LMS Adaptive Filter Implementation using Distributed Arithmetic Methodology

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Abstract— Presentation of an efficient architecture for the implementation of a delayed least mean square adaptive filter. For achieving lower adaptation-delay and area-delay-power efficient implementation, we use a novel partial product generator and propose a strategy for optimized balanced pipelining across the time-consuming combinational blocks of the structure. From synthesis results, we find that the proposed design offers less area-delay product (ADP) and less energy-delay product (EDP) than the best of the existing systolic structures. An efficient fixed-point implementation scheme of the proposed architecture, and derive the expression for steady-state error shows that the steady-state mean squared error obtained from the analytical result matches with the simulation result.

Keywords—Adaptive, Filter, Distributed, Arithmetic, LMS.

I. Introduction

Speech is the most fundamental way of communication used by human being. Speech signal is one dimensional signal and has comparatively low bandwidth of 8 kHz. This is very useful in various applications with different evolving technologies. Noise is an undesirable signal. When it is mixed with speech signal, it is very difficult to deliver actual information from one place to another. To differentiate original information containing signal from unwanted noise; filtering is a basic and common method. Filters extract useful information from its input depending upon its configuration.

Digital representation of speech signal eases its handling and further processing. Hence digital filters are useful for acquiring desired characteristics of speech signal by avoiding its noise contents. One of the digital filters is adaptive filter. Adaptive filters detect time varying potentials and the dynamic variations of the signals. Accordingly filters modify their internal structure, behavior as per input signal. The types of adjustable coefficients are reflection coefficients, rotation parameters, tap weights or synaptic weights etc. Filters adapt their configuration according to present conditions. Practical Applications in which Noise cancellation by adaptive filters is used are; the cancelling of various forms of periodic interference in electrocardiography and in speech signals, the broad-band interference in the side-lobes of an antenna array can also be cancelled.

ADAPTIVE FILTERING:

Fixed coefficient filters have fixed internal parameters and structure. To work properly, some filters may require matching of statistical characteristics of input signal with prior information along with that filter. These types of conditions may not meet all the time. Filter may require changing its coefficient according to input conditions or it may not have prior knowledge about incoming input. So filter must adjust its characteristics for unknown conditions with the help of some predefined algorithms, to make changes as per requirement any time. It may lead to increase in hardware as well as software cost design. Hence in such cases adaptive filters are useful.

A self-designing device that operates on a recursive algorithm to separate out required information from unwanted signal is known as adaptive filter.

Such filters perform satisfactorily in conditions where system doesn't have complete knowledge of signal characteristics. Recursive algorithm used in adaptive filter starts from predefined set of initial conditions and updates the parameters of filter from one to next iteration and hence parameters become data dependent. Adaptive filters can be categorized in two types as linear and nonlinear. If output of filter does not obey principle of superposition for combination of its inputs then it is nonlinear adaptive filter. On the other hand if output is linear function of applied inputs to filter then it is a linear adaptive filter

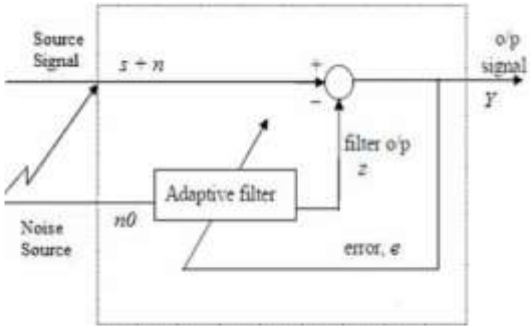

Figure 1: Basic adaptive noise cancelled

Adaptive noise canceller receives two inputs namely primary input and reference input. Primary input is combination of source signal and noise signal uncorrelated with each other. While the reference input is another noise signal, correlated in some extent with noise only. Reference input goes through adaptive filter producing which is near estimate of primary input. This filter output is subtracted from primary input resulting in some residue i.e. error. Main purpose of using adaptive noise canceller here is to have output which is best fit in the least squares sense to the signal. To achieve output, the error is fed back to adaptive filter that adjusts the filter using adaptive algorithm. Thus minimizes total system output power.

Linear adaptive filters work on recursive algorithm which considers following important factors. These are number of iterations required by the algorithm when stationary inputs are applied, to achieve optimum solution in the mean square sense. If small disturbances internal, external cause small estimation errors then adoptive filter is said to be robust. It includes number of operations of a single iteration and required memory to store data and program. As explained above, adaptive filter uses adaptive algorithm for adjustment of internal parameters to have correct output. Some basic adaptive algorithms along with approaches on which they are based are explained below:

With the help of this approach filters are designed using statistical formulation. Adaptive filter precisely uses second order function of tap weights. Updating of tap weights for recursive algorithm is carried out using Wiener-Hopf equations. Basic algorithms under this approach are as follows

This was introduced by Widrow and Hoff in 1959. Every tap weight in filter is updated in the direction of the gradient of the squared amplitude of an error signal with respect to that tap weight . This technique doesn't require prior knowledge of the detailed properties of the noise signal. In case of speech signal this technique takes advantage of the quasi-periodic nature of the speech. The coefficient update equation is given by,

$$w(k+1) = w(k) + 2\mu * x(k) * e(k) \tag{1.1}$$

Here $w(k+1)$ is filter coefficient for next iteration, is filter coefficient of present iteration, x(k) is input value, e(k) is error value and : Step size which determines convergence or divergence rate. LMS is a simple technique with unbiased convergence in the mean to the Wiener solution and has the existence of a proof of convergence in a stationary environment but offers lower convergence rate. Adaptive filter in this case is used in transversal structure.

Stochastic gradient approach can also be implemented by using Adaptive filter in lattice Structure. In such case it is well known as gradient adaptive lattice algorithm. It performs well in noise cancellation. It gives good results in terms of SNR, correlation coefficient and convergence time.

This approach uses method of least squares. Adaptive filter used with this approach minimizes a weighted sum of the squared estimation errors in a recursive manner. So the filter is called as recursive least squares (RLS) adaptive filter. It uses all the information of input data from the start of adaption to the present. Advantageous part of using this filter is that it produces the exact solutions to appropriately-formulated optimization problem at each iteration. It provides extremely fast convergence. On the other hand it has more computational complexity and also has potentially poor tracking performance if filter requires changes. RLS gives better signal to noise ratio in case of small filter length. Depending on the approaches used, RLS filters are classified into Standard RLS, Square root RLS and Fast RLS.

II. LITERATURE REVIEW

De-noising or enhancement of speech signals plays a very important role in speech recognition and communication. Research has been conducted in force from 1970's and a vast number of techniques and algorithms have been proposed. The Kalman and extended Kalman filter based algorithms, technique using spectral subtraction and its modification are the most well known enhancement methods, and references therein. Recently, techniques using two or more microphones (mic array) have also been developed, see,. However, if the speech signal is corrupted by a harsh noise, all the above-mentioned techniques will lose its denoising power, leading to poor speech recognition rate and communication quality.

On the other hand, in many real-life applications, speech recognition based hands free electronic devices have to be operated in very noisy environments, and their performance degenerates considerably such that the lowest quality required cannot be ensured. That is one of the many reasons why more sophisticated and powerful techniques and systems are being pursued extensively for speech enhancement in the speech signal processing community.

Recently, both bone- and air-conducted speech signals have been used to improve the accuracy of speech enhancement in very noisy environments. The former is acquired by putting a vibration pickup on the human body, which is usually not influence or contaminated by the background noise. The enhancer is an adaptive noise canceller (ANC), with the bone-conducted speech taken as its reference signal and the air-conducted speech adopted as the primary noise. The ANC consists of an FIR filter updated by the LMS or an advanced adaptive algorithm. The linearity of transmission path from the vibration pickup (bone-conducted speech) to the microphone (air-conducted sound pressure) may be beautifully realized by the adaptive FIR filter. However, the transmission path also presents nonlinearity such that the bone-conducted speech contains much less high-frequency components than the air-conduced speech signal usually does. The speech recovery is not adequate by using of such a linear ANC. That's because the high-frequency spectrum of the speech cannot be reconstructed by a linear filter. Namely, nonlinear filter has to be introduced. A nonlinear ANC was proposed to make a difference. A neural network (NN), i.e. a multilayer perception (MLP), was introduced to implement the nonlinearity. They used the well-known back propagation algorithm to update their ANC. Finding an initial network with good initial weights and proper size (number of hidden units) poses a difficult problem with their system.

In this paper, we propose a nonlinear ANC by using of Volterra filter. The proposed system, enjoying nice convergence and computational efficient y, is capable of recovering the high-frequency components of the speech signal in very noisy situations. Simulations using real bone- and air-conducted speech measurements are performed to demonstrate the effectiveness and superiority of the proposed system over the previous one using only the FIR filter.

Nonlinear ANC for Speech Enhancement

Here, we also use an ANC system to perform the enhancement task, just as what were done. However, we introduce a Volterra filter, rather than an FIR filter or an NN, to recover both the low-frequency and the high-frequency components of the speech signal, by using of a bone-conducted measurement and an air-conducted speech contaminated severely by an additive noise. The block diagram of the proposed ANC is depicted in Fig. 2

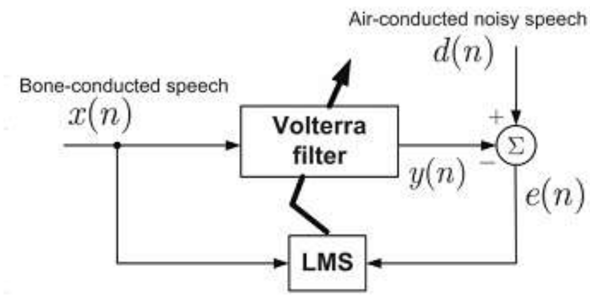

Figure 2: Block diagram of a nonlinear ANC with a volterra filter for speech enhancement

It should be noted that the Volterra filter is a well-known nonlinear filter and has been used in many real applications such as system identification echo cancellation, active noise control, fetal ECG extraction, time-series prediction.

In Fig. 2, the bone-conducted speech is denoted by X(n). The air-conducted speech is shown by d(n) which consists of two signal sources, namely a clean speech signal s(n) to be recovered by the ANC and an additive noise v(n) with very large power that makes the speech recognition engine lose its ability to work properly. The output of the Volterra filter is the recovered version of the clean speech signal s(n).

The output of the Volterra filter is calculated as:

$$y(n) = \sum_{i=0}^{L_1-1} h_1(i;n)x(n-i) + \sum_{i=0}^{L_2-1}\sum_{j=i}^{L_2-1} h_2(i,j;n)x(n-i)x(n-j) + \cdots \quad (2.1)$$

where h1(I,n) and h2(I,j,n) are the filter coefficient of the 1st and 2nd-order Volterra kernel, L1 and L2indicate the length of both kernels. The Volterra series may contain kernels with orders as high as desired to express high nonlinearity. However, it is truncated properly in practice to obtain a compact and useful expansion for a specific task to be accomplished. If only the 1st-order kernel is used, the Volterra filter will reduce exactly to the linear FIR filter. Therefore, if the truncation is done at an order larger than 2, the Volterra filter will have ability to express both linearity and nonlinearity. In this work, up to the 2nd-order kernel is used in our simulations. The Volterra series has been applied to functional expansion, system identification biomedical engineering, and various nonlinear adaptive filtering and so on, see and references therein. To the best of our knowledge, application to speech de-noising in the context of ANC using both bone-and air-conducted measurements has not been attempted yet.

The LMS algorithm is used to update the Volterra filter weights as follows

$$h_1(i;n+1) = h_1(i;n) + \mu_1 e(n)x(n-i) \quad (2.2)$$

$$h_2(i,j;n+1) = h_2(i,j;n) + \mu_2 e(n)x(n-i)x(n-j) \quad (2.3)$$

III. PROPOSED SYSTEM

Many practical signal processing applications cannot be successfully solved by using fixed digital filters because the complete range of input conditions may not be known exactly or even statistically, and the design criteria change during the normal operation of the filter. Most of these applications can be successfully solved by using special type of filters known as Adaptive filters. The distinguishing feature of adaptive filters is that they can modify their response to improve their performance during operation periodically without any intervention from the user. Adaptive filters are self-adjusting, time-varying and nonlinear systems.

Adaptive filter operates satisfactorily in an unknown environment and can track time variations of input statistics. It is this ability that makes it a powerful device for signal processing and control applications. Adaptive filters have been successfully applied in highly diverse fields such as communications, radar, sonar, seismology and bio-medical engineering. Adaptive filtering applications can be classified into four basic classes which are Identification, Inverse Modeling, Prediction and Interference cancellation. Channel Equalization comes under Inverse Modeling class of adaptive filtering. Given a channel of unknown impulse response, the purpose of an adaptive equalizer is to operate on the channel output such that the cascade connection of the channel and the equalizer provides an approximation to an ideal transmission medium. The goal of the adaptive channel equalizer is to replicate the performance of the optimum filter without using the exact statistical properties of the relevant signals.

The underwater acoustic channels are stochastic and pose great challenges for high performance and high rate communications. Accurate channel equalizer is necessary for coherent detection of the underwater acoustic signals. The channel information is obtained by training the equalizer using an adaptive algorithm by giving a desired signal to obtain optimum filter coefficients. The paper aims at designing an adaptive filter to combat additive white Gaussian noise in wireless underwater acoustic communication.

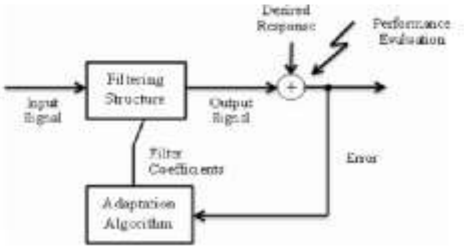

Figure 3: Basic modules of adaptive filter

The adaptive algorithm uses the value of the criterion of performance, the measurements of the input and desired signals so as to modify the parameters of the filter to improve its performance.

Adaptive filters are designed for a specific type of input signal (speech, binary data, etc.), for specific types of interferences (additive white noise, sinusoidal signals, echoes of the input signals, etc.), and for specific types of signal transmission paths (e.g., linear time-invariant or time varying). After choosing the filtering structure, criterion of performance and the adaptive algorithm, the only unknowns, when the adaptive filter starts its operation, are a set of parameters that are to be determined by the adaptive algorithm using signal measurements. If the characteristics of the relevant signals are constant, the goal of the adaptive filter is to find the parameters that give the best performance and then to stop the adjustment. However, when the characteristics of the relevant signals change with time, the adaptive filter should first find and then continuously readjust its parameters to track these changes.

In the current implementation of adaptive filter, the criterion of performance is mean square value of the estimation error which is used to optimize the filter design. The Mean Square Error (MSE) criterion has second order dependence on the cost function described by the error performance surface and has distinct minimum that uniquely defines the optimum statistical design of the filter.

Computational block is the noise free output generator .the weights or coefficients for the noise removal are calculated by the weight update block and are the delay blocks where input sample and error sample has the same delay.

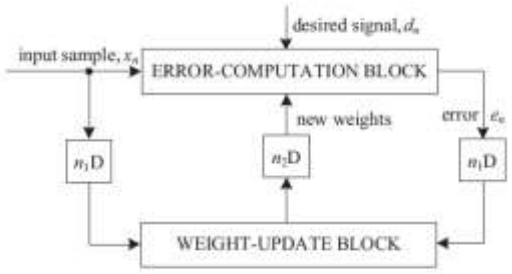

Figure 4: block diagram of implementation

IV. Results & Discussions

System generator schematic

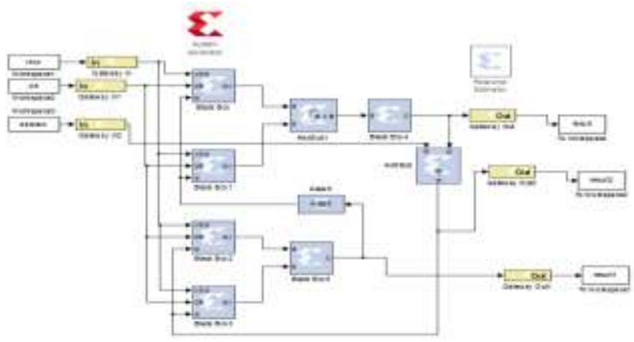

Figure 5: system generator model for the LEAST MEAN SQUARE ERROR

The above fig represents the black box and adders in the system generator of Mat Lab using Xilinx blocks. The resultant blocks are simulation waveforms. Black box needs a code to be attached for its executing.

Waveform result

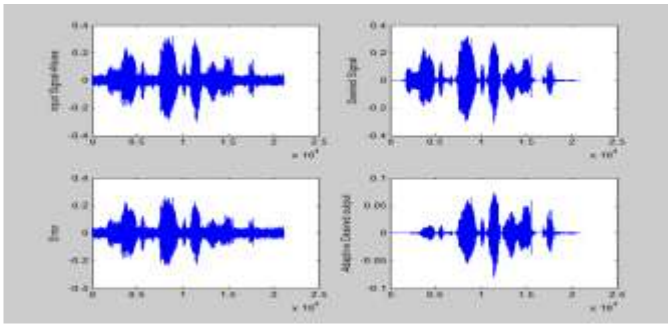

Figure 6: input signal and desired signal

The figure 6 (a) input signal along with noise and the fig 6(b) desired signal is given as the input fig 6 (c) error signal and the resultant is the fig 6 (d) error free signal.

PPG result

Error update block

Figure 7: Error update block simulation

Xinput and clk are the inputs .based on the weights are multiplied with the inputs .yn are the resultants of the simulation in error block

Weight update block

Figure 8: weight update block simulation

Weights are generated based on the xinputs and the previous weights.

Top module result

Figure 9: error free resultant simulation

The resultant is the top module result which has the noise free speech signal.

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