptive noise cancellation method using the LMS algorithm for removing the 60 Hz PLI. Lin and Hu [9] developed an efficient RLS adaptive notch filter for the suppression of PLI in the ECG signal. They also proposed a PLI detector that employed an optimal linear discriminant analysis algorithm for the detection of PLI in the ECG signal [9].

Rahman et al. [10–12, range] employed Normalized Sign Regressor Least Mean Square (NSRLMS), Normalized Sign Error Least Mean Square (NSELMS), and Normalized Sign-Sign Least Mean Square (NSSLMS) algorithms for canceling various artifacts such as baseline wander, 60 Hz PLI, muscle artifacts, and motion artifacts from the ECG signal. Rahman et al. [13] employed LMS, SRLMS, SELMS, and SSLMS algorithms for canceling various artifacts as mentioned

* Corresponding author.
E-mail addresses: w1805470@my.westminster.ac.uk (M.M.U. Faiz), kalei@westminster.ac.uk (I. Kale).

https://doi.org/10.1016/j.array.2022.100133
Received 20 August 2021; Received in revised form 18 October 2021; Accepted 20 February 2022
Available online 6 March 2022

above from the ECG signal. In [13], it is shown that the performance of the SRLMS algorithm is superior to the LMS algorithm in terms of SNR improvement. Rahman et al. [14] expanded the work in [10–12, range] by employing Block-Based Normalized Sign Regressor Least Mean Square (BBNSRLMS), Block-Based Normalized Sign Error Least Mean Square (BBNSELMS), and Block-Based Normalized Sign-Sign Least Mean Square (BBNSSLMS) algorithms for canceling various artifacts as mentioned above from the ECG signal.

Islam et al. [15] added the four types of Alternating Current (AC) and Direct Current (DC) interference/noise with ECG signals and nullified these noises using the LMS and RLS algorithms. Vullings et al. [16] developed an adaptive Kalman filter to enhance the quality of the ECG signal. Dhubkarya et al. [17] implemented an adaptive noise canceller for denoising an ECG signal and tested the performance of the system using various algorithms such as LMS, Normalized Least Mean Square (NLMS), and RLS. Chandrakar and Kowar [18] employed the RLS algorithm for the removal of different kinds of noises from the ECG signal. Kim et al. [19] proposed a motion artifact removal method using a cascaded 2-stage LMS adaptive filter for an ambulatory ECG monitoring system. Mugdha et al. [20] conducted a study of the RLS algorithm in noise removal from ECG signals and concluded that the RLS algorithm is more efficient in removing noises from ECG signals than the LMS algorithm.

Ebrahimzadeh et al. [21] compared various kinds of ECG noise reduction algorithms such as LMS, Block-Based Least Mean Square (BBLMS), NLMS, Unbiased and Normalized Adaptive Noise Reduction (UNANR), and RLS. Sharma et al. [22] used an adaptive noise canceller that employs LMS algorithm for ECG noise removal and concluded that an increase in the step-size increases the noise as well as the rate of convergence. Satheeskumaran and Sabrigiriraj [23] proposed a Variable Step Size Delayed Least Mean Square (VSSDLMS) adaptive filter to remove the artifacts from the ECG signal. Sehamby and Singh [24] used an LMS-based adaptive noise canceller to derive a noise-free fetal ECG signal. Haritha et al. [25] surveyed different filters and denoising techniques used for ECG signals. Qureshi et al. [26] proposed a cascaded 3-stage adaptive noise canceller to eliminate three types of artifacts from the ECG signal, viz. baseline wander, 60 Hz PLI, and motion artifacts. The same algorithm was used in all three stages of the cascaded adaptive noise canceller. The results of a cascaded 3-stage LMS-based adaptive noise canceller were compared with those of a cascaded 3-stage NLMS-based adaptive noise canceller, a cascaded 3-stage Log LMS-based adaptive noise canceller, and a cascaded 3-stage SRLMS-based adaptive noise canceller. Warmerdam et al. [27] proposed a fixed-lag Kalman smoother to filter PLI from ECG recordings with minimal distortion of the ECG waveform.

Sutha and Jayanthi [28] discuss prototype hardware developed to monitor and record the raw mother ECG signal containing the fetal ECG and a signal processing algorithm to extract the fetal ECG. The adaptive noise canceller employed in their work uses the SSLMS algorithm [28]. Gilani et al. [29] employed an LMS-based adaptive noise canceller to remove the 50 Hz PLI from the ECG signal. Venkatesan et al. [30] studied a Delayed Error Normalized Least Mean Square (DENLMS) adaptive filter with pipelined architecture to remove the white Gaussian noise from the ECG signal. Srinivasa and Pandian [31] eliminate the 50 Hz PLI from ECG signal using an LMS-based adaptive noise canceller. Xiong et al. [32] have shown that the cosine-based adaptive algorithm is superior to the standard LMS algorithm in reducing the high amplitude motion artifact noise from the ECG signal. Saxena et al. [33] remove the 50 Hz PLI from the ECG signal using an NLMS-based adaptive noise canceller. Manju and Sneha [34] performed ECG denoising using Weiner filter and Kalman filter. Their results have shown that the Wiener filter performs better than the Kalman filter for ECG noise removal. Khiter et al. [35] proposed a novel adaptive denoising method called self correcting leaky normalized least mean square algorithm with varied step size and leakage coefficient for reducing the muscle artifacts from the ECG signal. Yadav et al. [36] applied the symbiotic organisms search algorithm for estimating the weight vectors of an optimized adaptive noise canceller for reducing the artifacts from the ECG signal.

In this paper, we will employ a cascaded 4-stage adaptive noise canceller to remove the four types of artifacts from the ECG signal, viz. baseline wander, motion artifacts, muscle artifacts, and 60 Hz PLI. The contributions of this paper are: (1) We first determine the best performing adaptive algorithms in terms of SNR improvement among the eight adaptive algorithms studied in this paper, viz. Least Mean Square (LMS), Least Mean Fourth (LMF), Least Mean Mixed-Norm (LMMN), Sign Regressor Least Mean Square (SRLMS), Sign Error Least Mean Square (SELMS), Sign-Sign Least Mean Square (SSLMS), Sign Regressor Least Mean Fourth (SRLMF), and Sign Regressor Least Mean Mixed-Norm (SRLMMN) for removing the aforementioned four artifacts from the ECG signal, (2) We then employ the four shortlisted algorithms, viz. LMMN, LMF, LMMN, LMF in the proposed cascaded 4-stage adaptive noise canceller for removing the aforementioned four artifacts from the ECG signal, and (3) We then compare the performance of the proposed cascaded 4-stage adaptive noise canceller employing the LMMN, LMF, LMMN, LMF algorithms with those that employ the LMS, LMS, LMS, LMS algorithms, the LMF, LMF, LMF, LMF algorithms, the LMMN, LMMN, LMMN, LMMN algorithms, and the SRLMMN, SRLMF, SRLMMN, SRLMF algorithms. We were able to achieve a significant improvement in the SNR of the filtered ECG signal after the application of our proposed scheme over other schemes. The remainder of this paper is organized as follows. Various adaptive algorithms studied in this paper are discussed in Section 2. The proposed cascaded 4-stage adaptive noise canceller is discussed in Section 3. Simulation results are discussed in Section 4. Finally, the paper is concluded in Section 5.

2. Adaptive algorithms

In this work, we have studied eight adaptive algorithms, viz. LMS, LMF, LMMN, SRLMS, SELMS, SSLMS, SRLMF, and SRLMMN for the removal of multiple artifacts present in the ECG signal. The weight update equations of these eight adaptive algorithms are given in Table 1 wherein $\mathbf{w}_i \in \mathbb{R}^{M\times 1}$ is the updated weight vector at iteration $i \geq 0$, M is the adaptive filter length, μ is the step-size, $\mathbf{u}_i \in \mathbb{R}^{1\times M}$ is the regressor or input vector with variance σ_u^2, δ is the mixing parameter ranging between $0 \leq \delta \leq 1$, e_i is the estimation error given by

$$e_i = d_i - \mathbf{u}_i \mathbf{w}_{i-1}, \tag{1}$$

where d_i is the desired value, and

$$\operatorname{sgn}[x] = \begin{cases} -1, & \text{if } x < 0, \\ 0, & \text{if } x = 0, \\ 1, & \text{if } x > 0. \end{cases} \tag{2}$$

The LMMN algorithm is a combination of the LMS and LMF algorithms as long as the mixing parameter is ranging between $0 < \delta < 1$. The LMMN algorithm reduces to LMF and LMS algorithms when the mixing parameter becomes zero and one, respectively.

The sign adaptive filters are used for the processing and analysis of ECG signals as they are computationally less complex. However, the performance of a sign adaptive filter is compromised because of the clipping effect due to the application of signum function to either the regressor vector, estimation error, or both. The SRLMS, SELMS, and SSLMS algorithms are also known in the literature as the Sign Regressor Algorithm (SRA), Sign Algorithm (SA), and Sign-Sign Algorithm (SSA), respectively. The SRLMMN algorithm is a combination of the SRLMS and SRLMF algorithms as long as the mixing parameter is ranging between $0 < \delta < 1$. The SRLMMN algorithm reduces to SRLMF and SRLMS algorithms when the mixing parameter becomes zero and one, respectively. Note that the SRLMF [37] and SRLMMN [38] algorithms were developed by us and are being employed in this work for the removal of multiple artifacts present in the ECG signal.

Table 1
Weight update equations of various adaptive algorithms.

Adaptive algorithm	Weight update equation
LMS [39,40]	$\mathbf{w}_i = \mathbf{w}_{i-1} + \mu\ \mathbf{u}_i^{\mathrm{T}} e_i$
LMF [40,41]	$\mathbf{w}_i = \mathbf{w}_{i-1} + \mu\ \mathbf{u}_i^{\mathrm{T}} e_i^3$
LMMN [42]	$\mathbf{w}_i = \mathbf{w}_{i-1} + \mu\ \mathbf{u}_i^{\mathrm{T}} e_i[\delta + (1-\delta)e_i^2]$
SRLMS [43]	$\mathbf{w}_i = \mathbf{w}_{i-1} + \mu\ \mathrm{sgn}[\mathbf{u}_i]^{\mathrm{T}} e_i$
SELMS [44]	$\mathbf{w}_i = \mathbf{w}_{i-1} + \mu\ \mathbf{u}_i^{\mathrm{T}} \mathrm{sgn}[e_i]$
SSLMS [45]	$\mathbf{w}_i = \mathbf{w}_{i-1} + \mu\ \mathrm{sgn}[\mathbf{u}_i]^{\mathrm{T}} \mathrm{sgn}[e_i]$
SRLMF [37]	$\mathbf{w}_i = \mathbf{w}_{i-1} + \mu\ \mathrm{sgn}[\mathbf{u}_i]^{\mathrm{T}} e_i^3$
SRLMMN [38]	$\mathbf{w}_i = \mathbf{w}_{i-1} + \mu\ \mathrm{sgn}[\mathbf{u}_i]^{\mathrm{T}} e_i[\delta + (1-\delta)e_i^2]$

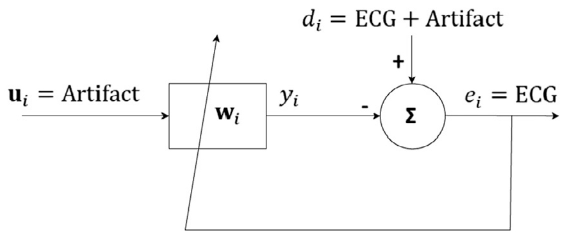

Fig. 1. Adaptive noise canceller.

3. Proposed cascaded 4-stage adaptive noise canceller

A single-stage adaptive noise canceller for removing a single artifact from the ECG signal is shown in Fig. 1. As can be seen from this figure d_i forms the primary input of the adaptive noise canceller, d_i contains the ECG signal with an additive artifact, $\mathbf{u}_i$ forms the secondary or reference input of the adaptive noise canceller, $\mathbf{u}_i$ contains the reference artifact that is correlated only with the artifact present in the corrupted ECG signal d_i, $\mathbf{w}_i$ are the adaptive filter coefficients, y_i is the adaptive filter output, and e_i is the filtered ECG signal free from the artifact.

A proposed cascaded 4-stage adaptive noise canceller for removing the four artifacts from the ECG signal is shown in Fig. 2. As can be seen from this figure d_{i1} forms the primary input of the first adaptive noise canceller, d_{i1} contains the ECG signal with four additive artifacts, viz. baseline wander, motion artifacts, muscle artifacts, and 60 Hz PLI, $\mathbf{u}_{i1}$ forms the secondary or reference input of the first adaptive noise canceller, $\mathbf{u}_{i1}$ contains the reference baseline wander that is correlated only with the baseline wander present in the corrupted ECG signal d_{i1}, $\mathbf{u}_{i2}$ forms the secondary or reference input of the second adaptive noise canceller, $\mathbf{u}_{i2}$ contains the reference motion artifacts that is correlated only with the motion artifacts present in the corrupted ECG signal d_{i1}, $\mathbf{u}_{i3}$ forms the secondary or reference input of the third adaptive noise canceller, $\mathbf{u}_{i3}$ contains the reference muscle artifacts that is correlated only with the muscle artifacts present in the corrupted ECG signal d_{i1}, $\mathbf{u}_{i4}$ forms the secondary or reference input of the fourth adaptive noise canceller, $\mathbf{u}_{i4}$ contains the reference 60 Hz PLI that is correlated only with the 60 Hz PLI present in the corrupted ECG signal d_{i1}, $\mathbf{w}_{i1}$ to $\mathbf{w}_{i4}$ are the respective adaptive filter coefficients, y_{i1} to y_{i4} are the respective adaptive filter outputs, e_{i1} is the partially corrupted ECG signal free from baseline wander, e_{i1} will act as the primary input d_{i2} to the second adaptive noise canceller, e_{i2} is the partially corrupted ECG signal free from baseline wander and motion artifacts, e_{i2} will act as the primary input d_{i3} to the third adaptive noise canceller, e_{i3} is the partially corrupted ECG signal free from baseline wander, motion artifacts, and muscle artifacts, e_{i3} will act as the primary input d_{i4} to the fourth adaptive noise canceller and e_{i4} is the filtered ECG signal free from baseline wander, motion artifacts, muscle artifacts, and 60 Hz PLI. One unique and powerful feature of our proposed cascaded 4-stage adaptive noise canceller is that it employs only those adaptive algorithms in the four stages, which are shown to be effective in the subsequent section in removing the aforementioned four artifacts from the ECG signal.

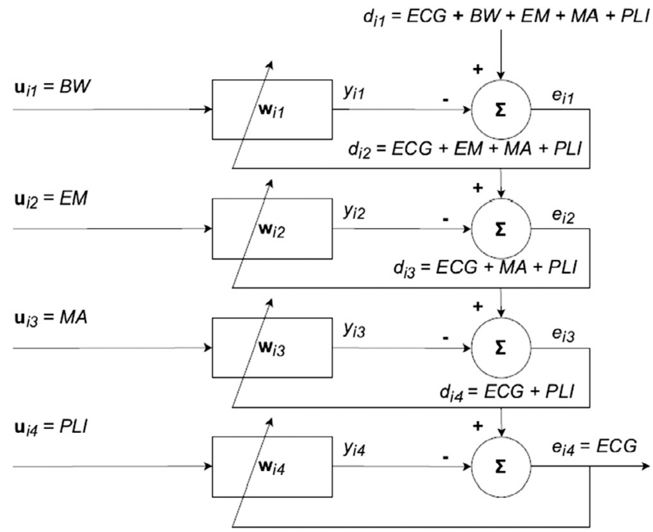

Fig. 2. Proposed cascaded 4-stage adaptive noise canceller.

4. Simulation results

4.1. Baseline wander removal

In this experiment, the step-size is fixed at $\mu = 0.01$, the adaptive filter length is fixed at $M = 5$, the noise variance is fixed at $\sigma_v^2 = 0.1$, and the number of iterations is fixed at $L = 10$ for all the eight adaptive algorithms studied. In addition to the above settings, the mixing parameter is fixed at $\delta = 0.5$ for the LMMN and SRLMMN algorithms.

In this case, 3600 samples of the clean ECG signal are taken from the MIT-BIH Arrhythmia Database (MITDB) Record: 105 [46], and they are later added with the 3600 samples of baseline wander taken from the MIT-BIH Noise Stress Test Database (NSTDB) Record: bw [46].

All eight adaptive algorithms studied in this paper, viz. LMS, LMF, LMMN, SRLMS, SELMS, SSLMS, SRLMF, and SRLMMN are tested separately by plugging them in a single-stage adaptive noise canceller as described in Fig. 1 for baseline wander removal. The SNR before and after adaptive filtering is recorded in Table 2. The SNR is calculated by using the built-in MATLAB function, viz. $snr(x, y)$. The SNR before and after adaptive filtering in Table 2 is calculated as described by the MATLAB code fragment in Appendix A. Here, y is the adaptive filter output. Note that the ECG signal and baseline wander have a gain of 200 each. Therefore, we divide these signals by 200 as shown in the MATLAB code fragment in Appendix A.

As can be seen from Table 2 the LMMN algorithm outperforms the other seven algorithms in terms of SNR improvement. The Mean Square Error (MSE) plot after baseline wander removal using a single-stage adaptive noise canceller employing the SSLMS adaptive algorithm, which is the worst-case scenario among the eight algorithms studied is shown in Fig. 3.

4.2. Motion artifacts removal

In this experiment, the step-size is fixed at $\mu = 0.01$, the adaptive filter length is fixed at $M = 5$, the noise variance is fixed at $\sigma_v^2 = 0.1$, and the number of iterations is fixed at $L = 10$ for all the eight adaptive algorithms studied. In addition to the above settings, the mixing parameter is fixed at $\delta = 0.5$ for the LMMN and SRLMMN algorithms.

In this case, 3600 samples of the clean ECG signal are taken from the MIT-BIH Arrhythmia Database (MITDB) Record: 105 [46], and they

Table 2
Baseline wander removal using a single-stage adaptive noise canceller.

Adaptive algorithm	SNR before filtering (dB)	SNR after filtering (dB)	SNR improvement (dB)
LMS	7.9251	7.9446	0.0195
LMF	7.9251	7.9513	0.0262
LMMN	7.9251	8.9812	1.0561
SRLMS	7.9251	3.3297	−4.5954
SELMS	7.9251	3.9091	−4.0160
SSLMS	7.9251	1.1036	−6.8215
SRLMF	7.9251	8.2505	0.3254
SRLMMN	7.9251	5.2039	−2.7212

Table 3
Motion artifacts removal using a single-stage adaptive noise canceller.

Adaptive algorithm	SNR before filtering (dB)	SNR after filtering (dB)	SNR improvement (dB)
LMS	5.7109	3.7061	−2.0048
LMF	5.7109	5.7874	0.0765
LMMN	5.7109	4.4862	−1.2247
SRLMS	5.7109	2.1133	−3.5976
SELMS	5.7109	1.4867	−4.2242
SSLMS	5.7109	0.6071	−5.1038
SRLMF	5.7109	4.0887	−1.6222
SRLMMN	5.7109	2.7931	−2.9178

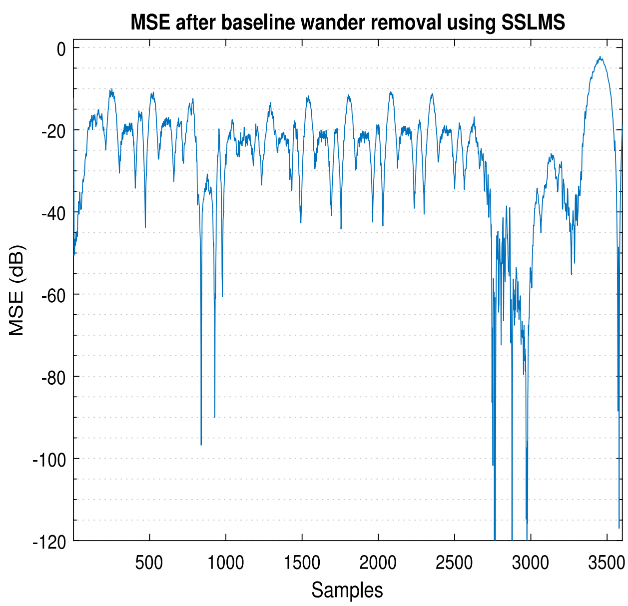

Fig. 3. MSE after baseline wander removal using a single-stage adaptive noise canceller employing the SSLMS adaptive algorithm (worst-case scenario)

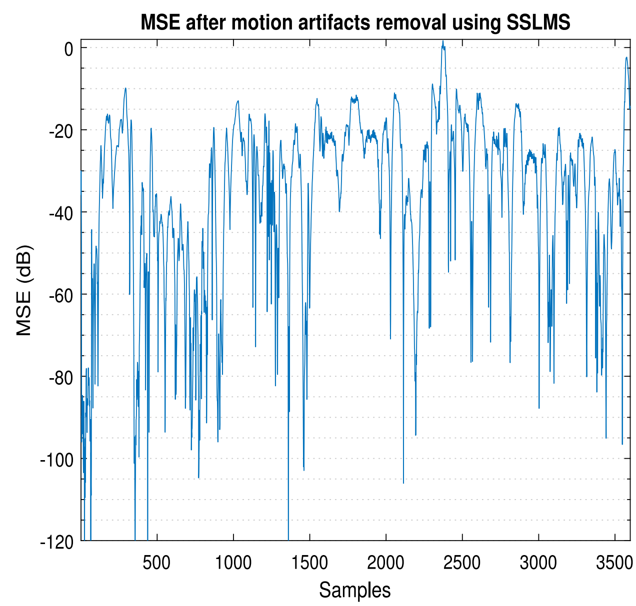

Fig. 4. MSE after motion artifacts removal using a single-stage adaptive noise canceller employing the SSLMS adaptive algorithm (worst-case scenario).

are later added with the 3600 samples of motion artifacts taken from the MIT-BIH Noise Stress Test Database (NSTDB) Record: em [46].

All eight adaptive algorithms studied in this paper, viz. LMS, LMF, LMMN, SRLMS, SELMS, SSLMS, SRLMF, and SRLMMN are tested separately by plugging them in a single-stage adaptive noise canceller as described in Fig. 1 for motion artifacts removal. The SNR before and after adaptive filtering is recorded in Table 3. The SNR before and after adaptive filtering in Table 3 is calculated by replacing line five in Appendix A MATLAB code fragment with $load('emm')$; Note that the motion artifacts have a gain of 200. Therefore, we divide this signal by 200 as shown in the MATLAB code fragment in Appendix A. As can be seen from Table 3 the LMF algorithm outperforms the other seven algorithms in terms of SNR improvement. The MSE plot after motion artifacts removal using a single-stage adaptive noise canceller employing the SSLMS adaptive algorithm, which is the worst-case scenario among the eight algorithms studied is shown in Fig. 4.

4.3. Muscle artifacts removal

In this experiment, the step-size is fixed at $\mu = 0.01$, the adaptive filter length is fixed at $M = 5$, the noise variance is fixed at $\sigma_v^2 = 0.1$, and the number of iterations is fixed at $L = 100$ for all the eight adaptive algorithms studied. In addition to the above settings, the mixing parameter is fixed at $\delta = 0.5$ for the LMMN and SRLMMN algorithms.

In this case, 3600 samples of the clean ECG signal are taken from the MIT-BIH Arrhythmia Database (MITDB) Record: 105 [46], and they are later added with the 3600 samples of muscle artifacts taken from the MIT-BIH Noise Stress Test Database (NSTDB) Record: ma [46].

All eight adaptive algorithms studied in this paper, viz. LMS, LMF, LMMN, SRLMS, SELMS, SSLMS, SRLMF, and SRLMMN are tested separately by plugging them in a single-stage adaptive noise canceller as described in Fig. 1 for muscle artifacts removal. The SNR before and after adaptive filtering is recorded in Table 4. The SNR before and

Table 4
Muscle artifacts removal using a single-stage adaptive noise canceller.

Adaptive algorithm	SNR before filtering (dB)	SNR after filtering (dB)	SNR improvement (dB)
LMS	17.8230	23.8256	6.0026
LMF	17.8230	21.0251	3.2021
LMMN	17.8230	26.1239	8.3009
SRLMS	17.8230	10.0358	−7.7872
SELMS	17.8230	19.2611	1.4381
SSLMS	17.8230	5.4269	−12.3961
SRLMF	17.8230	16.5538	−1.2692
SRLMMN	17.8230	12.3562	−5.4668

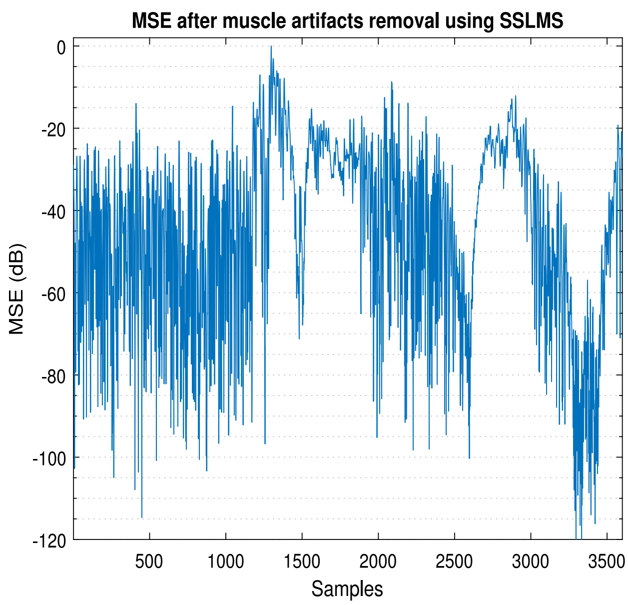

Fig. 5. MSE after muscle artifacts removal using a single-stage adaptive noise canceller employing the SSLMS adaptive algorithm (worst-case scenario).

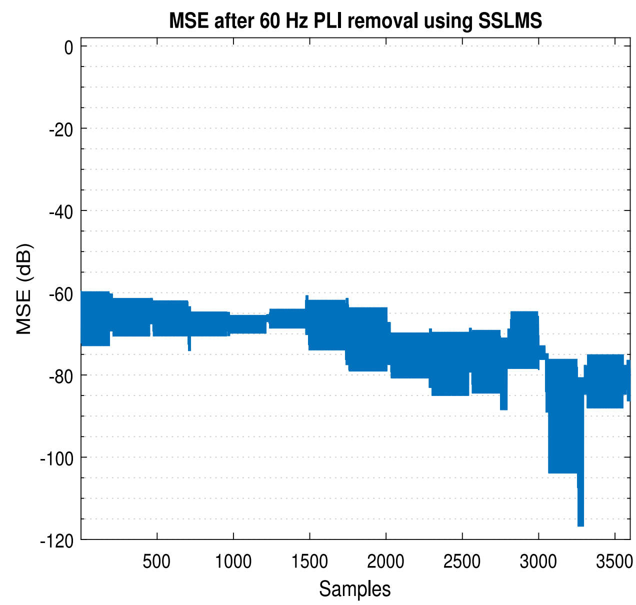

Fig. 6. MSE after 60 Hz PLI removal using a single-stage adaptive noise canceller employing the SSLMS adaptive algorithm (worst-case scenario).

after adaptive filtering in Table 4 is calculated by replacing line five in Appendix A MATLAB code fragment with $load('mam')$; Note that the muscle artifacts have a gain of 200. Therefore, we divide this signal by 200 as shown in the MATLAB code fragment in Appendix A. As can be seen from Table 4 the LMMN algorithm outperforms the other seven algorithms in terms of SNR improvement. The MSE plot after muscle artifacts removal using a single-stage adaptive noise canceller employing the SSLMS adaptive algorithm, which is the worst-case scenario among the eight algorithms studied is shown in Fig. 5.

4.4. 60 Hz PLI removal

In this experiment, the step-size is fixed at $\mu = 0.01$, the adaptive filter length is fixed at $M = 5$, and the number of iterations is fixed at $L = 10$ for all the eight adaptive algorithms studied. In addition to the above settings, the mixing parameter is fixed at $\delta = 0.5$ for the LMMN and SRLMMN algorithms.

In this case, 3600 samples of the clean ECG signal are taken from the MIT-BIH Arrhythmia Database (MITDB) Record: 105 [46], and they are later added with the 3600 samples of synthetic PLI with amplitude 100 mV, frequency 60 Hz, and sampled at 360 Hz, which has been chosen to be the same as the rest of the ECG signals used throughout our experiments.

All eight adaptive algorithms studied in this paper, viz. LMS, LMF, LMMN, SRLMS, SELMS, SSLMS, SRLMF, and SRLMMN are tested separately by plugging them in a single-stage adaptive noise canceller as described in Fig. 1 for the 60 Hz PLI removal. The SNR before and after adaptive filtering is recorded in Table 5. The SNR before and after adaptive filtering in Table 5 is calculated as described by the MATLAB code fragment in Appendix B. Here, y is the adaptive filter output. Note that the ECG signal has a gain of 200. Therefore, we divide this signal by 200 as shown in the MATLAB code fragment in Appendix B.

As can be seen from Table 5 the LMF algorithm outperforms the other seven algorithms in terms of SNR improvement. The MSE plot after 60 Hz PLI removal using a single-stage adaptive noise canceller employing the SSLMS adaptive algorithm, which is the worst-case scenario among the eight algorithms studied is shown in Fig. 6.

4.5. Multiple artifacts removal

In this experiment, the step-size is fixed at $\mu = 0.01$, the adaptive filter length is fixed at $M = 5$, the noise variance is fixed at $\sigma_v^2 = 0.1$, and the number of iterations is fixed at $L = 10$ for all the algorithms presented in Table 6. In addition to the above settings, the mixing parameter is fixed at $\delta = 0.5$ for the LMMN and SRLMMN algorithms.

In this case, 3600 samples of the clean ECG signal are taken from the MIT-BIH Arrhythmia Database (MITDB) Record: 105 [46], and they are later added with the 3600 samples of baseline wander taken from the MIT-BIH Noise Stress Test Database (NSTDB) Record: bw [46], the 3600 samples of motion artifacts taken from the MIT-BIH Noise Stress Test Database (NSTDB) Record: em [46], the 3600 samples of muscle artifacts taken from the MIT-BIH Noise Stress Test Database (NSTDB) Record: ma [46], and the 3600 samples of synthetic PLI with amplitude 100 mV, frequency 60 Hz, and sampled at 360 Hz.

The four adaptive algorithms, viz. LMMN, LMF, LMMN, and LMF shortlisted from the four experiments as discussed in Sections 4.1–4.4 are tested by plugging them in the proposed cascaded 4-stage

Table 5
60 Hz PLI removal using a single-stage adaptive noise canceller.

Adaptive algorithm	SNR before filtering (dB)	SNR after filtering (dB)	SNR improvement (dB)
LMS	14.6914	14.2872	−0.4042
LMF	14.6914	16.4652	1.7738
LMMN	14.6914	15.3068	0.6154
SRLMS	14.6914	14.1104	−0.5810
SELMS	14.6914	16.0296	1.3382
SSLMS	14.6914	13.6714	−1.0200
SRLMF	14.6914	15.2992	0.6078
SRLMMN	14.6914	14.2847	−0.4067

adaptive noise canceller as described in Fig. 2 for removing baseline wander, motion artifacts, muscle artifacts, and 60 Hz PLI from the ECG signal, respectively. We then compare the performance of the proposed cascaded 4-stage adaptive noise canceller employing the LMMN, LMF, LMMN, LMF algorithms with that employing the LMS, LMS, LMS, LMS algorithms, the LMF, LMF, LMF, LMF algorithms, the LMMN, LMMN, LMMN, LMMN algorithms, and the SRLMMN, SRLMF, SRLMMN, SRLMF algorithms. The SNR before and after adaptive filtering is recorded in Table 6. As can be seen from this table, we have achieved a significant improvement in the SNR by employing the LMMN, LMF, LMMN, LMF algorithms in the proposed cascaded 4-stage adaptive noise canceller. The SNR before and after adaptive filtering in Table 6 is calculated as described by the MATLAB code fragment in Appendix C. Here, y is the adaptive filter output. Note that the ECG signal, baseline wander, motion artifacts, and muscle artifacts have a gain of 200 each. Therefore as before, we divide these signals by 200 as shown in the MATLAB code fragment in Appendix C.

As an example, in row 2 of Table 6, the LMMN algorithm is used in adaptive noise cancellers 1 and 3 in Fig. 2 for removing baseline wander and muscle artifacts, respectively. The LMF algorithm in row 2 of Table 6 is used in adaptive noise cancellers 2 and 4 in Fig. 2 for removing motion artifacts and 60 Hz PLI, respectively. The MSE plot after multiple artifacts removal using the proposed cascaded 4-stage adaptive noise canceller employing the SRLMMN, SRLMF, SRLMMN, SRLMF algorithms, which is the worst-case scenario among the algorithms studied in Table 6 is shown in Fig. 7. The MSE plot after multiple artifacts removal using the proposed cascaded 4-stage adaptive noise canceller employing the LMMN, LMF, LMMN, LMF algorithms, which is the best-case scenario among the algorithms studied in Table 6 is shown in Fig. 8. Figs. 9(a) and 10(d) show the clean ECG signal free from artifacts, Figs. 9(b) and 10(e) show the ECG signal with additive baseline wander, motion artifacts, muscle artifacts, and 60 Hz PLI, Fig. 9(c) shows the filtered ECG signal from the proposed cascaded 4-stage adaptive noise canceller employing the SRLMMN, SRLMF, SRLMMN, SRLMF algorithms for multiple artifacts removal, which is the worst-case scenario among the algorithms studied in Table 6, and Fig. 10(f) shows the filtered ECG signal from the proposed cascaded 4-stage adaptive noise canceller employing the LMMN, LMF, LMMN, LMF algorithms for multiple artifacts removal, which is the best-case scenario among the algorithms studied in Table 6. As can be seen from Fig. 10(f) the LMMN, LMF, LMMN, LMF algorithms are found to be effective in removing the respective multiple artifacts from the ECG signal demonstrating our proposed scheme outperforms those in the open literature, which primarily concentrate on LMS. It is worth noting that the last three schemes in Table 6, viz. the LMF, LMF, LMF, LMF algorithms, the LMMN, LMMN, LMMN, LMMN algorithms, and the SRLMMN, SRLMF, SRLMMN, SRLMF algorithms have also not been tested before in the literature.

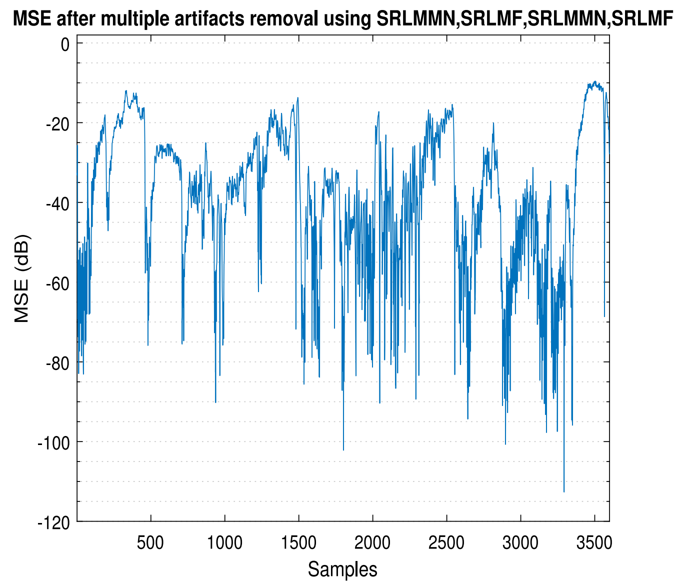

Fig. 7. MSE after multiple artifacts removal using the proposed cascaded 4-stage adaptive noise canceller employing the SRLMMN, SRLMF, SRLMMN, SRLMF adaptive algorithms (worst-case scenario).

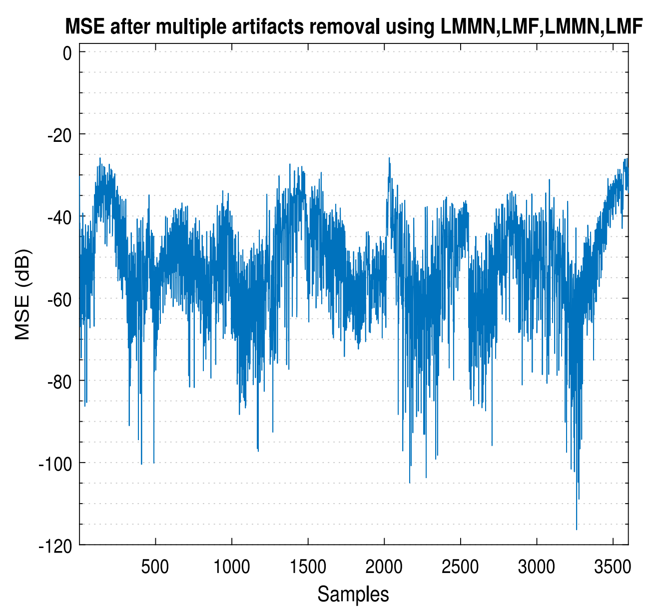

Fig. 8. MSE after multiple artifacts removal using the proposed cascaded 4-stage adaptive noise canceller employing the LMMN, LMF, LMMN, LMF adaptive algorithms (best-case scenario).

5. Conclusions

From our experiments, we have found that the LMMN algorithm is best suited for removing the baseline wander and muscle artifacts and the LMF algorithm is best suited for removing the motion artifacts and 60 Hz PLI. We employed the LMMN, LMF, LMMN, LMF algorithms in the proposed cascaded 4-stage adaptive noise canceller

Table 6
Multiple ECG artifacts (Baseline Wander, Motion, Muscle, 60 Hz PLI) removal using the proposed cascaded 4-stage adaptive noise canceller.

Adaptive algorithm	SNR before filtering (dB)	SNR after filtering (dB)	SNR improvement (dB)
LMMN, LMF, LMMN, LMF	2.2116	14.9435	12.7319
LMS, LMS, LMS, LMS	2.2116	14.0935	11.8819
LMF, LMF, LMF, LMF	2.2116	14.8909	12.6793
LMMN, LMMN, LMMN, LMMN	2.2116	14.2994	12.0878
SRLMMN, SRLMF, SRLMMN, SRLMF	2.2116	13.6959	11.4843

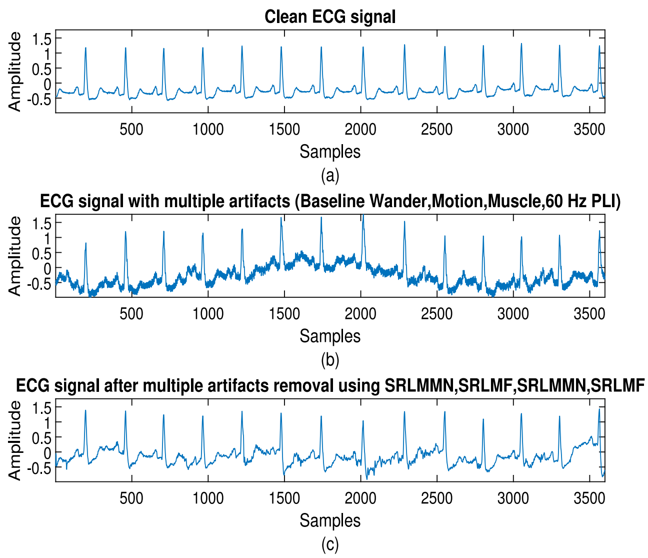

Fig. 9. (a) MIT-BIH Arrhythmia Database (MITDB) Record: 105, (b) MIT-BIH Arrhythmia Database (MITDB) Record: 105 + MIT-BIH Noise Stress Test Database (NSTDB) Record: bw + MIT-BIH Noise Stress Test Database (NSTDB) Record: em + MIT-BIH Noise Stress Test Database (NSTDB) Record: ma + 60 Hz PLI, (c) Recovered MIT-BIH Arrhythmia Database (MITDB) Record: 105 using the proposed cascaded 4-stage adaptive noise canceller employing the SRLMMN, SRLMF, SRLMMN, SRLMF adaptive algorithms for multiple artifacts removal (worst-case scenario).

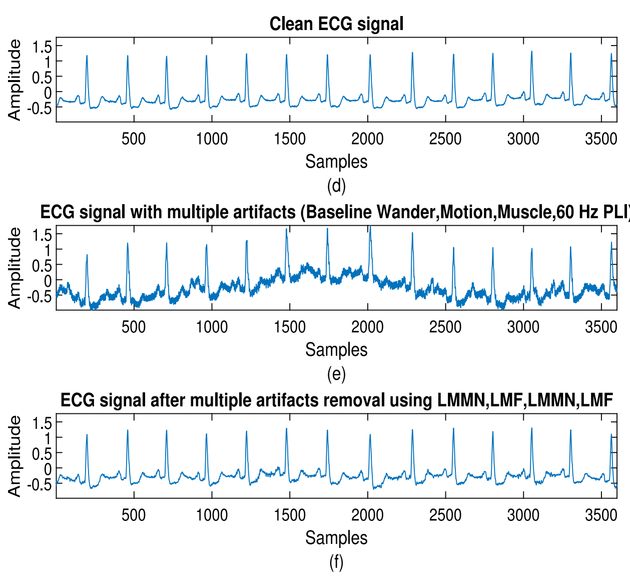

Fig. 10. (d) MIT-BIH Arrhythmia Database (MITDB) Record: 105, (e) MIT-BIH Arrhythmia Database (MITDB) Record: 105 + MIT-BIH Noise Stress Test Database (NSTDB) Record: bw + MIT-BIH Noise Stress Test Database (NSTDB) Record: em + MIT-BIH Noise Stress Test Database (NSTDB) Record: ma + 60 Hz PLI, (f) Recovered MIT-BIH Arrhythmia Database (MITDB) Record: 105 using the proposed cascaded 4-stage adaptive noise canceller employing the LMMN, LMF, LMMN, LMF adaptive algorithms for multiple artifacts removal (best-case scenario).

to remove the respective ECG artifacts as mentioned above. We succeeded in achieving an SNR improvement of 12.7319 dBs, which is better than the other compared methods. It is found that the proposed cascaded 4-stage adaptive noise canceller employing the LMMN, LMF, LMMN, LMF algorithms outperforms those that employ the LMS, LMS, LMS, LMS algorithms, the LMF, LMF, LMF, LMF algorithms, the LMMN, LMMN, LMMN, LMMN algorithms, and the SRLMMN, SRLMF, SRLMMN, SRLMF algorithms in terms of SNR improvement. It is also found that the performance of a single-stage adaptive noise canceller employing the SSLMS algorithm is comparatively poor in terms of SNR improvement as compared to the other seven algorithms studied in this work, viz. LMS, LMF, LMMN, SRLMS, SELMS, SRLMF, and SRLMMN. The different types of normalized adaptive algorithms and their respective sign counterparts in identifying the best candidates for the removal of multiple artifacts from the ECG signal using adaptive filters in cascade as discussed in this work will be the subject of our future studies.

CRediT authorship contribution statement

Mohammed Mujahid Ulla Faiz: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Writing – original draft, Writing – review & editing, Visualization. **Izzet Kale:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Writing – review & editing, Visualization, Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

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

Appendix A

$var\_noise = 0.1;$

$sqn = sqrt(var\_noise);$

$load('105m');$

$input = val(1,:)/200;$

$load('bwm');$

$v = sqn * val(1,:)/200;$

$snr\_before = snr(input, v);$

$snr\_after = snr(input, y);$

Appendix B

$load('105m');$

$input = val(1, :)/200;$

$f = 60;$

$fs = 360;$

$t = [1 : N]/fs;$

$v = 0.1 * sin(2 * pi * f * t + randn);$

$snr\_before = snr(input, v);$

$snr\_after = snr(input, y);$

Appendix C

$var\_noise = 0.1;$

$sqn = sqrt(var\_noise);$

$load('105m');$

$input = val(1, :)/200;$

$load('bwm');$

$v1 = sqn * val(1, :)/200;$

$load('emm');$

$v2 = sqn * val(1, :)/200;$

$load('mam');$

$v3 = sqn * val(1, :)/200;$

$f = 60;$

$fs = 360;$

$t = [1 : N]/fs;$

$v4 = 0.1 * sin(2 * pi * f * t + randn);$

$v = v1 + v2 + v3 + v4;$

$snr\_before = snr(input, v);$

$snr\_after = snr(input, y);$

References

[1] Widrow B, Glover Jr JR, McCool JM, Kaunitz J, Williams CS, Hearn RH, Zeidler JR, Dong Jr E, Goodlin RC. Adaptive noise cancelling: Principles and applications. Proc IEEE 1975;63(12):1692–716.

[2] Widrow B, Stearns SD. Adaptive signal processing. 1st ed. Pearson; 1985.

[3] Thakor NV, Zhu YS. Applications of adaptive filtering to ECG analysis: Noise cancellation and arrhythmia detection. IEEE Trans Biomed Eng 1991;38(8):785–94.

[4] Hamilton PS. A comparison of adaptive and nonadaptive filters for reduction of power line interference in the ECG. IEEE Trans Biomed Eng 1996;43(1):105–9.

[5] Ziarani AK, Konrad A. A nonlinear adaptive method of elimination of power line interference in ECG signals. IEEE Trans Biomed Eng 2002;49(6):540–7.

[6] Raya MAD, Sison LG. Adaptive noise cancelling of motion artifact in stress ECG signals using accelerometer. In: Proc. of the second joint EMBS-BMES Conf., Houston, Texas, USA; 2002, p. 1756–7.

[7] Martens SMM, Mischi M, Oei SG, Bergmans JWM. An improved adaptive power line interference canceller for electrocardiography. IEEE Trans Biomed Eng 2006;53(11):2220–31.

[8] Behbahani S. Investigation of adaptive filtering for noise cancellation in ECG signals. In: Proc. of the second int. multi-symp. on computer and computational sciences (IMSCCS 2007). Iowa City, Iowa, USA; 2007, p. 144–9.

[9] Lin YD, Hu YH. Power-line interference detection and suppression in ECG signal processing. IEEE Trans Biomed Eng 2008;55(1):354–7.

[10] Rahman MZU, Shaik RA, Reddy DVRK. An efficient noise cancellation technique to remove noise from the ECG signal using normalized signed regressor LMS algorithm. In: Proc. of the 2009 IEEE int. conf. on bioinformatics and biomedicine (BIBM 2009). Washington, D.C. USA; 2009, p. 257–60.

[11] Rahman MZU, Shaik RA, Reddy DVRK. Cancellation of artifacts in ECG signals using sign based normalized adaptive filtering technique. In: Proc. of the 2009 IEEE symp. on industrial electronics and applications (ISIEA 2009). Kuala Lumpur, Malaysia; 2009, p. 442–5.

[12] Rahman MZU, Shaik RA, Reddy DVRK. Noise cancellation in ECG signals using normalized sign-sign LMS algorithm. In: Proc. of the 2009 IEEE int. symp. on signal process. and information tech. (ISSPIT 2009). Ajman, UAE; 2009, p. 288–92.

[13] Rahman MZU, Shaik RA, Reddy DVRK. Noise cancellation in ECG signals using computationally simplified adaptive filtering techniques: Application to biotelemetry. Signal Process: Int J 2009;3(5):120–31.

[14] Rahman MZU, Shaik RA, Reddy DVRK. Efficient sign based normalized adaptive filtering techniques for cancelation of artifacts in ECG signals: Application to wireless biotelemetry. Signal Process 2011;91(2):225–39.

[15] Islam SZ, Islam SZ, Jidin R, Ali MAM. Performance study of adaptive filtering algorithms for noise cancellation of ECG signal. In: Proc. of the 2009 int. conf. on information, communications and signal process. (ICICS 2009). Macau, China; 2009, p. 1–5.

[16] Vullings R, Vries BD, Bergmans JWM. An adaptive Kalman filter for ECG signal enhancement. IEEE Trans Biomed Eng 2011;58(4):1094–103.

[17] Dhubkarya DC, Katara A, Thenua RK. Simulation of adaptive noise canceller for an ECG signal analysis. ACEEE Int J Signal Image Process 2012;3(1):1–4.

[18] Chandrakar C, Kowar MK. Denoising ECG signals using adaptive filter algorithm. Int J Soft Comput Eng 2012;2(1):120–3.

[19] Kim H, Kim S, Helleputte NV, Berset T, Penders J, Hoof CV, Yazicioglu RF. Motion artifact removal using cascade adaptive filtering for ambulatory ECG monitoring system. In: Proc. of the 2012 IEEE biomedical circuits and systems conf. (BioCAS 2012). Hsinchu, Taiwan; 2012, p. 1.

[20] Mugdha AC, Rawnaque FS, Ahmed MU. A study of recursive least squares (RLS) adaptive filter algorithm in noise removal from ECG signals. In: Proc. of the 2015 int. conf. on informatics, electronics & vision (ICIEV 2015). Fukuoka, Japan; 2015, p. 1–6.

[21] Ebrahimzadeh E, Pooyan M, Jahani S, Bijar A, Setaredan SK. ECG signals noise removal: Selection and optimization of the best adaptive filtering algorithm based on various algorithms comparison. Biomed Eng: Appl Basis Commun 2015;27(4):1–13.

[22] Sharma I, Mehra R, Singh M. Adaptive filter design for ECG noise reduction using LMS algorithm. In: Proc. of the 2015 int. conf. on reliability, infocom technologies and optimization (ICRITO 2015). Noida, India; 2015, p. 1–6.

[23] Satheeskumaran S, Sabrigiriraj M. VLSI implementation of a new LMS-based algorithm for noise removal in ECG signal. Int J Electron 2015;103(6):975–84.

[24] Sehamby R, Singh B. Noise cancellation using adaptive filtering in ECG signals: Application to Biotelemetry. Int J Bio–Sci Bio–Technol 2016;8(2):237–44.

[25] Haritha C, Ganesan M, Sumesh EP. A survey on modern trends in ECG noise removal techniques. In: Proc. of the 2016 int. conf. on circuit, power and computing technologies (ICCPCT 2016). Nagercoil, India; 2016, p. 1–7.

[26] Qureshi R, Uzair M, Khurshid K. Multistage adaptive filter for ECG signal processing. In: Proc. of the 2017 int. conf. on communication, computing and digital systems (C-CODE 2017). Islamabad, Pakistan; 2017, p. 363–8.

[27] Warmerdam GJJ, Vullings R, Schmitt L, Van Laar JOEH, Bergmans JWM. A fixed-lag Kalman smoother to filter power line interference in electrocardiogram recordings. IEEE Trans Biomed Eng 2017;64(8):1852–61.

[28] Sutha P, Jayanthi VE. Fetal electrocardiogram extraction and analysis using adaptive noise cancellation and wavelet transformation techniques. J Med Syst 2017;42(21):1–18.

[29] Gilani SO, Ilyas Y, Jamil M. Power line noise removal from ECG signal using notch, band stop and adaptive filters. In: Proc. of the 2018 int. conf. on electronics, information, and communication (ICEIC 2018). Honolulu, Hawaii, USA; 2018, p. 1–4.

[30] Venkatesan C, Karthigaikumar P, Varatharajan R. FPGA implementation of modified error normalized LMS adaptive filter for ECG noise removal. Cluster Comput 2018;22:12233–41.

[31] Srinivasa MG, Pandian PS. Elimination of power line interference in ECG signal using adaptive filter, notch filter and discrete wavelet transform techniques. Int J Biomed Clin Eng 2019;8(1):32–56.

[32] Xiong F, Chen D, Chen Z, Dai S. Cancellation of motion artifacts in ambulatory ECG signals using TD-LMS adaptive filtering techniques. J Vis Commun Image Represent 2019;58:606–18.

[33] Saxena S, Jais R, Hota MK. Removal of powerline interference from ECG signal using FIR, IIR, DWT and NLMS adaptive filter. In: Proc. of the 2019 int. conf. on communication and signal process. (ICCSP 2019). Chennai, India; 2019, p. 12–6.

[34] Manju BR, Sneha MR. ECG denoising using Wiener filter and Kalman filter. Procedia Comput Sci 2020;171:273–81.

[35] Khiter A, Adamou-Mitiche ABH, Mitiche L. Muscle noise cancellation from ECG signal using self correcting leaky normalized least mean square adaptive filter under varied step size and leakage coefficient. Trait Signal 2020;37(2):263–9.

[36] Yadav S, Saha SK, Kar R, Mandal D. Optimized adaptive noise canceller for denoising cardiovascular signal using SOS algorithm. Biomed Signal Process Control 2021;69(102830):1–17.

[37] Faiz MMU, Zerguine A, Zidouri A. Analysis of the sign regressor least mean fourth adaptive algorithm. EURASIP J Adv Signal Process 2011;2011:373205, 1–12.

[38] Faiz MMU, Zerguine A. On the convergence, steady-state, and tracking analysis of the SRLMMN algorithm. In: Proc. of the 23rd European signal process. conf. (EUSIPCO 2015). Nice, France; 2015, p. 2691–5.

[39] Widrow B, McCool JM, Larimore MG, Johnson Jr CR. Stationary and nonstationary learning characteristics of the LMS adaptive filter. Proc IEEE 1976;64(8):1151–62.

[40] Sayed AH. Fundamentals of adaptive filtering. 1st ed. Wiley-IEEE Press; 2003.

[41] Walach E, Widrow B. The least mean fourth (LMF) adaptive algorithm and its family. IEEE Trans Inform Theory 1984;30(2):275–83.

[42] Chambers JA, Tanrikulu O, Constantinides AG. Least mean mixed-norm adaptive filtering. Electron Lett 1994;30(19):1574–5.
[43] Eweda E. Analysis and design of a signed regressor LMS algorithm for stationary and nonstationary adaptive filtering with correlated Gaussian data. IEEE Trans Circuits Syst 1990;37(11):1367–74.
[44] Eweda E. Convergence analysis of the sign algorithm without the independence and Gaussian assumptions. IEEE Trans Signal Process 2000;48(9):2535–44.
[45] Eweda E. Transient and tracking performance bounds of the sign-sign algorithm. IEEE Trans Signal Process 1999;47(8):2200–10.
[46] PhysioBank ATM. 2021, Available: https://archive.physionet.org/cgi-bin/atm/ATM, Accessed on: 10 Feb. 2021.

Mohammed Mujahid Ulla Faiz received his Diploma from M.N. Technical Institute, Bangalore, Karnataka, India, in 1999, and his B.E. degree from Dr. Ambedkar Institute of Technology, Bangalore, in 2003, both in Electronics and Communication Engineering. He received his M.S. degree in Electrical Engineering from King Fahd University of Petroleum & Minerals, Dhahran, Saudi Arabia, in 2010. He is currently a Ph.D. Candidate with the Applied DSP and VLSI Research Group at the University of Westminster, London, U.K. His research interests include Digital Signal Processing, Adaptive Filtering, Biomedical Signal Processing, and Engineering Education.

Izzet Kale was born in Cyprus. He received the B.Sc. (Hons.) degree in electrical and electronic engineering from the Polytechnic of Central London, London, U.K., the M.Sc. degree in the design and manufacture of microelectronic systems from the University of Edinburgh, Edinburgh, U.K., and the Ph.D. degree in techniques for reducing digital filter complexity from the University of Westminster, London, U.K. He joined the Staff of the University of Westminster in 1984 and has been with them since and is currently the Research Director for the College of Design, Creative and Digital Industries. He is also the Founder and the Director of the Applied DSP and VLSI Research Group at the University of Westminster, where he has undertaken and lead numerous applied research and development projects and contracts for European, U.S., and Japanese corporations, working on innovative silicon integrated product development for commercial applications. He is currently a Professor of Applied DSP and VLSI Systems. His research and teaching activities include digital and analog signal processing, silicon circuit and system design, digital fixed and adaptive filter design and implementation, and analog/digital and digital/analog sigma–delta converters. He is currently working on efficiently implementable ultralow-power DSP algorithms/architectures and sigma–delta modulator structures for use in the communications and biomedical industries, and also invasive and non-invasive biomedical sensors and systems.