IOSR Journal of Electronics and Communication Engineering (IOSR-JECE)
e-ISSN: 2278-2834,p- ISSN: 2278-8735.Volume 12, Issue 4, Ver. III (Jul.-Aug. 2017), PP 01-06
www.iosrjournals.org

Statistical Analysis of a New Optimally Controlled Adaptive Algorithm for Acoustic Echo Cancellation

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Abstract: *One of the major issues involved in today's Telecommunication technology is Acoustic echo during the conversations or full duplex configuration in Hands free communication systems. Acoustic echo cancellation is one of the most formidable system identification problems and several appealing solutions have been developed in past years. Predominantly used adaptive filter is NLMS algorithm, which has to confront the compromise between rapid convergence and low misalignment to meet these contrary requirements, choosing the best possible step- size is the matter of interest. In this paper, a new efficient NLMS based algorithm similar to the state variable model has been presented. The algorithm depends on the minimization of the misalignment by an interesting optimization criterion follows an iterative procedure for the evaluation of individual control factors. Simulations performed for acoustic echo cancellation evident for good behavior and effectiveness of the approach.*

Keywords: *Control factor, Misalignment, NLMS, Optimally controlled, Convergence*

Date of Submission: 15-07-2017 Date of acceptance: 29-07-2017

I. Introduction

The acoustic echo cancellation problem arises when acoustic coupling between a loudspeaker and a microphone occurs in applications like hands-free telephone and teleconferencing. Due to this coupling the far-end talker's signal being fed back to the far-end taker creating annoying echoes and instability in the system [7]-[9]. 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 as illustrated in Fig. 1. 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. Adaptive filters are widely used in many system identification scenarios. In this frame of reference, the primitive idea is to update each coefficient of the filter independently of the others, by adjusting the adaptation step size in proportion to the magnitude of the estimated filter coefficient [10], [14]. In this way, among all the coefficients, the adaptation gain is "proportionately" redistributed. Emphasizing the large ones in order to boost up their convergence and, apparently, to increase the overall convergence rate.

In this paper, we propose an optimally controlled NLMS based adaptive filter for system identification. First, we consider a more general framework, assuming that the unknown system is modeled by a time-varying system following a first-order Markov model. In this way, we deal with a state variable model, similar to Kalman filtering [4], [10].

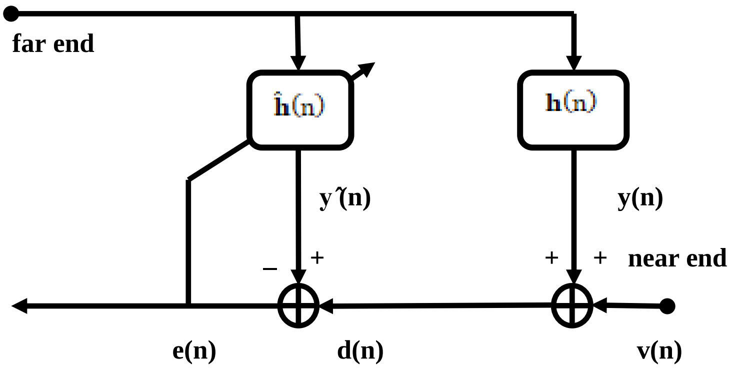

Fig. 1 Acoustic echo cancellation configuration

Here we follow an interesting optimization criterion based on the minimization of the system misalignment, which is a reasonable approach for system identification problems, e.g., see [12], and the references therein. The individual control factors results in a more rigorous way, depending on the coefficients' misalignment (instead on the coefficients' magnitude, as in the case of the classical proportionate-type algorithms). Simulations performed in the context of acoustic echo cancellation (AEC) indicate that the proposed algorithm could be an attractive choice for system identification problems.

II. NLMS Based Optimal Algorithm

Let us consider a system identification problem, where adaptive filter is used to model an unknown system, both driven by the same zero-mean input signal $x(n)$. In this context, the output (microphone or desired) signal at the discrete-time index n is

$$d(n) = \mathbf{h}^T(n)\mathrm{x}(n) + v(n), \tag{1}$$

Where **h** (n) = [$h_0(n)$ $h_1(n)$ $h_2(n)$ ...... $h_{L-1}(n)$ $]^T$ is the impulse response(of length L) of the system (from the loudspeaker to the microphone) that we need to identify, and v(n) is the system noise, usually considered as a zero-mean white Gaussian noise signal. The variance of this additive noise is σ_v^2 ,

x (n) = [$x(n)$ $x(n-1)$ $x(n-2)$ ...... $x(n-L+1)$ $]^T$ is a vector containing the L most recent time samples of the zero-mean input (loudspeaker) signal x(n), superscript T denotes transpose of a vector or a matrix.

Let us assume that $h(n)$ follows a simplified first-order Markov model

$$h(n) = h(n-1) + w(n) \tag{2}$$

where w(n) is a zero-mean white Gaussian noise signal vector, which is uncorrelated with h(n − 1). The correlation matrix of $w(n)$ is assumed to be $\mathbf{R_w} = \sigma_w^2\mathbf{I}_L$, where $\mathbf{I}_L$ is the $L \times L$ identity matrix of $w(n)$ and the variance , σ_w^2 it captures the uncertainties in $h(n)$. This model can be valid in many system identification problems, like in acoustic echo cancellation [4], [6]. The objective is to estimate or identify **h** (n) with an adaptive filter, defined by **h** (n) = [$\hat{h}_0(n)$ $\hat{h}_1(n)$ $\hat{h}_2(n)$ ...... $\hat{h}_{L-1}(n)$ $]^T$ a state variable model, similar to kalman filtering.

2.1 NLMS algorithm:

The NLMS algorithm is defined by the update

$$\hat{h}(n) = \hat{h}(n-1) + \mu\mathrm{x}(n)e(n) \tag{3}$$

$$\mu = \frac{\alpha}{\mathrm{x}^T(n)\mathrm{x}(n) + \delta}$$

where μ is the step size parameter

$$e(n) = d(n) - \hat{h}^T(n-1)x(n) \tag{5}$$

is the error signal of the adaptive filter.

2.2 JO- NLMS algorithm:

The JO- NLMS algorithm is defined as follows

Let us define posterior misalignment as $q(n) = h(n) - \hat{h}(n)$, the update results in

$$q(n) = q(n-1) + w(n) - \mu x(n)e(n) \tag{6}$$

$$e(n) = x^T(n)q(n-1) + x^T(n)w(n) + v(n) \tag{7}$$

$$\mu(n) = \frac{1}{(L+2)\sigma_x^2 + \xi}$$

where $\xi = L\sigma_v^2/[m(n-1) + L\sigma_w^2]$. So, the filter update is

$$\hat{h}(n) = \hat{h}(n-1) + \mu\mathrm{x}(n)e(n) \tag{9}$$

The step-size from (10) is introduced in (9) to update the parameter $m(n)$

$$m(n) = [1 - \mu(n)\sigma_x^2][m(n-1) + L\sigma_w^2] \tag{10}$$

Summarizing the resulting JO-NLMS based algorithm defined by relations (8), (9) and (10), using the initialization $\hat{h}(n) = 0$ and $m(0) = \varepsilon$, (where ε is a positive constant). This algorithm is very similar to the simplified kalman model [4], [10].

III. Proposed Algorithm: Optimally Controlled NLMS

We extend JO NLMS algorithm to an optimized NLMS with individual control factors. The update equation is [8]:

$$\hat{h}(n) = \hat{h}(n-1) + \mu\mathbf{A}(n-1)\mathrm{x}(n)e(n) \tag{11}$$

μ is the step-size $\mu = \frac{\alpha}{\mathrm{x}^T(n)\mathrm{x}(n)+\delta}$

where $\mathbf{A}(n)$ is a diagonal matrix $(L \times L)$ containing the control factors at time index n, the filter update (11) can also be written in terms of posterior misalignment as

$$q(n) = q(n-1) + w(n) - \mu\mathbf{A}(n-1)\mathrm{x}(n)e(n) \tag{12}$$

3.1 Analysis of convergence and misalignment:

Taking ℓ_2 norm in (12) on both then mathematical expectations on both sides removing correlated products

$$\mathrm{E}[\|q(n)\|_2^2 = \mathrm{E}[\|q(n-1)\|_2^2 + L\sigma_w^2 - 2\mu\mathrm{E}[\mathrm{x}^T(n)\mathbf{A}(n-1)\mathrm{q}(n-1)e(n)] - 2\mu\mathrm{E}[\mathrm{x}^T(n)\mathbf{A}(n-1)w(n)e(n) + \mu^2\mathrm{E}[e^2(n)\mathrm{x}^T(n)\mathbf{A}^2(n-1)\mathrm{x}(n)] \tag{13}$$

Finally after some recommended computations

$$m(n) = m(n-1) + L\sigma_w^2 - 2\mu\{[\mathbf{R_q}(n-1) + \sigma_w^2 I_L]\mathbf{A}(n-1)\} + \quad \mu^2\sigma_x^2\mathrm{tr}[\mathbf{A}^2(n-1)]\{\sigma_v^2 + \sigma_x^2[m(n-1) + L\sigma x2\sigma w2\} \tag{14}$$

Imposing $\partial m(n)/\partial\mu(n) = 0$ to (14), (Considering the step size is time dependent), optimal step size is obtained by

$$\mu(n) = \frac{\mathrm{tr}\{[\mathbf{R_q}(n-1)+\sigma_w^2 I_L]\mathbf{A}(n-1)\}}{\mathrm{tr}[\mathbf{A}^2(n-1)]\{\sigma_v^2+\sigma_x^2[m(n-1)+L\sigma_w^2]\}} \tag{15}$$

The update of $m(n)$ becomes

$$m(n) = m(n-1) + L\sigma_w^2 - \frac{-\sigma_x^2\{\mathrm{tr}\{[\mathbf{R_q}(n-1)+\sigma_w^2 I_L]\mathbf{A}(n-1)\}\}^2}{\mathrm{tr}[\mathbf{A}^2(n-1)]\{\sigma_v^2+\sigma_x^2[m(n-1)+L\sigma_w^2]\}} \tag{16}$$

After several computations and simplifications, the optimal step size results in

$$\mu(n) = \frac{1}{c\{\sigma_v^2+\sigma_x^2[m(n-1)+L\sigma_w^2]\}} \tag{17}$$

The update of the parameter becomes

$$m(n) = m(n-1) + L\sigma_w^2 - c\mu(n)\sigma_x^2\|\gamma(n-1)\|_2^2 \tag{18}$$

Finally the filter update is obtained as

$$\hat{h}(n) = \hat{h}(n-1) + c\mu(n)\gamma(n-1)\mathrm{x}(n)e(n) \tag{19}$$

where element wise product between γ(n-1) and x(n).

$$c = \frac{L}{m(n-1)+L\sigma_w^2} \tag{20}$$

The vector contains the diagonal elements of the matrix

$$\gamma(n) = \gamma(n-1) + \sigma_w^2 1_{L\times1} + c\mu(n)\sigma_x^2\{\sigma_v^2 + \sigma_x^2[m(n-1) + L\sigma_w^2] - 2c\mu(n)\} \times \gamma(n-1) * \gamma(n-1) \tag{21}$$

Where $1_{L\times1}$ denotes a column vector with all its L elements equal to one. Summarizing the result, the optimally controlled NLMS (OC-NLMS) algorithm with individual control factors is defined by relations (17)-(20) and (21).

$$\hat{\sigma}_w^2(n) = \frac{1}{L}\left\|\hat{\boldsymbol{h}}(n) - \hat{\boldsymbol{h}}(n-1)\right\|_2^2$$

The interesting parameter in proposed algorithm is $m(n)$ this can b used to evaluate the overall performance of the algorithm. A well known performance measure is echo to return loss enhancement (ERLE), as it requires priori knowledge of the impulse response or the echo signal. Here we propose to monitor the parameter $M(n) = \left\|\hat{h}(n)\right\|_2^2/m(n)$, which has similar significance with ERLE.

IV. Simulation Environment

Simulations are performed for the acoustic echo cancellation using MATLAB [4], [6]. In this context, an adaptive filter is used to estimate the impulse response. The length of the impulse used in the experiments L=10, the same length is set for the adaptive filter. The input signal, $x(n)$, is a white Gaussian noise, the output of the echo is corrupted by an independent white Gaussian noise $v(n)$, the SNR is 20dB. Here it is assumed that σ_v^2 is known, in practice it can be estimated [5]. An echo path change scenario is simulated, by shifting or inversing the impulse response, in the middle of the simulation.

4.1 **Simulation results:**

Interpreting the results**,** fig. 2, depicts the performance measure is mean square error (in dB), as noticed in the figure Mean square error is better for proposed OC-NLMS algorithm compared to JO-NLMS algorithm.

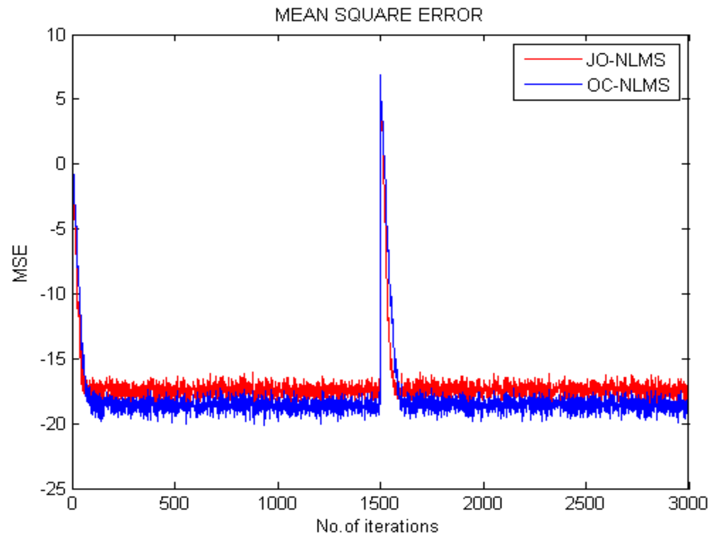

Fig. 2. Mean square error (dB) of JO-NLMS and OC-NLMS

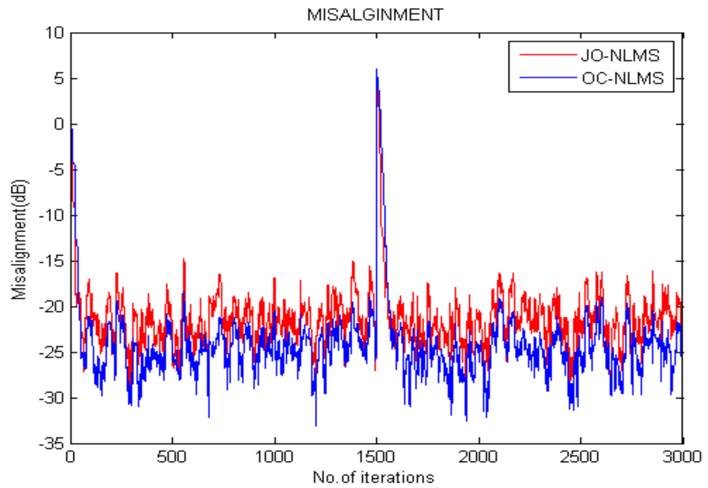

Fig.3. Evaluation of Misalignment of JO-NLMS and OC-NLMS algorithm

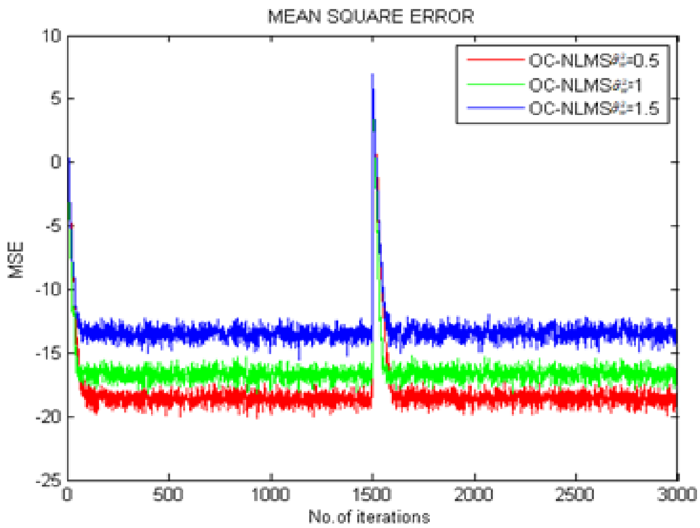

Fig.4. Performance of OC-NLMS algorithm as σ_w^2 varies MSE changes

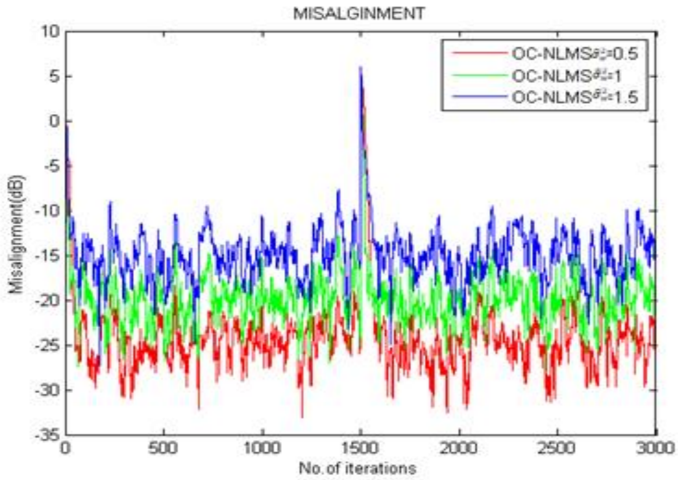

Fig.5. Performance of OC-NLMS algorithm as σ_w^2 varies Misalignment changes

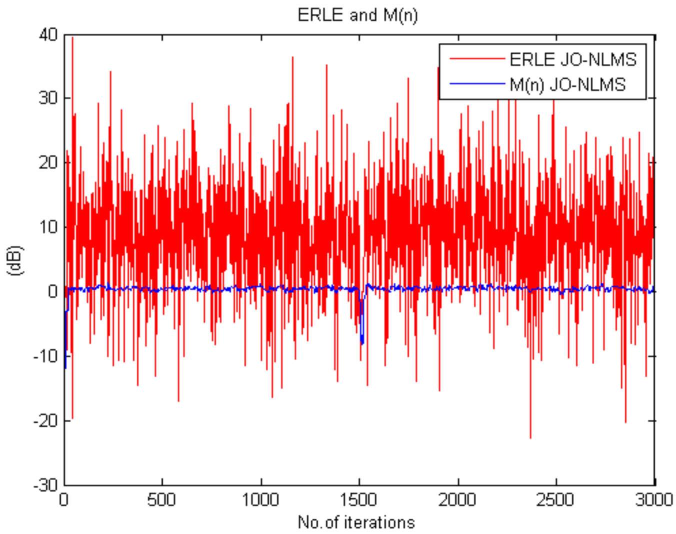

Fig. 6. Evaluation of the parameter M(n) and ERLE of JO-NLMS

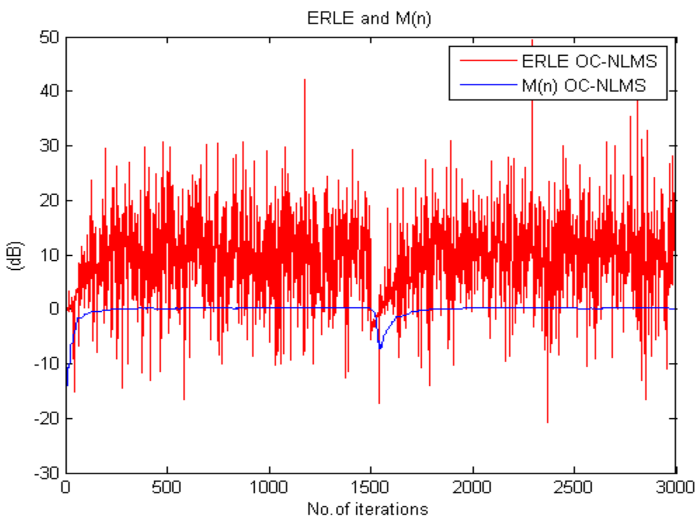

Fig. 7. Evaluation of the parameter M(n) and ERLE of OC-NLMS

The other essential performance measure is normalized misalignment (in dB) defined as $20\log_{10}\left\|\mathrm{h}(n)-\hat{\mathrm{h}}(n)\right\|_2/\|\mathrm{h}(n)\|_2$. As we can notice from this figure, the algorithm has better convergence rate, while achieving lower misalignment level as depicted in fig. 3.The variance σ_w^2 captures the uncertainties in echo path, σ_w^2 is varied for analysing the performance of the system. The observations describe that as the uncertainties in echo path increases the convergence of the algorithm is increasing, but the misalignment increases. The proposed algorithm traces the uncertainties in the echo path and works well for the large uncertainties in terms of convergence, as illustrated in figures (4) and (5).The parameter $M(n)=\left\|\hat{h}(n)\right\|_2^2/m(n)$ proposed to monitor the performance, which has similar significance with ERLE [4] in both the algorithms as depicted in the figures (6), (7).

Comparison of JO-NLMS and OC-NLMS algorithms in terms of Steady state error, ERLE and percentage of misalignment is illustrated in the table

TABLE FOR COMPARISON

Measure of performance	JO-NLMS	OC-NLMS
Steady state error(dB)	-17.366	-19.7320
ERLE(dB)	38.250	49.4520

V. Conclusion

In this paper, we presented a qualitative optimized NLMS based algorithm which has a great potential in the context of sparse system identification. The optimization criterion employed is a minimization of the system misalignment, which is a natural approach the proposed algorithm OC-NLMS ensures better convergence, good traceable expression and controllable low misalignment compared to JO-NLMS which indicates qualitative performance of the system. Consequently, it is characterized as resisting the uncertainties in the echo path. Simulations justify performance and effectiveness of the approach, reducing the computational complexity in estimations of the parameters will be the next work in the future.

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IOSR Journal of Electronics and Communication Engineering (IOSR-JECE) is UGC approved Journal with Sl. No. 5016, Journal no. 49082.

Shaik Sazia Athar. "Statistical Analysis of a New Optimally Controlled Adaptive Algorithm for Acoustic Echo Cancellation." IOSR Journal of Electronics and Communication Engineering (IOSR-JECE) 12.4 (2017): 01-06