Adaptive Noise Cancellation using Multirate Technique

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ABSTRACT

In many application of noise cancellation, the changes in signal characteristics could be quite fast. This requires the utilization of adaptive algorithms, which converge rapidly. Least Mean Squares (LMS) and Normalized Least Mean Squares (NLMS) adaptive filters have been used in a wide range of signal processing application because of its simplicity in computation and implementation. Unfortunately, practical implementations of the algorithm are often associated with high computational complexity and/or poor numerical properties. Recently adaptive filtering was presented, have a nice tradeoff between complexity and the convergence speed. Here LMS is introduced and used for noise cancellation in audio signal ,speech signal. This paper presents development of a new adaptive structure based on multirate filter and testing the same for deterministic, speech and music signals. A new class of FIR filtering algorithm based on the multirate approach is proposed. They not only reduce the computational complexity in FIR filtering, but also retain attractive implementation related properties such as regularity and multiply-and-accumulate (MAC)-structure. By virtue of the advantages of multirate FIR filtering algorithm, the proposed scheme can reduce the required computational complexity and reserve the MAC structure. It is observed that the convergence rate and steady state error is improved. An application of this approach in Adaptive Noise Canceller is considered.

Keyword: - *Adaptive filter, Multirate filter, Adaptive Noise Cancellation*

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1. INTRODUCTION

Noise is present in virtually all signals. In some situations it is negligible; in other situations it all but obliterates the signal of interest. Removing unwanted noise from signals has historically been a driving force behind the development of signal processing technology, and it continues to be a major application for digital signal processing systems [1]. The usual method of estimating a signal corrupted by additive noise is to pass the composite signal through a filter that tends to suppress the noise while leaving the signal relatively unchanged. Filters used for the foregoing purpose can be fixed or adaptive. The design of fixed filters is based on prior knowledge of both the signal and the noise, but adaptive filters have the ability to adjust their own parameters automatically, and their design requires little or no prior knowledge of signal or noise characteristics [2][3]. Multirate Signal Processing is the sub-area of DSP concerned with techniques that can be used to efficiently change the sampling rates within a system. There are many applications where the signal of a given sampling rate needs to be converted into an equivalent signal with a different sampling rate. The process of decimation and interpolation are the fundamental operations of interest in multirate signal processing. They allow the sampling frequency to be decreased or increased without significant undesirable effects of errors such as quantization and aliasing [4][5]. The various aspects of multirate systems in statistical processing are reported in [6][7][8]. John Shynk [9] presents an overview of several frequency-domain adaptive filters that efficiently process discrete-time signals using block and multirate filtering techniques. A multirate adaptive filtering structure using VLSI architecture is reported in [10]. The concept of multistage multirate adaptive filters is discussed in [11][12]. The applications of the approach in biomedical engineering [13], sub-band filtering [14], Adaptive Line Enhancement [15], Echo cancellation [16] are well proven. The work by different researchers in this direction is a motivation for working on case study of noise cancellation. The concept in [15] is extended to the Adaptive Noise Canceller (ANC) configuration, in this paper, the organization of this paper is as follows; the conventional Adaptive Noise Canceller (ANC) is introduced in section 2. The LMS algorithm are also briefed.

1.2 Adaptive Algorithm

The adaptive filter, is using the result of the filter parameters of past to automatically adjust the filter parameters of the present, to adapt to the unknown signal and noise or over time changing statistical properties in order to achieve optimal filtering. Adaptive filter has "self-regulation" and "tracking" capacities. Filter out an increase noise usually means that the contaminated signal through the filter aimed to curb noise and signal relatively unchanged. For the purpose of the filter can be fixed, and can also be adaptive. Fixed filter designers assume that the signal characteristics of the statistical computing environment fully known, it must be based on the prior knowledge of the signal and noise [2]. However, in most cases it is very difficult to meet the conditions; most of the practical issues must be resolved using adaptive filter. Adaptive filter is through the observation of the existing signal to understand statistical properties, which in the normal operation to adjust parameters automatically, to change their performance, so its design does not require of the prior knowledge of signal and noise characteristics.

Here we are taking x(n) as input signal, d(n) as desired signal, e(n) as error signal, w(n) as weighted signal and y(n) as estimated filter output. Block diagram for adaptive filtering is illustrated in Figure.1.
adaptive filter for noise cancellation.

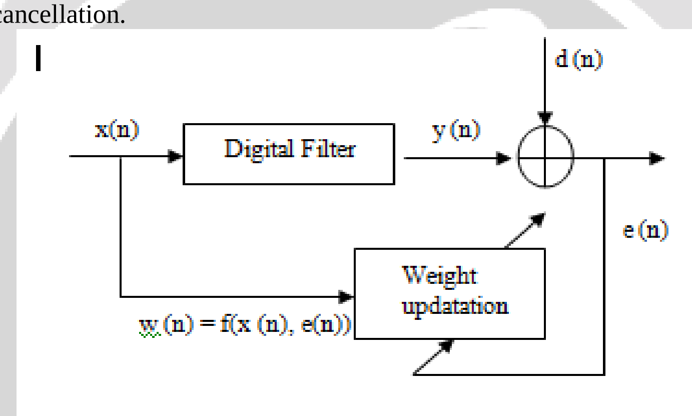


Fig -1: Adaptive Filter Configuration

From figure 1, the filtered output can be written as

$$y(n) = w^T(n-1)\, x(n) \tag{1}$$

Here weight vector

$$W(n) = [\, w_0(n)\ w_1(n) \ \ldots\ldots\ldots\ldots\ldots\ w_N(n)]$$

$$x(n) = X(n) = [x(n)\ x(n-1), \ldots\ldots\ldots\ldots, x(n-N+1)]^T$$

$x^T(n)$ contains the current and past input samples.

Estimation error denoted by e(n) is the difference between the desired signal and the estimated signal,

$$e(n) = d(n) - y(n)$$

$$e(n) = d(n) - w^T(n-1)\, x(n) \tag{2}$$

Now mean square error (MSE) can be defined as:

$$\varepsilon = E[e^2(n)] = E[d2(n)] + w'(n-1)\, R\, w(n-1) - 2\, w'(n-1)\, p \tag{3}$$

Where R=E [x (n) x' (n)] which is an N× N autocorrelation matrix and p=E [d (n) x (n)] which is an L× 1 cross-correlation vector. Where E [.] denotes expectation or mean function. The optimum coefficient vector w (n) which minimizes the MSE function can be derived by solving

$$\frac{\partial e^2}{\partial w^T} = 0 \tag{4}$$

After solving equation (3) the optimum coefficient vector can be expressed as

$$w^* = R^{-1} p \tag{5}$$

Equation (4) is known as Wiener-Hopf solution [9].By putting the optimum value of w in equation (3) we can easily get MMSE i.e. minimum mean square error. If we plot mean square error function which is obviously quadratic, with filter coefficient. It will be like Bowl-shaped surface with a unique bottom (minimum MSE) at the optimum vector w (n). This Quadratic performance surface is always positive and thus is concave upward. The recursive Adaptive algorithm is the process of seeking the minimum point on the performance surface.

2. ADAPTIVE ALGORITHM

2.1 Least Mean Square (LMS) Algorithm

This algorithm is based on the Steepest Descent [2] method that adapts the coefficient sample by sample toward the optimum vector on the performance surface. In steepest descent algorithm the next coefficient vector is updated by an amount proportional to the negative gradient of the MSE function at time n.

$$\text{i.e} \qquad w(n) = w(n-1) - \tfrac{1}{2}\mu \nabla_w (e2(n)) \tag{6}$$

where $\nabla_w (e2(n))$ or ∇_n is gradient estimated vector or gradient estimator. The LMS algorithm developed by 'Widrow' uses the instantaneous squared error rather than mean square error :

$$\varepsilon = e2(n)$$

In the n-th iteration the LMS algorithm selects w (n), which minimizes the square error e2 (n).

Now for estimating the error e2 (n) as a mean square error we take gradient estimation that is following-

$$\nabla_w(e^2) = \frac{\partial e^2}{\partial w^T}$$

$$= \partial(d(n) - w^T((n-1)x(n))^2 \frac{1}{\partial w^T}$$

$$= -2\,d\,x + 2\,w^T x\,x$$

$$= -2(d - w^T x)\,x$$

$$= -2ex \tag{7}$$

Now putting the gradient value in equation (4) we get the next updated vector

$$w(n) = w(n-1) + 2\mu\, e(n)\, x(n) \tag{8}$$

where μ is constant for LMS algorithm and for better convergence

$$0< \mu < 2/ (max)$$

Where max is the trace of autocorrelation matrix(R).Generally it is taken as 0.1. Complete architecture of adaptive filtering process using LMS algorithm for noise cancellation is illustrated in Figure.2. n(n) is noise signal which is added to the original signal and that signal is given to adaptive filter as input.

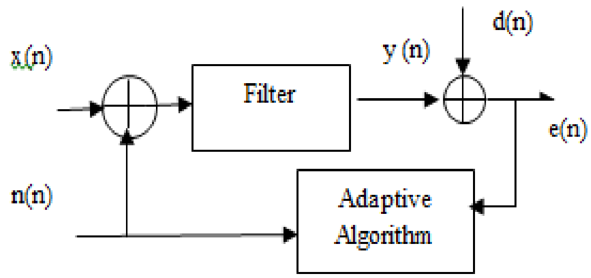


Fig -2 Adaptive filter for noise cancellation [2]

Where,
μ = step size parameter, e(n)= error signal, x(n) =Input signal, d(n) =desired signal,

Filter output:

$$y(n) = W^{T}(n)x(n) \tag{9}$$

Estimation error or error signal:

$$e(n) = d(n) - y(n) \tag{10}$$

Tap weight adaptation:

$$W(n+1) = W(n) + \mu(n)e^{*}(n)x(n) \tag{11}$$

Equations (2) and (3) define the estimation error e(n) the computation of which is based on the current estimate of the tap weight vector W(n). Note that the second term, x(n) (n) on the right hand side of equation (4) represents the adjustments that are applied to the current estimate of the tap weight vector W(n) . The iterative procedure is started with an initial guess W(0).The algorithm described by equations (2) and (3) is the complex form of the adaptive least mean square (LMS) algorithm. At each iteration or time update, this algorithm requires knowledge of the most recent values u(n), d(n) W(n) The LMS algorithm is a member of the family of stochastic gradient algorithms. In particular, when the LMS algorithm operates on stochastic inputs, the allowed set of directions along which we "step" from one iteration to the next is quite random and therefore cannot be thought of as consisting of true gradient directions.

3. Proposed Scheme

The proposed structure of adaptive noise cancellation scheme using multirate technique is shown in Fig. 2. Starting with the basic framework for Adaptive filters, a structure has been built eliminating the basic faults arising like computational complexities, aliasing and spectral gaps. The H0, H1, Ha are the analysis filters and G0, G1 are the reconstruction filters. The decimation and interpolation factors have been taken as ‗2' as the number of sub-bands are 2. The proposed scheme achieves a lower computational complexity, and this design ensures no aliasing components in the output of the system. The system consists of two main sub-bands and an auxiliary sub-band. The auxiliary sub-band contains the complement of the signals in the main sub-band. In the fig. 2, Ha(z) is the analysis filter for the auxiliary sub-band and H0(z) and H1(z) are the analysis filters for the main bands. G0(z) and G1(z) are reconstruction filters for the main bands. These filters are related to each other as;

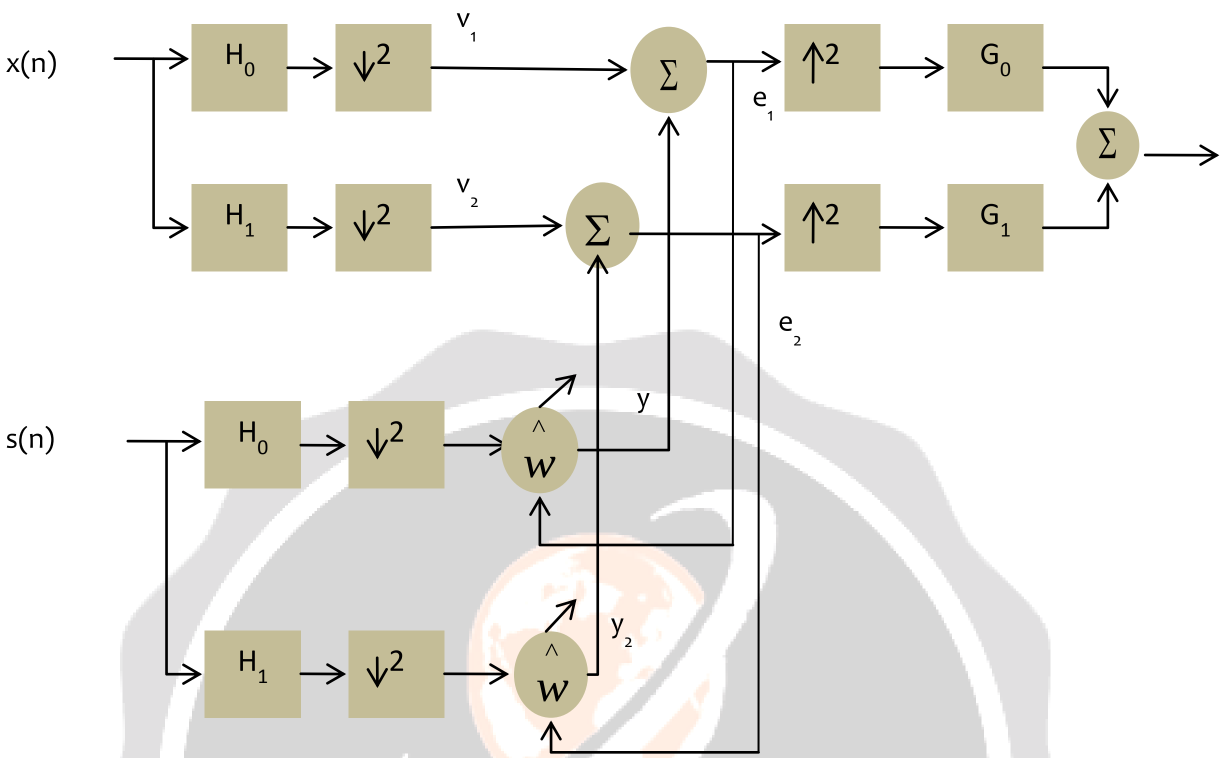
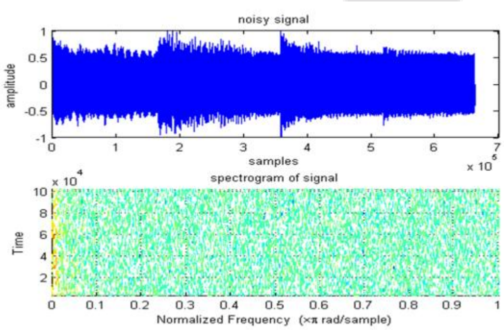


Fig.-3 Adaptive signal cancellation using multirate technique

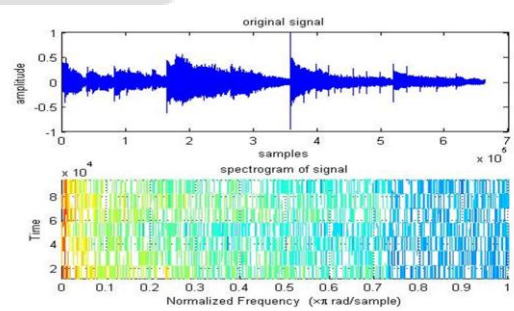
$$H_1(z) = H_0(-z) \tag{12}$$
$$G_0(z) = 2H_1(-z) \tag{13}$$
$$G_1(z) = -2H_0(-z) \tag{14}$$
$$Ha(z) = z^{-m} - [H_0^2(z) - H_1^2(z)] \tag{15}$$

The coefficients of all filters are calculated and the scheme is tested for different input types.

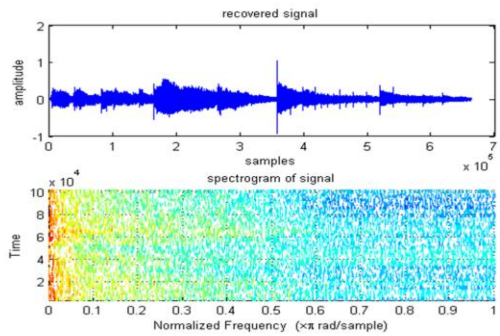
4. SIMULATION RESULTS



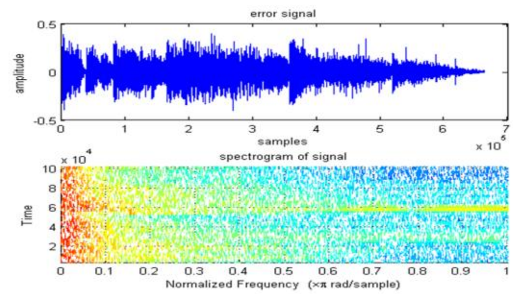
(a)



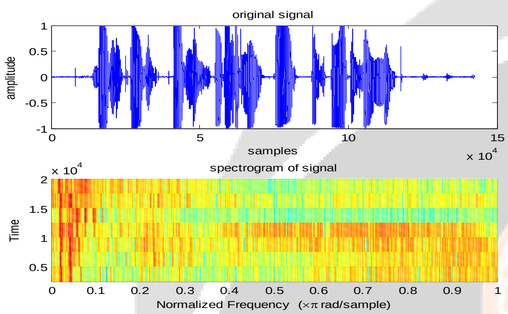
(b)



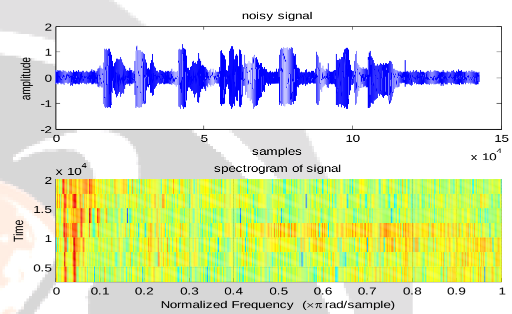
(c)



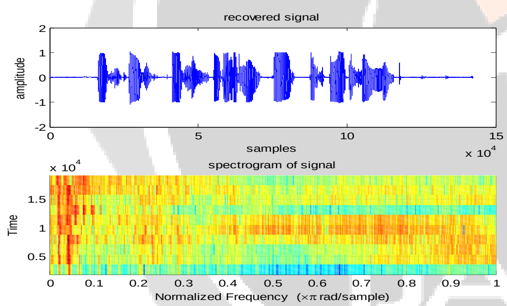
(d)



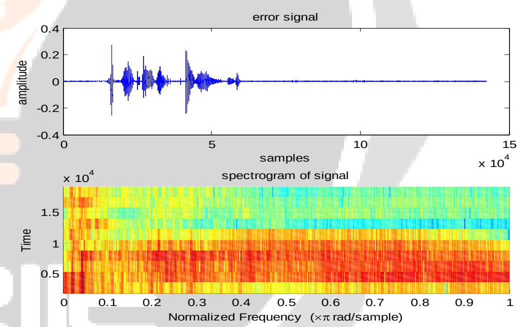
(e)



(f)



(g)



(h)

Simulation results are shown with spectrogram. LMS algorithm is used with proposed scheme.

5. CONCLUSION

Noise Cancellation is chosen as the application because noise is one of the main hindering factors that affect the information signal in any system. Noise and signal are random in nature. As such, in order to reduce noise, the filter coefficients should change according to changes in signal behavior. The adaptive capability will allow the processing of inputs whose properties are unknown. Multirate techniques can be used to overcome the problem of large computational complexity and slow convergence rate. The simulations and experiments demonstrate the efficacy of the proposed structure.

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