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Research Article

A Novel Pipelined Adaptive RLS Filter for ECG Noise Cancellation

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Abstract: Filtering the noise present in ECG signals by adaptive signal processing is the aim of the study. Adaptive digital filters are difficult to pipeline due to the presence of long feedback loops, careful calibration of step size and depth of pipelining. DLMS filters are designed to reduce the adaptation delay in the existing method. However with the LMS algorithm, the resulting rate of convergence is typically an order of magnitude slower than the RLS algorithm. The exponentially weighted RLS algorithm which converges in the mean square sense in about 2M iterations, where M is the number of taps in the transversal filter. The fine-grain structure of RLS and RRLS adaptive filters are designed. Signal to Noise Ratio (SNR) analysis for these filters are performed on a preliminary basis with different structures. Pipelined implementation of these adaptive filters yield higher throughput, higher sample rates and low power designs. The filter structures are designed and simulated in MATLAB SIMULINK. These structures are used for the noise cancellation in ECG signals.

Keywords: ECG (Electrocardiography) signals, fine-grain structure, pipelining, RLS (Recursive Least Square) filter, VLSI (Very Large Scale Integration)

INTRODUCTION

The Least Mean Square (LMS) adaptive filter is the most popular and most widely used adaptive filter, because it's simple and also because of its satisfactory convergence performance (Meher and Park, 2013). The adaptive filters are mainly used in signal processing application. The filters should be designed by satisfying following constraints such as area, speed and power. Different structures for adaptive filters are designed based on their application. LMS algorithms are simpler in evaluation process, but they attain lower quality in the cancellation of disturbing signals. Contrary, RLS algorithms achieve higher quality in the disturbing signal cancellation, but they have large numerical claims for RLS filter coefficient evaluation (Oravec *et al*., 2008).

One of the main problem in biomedical data processing like electrocardiography is the separation of the signal from noises caused by power line interference, external electromagnetic fields, random body movements and respiration. The RLS algorithms are known to pursue fast convergence even when the Eigen value spread of the input signal correlation matrix is large. These algorithms have excellent performance when working in time-varying environments (Chandrakar and Kowar, 2012). The throughput is one of parameter that should be increased but it reduces the rate of convergence by using the available PEs (VijayaLakshmi and Raghuram, 2012). Parallel and sequential LMS-based adaptive FIR filters are one of the methods that are applied to remove power-line interference from ECG signal and white noise from speech signal. The parallel architectures is well suited for small size filters, while the sequential one is more appropriate for a large-size filter (Mohammed and Hassan, 2011). Recently (Bhotto and Antoniou, 2011) presented the robust recursive least square adaptive filter algorithm that uses prior error dependent weights. The robust RLS adaptive-filtering algorithm that yields an excellent solution of the weighted least squares optimization problem. Fine grain pipelining is one of the technique of decomposing the computation intensive multipliers into small segments. In this method a delay unit is inserted in the small segment of the multiplier so that the critical path and the execution time can be reduced (Jaya and Madhumita, 2010). The simulation result shows that the performance of robust recursive least square algorithm is better than the previous counterpart.

MATERIALS AND METHODS

An adaptive filter is a filter that self-adjusts its transfer function according to an optimization algorithm driven by an error signal. Because of the complexity of the optimization algorithms, most adaptive filters are digital filters. The block diagram, shown in the following Fig. 1, serves as an adaptive filter for noise cancellation application by using Least Mean Square (LMS) and Recursive Least Square (RLS) algorithms.

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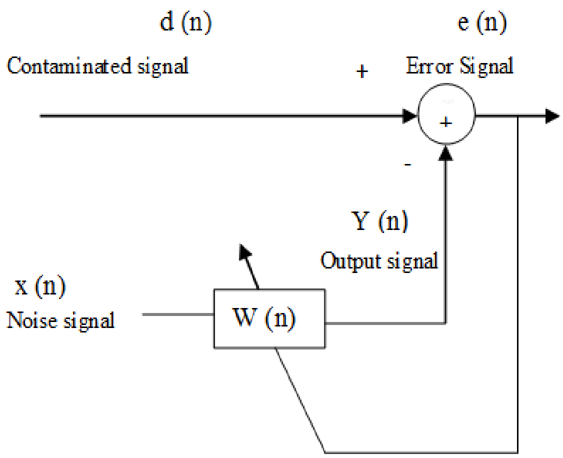

Fig. 1: Structure of adaptive noise cancellation

The idea behind the block diagram is that a variable filter extracts an estimate of the desired signal. The adaptive filters are used for various application such as adaptive identification, adaptive inverse, adaptive prediction and adaptive noise cancellation. This study discuss on the noise cancellation of ECG signal.

Recursive least square algorithm: The Recursive Least Squares (RLS) algorithm is one of the most well-known algorithms used in adaptive filter. When new samples of the incoming signals are received at every iteration, the solution for the least-squares problem can be computed in recursive form resulting in the recursive least-squares algorithm. The Recursive Least Squares (RLS) algorithms attempt to minimize the cost function:

$$\xi\ (n) = \sum_{k=1}^{n} \lambda^{n-k} e_n^2\ (k) \tag{1}$$

where, k = 1 is the time at which the RLS algorithm commences and λ is a small positive constant very close to, but smaller than 1. With values of $\lambda<1$ more importance is given to the most recent error estimates and thus the more recent input samples, this results in a scheme that places more emphasis on recent samples of observed data and tends to forget the past.
The RLS algorithm is shown below:

Step 1: Initialize Weights:

$$w\ (0) = 0 \tag{2}$$

Step 2: Initialize inverse correlation matrix:

$$P\ (0) = \delta^{-1} I \tag{3}$$

Step 3: Compute gain vector:

$$\pi\ (n) = P\ (n-1)\ u\ (n) \tag{4}$$

$$k\ (n) = \frac{\pi(n)}{\lambda + u^t(n)\pi(n)} \tag{5}$$

Step 4: Compute error:

$$e\ (n) = d\ (n) - w^t\ (n-1)\ u\ (n) \tag{6}$$

Step 5: Compute inverse correlation matrix:

$$P\ (n) = \lambda^{-1} P\ (n-1) - \lambda^{-1} k\ (n)\ u^t\ (n)\ P\ (n-1) \tag{7}$$

Step 6: Update the coefficients:

$$w\ (n) = w\ (n-1) + k\ (n)\ e\ (n) \tag{8}$$

Robust recursive least square algorithm: The Robust Recursive Least-Squares (RRLS) adaptive filtering algorithm that utilizes a priori error-dependent weights and the Robustness against predominant noise is accomplished by choosing the weights on the fundamental of the L1 norms of the cross correlation vector and the input-signal autocorrelation matrix. This algorithm also uses a variable forgetting factor that cause fast tracking. This algorithm is robust with respect to noise as well as long bursts of noise in the sense that it converges back to the steady state much quicker than during the initial convergence. This algorithm also tracks sudden system agitation in non-stationary environment. The RRLS algorithm is shown below.
Given d_k and X_k, Choose P, λ_f, $S0 = \varepsilon^{-1} I$ and compute:

$$e_k = d_k - w_{k-1}^T x_k \tag{9}$$

$$t_k = S_{k-1} x_k \tag{10}$$

$$\tau_k = x_k^T t_k \tag{11}$$

$$\hat{\tau_k} = \frac{\lambda_k}{\delta_k} + \tau_k \tag{12}$$

$$\hat{t_k} = \frac{1}{\hat{\tau_k}} t_k \tag{13}$$

$$S_k = \frac{1}{\lambda_k} \left(S_{k-1} - \hat{t_k} * t_k^T \right) \tag{14}$$

$$w_k = w_{k-1} + e_k \hat{t_k} \tag{15}$$

For stationary environment, compute:

$$\lambda_k = \lambda_f \tag{16}$$

$$||x_k||_1 = ||x_{k-1}||_1 + |x_k| - |x_{k-M}| \tag{17}$$

$$\delta_k = \min\left(0.1, \frac{1}{||x_k||_1 |e_k|}\right) \tag{18}$$

For non-stationary environment, compute:

$$g_k = \left[e_k^2 + \epsilon, g_{k-1}^T(1,1\colon P-1)\right]^T \tag{19}$$

$$C = \text{median}\ (g_k) \tag{20}$$

$$\sigma_{1,k}^2 = \beta\sigma_{1,k-1}^2 + (1-\beta)\min\ (\sigma_{1,k-1}^2, C) \tag{21}$$

$$\sigma_{2,k}^2 = \varepsilon\sigma_{2,k-1}^2 + (1-\varepsilon)\ C \tag{22}$$

$$\text{if} \sqrt{\min(\ g_k)} > 4\sigma_{1,k}$$

$$\lambda_k = \max\left[0.1, \min\ (\lambda_f, \frac{\theta_{1,k}\tau_k}{\theta_{2,k}-\theta_{1,k}+\theta_{1,k}\tau_k})\right] \tag{23}$$

$$\delta_k = 1 - \lambda_k \tag{24}$$

$$\text{else}\ \delta_k = \min\ (1, \frac{1}{||x_k||_1 |e_k|})$$

The Electrocardiogram (ECG) is a time varying signal reflecting the ionic current flow which causes the cardiac fibers to contrast and subsequently relax. Based on the electrodes placed on the skin the electrical activity of the heart is measured.

Power line interference noise: Power line interference consists of 60/50 Hz pickup and harmonics that can be modeled as sinusoids and combination of sinusoids. According to Thakor and Zhu (2001), the frequency content of this kind of noise is 60/50 Hz with harmonics and the amplitude is 50% of peak-to-peak ECG amplitude.

Electrode contact noise: Improper contact of the electrodes interrupts for a short period the connection between patient and measuring system creating electrode contact noise. The duration of noise signal is 1 sec and amplitude is maximum recorded output with frequency of 60 Hz.

Motion artifact: The cause of motion artifact is assumed to be vibrations or movements of the subject. The duration of this kind of noise signal is 100-500 msec with amplitude of 500% peak to peak ECG amplitude.

Muscle contractions: This type of noise generates millivolt level artifactual potentials. The standard deviation of this kind of noise is 10% of peak to peak ECG amplitude with duration of 50 msec and the frequency content being dc to 10 KHz.

Baseline wander: Low frequency wander can be caused by respiration or patient movement. This kind of noise causes problems in the detection of peaks. Due to wander T peak would be higher than R peak and it might be detected as R peak instead. Amplitude variation is 15% of peak to peak ECG amplitude and baseline variation is 15% of ECG amplitude at 0.15 to 0.3 Hz.

IMPLEMENTATION OF ADAPTIVE FILTERS

The basic Fourier transform theory states that linear convolution of two sequences in time domain is the same as the multiplication of two corresponding spectral sequence in the frequency domain. Thus filtering is an essence of multiplication of signal spectrum by the frequency domain impulse of the filter. Hence according to the equation of the FIR filter, we can write the output response as given in equation:

$$y\ (n) = \sum_{k=0}^{n} h\ (k)\ x\ (n-k) \tag{25}$$

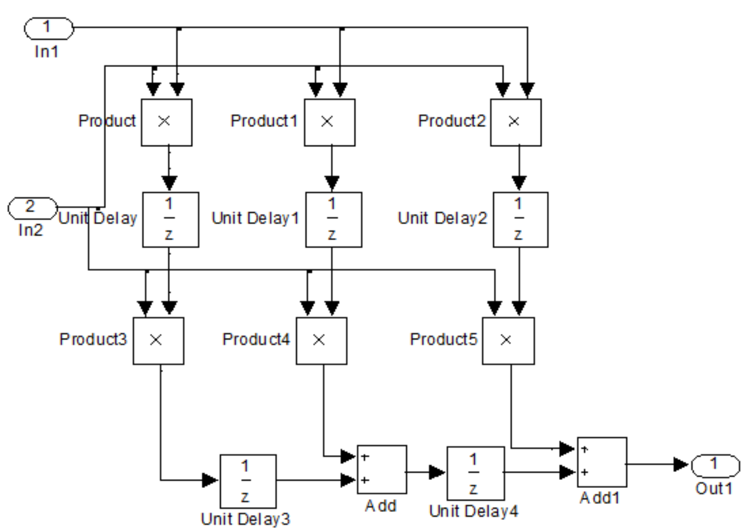

Fig. 2: Fine-grain pipeline structure

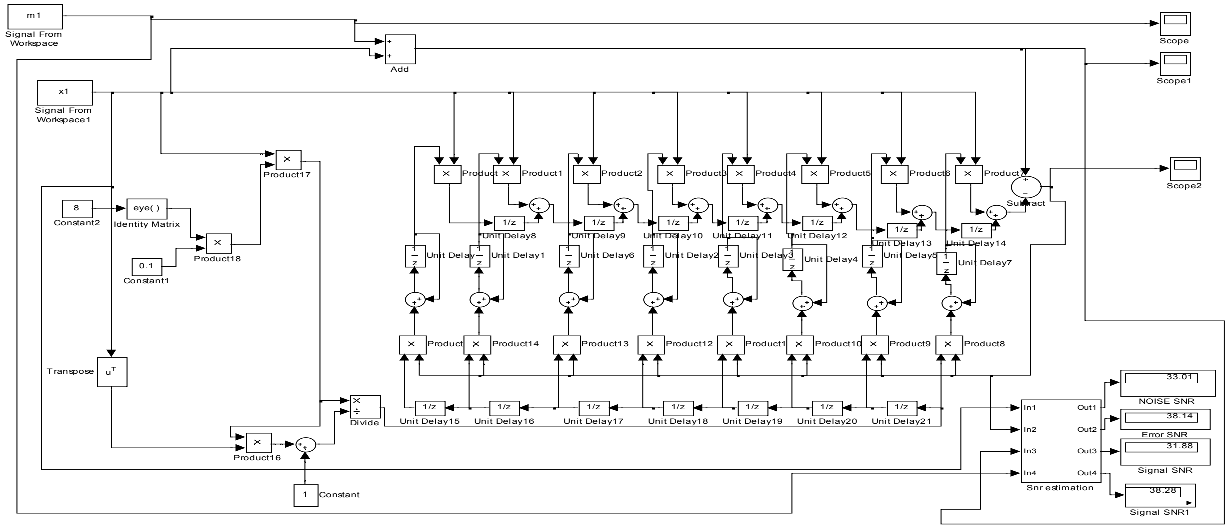

Fig. 3: Eight tap RLS adaptive filter fine-grain structure in SIMULINK

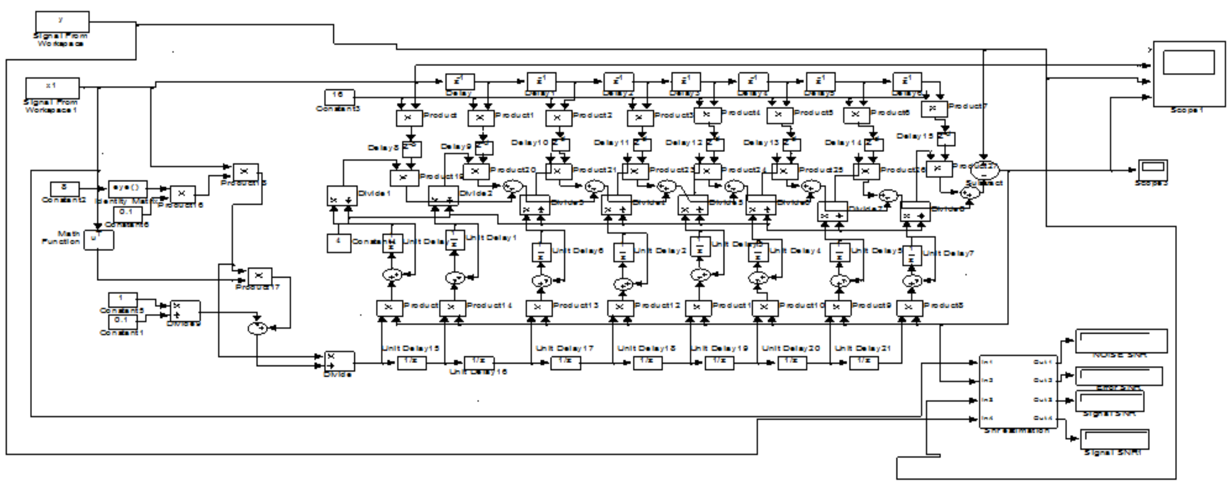

Fig. 4: Eight tap RRLS adaptive filter fine-grain structure in SIMULINK

According to the above equation one possible implementation structure of FIR filter can be designed. This structure is called direct form1. Adaptive filters consists of two process, filtering and updating. The non-adaptive filters have fixed coefficients but in adaptive filters the coefficients are initially zero and updated in every iteration with the help of error and gain functions.

We can transform a given system into a different network structure while maintaining the same system function. One of such transformation is the transposition technique. In this theorem we reverse the direction of all the branches, at the same time we interchange input and output. If we apply transposition theorem to the direct form-1 structure of FIR filter we can obtain the broad cast structure.

Fine-grain structure: There are many pipelining techniques available and used in many filter structures. Pipelined systolic architectures are used in different adaptive filters because of its uniform and regular structure but this structure is not applicable for standard RLS noise cancellation filter. Fine grain pipelining is a technique of decomposing the computation intensive multipliers into small segments. In this method a delay unit is inserted in the small segment of the multiplier so that the critical path and the execution time can be reduced. The fine grain structure is shown in the Fig. 2. Due to the approximation of the multiplier unit there is a deviation of the output response.

The adaptive filters with fine-grain pipeline structure for both RLS and RRLS using MATLAB SIMULINK are shown in Fig. 3 and 4 respectively.

RESULTS AND DISCUSSION

To show that RRLS algorithm is really effective in clinical situations, the method has been validated using

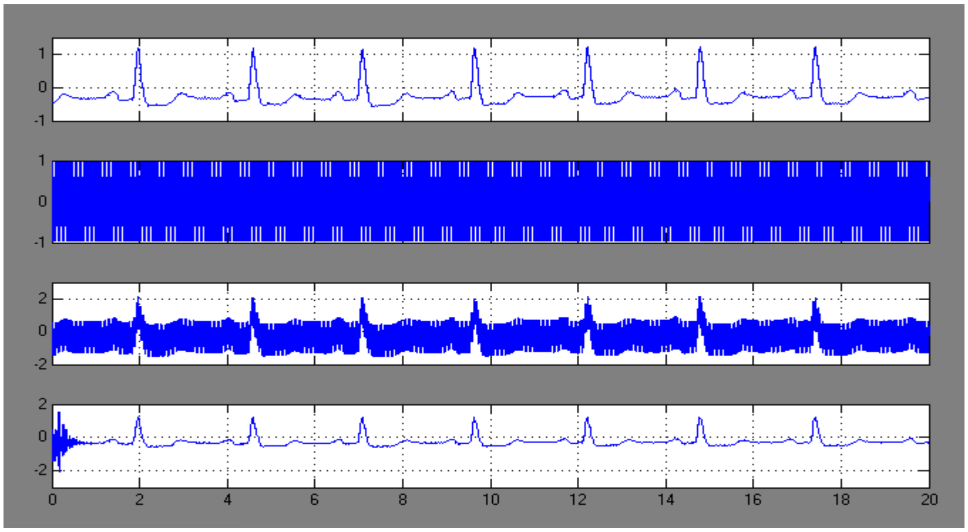

Fig. 5: The first waveform shows the ECG signal collected from database, the second waveform shows the 60 HZ PLI noise, the third waveform shows the ECG signal added with PLI noise and the fourth waveform shows the de-noised signal for the fine-grain pipeline RLS structure

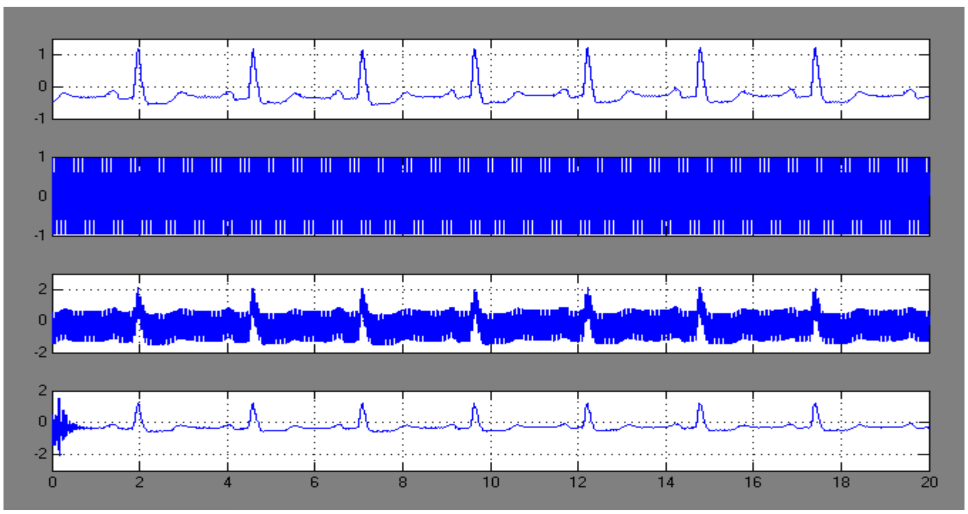

Fig. 6: The first waveform shows the ECG signal collected from database, the second waveform shows the 60 HZ PLI noise, the third waveform shows the ECG signal added with PLI noise and the fourth waveform shows the de-noised signal for the fine-grain pipeline RRLS structure

Table 1: Following table shows the result of RLS

Data	Algorithm	SNR before filtering (dbms)	SNR after filtering (dbms)		
			Without pipelining	With pipelining	SNR improvement
100	RLS	32.01	38.63	38.77	0.14
105	RLS	31.90	38.15	38.30	0.15
108	RLS	32.08	39.02	39.15	0.13
228	RLS	32.23	39.85	39.97	0.12

Table 2: Following table shows the result of RRLS

Data	Algorithm	SNR before filtering (dbms)	SNR after filtering (dbms)		
			Without pipelining	With pipelining	SNR improvement
100	RRLS	32.01	38.80	38.89	0.09
105	RRLS	31.90	38.32	38.33	0.03
108	RRLS	32.08	39.18	39.19	0.01
228	RRLS	32.23	40.01	40.03	0.02

several ECG recordings with a wide variety of wave morphologies from MIT-BIH (Rey Vega *et al*., 2009) arrhythmia database (MIT-BIH physioNet database). Power line interference may severely pervert a bio medical recording. Notch filters and adaptive cancellers have been evoked to inhibit this interference.

An improved adaptive canceller for the reduction of the underlying power line interference component and harmonics in Electrocardiogram (ECG) recordings is designed. To demonstrate Power Line Interference (PLI) cancellation chosen MIT-BIH record number 100. The input to the filter is ECG signal equivalents to the data 100 corrupted with synthetic PLI with amplitude 1 mv and frequency 60 Hz, sampled at 200 Hz. The reference signal is synthesized PLI, the output of the filter is retrieved signal. For all the figures number of samples is taken on x-axis and amplitude on y-axis, unless stated. Figure 5 and 6 shows the simulation results of RLS and RRLS filters respectively.

Table 1 shows the results of RLS filter. The comparison of SNR for different database with respect to pipelined and non-pipelined structures are tabulated. Table 2 shows the SNR comparison for RRLS filter structure. From the table, analysis says that the pipelined structure has better SNR for different ECG databases. The RLS structure has good SNR improvement for pipelined structure. In the case of RRLS there is not much improvement in the SNR for pipelined structure but it has good SNR improvement compared to RLS structure.

CONCLUSION

In this study pipelined structure of adaptive digital filter is designed for both RLS and RRLS adaptive algorithms. The simulation results shows that the SNR of the ECG signals are improved for pipelined structures. Pipelining also increases the speed of the adaptation process. When comparing the RLS algorithm, RRLS algorithm is better for noise cancellation of ECG signals.

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