

Performance Study of Adaptive Filtering and Noise Cancellation of Artifacts in ECG Signals

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Abstract— In Electrocardiogram (ECG) application, we face various types of artifacts added to the ECG signal. Different Researchers have been interested in this problem due to its importance. In this paper we introduce a study of different algorithms and their effects on the performance of the ECG noise canceller. We have used many kinds of algorithms such as: LMS (Least Mean Square), NLMS (Normalized Least Mean Square), Signed Regressor LMS (SRLMS), Sign LMS (SLMS), Sign-Sign LMS (SSLMS) and a new proposed modified LMS called Variable Step size Least Mean Square (VSLMS) using MATLAB software package as well as Unbiased Linear output Neural Network (ULNN) and Unbiased Non Linear output Neural Network (UNLNN). It is promising to clarify the difference among these algorithms with the aim of obtaining better performance.

Keywords— ECG signal, adaptive noise canceller, neural network, LMS, artifacts.

I. INTRODUCTION

Heart related problems are increasing day by day and Electrocardiogram (ECG) signal are very important in diagnosis of heart related problems. There are various artifacts which get added in these signals and change the original signal therefore there is a need of removal of these artifacts from the original signal. The predominant artifacts present in the ECG includes: Baseline Wander (BW), Power-Line Interference (PLI), Muscle Artifacts (MA) and Electrode Motion artifacts (EM). These artifacts strongly affects the ST segment, degrades the signal quality, frequency resolution, produces large amplitude signals in ECG that can resemble PQRST waveforms and masks tiny features that are important for clinical monitoring and diagnosis. Cancellation of these artifacts in ECG signals is an important task for better diagnosis [1].

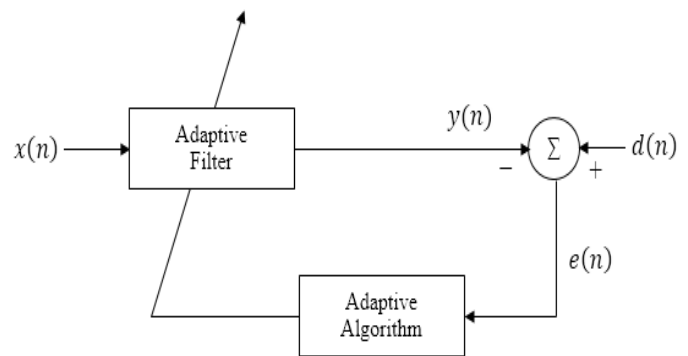


Fig. 1. Adaptive filter

Many approaches have been reported in the literature to address ECG enhancement using both adaptive and non-adaptive techniques [2–5].

The adaptive filtering has become one of the effective and popular approaches for the processing and analysis of the biomedical signals such as ECG signal. Figure 1 illustrates the general Adaptive filter [6].

In this paper we use adaptive filters and neural networks to build an ECG noise cancellation. Each type of these cancellers is tested under different learning algorithms to remove different kinds of noise (artifacts) such as BW, MA and EM. Signal to noise ratio (SNR) will be considered in the performance evaluation in this paper. The evaluation of the performance is by measuring the signal-to-noise ratio (SNR) improvement and compared with LMS algorithm.

II. ADAPTIVE NOISE CANCELLATION

Adaptive Noise Cancellation (ANC) is an alternative technique of estimating signals corrupted by additive noise or interference. Its advantage lies in that, with no apriori estimates of signal or noise, levels of noise rejection are attainable that would be difficult or impossible to achieve by other signal processing methods of removing noise [7].

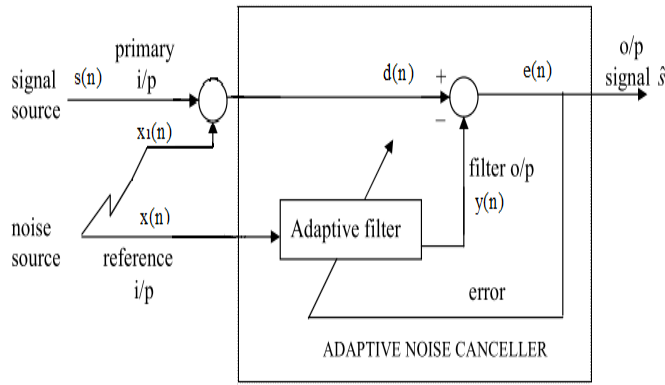


Fig. 2. Adaptive Noise Cancellation system

The ANC system has two inputs – primary and reference. The primary input receives a signal $s(n)$ from the signal source (ECG signal source) that is corrupted by the presence of noise $x_1(n)$ uncorrelated with the signal. The reference input receives a noise $x(n)$ uncorrelated with the signal but correlated in some way with the noise. The noise $x(n)$ passes through a filter to produce an output $y(n)$ that is a close estimate of primary input noise. This noise estimate $y(n)$ is subtracted from the corrupted signal $d(n)$ to produce an estimate of the signal at $e(n)$, the ANC system output which is supposed to be the same or very similar to primary signal $s(n)$ [7]. Figure 2 shows adaptive noise cancelling system.

A. Adaptive Learning Algorithms

1) LMS algorithm: The LMS algorithm is a method to estimate gradient vector with instantaneous value. It changes the filter tap weights so that $e(n)$ is minimized in the mean-square sense. The conventional LMS algorithm is a stochastic implementation of the steepest descent algorithm. It simply replaces the cost function $\xi(n) = E[e^2(n)]$ by its instantaneous coarse estimate. The error estimation $e(n)$ is

$$e(n) = d(n) - w(n)x(n) \quad (1)$$

Coefficient updating equation is

$$w(n+1) = w(n) + \mu x(n)e(n) \quad (2)$$

Where μ is an appropriate step size to be chosen as $0 < \mu < 0.2$ for the convergence of the algorithm. μ controls the stability and convergence speed of the LMS algorithm. The larger step sizes make the coefficients to fluctuate wildly and eventually become unstable. The most important members of simplified LMS algorithms are:

2) SRLMS Algorithm: The signed regressor algorithm is obtained from the conventional LMS recursion by replacing the tap-input vector $x(n)$ with the vector $\text{sgn}\{x(n)\}$. Consider a signed regressor LMS based adaptive filter that processes an input signal $x(n)$ and generates the output $y(n)$ as per the following:

$$y(n) = w^t(n)x(n) \quad (3)$$

Where, $w(n) = [w_0(n), w_1(n), \dots, w_{l-1}(n)]^t$ is a l -th order adaptive filter. The adaptive filter coefficients are updated by the Signed-regressor LMS algorithm as,

$$w(n+1) = w(n) + \mu \text{sgn}\{x(n)\}e(n) \quad (4)$$

Because of the replacement of $x(n)$ by its sign, implementation of this recursion may be cheaper than the conventional LMS recursion, especially in high speed applications such as biotelemetry these types of recursions may be necessary.

3) SLMS Algorithm: This algorithm is obtained from conventional LMS recursion by replacing $e(n)$ by its sign. This leads to the following recursion:

$$w(n+1) = w(n) + \mu x(n) \text{sgn}\{e(n)\} \quad (5)$$

4) SSLMS Algorithm: This can be obtained by combining signed-regressor and sign recursions, resulting in the following recursion:

$$w(n+1) = w(n) + \mu \text{sgn}\{x(n)\} \text{sgn}\{e(n)\} \quad (6)$$

Where $\text{sgn}\{\cdot\}$ is well known signum function, $e(n) = d(n) - y(n)$ is the error signal. The sequence $d(n)$ is the so-called desired response available during initial training period. However the sign and sign – sign algorithms are both slower than the LMS algorithm. Their convergence behaviour is also rather peculiar. They converge very slowly at the beginning, but speed up as the MSE level drops.

5) NLMS Algorithm: In NLMS, the step size takes the form of,

$$\mu(n) = \frac{\alpha}{c + \|x(n)\|^2} \quad (7)$$

Where: α is the NLMS adaption constant, which optimize the convergence rate of the algorithm and should satisfy the condition $0 < \alpha < 2$, and c is the constant term for normalization and is always less than 1.

In NLMS algorithm, the filter weights are updated by

$$w(n+1) = w(n) + \frac{\alpha}{c + \|x(n)\|^2} x(n)e(n) \quad (8)$$

B. New Proposed modified LMS Algorithm

The principle means of comparison is the error cancellation capability of the methods. This property depends on a few parameters, such as: step size for the LMS algorithm, therefore the LMS algorithm with variable step size is used. The step is adjusted with the increase in the number of iteration to match with the convergence of adaptive filter. The effect of this algorithm is compared with the other algorithms at the same time.

The proposed modified LMS algorithm is a Variable Step size Least Mean Square (VSLMS) which its step size will vary with the increase in the number of iteration.

The equation of the weights updating for the VSLMS algorithm is

$$i = 1: N \quad \text{Where } N \text{ is number of iterations} \quad (9)$$

$$w(n+1) = w(n) + 2 \frac{\mu}{i} x(n)e(n)$$

C. Neural Network

Through last years, neural networks (NN) have demonstrated its ability to solve wide range of problems in an easier and convenient way. The most common neural network model is the Multilayer Perceptron (MLP). This type of neural network is known as a supervised network because it requires a desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown [8].

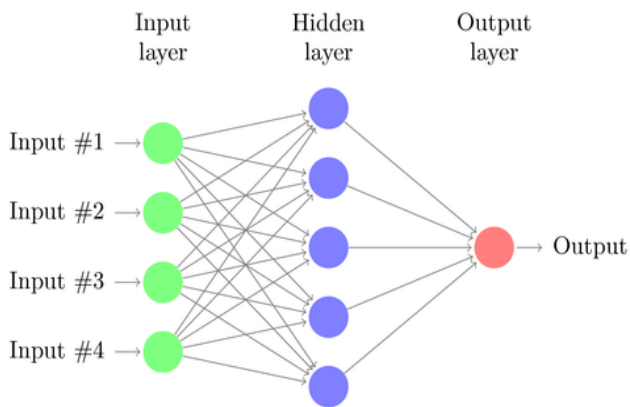


Fig. 3. Graphical representation of an MLP or multi-layer NN

A graphical representation of an MLP is shown in Fig. 3.

A neuron is an information-processing unit that is fundamental to the operation of a neural network. In mathematical terms, we may describe a neuron i by writing the following pair of equations:

$$u_i = \sum_{j=1}^m w_{ij} x_j \quad (10)$$

Where m is number of inputs

$$y_i = f(u_i + b_i) \quad (11)$$

Where $x_1, x_2, x_3, \dots, x_m$ are the input signals; $w_{i1}, w_{i2}, w_{i3}, \dots, w_{im}$ are synaptic weights of neuron i ; u_i is linear combiner output due the input signals; b_i is the bias; $f(\cdot)$ is the activation function; and y_i is the output signal of the neuron [8].

In this paper, If the NN has a linear activation function $f(\cdot)$ in its output unit, it will be called ULNN, and if it has a nonlinear activation function in its output unit, it will be called UNLNN.

The equation of the activation function in the hidden layer for ULNN and UNLNN is

$$f(u_i + b_i) = \tanh(a(u_i + b_i)) \quad (12)$$

A well known Back-Propagation (BP) algorithm is the basic method of training in the multi-layer NN.

III. SIMULATION RESULTS

In the simulation section, it has been used ECG recording taken from MIT-BIH arrhythmia database [10]. The concept of filtering is tested with real noise obtained from MIT-BIH Noise Stress Test Database (NSTDB). In our simulation we used 3600 samples of the ECG signals. For evaluating the performance of the proposed filter structures we have measured the SNR improvement and compared with LMS algorithm.

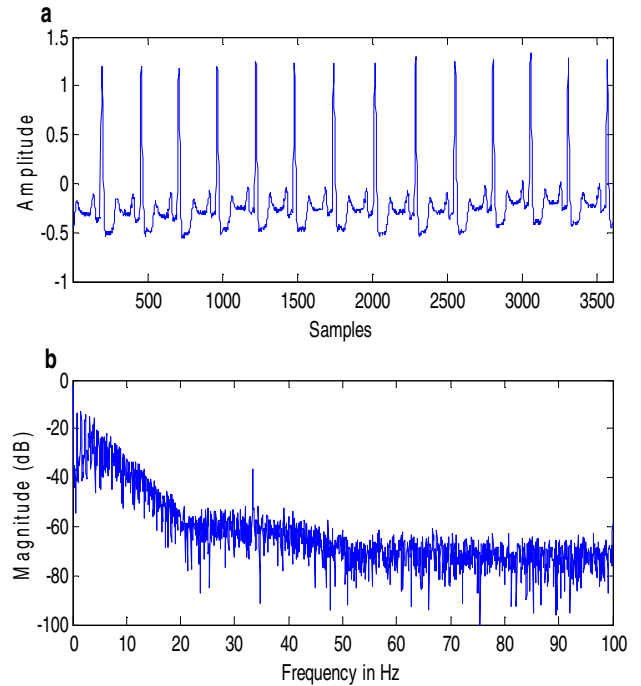


Fig. 4. MIT-BIH recorded ECG signal (data 105) and its frequency spectrum

Figure 4 shows clean ECG (data 105 of MIT-BIH database) and its frequency spectrum. Various adaptive filter structures are implemented using LMS, SRLMS, SLMS, SSLMS, NLMS and VSLMS as well as using ULNN and UNLNN.

A. Noise generator

The reference signal $x(n)$ shown in Fig. 2 is taken from noise generator. In order to test the filtering capability in non-stationary environment we have considered real BW, MA and EM noises. These are taken from MIT-BIH Noise Stress Test Database (NSTDB).

1) Baseline wander (BW) reduction

In this case we used 3600 samples of the ECG signal corrupted with real BW. The corrupted ECG signal is applied as primary input to the adaptive filter of Fig. 2. The noise generator a real BW is given as reference signal.

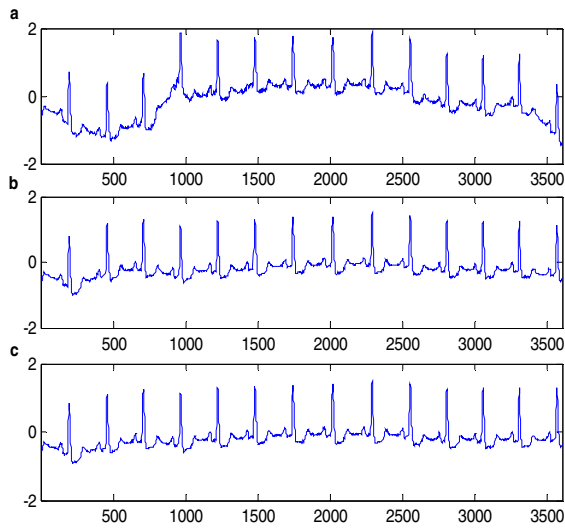


Fig. 5. Filtering results of baseline wander reduction (x-axes are samples and y-axes are amplitude): (a) ECG with real BW, (b) recovered signal using LMS algorithm, (c) recovered signal using SRLMS algorithm

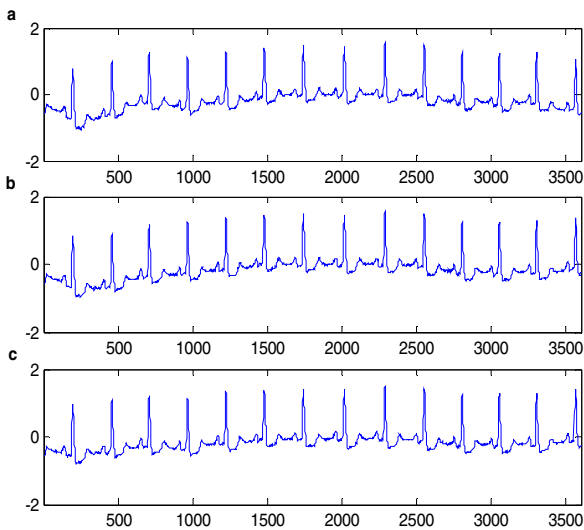


Fig. 6. Filtering results of baseline wander reduction (x-axes are samples and y-axes are amplitude): (a) recovered signal using SLMS algorithm, (b) recovered signal using SSLMS algorithm, (c) recovered signal using NLMS algorithm

The simulation results of all algorithms for adaptive filter and NN were shown in Fig. 5, Fig. 6 and Fig. 7. From Fig. 7(c) it is clear that the output from ULNN is the best one.

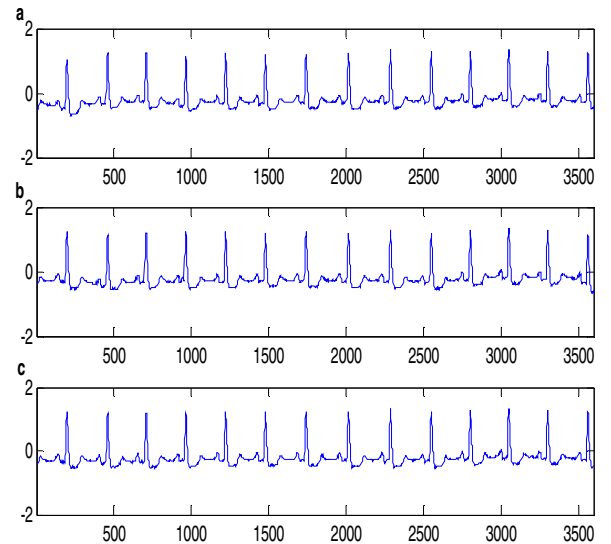


Fig. 7. Filtering results of baseline wander reduction (x-axes are samples and y-axes are amplitude): (a) recovered signal using VSLMS algorithm, (b) recovered signal using UNLNN, (c) recovered signal using ULNN

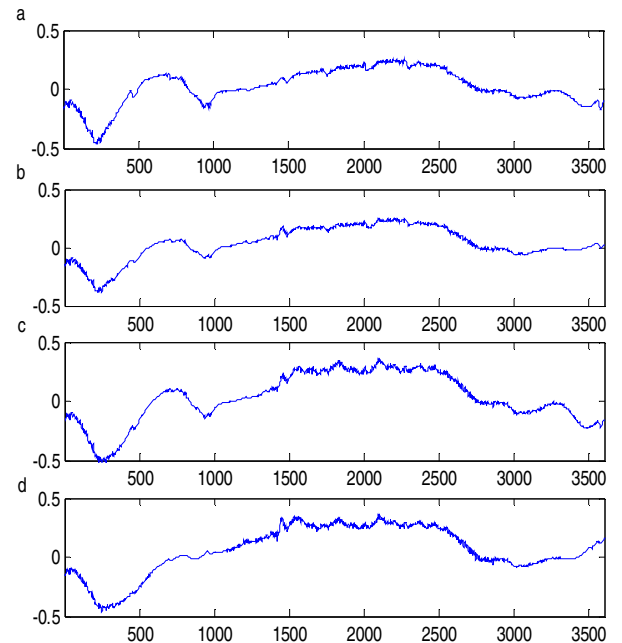


Fig. 8. Filtering results of baseline wander reduction (x-axes are samples and y-axes are amplitude difference): (a) difference signal after LMS filtering, (b) difference signal after SRLMS filtering, (c) difference signal after SLMS filtering, (d) difference signal after SSLMS filtering

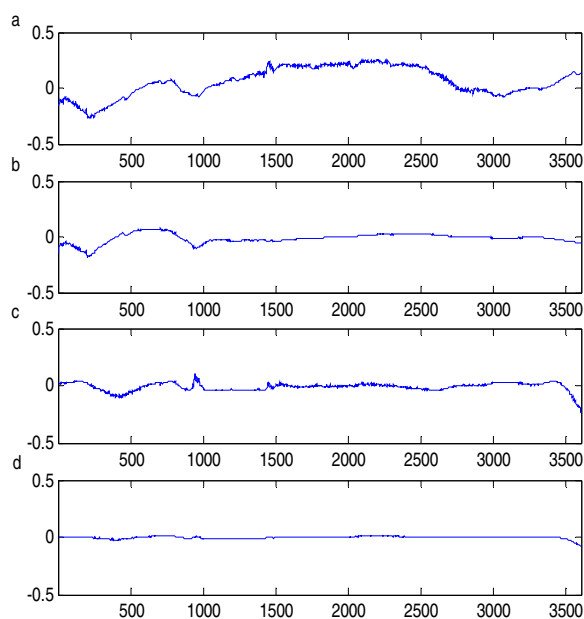


Fig. 9. Filtering results of baseline wander reduction (x-axes are samples and y-axes are amplitude difference): (a) difference signal after NLMS filtering, (b) difference signal after VSLMS filtering, (c) difference signal after UNLNN, (d) difference signal after ULNN

TABLE 1. SNR IMPROVEMENT AS A PERFORMANCE MEASURE OF DIFFERENT ALGORITHMS FOR THE REMOVAL OF BW

Rec. no = 105	
Algorithm	SNR dB
LMS	18.0169
SRLMS	19.0998
SLMS	11.4678
SSLMS	11.6258
NLMS	19.3214
VSLMS	42.0825
UNLNN	46.4830
ULNN	71.7024

Figures 8 and 9 show the difference signals between original and restored ones using various algorithms.

Figure 9(d) shows the restored, difference signals for ULNN, it is clear that the amplitude of the difference almost approaches the DC line.

Figures 9(b) and 9(c) show the restored, difference signals for VSLMS algorithms and UNLNN, here the amplitude of the difference for VSLMS algorithm is lower than that of all other filter algorithms. The amplitude of the difference for UNLNN is lower than that of VSLMS algorithm.

The relative performance is measured with SNR. These are presented in TABLE 1. It is obvious that the SNR of ULNN (71.7024 dB) is the best SNR among others and the SNR of UNLNN (46.4830 dB) comes in the second order. This shows that the neural network whether is linear output or nonlinear output is the best tool for cancellation BW from ECG signal.

Also, We can see that VSLMS algorithm in which the step size is variable comes after NN, where it improves the SNR to 42.0825 dB and is better than all LMS algorithms (LMS, SLMS, SRLMS and SSLMS).

2) Cancellation of muscle artifacts (MA)

In this case we have used 3600 samples of the ECG signal corrupted with real MA. The corrupted ECG signal is applied as primary input to the adaptive filter of Figure 2. The noise generator which is a real MA is given as a reference signal.

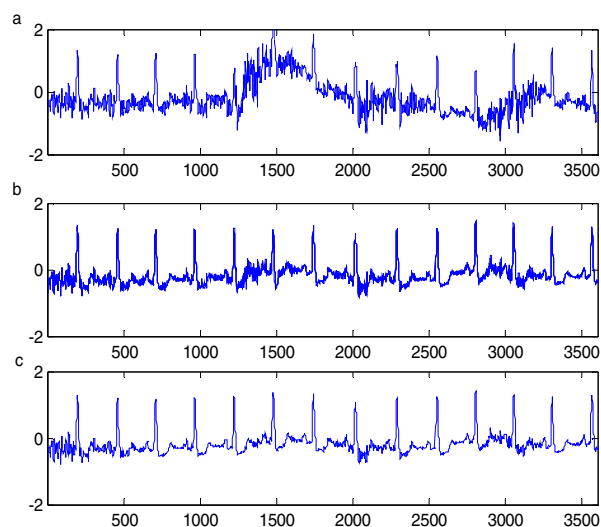


Fig. 10 Filtering results of muscle artifacts removal reduction (x-axes are samples and y-axes are amplitude): (a) ECG with real MA, (b) recovered signal using LMS algorithm, (c) recovered signal using SRLMS algorithm

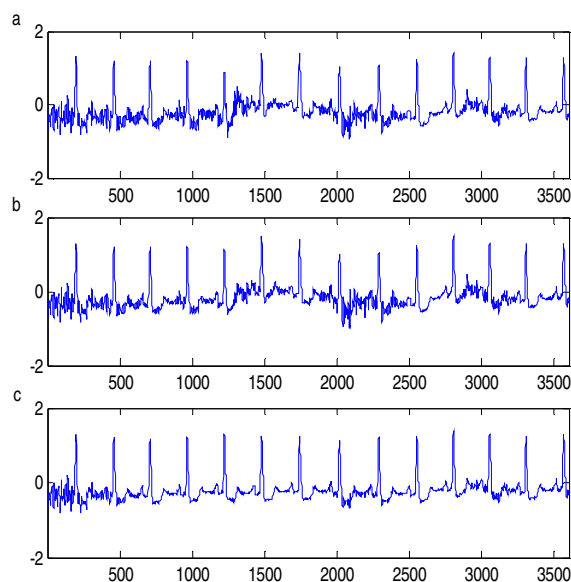


Fig. 11. Filtering results of muscle artifacts removal reduction (x-axes are samples and y-axes are amplitude): (a) recovered signal using SLMS algorithm, (b) recovered signal using SSLMS algorithm, (c) recovered signal using NLMS algorithm

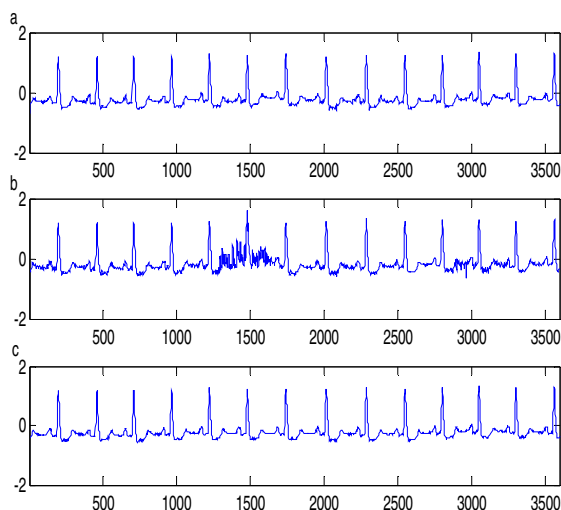


Fig. 12. Filtering results of muscle artifacts removal reduction (x-axes are samples and y-axes are amplitude): (a) recovered signal using VSLMS algorithm, (b) recovered signal using UN-LNN, (c) recovered signal using ULNN

The simulation results of all algorithms for adaptive filter and NN were shown in Fig. 10, Fig. 11 and Fig. 12. From these figures, it is clear that the output of ULNN has higher resolution than others.

Figure 12(a) and (b), we can see that VSLMS is better than UNLNN where VSLMS output doesn't have distortion in ECG signal. However, ULNN has a similar result to VSLMS.

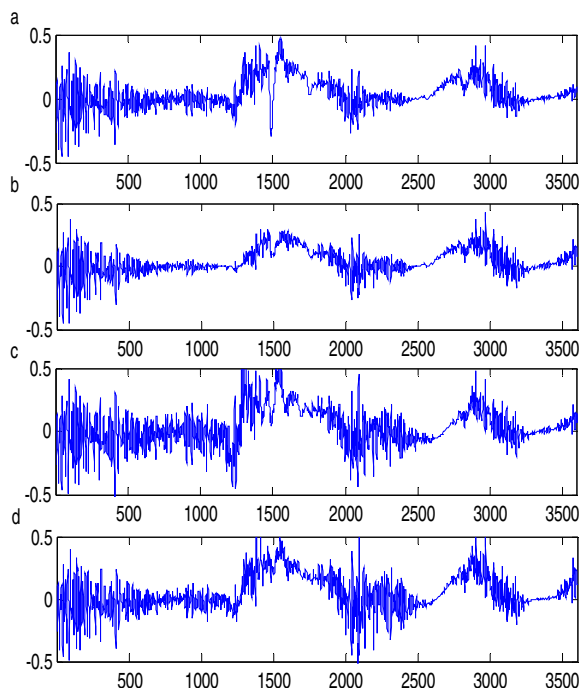


Fig. 13. Typical filtering results of muscle artifacts(MA) removal (x-axes are samples and y-axes are amplitude difference): (a) difference signal after LMS filtering, (b) difference signal after SRLMS filtering, (c) difference signal after SLMS filtering, (d) difference signal after SSLMS filtering

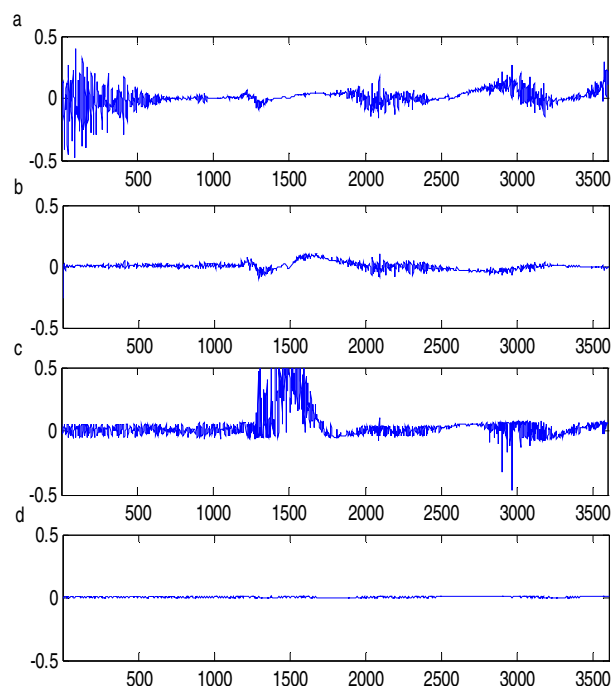


Fig. 14. Filtering results of muscle artifacts removal (x-axes are samples and y-axes are amplitude difference): (a) difference signal after NLMS filtering, (b) difference signal after VSLMS filtering, (c) difference signal after UNLNN, (d) difference signal after ULNN

TABLE 2. SNR IMPROVEMENT AS A PERFORMANCE MEASURE OF DIFFERENT ALGORITHMS FOR THE REMOVAL OF MA

Rec. no = 105	
Algorithm	SNR dB
LMS	22.2817
SRLMS	25.2002
SLMS	17.7325
SSLMS	17.8147
NLMS	33.4829
VSLMS	50.3318
UNLNN	24.0196
ULNN	115.4036

Figures 13 and 14 demonstrate the signal of amplitude difference between the original and the restored muscle artifacts (MA) signal. Figure 14(d) shows that the difference signal (error signal) for ULNN has the lowest value among all other algorithms and its SNR is the highest one (115.4036 dB).

Table 2 emphasises on that the ULNN is of the best performance (highest SNR). The SRLMS, NLMS and VSLMS algorithms have the SNR 25.2002 dB, 33.4829 dB and 50.3318 dB respectively, all of them show a superiority over UNLNN and the VSLMS has a SNR equals approximately double of the SNR of UNLNN. Therefore, it is found that the UNLNN is not suitable for muscle artifacts cancellation.

3) Electrode motion (EM) artifacts cancellation

To show the concept of artifacts removal in the presence of non-stationary noise, we have also considered EM artifacts. In this case we used 3600 samples of the ECG signal corrupted with real EM. The corrupted ECG signal is applied as primary input to the adaptive filter of Fig. 2. The noise generator a real EM is given as reference signal.

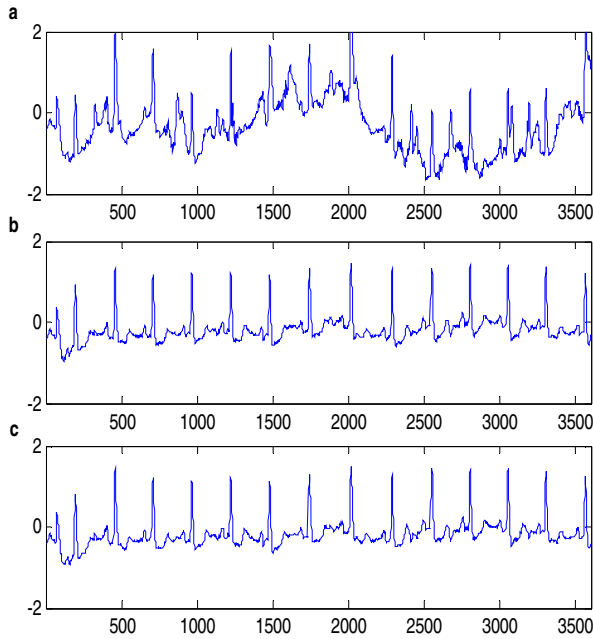


Fig. 15. Filtering results of electrode motion (EM) artifacts removal reduction (x-axes are samples and y-axes are amplitude): (a) ECG with real EM, (b) recovered signal using LMS algorithm, (c) recovered signal using SRLMS algorithm

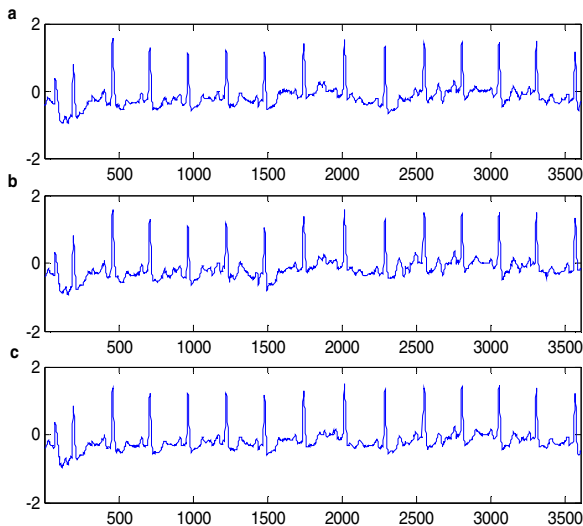


Fig. 16. Filtering results of electrode motion (EM) artifacts removal reduction (x-axes are samples and y-axes are amplitude): (d) recovered signal using SLMS algorithm, (e) recovered signal using SSLMS algorithm, (f) recovered signal using NLMS algorithm

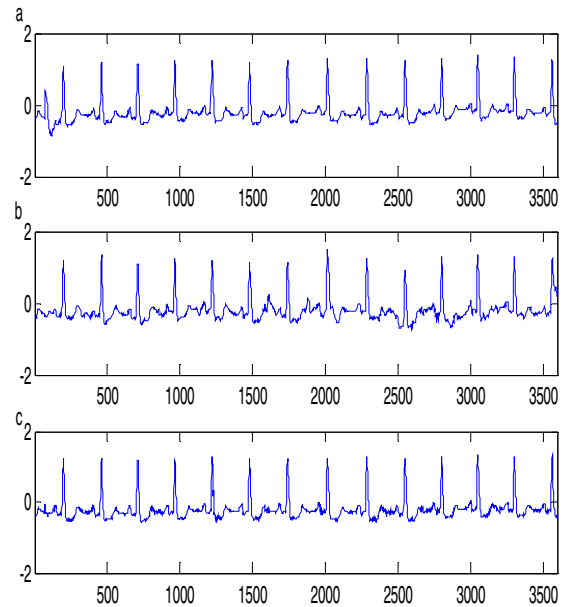


Fig. 17. Filtering results of electrode motion (EM) artifacts removal reduction (x-axes are samples and y-axes are amplitude): (a) recovered signal using VSLMS algorithm, (b) recovered signal using UNLNN, (c) recovered signal using ULNN

From Figures 15, 16 and 17, it is clear that the output signal from the ULNN has a higher resolution.

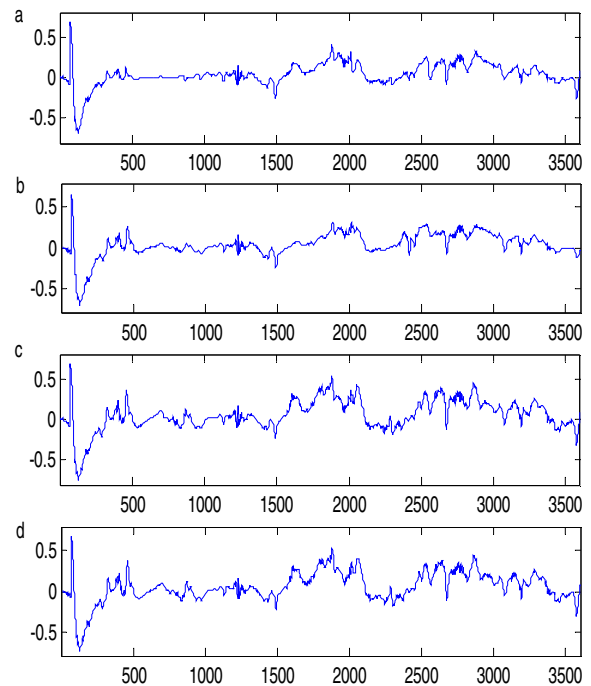


Fig. 18. Filtering results of electrode motion (EM) artifacts removal (x-axes are samples and y-axes are amplitude difference): (a) difference signal after LMS filtering, (b) difference signal after SRLMS filtering, (c) difference signal after SLMS filtering, (d) difference signal after SSLMS filtering

IV. CONCLUSION

The main purpose of this paper is to study the performance of the adaptive noise canceller using different kinds of learning algorithms including the modified LMS (VSLMS). Both adaptive filters and neural networks are used in this paper. Noise canceller is tested to remove various artifacts from the ECG signal such as: BW, MA and EM obtained from the MIT-BIH database. Simulation experiments show that the performance of noise canceller driven by ULNN is of the best performance among all other tools and algorithms. The UNLNN is better in cancellation BW than itself in case of cancellation the MA and EM artifacts. The modified algorithm (VSLMS) is better than UNLNN in the case of cancelling the MA and EM artifacts. The simulation results demonstrate that the modified algorithm (VSLMS) is of the best performance among the linear filter uses other LMS algorithms such as: LMS, SLMS, SRLMS and SSLMS. The sign algorithms group are used signum function in order to facilitate implementation of LMS algorithm as FPGA implementation.

REFERENCES

- [1] M. Z. U. Rahman, R. A. Shaik, and D. V. Rama Koti Reddy, "Efficient sign based normalized adaptive filtering techniques for cancelation of artifacts in ECG signals: Application to wireless biotelemetry," *Signal Processing*, vol. 91, pp. 225-239, 2// 2011.
- [2] N. V. Thakor and Z. Yi-Sheng, "Applications of adaptive filtering to ECG analysis: noise cancellation and arrhythmia detection," *Biomedical Engineering, IEEE Transactions on*, vol. 38, pp. 785-794, 1991.
- [3] J. A. Van Alste and T. S. Schilder, "Removal of Base-Line Wander and Power-Line Interference from the ECG by an Efficient FIR Filter with a Reduced Number of Taps," *Biomedical Engineering, IEEE Transactions on*, vol. BME-32, pp. 1052-1060, 1985.
- [4] J. M. Lski and N. Henzel, "ECG baseline wander and powerline interference reduction using nonlinear filter bank," *Signal Process.*, vol. 85, no. 4, pp. 781-793, 2005.
- [5] V. Almenar and A. Albiol, "A new adaptive scheme for ECG enhancement," *Signal Processing*, vol. 75, pp. 253-263, 1999.
- [6] P. S. R. Diniz, *Adaptive Filtering: Algorithms and Practical Implementations*, ISBN 978-0-387-31274-3, Kluwer Academic Publisher © 2008 Springer Science+Business Media, LLC, pp.77-195.
- [7] B. Widrow and S. D. Stearns, *Adaptive Signal Processing*, Prentice-Hall, Englewood Cliffs, New Jersey, 1985.
- [8] S. Haykin, *Neural Networks: A Comprehensive Foundation*: Prentice Hall, 1999.
- [9] Z.-M. Tian and A.-Z. Wang, "The Research of Adaptive Noise Cancellation Technology Based on Neural Network," in *Computing, Measurement, Control and Sensor Network (CMCSN), 2012 International Conference on*, 2012, pp. 144-147.
- [10] www.physionet.org

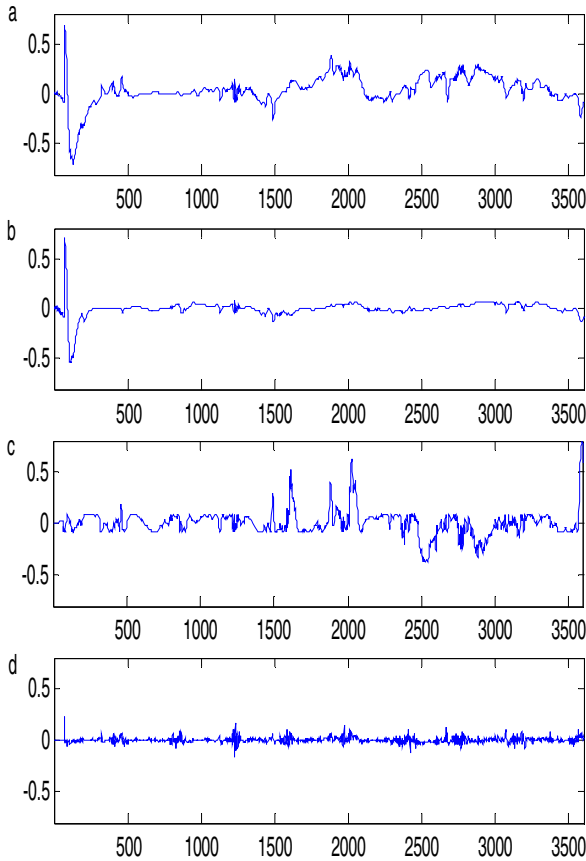


Fig. 19. Filtering results of electrode motion (EM) artifacts removal (x-axes are samples and y-axes are amplitude difference): (a) difference signal after NLMS filtering, (b) difference signal after VSLMS filtering, (c) difference signal after UNLNN, (d) difference signal after ULNN

TABLE 3. SNR IMPROVEMENT AS A PERFORMANCE MEASURE OF DIFFERENT ALGORITHMS FOR THE REMOVAL OF EM

Rec. no = 105	
Algorithm	SNR dB
LMS	18.9086
SRLMS	17.7993
SLMS	13.290
SSLMS	12.9363
NLMS	18.5309
VSLMS	31.5860
UNLNN	21.6176
ULNN	55.8320

From figures 18 and 19, it is obvious that difference signal (figure (19-d)) obtained by ULNN is of the lowest value among all other algorithms.

Table 3 assures that ULNN tool is of the best performance in EM cancellation. Also, it is reported that UNLNN does not perform well in EM artifacts removal compared to VSLMS.