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A Comparative Study of Acoustic Echo Cancellation Algorithms in Sparse Impulse Response.

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Abstract
This paper aims at studying and comparing the performance of typical sparse algorithms for acoustic echo cancellation. When the echo path is sparse, the conventional Normalized Least Mean Square (NLMS) algorithm suffers from slow convergence. Thus, sparse adaptive filtering algorithms were introduced to overcome the convergence problem of adaptive filters in sparse impulse response. To determine the algorithm with best performance in echo cancellers, the comparison between these algorithms based on Echo Return Loss Enhancement (ERLE) and Mean Square Error (MSE) is carried out using MATLAB.
Keywords: Sparse Adaptive algorithms, MATLAB, Echo cancellation, ERLE, MSE

I. INTRODUCTION

The acoustic echo cancellation problem arises due to coupling between a loudspeaker and a microphone. This may occur in applications such as hands-free telephone and teleconferencing. The coupling result in the far-end talker's signal being fed back to the far-end taker resulting in disturbing echoes and instability sometimes. 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 [1]. This is illustrated in Fig. 1.1.The echo path is assumed unknown and time-varying. As a result, the adaptive echo canceller has the task of estimating the echo path and also keeping track of changes in it [1].

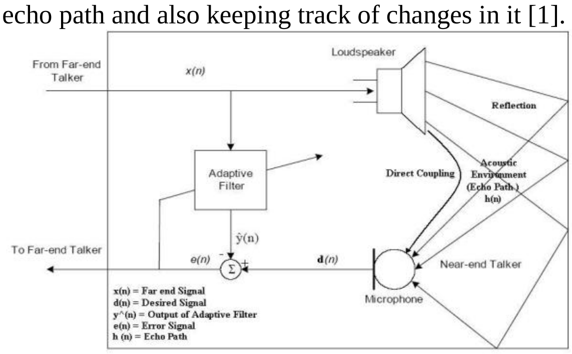

Fig 1: Echo Cancellation Process

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. Adaptive algorithms are used to search the optimum $h(n)$. The filter $h(n)$ denotes the impulse response of acoustic environment, $\hat{h}(n)$ denotes the adaptive filter used for cancellation of echo signal. The main aim of adaptive filtering technique is to equate the output y(n) to the desired output $d(n)$. The error signal $e(n) = d(n) - y(n)$ is given back at each iteration, so the filter coefficients are changed algorithmically to minimize $e(n)$ known. Calculating the mentioned error signal $e(n)$ is the aim of adaptive filter. Adaptive filters works on adaptive algorithms according to which they change their coefficients. When the filter output obtained is same as the desired signal, the echoed signal is cancelled out.

In the acoustic echo cancellation process, the channel of transmission is sparse .This means few coefficients are active and others are zero or close to zero. Thus echo cancellers must be robust to sparseness [5]. Classical adaptive algorithms like Normalized least mean square algorithm (NLMS) have slow convergence in sparse response because of uniform step size across all its filter coefficients. In order to improve the convergence problem, the proportionate normalized least-mean square algorithm (PNLMS) was developed .

The basic idea behind these proportionate algorithms was to update filter coefficients independently by adjusting the step size in proportion to the estimated filter coefficients [2]. This lead to fast initial convergence but in order to improve the overall convergence performance, improved versions of PNLMS as Improved PNLMS (IPNLMS) and Mu-law PNLMS (MPNLMS) were developed.

The IPNLMS performed as a combination of both NLMS and PNLMS algorithms with the help of a controlling factor[5].This algorithm have shown better convergence results in both and non sparse impulse response. The MPNLMS algorithm improved the convergence of PNLMS by choosing optimal proportionate step sizes (by taking logarithmic values of the coefficients) during adaptation process [6].

Section-2 describes what the sparse impulse response is. Section-3 gives review of all algorithms for echo cancellation such as NLMS, PNLMS, IPNLMS and MPNLMS. Section-4 gives the relative comparison of computational complexity of all the described algorithms Section-5 shows the results, observations and comparison of these algorithms on the basis of ERLE and MSE.Section-6 defines the conclusions and the future work.

II. SPARSE RESPONSE

A sparse impulse response has most of its components with zero or small magnitude and can be found in telephone networks. Due to the presence of bulk delays in the path only 8-10% exhibits an active region [8]. Fig 1.2 shows a typical sparse impulse response that can be realized in reality.

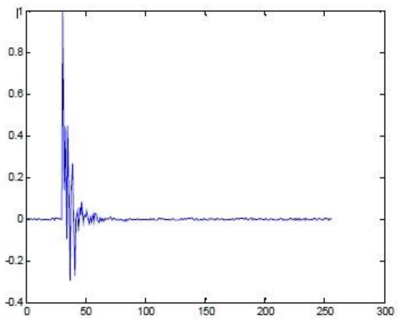

Fig 2 -An example of sparse impulse response

Sparse impulse responses are encountered in several applications, such as in acoustic and digital network echo cancellers.

The degree of sparseness for an impulse response can be quantified as:

$$\xi(n) = \frac{L}{L-\sqrt{L}}\left\{1 - \frac{\|h(n)\|_1}{\sqrt{L}\|h(n)\|_2}\right\} \quad (1)$$

and $0 \le \xi(n) \le 1.$

During the conduct of experiments, a sparse impulse response generator is used to provide synthetic sparse impulse response as described in section 6.

III. REVIEW OF ALGORITHMS

In derivations and descriptions, the following notations are used

$x(n) =$ Far end signal

$y(n) =$ Echo and Background noise

$x(n) = [x(n) \dots \dots x(n-L+1)]^T$

$h(n) = [h_0 \dots \dots h_{L+1}]^T$ True Echo Path

$\hat{h}(n) = [\hat{h}_0 \dots \dots \hat{h}_{L+1}]^T$ Estimated echo path

$e(n) =$ error signal

3.1 NLMS Algorithm

NLMS differs from LMS in the way the taps weights are updated. The adjustment applied iteratively to the tap vector is normalized w.r.t squared Euclidean norm. NLMS serves as a reference algorithm in echo cancellers. The error signal and the coefficient update equation of the NLMS algorithm are given by [4]

$$e(n) = y(n) - \hat{h}^T(n-1)x(n) \quad (2)$$

$$\hat{h}(n) = \hat{h}(n-1) + \frac{\mu x(n)e(n)}{x(n)x^T(n) + \delta_{NLMS}} \quad (3)$$

Equation (2) is common for all algorithms. In case of sparse impulse response, this algorithm converges very slowly. Thus it fails in providing adequate desired signal [3].

3.2 PNLMS Algorithm

In this algorithm, an adaptive individual step-size is assigned to each filter coefficient. The step-sizes are calculated from the last estimate of the filter coefficients in such a way that a larger coefficient receives a larger increment, thus increasing the convergence rate of that co-efficient [2]. This has the effect that active coefficients are adjusted faster than non-active coefficients (i.e. small or zero coefficients).Hence, PNLMS converges much faster than NLMS for sparse impulse responses (i.e., responses for which only a small percentage of coefficients is significant). However, this fast convergence was seen only for initial phase [7].

For an adaptive filter, PNLMS algorithm is presented as

$$\hat{h}(n) = \hat{h}(n-1) + \frac{\mu Q(n-1)x(n)e(n)}{x(n)Q(n-1)x^T(n) + \delta_{PNLMS}} \quad (4)$$

$$Q(n-1) = diag\{q_0(n-1), \dots, q_{L-1}(n-1)\} \quad (5)$$

$$q_l(n) = \frac{k_l(n)}{\frac{1}{L}\sum_{i=0}^{L-1} k_i(n)}, \quad 0 \le l \le L-1 \quad (6)$$

$$\boldsymbol{k_l(n) = max\{\rho max[\Upsilon_p, |\hat{h}_0|, |\hat{h}_1|, \dots |\hat{h}_{L-1}|]\}} \quad (7)$$

$$and \ \delta_{PNLMS} = \delta_{NLMS}/L \quad (8)$$

In this algorithm, a time varying step-size control matrix $Q(n-1)$, whose elements are roughly proportional to the absolute values of the corresponding coefficients, is included in the update equation [4]. Equations (3), (4),(5) are common for all proportionate algorithms. As a result, the large coefficients at a given iteration get significantly more update energy than the small ones. The parameter μ is a fixed step-size factor, is a small constant needed in order to avoid division by zero, and ρ and δ are small positive constants which are important when all the coefficients are zero (such as in the beginning of the adaptation process) or when a coefficient is much smaller than the largest one [6].

3.3 IPNLMS ALGORITHM

In this a controlling factor α is introduced in the diagonal step size control matrix. This factor helps in switching between NLMS and PNLMS algorithms.

The IPNLMS algorithm chose the elements of $Q(n)$ as:

$$q_l(n) = \frac{1-\alpha}{2L} + (1+\alpha)\frac{|\hat{h}_{1(n)}|}{2\|\hat{h}(n)\|} \qquad (9)$$

For α = -1, IPNLMS behaves like NLMS and when α = 1, it behaves like PNLMS. For fast convergence, favorably this value is kept as 0,-0.5 or -0.75. Also the computational complexity of this algorithm is very high [3].

3.4 MPNLMS ALGORITHM

In the μ-law improved proportionate normalized least mean-square (MPNLMS) algorithm, the step-sizes are optimal in the sense of minimizing the convergence rate (considering white noise input signal) [5] The resulting algorithm employs a nonlinear (logarithm) function of the coefficients in the step-size control. Instead of using magnitude directly the logarithm of magnitude is used as step gain of each coefficient. It consistently converges to steady state for sparse impulse response.

The diagonal elements of $Q(n)$ in MPNLMS are chosen as in PNLMS but the difference lies within $\boldsymbol{k_l(n)}$:

$$\boldsymbol{k_l(n)} = \boldsymbol{max\{\rho max[\Upsilon_p, F|\hat{h}_0|, F|\hat{h}_1|, \ldots F|\hat{h}_{L-1}|]\}} \qquad (10)$$

$$F|\hat{h}_l(n)| = \frac{\ln(1+\mu|\hat{h}_l(n)|)}{\ln(1+\mu)} \qquad (11)$$

Though it improves the convergence rate but the computational load increases and mu-law is defined only in [0,1].If the magnitude of coefficients falls out of this range then this algorithm fails [5].

IV. PERFORMANCE MEASURES

One of the performance measures for echo canceller is ERLE. It measures the attenuation of the echo signals in an acoustic echo cancellation system. Higher ERLE corresponds to higher reduction in echo. It is expressed in decibels (dB) and calculated as

$$ERLE(n) = 10log_{10}\frac{y^2(n)}{e^2(n)}dB \qquad (12)$$

Another measure of performance is MSE. It gives the expected value of square of error. The lower MSE value is favorable. The formula for calculation of MSE is:

$$MSE(n) = E\{e^2(n)\} \qquad (13)$$

V. COMPUTATIONAL COMPLEXITY

The relative complexity of the NLMS, PNLMS, IPNLMS and MPNLMS in terms of total additions(A), multiplications(M), divisions(D), logarithms(Log) per iteration is given in Table-I.

Table-I Relative Complexity of Algorithms

Algorithm	A	M	D	Log
NLMS	L+3	L+3	1	0
PNLMS	2L+1	5L+2	2	0
IPNLMS	3L+2	5L+2	2	0
MPNLMS	3L+1	6L+2	2	L

As we can see from the table that the increase in complexity is compromised by the algorithm's performance [8].Depending on the particular application, the tradeoff between performance and complexity can be decided upon.

VI. SIMULATION RESULTS

The simulation is performed using synthetic data via MATLAB. The MSE and ERLE values for all the algorithms are plotted. In simulation the input source signal x(n) is filtered through the built in FIR filter using the generated impulse response $h(n)$.A white Gaussian noise $w(n)$ with 30dB SNR is added to the filtered signal to obtain the output signal $y(n)$.The source signal $x(n)$ is now fed as input the adaptive filter whereas $y(n)$ is used as the desired signal. The adaptive filter with 256 taps is used. The adaptive process is repeated 10 times and averaged over 100 blocks to obtain the ensemble average of the MSE and ERLE values. The step size parameter μ is kept 0.4 for fast convergence.

The sparse impulse response is generated synthetically using method proposed in [5]. It expresses the sparse impulse response as :

$$h(n) = \begin{bmatrix} 0_{L_p*L_p} & 0_{L_p*L_u} \\ 0_{L_u*L_p} & B_{L_p*L_p} \end{bmatrix} u + p \qquad (14)$$

where vector u is defined as

$$u_{L*1} = \begin{bmatrix} 0_{L_{p*1}} & 1 & e^{\frac{-1}{\psi}} & e^{\frac{-2}{\psi}} & \ldots & e^{\frac{-(L_u-1)}{\psi}} \end{bmatrix}^T \qquad (15)$$

L_p models the bulk delay. $L_u = L - L_p$ is the length of the decaying window controlled by ψ. Smaller the ψ, more sparse is the system. Here impulse length L is set 256, bulk delay L_p =20 and ψ=8. The constant p is zero mean white Gaussian noise vector with length L.

Fig 3 shows the comparative plot of average MSE for all the sparse algorithms. Fig 4 shows the comparative plot of average ERLE for all the sparse algorithms. Each algorithm's output is represented by different colored line in the graphs. Fig 5 shows the generated sparse impulse response for which for which the comparison of the different echo cancellation algorithms is made.

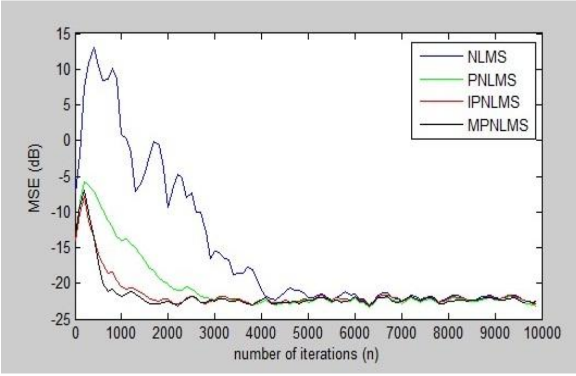

Fig 3: Plot of MSE for four different algorithms

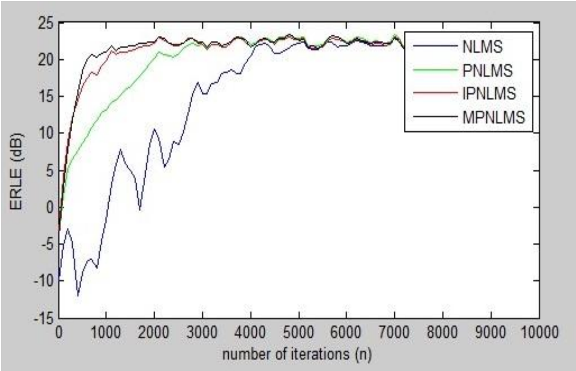

Fig 4: Plot of ERLE for four different algorithms

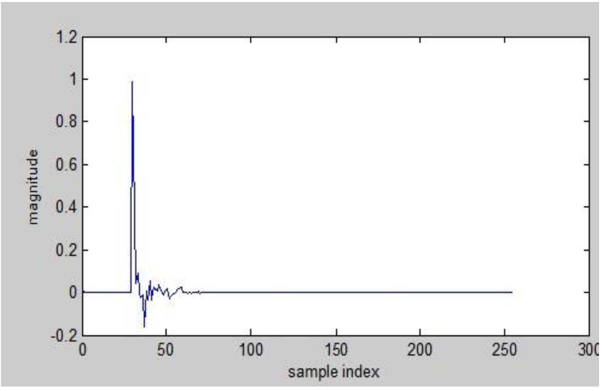

Fig 5: The generated sparse impulse response

VII. CONCLUSION

This paper aimed at finding the best sparse echo cancellation algorithm in the terms of performance measures i.e. ERLE and MSE. The simulation results show that for sparse systems, MPNLMS gives lowest values of MSE and the highest values of ERLE.

Thus, MPNLMS gives the best performance in terms of the measures MSE and ERLE as compared to other sparse adaptive filtering algorithms but at the cost of increased computational complexity. NLMS performs badly in sparse systems. However all these sparse algorithms have slow convergence rate during dispersive impulse response. The future work will be directed to algorithms that work well in time varying impulse response.

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