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

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A R T I C L E I N F O A B S T R A C T

*Keywords:*

ECG LMS LMF LMMN PLI

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.

# 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 sub- tracted 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](#_bookmark26),[2](#_bookmark27)].

Thakor and Zhu [[3](#_bookmark28)] 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](#_bookmark28)]. Hamilton [[4](#_bookmark29)] 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](#_bookmark30)] 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](#_bookmark30)]. Raya and Sison [[6](#_bookmark31)] proposed an adaptive noise

cancellation method to remove motion artifacts in stress ECG signals by using an accelerometer. The adaptive noise cancellers in [[6](#_bookmark31)] are imple- mented using the two of the most widely employed adaptive filtering algorithms, viz. LMS and Recursive Least Squares (RLS). Martens et al.

[[7](#_bookmark32)] proposed an improved adaptive noise canceller for the reduction of the fundamental PLI component and harmonics in the ECG signal. Behbahani [[8](#_bookmark33)] simulated and tested an adaptive noise cancellation method using the LMS algorithm for removing the 60 Hz PLI. Lin and Hu [[9](#_bookmark34)] 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](#_bookmark34)].

Rahman et al. [[10](#_bookmark35)–[12](#_bookmark36), 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 base- line wander, 60 Hz PLI, muscle artifacts, and motion artifacts from the ECG signal. Rahman et al. [[13](#_bookmark37)] employed LMS, SRLMS, SELMS, and SSLMS algorithms for canceling various artifacts as mentioned

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above from the ECG signal. In [[13](#_bookmark37)], 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](#_bookmark38)] expanded the work in [[10](#_bookmark35)–[12](#_bookmark36), 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](#_bookmark39)] added the four types of Alternating Current (AC) and Direct Current (DC) interference/noise with ECG signals and nul- lified these noises using the LMS and RLS algorithms. Vullings et al.

[[16](#_bookmark40)] developed an adaptive Kalman filter to enhance the quality of the ECG signal. Dhubkarya et al. [[17](#_bookmark41)] 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](#_bookmark42)] employed the RLS algorithm for the removal of different kinds of noises from the ECG signal. Kim et al. [[19](#_bookmark43)] proposed a motion artifact removal method using a cascaded 2-stage LMS adaptive filter for an ambulatory ECG monitoring system. Mugdha et al. [[20](#_bookmark44)] 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](#_bookmark45)] 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](#_bookmark46)] 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](#_bookmark47)] proposed a Variable Step Size Delayed Least Mean Square (VSSDLMS) adaptive filter to remove the artifacts from the ECG signal. Sehamby and Singh

[[24](#_bookmark48)] used an LMS-based adaptive noise canceller to derive a noise- free fetal ECG signal. Haritha et al. [[25](#_bookmark49)] surveyed different filters and denoising techniques used for ECG signals. Qureshi et al. [[26](#_bookmark50)] 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-

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 algo- rithms, 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](#_bookmark1). The proposed cascaded 4-stage adaptive noise canceller is discussed in Section [3](#_bookmark4). Simulation results are discussed in Section [4](#_bookmark6). Finally, the paper is concluded in Section [5](#_bookmark17).

# 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](#_bookmark2) [1](#_bookmark2)

wherein **𝐰***𝑖* ∈ R*𝑀*×1 is the updated weight vector at iteration *𝑖* ≥ 0, *𝑀* is

the adaptive filter length, *𝜇* is the step-size, **𝐮***𝑖* ∈ R1×*𝑀* is the regressor

or input vector with variance *𝜎*2, *𝛿* is the mixing parameter ranging

stage LMS-based adaptive noise canceller were compared with those of a cascaded 3-stage NLMS-based adaptive noise canceller, a cascaded

between 0

*𝑢*

≤ *𝛿* ≤ 1, *𝑒𝑖* is the estimation error given by

3-stage Log LMS-based adaptive noise canceller, and a cascaded 3-

*𝑒𝑖* = *𝑑𝑖* − **𝐮***𝑖***𝐰***𝑖*−1*,* (1)

stage SRLMS-based adaptive noise canceller. Warmerdam et al. [[27](#_bookmark51)] proposed a fixed-lag Kalman smoother to filter PLI from ECG recordings with minimal distortion of the ECG waveform.

Sutha and Jayanthi [[28](#_bookmark52)] 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

where *𝑑𝑖* is the desired value, and

⎧−1*,* if *𝑥 <* 0*,* sgn[*𝑥*] = ⎪ 0*,* if *𝑥* = 0*,*

⎨

⎪ 1*,* if *𝑥 >* 0*.*

⎩

(2)

adaptive noise canceller employed in their work uses the SSLMS algo- rithm [[28](#_bookmark52)]. Gilani et al. [[29](#_bookmark53)] employed an LMS-based adaptive noise canceller to remove the 50 Hz PLI from the ECG signal. Venkatesan et al. [[30](#_bookmark54)] 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](#_bookmark55)] eliminate the 50 Hz PLI from ECG signal using an LMS-based adaptive noise canceller. Xiong et al. [[32](#_bookmark56)] 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](#_bookmark57)] remove the 50 Hz PLI from the ECG signal using an NLMS-based adaptive noise canceller. Manju and Sneha [[34](#_bookmark58)] 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](#_bookmark59)] 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](#_bookmark60)]

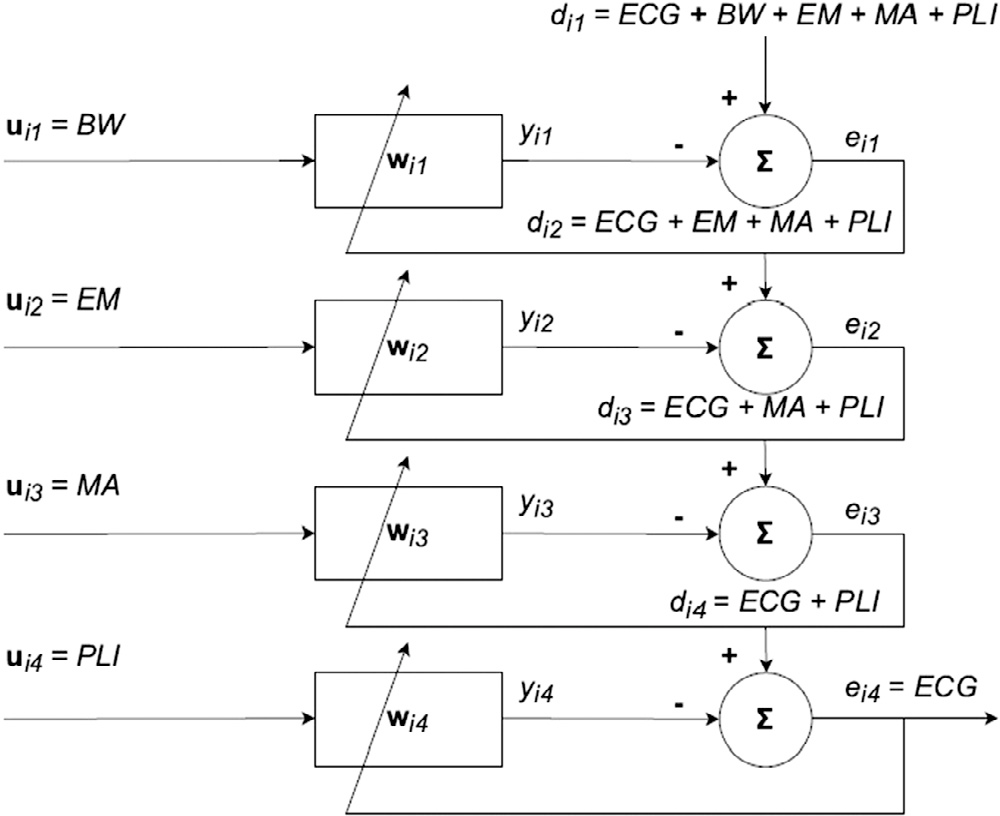
as long as the mixing parameter is ranging between 0 *< 𝛿 <* 1. The The LMMN algorithm is a combination of the LMS and LMF algorithms

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

between 0 *< 𝛿 <* 1. The SRLMMN algorithm reduces to SRLMF and and SRLMF algorithms as long as the mixing parameter is ranging

SRLMS algorithms when the mixing parameter becomes zero and one, respectively. Note that the SRLMF [[37](#_bookmark61)] and SRLMMN [[38](#_bookmark62)] 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](#_bookmark63),[40](#_bookmark64)] **𝐰***𝑖* = **𝐰***𝑖*−1 + *𝜇* **𝐮**T *𝑒𝑖*

*𝑖*

LMF [[40](#_bookmark64),[41](#_bookmark65)] **𝐰***𝑖* = **𝐰***𝑖*−1 + *𝜇* **𝐮**T *𝑒*3

*𝑖 𝑖*

LMMN [[42](#_bookmark66)] **𝐰***𝑖* = **𝐰***𝑖*−1 + *𝜇* **𝐮**T *𝑒𝑖* [*𝛿* + (1 − *𝛿*)*𝑒*2]

*𝑖 𝑖*

SRLMS [[43](#_bookmark67)] **𝐰***𝑖* = **𝐰***𝑖*−1 + *𝜇* sgn[**𝐮***𝑖*]T *𝑒𝑖*

SELMS [[44](#_bookmark68)] **𝐰***𝑖* = **𝐰***𝑖*−1 + *𝜇* **𝐮**Tsgn[*𝑒𝑖* ]

*𝑖*

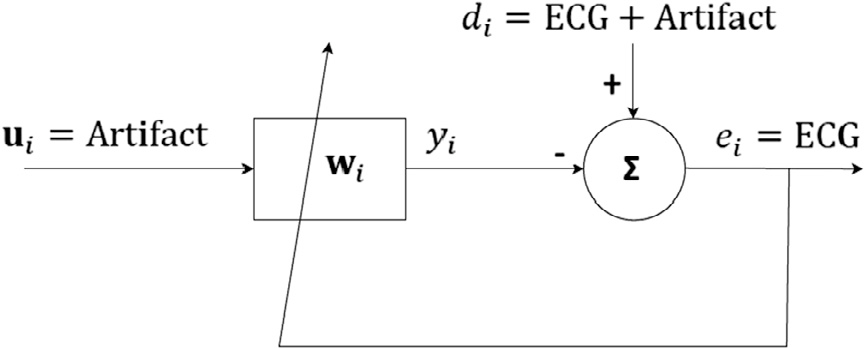
SSLMS [[45](#_bookmark69)] **𝐰***𝑖* = **𝐰***𝑖*−1 + *𝜇* sgn[**𝐮***𝑖*]Tsgn[*𝑒𝑖* ]

SRLMF [[37](#_bookmark61)] **𝐰***𝑖* = **𝐰***𝑖*−1 + *𝜇* sgn[**𝐮***𝑖*]T *𝑒*3

*𝑖*

SRLMMN [[38](#_bookmark62)] **𝐰***𝑖* = **𝐰***𝑖*−1 + *𝜇* sgn[**𝐮***𝑖*]T *𝑒𝑖* [*𝛿* + (1 − *𝛿*)*𝑒*2]

*𝑖*



**/ig. 1.** Adaptive noise canceller.

# Proposed cascaded 4-stage adaptive noise canceller

from the ECG signal is shown in [Fig.](#_bookmark3) [1](#_bookmark3). As can be seen from this figure *𝑑𝑖* A single-stage adaptive noise canceller for removing a single artifact forms the primary input of the adaptive noise canceller, *𝑑𝑖* contains the ECG signal with an additive artifact, **𝐮***𝑖* forms the secondary or reference input of the adaptive noise canceller, **𝐮***𝑖* contains the reference artifact

signal *𝑑𝑖*, **𝐰***𝑖* are the adaptive filter coefficients, *𝑦𝑖* is the adaptive filter that is correlated only with the artifact present in the corrupted ECG output, and *𝑒𝑖* is the filtered ECG signal free from the artifact.

A proposed cascaded 4-stage adaptive noise canceller for removing

seen from this figure *𝑑𝑖*1 forms the primary input of the first adaptive the four artifacts from the ECG signal is shown in [Fig.](#_bookmark5) [2](#_bookmark5). As can be noise canceller, *𝑑𝑖*1 contains the ECG signal with four additive artifacts,

viz. baseline wander, motion artifacts, muscle artifacts, and 60 Hz PLI,

**𝐮***𝑖*1 forms the secondary or reference input of the first adaptive noise canceller, **𝐮***𝑖*1 contains the reference baseline wander that is correlated only with the baseline wander present in the corrupted ECG signal *𝑑𝑖*1,

**𝐮***𝑖*2 forms the secondary or reference input of the second adaptive noise

canceller, **𝐮***𝑖*2 contains the reference motion artifacts that is correlated only with the motion artifacts present in the corrupted ECG signal *𝑑𝑖*1,

**𝐮***𝑖*3 forms the secondary or reference input of the third adaptive noise

canceller, **𝐮***𝑖*3 contains the reference muscle artifacts that is correlated only with the muscle artifacts present in the corrupted ECG signal *𝑑𝑖*1,

**𝐮***𝑖*4 forms the secondary or reference input of the fourth adaptive noise

canceller, **𝐮***𝑖*4 contains the reference 60 Hz PLI that is correlated only with the 60 Hz PLI present in the corrupted ECG signal *𝑑𝑖*1, **𝐰***𝑖*1 to

**𝐰***𝑖*4 are the respective adaptive filter coefficients, *𝑦𝑖*1 to *𝑦𝑖*4 are the

respective adaptive filter outputs, *𝑒𝑖*1 is the partially corrupted ECG signal free from baseline wander, *𝑒𝑖*1 will act as the primary input *𝑑𝑖*2 to the second adaptive noise canceller, *𝑒𝑖*2 is the partially corrupted ECG signal free from baseline wander and motion artifacts, *𝑒𝑖*2 will act as the primary input *𝑑𝑖*3 to the third adaptive noise canceller, *𝑒𝑖*3 is

artifacts, and muscle artifacts, *𝑒𝑖*3 will act as the primary input *𝑑𝑖*4 to the partially corrupted ECG signal free from baseline wander, motion the fourth adaptive noise canceller and *𝑒𝑖*4 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.

**/ig. 2.** Proposed cascaded 4-stage adaptive noise canceller.

# Simulation results

* 1. *Baseline wander removal*

In this experiment, the step-size is fixed at *𝜇* = 0*.*01, the adaptive filter length is fixed at *𝑀* = 5, the noise variance is fixed at *𝜎*2 = 0*.*1, and the number of iterations is fixed at *𝐿* = 10 for all the eight

*𝑣*

mixing parameter is fixed at *𝛿* = 0*.*5 for the LMMN and SRLMMN adaptive algorithms studied. In addition to the above settings, the

algorithms.

In this case, 3600 samples of the clean ECG signal are taken from the MIT-BIH Arrhythmia Database (MITDB) Record: 105 [[46](#_bookmark70)], 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](#_bookmark70)].

All eight adaptive algorithms studied in this paper, viz. LMS, LMF, LMMN, SRLMS, SELMS, SSLMS, SRLMF, and SRLMMN are tested sep-

arately by plugging them in a single-stage adaptive noise canceller as described in [Fig.](#_bookmark3) [1](#_bookmark3) for baseline wander removal. The SNR before and

by using the built-in MATLAB function, viz. *𝑠𝑛𝑟*(*𝑥, 𝑦*). The SNR before after adaptive filtering is recorded in [Table](#_bookmark8) [2](#_bookmark8). The SNR is calculated

MATLAB code fragment in [Appendix](#_bookmark23) [A](#_bookmark23). Here, *𝑦* is the adaptive filter and after adaptive filtering in [Table](#_bookmark8) [2](#_bookmark8) is calculated as described by the

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](#_bookmark23) [A](#_bookmark23).

As can be seen from [Table](#_bookmark8) [2](#_bookmark8) 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.](#_bookmark10) [3](#_bookmark10).

* 1. *Motion artifacts removal*

In this experiment, the step-size is fixed at *𝜇* = 0*.*01, the adaptive filter length is fixed at *𝑀* = 5, the noise variance is fixed at *𝜎*2 = 0*.*1, and the number of iterations is fixed at *𝐿* = 10 for all the eight

*𝑣*

mixing parameter is fixed at *𝛿* = 0*.*5 for the LMMN and SRLMMN adaptive algorithms studied. In addition to the above settings, the

algorithms.

In this case, 3600 samples of the clean ECG signal are taken from the MIT-BIH Arrhythmia Database (MITDB) Record: 105 [[46](#_bookmark70)], and they

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 |







**/ig. 3.** MSE after baseline wander 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](#_bookmark70)].

All eight adaptive algorithms studied in this paper, viz. LMS, LMF, LMMN, SRLMS, SELMS, SSLMS, SRLMF, and SRLMMN are tested sep-

arately by plugging them in a single-stage adaptive noise canceller as described in [Fig.](#_bookmark3) [1](#_bookmark3) for motion artifacts removal. The SNR before and after adaptive filtering is recorded in [Table](#_bookmark9) [3](#_bookmark9). The SNR before and after adaptive filtering in [Table](#_bookmark9) [3](#_bookmark9) is calculated by replacing line five

in [Appendix](#_bookmark23) [A](#_bookmark23) 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](#_bookmark23) [A](#_bookmark23). As can be seen from [Table](#_bookmark9) [3](#_bookmark9) 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.](#_bookmark11) [4](#_bookmark11).

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

* 1. *Muscle artifacts removal*

In this experiment, the step-size is fixed at *𝜇* = 0*.*01, the adaptive filter length is fixed at *𝑀* = 5, the noise variance is fixed at *𝜎*2 = 0*.*1, and the number of iterations is fixed at *𝐿* = 100 for all the eight

*𝑣*

mixing parameter is fixed at *𝛿* = 0*.*5 for the LMMN and SRLMMN adaptive algorithms studied. In addition to the above settings, the

algorithms.

In this case, 3600 samples of the clean ECG signal are taken from the MIT-BIH Arrhythmia Database (MITDB) Record: 105 [[46](#_bookmark70)], 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](#_bookmark70)].

All eight adaptive algorithms studied in this paper, viz. LMS, LMF, LMMN, SRLMS, SELMS, SSLMS, SRLMF, and SRLMMN are tested sep-

arately by plugging them in a single-stage adaptive noise canceller as described in [Fig.](#_bookmark3) [1](#_bookmark3) for muscle artifacts removal. The SNR before and after adaptive filtering is recorded in [Table](#_bookmark12) [4](#_bookmark12). The SNR before and

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 |







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

in [Appendix](#_bookmark23) [A](#_bookmark23) MATLAB code fragment with *𝑙𝑜𝑎𝑑*('*𝑚𝑎𝑚*'); Note that the after adaptive filtering in [Table](#_bookmark12) [4](#_bookmark12) is calculated by replacing line five

muscle artifacts have a gain of 200. Therefore, we divide this signal by 200 as shown in the MATLAB code fragment in [Appendix](#_bookmark23) [A](#_bookmark23). As can be seen from [Table](#_bookmark12) [4](#_bookmark12) 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.](#_bookmark13) [5](#_bookmark13).

* 1. *60 Hz PLI removal*

In this experiment, the step-size is fixed at *𝜇* = 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 *𝛿* = 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](#_bookmark70)], 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 sep-

arately by plugging them in a single-stage adaptive noise canceller as described in [Fig.](#_bookmark3) [1](#_bookmark3) for the 60 Hz PLI removal. The SNR before and after adaptive filtering is recorded in [Table](#_bookmark16) [5](#_bookmark16). The SNR before and after adaptive filtering in [Table](#_bookmark16) [5](#_bookmark16) is calculated as described by the MATLAB

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

code fragment in [Appendix](#_bookmark24) [B](#_bookmark24). 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](#_bookmark24) [B](#_bookmark24).

As can be seen from [Table](#_bookmark16) [5](#_bookmark16) 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.](#_bookmark15) [6](#_bookmark15).

* 1. *Multiple artifacts removal*

In this experiment, the step-size is fixed at *𝜇* = 0*.*01, the adaptive filter length is fixed at *𝑀* = 5, the noise variance is fixed at *𝜎*2 = 0*.*1, and the number of iterations is fixed at *𝐿* = 10 for all the algorithms

*𝑣*

parameter is fixed at *𝛿* = 0*.*5 for the LMMN and SRLMMN algorithms. presented in [Table](#_bookmark20) [6](#_bookmark20). In addition to the above settings, the mixing

In this case, 3600 samples of the clean ECG signal are taken from the MIT-BIH Arrhythmia Database (MITDB) Record: 105 [[46](#_bookmark70)], 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](#_bookmark70)], the 3600 samples of motion artifacts taken from the MIT-BIH Noise Stress Test Database (NSTDB) Record: em [[46](#_bookmark70)], the 3600 samples of muscle artifacts taken from the MIT-BIH Noise Stress Test Database (NSTDB) Record: ma [[46](#_bookmark70)], 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](#_bookmark7)–

[4.4](#_bookmark14) 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.](#_bookmark5) [2](#_bookmark5) for removing base- line 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 fil- tering is recorded in [Table](#_bookmark20) [6](#_bookmark20). 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](#_bookmark20) [6](#_bookmark20) is calculated as described by the MATLAB code fragment in

[Appendix](#_bookmark25) [C](#_bookmark25). 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](#_bookmark25) [C](#_bookmark25).

As an example, in row 2 of [Table](#_bookmark20) [6](#_bookmark20), the LMMN algorithm is used in adaptive noise cancellers 1 and 3 in [Fig.](#_bookmark5) [2](#_bookmark5) for removing baseline wander and muscle artifacts, respectively. The LMF algorithm in row 2 of [Table](#_bookmark20) [6](#_bookmark20) is used in adaptive noise cancellers 2 and 4 in [Fig.](#_bookmark5) [2](#_bookmark5) 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 al- gorithms studied in [Table](#_bookmark20) [6](#_bookmark20) is shown in [Fig.](#_bookmark18) [7](#_bookmark18). The MSE plot after multiple artifacts removal using the proposed cascaded 4-stage adaptive noise canceller employing the LMMN, LMF, LMMN, LMF algorithms, [which](#_bookmark20) is the best-case scenario among the algorithms studied in [Ta-](#_bookmark20) [ble](#_bookmark20) [6](#_bookmark20) is shown in [Fig.](#_bookmark19) [8](#_bookmark19). [Figs.](#_bookmark21) [9](#_bookmark21)(a) and [10](#_bookmark22)(d) show the clean ECG signal free from artifacts, [Figs.](#_bookmark21) [9](#_bookmark21)(b) and [10](#_bookmark22)(e) show the ECG signal with additive baseline wander, motion artifacts, muscle artifacts, and 60 Hz PLI, [Fig.](#_bookmark21) [9](#_bookmark21)(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](#_bookmark20) [6](#_bookmark20), and [Fig.](#_bookmark22) [10](#_bookmark22)(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](#_bookmark20) [6](#_bookmark20). As can be seen from [Fig.](#_bookmark22) [10](#_bookmark22)(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](#_bookmark20) [6](#_bookmark20), 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.

# 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 ar- tifacts and 60 Hz PLI. We employed the LMMN, LMF, LMMN, LMF







**/ig. 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).







**/ig. 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).

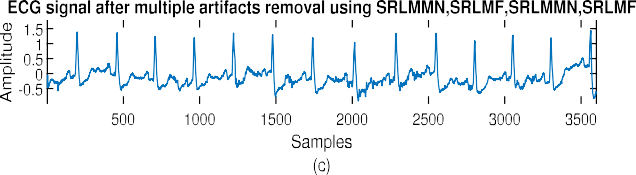
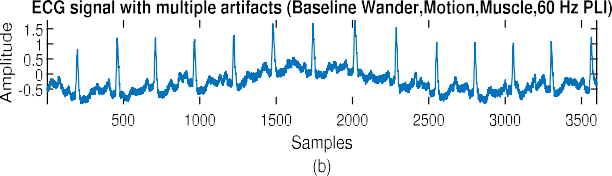
algorithms in the proposed cascaded 4-stage adaptive noise canceller

**Table 6**

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

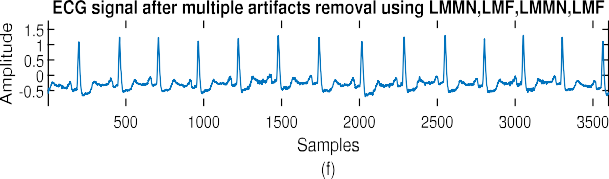
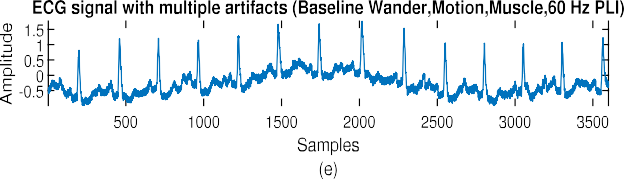
|  |  |  |  |
| --- | --- | --- | --- |
| Adaptive algorithm | SNR before filtering (dB) | SNR after filtering (dB) | SNR improvement (dB) |
| LMMN, LMF, LMMN, LMF | 2.2116 | 14.9435 | 12.7319 |
| LMS, LMS, LMS, LMS | 2.2116 | 14.0935 | 11.8819 |
| LMF, LMF, LMF, LMF | 2.2116 | 14.8909 | 12.6793 |
|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

to remove the respective ECG artifacts as mentioned above. We suc- ceeded in achieving an SNR improvement of 12.7319 dBs, which is better than the other compared methods. It is found that the pro- posed 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

**/ig. 9.** (a) MIT-BIH Arrhythmia Database (MITDB) Record: 105, (b) MIT-BIH Arrhyth- mia 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).



**/ig. 10.** (d) MIT-BIH Arrhythmia Database (MITDB) Record: 105, (e) MIT-BIH Arrhyth- mia 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).

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

# Declaration of competing interest

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

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# Appendix A

*𝑣𝑎𝑟*\_*𝑛𝑜𝑖𝑠𝑒* = 0*.*1;

*𝑠𝑞𝑛* = *𝑠𝑞𝑟𝑡*(*𝑣𝑎𝑟*\_*𝑛𝑜𝑖𝑠𝑒*);

*𝑙𝑜𝑎𝑑*('105*𝑚*');

*𝑖𝑛𝑝𝑢𝑡* = *𝑣𝑎𝑙*(1*,* ∶)∕200;

*𝑙𝑜𝑎𝑑*('*𝑏𝑤𝑚*');

*𝑣* = *𝑠𝑞𝑛* ∗ *𝑣𝑎𝑙*(1*,* ∶)∕200;

*𝑠𝑛𝑟*\_*𝑏𝑒𝑓 𝑜𝑟𝑒* = *𝑠𝑛𝑟*(*𝑖𝑛𝑝𝑢𝑡, 𝑣*);

*𝑠𝑛𝑟*\_*𝑎𝑓 𝑡𝑒𝑟* = *𝑠𝑛𝑟*(*𝑖𝑛𝑝𝑢𝑡, 𝑦*);

# Appendix B

*𝑙**𝑜𝑎𝑑*('105*𝑚*');

*𝑖𝑛𝑝𝑢𝑡* = *𝑣𝑎𝑙*(1*,* ∶)∕200;

*𝑓* = 60;

*𝑓 𝑠* = 360;

*𝑡* = [1 ∶ *𝑁* ]∕*𝑓 𝑠*;

*𝑣* = 0*.*1 ∗ *𝑠𝑖𝑛*(2 ∗ *𝑝𝑖* ∗ *𝑓* ∗ *𝑡* + *𝑟𝑎𝑛𝑑𝑛*);

*𝑠𝑛𝑟*\_*𝑏𝑒𝑓 𝑜𝑟𝑒* = *𝑠𝑛𝑟*(*𝑖𝑛𝑝𝑢𝑡, 𝑣*);

*𝑠𝑛𝑟*\_*𝑎𝑓 𝑡𝑒𝑟* = *𝑠𝑛𝑟*(*𝑖𝑛𝑝𝑢𝑡, 𝑦*);

# Appendix C

*𝑣𝑎𝑟*\_*𝑛𝑜𝑖𝑠𝑒* = 0*.*1;

*𝑠𝑞𝑛* = *𝑠𝑞𝑟𝑡*(*𝑣𝑎𝑟*\_*𝑛𝑜𝑖𝑠𝑒*);

*𝑙𝑜𝑎𝑑*('105*𝑚*');

*𝑖𝑛𝑝𝑢𝑡* = *𝑣𝑎𝑙*(1*,* ∶)∕200;

*𝑙𝑜𝑎𝑑*('*𝑏𝑤𝑚*');

*𝑣*1 = *𝑠𝑞𝑛* ∗ *𝑣𝑎𝑙*(1*,* ∶)∕200;

*𝑙𝑜𝑎𝑑*('*𝑒𝑚𝑚*');

*𝑣*2 = *𝑠𝑞𝑛* ∗ *𝑣𝑎𝑙*(1*,* ∶)∕200;

*𝑙𝑜𝑎𝑑*('*𝑚𝑎𝑚*');

*𝑣*3 = *𝑠𝑞𝑛* ∗ *𝑣𝑎𝑙*(1*,* ∶)∕200;

*𝑓* = 60;

*𝑓 𝑠* = 360;

*𝑡* = [1 ∶ *𝑁* ]∕*𝑓 𝑠*;

*𝑣*4 = 0*.*1 ∗ *𝑠𝑖𝑛*(2 ∗ *𝑝𝑖* ∗ *𝑓* ∗ *𝑡* + *𝑟𝑎𝑛𝑑𝑛*);

*𝑣* = *𝑣*1 + *𝑣*2 + *𝑣*3 + *𝑣*4;

*𝑠𝑛𝑟*\_*𝑏𝑒𝑓 𝑜𝑟𝑒* = *𝑠𝑛𝑟*(*𝑖𝑛𝑝𝑢𝑡, 𝑣*);

*𝑠𝑛𝑟*\_*𝑎𝑓 𝑡𝑒𝑟* = *𝑠𝑛𝑟*(*𝑖𝑛𝑝𝑢𝑡, 𝑦*);

# References

1. [Widrow B, Glover Jr JR, McCool JM, Kaunitz J, Williams CS, Hearn RH,](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb1) [Zeidler JR, Dong Jr E, Goodlin RC. Adaptive noise cancelling: Principles and](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb1) [applications. Proc IEEE 1975;63(12):1692–716.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb1)
2. [Widrow B, Stearns SD. Adaptive signal processing. 1st ed. Pearson; 1985.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb2)
3. [Thakor NV, Zhu YS. Applications of adaptive filtering to ECG analy-](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb3) [sis: Noise cancellation and arrhythmia detection. IEEE Trans Biomed Eng](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb3) [1991;38(8):785–94.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb3)
4. [Hamilton PS. A comparison of adaptive and nonadaptive filters for reduction of](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb4) [power line interference in the ECG. IEEE Trans Biomed Eng 1996;43(1):105–9.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb4)
5. [Ziarani AK, Konrad A. A nonlinear adaptive method of elimination of power line](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb5) [interference in ECG signals. IEEE Trans Biomed Eng 2002;49(6):540–7.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb5)
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](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb7) [line interference canceller for electrocardiography. IEEE Trans Biomed Eng](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb7) [2006;53(11):2220–31.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb7)
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](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb9) [processing. IEEE Trans Biomed Eng 2008;55(1):354–7.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb9)
10. Rahman MZU, Shaik RA, Reddy DVRK. An efficient noise cancellation technique to remove noise from the ECG signal using normalized signed regressor LMS al- gorithm. 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](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb13) [using computationally simplified adaptive filtering techniques: Application to](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb13) [biotelemetry. Signal Process: Int J 2009;3(5):120–31.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb13)
14. [Rahman MZU, Shaik RA, Reddy DVRK. Efficient sign based normalized adaptive](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb14) [filtering techniques for cancelation of artifacts in ECG signals: Application to](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb14) [wireless biotelemetry. Signal Process 2011;91(2):225–39.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb14)
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](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb16) [enhancement. IEEE Trans Biomed Eng 2011;58(4):1094–103.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb16)
17. [Dhubkarya DC, Katara A, Thenua RK. Simulation of adaptive noise canceller for](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb17) [an ECG signal analysis. ACEEE Int J Signal Image Process 2012;3(1):1–4.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb17)
18. [Chandrakar C, Kowar MK. Denoising ECG signals using adaptive filter algorithm.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb18) [Int J Soft Comput Eng 2012;2(1):120–3.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb18)
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](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb21) [removal: Selection and optimization of the best adaptive filtering algorithm](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb21) [based on various algorithms comparison. Biomed Eng: Appl Basis Commun](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb21) [2015;27(4):1–13.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb21)
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](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb23) [algorithm for noise removal in ECG signal. Int J Electron 2015;103(6):975–84.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb23)
24. [Sehamby R, Singh B. Noise cancellation using adaptive filtering in ECG signals:](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb24) [Application to Biotelemetry. Int J Bio–Sci Bio–Technol 2016;8(2):237–44.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb24)
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](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb27) [fixed-lag Kalman smoother to filter power line interference in electrocardiogram](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb27) [recordings. IEEE Trans Biomed Eng 2017;64(8):1852–61.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb27)
28. [Sutha P, Jayanthi VE. Fetal electrocardiogram extraction and analysis using](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb28) [adaptive noise cancellation and wavelet transformation techniques. J Med Syst](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb28) [2017;42(21):1–18.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb28)
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](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb30) [modified error normalized LMS adaptive filter for ECG noise removal. Cluster](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb30) [Comput 2018;22:12233–41.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb30)
31. [Srinivasa MG, Pandian PS. Elimination of power line interference in ECG signal](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb31) [using adaptive filter, notch filter and discrete wavelet transform techniques. Int](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb31) [J Biomed Clin Eng 2019;8(1):32–56.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb31)
32. [Xiong F, Chen D, Chen Z, Dai S. Cancellation of motion artifacts in ambulatory](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb32) [ECG signals using TD-LMS adaptive filtering techniques. J Vis Commun Image](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb32) [Represent 2019;58:606–18.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb32)
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.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb34) [Procedia Comput Sci 2020;171:273–81.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb34)
35. [Khiter A, Adamou-Mitiche ABH, Mitiche L. Muscle noise cancellation from ECG](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb35) [signal using self correcting leaky normalized least mean square adaptive filter](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb35) [under varied step size and leakage coefficient. Trait Signal 2020;37(2):263–9.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb35)
36. [Yadav S, Saha SK, Kar R, Mandal D. Optimized adaptive noise canceller for](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb36) [denoising cardiovascular signal using SOS algorithm. Biomed Signal Process](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb36) [Control 2021;69(102830):1–17.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb36)
37. [Faiz MMU, Zerguine A, Zidouri A. Analysis of the sign regressor least mean](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb37) [fourth adaptive algorithm. EURASIP J Adv Signal Process 2011;2011:373205,](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb37) [1–12.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb37)
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](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb39) [nonstationary learning characteristics of the LMS adaptive filter. Proc IEEE](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb39) [1976;64(8):1151–62.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb39)
40. [Sayed AH. Fundamentals of adaptive filtering. 1st ed. Wiley-IEEE Press; 2003.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb40)
41. [Walach E, Widrow B. The least mean fourth (LMF) adaptive algorithm and its](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb41) [family. IEEE Trans Inform Theory 1984;30(2):275–83.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb41)
42. [Chambers JA, Tanrikulu O, Constantinides AG. Least mean mixed-norm adaptive](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb42) [filtering. Electron Lett 1994;30(19):1574–5.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb42)
43. [Eweda E. Analysis and design of a signed regressor LMS algorithm for stationary](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb43) [and nonstationary adaptive filtering with correlated Gaussian data. IEEE Trans](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb43) [Circuits Syst 1990;37(11):1367–74.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb43)
44. [Eweda E. Convergence analysis of the sign algorithm without the independence](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb44) [and Gaussian assumptions. IEEE Trans Signal Process 2000;48(9):2535–44.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb44)
45. [Eweda E. Transient and tracking performance bounds of the sign-sign algorithm.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb45) [IEEE Trans Signal Process 1999;47(8):2200–10.](http://refhub.elsevier.com/S2590-0056(22)00004-2/sb45)
46. PhysioBank ATM. 2021, Available: [https://archive.physionet.org/cgi-bin/atm/](https://archive.physionet.org/cgi-bin/atm/ATM) [ATM](https://archive.physionet.org/cgi-bin/atm/ATM), Accessed on: 10 Feb. 2021.

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