Performance Variation of LMS And Its Different Variants

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Abstract

Acoustic echo cancellation is an essential and important requirement for various applications such as, telecasting, hands-free telephony and video-conferencing. Echo cancellers are required because of loud-speaker signals are picked up by a microphone and are fed back to the correspondent, resulting in an undesired echo. These days, adaptive filtering methods are used to cancel the affect of these echoes. Different variants of LMS adaptive algorithms have been. Implemented and they are compared based upon their performance according to the choice of step size.

Keywords: Echo, Algorithm, Adaptive, LMS, .

1. INTRODUCTION

Adaptive filters appear in many signal processing and communication systems for applications such as channel equalization, echo cancellation, noise reduction, radar and sonar signal processing, beam-forming,. Adaptive filters work on the principle of minimizing an error function, generally the mean squared difference (or error), between the filter output signal and a target (or desired) signal. Adaptive filters are used for estimation and identification of non-stationary signals, channels and systems. LMS algorithm and RLS and their variant are used to solve the problem. In today's scenario most of the systems are hands free, examples of these systems are hands-free telephones and video-conferencing these systems provide a comfortable and efficient way of communication. There is a major problem with these systems, signal degradation occurs when loudspeaker signals are picked up by a micro-phone and are sent back for processing. Therefore an undesired echo came in picture.In such hands-free systems, acoustic echo cancellers are necessary for full-duplex communication. Conventional techniques used in classical telephony such as clipping and voice controlled switching [1] have limited performance. More advanced adaptive filtering technique are expected to provide a better signal quality.

2. ADAPTIVE FILTERING TECHNIQUES

As Adaptive filters have applications in various applications such as identification, Acoustic echoes cancellation& inverse modeling, in this paper echo cancellation application is considered. Acoustic echoes are suppressed with the help of adaptive filtering techniques [2]. This algorithm basically adapts to a solution minimizing the mean-square error. It is based on the steepest-descent method. How filters weights are adapted, it is shown in fig an adaptive filter converges to an estimate of the impulse response of the acoustic path [3]. Of all existing adaptive algorithms the Least Mean algorithm is the best known. An FIR or IIR filter [6] is updated iteratively.

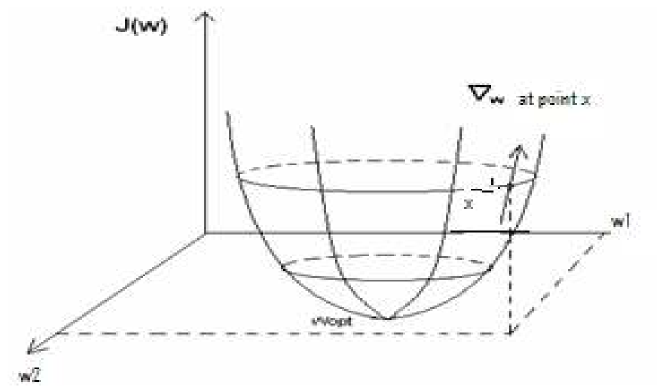

FIGURE1: Steepest Descent Method

Following equations explain that how filter weights are updated and error is minimized

$W(n+1)=w(n)+2\mu x(n)[d(n) - x^T(n)\ w(n)]$

$=w(n)+2\mu x(n)[d(n) - w^T(n)\ x(n)]$

$=w(n) +2\mu e(n)\ x(n)$

Here $y(n) = w^T(n)\ x(n)$ is filter output

And $e(n) = d(n)-y(n)$ is error signal

$W(n) = [w_0(n)\ w_1(n)\ldots\ldots w_{M-1}(n)]^T$ Are filter taps which updated to find the minima?

$$\varepsilon(n+1) = y(n+1) - h^T(n+1)x(n+1)$$

LMS algorithm is n very simple and requires only *O(2Nz* multiplications and *O(2N).* Another variant of LMS is NLMS.[6] The motivation of this algorithm is that the power of the input signal varies with time, so the step size between two adjacent filter coefficients will vary as well, then also the convergence speed. The convergence speed will slow down with small signals, and for the loud ones the over-shoot error would increase. So the idea is to continuously adjust the step size parameter with the input power. Therefore, the step size is normalized by the current input power, resulting in the Normalized Least Mean Square algorithm .The Normalized Least Mean Square (NLMS)[15] algorithm is a modified version of the LMS algorithm. In the LMS algorithm, the correction factor to the tap weight vector W (n) is computed as mu U (n) e(n).Since this quantity is directly proportional to the tap input vector U(n), the error in the gradient estimate gets magnified for large U(n). This problem can be avoided by sa the correction factor by the squared Euclidean norm of the tap input vector U(n) (the average power of the input signal). This variant of the LMS algorithm, with the normalized correction factor, is called the Normalized LMS (NLMS) algorithm. The LMS [6][11][13] and their different variants can be driven using the following functions

Let us define an *error* signal *e* (*n*+1) at time *n*+1 as

$$e(n+1) = y(n+1) - \hat{y}(n+1)$$

Here $y(n+1) = h^{T}{}_{t}x(n+1)$ is the output of a system and $h_t = [h_{t,0}\ h_{t,1} .....h_{t1L-1}]^T$ Are responses of system And $\hat{y}(n+1) = h^{T}(n)x(n+1)$ is the model filter output and $h(n) = [h_0(n)\ h_{1(n)} .....h_{L-1}(n)]^T$ is the model filter. One easy way to find adaptive algorithms that adjust the new weight vector h(*n*+1) from the old one h(*n*) is to minimize the following function $J[h(n+1)] = d[h(n+1), h(n)] + \eta\varepsilon^2(n+1)$

Here value of η plays an important role in updating the coefficients values. If η is very small that the algorithm makes very small updates. On the other hand, if η is very large, the minimization of *J*[**h**(*n*+1)] is almost equivalent to minimizing *d*[**h**(*n*+1), Hence, the different weight coefficients *hl*(*n*+1), *l* = 0,1, ...,*L*−1, are found by solving the following equations:

$$\frac{\partial d[h(n+1), h(n)]}{\partial h_1(n+1)} - 2\eta x(n+1-1)\varepsilon(n+1) = 0$$

if the new weight vector **h**(*n*+1) is close to the old weight vector **h**(*n*), replacing the *a posteriori* error signal with the *a priori* error signal *e*(*n*+1) is a reasonable approximation and equation. $\frac{\partial d[h(n+1), h(n)]}{\partial h_1(n+1)} - 2\eta x(n+1-1)e(n+1) = 0$ is much easier to solve for all distance measures d. The LMS algorithm is easily obtained from above equation by using the squared Euclidean distance $d\varepsilon[h(n+1), h(n)] = \amalg h(n+1) - h(n) \amalg_2^2$ .Using these equations and doing different mathematical operations we can find out different variants of the algorithm. Different variants of LMS [9][10] are NLMS,SIGN SIGN,SIGN DATA and SIGN ERROR. We will compare the performance of all these. Following are the comparison of different algorithms

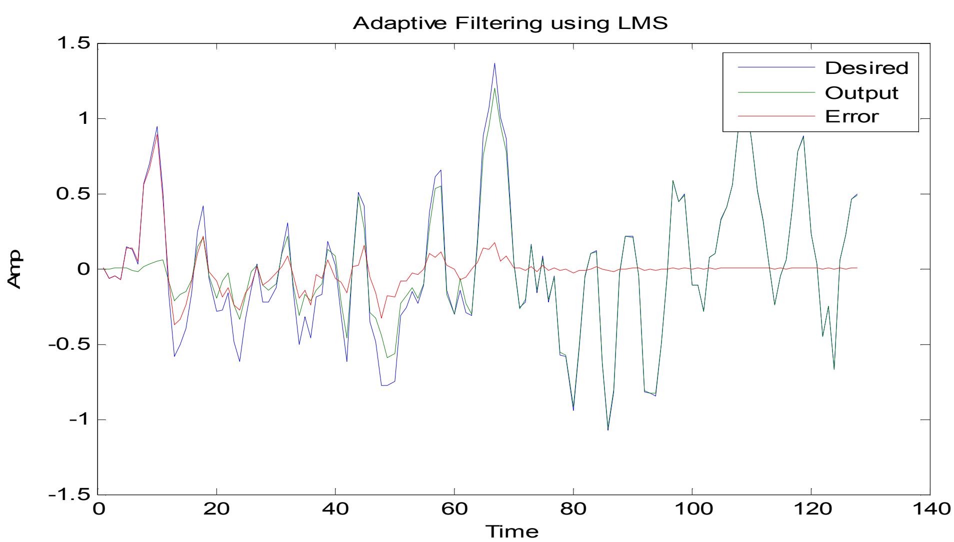

FIGURE 2 : LMS Adaptive Filtering With μ=.5

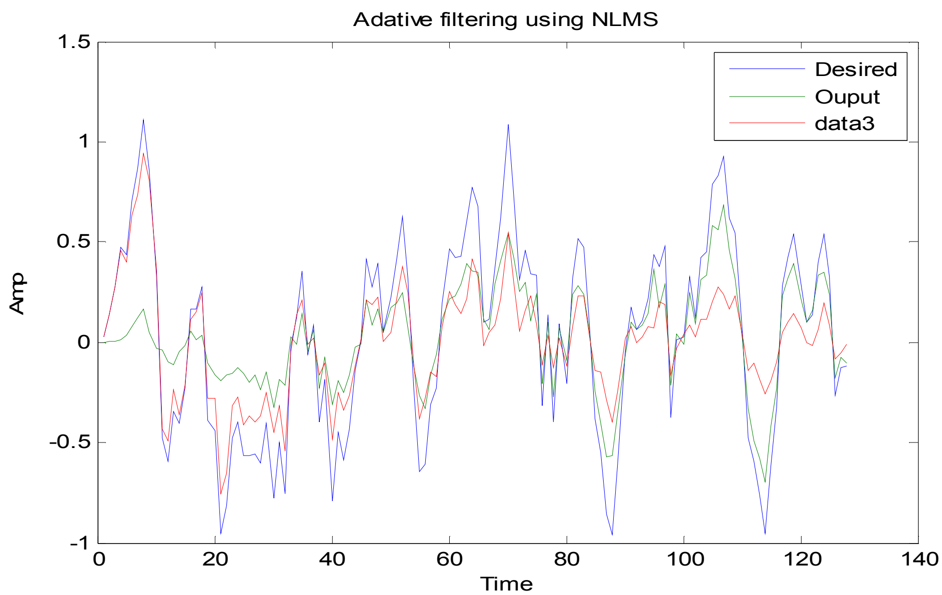

FIGURE 3: NLMS Adaptive Filtering with μ=.5

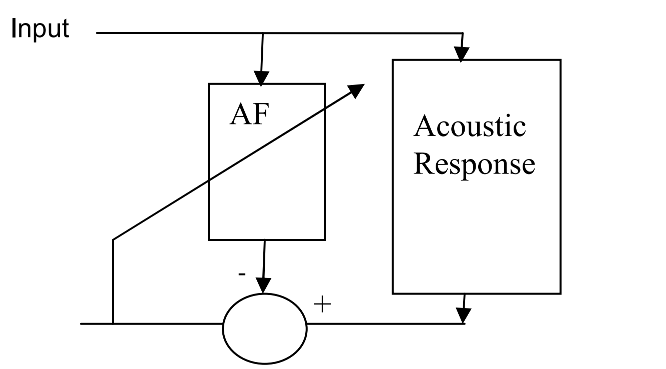

FIGURE 4: Adaptive System

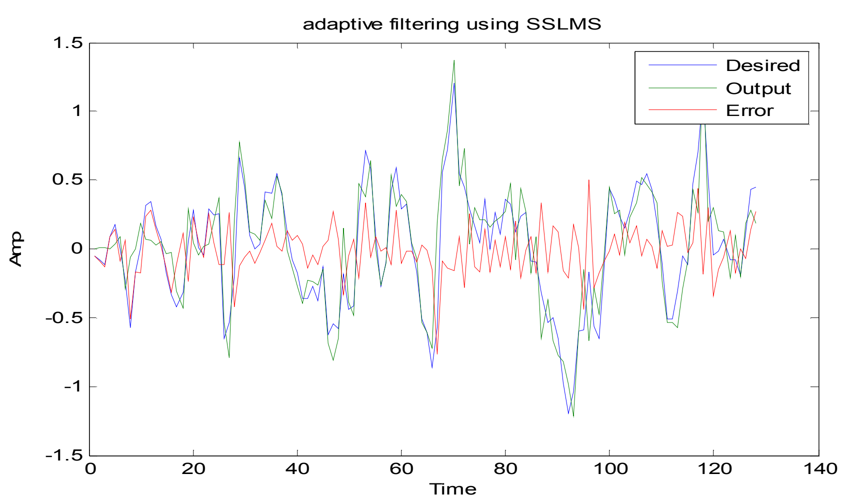

FIGURE 5:SLMS Adaptive Filtering With μ=.5

All above results are for step sige of .5.when we change the step size from .5 to near to 2 which is upper range of step size limit performance degrades

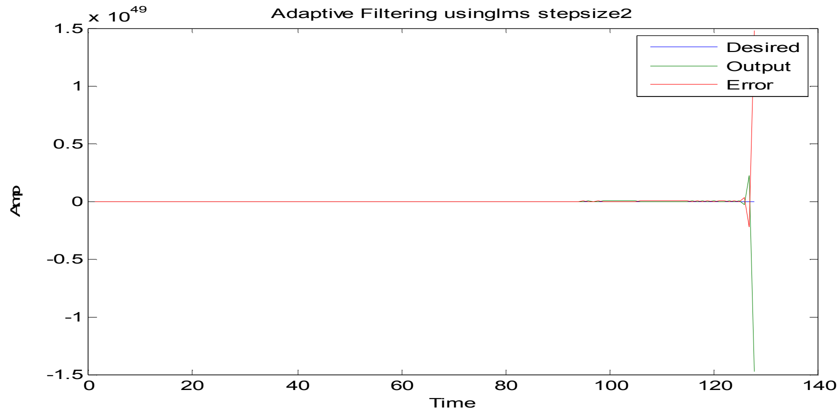

FIGURE 6: LMS Adaptive filtering with step sige of 2

3. CONCLUSION

As seen from different graphs it is clear that the choice of step size between the specified range is very important .If it is too low or near to upper range convergence is poor and desired signal is not obtained as shown in different figure. Thus different variants of LMS indicate different performance properties according to the choice of step size.

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