Abstract - Different forms of noise are caused by electrocardiogram (ECG) signals, which vary based on frequency content. To enhance accurateness and dependability, the elimination of such a trouble is necessary. Denoising ECG pointers is difficult as it is difficult to add secure coefficient filter. It is possible to use adaptive filtering techniques, in which the feature vectors can be changed to top dynamic signal changes. With a degree of sparsity, such as non-sparse, partial sparse and sparse, the framework shifts. The Least Mean Square (LMS) and Zero Attractor LMS (ZA-LMS) convex filtering combination is ideal for both Sparse and Non-Sparse settings. Popular the proposed design, the Systolic Architecture is introduced in direction to improve device efficiency and to reduce the combinational delay path. Systolic architectures are developed using the Xilinx device generator tool for normal Least Mean Square (LMS), Zero Attractor LMS (ZA-LMS) and Convex combinations of Least Mean Square (LMS) and Zero Attractor LMS (ZA-LMS) interfaces. Simulation remains performed with various ECG signals obtained from MIT-BIH database as input to designed filtering and its SNR is obtained. The study shows that the SNR value in systolic architectures is higher than in filter bank structures. For systolic LMS buffers, the SNR value is 4.5 percent greater than the structure of the Lms algorithm. The SNR for the systolic separation technology of ZA-LMS is 2.5 percent higher than the separation technology of ZA-LMS. The SNR value for LMS and ZA-LMS filtering structure convex combinations is 6% higher than that for LMS and ZA-LMS filtering structure convex combinations.

Keywords - Digital Signal Processing, LMS algorithm, ZA-ENSLMS algorithm

1. Introduction

Adaptive Filter

A proposed technique remains a computing system that efforts to iteratively classical the interaction among two signals in real time. Adaptive filtering is repeatedly realized moreover as a series of programmed instructions serially on an arithmetical processing system such as a microprocessor before Digital Signal Processing chip, or as a regular of logic operations implemented in Field Programmable Gate Array or in a semicustom or custom Very Large-Scale Integrated circuit. A proposed technique constitutes an essential part of the processing of statistical signals.

The device works in realistic circumstances in an unpredictable setting where the input state is not apparent and/or there is unwanted noise. The filter bank, which is a powerful device with a wide variety of engineering applications, offers a highly efficient solution to this more difficult problem.

Adaptive filtering consists of three basic components: the h(n) adaptive filter, the e(n) error, and the: y(n)=x(n)*h(n) adaptation function, as shown in Figure 1. The aim of the device is to adjust the buffer in such a way that the x(n) input signal is filtered to produce a y(n) output signal that reduces the e(n) error signal when subtracted from the d(n) signal desired. To show that the device is adaptive, the arrow through the fir algorithm is the normal notation. This means it is possible to change all transfer function in such a way that the Mean Square Error should be reduced. Finite Impulse Response or Infinite Impulse Response interfaces, or even a non-linear system, may be an interlayer. Many filter methods use a type of Finite Impulse Response to ensure the stability of the adaptive algorithm.

Fig.1: Adaptive Filter

The filter bank applications can be grouped into four basic groups based on the implementation architecture:
adaptive detection, adaptive inverse, adaptive prediction, and active noise cancellation.

The aim of an adaptive noise canceller is to remove noise from the received signal in an adaptively controlled manner to boost the signal-to-noise ratio, as shown in Figure 2 above. A special type of noise cancellation is echo cancellation, heard on telephone circuits. In electrocardiography, noise cancellation is also used [1].

2. Existing Method

LMS Algorithm

In adaptive filters, an adaptive algorithm is shown in Figure 3 which updates the weight vectors to minimize cost-effectiveness. Least Mean Square (LMS), Normalized Least Mean Square (NLMS), Error Nonlinear Least Mean Square (ENLMS) and Block Dependent LMS algorithm (BB-LMS) are the LMS algorithms used for adaptive applications [2]. The Least Mean Square (LMS) algorithm is a filter bank class used to closely approximate the desired signal by finding the pixel value associated with the least mean error signal squares, i.e., the alteration between the desired indicator and the actual indicator [3]. It remains a form of stochastic gradient descent in which the filter weights are only adapted at the current time depending on the error. The weight update equation is indicated in Equation (3.1) according to this LMS algorithm.

\[ W(n+1) = w(n) + 2\mu e(n)x(n) \]  (3.1)

where,
\[ \mu \] - scale of the move
\[ W(n) \] - course of the tap weight
\[ E(n) \] - the indication of error
\[ x(n) \] - the entry for a filter

Nil Attracting-Algorithm for Lms

An alternative approach to define a sparse method that adds a cost function l1 standard penalty resulting in an updated LMS update comparison known as the ZA-LMS algorithm that is fewer complex and yields less error than the PNLMS algorithm [4]. The implementation of the L1 standard drawback in the LMS modernize equation results in an LMS algorithm of zero attraction. In all the taps, its weight update equation has zero attractor [5].

Due to the presence of zero attractor, particularly in the inactive taps, this approach coefficient is reduced, which decreases error in sparse systems [6]. Further modifications were made to the ZA-LMS algorithm recognized as 'Reweighted Zero attracting-LMS' (RZA-LMS), in which zero attractors have been reweighted to the opposite of the magnitude of the tap, limiting the reduction to inactive taps only. This is ZA-LMSS, according to the co-efficient modernize equation of the algorithm is given in Equation (3.2),

\[ W_k(m) = W_k(m-1) - \rho \text{sgn}\{W_k(m-1)\} + 2\mu E(m)X(m) \]  (3.2)

Lms and Za-Lms Algorithms Combination

As shown in Figure 4, for sparse as fine as non-sparse conditions, the convex adaptive arrangement of LMS and ZA-LMS algorithms operates. Dynamically, the convergence is enhanced via the LMS algorithm for the non-sparse signal and the convergence is enhanced via the ZA-LMS algorithm for the sparse signal. A vector \( A(m) \) is used instead of \( \lambda(m) \), i.e.,

\[ \lambda(m)=\frac{1}{1+\exp(-A(m))} \]
\[ A(m+1) = A(m) + \mu aE(m)[Y1(m)-Y2(m)] \]  (3.3)

In Equation (3.3) with \( \mu a \)-step scale, the modernized equation of \( A(m) \) is provided.
For three different types of structures, namely, non-sparse, semi-sparse and sparse, we have performed this exercise [7]. The analysis shows that while the proposed combined filter always converges to the LMS-based filter for a non-sparse system i.e., the better of the two filters in terms of less steady state EMSE for the non-sparse case), for semi-sparse systems, it actually converges to a solution that can outperform both constituent filters by generating less EMSE than that generated by either of the two constituents. The proposed scheme usually converges with the ZA-LMS unit for sparse systems [8].

However, it is also possible to converge to a solution that like the semi-sparse case, outperforms all the component filtering by changing a proportionality constant associated with the zero attractor in the ZA-LMS algorithm [9]. A simplified update formula for the mixing parameter in the adaptive convex combination is also provided in this paper, using some approximations for the corresponding gradient expression [10].

3. Proposed Method

Systolic Architecture

A network of processing elements (PE) that rhythmically compute and transfer data through the device is a systolic architecture [1]. The systolic structure is also known as the systolic series. In a systolic array, all PEs are uniform and they pump data in and out continuously so that a constant flow of data is preserved [12]. PE is also known as Neuron. A sequence of operations on data flowing between them is carried out by each cell. Generally, in each cell, the operations are the same [13].

4. Results and Discussion

The polluted ECG indicator is applied to the detector as the input and PLI noise is applied to the barrier as the reference input signal. The blocks used are adder, multiplier, unit delay, divider, constant, workspace signal and scope in the LMS structure.

Simulation performance of 16-tap convex filter structure in simlink combination of ENSLMS and ZA-ENSLMS

The ECG signals were derived from the MIT-BIH arrhythmia database of benchmarks. The recordings were digitized over a 10mV spectrum at 360 trials per second per channel with an 11-bit resolution.

Fig. 5: 16-tap output Convex ENSLMS and ZA-ENSLMS filtering structure combination for Speech Signal Denoising

The above Figure 5 shows the performance of the 16-tap convex ENSLMS and ZA-ENSLMS filtering structure combination for denoising the speech signal. The noisy voice is entirely denoted by modified fir filter and a denoised voice signal is obtained.

5. Implementation Results

For implementation purposes, the Xilinx Virtex 5 FPGA is recycled. Following efficient simulation, hardware co-simulation is completed. During the co-simulation stage, the bit stream file is automatically generated and associated with the JTAG co-simulation block. Now when the design is simulated, it runs between the FPGA and the machine through the JTAG block.

6. Conclusion and Future Work

By integrating systolic architecture, the efficiency of adaptive filtering is increased. Various adaptive filtering such as Convex Combination of ENSLMS and ZA-ENSLMS filtering and Systolic Architecture for Rounded Combination of ENSLMS and ZA-ENSLMS filter is designed for Different Tap Duration and simulated using Simulink and implemented in Xilinx System Generator for Xilinx System Generator to contain power line interference noise obtained later the MIT-BIH database. The output of various adaptive filters is evaluated from the simulation results with regard to the SNRs obtained. The study shows that the SNR value in systolic architectures is higher than in filter bank structures. The results show a 4.36 percent, 3.78 percent and 5.38 percent increase in the SNR for 4-tap, 8-tap and 16-tap Systolic Convex combination of Error Non-linear Sign Least Mean Square (ENSLMS) and Zero Attractor Error Non-linear Sign LMS (ZA-ENSLMS) filtering structure respectively and a 7.26 percent reduction in MSE of 12.11 percent and 10.6 percent for 4-tap, 8-tap and 16-tap Systolic Convex transdermal patch respectively. Optimization of the Potential Region in VLSI Architecture is not achieved in the proposed architecture. The proposed Area Optimization architecture can therefore be implemented with high-level transformation techniques.
References

[1]. Supriya, M., Dhivyadevi, R., Shanmugaraja, T., Venkatesh, T., 'Multi-ported memory on fpga for a high performance fir filters', International Journal of Advanced Science and Technology, 2020, 29(7 Special Issue), pp. 1464-1472

[2]. Shanmugaraja, T., Jai Shankar, B., Siddharthraj, K., Dhivyadevi, R., Supriya, M., 'Parametric optimization of architectural modified fir filter', International Journal of Advanced Science and Technology, 2020, 29(7 Special Issue), pp. 1481-1487

[3]. Arenas-Garcia, Gomez-Verdejo V & Figueiras-Vidal A R, 'New algorithms for improved adaptive convex combination of LMS transversal filters', IEEE. Transaction on Instrumentation and Measurement, vol. 54, no. 6, pp. 2239–2249, 2005.

[4]. Arenas-Garcia J & Figueiras-Vidal A R, 'Adaptive combination of proportionate filters for sparse echo cancellation,' IEEE Transaction on Audio Speech Language Process, vol. 17, no. 6, pp. 1087–1098, 2009.

[5]. Bijit Kumar Das & Chakraborty M, 'Sparse Adaptive Filtering by an Adaptive Convex Combination of the LMS and the ZA-LMS Algorithms', IEEE Transactions on circuits and systems, vol. 61, pp. 1510-1516, 2014.

[6]. Bailmare R H, Honal S J and Kinge P V, 'Design and Implementation of Adaptive FIR filter using Systolic Architecture', International Journal of Current Engineering and Technology, vol.4, pp.1162-1170, 2014.

[7]. Dunweiler D L, 'Proportionate normalized least mean square adaptation in echo cancelers,' IEEE Transaction on Speech Audio Processing, vol. 8, pp. 508-518, 2000.

[8]. Gu Y, Chen Y & Hero A O, 'Sparse LMS for system identification', in. IEEE ICASSP Proceeding, Taipei, Taiwan, vol. 43, pp. 2135-2152, 2009.

[9]. Hongyang Deng & Milo’s Dorosloavaki, ‘Proposinate Adaptive Algorithms for Network Echo Cancellation’, International Journal of Current Engineering and Technology, vol. 40, pp. 2799–2803, 2006.

[10]. Jacob Benesty & Steven L Gay, ‘An Improved PNLMS algorithm’, IEEE. Transaction on Instrumentation & Measurement, vol. 12, no. 3, pp. 181–182, 2002.

[11]. Jerónimo Arenas-Garcia & Anibal R Figueiras-Vidal, ‘An Adaptive Combination of Proportionate Filters for Sparse Echo Cancellation’, IEEE Transaction on Audio Speech Language Process, vol. 48, pp 460-470, 2009.

[12]. Lan-Da Van & Wu-Shiung Feng, ‘An efficient systolic architecture for the delay least-mean-square (DLMS)’, International Journal of Current Engineering and Technology, vol. 9, pp. 1968-1980, 2013.

[13]. Mohammad Zia ur Rahman, Rafi AhamedShaik & Dr Rama koti reddy, ‘Base line wander & power line interference elimination from cardiac signals using Error Nonlinearity LMS algorithm’, Proceedings of International Conference on systems in medicine & biology, vol. 59, pp. 141-156, 2010.