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Echo Cancellation using an Affine Combination of Two LMS Adaptive Filters

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ABSTRACT
This paper studies the statistical behavior of an affine combination of the outputs of two least mean-square(LMS) adaptive filters that simultaneously adapt using the same white Gaussian inputs. The purpose to combine two filters is to obtain a new LMS adaptive filter with fast convergence and small steady-state mean-square deviation (MSD). The combination factor λ(n) is optimized which minimizes the mean-square error (MSE) and gives good steady state response. Here Two schemes proposed to find out the optimal mixing parameter to get optimized sequence λ(n) are stochastic gradient search method and error power based scheme. By using this affine combination, we can cancel the echo signal with high convergence speed.

Keywords **- Adaptive filters, affine combination, convex combination, least mean square, step size, stochastic algorithms, affine combination**

I. INTRODUCTION
The common problem in designing adaptive filters is to overcome the trade- off between the convergence speed and final misadjustment, i.e faster converging filter gives large steady state deviation and slowly converging filter gives small deviation from steady - state value. This trade off can be controlled by this affine combination.

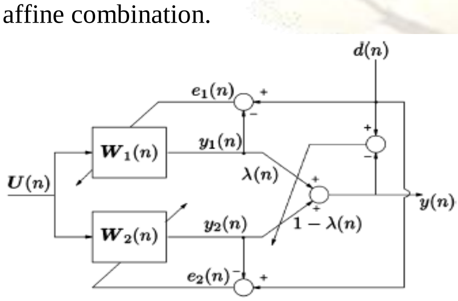


Fig.1 Adaptive combining of two transversal adaptive filters

In this scheme where adaptive filter W1(n) uses a larger step size than adaptive filterW2(n) . The main goal is the selection of the scalar mixing parameter λ(n) for combining the two filter outputs. The mixing parameter is defined as a sigmoid function whose free parameter is adaptively optimized using a stochastic gradient search which minimizes the quadratic error of the overall filter, which leads to an optimal affine sequence λ_0 (n).

Finally, two realizable schemes for updating λ(n) are proposed. The first scheme is based on a stochastic gradient approximation. The second scheme is based on the relative values of averaged estimates of the individual error powers. Both schemes are briefly studied, and their support the theoretical findings and show that the analysis performances are compared to that of the optimal affine combiner. Finally we apply this scheme to the echo cancellation

II. OPTIMAL AFFINE COMBINER
The affine combination is shown in Fig. 1. Each filter uses the LMS adaptation rule but with different step sizes μ_1 and μ_2

$W_i(n+1) = W_i(n) + \mu_i e_i(n)U(n)$
(1)

Where
$e_i(n) = d(n) - W_i^T(n)U(n)$
(2)
$d(n) = e_0(n) + w_0^T U(n)$
(3)
where $W_i(n)$,i=1, 2 are the N-dimensional adaptive coefficient vectors, is assumed zero-mean,and statistically independent of any other signal in the system . $U_i(n)$is the input vector. It will be assumed, without loss, that $\mu_1 > \mu_2$, so that will, in general, $W_1(n)$ converges faster than $W_2(n)$. Also, $W_2(n)$ will converge to the lowest individual steady-state weight misadjustment. The weight vectors $W_1(n)$ and $W_2(n)$ are coupled both deterministically and statistically through and U(n) and $e_0(n)$.

The outputs of the two filters are combined as in Fig.1

$Y(n) = \lambda(n)y_1(n) + [1-\lambda(n)]\, y_2(n)$
(4)

Where $Y_i(n)= W_i^T(n)U(n)$ i=1,2 and over all system error is
$e(n) = d(n)- y(n)$
(5)

Equation (4) can be re –written as

$Y(n) = \lambda(n)\, W_1^T(n)\, U(n) + [1-\lambda(n)]\, W_2^T(n)\, U(n)$

$= \{\lambda(n)\, [w_1(n) – w_2(n)] + w_2(n)\}^T U(n)$

$= \{\lambda(n)\, w_{12}(n) + w_2(n)\}^T\, U(n)$
(6)

where $W_{12}(n)= W_1(n)- W_2(n)$

Equation 6 shows that y(n) can be interpreted as a combination of $W_2(n)$ and a weighted version of the difference filter $W_{12}(n)$.. It also shows that the combined adaptive filter has an equivalent weight vector given by

$w_{eq} = \lambda(n)\, w_{12}(n) + w_2(n)$
(7)

Subtracting (1) for i=2 from (1) for yields a recursion for $w_{12}(n+1) =$

$[I – \mu_1 U(n)U^T(n)]\, w_{12} + (\mu_1 – \mu_2)e_2(n)U(n)$
(8)

A rule to find λ, which minimizes MSE

$e(n) = e_0(n) + [w_{02}(n) – \lambda(n)w_{12}(n)]^T U(n)$
(9)

$= -2E\, [e(n)w_{12}^T(n)U(n)/w_2(n),w_{12}(n)]= 0$
(10)

$[w_{02}(n) – \lambda(n)w_{12}(n)]^T R_u\, w_{12}(n) = 0$
(11)

$\lambda_0(n) = w_{02}^T(n)R_u w_{12}(n)/w_{12}^T(n)R_u w_{12}(n)$
(12)

which is the expression for the optimum affine combiner , as a function of unknown system response.

III. ITERATIVE ALGORITHMS TO ADJUST AFFINE COMBINER

The previous derivation of the optimal linear combiner was based upon prior knowledge of the unknown system response.. Clearly, this is not the case in reality. However, the theoretical model and its derived properties can be used to upper bound the performance of practical algorithms for adjusting without such knowledge. Algorithms that yield close-to-optimal performance for typical unknown responses can be considered as good candidates for practical applications.

Performance close to the optimal suggests that further analytical study of a new algorithm could be worth the effort. This is especially important for the adaptive combiner structure. There are two algorithms for the adjustment of optimal affine combiner λ . The first algorithm is based upon a stochastic gradient search for the optimal . The second is based on the ratio of the average error powers from each individual adaptive filter. The performances of these algorithms are then compared to optimal performance

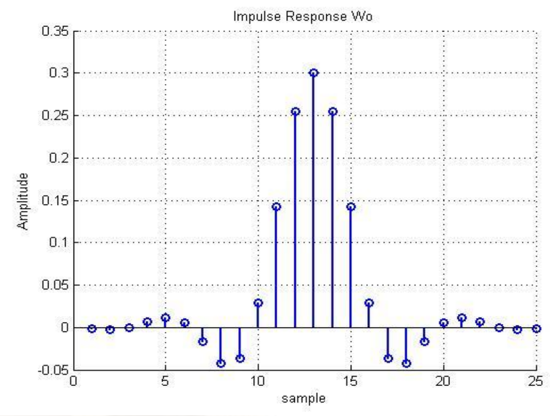


Fig2: Unknown System Response

3.1 Stochastic Gradient Approach:

Consider a stochastic gradient search to estimate the optimum instantaneous value of λ. The stochastic gradient algorithm to update λ is

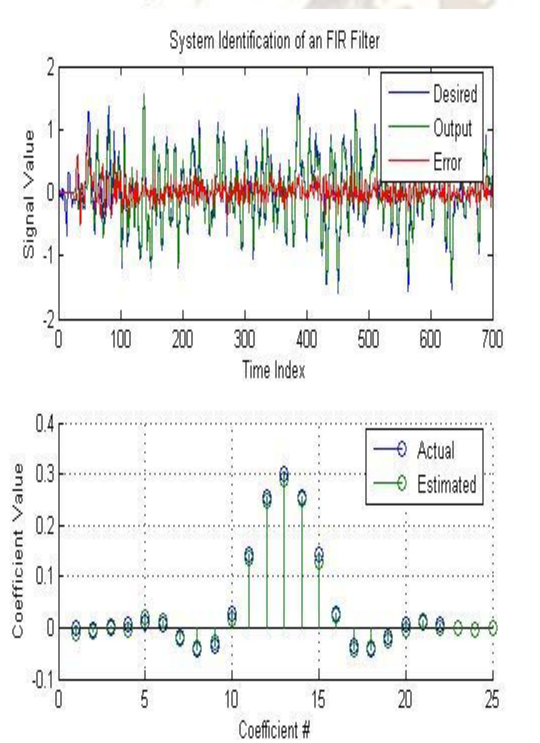
$\lambda(n+1) = \lambda_1(n) +$
$\mu_\lambda[d(n)n – w_{12}^T(n)U(n)]w_{12}^T(n)U(n)$ (13)

$w_{12}(n) = \lambda_1(n)w_1(n) = [1 - \lambda_1(n)]w_2(n)$ (14)

Equation (13) is a linear first order stochastic time-varying recursion in the scalar parameter $\lambda_1(n)$. The stochastic behavior of this recursion has been analyzed .The accuracy of the theoretical analysis and the performance of the proposed algorithm for adjusting $\lambda_1(n)$ are evaluated here. Appropriate values of μ_λ were chosen so that the algorithm was able to track

The stochastic gradient algorithm requires a good estimate of the noise power to reasonably select and mildly constrain in recursion (13). The accuracy of this estimate could limit the usefulness of the stochastic gradient algorithm for some applications. A different scheme for choosing , based on the average error powers of the two filters is proposed.

Fig3 : System Identification using Affine LMS of Stochastic Gradient Approach



MSE of affine combination is always less than either LMS1 and LMS2.This behavior is expected from an optimal combiner and verified . These curves represent the best performance that could be obtained using two LMS

3.2 Error Power Based Scheme:

A function of time averaged error powers could be a good candidate for an estimator of the optimum $\lambda(n)$ for each n . The individual adaptive error powers are good indicators of the contribution of each adaptive output to the quality of the present estimation of d(n). These errors are readily available and do not need an estimate of the additive noise power.

Consider a uniform sliding time average of the instantaneous Errors

$$e_1^2(n) = 1/k\ \Sigma_{m-n-k+1}^{n}\ e_1^2(m) \qquad (15)$$

$$e_2^2(n) = 1/k\ \Sigma_{m-n-k+1}^{n} e_2^2(m) \qquad (16)$$

where is the averaging window. Then, consider the instantaneous value of $\lambda(n)$ determined as

$$\lambda_2(n) = 1- k\mathrm{erf}\ (e_1^2(n)/e_2^2(n)) \qquad (17)$$

$$\mathrm{erf}(x) = 2/\sqrt{\pi} \int_0^x e^{-t2/2}\, dt \qquad (18)$$

Fig shows the behaviors of using error power based scheme to update affine combiner and MSE of individual and combined. These results clearly show that the proposed algorithm leads to a very good practical implementation of the linear combiner.

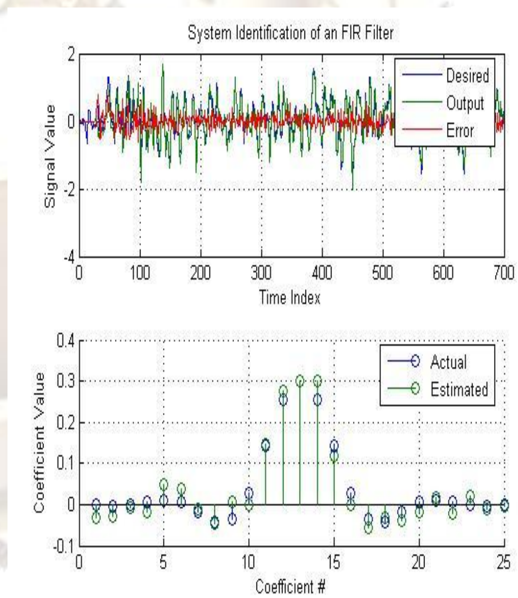


Fig 4.: System identification using error power based scheme

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4. ECHO CANCELLATION SIMULATION & RESULTS:

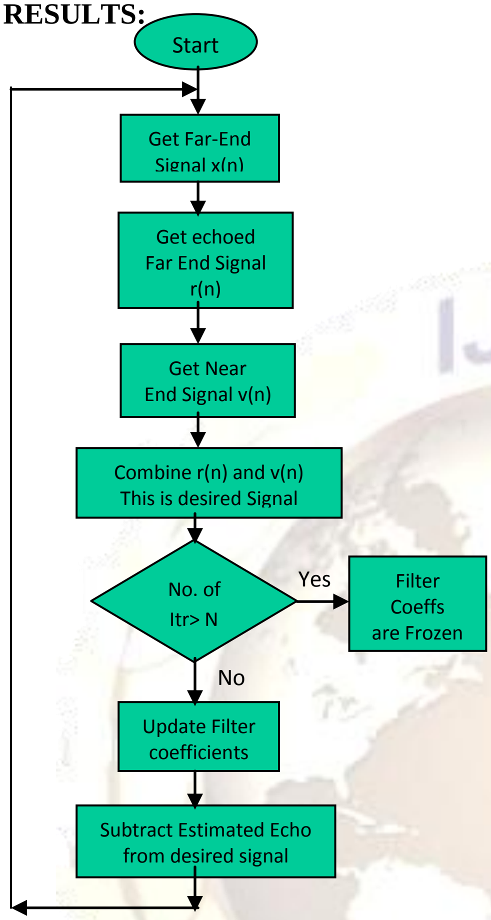


Fig 5: flow chart for echo cancellation procedure

4.1 Description of the Simulation Setup

This section describes the simulation environment, its requirements and the procedures adopted.

1. The input signals, both far-end and near-end signals, were simulated and given to the AEC, which executed on a PC with the MATLAB environment.
2. The input signals seven seconds in duration.
3. A sampling rate of 8000 Hz was used for all the signals in the simulation.
4. The graphs plotted have x-axes denoting the time and y-axes denoting the amplitude or magnitude of the signal.

4.2. Results:

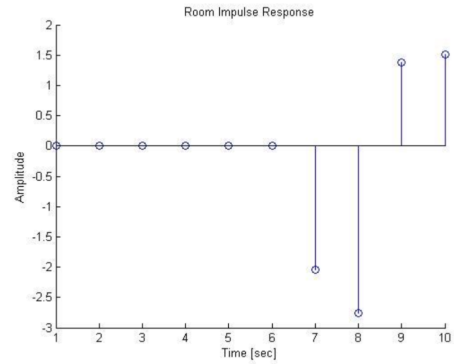
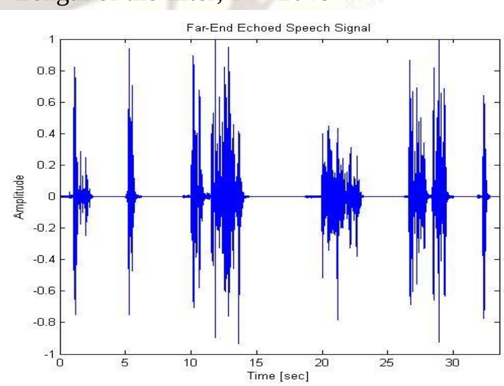


Fig 6 : Room Impulse Response

This figure shows a typical room impulse response. Each coefficient adds certain delay to the input. This is echoed output of input speech. Impulse response of two artificially generated echo channels, the first being a dispersive channel with 256 active coefficients, and the second being strongly sparse, with only 16 active coefficients. The far-end signal was delayed and scaled in order to produce the echo signal, *r(n)*, which is presented in Figure 6. The echo signal was produced when the far-end signal, *x(n)*, passed through the echo path, *h*. The echo signal was added to the near-end signal, *v(n)*, in order to produce the desired signal, *d(n)*, which became the input for the adaptive filter. The plot of the near end signal, *v(n)*, and the plot of the desired signal, *d(n)*. is presented in Fig 7.

Various parameters for the algorithm such as the convergence factor, no of iterations should be initialized. Additionally, the length of the filter had to be established beforehand. The values of these parameters, which were used in the simulation, are Length of the filter, N = 2048



Convergence factor, μ= 005. This value was found to produce faster convergence of the NLMS algorithm.
A small constant, δ= 0.9

Fig 7: far ended echoed speech signal

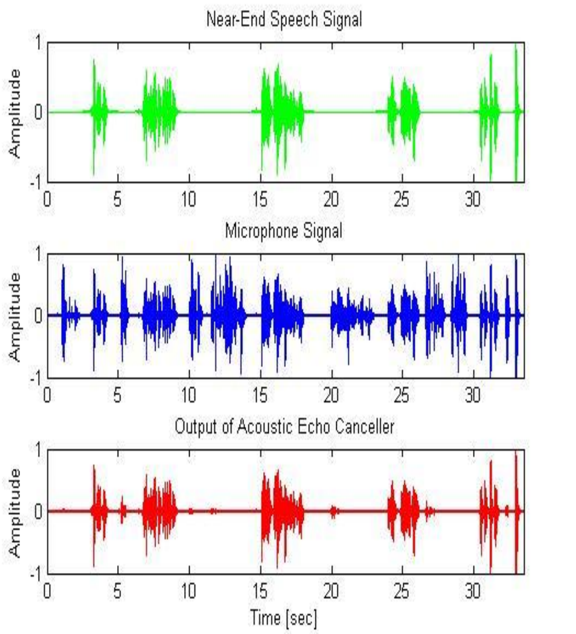


Fig 8: Near end &Output signal of echo canceller

4.3Evaluation of Echo cancellation algorithm:

In order to evaluate the effective working of the algorithm, some basic tests were conducted. This section provides a brief account of these tests.

4.3.1 Convergence Test

The first and paramount test of the algorithm was whether or not the algorithm converged. Here a sparse room impulse response is considered for simulation. It is derived by assuming room impulse response is a band pass filter. First, adaptive algorithm is used to identify the room impulse response. Using this room impulse response, Echo generated within the room is estimated and subtracted from the output of room. Hence, Echo cancellation is performed. As more no. of iterations are considered, identification of room impulse response becomes more accurate and echo cancellation is performed better. The mean square error is found between original signal and echo cancelled signal. As more no of iterations, less is the error.

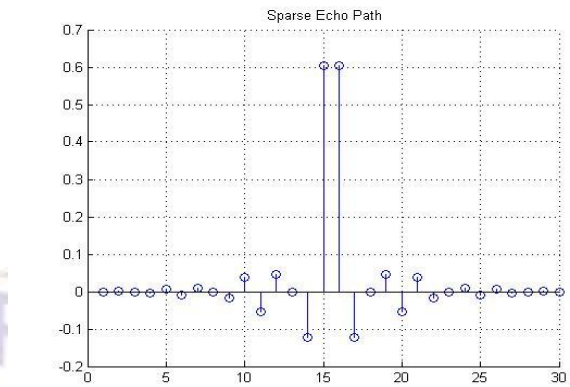


Fig 9: Sparse Echo path used for simulation

4.3.2 Auditory Test

The last test consisted of listening to the output for appropriate cancellation of echoes. The audio of the output signals was presented to a panel of five members with no technical expertise in this field. The panel was almost not able to distinguish the near end signal, *v(n)*, and the output signal with the residual echo, *e(n)*, removed. Some discrepancies in the audio could be attributed to the fact that the real-time applications cannot escape the factor called noise.

6. CONCLUSIONS AND FUTURE SCOPE

. One of the major problems in a telecommunication application over a telephone system is echo. The Echo cancellation algorithm presented in this thesis successfully attempted to find a software solution for the problem of echoes in the telecommunications environment. The proposed algorithm was completely a software approach without utilizing any DSP hardware components. The algorithm was capable of running in any PC with MATLAB software installed.

The algorithm proposed in this thesis presents a solution for single channel acoustic echoes. However, most often in real life situations, multichannel sound is the norm for telecommunication. For example, when there is a group of people in a teleconference environment and everybody is busy talking, laughing or just communicating with each other multichannel sound abounds. Since there is just a single microphone the other end will hear just a highly incoherent monographic sound. In order to handle such situations in a better way the echo cancellation algorithm developed during this research should be extended for the multichannel case

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