Impulsive Noise Cancellation of ECG signal based on SSRLS

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Abstract

In this paper, an enhanced adaptive impulsive noise cancellation technique based on State Space Recursive Least Square (SSRLS) algorithm is proposed. The technique is applied to the Electrocardiogram (ECG) signal, where impulsive noise affects the ECG analysis. Due to state space model-dependent recursive parameters, the presented scheme does not require the reference signal and exhibits better impulsive noise cancellation in ECG signal when compared with existing Normalized Least Mean Square (NLMS) and, Recursive Least Square (RLS) techniques. The fastest convergence and excellent tracking characteristics of proposed scheme demonstrated by the simulation results in mean square error (MSE) sense proved it to be the effective solution of impulsive noise cancellation in ECG signals.

Keywords: Impulsive Noise; Adaptive Filter; ECG; NLMS; RLS; SSRLS; MSE

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1. Introduction

Noise is practically impulsive in nature, which has more catastrophic effects in communication systems as well as in Electrocardiography (ECG) signals. It is non-Gaussian generated by human activities and completely destroys the information [1]. Methods must be investigated to mitigate this type of noise. Nowadays active area of research is to inspect the impulsive noise behavior and suggest solutions to improve the performance of systems by suppressing it. For noise cancellation, various techniques are reported in literature which attempt to recover the original ECG signal [2, 3]. The electrical activity of the heart is recorded as an ECG signal. It is used to analyze the conduction system of the heart. The electrical pulses generated by the polarization and depolarization of cardiac tissues are picked and is then translated into waveforms. This waveform is prone to man-made noise which is impulsive noise. The adaptive Filters with non-stationary statistical characteristics, low cost and their ability to adapt to the unknown environment make them most suitable for the ECG noise cancellation applications over the past half-decade [4].

The performance comparison study of the adaptive filters namely least mean square (LMS), normalized LMS (NLMS) and Normalized signed LMS (NSLMS) was carried out for removing power line interference from the ECG signal [5]. The Normalized signed LMS (NSLMS) out performs the LMS algorithm in terms of boosting up the speed and reducing the computational complexity. The Adaptive filter based on Recursive Least Squares (RLS) is proposed to reduce the ECG signal noise like Power line interference (PLI) and Base Line wandering Interference , which successfully removed artifacts preserving the ECG [6]. In [7], SSRLS filter has been used to remove 50 Hz PLI and it gives better results in comparison with the Notch filters with different attenuation levels in frequency domain. Motivated by the performance of SSRLS in [7], in this paper we have specifically presented an impulsive noise canceller of ECG signal based on SSRLS filter in time domain. In addition comparison of SSRLS with existing techniques is carried out. Section II of the paper briefly describes the basic principle of active noise cancellation. In Section III, the review of different adaptive filters is given, and the comparative analysis supported with the simulation results is discussed in section-IV. In the end, the conclusion is presented.

2. Noise Cancellation

The basic principle of the Noise canceller is to reduce the unwanted noise by utilizing the additional noise specifically designed to cancel the first.
The desired signal $d(n)$ is compared with the input of the noise canceller which is a noisy source $N_1(n)$. Another noise source $N_0(n)$ corrupts the desired signal as shown in Fig.1. The coefficients of the adaptive filter recursively vary to assure error signal $e(n)$, which is produced by the difference of desired signal $d(n)$ and the adaptive filter output $y(n)$, to be the noiseless version of the signal $s(n)$.

3. Adaptive Algorithms

There are many adaptive algorithms used for noise removal. The brief summaries of adaptive algorithms which are used in this research are as follow.

3.1 NLMS Algorithm

The variant of Least Mean Square (LMS) algorithm is Normalized Least Mean Square which gives faster convergence than LMS. The limitation of the LMS algorithm is its sensitivity to its input signal scaling. The convergence is very slow and step size should be chosen carefully to guarantee algorithm stability. The whole algorithm remains same only filter tap weights are updated by following recursive formula:

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

(1)

Where $\epsilon$ a small number is added for algorithm stability, $\mu$ is the step size of filter and $e(n)$ is error signal.

3.2 RLS Algorithm

The Gauss Recursive least squares (RLS) adaptive filter is one in which autocorrelation matrix estimation is used to de-correlate the current input data. The coefficients of the filter adapt to minimize the cost function based on linear least squares of the deterministic input signals [8]. Also, The RLS exhibits extremely fast convergence over all variants of LMS but at high computational complexity. The filter weights $w$ are updated in RLS algorithm by following equations.

$$ w(n+1) = w(n) + k(n)x(n) $$

(2)

$$ k(n) = \frac{\lambda^{-1} \varphi^{-1}(n-1)x(n)}{1 + \lambda^{-1} x^T(n) \varphi^{-1}(n-1)x(n)} $$

(3)

$$ \varphi^{-1}(n) = \lambda^{-1} \varphi^{-1}(n-1) - \lambda^{-1} k(n) x^T(n) \varphi^{-1}(n-1) $$

(4)

Where $\lambda$ is the forgetting is factor and $\varphi^{-1}$ is the cross correlation matrix. The $\lambda$ is initialized with 1 and $\varphi^{-1}$ with $\delta^{-1} I$. I is the identity matrix.
3.3 SSRLS Algorithm

An extension of RLS algorithm in state space representation is **State Space Recursive Least Squares (SSRLS)** algorithm. It is used to remove noise and its performance can be evaluated in a non-stationary environment (impulsive noise). The steps of SSRLS form II filter along with sinusoidal model for implementation are as follow [9].

\[
\hat{x}[n] = \hat{x}[n] + K[n] \varepsilon[n]
\]

(5)

\[
\hat{x}[n] = A \hat{x}[n-1]
\]

(6)

\[
\varepsilon[n] = y[n] - \bar{y}[n]
\]

(7)

\[
\bar{y}[n] = Cx[n]
\]

(8)

\[
\Phi[n] = \lambda \left( A^{-T} \Phi[n-1] A^{-1} + C^T C \right)
\]

(9)

\[
K[n] = \Phi^{-1}[n] C^T
\]

(10)

Where \( x[n] \) is the input state, \( \varepsilon[n] \) is the prediction error, \( K(n) \) is observer gain, \( n \) is predicted input state, \( \hat{x} \) is estimated state, \( \bar{y}[n] \) is the predicted output state and \( \Phi[n] \) is the correlation matrix.

### 4. Simulation Results

In this section, we compare the performance of the different adaptive filters in impulsive noise cancellation of ECG signal by computer simulation using MATLAB version 12. This is shown by initially generating impulsive noise by following steps mentioned in [1] and depicted in Fig.2. The parameters used for simulating impulsive noise are below:

**Table 1. Parameter set for simulation of Impulsive Noise**

| Parameters                  | Symbol | Value  |
|-----------------------------|--------|--------|
| Sampling Frequency          | \( f \) | 10     |
| Total time                  | \( T \) | 100    |
| Average Time between samples| \( \beta \) | 1s     |
| Mean of log amplitude       | \( A \) | 10dB   |
| Mean of Additive Gaussian Noise | \( m \) | 0.1    |
| Standard deviation of Gaussian Noise | \( \sigma \) | 0.4    |
| Standard deviation of log amplitude | \( B \) | 5dB    |
Fig. 3(a) represents the Pure ECG signal having sampling frequency of 360 Hz and its peak to peak amplitude normalized at 1. This signal has been taken from MIT-BIH database [10]. The comparison of original ECG signal and impulse noise affected ECG signal in time domain is illustrated in Fig. 3 (b).

The objective of algorithm is to make the output $y(n)$ of the filter, equal to the reference noise signal $n_2(n)$. Having this equivalence, it is easy to deduce that the error is equal to the desired signal $s(n)$.

$$ e(n) = d(n) - y(n) = s(n) + n_2(n) - n_2(n) = s(n) $$  \hspace{0.5cm} (11)

The system output error signal $e(n)$ should contain the original signal $s(n)$ in an optimum sense. The length of all the three adaptive filters is fixed to 5. The step size parameter for NLMS Algorithm is chosen to be equal to 0.0002 and forgetting factor for RLS is 1 and for SSRLS is set to 0.99. The error signals obtained by above mentioned adaptive filters are shown in Fig. 5.
The results from Fig. 4 represent that the largest peaks of impulsive noise from the noisy ECG signal are removed by the SSRLS algorithm, while other two investigated algorithms fail to remove the noise with large amplitudes. The error plots of three algorithms are also compared with the original signal. From Fig. 4(part a & b), we can conclude the SSRLS and RLS filters of least square family are reducing impulsive noise from the ECG signal in a better way than NLMS adaptive algorithm. In part (c) it can be easily seen that SSRLS is outperforming RLS in removing impulsive noise from ECG signal.

The mean square error in terms of decibel simulation results also confirms that SSRLS give lowest MSE and fastest convergence while cancelling impulsive noise as depicted in Fig. 5. The MSE of SSRLS filter is below -20dB whereas NLMS and RLS algorithms MSE is below 10 dB. The above plot shows that the value of MSE of NLMS and RLS algorithm both goes up to positive scale while that of SSRLS remains in negative scale indicating that it provides minimum error. Moreover, the result clearly states that SSRLS algorithm has suppressed almost all the high amplitude of noisy ECG signal.
5. Conclusion

In this work, an adaptive noise cancellation technique based on state space recursive least square (SSRLS) algorithm is presented. The proposed scheme is applied on Electrocardiogram (ECG) signal showing fast rate of convergence and excellent tracking performance due to its state space model-dependent recursive parameters. The presented method came out to be very effective in impulsive noise cancellation of ECG signal without requiring reference noise source. The performance comparison of SSRLS with Normalized Least Mean Square (NLMS) and Recursive Least Square (RLS) exhibits better results in terms of convergence speed and MSE cancellation and this is verified by the simulation results.

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