Low-Power, High-Throughput, and Low-Area Adaptive FIR Filter Based on Distributed Arithmetic

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Abstract: In this paper, a simple and efficient Least Mean Square (LMS) Algorithm is used for cancellation of noise in electrocardiographic (ECG) signals. As LMS Algorithm has a drawback of reduced convergence speed for stationary signals & Poorer tracking probability for non-stationary Signals. The proposed implementation is Block Based Error Non linear signed regressive LMS Algorithm where increased convergence speed for stationary signals & Good tracking capability for non-stationary signals is achieved. The scheme employ that the step size can be chosen independent of the input signal power and the number of tap weights. Simulation studies shows that the proposed realization gives better performance compared to existing realizations based on using Xilinx tool.

Keywords: Adaptive Filtering, Electrocardiographic (ECG), Least Mean Square (LMS) Algorithm, Noise Cancellation.

I. INTRODUCTION

Adaptive noise Cancellation is an alternative technique of estimating signals corrupted by additive noise or interference. Its advantage lies in that, with no prior 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. Its cost, inevitably, is that it needs two inputs: a primary input containing the corrupted signal and a reference input containing noise correlated in some unknown way with the primary noise. The reference input is adaptively filtered and subtracted from the primary input to obtain the signal estimate. Adaptive filtering before subtraction allows the treatment of inputs that are deterministic or stochastic, stationary or time-variable. On analyzing the effect of uncorrelated noises in primary and reference inputs, and presence of signal components in the reference input on the ANC performance, it is shown that in the absence of uncorrelated noises and when the reference is free of signal noise in the primary input can be essentially eliminated without signal distortion.

II. TYPES OF FILTERS

The usual method of estimating a signal corrupted by additive noise is to pass it through a filter that tends to suppress the noise while leaving the signal relatively unchanged i.e. direct filtering. The design of such filters is the domain of optimal filtering, which originated with the pioneering work of Wiener and was extended and enhanced by Kalman, Bucy and others. Filters used for direct filtering can be either Fixed or Adaptive.

A. Fixed Filters

The design of fixed filters requires a priori knowledge of both the signal and the noise, i.e. if we know the signal and noise beforehand; we can design a filter that passes frequencies contained in the signal and rejects the frequency band occupied by the noise as shown in Fig.1.

![Fig.1. Basic Fixed Filter.](image)

B. Adaptive Filters

Adaptive filters, on the other hand, have the ability to adjust their impulse response to filter out the correlated signal in the input. They require little or no a priori knowledge of the signal and noise characteristics. If the signal is narrowband and noise broadband, which is usually the case, or vice versa, no a priori information is needed; otherwise they require a signal (desired response) that is correlated in some sense to the signal to be estimated. Moreover adaptive filters have the capability of adaptively tracking the signal under non-stationary conditions.

Adaptive Noise Canceller: As shown in the fig.2, an Adaptive Noise Canceller (ANC) has two inputs – primary and reference. The primary input receives a signal s from the signal source that is corrupted by the presence of noise n uncorrelated with the signal. The reference input receives a noise n₀ uncorrelated with the signal but correlated in some way with the noise n. The noise no passes through a filter to produce an output n' that is a close estimate of primary
input noise. This noise estimate is subtracted from the corrupted signal to produce an estimate of the signal i.e., the ANC system output.

![Adaptive Noise Cancellation Diagram](image)

**Fig.2. Adaptive Noise Cancellation.**

Noise Cancellation is a variation of optimal filtering that involves producing an estimate of the noise by filtering the reference input and then subtracting this noise estimate from the primary input containing both signal and noise. In noise canceling systems a practical objective is to produce a system output \( s' = s + n - \hat{n} \), that is a best fit in the least squares sense to the signal \( s \). This objective is accomplished by feeding the system output back to the adaptive filter and adjusting the filter through an LMS adaptive algorithm to minimize total system output power. In other words the system output serves as the error signal for the adaptive process. Adaptive noise canceller makes use of an auxiliary or reference input which contains a correlated estimate of the noise to be cancelled. The reference can be obtained by placing one or more sensors in the noise field where the signal is absent or its strength is weak enough. Subtracting noise from a received signal involves the risk of distorting the signal and if done improperly, it may lead to an increase in the noise level. This requires that the noise estimate \( \hat{n} \) should be an exact replica of \( n \). If it were possible to know the relationship between \( n \) and \( \hat{n} \), or the characteristics of the channels transmitting noise from the noise source to the primary and reference inputs are known, it would be possible to make \( \hat{n} \) a close estimate of \( n \) by designing a fixed filter. However, since the characteristics of the transmission paths are not known and are unpredictable, filtering and subtraction are controlled by an adaptive process.

Hence an adaptive filter is used that is capable of adjusting its impulse response to minimize an error signal, which is dependent on the filter output. The adjustment of the filter weights, and hence the impulse response, is governed by an adaptive algorithm. With adaptive control, noise reduction can be accomplished with little risk of distorting the signal. In fact, Adaptive Noise Cancelling makes possible attainment of noise rejection levels that are difficult or impossible to achieve by direct filtering. The error signal to be used depends on the application. The criteria to be used may be the minimization of the mean square error, the temporal average of the least squares error etc. Different algorithms are used for each of the minimization criteria e.g. the Least Mean Squares (LMS) algorithm, the Recursive Least Squares (RLS) algorithm etc. To understand the clear concept of adaptive noise cancellation, the minimum mean-square error criterion is used. The steady-state performance of adaptive filters based on the minimum mean square error (mmse) criterion closely approximates that of fixed Wiener filters. Hence, Wiener filter theory provides a convenient method of mathematically analyzing statistical noise canceling problems.

**Applications of Adaptive Noise Cancellers:** In depth quantitative analysis of its use in canceling sinusoidal interferences as a notch filter, For bias or low-frequency drift removal. As adaptive line enhancer. Use of ANC without a Reference input for canceling periodic Interference, Adaptive self-tuning filter, Antenna sidelobe interference canceling and Cancellation of noise in speech signals, etc.

### III.THE EXISTING SYSTEM

The existing system uses Least mean squares (LMS) algorithms which is a class of adaptive filter, used to mimic a desired filter by finding the filter coefficients that relate to producing the least mean squares of the error signal (difference between the desired and the actual signal). It is a stochastic gradient descent method in that the filter is only adapted based on the error at the current time, which uses a gradient-based method of steepest decent. LMS algorithm uses the estimates of the gradient vector from the available data. LMS incorporates an iterative procedure that makes successive corrections to the weight vector in the direction of the negative of the gradient vector which eventually leads to the minimum mean square error. Compared to other algorithms LMS algorithm is relatively simple, it does not require correlation function calculation nor does it require matrix inversions.

**A. Least Mean Square Algorithm**

The extraction of high-resolution ECG signals from recordings contaminated with back ground noise is an important issue to investigate. The goal for ECG signal enhancement is to separate the valid signal components from the undesired artifacts, so as to present an ECG that facilitates. Easy and accurate interpretation. Many approaches have been reported in the literature to address ECG enhancement. In recent years, adaptive filtering has become one of the effective and popular approaches for the processing and analysis of the ECG and other biomedical signals. Adaptive filters permit to detect time varying potentials and to track the dynamic variations of the signals. Besides, they modify their behavior according to the input signal. Therefore, they can detect shape variations in the ensemble and thus they can obtain a better signal estimation. Adaptive solution based on the LMS algorithm is suggested for noise cancellation in ECG. The reference inputs to the LMS algorithm are deterministic functions and are defined by a periodically extended, truncated set of orthonormal basis functions. The LMS algorithm operates on an "instantaneous" basis such that the estimate. In a recent study, however, a steady state convergence analysis for the LMS algorithm with deterministic reference inputs showed that the steady-state weight vector is biased, and thus, the adaptive estimate does not approach the Wiener solution.
Low-Power, High-Throughput, and Low-Area Adaptive FIR Filter Based on Distributed Arithmetic

To handle this drawback another strategy was considered for estimating the coefficients of the linear expansion, namely, the block LMS (BLMS) algorithm, in which the coefficient vector is updated only once every occurrence based on a block gradient estimation. The weights will be computed using LMS algorithm based on Minimum Squared Error (MSE) criterion. Therefore the spatial filtering problem involves estimation of signal from the received signal s(t) by minimizing the error between the reference signal d(t) , which closely matches or has some extent of correlation with the desired signal estimate and the output y(t) (equal to w*x(t)). This is a classical Weiner filtering problem for which the solution can be iteratively found using the LMS algorithm as shown in Fig. 3. The LMS algorithm is initiated with an arbitrary value w(0) for the weight vector at n=0. The successive corrections of the weight vector eventually lead to the minimum value of the mean squared error. The output of the adaptive filter is given by

\[ y(n) = w^T(n)x(n) \]  

(1)

The error signal, \( e(n) \) is obtained by subtracting the signal \( d(n) \) from the output of the filter \( y(n) \) which is given by, \( e(n) = d(n) - y(n) \). The weight update equation of the LMS algorithm is obtained as follow

\[ w(n+1) = w(n) + 2\mu x(n) [e(n)] \]  

(2)

where, \( w(n) = [w_0(n) w_1(n) ... w_{L-1}(n)]^T \) is the tap weight vector at the nth index, \( x(n) = [x(n) x(n-1) ... x(n-L+1)]^T \) is the number of iterations and \( L \) is the filter tap length with \( d(n) \) being so-called the desired response available during initial training period, and \( \mu \) denoting so-called step-size parameter. The value of \( \mu \) varies between 0 to 1 which is a positive parameter controlling the stability and the convergence speed. A larger value for \( \mu \) can increase the convergence speed, but a smaller value can ensure better stability.

### B. LMS-Based Adaptive Filter Structure

![Fig.3. Architecture of LMS adaptive filter.](image)

**Advantages of LMS Algorithm:**
- Simplicity in implementation.
- Stable and robust performance against different signal conditions. Convergence for non stationary signals.

### IV. THE PROPOSED SYSTEM

New algorithms that make use of the signum (polarity) of either the error or the input signal, or both, have been derived from the LMS algorithm for the simplicity of implementation, enabling a significant reduction in computing time, particularly the time required for “multiply and accumulate” (MAC) operations. These algorithms are attractive for their assured convergence and robustness against the disturbances in addition to the ease of implementation. The advantage of the BBENSRLMS algorithm is that the step size can be chosen independent of the input signal power and the number of tap weights. Hence, the ENLMS algorithm has a convergence rate and a steady-state error better than the LMS algorithm. Types of Block Based Sign Algorithms:
- Block Based Error Non Linear Signed LMS Algorithm.
- Block Based Error Non Linear Signed Regressor LMS Algorithm. \((4,1)\)
- Block Based Error Non Linear Sign-Sign Algorithm.

### A. Block Based Error Nonlinear Signed Regressive LMS Algorithm

A common major drawback of adaptive noise cancellers using LMS-based algorithms is the large value of excess mean-square error which results in signal distortion in the noise-cancelled signal. On the other hand, some additional computations are required to compute \( \mu \). In order to cope up with both the complexity and convergence issues without any restrictive trade off, block based error non linear signed regressive LMS algorithm is proposed. The number of computations required for the proposed Block-Based ENRLMS is independent of filter length. The BBENSRLMS algorithm is initiated with an arbitrary value \( w(0) \) for the weight vector at \( n=0 \). The successive corrections of the weight vector eventually lead to the minimum value of the mean squared error. The output of the adaptive filter is given by

\[ y(n) = w^T(n)x(n) \]  

(3)

The error signal, \( e(n) \) is obtained by subtracting the signal \( d(n) \) from the output of the filter \( y(n) \) which is given by,

\[ e(n) = d(n) - y(n) \]  

(4)

The weight update equation of the LMS algorithm is obtained as follows.

\[ w(n+1) = w(n) + \mu x(n) [e(n)] \]  

(5)

where, \( w(n) = [w_0(n) w_1(n) ... w_{L-1}(n)]^T \) is the tap weight vector at the nth index, \( x(n) = [x(n) x(n-1) ... x(n-L+1)]^T \) is the number of iterations and \( L \) is the filter tap length with \( d(n) \) being so-called the desired response available during initial training period, and \( \mu \) denoting so-called step-size parameter. The value of \( \mu \) varies between 0 to 1 which is a positive parameter controlling the stability and the convergence speed. A larger value for \( \mu \) can increase the convergence speed, but a smaller value can ensure better stability.

### B. BB-ENSRLMS Based Adaptive Filter Structure

The realizations of a three-tap adaptive filter based on the
BB- ENSRLMS algorithm is shown in the fig.4, which adjust its coefficients. The BB- ENSRLMS adaptive filter (BBENSRLMS) can be described by the following equations:

\[ y_k = w_0, k x_k + w_1, k x_k-1 + \ldots + w_N-1, k x_k-N+1 \]  \hspace{1cm} (6)

\[ W_{i,k+1} = W_{i,k} + \frac{\mu}{e_k} e_k x_{i,k-1} \]  \hspace{1cm} (7)

Where \( w_{i,k} \) and \( e_k \) are defined and

\[ e_L \{ \text{max} e_k \} \} ; Z_i = \{ L_i L_{i+1} \ldots L_{i+L-1} \}; i \in Z. \]  \hspace{1cm} (8)

Fig.4. Architecture of BBENSRLMS adaptive filter.

Advantages of Bbensrlms Algorithm:
- Increased convergence speed for stationary signals, Good tracking capability for non-stationary signals.

V. RESULTS AND DISCUSSION

The Least mean square (LMS) algorithm is one of the oldest algorithm in denoising the ECG signal. This algorithm when implemented in adaptive filter leads to high computational complexity. So in order to minimize the computational complexity, the Block based error nonlinear Signed regresor algorithm is chosen multiplications of input samples with a fixed positive number.

- Block Based error nonlinear Signed regresor.
- Algorithm (BBENSRLMS) reduces the computational.
- Complexity by the reduction of multipliers and the step size can be chosen independent of the input signal power.

VI. SIMULATION OF LMS AND BBENSRLMS ALGORITHM

Based upon the architecture of BBENSRLMS adaptive filter structures the block based module is simulated in Modelsim in which the largest magnitude value is calculate from the available ECG sample value provided that the value of block size is equal to 10 and the signum function is applied to the obtained largest magnitude value. The simulated output waveform is obtained which is shown in fig.5. Since the ECG sample values are real values, ordinary binary multiplier cannot be preferred and so the single precision floating point multipliers which do the multiplication operation with the real values is designed and simulated in Modelsim. The outputs of floating point multiplier obtained for three different cases. The output waveform shown in fig.6 is for the case where both the numbers are positive. Similarly the single precision floating point adder which performs addition operation with the real values is designed and simulated in Modelsim. The outputs obtained for two different cases. The output waveform shown in fig.7 is for the case where both the numbers are positive. The single precision floating point adders, multipliers and divider takes the input which should be in the form of floating point representation.
Low-Power, High-Throughput, and Low-Area Adaptive FIR Filter Based on Distributed Arithmetic

- Block size=10.
- Inputs are obtained from the benchmark MIT-BIH arrhythmia database ECG records as reference to our work.
- Outputs are highest magnitude value $=3.2572799778959$ and sgn=+1.

So the ECG samples from MIT-BIH Arrhythmia records whose values are real numbers, has to be converted into floating point format so that the designed adder multiplier and divider can be made useful. The number conversion function which converts real value to 32 bit floating point value is designed and simulated. The output waveform for the number conversion function is shown in fig.8. With all the obtained results of individual components, the integration of all the modules has been performed based on the architecture of LMS algorithm with the input of 1400 samples of ECG signal obtained from MIT-BIH arrhythmia database and the output waveform is obtained Which is shown in fig.9.

**Fig.8. Simulation Waveform of Floating point multiplier.**

- Inputs are
  01000001010001111000000000000000(+8.95)
  01000000110000000000000000000000(+4.25)
- Output
  01000010010011111000000000000000(+32.0375).

**Fig.9. Simulation Waveform of Floating point adder.**

- Inputs are
  0100000001000100110011001100110011(+2.3) and
  010000011101100110011001100110011(+7.4)
- Output
  010000010001100110011001100110011(+9.7).

Like LMS, the extra module i.e., floating point divider is added along with all the integrated modules of LMS filter and the simulation has been performed for BBENSRLMS. Filter with the same 1400 input samples of ECG signal obtained from MIT-BIH arrhythmia database and the output waveform is obtained which is shown in fig.10.

**Fig.10. Simulation Waveform of Real to Floating point Number Conversion.**

- Input -15.75
- Output 11000000101111100000000000000000

The floating point divider which does the division operation. With single precision floating value as its inputs and produce the output waveform which is shown in fig.11.
difference between those two signals greater than zero. The only option is to minimize the between the signal \( s(n) \) and the error signal \( e(n) \) will always be

nature of the error signal, the error signal will never become

some way, preferably equal, to get the best results. Do to the

\( s(n) \) corrupted by another noise \( N \)

compared with a desired signal \( d(n) \), which consists of a signal

\( s(n) \) corrupted by another noise \( N' \). The adaptive filter

coefficients adapt to cause the error signal to be a noiseless

version of the signal \( s(n) \). Both of the noise signals for this

configuration need to be uncorrelated to the signal \( s(n) \). In

addition, the noise sources must be correlated to each other in

some way, preferably equal, to get the best results. Do to the

nature of the error signal, the error signal will never become

zero. The error signal should converge to the signal \( s(n) \), but

not converge to the exact signal. In other words, the difference

between the signal \( s(n) \) and the error signal \( e(n) \) will always be
greater than zero. The only option is to minimize the difference between those two signals.

**Synthesis Report:** Xilinx ISE 13.3 tool has been used to map the design to FPGA Xilinx Virtex-5lx110ttf1136 with speed grade -1. The existing method, LMS and the proposed design, BBENSRLMS are then analyzed and comparison done respectively

**TABLE I: Comparison of LMS and BBENSRLMS Adaptive Filter**
VII. CONCLUSION

In this project, low area and reduced delay adaptive filter has been designed which benefits from the concept of block separation and signum function and hence helping in delay reduction. The design has been described using VHDL and implemented on VirtexV Pro based 5vx110tff1136-1 FPGA using ISE13.3. The overall design shows that the effective speed of operation increases by 2.06% and achieves high SNR with less computational complexity. The input and the desired response signals are properly chosen in such a way that the filter output is the best least square estimate of the original ECG signal. From the above discussions, it is clear that the BBENSRMLS converges faster and computational complexity is reduced when compared to the LMS algorithm. So BBENSRMLS algorithm can be used in wireless biotelemetry systems. In the future work, the application of Block Based Error nonlinear Signed Regressor Least Mean Square Algorithm for the noise cancellation in DCT Domain may lead to better signal to noise ratio.

VIII. REFERENCES