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Mrs. Nirupama K, Mrs. Nisha G R (Author)

156-167

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PDF

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168-175

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PDF

Dry Hand Washing Machine Using Fog Disinfectant

Mr. Suhandas, Ms. Shifali A Rai, Ms. Madhuri Sharma, Ms. Shravya S, Ms. Sameeksha S Shetty (Author) 176-181

DOI : <https://doi.org/10.32628/IJSRSET12291328>

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NVSSLMS Algorithm Adaptive Method Implementation for Acoustic Echo Cancellation

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ABSTRACT

This paper presents a new method for variable step size for LMS algorithm. The proposed algorithm is based on an absolute mean of estimation current and prior error vector. It is called New Varying Step Size LMS Algorithm (NVSSLMS). The main goal of this algorithm is performance enhancement of adaptive echo cancellation system. The proposed time varying step size method begins the learning process with high learning rate value (μ_{MAX}) and then , it decays in an exponential profile to its minimum value (μ_{MIN}) .The proposed algorithm is tested with real speech input signal and the result shows that it has fast convergence time, low level of misadjustment , and high Echo Return Loss Enhancement (ERLE) compared with LMS and other Variable Step Size LMS algorithm (VSSLMS) which proposed by R.H. Kwong and E.W. Johnston under similar conditions. The amount of ERLE enhancement using proposed algorithm compared with LMS and VSSLMS

algorithms is about 10 dB and 8 dB respectively.

Keywords: Adaptive Acoustic Echo Canceller, LMS algorithm, Variable step size LMS algorithm.

I. INTRODUCTION

The acoustic echo cancellation problem arises whenever a coupling between a loudspeaker and a microphone occurs in such applications as hands-free telephone and teleconferencing. This coupling result in the far-end talker's signal being fed back to the far-end taker creating annoying echoes and in some instances instability. The key to reducing the undesirable echoes electrically is to generate a replica of the microphone signal and subtract it from the actual microphone signal. This is illustrated in Fig. 1. Each side of the communication process is called an 'End'. The remote end from the speaker is called the far end, and the near end refers to the end being measured. The sound waves emanating from the loudspeaker propagate through the echo path of the acoustic environment. The echo path is a priori unknown and also time-varying. Even a slight movement of furniture or people in the acoustic environment can lead to drastic changes in the echo path. As a result, the adaptive echo canceller has the task of not only estimating the echo path, but also keeping track of changes in it. Traditional approaches to acoustic echo cancellation have used filtering algorithms which try to estimate the

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168

impulse response of the acoustic path, $h(n)$, and filter the incoming signal from the far end, $x(n)$. A common approach for estimating $h(n)$ is the Least Mean Square (LMS) algorithm.

However, a very serious problem associated with the LMS algorithm is the choice of the step-size (μ) parameter. The choice of the step size reflects a tradeoff between misadjustment and the speed of adaptation. It was shown that a small step size gives small misadjustment but also a longer Convergence time constant. On the other hand a large step size will in general provide faster convergence and better tracking capabilities at the cost of higher misadjustment. Any selection of the step-size must therefore be a trade-off between the steady-state misadjustment and the speed of adaptation. Subsequent works have discussed the issue of optimization of the step size or methods of varying the step size to improve performance. The objective of the alternative LMS-based algorithms is either to reduce computational complexity, reduce convergence time or enhance the performance in terms of the so called Echo Return Loss Enhancement (ERLE).

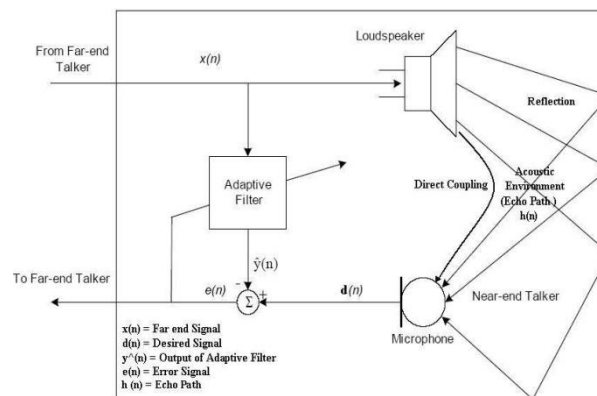


Fig 1. Adaptive Acoustic Echo Cancellation Scheme.

In this paper time varying step size LMS algorithm is proposed due to it has a powerful effect on the performance of the system also the structure of the AEC will not be changed. Moreover, this technique requires fewer overhead in computations, which is an important factor for hardware implementation. The proposed algorithm in this paper is called NVSSLMS algorithm (New Varying Step Size LMS). This a new proposed algorithm shows through computer simulation good performance compared with traditional LMS and other variable step size LMS algorithm (VSSLMS) which proposed by R.H. Kwong and E.W. Johnston in 1992 . The method in provides an important theoretical support of all error based variable step size LMS methods.

II. ADAPTIVE ECHO CANCELLER

The traditional solution to the acoustic echo problem is the acoustic echo canceller (AEC). An acoustic echo canceller achieves the echo removal by modeling the echo path impulse response with an adaptive filter and subtracting echo estimation from the microphone signal. The adaptive filter is the critical part of the AEC that performs the work of estimating the echo path of the room to get a replica of the echo signal. It needs an adaptive update to adapt to the environmental change, for example, people moving in the room. An important

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issue of the adaptive filter is the convergence speed that measures how fast the filter converges to the best estimate of the room acoustic path. The acoustic echo path is assumed to be a linear filter with length L.

$$H = (h_1, h_2, h_3, \dots, h_L)^T \quad (1)$$

Where L is the length of the echo path, and ()^T denotes the transpose of a matrix or a vector.

Then the microphone signal is expressed as:

$$d(n) = H^T \cdot X(n) + v(n) + r(n) \quad (2)$$

where $X(n) = (x(n-L+1), x(n-L+2), \dots, x(n))^T$ and n is the time index. Therefore, $H^T \cdot X(n)$ is the echo signal, $v(n)$ is the near end signal, $r(n)$ stands for the noise signal and $d(n)$ is the desired signal. A modeling adaptive FIR filter $H^{\wedge} = (h_1^{\wedge}, h_2^{\wedge}, h_3^{\wedge}, \dots, h_L^{\wedge})^T$ is used to approximate the true echo path h. The echo estimate will be

$$y^{\wedge}(n) = H^{\wedge T} X(n) \quad (3)$$

Where $y^{\wedge}(n)$ is the output of the adaptive FIR filter and represents the echo estimate. Adaptive algorithms are used to search the optimum h^{\wedge} . Once the adaptive FIR filter converges, the residual signal will be the echo-cancelled outgoing signal so that only near end signal is enhanced. The echo signal can be cancelled successfully when the modeling filter approaches the true echo path. The echo-cancelled outgoing signal is

$$e(n) = d(n) - y^{\wedge} \quad (4)$$

where $e(n)$ is the output signal for the AEC scheme that is used for adapt the weights or impulse response of the FIR filter. The adaptive algorithm should provide real time operation, fast convergence, and high Echo Return Loss Enhancement (ERLE). ERLE is defined as the ratio of send-in power (P_d) and the power of a residual error signal immediately after the cancellation (P_e) (i.e. at steady state),

and it is measured in dB. ERLE measures the amount of loss introduced by the adaptive filter alone. ERLE depends on the size of the adaptive filter and the algorithm design. The higher the value of ERLE, the better the echo canceller. ERLE is a measure of the echo suppression achieved and is given by (5)

$$ERLE = 10 \cdot \text{Log}_{10}(P_d/P_e) \quad (5)$$

III. ADAPTIVE FIR LMS ALGORITHM

The simple structure for adaptive Echo Canceller was the Finite Impulse Response filter (FIR) which can be trained by the Least Mean Square adaptive algorithm (LMS). Fig. 2 shows the structure of the adaptive FIR filter; where Z^{-1} is unit time delay

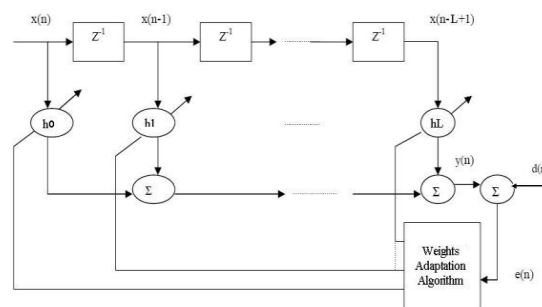


Fig 2. Structure of Adaptive FIR filter

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This LMS algorithm, which was first proposed by Widrow and Hoff in 1960, is the most widely used adaptive filtering algorithm. Detailed considerations of LMS algorithm are given in. The method of steepest descent updates filter coefficients according to Equation (6),

$$H(n+1) = H(n) + 2 \mu e(n) X_L(n) \quad (6)$$

Where μ is the fixed step size, this algorithm suffers from slow convergence since the convergence time of LMS algorithm is inversely proportional to the step size. However, if large step size is selected, then fast convergence will be obtained but this selection results in deterioration of the steady state performance (i.e. increased the misadjustment (excess error)). Also a small value of the step size will cause slow convergence but will enhance or decrease the steady state error level. Therefore, several methods of varying the step size to improve performance of the LMS algorithm, especially in time varying environments are proposed. In such environments, the step size must be adjusted automatically in order to obtain the following features: Adaptive filter must be able to track any change in the system, i.e. to reduce the lag factor which was a decreasing function of the step size. Reduce the tradeoff between the low level of misadjustment and fast convergence, i.e. both requirements, must be obtained

IV. A NEW VARYING STEP SIZE LMS ALGORITHM

To overcome the main drawback of the LMS algorithm, a modified version of the LMS algorithm is presented, which used time varying step size instead of the fixed step size as shown in this section. As explained previously this paper proposed a new algorithm which is called NVSSLMS. This time varying step size is adjusted according to absolute mean value of the current and the previous estimation error's vector

$$\mu(n+1) = \mu(n)(1 - \text{Abs}(\text{mean}(e(n)) * \delta)) \quad (7)$$

where $0 < \delta < 1$, and $\text{mean}(e(n)) = (\sum_{k=0}^{L-1} e(n-k)) / L$

i.e. $\text{mean}(e(n))$ is the mean value of previous and current estimation values of error signal. Then,

$$\mu(n+1) = \mu_{\max} \text{ if } \mu(n+1) > \mu_{\max} \text{ or } \mu(n+1) = \mu_{\min} \text{ if } \mu(n+1) < \mu_{\min}$$

Otherwise

$$\mu(n+1) = \mu(n+1)$$

The main idea of (7) is to make the step size take a large value at the beginning of the learning process, and then it decays gradually until it reaches a fixed selected value in the rest of the learning process.

The way in which $\mu(n+1)$ is changing depends on previous value of step size $\mu(n)$ and also on the absolute mean of estimation error vector $e(n)$. Number of error signal elements in $e(n)$ vector will depend upon the value of the FIR taps (L). The main reason of using error vector $e(n)$ in (7) is that to make use of gradually decreasing the error signal from large value to small one. Furthermore, it is not required to recalculate again when the adaptive step size is adjusted and in turns, the proposed formula in (7) is simple when it is implemented in hardware. As shown in equation (7) one can start with large step size, to enhance the convergence speed, and gradually reduce it to attain its minimum value, to achieve a low level of misadjustment. To achieve best performance the step size should decrease to the next, smaller step in smoothing transient and in an exponential manner.

To ensure stability, the variable step size $\mu(n+1)$ is constrained to the pre-determined maximum μ_{max} and minimum step size values μ_{min} , such that $\mu(n+1)$ is set to μ_{min} or μ_{max} when it falls below or above these lower and upper bounds, respectively [3-5]. The constant μ_{max} is normally selected near the point of instability of the conventional LMS algorithm to provide the maximum possible convergence speed. Given that the initial value of step size $\mu(1)$ (i.e. when $n=1$) equals to μ_{max} . The value of μ_{min} is chosen as a compromise between the desired level of steady state misadjustment and the required tracking capabilities of the algorithm. The parameter δ controls the convergence time as well as the level of misadjustment of the algorithm at a steady state.

Then the update equation (6) for the weight vector will be $H(n+1) = H(n) + 2 \mu(n)X(n)$

Table 1 NVSSLMS Algorithm

Initial Conditions	$X(0)=H(0)=[0,0,\dots,0]^T$ Assign values for μ_{MAX} , μ_{MIN} , and δ .
For each instant of time index $n=1, 2, \dots, \dots$, iteration, Compute	
Adaptive FIR filter output	$y^{\wedge}(n) = H^{\wedge T} X(n)$
Output Estimation Error	$e(n) = d(n) - y^{\wedge}$
Step Size Adaptation	$\mu(n+1) = \mu(n)(1 - Abs(mean(e(n)))\delta)$
Check The Upper and Lower bound of the $\mu(n+1)$	$\mu(n+1) = \mu_{MAX}$ if $\mu(n+1) > \mu_{MAX}$ or $\mu(n+1) = \mu_{min}$ if $\mu(n+1) < \mu_{min}$ Otherwise $\mu(n+1) = \mu(n+1)$
Weights Adaptation	$H(n+1) = H(n) + 2 \mu(n)e(n)X(n)$

In this paper in addition to LMS, a comparison between the performance of the NVSSLMS and another Variable Step Size (VSSLMS) [3] algorithm is introduced. The steps required by the VSSLMS algorithm are shown below:

$$\mu_{n+1} = \alpha\mu + \gamma e_n^2 \quad (10)$$

$$0 < \alpha < 1 \quad \gamma > 0$$

If $\mu_{n+1} > \mu_{max}$ then $\mu_{n+1} = \mu_{max}$

$\mu_{n+1} < \mu_{min}$ then $\mu_{n+1} = \mu_{min}$

Otherwise $\mu_{n+1} = \mu_{n+1}$

V. SIMULATIONS

A. Simulation Methodology

The proposed a new variable step-size NVSSLMS algorithm is implemented in adaptive echo cancellation setup. The performance of the proposed algorithm is compared with the fixed step size LMS algorithm and with a variable step-size VSSLMS algorithm [3]. Computer simulations based on the adaptive echo cancellation setup shown in Fig. 1 were performed to examine the performance enhancement of the new algorithm.

Number of tap weights (i.e. L) is equal to 2048; real speech signal $v(n)$ (near end speech signal) is used as input to the adaptive FIR filter, shown in Fig. 3.a, which it is sampled at 8 kHz. This input signal is then convolved with the impulse response of the echo path (H) (Fig. 3.b) which uses a long finite impulse response filter. Figure 3.c shows a real far end speech echoed signal. A measured microphone signal $d(n)$ is shown in Fig. 3.d which

contains the near end speech $v(n)$, the far end echoed speech signal that has been echoed throughout the room and added white Gaussian noise $r(n)$ with zero mean and variance one. The far-end and near-end speech signals were taken from the speech sample in Matlab2010b. Both signals were 10 sec in duration with a sampling rate of 8 kHz, The goal of the adaptive acoustic echo canceller is to cancel out the far end speech, such that only the near-end speech is transmitted back to the far end listener..

The step size for LMS algorithm is equal to 0.01, in order to ensure stability (or convergence) of the LMS algorithm; the step size parameter is bounded by the following equation [2]:

$$0 < \mu < \frac{2}{\text{tapweightpower}} \quad (12)$$

The μ_{\max} and μ_{\min} values of VSSLMS algorithm have been chosen as given in [3] i.e. $\mu_{\max}=0.1$, and $\mu_{\min}=10^{-5}$ (Which is found to be a good choice in stationary and nonstationary environments and as given in the paper). The same values of these parameters were used also for NVSSLMS algorithm. μ_{\min} is chosen to provide a minimum level of tracking ability. Usually, μ_{\min} will be near the value of μ that would be chosen for the fixed step size LMS algorithm [3-5]. A typical value of α that was found to work well in simulations is $\alpha = 0.97$. The parameter γ is usually small 4.8×10^{-4} [3-5]. While the δ parameter for NVSSLMS algorithm is equal to 0.0001.

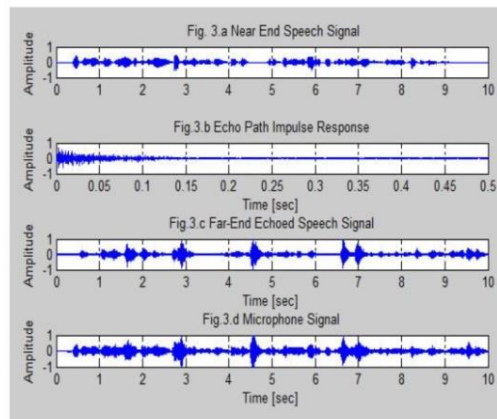


Fig 3: a: Near End Speech Signal; b: Room Impulse Response Signal; c: Far End Echoed Speech Signal; d: Microphone Signal.

B. Simulation Results

Fig.4 shows the estimation error square using different algorithms. It is clearly that the proposed algorithm has faster convergence time and small misadjustment compared with other algorithms. Moreover, figure5 shows the output error signal of adaptive echo cancellation for all algorithms. As shown, the proposed algorithm canceled the echo and added white Gaussian noise better than other algorithms. Therefore, the output error signal of the proposed algorithm is the best estimate of near end speech signal that was shown previously in Fig.3.a.

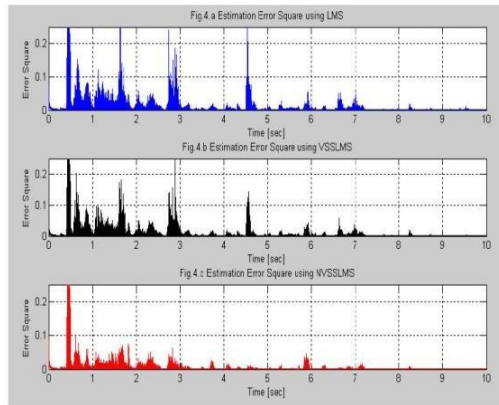


Fig 4: Estimation Error Square signal of adaptive echo canceller using different algorithms

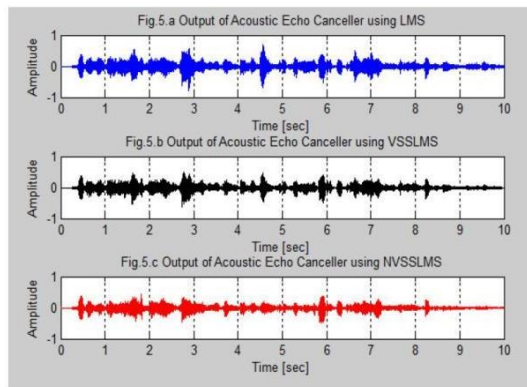


Fig 5: Output error signal of adaptive echo canceller using different algorithms

Fig.6 shows ERLE curve (equation (5)) for all algorithms. This figure shows that the NVSSLMS algorithm has higher ERLE value than all algorithms at the end of the convergence period, which means that it achieved to better echo suppression than all other algorithms. The amount of ERLE enhancement using proposed algorithm compared with LMS and VSSLMS algorithms is about 10dB and 8dB respectively.

From the simulation results, it is evident that, the variable step-size LMS adaptive algorithm gives a smaller error and provides good performance than the fixed step-size LMS adaptive algorithm and another VSSLMS algorithm.

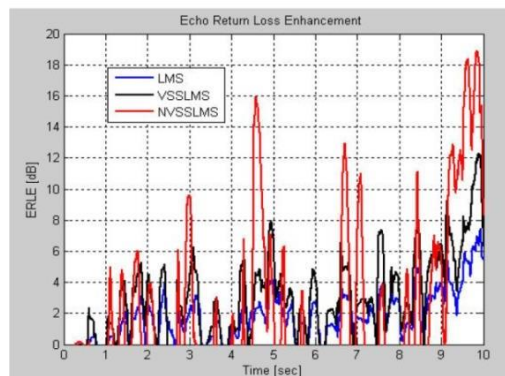


Fig 6: ERLE for all algorithms

VI. CONCLUSION

This paper focused in performance improvement of adaptive echo cancellation using new time varying step size LMS algorithms. The performance of the proposed algorithm was compared with that of the standard LMS as well as other variable step-size LMS algorithms through simulations. Results show that the proposed algorithm has a significant convergence rate improvement, low level of mis-adjustment in steady state and higher level of ERLE over fixed step size LMS and VSSLMS algorithms.

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