A Hybrid of SC-IPNLMS and SC-MPNLMS Adaptive Algorithms for Acoustic Echo Cancellation

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Abstract- In acoustic echo cancellation (AEC), sparseness in impulse response may vary with change in atmospheric and environmental conditions. Thus algorithm used in adaptive filter design must work well for both sparse and dispersive impulse response. In this paper, a HYBRID of sparseness controlled algorithms is proposed that is robust to sparseness variation. The performance of the proposed Hybrid algorithm is analyzed, simulated and compared to the original SC-IPNLMS and SC-MPNLMS in sparse and dispersive impulse response using different input signals. The significant improvement of this hybrid sparseness controlled algorithm is shown using MATLAB simulations in terms of the performance measures kept under study are mean square error (MSE), echo return loss enhancement (ERLE) and normalized misalignment (NPM).

Keywords- Acoustic echo cancellation (AEC), sparse and dispersive impulse response, sparseness controlled algorithms, MSE, ERLE, NPM

1. Introduction

Reliable telephony networks demands the cancellation of echo for improved voice quality. Echo canceller employs adaptive filters for system identification and hence effective removal of echo [1]. For adaptive filter's fast convergence, sparse system identification is a must requirement. The need of this sparse system identification is needed in applications such as network or acoustic echo cancellation and channel equalization where the channel may be sparse or long.

The term sparse indicates that large fraction of energy is concentrated in small fraction of duration. The cause of this sparseness is the bulk delay corresponding to the direct propagation delay between loudspeaker and microphone in case of LMRS system. Generally the length of acoustic echo response is 100-400 ms and adaptive filter of length 1024 is required to achieve the adequate level of echo cancellation [2].

NLMS serves as workhorse for echo cancellers but in case of sparse impulse response it gives poor performance due to the coefficient noise occurring during adaptation for non zero valued coefficients and the adaptive filter have to operate on long filter [3]. To deal with the need of rapid identification of active coefficients in sparse impulse response a family of proportionate algorithms including PNLMS, IPNLMS, MPNLMS and their variants were developed. The basic idea behind these algorithms was to update the filter coefficients proportional to the magnitude of the last estimated filter coefficients. The IPNLMS provided a controlled behavior of NLMS and PNLMS for improved robust performance. MPNLMS involves updating coefficients proportional to logarithm of the estimated filter coefficients [9]. However these sparse algorithms converged well in case of sparse impulse response but have slow convergence rate during dispersive impulse response.

To address the convergence problem of proportionate algorithms in dispersive impulse response, sparseness controlled improved version of these algorithms were proposed in [7].

These sparseness-controlled algorithms compute the sparseness measure of the estimated impulse response and incorporate it into the sparse algorithms developed earlier.

These algorithms achieve fast convergence for both sparse and dispersive AIRs which is effective for AEC [9]. This paper introduces a hybrid algorithm of SC-IPNLMS and SC-MPNLMS which outperforms both algorithms in terms of various performance measures.

2. Sparseness Controlled Echo Cancellation Algorithms

Let us consider a loudspeaker-Room-Microphone system (LMRS) as shown in Fig 1 and an adaptive filter $\hat{h}(n) = [\hat{h}_0 \ldots \ldots \hat{h}_{L+1}]^T$ deployed to cancel the echo. Consider the input signal $x(n) = [x(n) \ldots \ldots x(n-L+1)]^T$ and the unknown impulse response taken as $h(n) = [h_0 \ldots \ldots h_{L+1}]^T$.

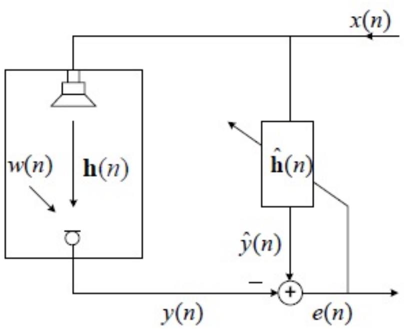

Fig 1: Adaptive system for acoustic echo cancellation system.

Thus the output of the LMRS is given by:

$$y(n) = h^T(n)x(n) + w(n) \quad (1)$$

Where w(n) is additive noise and the error signal is given by:

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

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

$$Q(n-1) = diag\{q_0(n-1), \ldots, q_{L-1}(n-1)\} \quad (4)$$

where μ is the step size and δ is the regularization parameter. The step size control matrix $Q(n)$ is introduced whose elements are chosen according to the specific algorithm [3].

The PNLMS, IPNLMS and MPNLMS have been developed for sparse system identification [9]. Diagonal elements of matrix $Q(n)$for MPNLMS are given by:

$$q_l(n) = \frac{k_l(n)}{\frac{1}{L}\sum_{i=0}^{L-1} k_i(n)}, 0 \le l \le L-1 \quad (5)$$

$$k_l(n) = \max\{\rho \times \max[\Upsilon_p, F|\hat{h}_0|, F|\hat{h}_1|, \ldots F|\hat{h}_{L-1}|]\} \quad (6)$$

The step size is made proportional to magnitude of estimated impulse response. MPNLMS converges faster but it used logarithms of magnitudes instead of using magnitudes directly as step gain for each coefficient [7]. Thus, for MPNLMS $F|\hat{h}_l(n)|$ is given by:

$$F|\hat{h}_l(n)| = \frac{\ln(1+\mu|\hat{h}_l(n)|)}{\ln(1+\mu)} \quad (7)$$

However the IPNLMS algorithm [4] is a mixture of NLMS and PNLMS with the introduction of factor α in the elements of the step size control matrix. Thus its diagonal matrix elements are given by:

$$q_l(n) = \frac{1-\alpha}{2L} + (1+\alpha) \quad (8)$$

IPNLMS behaves like NLMS for $\alpha = -1$ and it behaves like PNLMS when $\alpha = 1$. For fast convergence, favorably this value is kept as 0,-0.5 or -0.75.

2.1 SC-MPNLMS Algorithm

The degree of sparseness for an impulse response for AIR is usually quantified as in [5] :

$$\xi(n) = \frac{L}{L-\sqrt{L}}\left\{1 - \frac{\|h(n)\|_1}{\sqrt{L\|h(n)\|_2}}\right\} \quad (9)$$

The range for value of this sparseness always lies between [0-1]. The estimated measure of sparseness is included within the step size control elements [6]. It can be seen that in proportionate algorithms, $\rho(n)$ act as major factor in choosing the step size control elements $q_l(n)$. For small value of ρ, the effect of proportionate term is more and for higher values of ρ, the influence of proportionate term is reduced and all the coefficients are updated at a uniform rate. In SC-MPNLMS, $\rho(n)$ is taken as

$$\rho(n) = e^{-\lambda\xi(n)}, \quad 4 \leq \lambda < 6 \tag{10}$$

Low values were allocated to $\rho(n)$ for sparse impulse response (when $\widehat{\xi}(n) > 0.4$) Thus, SC-MPNLMS inherited proportionality step size control and performs like MPNLMS. Whereas for dispersive impulse response ($\hat{\xi}(n) < 0.4$) SC-MPNLMS behaves like NLMS as it has a uniform adaptation rate for all coefficients [8].

2.2 SC-IPNLMS Algorithm

The inclusion of $\hat{\xi}(n)$ within IPNLMS is done differently as

$$q_l(n) = \left[\frac{1 - 0.5\,\widehat{\xi}(n)}{L}\right]\frac{(1-\alpha)}{2L} + \left[\frac{1 - 0.5\,\widehat{\xi}(n)}{L}\right]\frac{(1+\alpha)\left|\hat{h}_{1(n)}\right|}{2\left\|\hat{h}(n)\right\| + \delta} \tag{11}$$

For larger values of $\widehat{\xi}(n)$, the proportionate term overweighs whereas for smaller values of $\widehat{\xi}(n)$, NLMS term has higher weight (uniform adaptation)[8].

3. HYBRID SC-IMPNLMS Algorithm

A different technique can be followed for an algorithm which can work effectively and robust to sparse impulse response for AEC by employing the SC-IPNLMS approach [8] to the diagonal matrix selection criteria of SC-MPNLMS. As MPNLMS performs badly in non-sparse systems, the proposed Hybrid SC-IMPNLMS algorithm improves the performance of MPNLMS by emphasizing the proportionate term if the impulse response is significantly non-sparse.

The computation of $q(n)$ for the Hybrid SC-IMPNLMS can be represented as

$$q_l(n) = \left[\frac{1 - 0.5\,\widehat{\xi}(n)}{L}\right] + \left[\frac{1 + 0.5\,\widehat{\xi}(n)}{L}\right] \tag{12}$$

This can be further modified as:

$$q_l(n) = \sqrt{\frac{1 - 0.5\,\widehat{\xi}(n)}{2L}} + \sqrt{\frac{1 + 0.5\,\widehat{\xi}(n)}{2L}} \tag{13}$$

On the same technical lines as in IPNLMS, the constant 0.5 is chosen empirically to make balance between sparse and dispersive case performance. Normalization by 2L and the square-root of the constant terms is added to reduce the coefficient noise that is introduced when $\widehat{\xi}(n)$ is high.

For relatively less sparse impulse responses, the SC-IMPNLMS will allocate a higher weighting to the first term. Thus the algorithm will behave like NLMS in this situation which performs at its best for dispersive AIR. When the impulse response will become sparse, this hybrid algorithm gives higher weight to the proportionate term and thus behaves much like MPNLMS which is known for its best performance in sparse channels. In order to avoid the dividing by zero or a small number in the computation of sparseness measure at the early stages of the adaptive process, this adapting process can be employed for n ≥ L. For n < L the elements of the matrix $q_l(n)$ are chosen as the way they are calculated in normal MPNLMS algorithm.

4. Simulation Results

The simulation is performed using synthetic data via MATLAB. The MSE, ERLE and NPM values for all the algorithms are plotted. These performance measures for echo canceller are calculated as:

- $\mathrm{ERLE(n)} = 10\log_{10}\frac{\mathrm{y^2(n)}}{\mathrm{e^2(n)}}\mathrm{dB}$ (14)

It measures the attenuation of the echo signals in an acoustic echo cancellation system. Higher ERLE corresponds to higher reduction in echo

- $\mathrm{MSE(n)} = \mathrm{E}\{\mathrm{e}^2\,\mathrm{(n)}\}$ (15)

It gives the expected value of square of error. The lower MSE value is favorable

- $\mathrm{NPM(n)} = 2 \times \log\left(\frac{1}{\|\mathrm{h}\|}\left\| 1 - \frac{\mathrm{h^T \hat{h}(n)}}{\mathrm{\hat{h}^T \hat{h}(n)}}\,\mathrm{\hat{h}(n)} \right\|\right) \mathrm{dB}$ (16)

NPM measures the closeness of estimated impulse response $\mathrm{h(n)}$ to that of the unknown impulse response h(n).
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, NPM and ERLE values.

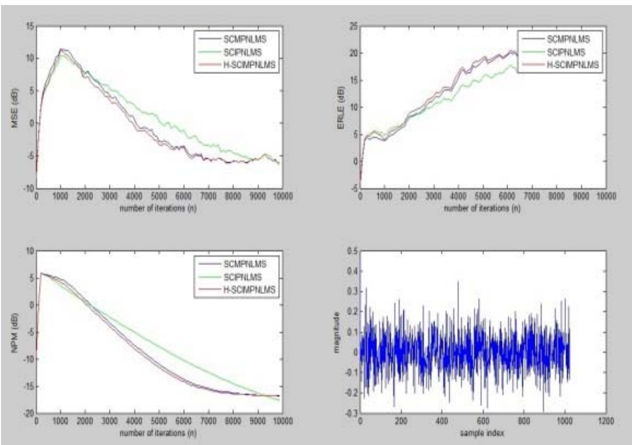

Fig 2: Comparative performance measure plots of Hybrid SC-IMPNLMS with existing algorithms in dispersive impulse response.

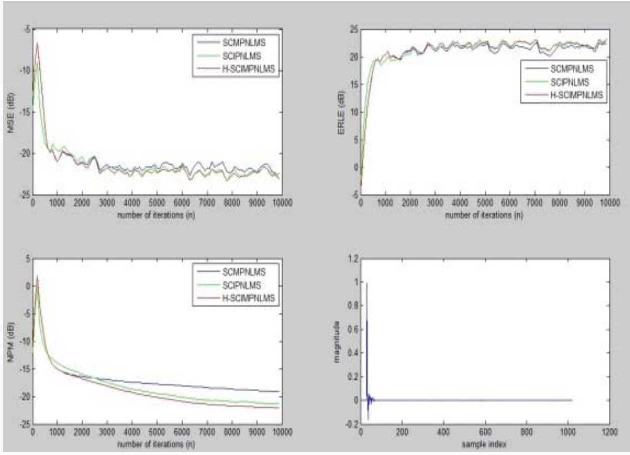

Fig 3: Comparative performance measure plots of Hybrid SC-IMPNLMS with existing algorithms in sparse impulse response.

The above shown Fig. 3 and 4 shows the comparative plots of SC-MPNLMS, SC-IPNLMS and Hybrid SC-IMPNLMS for dispersive and sparse impulse response respectively. At few of the iterations they have a close behavior while significant difference can be spotted at others. For making a comparison of values by which Hybrid algorithm is better than the previous ones, average values of the three performance measures over a total of 10,000 iterations are considered. The below given tables will show the average values of the performance measures of SC-MPNLMS, SC-IPNLMS and Hybrid SC-IMPNLMS.

Table 1: Comparison of average performance measures of SC-MPNLMS, SC-IPNLMS and Hybrid SC-IMPNLMS in dispersive impulse response.

ALGORITHM	MSE(dB)	ERLE(dB)	NPM(dB)
SC-MPNLMS	3.9286	18.3134	-4.7691
SC-IPNLMS	3.8163	17.0034	-2.1704
Hybrid SC-IMPNLMS	3.3322	18.5052	-5.2421

Table 2: Comparison of average performance measures of SC-MPNLMS, SC-IPNLMS and Hybrid SC-IMPNLMS in sparse impulse response

ALGORITHM	MSE(dB)	ERLE(dB)	NPM(dB)
SC-MPNLMS	-19.0311	21.1692	-15.8171
SC-IPNLMS	-20.2305	21.5325	-8.5343
Hybrid SC-IMPNLMS	-19.2114	21.5708	-16.8930

From the values in Tables 1 and 2, the improvement in terms of NPM made by Hybrid SC-IPNLMS over SC-MPNLMS is 3dB in dispersive case, 8dB in sparse case and over SC-IPNLMS is around 1dB and in dispersive case and sparse case respectively. However, we can see that Hybrid SC-IMPNLMS performs close (slightly better) to existing algorithms in terms of MSE and ERLE in both the cases.

5. Conclusion

The hybrid SC-IMPNLMS framed by hybridization of weight update criteria of IPNLMS and SC-MPNLMS performs better than the existing algorithms. Computer Simulations, using hybrid SC-IMPNLMS adaptive algorithm show performance superiority of the acoustic echo canceller (AEC) for both sparse and dispersive impulse responses. The future scope of this hybrid algorithm is its application in hearing aids for feedback cancellation and combination of the algorithm with partial updating methods to improve the system performance in terms of computational complexity.

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