An Overview on Acoustic Echo Cancellation Using Adaptive Filter

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Abstract: ***The filter performs simple operation to detect analyze the noise on block boundary and attenuates by applying different filter .The paper describes the concept of cancellation of noise and alternative method of reducing the corruption of signals due to noise or interference .The paper deals with different uses of adaptive filter .It also describes about the cancellation of echo using different techniques like LMS (Least mean square), RLS (Recursive least squares), NLMS(Normalized least mean square),IPNLMS (Improved proportionate normalized least mean square) , VSLMS(Variable step size least mean square),VSNLMS(Variable step size normalized least mean square),.LMS is commonly used among all the algorithm because of its simplicities***

Keywords: Adaptive filter ,LMS(Least mean square value), Adaptive noise cancellation RLS (Recursive least squares), NLMS(Normalized least mean square),IPNLMS (Improved proportionate normalized least mean) VSLMS(Variable step size least mean square),VSNLMS(Variable step size normalized least mean square).

1. Introduction

A**daptive filter** is a system with a linear filter that has a transfer function controlled by variable parameters and a means to adjust those parameters according to an optimization algorithm. Because of the complexity of the optimization algorithms, almost all adaptive filters are digital filters Adaptive filters are required for some applications because some parameters of the desired processing operation (for instance, the locations of reflective surfaces in a reverberant space) are not known in advance or are changing. The closed loop adaptive filter uses feedback in the form of an error signal to refine its transfer function. Generally speaking, the closed loop adaptive process involves the use of a cost function, which is a criterion for optimum performance of the filter, to feed an algorithm, which determines how to modify filter transfer function to minimize the cost on the next iteration. The most common cost function is the mean square of the error signal.

As the power of digital signal processors has increased, adaptive filters have become much more common and are now routinely used in devices such as mobile phones and other communication devices, camcorders and digital cameras, and medical monitoring equipment. Adaptive filters are one of the important tool in the digital signal processing. They are mainly used whenever the statistical characteristics of the signal is said to be non-stationary in nature. In these type of filter ,the coefficients tend to get updated as per the conditions prevailing so as to minimize the error. Hence the key component of the adaptive filter is the adaptive algorithm. These algorithms are the set of rules which defines how the updating is made. The important requirements of these adaptive algorithm are that they should adapt to the changing statistics and track the solution as the time changes. Based on the adaptive algorithms, adaptive filters are classified broadly into two broad classifications. One is the sample by sample approach and the other is the block approach .Sample by sample algorithms are further classified as time domain and frequency domain algorithms [1]

NOISE CANCELLATION :-

Fig. 1 shows the basic problem and the adaptive noise cancelling solution to it. A signal **s** is transmitted over a channel to a sensor that also receives a noise $\mathbf{v_1}$ with uncorrelated the signal. The primary input to the canceller is combination of both signal and noise $\mathbf{s+ v_1}$. A second sensor receives a noise $\mathbf{v_2}$ uncorrelated with the signal but correlated with the noise $\mathbf{v_1}$. This sensor provides the reference input to the canceller. This noise $\mathbf{n_1}$ is filtered to produce an output **y** that is as close a replica of $\mathbf{v_1}$. This output of the adaptive filter is subtracted from the primary input $\mathbf{s+v_1}$ to produce the system output $\mathbf{Z=s+v_1 -y}$[2].

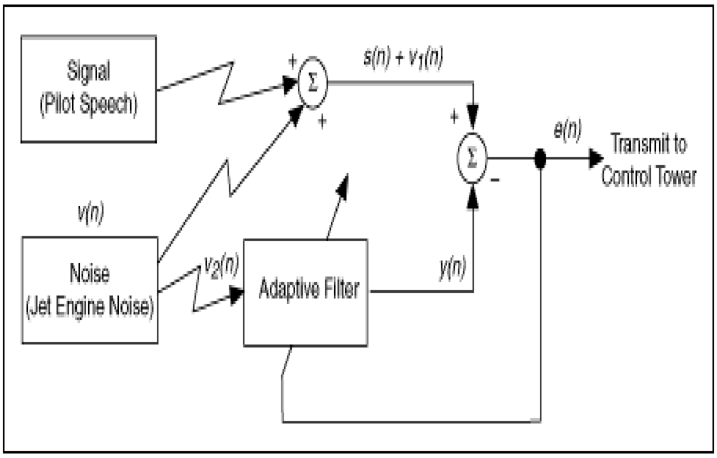

Figure.1:- Adapitive noise cancellation concept

I . LMS Algorithm:-

The LMS is the most popular algorithm due to its simplicity. We can notice that the update function is obtained by the multiplication of the step size with the current value of the error signal and input signal and does not depend on any other previous value. The main drawback of the LMS algorithm is that the convergence is slow due to the step size restriction which depends on the eigen value of the auto correlation matrix of the input signals. Several methods have been used to speed up the convergence of the LMS algorithm at the cost of increased complexity.

II. Normalized Least Mean Square Algorithm:

The normalized least mean square algorithm is the normalized form of the LMS algorithm .In this algorithm the difficulty encountered by the LMS in the selection of step size is eliminated by normalizing the step size. The main advantage of NLMS is that the gradient noise amplification is very much reduced due to the norm function present in the denominator of the weight update equation. The convergence is also faster than the LMS. The main disadvantage with this algorithm is that the computational complexity is more than LMS. The modified equation governing the NLMS is given by

$$w(n+1) = w(n)+\frac{\mu e(n)x(n)}{x(n)+p} \qquad \text{.......(1)}$$

Where p=small positive value which is used when norm of x(n) becomes very small. [1]

III. Recursive Least Squares (RLS) Algorithm

The other class of adaptive filtering techniques is known as Recursive Least Squares (RLS) algorithms. These algorithms attempt to minimize the cost function Where k=1 is the time at which the RLS algorithm commences and is a small positive constant very close to, but smaller than 1. With values of 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. Unlike the LMS algorithm and its derivatives, the RLS algorithm directly considers the values of previous error estimate.RLS algorithms are known for excellent performance when working in time varying environments. These advantages come with the cost of an increased computational complexity and some stability problems[3]

IV. Variable Step Size LMS Algorithm:-

Step Size least mean square algorithm (VSS LMS). The error power reflects the convergence state of the adaptive filter, where a converging system has a higher error power while the converged system has a smaller error power. Therefore, scalar step size increases or decreases as the squared error increases or decreases, thereby allowing the adaptive filter to track changes in the system and produces a smaller steady state error. The step size of the VSS algorithm is adjusted as follows:

$$m(n+1) - am(n) + be2(n) \qquad \text{.........(2)}$$

The variable step size algorithm, as appeared in is of the form

$$w(n+1)=w(n)+m(n)x(n)e(n) \qquad \text{...... (3)}$$

Where $e(n)=d(n)-x(n).w(n)$ ....(4)

Step size is updated as

$m'(n+1)=am(n)-be2(n)$ with $0<a<1$, $b>0$ ...... (5)

To ensure stability, the variable step size m(*n*) is constrained to the pre-determined maximum and minimum step size values of the LMS algorithm, while a and b are the parameters controlling the recursion. Simply, the VSS algorithm's step size value change by tracking the error square or the error power. A large error increases the step size to provide faster tracking while a small error reduces the step size for smaller steady state error. Although this approach can improve the step size trade-off effect, the drawback is that the maximum and minimum step sizes would require to be known as priori. This is essential in order to achieve the fastest convergence rate while not causing instability.

A different technique usually known as the gradient adaptive step size, is as follows

$m(n)=m(n-1) + f\, e(n)e(n-1)XT(n-1)X(n)$ ....(6)

where f is a small positive constant which controls the recursion. The recursion of m(*n*) in equation 4.5 is such that the gradient (*e*(*n*)**XT**(*n*)) is larger during the converging period while becoming zero after convergence[3]

V. Variable Step Size Normalised LMS Algorithm.

The VSLMS algorithm still has the same drawback as the standard LMS algorithm in that to guarantee stability of the algorithm, a statistical knowledge of the input signal is required prior to the algorithms commencement. Also, recall the major benefit of the NLMS algorithm is that it is designed to avoid this requirement by calculating an appropriate step size based upon the instantaneous energy of the input signal vector. It is a natural progression to incorporate this step size calculation into the variable step size algorithm, in order increase stability for the filter without prior knowledge of the input signal statistics. This is what I have tried to achieve in developing the Variable step size normalised least mean square (VSNLMS) algorithm. In the VSNLMS algorithm the upper bound available to each element of the step size vector, μ(n), is calculated for each iteration. As with the NLMS algorithm the step size value is inversely proportional to the instantaneous input signal energy[4]

VI. IPNLMS Algorithm

Proportionate adaptive filters, such as the improved proportionate normalized least-mean-square (IPNLMS) algorithm, have been proposed for echo cancellation as an interesting alternative to the normalized least-mean-square (NLMS) filter. Proportionate schemes offer improved performance when the echo path is sparse. An improvement of PNLMS is the IPNLMS algorithm, which employs a combination of proportionate (PNLMS) and non-proportionate (NLMS) updating technique, with the relative significance of each controlled by a factor α . The update is accomplished by replacing the diagonal matrix Q defined in equation 7 by a diagonal matrix K whose diagonal elements k_u are obtained by replacing the corresponding elements q_u of Q a

$Q(n)=\text{diag}\{q_0(n)\ \ q_1(n)\ldots\ldots\ldots\ldots q_{L-1}(n-1)\}$ ......(7)

2. Conclusion

Here ,in this paper we all have represented a new approach over the classical problem of super resolution restoration of single high resolution image the measurement .Here mention that the problem can be overcome to several recursive equation propagating in time. Based on this equation ,a block LMS restoration algorithm was proposed .This approach give very encouraging results , both the computational and the output quality aspects. In this approach one direct consequence of the presented work is the need for simple , yet reliable ,algorithm for the task if mention estimation and estimation for the blur function.This paper has discussed the LMS adaptive algorithms used .in adaptive filters.LMS algorithm is used when cost is the major criteria. The performance of hybrid algorithms are better than their parents .Hence in future it is required to make an adaptive algorithm which has less computational complexity ,more stability, less steady state error and with good converge and tracking capability.

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