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Optimized Variable Step Size Normalized LMS Adaptive Algorithm for Echo Cancellation

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Abstract— The echo cancallation is rapidly becoming a variable alternative to the conventional method of echo suppression. Echo cancallation using an adaptive filtering algorithm to model the echo path becouse impulse reponse is highly time varing and compute the replica of the echo component present in the speech signal. This research paper, we present the new optimized variable step size normalized least means sqaure algorithmin the context of acoustic echo cancellation. This new algorithm is design in such a way that the step size adjustment is controlled by using the suqaure of the means sqaure error and gives the unique minima of weight vector. New algorithm is suitable for real world application as compared to the old conventional adaptive algorithm.

Keywords— *Echo, Adaptive Filtering, System Identification, LMS, NLMS, VSS Adaptive Algorithm.*

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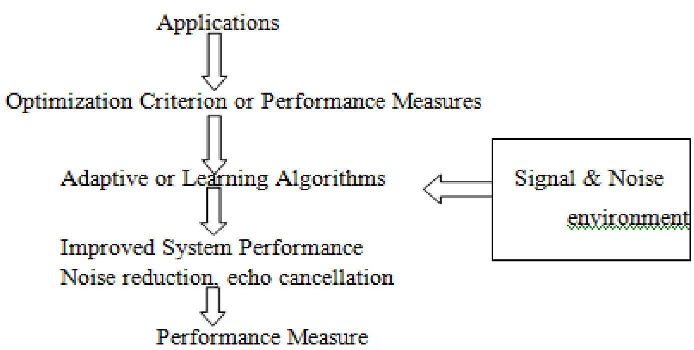
I. INTRODUCTION

The word filter is used for any hardware or software that can be applied to a set of noisy data to extract the information about the prescribed quantity of interest. So a filter can be considered as a device which manipulates its input into desired output [1], [2]. The linear filter problem is to design a linear filter in such a way that for noisy data as input effect of noise can removed or suppressed at the output [2]. In statistical approach to solve the linear filtering problem, the availability of certain statistical parameter (i.e. means and covariance) of the useful signals and unwanted additive noise is assumed. The error is suppressed according to the statistical criterion. The useful criterion is minimization of the means square value of the error signal the resulting solution is known as Wiener filter [1], [2], which is said to be optimum in means square since. Wiener filter is not much popular in practical applications. For practical applications adaptive filters are used more realistic approach of gradient based adaption. The filter of this type is more generally used in time domain in tapped delay line form and the least means square algorithm are used to obtain the filter parameter.

The main drawback of the LMS algorithm is that convergence speed decrease as the ratio of the maximum to minimum eigenvalue of the autocorrelation matrix increase. One approach to increase the convergence rate is to use NLMS and RLS adaptive algorithm. But RLS demand higher storage requirements and the computational intensive over LMS.A very serious problem associated with LMS and NLMS is the choice of step-size parameter that is a trade-off between steady state misadjustment and the speed of convergence [3].

II. ADAPTIVE FILTER



A For acoustic echo cancellation application, the adaptive filtering algorithm used must have the following characteristics:

I. Fast initial convergence.
II. Good tracking ability (to track change in the echo path response.)
III. Immunity from divergence from double-talks (when the near-end speaker becomes active).
IV. Robustness with low computational complexity.

The design of a wiener filter requires a priori information about the statistic of the data to be processed. The filter is optimum when the statistical characteristics of the input data match a priori information on which the design of the filter is based. When this information is not known completely, however, it may not be possible to design the wiener filter or else the design may not longer to optimum. A straight forward approach for such situation is estimate and plugs procedure. In this procedure filter first estimates the statistical parameter of the relevant signals and then plugs the results into no-recursive formula for computation of filter output. For real time application this procedure has disadvantage of requiring elaborate and costly hardware. A more efficient method is to use an adaptive filter. It is a system that is self designed by using a recursive algorithm to update itself. It makes possible to operate the filter in environment where complete knowledge of the signal characteristics is not available. The algorithm starts from some predetermined set of initial conditions, representing whatever we know about the environment. Yet in stationary environment after successive iterations of the algorithm, it converges to optimum wiener solution in some statistical scene.

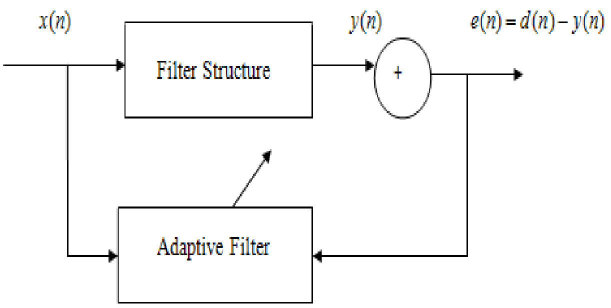


Fig.1 Block Daigram for system identification

In a non-stationary environment, the algorithm gives the tracking capability, it can track time variation in the statics of the input data provided that variation is sufficiently slow. Since the parameter of the adaptive algorithm is updated from one iteration to the next, the parameter becomes data dependent. This may results in degraded performance of the filter. The basic schematic of an adaptive filter is shown in fig.1.1. The operation of a linear adaptive filtering algorithm involves two basic processes which work interactively with each other:

1. A filtering process designed to produce an output in response to a sequence of input data. Different filter structures are available for this purpose, which a designer may choose according to application requirement.

2. An adaptive process controls an adjustable set of parameters used in the filtering process. Different adaptive algorithms are available based on their criterion for minimizing the error function.

Adaptive transversal filter can be classified in two ways and length selection of adaptive filter is most important in the context of the echo cancellation.

1. Short length filter.
2. Long length filter.

A. Short length filter

- 125 to 256 tap or 16 – 32 ms if data is sampled at 8 kHz which is typical for voice.
- Fast convergence but final solution has more residual error since the true response is IIR.
- Less complexity since algorithm complexity depend on the order of the filter.

B. Large length filter

- 512 to 1025 tap or 64-128 ms.
- Slower convergence but final solution has less error.
- Computational complexity has been increased because order o algorithm is N^2.

C. Echo

Echo is a process which a delayed and distorted version of an original sound or signal is reflected back to source.

There are two types of echo

1. Acoustic echo.
2. Hybrid echo.

1. Acoustic Echo: Acoustic echo occur when some of the sound from the speaker part of the telephone gets picked up and transmitted back by the microphone.

There are two types of the source of echo.

(i) Acoustic Isolation Echo

It is also known as a acoustic coupling is generated when the headset and microphone are poorly isolated from one another.

(ii) *Ambient Acoustic*

Ambient acoustic echo is generated when a telephone conversation is held in an acoustically reflective environment.

D. Basic concept of Echo Cancellation

In acoustic echo cancelation, the estimates of the near-end echo path response is computed which is used to generate an estimate of echo. The estimate of echo is substracted from the near-end microphone output to subtract the actual echo.

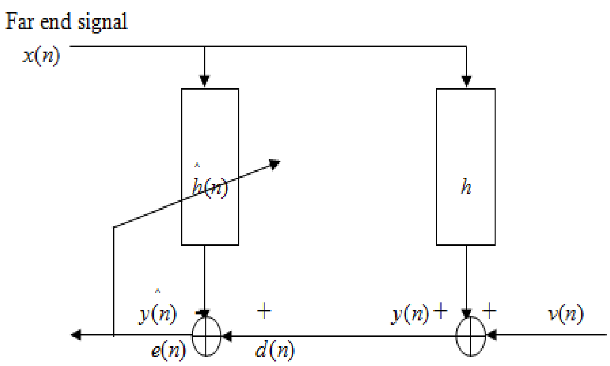


Fig.1 Function diagram for system identification

Where,

$x(n)$ Far-end signal

$v(n)$ Near-end signal

$d(n)$ Echo or desired signal

The problem then reduces to similar to the room echo path response h by an impulse response $\hat{h}(n)$ of the adaptive filter. So that feeding a same input to the adaptive filter the estimate of actual echo, $\hat{y}(n)$ is obtained. The use of adaptive filter in

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the echo cancellation is necessary because the path of echo's are highly time varying, so that the use of fixed filter is not suitable.

In hand free telephony, the objective is to permit two or more people, sitting in two different rooms, two converge with each other. In simple configuration, there are two separate rooms one is far end room and another is near end room. Each room contains a microphone and a loudspeaker pair which is used by one speaker to converge with other.

The far-end signal broadcast to the near end signal $x(n)$ is broadcast to the near end room. The near end room has a microphone which is for the use of near end speaker but this near end speaker also receives a delayed and distorted version of the far end signal $x(n)$ as an echo $d(n)$ due to the room.

This echo passes through the near - end microphone and is broadcasted back to the far-end room, due to this, far - end receiver discomfort happens and who listen its own speech.

III. OPTIMIZED ADAPTIVE VSS-NLMS ALGORITHM (OAVSS-NLMS)

The step size plays an important role in controlling the performance of the LMS adaptive filter. The problem of the conventional LMS algorithm is that the fixed step-size governs the trade-off between the convergence rate and the steady state error. A large step reduces the transient time but will result in a larger steady state mean square error.

On other hand, to achieve the smaller steady-state error, a small step size has to be used which will cause a slower convergence rate. The selection of the step-size is very important for accuracy and robustness and the fast convergence rate.

To achieve high performance described by the proposed algorithm, the selection of step- size is very important and RLS algorithm performance known as the time-varying step size algorithm. It is possible that the optimum step size can be determined by solving the difference equation for the minimum MSE at each iteration. A number of time varying step sizes have been proposed to improve the step-size trade-off effect, which are fundamental tools in achieving desired adaptive performance. To ensure stability of the LMS algorithm, the step size parameter is bounded by the following equation [**2**]

$$0 \prec \mu \prec 2/\lambda_{\max}. \tag{1}$$

As we know that about the NLMS adaptive algorithm,
Consider the LMS recursion algorithm,

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

Where the step-size parameter varies with time and we conclude that the stability, convergence, stability and steady-state behaviour of the recursive algorithm, are influenced by the length of filter and the power of the signal.

Determining the upper vault step size is a problem for the variable step size algorithm if the input signal to the adaptive filter is non-stationary. The fastest convergence is achieved with the choice of step size as follows:

$$\mu = 2/\lambda_{\max} + \lambda_{\min}$$

This means that faster convergence can be achieved when λ_{max} is close to λ_{min}, that is, the maximum achievable convergence speed depends on the eigenvalue spread of *R*.

Therefore we can set,

$$\mu(n) = \frac{1}{2x^T(n)x(n)}$$

$$= \frac{1}{2\|x(n)\|^2}$$

$$w(n+1) = w(n) + \frac{1}{\|x(n)\|^2} e(n)x(n) \tag{3}$$

Above equation can be found using a posterior error or using a constrained optimization procedure. In practice more relaxed recursion is used that guarantees reliable results.

To derive the proposed algorithm and obviously we know that the normalized version of NLMS algorithm which is given by below,

The step-size is proportional to the energy. The weight update recursion of the algorithm is of the form,

$$w_i(n+1) = w_i(n) + 2\mu_i(n)e(n)x(n-i),$$
$$i = 0,1,\ldots\ldots,M-1 \tag{4}$$

Where the $w_i(n)$ is the i^{th} coefficient of $w(n)$ at iteration n and $\mu_i(n)$ is the associated step-size. The step-sizes are determined in an ad hoc manner, based on monitoring sign changes in the instantaneous gradient estimate, indicate that algorithm is close to its optimal solution, hence the step size must decrease. Reverse is also true.

The weight update recursion of the algorithm is of the form

$$w(n+1) = w(n) + \mu(n)e(n)x(n) \tag{5}$$

The $\mu(n)$ is the diagonal matrix with the following elements in the diagonal: $\mu_0(n), \mu_1(n), \ldots.\mu_{N-1}(n)$

The step size updated expression is

$$\mu(n+1) = \alpha\mu(n)\gamma e^2(n) \tag{6}$$

Where $0 \prec \alpha \prec 1$, $\gamma \succ 0$, and $\mu(n+1)$ is set to $\mu_{\min}$ or $\mu_{\max}$ when it fall below or above one of them. The algorithm has preferable performance over the fixed step size LMS. At the early stage of the adaption, error is large causing step size to increase to provide faster convergence speed. When the error

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decreases, the step decreases thus yielding smaller misadjustment.

$$MSE = \left\{ \frac{E\left(e^2(n)\right)}{\left(y^2(n)\right)} \right\} \tag{7}$$

$$y(n) = h^T(n)x(n)$$

After convergence of the proposed algorithm we can write the equation,

$$MSE = \frac{Signal}{Noise} - 10\log\left(\frac{n}{\alpha} - 1\right)$$

Where ,

$$MSE = \frac{Signal}{Noise}$$

Suggest that an MSE of the same order as the N/S ratio is obtained when a convergence factor closed or equal to one is used. In the normalized LMS algorithm a convergence factor equal to one provides the fastest convergence rate, if the N/S ratio is large, a convergence factor equal to one appears to be the best choice. However when the N/S ratio decreases, MSE also becomes smaller unless a smaller convergence factor is used. The OAVSS-NLMS algorithm uses two values of α .

If $\alpha = 1 \& n = 2$ then MSE is,

$$MSE = \frac{Signal}{Noise} - 10\log\left(\frac{2}{1} - 1\right)$$

$$MSE = \frac{Signal}{Noise}$$

In this case the performance of the proposed algorithm is similar at the normalized LMS, but when $\alpha = .05$,

$$MSE = \frac{Signal}{Noise} - 10\log\left(\frac{2}{.05} - 1\right)$$

$$MSE = \frac{Signal}{Noise} - 10\log(39)$$

$$MSE = \frac{Signal}{Noise} - 16dB$$

There is a gain of 16 dB in MSE compared with the normalized LMS.

Proposed algorithm shows the idea is to use generalized step sizes. A larger output error will be more in such situation proposed algorithm adjust itself as per requirement and suitable for a real world applications like a acoustic echo cancellation.

IV. SIMULATION

The Conventional algorithm like a LMS algorithm step size was fix but in proposed adaptive algorithm step size is in generalized for and as per requirement it tune the coefficient or weight of the filter.

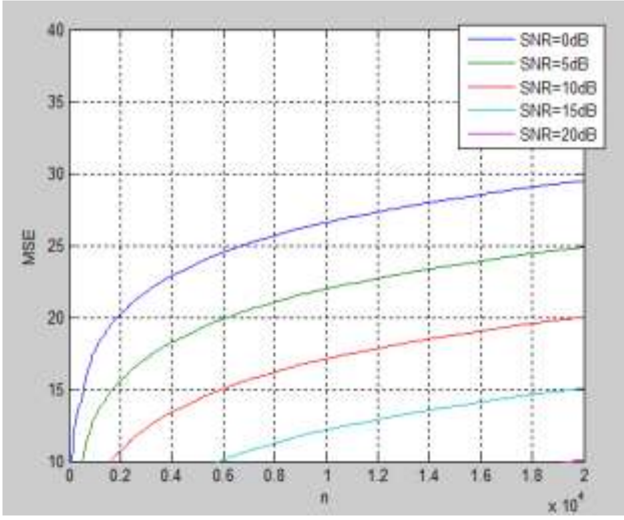

Fig.3 Comparision of the OVSS-NLMS with conventional approach with different MSE

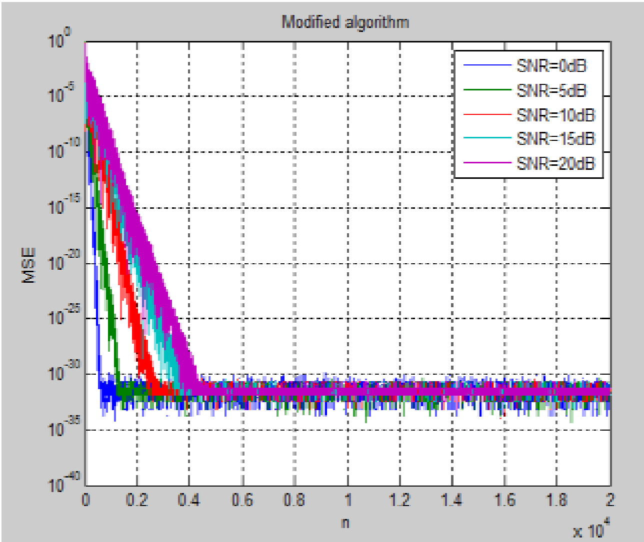

Fig. 4 Comparison of the OVSS-NLMS with conventional approach with different MSE

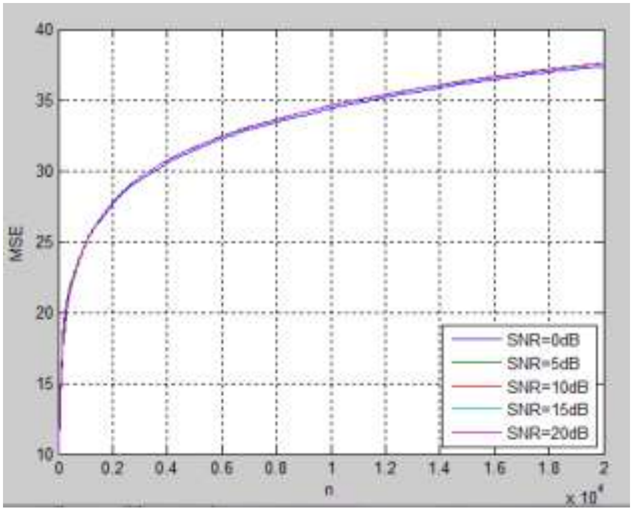

Fig 5 Optimized VSS-NLMS algorithm with different MSE

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V. CONCLUSION

In AEC, the acoustic echo paths are extremely long and highly vary with time. Therefore, the adaptive filter works most likely in this situation.. It can be deduced from above figures that Optimized variable step size normalized least means square adaptive algorithm case perform better than the other two algorithms, LMS and two step size NLMS algorithm in the context of echo cancellation. In NLMS algorithm, we need to find a compromise between fast convergence and low final misadjustment. In lot of applications, this compromise may not be satisfactory so a Optimized VSS-NLMS algorithm is required. It should be noted that the idea of proposed algorithm can be used in coincidence with other NLMS-based algorithms this improves the convergence rate and reduced the computational complexity.

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