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Impulsive Noise Cancellation from ECG Signal using Adaptive Filters and their Comparison

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Abstract

Impulsive Noise is the sudden burst noise of short duration. Mostly it causes by electronic devices and electrosurgical noise in biomedical signals at the time of acquisition. In this work, Electrocardiograph (ECG) signal is considered and tried to remove impulsive noise from it. Impulsive noise in ECG signal is random type of noise. The objective of this work is to remove the noise using different adaptive algorithms and comparison is made among those algorithms. Initially the impulsive noise in sinusoidal signal is synthesized and tested for different algorithms like LMS, NLMS, RLS and SSRLS. Further those algorithms are modified in a new way to weight variation. The proposed novel approach is applied in the corrupted ECG signal to remove the noise. The effectiveness of the proposed approach is verified for ECG signal with impulsive noise as compared to the traditional approaches as well as previously proposed approaches. Also the performance of our approach is validated by SNR computation. Significant improvement in SNR is achieved after removal of noise.

Keywords: *filtering algorithm, adaptive filter, LMS, NLMS, RLS, SSRLS*

1. Introduction

The attributes of human organ can be concentrated on gathering their relative physiological parameters. One such case of bio-medicinal signal is Electrocardiograph (ECG) that displays the characteristics of the heart. At the time of such information accumulation, many types of noise may occur and deviate the original signal. These noises may be due to the electrical gadgets or from the internal part of human body. Sudden burst of this kind of disturbances is said to be Impulsive. Electrocardiogram (ECG) signals are key for determination of heart related issues. ECG signals have low frequency of around 0.5Hz-100Hz. Noise considered here is impulsive by nature, which get incorporated into the ECG signal and change the original signal.

But a little amount of work related with this region of exploration has been done.From standard filtering algorithm to adaptive filtering algorithms have been applied to cancel the noise from the signal. Stil there is the gap to improve the accuracy by reducing error. The major works of them are referred in the following section. In this work, we have attempted to build up a framework which will reduce the impulsive noise from ECG signal by utilizing adaptive filtering theory. We have compared the Signal to Noise ratio (SNR) of different adaptive filters. At that point to choose the best framework we have thought about the Mean Square Error and the change in SNR of those filters.

Noise cancellation using different algorithms have been reparted since decades. Many types of algorithms for such purpose have been applied to signal processing [1-3], Image processing [4-5], Communication [6-7] fields. Some of them were applied to biomedical signals. The related literature is depicted is section 2.

In this paper, we have verified the adaptive algorithms such as LMS, NLMS and RLS on synthetic impulsive noisy signals. Further the cardiac signal corrupted with impulsive noise has been considered to test those algorithms. RLS algorithm found to be effective for removal of impulsive noise. Further RLS algorithm is modified with state space representation and called as SSRLS for this application. Though it has been applied by A.Mirza, et al., [8], and shown better convergence rate, they could not shown neither the improvement of SNR of the signal nor related to Mean Square Error (MSE). Also the accuracy of the recovered signal was not visually improved. The method is explained in section 3.4 and the improvement is exhibited in the result

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section i.e. section 4.

The paper is composed as follows. Section 2, presents the related literature. In section 3, different algorithms for Adaptive noise cancellation method has been discussed along with our approach to impulsive noise cancellation from ECG signal by using adaptive filter theory. Section 4 presents the result and finally section 5 concludes this paper.

2. Related Literature

Noise removal from bio-medical signal is highly essential before further processing. It has been used by many researchers since some decades; some of those works are cited here.

Finite Impulse Response (FIR) filter has been investigated in perspective of various windows and if there should be an occurrence of noise, for cancellation purpose Infinite Impulse Response (IIR) filters has been used for ECG signal. Kaiser Window based FIR filters has discovered perfect for removal of noises [9]. The proposed framework in [10] uses adaptive filters to minimize impulsive noise in ECG signal and keep up a key separation from the false positives generated by the impulsive noises. Additionally it can be used for system identification problem.

Noises that are impulsive by nature can be minimized by the gathering of nonlinear robust filters. A new way to deal with impulsive noise cancellation problem is application of myriad filter in a new way has been concentrated on in [11] for bio-medicinal signal. The proposed strategy in [11] depended on second order polynomial estimation.

Analysis has been done in view of MSE for various algorithms such as Least Mean Square (LMS), Normalized LMS (NLMS), Variable Step size LMS (VSLMS), Recursive Least Square (RLS) and Blind LMS. With the help of a delay all the inputs were given to the filter for processing. This helps for better estimation contrasted with the traditional LMS algorithm in [12]. In spite of the fact that human behavior is not precisely known it turns out to be exceptionally hard to decrease noises in bio-medical signals by the assistance of fixed filters with fixed coefficients. So adaptive filtering is required to conquer this sort of issue. In [13] two sorts of adaptive filters were taken into thought to lessen the noises from the ECG signal. In LMS adaptive Filter Mean Square Error diminishes and Signal to Noise Ratio undergoes a significant increment in contrast with RLS adaptive filter.

Sub-band decay utilizing wavelet analysis has been applied to the noisy ECG signal with PLI and impulsive noise in [14]. For cancellation of the impulsive noise morphological filtering algorithm is applied with one-dimensional structuring element. For removal of power line interference IIR Butterworth filter is utilized and PSD has been reduced in between 50 to 60 Hz.

Least Mean Squares (LMS) and Normalized Least Mean Squares (NLMS) algorithm for cancellation has been executed for ECG signal which is corrupted by Additive White Gaussian Noise (AWGN). A superior change in SNR has been acquired in NLMS algorithm when contrasted with LMS algorithm [15].

Impulsive noise has been demonstrated by using non-Gaussian stable procedure with no second order moments. Because of this reason Fx-LMS algorithm gets to be unstable for the impulsive noise. Fx-LMP algorithm is thus utilized which depends on minimization of least mean p-power (LMP) of the error signal. Change has been done taking into account a few statistical properties and contrasted with some current existing algorithms and active control of impulsive noise has been achieved in [16].

In [17], author have added SSRLS algorithm to RLS family. According to him SSRLS is best for estimating deterministic signal which is destroyed by the noise. Limitation of RLS algorithm has been overcome by this algorithm. This algorithm has a well tracking performance. Though it has a state space representation it is well suited for estimation theory, adaptive theory and control theory.

Authors have discussed in detail about the LMS and NLMS algorithm in [18]. They have added various types of norms to LMS algorithm and they have solved system identification problem.

3. Adaptive Algorithms for Noise Cancellation

The bio-medical signals are generally recorded with a noise. A wide range of noise exists in bio-medical environment. One of the noises is a waveform of an electrical action taken by human muscles. This can be modeled with a white Gaussian noise. But such model of noise is not generally genuine, in light of the fact that real time muscle noise in some cases is impulsive by nature. So filtering of this type of impulsive noise is an essential task because these types of noises have very high amplitude values. For diagnosis purpose filtering of this type of noises is an important issue now days. Here we have tested different adaptive algorithms with an impulsive noise affected ECG signal. On the basis of MSE and SNR calculation we have chosen the best one.

An adaptive filter may be understood as a self-adjusting filter that changes its coefficients to minimize the error. The most crucial property of adaptive filter is that it can work for known framework as well as unknown framework [19]. The proposed block diagram of the adaptive noise cancellation for ECG signal is as follows.

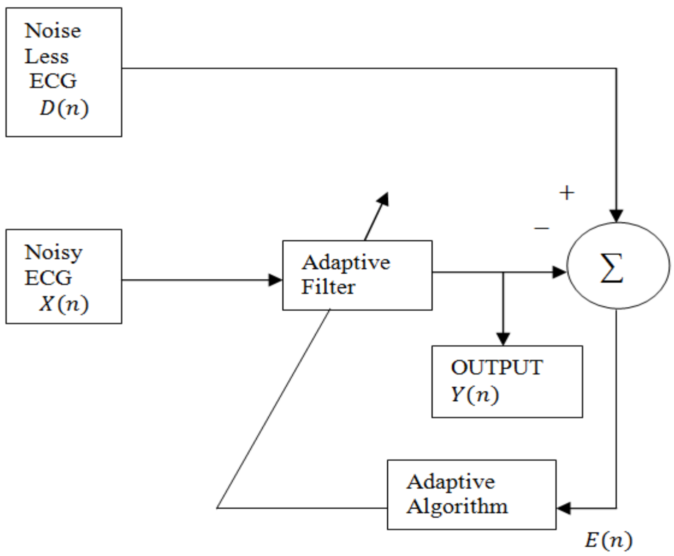

Figure 1. Block Diagram for Adaptive noise cancellation process

It is considered as the desired signal as $D(n)$ which is noise less ECG signal. For input $X(n)$ we have chosen an impulsive noise affected ECG signal. The error signal which is calculated by taking the difference between the desired signal and the output signal collected by passing the input signal through an adaptive filter is denoted by $E(n)$ [19].

$$E(n) = D(n) - Y(n) \tag{1}$$

The adaptive channel changes its weights as indicated by the error signal. At whatever point the error will be least, optimal point will be reached and at this case of time we will get our clean signal without impulsive noise. The output signal is given by:

$$Y(n) = W(n)X(n)^T \tag{2}$$

$W(n)$ is the adaptive filter co-efficient. Here now we will explore some adaptive algorithms which are used for impulsive noise cancellation purpose.

3.1. LMS Based Adaptive Algorithm

By using LMS algorithm system coefficients can be found. It uses gradient descent method in which the filter is adapted. The weight update relation is derived from [18-20] as:

$$W(n+1) = W(n) + 2\mu E(n)X(n) \tag{3}$$

A positive constant μ (learning rate) is taken which controls the stability and rate of convergence of the system.

3.2. NLMS Based Adaptive Algorithm

The Normalized LMS algorithm is the personalized version of LMS algorithm. The weight updating relation for NLMS algorithm can be given by [18-20]:

$$W(n+1) = W(n) + \mu . E(n) . \frac{X(n)}{\delta + \|X(n)\|^2} \quad (4)$$

The step size can support the convergence rate of the filter. The NLMS algorithm produces a higher convergence rate when contrasted with the LMS algorithm with a higher leftover error.

3.3. RLS Based Adaptive Algorithm

The RLS algorithm is based on least square method. The least-squares framework is a mathematical system for finding the best fitting curve to a given arrangement of data points. The least square problem can be solved by RLS algorithm which is best suitable for non-stationary environment. This algorithm finds the filter coefficients recursively. The RLS shows extremely fast convergence over all variations of LMS however with a high computational complexity. The following relations are associated with the RLS algorithm [19-20].

$$W(n+1) = W(n) + Z(n)X(n) \quad (5)$$

Where, $Z(n)$ is observer gain and can be denoted as:

$$Z(n) = \frac{\tau^{-1}\pi^{-1}(n-1)X(n)}{1+\tau^{-1}X^T(n)\pi^{-1}(n-1)X(n)} \quad (6)$$

Here τ is the forgetting factor and π is the cross correlation matrix. Here the forgetting factor is user defined and initialized with 1. π is the initialized with $\nabla^{-1}I$. Where ∇ is the regularization parameter and I is the identity matrix.

Then π can be given by the following relation.

$$\pi^{-1}(n) = \tau^{-1}\pi^{-1}(n-1) - \tau^{-1}Z(n)X^T(n)\pi^{-1}(n-1) \quad (7)$$

3.4. SSRLS Based Adaptive Algorithm

State space representation of RLS algorithm with some extension can be called as State Space Recursive Least Squares or SSRLS algorithm. This algorithm is very useful in non stationary environment like impulsive noise environment. SSRLS is exceptionally appropriate to evaluate a wide class of deterministic signals which are distorted by noise. The SSRLS algorithm has the steps as follows [8, 17].

Let $X'(n)$ is the input state and $E'(n)$ is the prediction error $Z(n)$ is the observer gain. n is the predicted input state and $\hat{n}$ is the estimated state, $Y(n)$ is the predicted output state and π is the cross correlation matrix then:

$$X'(n) = X'(n) + Z(n)E'(n) \quad (8)$$

$$X'(n) = PX'(n-1) \quad (9)$$

Now the estimated error $E(n)$will be:

$$E(n) = Y(n) - Y'(n) \quad (10)$$

Where,

$$Y'(n) = QX(n) \quad (11)$$

Here the pair (P, Q) is assumed to be l-step observable and can be represented as state transition matrix whose Eigen values are strictly on the unit circle.Now the cross-correlation matrix for SSRLS can be represented as:

$$\pi(n) = \tau\left(P^{-T}\pi(n-1)\right)P^{-1} + Q^T Q \quad (12)$$

Finally the observer gain can be calculated using the cross-correlation matrix as:

$$Z(n) = \pi^{-1}(n)Q^T \quad (13)$$

Then the weights are updated as equation (5).

4. Simulation, Results and Discussion

The database is of healthy people and noise has been added with it. This data is compared with the data collected from the hospital (SUM Hospital, Bhubaneswar, Odisha). At the time of data acquisition, deliberately the noise is created by electrical supply disturbances. The different parameters of the algorithm are listed in Table 1.

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Table 1. Parameters for Impulsive Noise cancellation

Parameters	Values
μ for adaptive algorithms	0.08
δ for NLMS algorithm	0.001
τ for RLS and SSRLS algorithm	0.9
No. of iteration	3600
Tap-weight	16

The simulation results of different algorithms are depicted from Figure 2 through Figure 5. In Figure 2 the top signal is the desired one, middle signal is represented for noisy. The output of the LMS algorithm application is shown in the bottom of Figure 2.

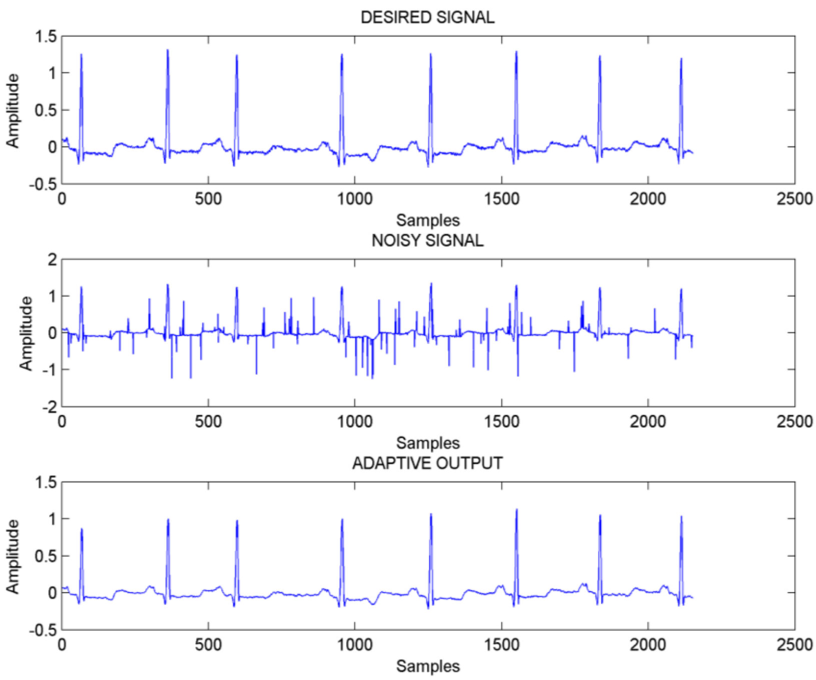

Figure 2. Impulsive noise cancellation using LMS algorithm

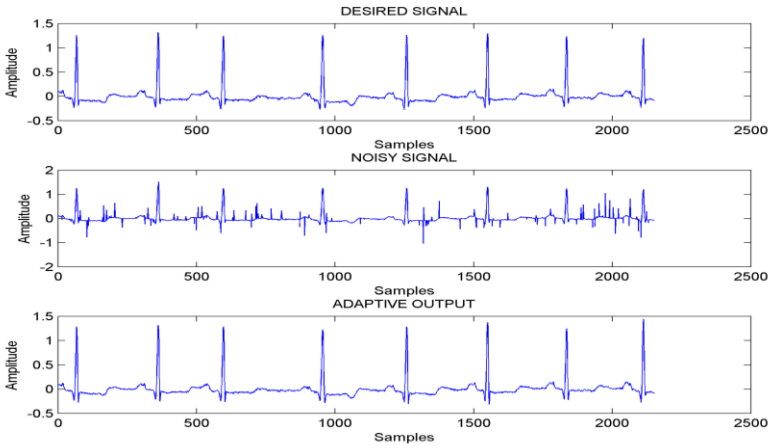

Figure 3. Impulsive noise cancellation using NLMS algorithm

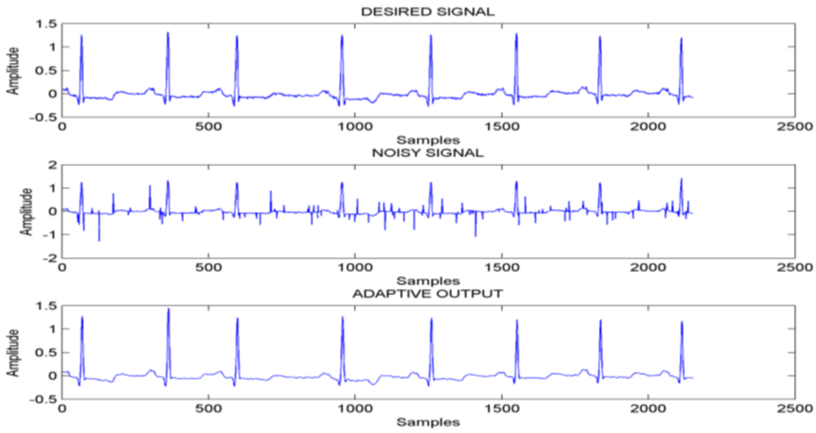

Figure 4. Impulsive noise cancellation using RLS algorithm

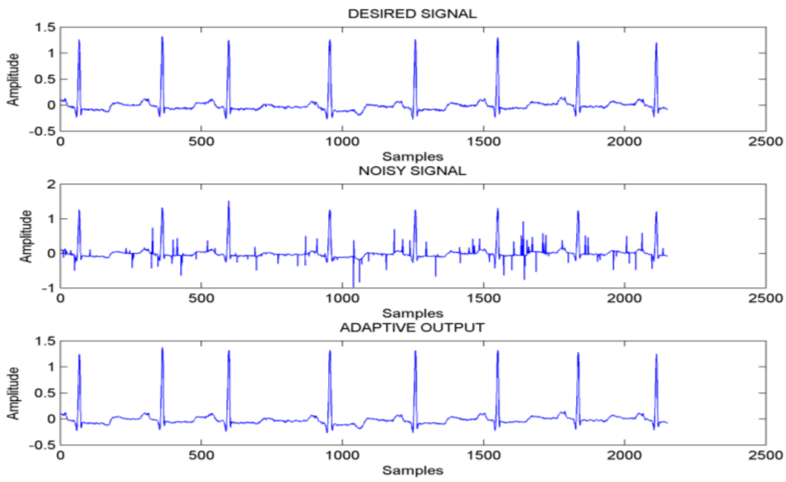

Figure 5. Impulsive noise cancellation using SSRLS algorithm

Similarly, Figure 3 is for NLMS, Figure 4 is for RLS application. Finally Figure 5 output is our proposed algorithm. From the visual output, it is found Figure 5 represents clean signal as compared to Figure 2, Figure 3, and Figure 4. In this case the whole signal is shown instead of the peaks only as in [8]. This is even better result than the output of [8].

Further to evaluate the visual output, we have checked its Mean Square Error (MSE) as shown in Figure 6. It is found that the error is less as compared to other algorithms. Simultaneously the convergence rate is faster than others which is around 150 iterations.

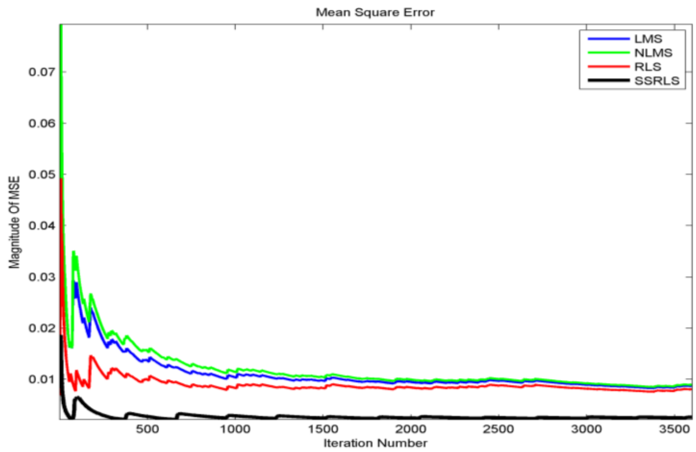

Figure 6. MSE comparision between LMS, NLMS, RLS and SSRLS

Also to validate the result, SNR of the signal is shown in Table 2. The SNR before application of the algorithm and after cancellation is noted. The significant change with application of SSRLS algorithm is clearly notified.

Table 2. SNR comparison between LMS, NLMS, RLS and SSRLS

FILTER TYPE	SNR BEFORE FILTERING	SNR AFTER FILTERING	SNR IMPROVEMENT
LMS	7.8499 dB	11.3658 dB	3.5159 dB
NLMS	7.0176 dB	12.5551 dB	5.5375 dB
RLS	7.1297 dB	13.8979 dB	6.7682 dB
SSRLS	7.3245 dB	14.4778 dB	7.1533 dB

5. Conclusion

In this work, we have analyzed different adaptive algorithms have been applied and tested for impulsive noise contaminated with cardiac signal. Both gradient based algorithm and least square algorithms have been successively applied. It is found that the modified RLS as SSRLS algorithm outperforms than other algorithms. It is also most stable, though complexity is in terms of $O(N^2)$. For future work the complexity can be reduced in one end and in the other end this can be implemented to hardware unit for ECG machine.

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