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

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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

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

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

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]	$\mathbf{w}_i = \mathbf{w}_{i-1} + \mu \ \mathrm{sgn}[\mathbf{u}_i]^{\mathrm{T}} e_i[\delta + (1-\delta) e_i^2]$
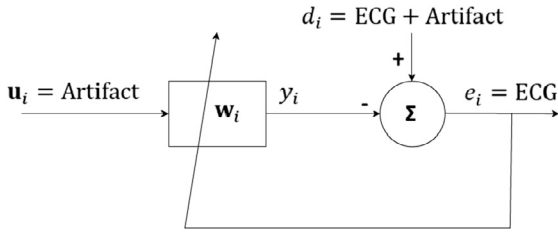
Fig. 1. Adaptive noise canceller.

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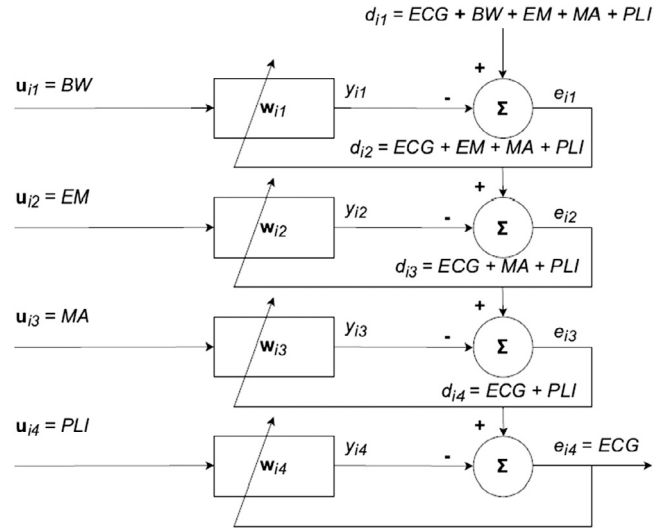
Fig. 2. Proposed cascaded 4-stage adaptive noise canceller.

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
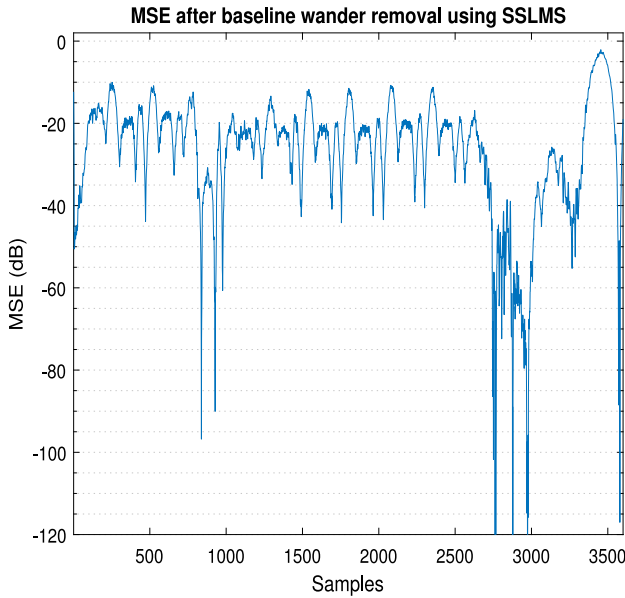
Fig. 3. MSE after baseline wander removal using a single-stage adaptive noise canceller employing the SSLMS adaptive algorithm (worst-case scenario)
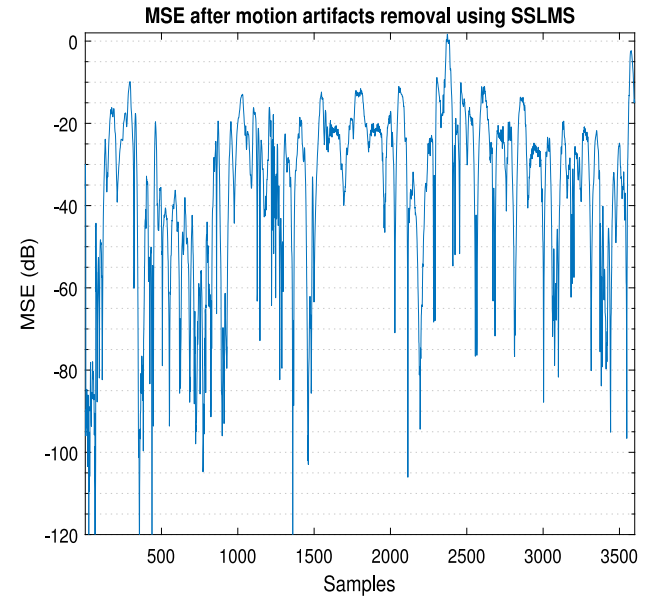
Fig. 4. MSE after motion artifacts removal using a single-stage adaptive noise canceller employing the SSLMS adaptive algorithm (worst-case scenario).

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.

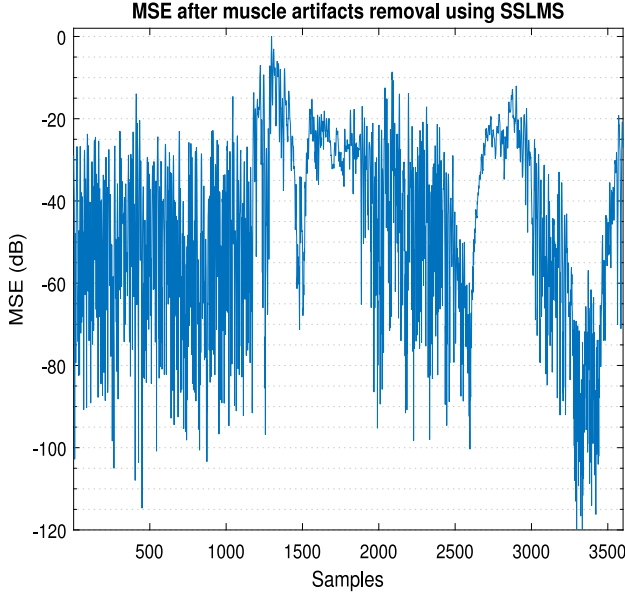| Adaptive algorithm	SNR before filtering (dB)	SNR after filtering (dB)	SNR improvement (dB)
LMS	17.8230	23.8256	6.0026
LMF	17.8230	21.0251	3.2021
LMMN	17.8230	26.1239	8.3009
SRLMS	17.8230	10.0358	−7.7872
SELMS	17.8230	19.2611	1.4381
SSLMS	17.8230	5.4269	−12.3961
SRLMF	17.8230	16.5538	−1.2692
SRLMMN	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
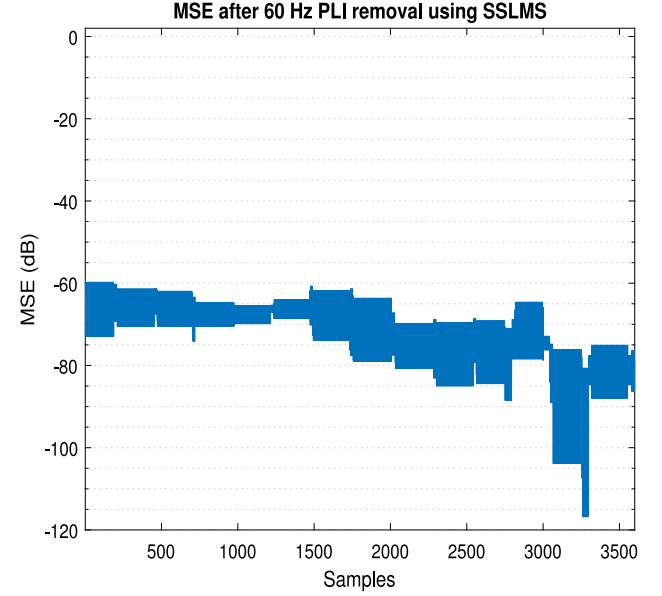
code fragment in Appendix B. Here, y is the adaptive filter output. Note that the ECG signal has a gain of 200. Therefore, we divide this signal by 200 as shown in the MATLAB code fragment in Appendix B.

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.

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
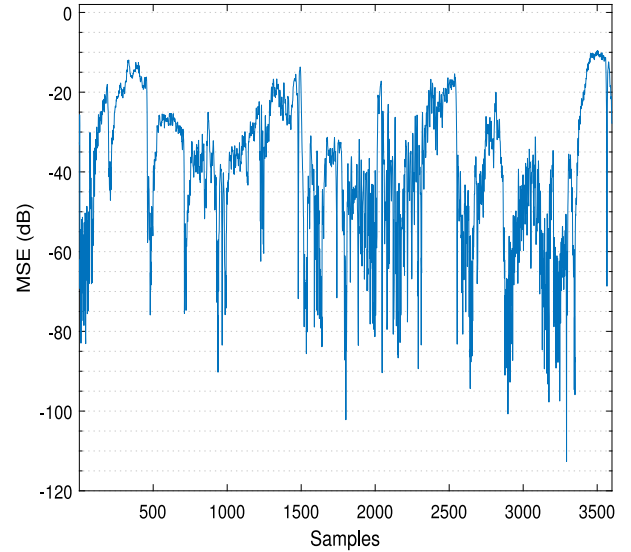

Fig. 7. MSE after multiple artifacts removal using the proposed cascaded 4-stage adaptive noise canceller employing the SRLMMN, SRLMF, SRLMMN, SRLMF adaptive algorithms (worst-case scenario).
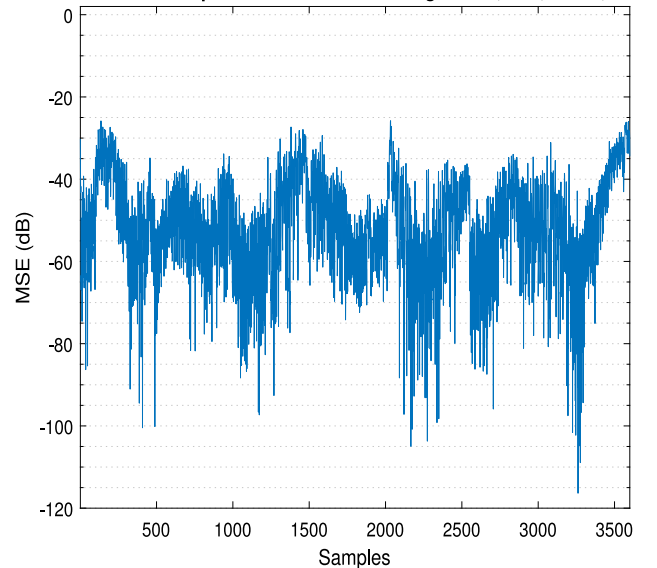

Fig. 8. MSE after multiple artifacts removal using the proposed cascaded 4-stage adaptive noise canceller employing the LMMN, LMF, LMMN, LMF adaptive algorithms (best-case scenario).

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.

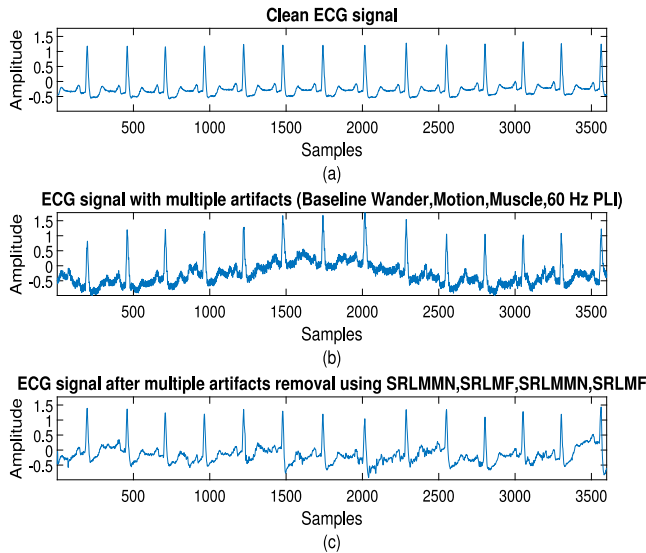| Adaptive algorithm	SNR before filtering (dB)	SNR after filtering (dB)	SNR improvement (dB)
LMMN, LMF, LMMN, LMF	2.2116	14.9435	12.7319
LMS, LMS, LMS, LMS	2.2116	14.0935	11.8819
LMF, LMF, LMF, LMF	2.2116	14.8909	12.6793
LMMN, LMMN, LMMN, LMMN	2.2116	14.2994	12.0878
SRLMMN, SRLMF, SRLMMN, SRLMF	2.2116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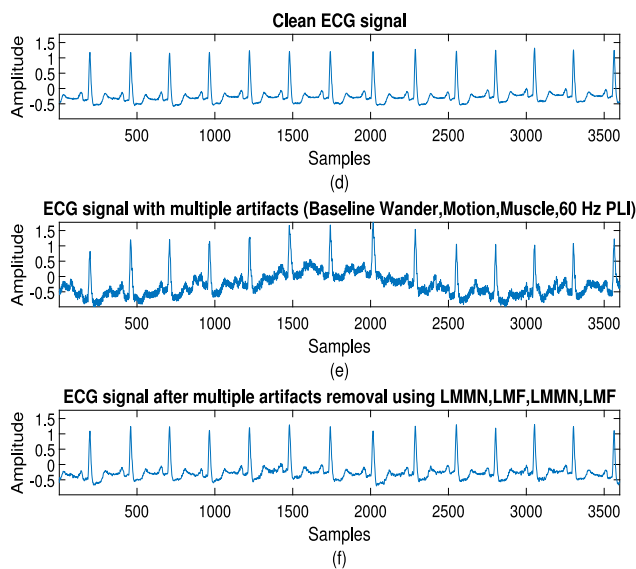

Fig. 10. (d) MIT-BIH Arrhythmia Database (MITDB) Record: 105, (e) MIT-BIH Arrhythmia Database (MITDB) Record: 105 + MIT-BIH Noise Stress Test Database (NSTDB) Record: bw + MIT-BIH Noise Stress Test Database (NSTDB) Record: em + MIT-BIH Noise Stress Test Database (NSTDB) Record: ma + 60 Hz PLI, (f) Recovered 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.

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

$var\_noise = 0.1;$

$sqn = sqrt(var\_noise);$

$load('105m');$

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

$load('bwm');$

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

$load('emm');$

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

$load('mam');$

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

$f = 60;$

$fs = 360;$

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

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

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

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

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

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