ISSN 2348 – 7968

A NOVEL SPARSE ADAPTIVE FILTER FOR ECHO CANCELLATION

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Abstract

In mobile environment, Acoustic Echo Cancellation (AEC) greatly changes due to the sparseness level of acoustic impulse response. To overcome this problem, we propose a Modified Sparseness Controlled Improved μ - Law Proportionate Normalised Least-mean-square (MSC-MPNLMS) algorithm that can not only work well in both spars and dispersive circumstances but also adapt dynamically to the level of sparseness. Simulation results with input as White Gaussian Noise (WGN) show the improved performance over existing methods.

***Keywords**:* Acoustic Echo Cancellation (AEC), Modified Sparseness Controlled Improved Proportionate Normalized Least Mean Square (MSC-MPNLMS), White Gaussian Noise (WGN)
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1. Introduction

Echo phenomenon is always present in telecommunications networks. It can be mainly observed in on long international telephone calls. Echo cancellation in telecommunication network requires Identification of unknown echo path impulse response. The length of network echo path is typically in the range between 32 and, 128milliseconds, which is characterized by bulk delay depending on network loading, encoding chg and jitter delay [1]. Because of this, "active" region of echo path is in the range between 8 and 12milliseconds, so it contains mainly "inactive" components where the coefficient magnitudes are close to zero, making the impulse response more sparse. In general, adaptive filters have been used to estimate the unknown echo path by using algorithm such as NLMS. But, as the length of echo paths are more, NLMS requires more number of taps (up to 1024 taps) which will make the convergence of NLMS becomes poor.

Several approaches have been proposed over recent years to get better performance than NLMS for Network echo cancellation (NEC). These include Variable step size (VSS) algorithms, partial update adaptive filtering techniques and sub-band adaptive filtering (SAF) techniques. There approaches aim to address the issues in echo cancellation. Including the performance with colored input signals and time varying echo paths and a computational complexity to name but a few. In contrast to these algorithms, sparse adaptive algorithms have been developed to address the performance of adaptive filters sparse system identification.

The first sparse adaptive algorithm for NEC is proportionate NLMS (PNLMS) in which each filter coefficient is updated independently of others, by adjusting the adaptation step size in proportion to the estimated filter coefficient. It is known that PNLMS has fast initial convergence rate. An improved PNLMS (IPNLMS) [15] algorithm was proposed to exploit the 'proportionate' idea by introducing a controlled mixture of proportionate (PNLMS) and non-proportionate (NLMS) adaptation. A sparseness-controlled IPNLMS algorithm was proposed in [16] to improve the robustness of IPNLMS to the sparseness variation in impulse responses. Composite PNLMS and NLMS (CPNLMS) [17] adaptation was proposed to control the switching of PNLMS++ between the NLMS and PNLMS algorithms. For sparse impulse responses, CPNLMS performs the PNLMS adaptation to update the large coefficients and subsequently switches to NLMS, which has better performance for the adaptation of the remaining small taps. The μ-law PNLMS (MPNLMS) [18] algorithm was proposed to address the uneven convergence rate of PNLMS during the estimation process. As proposed in [18], MPNLMS uses optimal step- size control factors to achieve faster overall convergence until the adaptive filter reaches its steady state. The authors proposed [pradeep] SC-PNLMS, SC-MPNLMS and SC-INLMS algorithms, which achieves improved convergence compared to classical NLMS and typical sparse adaptive filtering algorithms.[19] They have incorporated the sparseness measure into PNLMS, MPNLMS and IPNLMS for AEC to achieve fast convergence that is robust to the level of sparseness encountered in the impulse response of the echo path. The resulting SC-PNLMS, SC-MPNLMS and SC-IPNLMS algorithms take into account the

ISSN 2348 – 7968

sparseness measure via a modified coefficient update function.

This paper is organized as follows, in section 2.Review of section A,B,&C algorithms for Echo cancellation is presented. In section 3 explains the characterization of framework for robust convergence. In Section 4 proposed MSC-MPNLMS algorithm and Section 5 computational complexity is presented. In section 6&7 results and conclusions are presented.

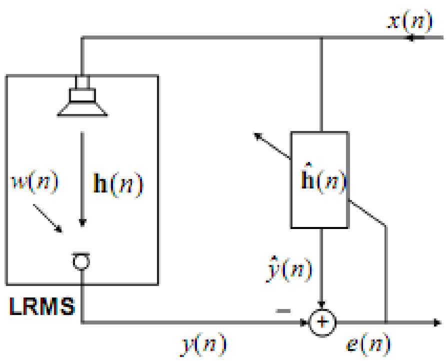

Fig.1. Adaptive system for acoustic echo cancellation in a Loudspeaker-Room- Microphone system (LRMS)

Figure 1 shows a Loudspeaker-Room-Microphone system (LRMS) and an adaptive filter $\hat{h}(n)=[\hat{h}_0(n)\hat{h}_1(n)...\hat{h}_{L-1}(n)]^T$ deployed to cancel acoustic echo, where L is the length of the adaptive filter assumed to be equal to the unknown room impulse response and $[\cdot]^T$ is the transposition operator. Defining the input signal $x(n)=[x(n)\ x(n-1)\ ...\ x(n-L+1)]^T$ and $\mathbf{h}(n)=[h_0(n)\ h_1(n)\ ...\ h_{L-1}(n)]^T$ as the unknown impulse response, the output of the LRMS is given by $y(n)=\mathbf{h}^T(n)x(n)+w(n)$, (1)

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

$$e(n)=y(n)-h^T(n-1)x(n). \qquad (2)$$

Several adaptive algorithms such as those described below have been developed for either AEC or NEC.

Many adaptive algorithms can be described by (2) and the following set of equations:

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

$\mathbf{Q}(n-1)=\mathrm{diag}\{q0(n-1)\ ...\ qL-1(n-1)\}$, (4)

where μ is a step-size and δ is the regularization parameter. The diagonal step-size control matrix **Q**(n) is introduced here to determine the step-size of each filter coefficient and is dependent on the specific algorithm.

A. The NLMS, PNLMS and MPNLMS algorithms

The NLMS algorithm is one of the most popular for AEC due to its straightforward implementation and low complexity compared to, for example, the recursive least squares algorithm. For NLMS, since the step-size is the same for all filter coefficients, $Q(n)=I_{L\times L}$ with $I_{L\times L}$ being an L×L identity matrix.

One of the main drawbacks of the NLMS algorithm is that its convergence rate reduces significantly when the impulse response is sparse, such as often occurs in NEC. The poor performance has been addressed by several sparse adaptive algorithms such as those described below that have been developed specifically to identify sparse impulse responses in NEC applications.

The PNLMS and MPNLMS algorithms have been proposed for sparse system identification. Diagonal elements q_l of the step-size control matrix Q(n) for the PNLMS [2] and MPNLMS [18] algorithms can be expressed as

$$q_l(n)=\frac{\kappa_l(n)}{\frac{1}{L}\sum_{i=0}^{L-1}\kappa_i(n)}, \qquad 0\le l\le L-1,$$

$$\kappa_l(n)=\max\Big\{\rho\times\max\{\gamma, F(|\hat{h}_0(n)|)\ \ldots\ F(|\hat{h}_{L-1}(n)|)\}, F(|\hat{h}_l(n)|)\Big\}$$

where $F(|\hat{h}_1(n)|)$ is specific to the algorithm. The parameter γ =0.01 in above equation prevents the filter coefficients $\hat{h}_1(n)$ from stalling when $\hat{h}(0)=0_{L\times 1}$ at initialization and ρ, with a typical value of 0.01, prevents the coefficients from stalling when they are much smaller than the largest coefficient.

The PNLMS algorithm achieves a high rate of convergence by employing step-sizes that are proportional to the magnitude of the estimated impulse response coefficients where elements $F(|\hat{h}_1(n)|)$ are given by

$$F(|\hat{h}_1(n)|)=|\hat{h}_1(n)| \qquad (5)$$

Hence, PNLMS employs larger step-sizes for 'active' coefficients than for 'inactive' coefficients and consequently achieves faster convergence than NLMS for sparse impulse responses. However, it is found that PNLMS achieves fast initial convergence followed by a slower second phase convergence [18].

The MPNLMS algorithm was proposed to improve the convergence of PNLMS. It achieves this by computing the optimal proportionate step- size during the adaptation process. The MPNLMS algorithm was derived such that all coefficients attain a converged value to within a vicinity □ of their optimal value in the same number of iterations [18]. As a consequence, $F(|\hat{h}_l(n)|)$ for MPNLMS is specified by

$$F(|\hat{h}_l(n)|) = \ln(1+\beta|\hat{h}_l(n)|) \quad (6)$$

with β =1/ ∈ and ∈ is a very small positive number chosen as a function of the noise level [18]. It has been shown that ∈ =0.001 is a good choice for typical echo cancellation. The positive bias of 1 in (8) is introduced to avoid numerical instability during the initialization stage when $|\hat{h}_l(0)|$ =0, ∀ l. It is important to note that both PNLMS and MPNLMS suffer from slow convergence when the unknown system h(n) is dispersive [14], [13]. This is because when h(n) is dispersive, $\kappa_l(n)$ in the above equation becomes significantly large for most $0 \leq l \leq L-1$. As a consequence, the denominator of $q_l(n)$ in above equation is large, giving rise to a small step-size for each large coefficient. This causes significantly degradation in convergence performance for PNLMS and MPNLMS when the impulse response is dispersive such as can occur in AIRs.

B. The IPNLMS algorithm

The IPNLMS [15] algorithm was originally developed for NEC and was further developed for the identification of acoustic room impulse responses [20]. It employs a combination of proportionate (PNLMS) and non-proportionate (NLMS) adaptation, with the relative significance of each controlled by a factor α_{IP} such that the diagonal elements of Q(n) are given as

$$q_l(n) = \frac{1-\alpha_{IP}}{2L} + \frac{(1+\alpha_{IP})|\hat{h}_l(n)|}{2\|\hat{h}(n)\|_1 + \delta_{1p}}, \quad 0 \leq l \leq L-1$$

, where $\|\cdot\|_1$ is defined as the l_1-norm and the first and second terms are the NLMS and the proportionate terms respectively. It can be seen that IPNLMS is the same as NLMS when $\alpha_{IP} = -1$ and PNLMS when $\alpha_{IP} = 1$. Use of a higher weighting for NLMS adaptation, such as $\alpha_{IP} = 0$, −0.5 or −0.75, is a favorable choice for most AEC/NEC applications [15]. It has been shown that, although the IPNLMS algorithm has faster convergence than NLMS and PNLMS regardless of the impulse response nature [15], we note from our simulations that it does not outperform MPNLMS for highly sparse impulse responses with the above choices of α_{IP}.

C. SC-PNLMS, SC-MPNLMS and SC-IPNLMS algorithms

In order to address the problem of slow convergence in PNLMS and MPNLMS for dispersive AIR, they used step size control elements. the proposed sparseness-controlled algorithms are robust to variations in the level of sparseness in AIR with only a modest increase in computational complexity. Moreover, they have shown that these proposed algorithms have same or faster convergence in NEC.

2.SPARSENESS MEASURE

Degree of sparseness can be qualitatively referred as a range of strongly dispersive to strongly sparse. Quantitatively, the sparseness of an impulse response can be measured by the following sparseness measure.

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

Where $\|h(n)\|_1 = \sum_{l=0}^{L-l} |h_l(n)|$

$$\|h(n)\|_2 = \sqrt{\sum_{l=0}^{L-1} h_l^2(n)}$$

L is the length of filter h. The measure takes values between 0 and 1 where the lower bound can be obtained by using the uniform filter $[1\ 1 \ldots 1]^T$ and the upper limit can be achieved by using the Dirac filter $[[1\ 0 \ldots 0]^T$.

3.SPARSE IMPULSE RESPONSE GENERATOR

Sparseness of impulse responses for Network and acoustic echo cancellation can be studied by generating synthetic impulses using random sequences. This can be achieved by first defining an L×1 vector.

$$u_{L\times1} = \left[0_{L_p\times1} \quad 1 \quad e^{-1/\Psi} \quad e^{-2/\Psi} \quad \ldots \quad e^{(L_u-1)/\Psi}\right]^T \quad (4)$$

Where the leading zeros with length Lp models the length of the bulk delay and Lu = L − Lp is the length of the decaying window which can be controlled by ψ. Smaller the ψ value yields more sparse system.

Defining a Lu × 1 vector b as a zero mean white Gaussian noise (WGN) sequence with variance σb2, the L × 1 synthetic impulse response can then be expressed as

$$B_{Lu\times Lu} = \text{diag}\{b\}$$

$$h(n) = \begin{bmatrix} O_{Lp\times Lp} & O_{Lp\times Lu}\gamma \\ O_{Lu\times Lp} & B_{Lp\times Lp} \end{bmatrix} u + p \qquad (5)$$

Where the L × 1 vector p ensures elements in the 'inactive' region are small but non-zero and is an independent zero mean WGN sequence with variance σp2.

The two impulse responses that can be attained using the approach, by setting the impulse length L =512, the bulk delay length Lp =32 and ψ to 8(more sparse), 20, 50 and 100(more sparse).

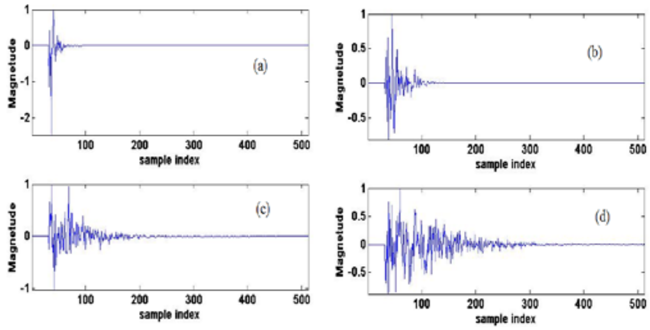

Fig. 2.Impulse responses controlled using (a) ψ = 8, (b) ψ = 20, (c) ψ =50 and (d) ψ =80 giving sparseness measure (a) ξ = 0.905, (b) ξ = 0.809, (c) ξ = 0.667 and (d) ξ = 0.5448.

4.Proportionate-Normalized Least Mean Square (PNLMS):

One of the first sparse adaptive filtering algorithms considered as a milestone for NEC is PNLMS, in which each filter coefficient is updated with an independent step-size that is linearly proportional to the magnitude of that estimated filter coefficient. It is well known that PNLMS has very fast initial convergence for sparse impulse responses after which its convergence rate reduces significantly, sometimes resulting in a slower overall convergence than NLMS.

In order to track sparse impulse response faster Proportionate NLMS (PNLMS) was introduced from the NLMS equation. The coefficient update equation of the PNLMS is slightly differ from NLMS with the extra step size update matrix Q as shown below and the rest of the terms are carried over from NLMS.

Where $\delta_{PNLMS} = cst.\sigma_x^2/L$

$$Q(n) = diag\{q_0(n), \ldots \ldots q_{L-1}(n)\} \qquad (6)$$

controls the step size. These control matrix elements can be expressed as

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

$$k_l(n) = \max\left(\rho * \max[\gamma, |h_0\hat{}(n)|, \ldots\ldots\ldots |h_{L-1}\hat{}(n)|], |h_l\hat{}(n)|\right) \qquad (7)$$

Parameters ρ and γ have typical values of 5 / L and 0.01 [8],

Improved Proportionate NLMS (IPNLMS) Algorithm
Initialization: $\hat{h}_l(0) = 0, l = 0,1,\ldots L-1$
Parameters: $-1 \leq \ < \mathbf{1}$; $0 < \alpha < 2$
$\delta_{IPNLMS} = cst.\sigma_x^2(1-\kappa)/2L$
$\varepsilon > 0$, very small number to avoid division by zero
Error: $e(n) = d(n) - \boldsymbol{x}^T(n)\boldsymbol{h}\hat{}(\boldsymbol{n}-\mathbf{1})$
Update: $h\hat{}(n) = h\hat{}(n-1) + \frac{\mu k(n-1)}{x^T(n)k(n-1)}$
$\boldsymbol{K}(n-1) = diag\{k_0(n-1), \ldots \ldots . k_{L-1}(n-1)\}$
where $k_l(n) = \frac{\kappa_l(n)}{\lVert\kappa(n)\rVert_1}$
$\kappa_l(n) = (1-\alpha)\frac{\lVert\boldsymbol{h}\hat{}(n)\rVert_1}{L} + (1+\alpha)\lvert\boldsymbol{h}_l\hat{}(n)\rvert$, $l = 0,1,..L-1$

The constant 1 inside the logarithm is to avoid obtaining negative infinity at the initial stage when $\hat{h_l}(0) = 0$. The denominator $ln(1+\frac{1}{\varepsilon})$ normalizes $F(|\hat{h_l}(n)|)$ to be in the range [0, 1]. The vicinity ε is a very small positive number, and its value should be chosen based on the noise level. ε = 0.001 is a good choice for echo cancellation, as the echo below -60 dB is negligible.

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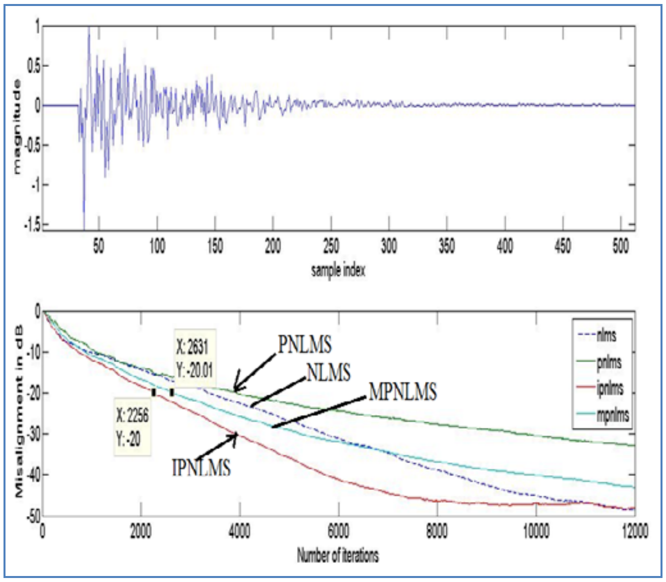

Fig.3: Relative convergence of NLMS, PNLMS,IPNLMS and MPNLMS using WGN input for (a) ψ=8 and (b) ψ=80 Initial step size μ=0.3 for NLMS, PNLMS,IPNLMS and MPNLMS and α=-0.75.

5. SPARSENESS CONTROLLED ADAPTIVE FILTER ALGORITHMS

Sparseness Measure:

Degree of sparseness can be qualitatively referred as a range of strongly dispersive to strongly sparse. Quantitatively, the sparseness of an impulse response can be measured by the following sparseness measure

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

Where $\|h(n)\|_1 = \sum_{l=0}^{L-l} |h_l(n)|$

$$\|h(n)\|_2 = \sqrt{\sum_{l=0}^{L-1} {h_l}^2(n)}$$

L is the length of filter h. The measure takes values between 0 and 1 where the lower bound can be obtained by using the uniform filter [1 1...1]T and the upper limit can be achieved by using the Dirac filter [[1 0 ...0]T.

Sparseness-controlled MPNLMS (SC-MPNLMS) algorithm:

In order to address the problem of slow convergence in PNLMS and MPNLMS for dispersive AIR, we require the $g_l(n)$ to be robust to the sparseness of the impulse response. Several choices can be employed to obtain the desired effect of achieving a high convergence when $\xi^\wedge(n)$ is small when estimating dispersive AIRs. We consider an example function

$$\rho(n) = e^{-\lambda \xi^\wedge(n)}$$

The variation of $\rho(n)$ in MPNLMS for the exponential function is as shown in figure below for the cases λ is 4, 6 and 8.

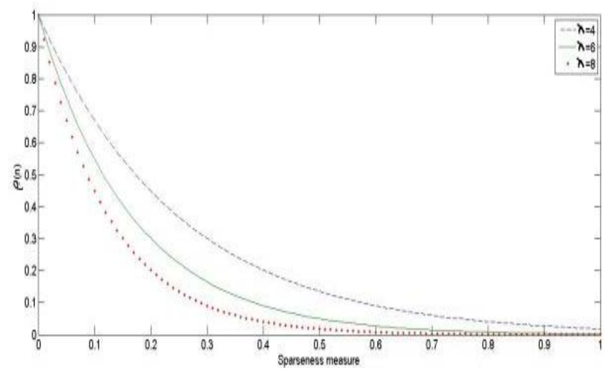

Fig 4: Variation of ρ against sparseness measure $\xi^\wedge(n)$ of impulse response for different values of λ

It can be noted that a linear function $\rho(n) = 1 - \xi^\wedge(n)$ also achieves our desired function. We have tested this case and found it to perform worse than more general form of 3 so we will not consider it further.

The choice of λ is important. As can be seen from above figure that, larger value of λ will cause the proposed SC-MPNLMS to inherit more of the MPNLMS properties compared to NLMS giving good convergence performance when Impulse response (IR) is sparse. On the other hand, when IR is dispersive, λ must be small for good convergence performance. Hence, as shown in above figure, that a good compromise is given by λ=6.

In addition, we note that when n=0, $\|h^\wedge(0)\|_2 = 0$ and hence, to prevent division by zero or small number, $\xi^\wedge(n)$ can be computed for $n > L$. When $n \le L$, we set $\rho(n) = 5/L$.

Sparseness controlled μ-Law Proportionate NLMS (SC-MPNLMS) Algorithm.

Initialization: $h_l^\wedge(0) = 0, l = 0,1, \ldots L-1$

Parameters: $\delta_p = 0.01$

$$0 < \alpha < 2$$

$$\delta_{SC-MPNLMS} = cst.\sigma_x^2/L$$

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Error:

$$e(n) = d(n) - \boldsymbol{x}^{\boldsymbol{T}}(n)\boldsymbol{h}^{\wedge}(\boldsymbol{n}-\boldsymbol{1})$$

Update:

$$h^{\wedge}(n) = h^{\wedge}(n-1) + \frac{\mu G(n-1)x(n)e(n)}{x^{T}G(n-1)x(n) + \delta_{PNLMS}}$$

$$\boldsymbol{G}(n-1) = diag\{g_0(n-1), \dots \dots . g_{L-1}(n-1)\}$$

$$g_l(n) = \frac{\gamma_l(n)}{\sum_{i=0}^{L-1}\gamma_l(n)}$$

$$\gamma_l(n) = max\left(\rho * \max\left[\delta_p, F(|h_0^{\wedge}(n-1)|), .. F(|h_{L-1}^{\wedge}(n-1)|)\right], F(|h_l^{\wedge}(n)|)\right)$$

$$\rho(n) = \begin{cases} {}^{5}/_{L} \ \ for\ n \leq L \\ e^{-\lambda\xi^{\wedge}(n)} \ \ for\ n > L \end{cases}$$

$$F(|h_l^{\wedge}(n)|) = \frac{ln\left(1 + \frac{|h_l^{\wedge}(n)|}{\varepsilon}\right)}{ln\left(1 + \frac{1}{\varepsilon}\right)}$$

MODIFIED SPARSENESS CONTROLLED MPNLMS (MSC-MPNLMS):

It can be seen that low values of $\rho(n)$ are allotted for large range of sparse impulse responses such as when $\xi^{\wedge}(n) > 0.4$. As a result of small values in $\rho(n)$, the proposed SC-MPNLMS inherits more of MPNLMS properties when estimated impulse response is sparse and distributes uniform.step size across $h_l^{\wedge}(n)$, as in NLMS, when estimated Impulse response is dispersive.

The choice of λ is important. As can be seen from above figure that, larger value of λ will cause the proposed SC-MPNLMS to inherit more of the MPNLMS properties compared to NLMS giving good convergence performance when Impulse response(IR) is sparse. On the other hand, when IR is dispersive, λ must be small for good convergence performance.

In addition, we note that when n=0, $\left\|\boldsymbol{h}^{\wedge}(0)\right\|_2 = 0$ and hence, to prevent division by zero or small number, $\xi^{\wedge}(n)$ can be computed for $n > L$. When $n \leq L$, we set ρ(n)=2.5⁄L.

In the earlier algorithm SC-MPNLMS, the sparseness measure used to measure the time varying sparseness of the impulse response.[20] But this sparseness measure is the good representation of sparse impulse response only. So, we can improve the performance of SC-MPNLMS by incorporating another sparseness measure which is average of the existing sparseness measure.

Convergence Performance of MSC-MPNLMS for AEC:

Figure 5 and 6 illustrates the performance of NLMS, MPNLMS, SC-MPNLMS and MSC-MPNLMS using WGN as the input signal. Step sizes are adjusted to achieve the same steady state misalignment for all algorithms. This corresponds to NLMS=0.4 , MPNLMS =0.3, SC-MPNLMS =0.7, MSC-MPNLMS =0.9.
So by including ζ12∞ in the above SC-MPNLMS algorithm in the place of ζ^, this new MSC-MPNLMS algorithm showing the improvement of 2 dB over SC-MPNLMS when impulse response is more sparse and it is showing the improvement of 4 dB when impulse response is less sparse or dense

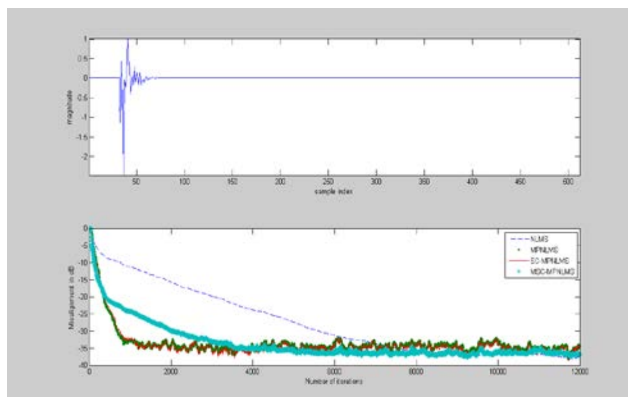

Fig 5: Relative Convergence of NLMS, MPNLMS, SC-MPNLMS and MSC-MPNLMS when impulse response is Dispersive

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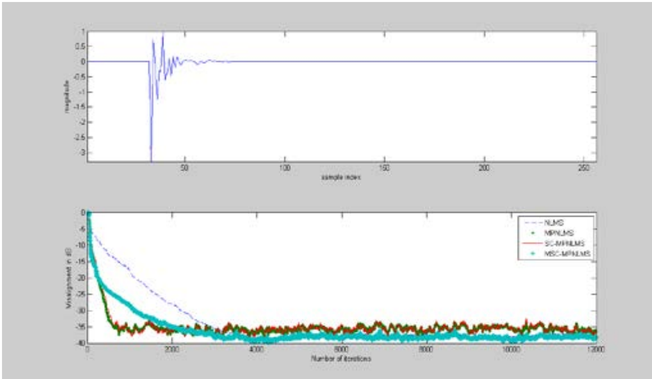

Fig 6: Relative Convergence of NLMS, MPNLMS, SC-MPNLMS and MSC-MPNLMS when impulse response is Sparse

Sparseness-Controlled IPNLMS (SC-IPNLMS) algorithm.

A different approach, compared to SC-MPNLMS, is chosen to incorporate sparseness-control into the IPNLMS algorithm (SC-IPNLMS) because, two terms are employed in IPNLMS for control of the mixture between proportionate and NLMS updates. The proposed SC-IPNLMS improves the performance of the IPNLMS by expressing ql(n) for n ≥ L as

$$q_l(n) = \left[\frac{1-0.5\xi(n)}{L}\right]\frac{(1-\alpha_{SC-IP})}{2L} + \left[\frac{1-0.5\xi(n)}{L}\right]\frac{(1-\alpha_{SC-IP})|h_l(n)|}{2\|h(n)\|_1+\delta_{IP}}$$

As can be seen, for large ξ^(n) when the impulse response is sparse, the algorithm allocates more weight to the proportionate term of IPNLMS. For comparatively less sparse impulse responses, the algorithm aims to achieve the convergence of NLMS by applying a higher weighting to the NLMS term. An empirically chosen weighting of 0.5 in the above equation is included to balance the performance between sparse and dispersive cases, which could be further optimized for a specific application. In addition, normalization by L is introduced to reduce significant coefficient noise when the effective step-size is large for sparse AIRs with high ξ^(n).

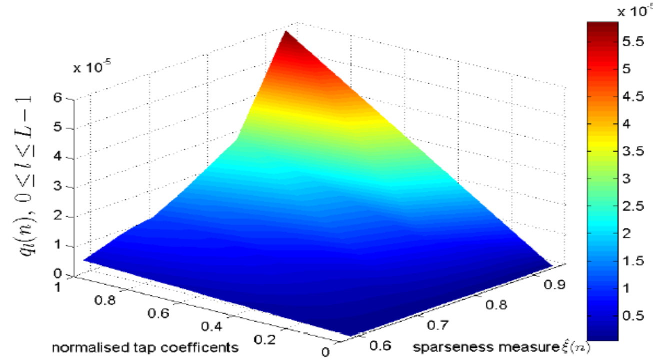

Fig 7: Magnitude of ql(n) for 0 ≤ l ≤ L-1 against the magnitude of coefficients $\hat{h_l}(n)$ in SC-IPNLMS and different sparseness measures of 8 systems.

Figure 7. illustrates the step-size control elements ql(n) for SC-IPNLMS in estimating different unknown AIRs. As can be seen, for dispersive AIRs, SC-IPNLMS allocates a uniform step-size across $\hat{h_l}(n)$ while, for sparse AIRs, the algorithm distributes ql(n) proportionally to the magnitude of the coefficients. As a result of this distribution, the SC- IPNLMS algorithm varies the degree of NLMS and proportionate adaptations according to the nature of the AIRs

Sparseness controlled Improved Proportionate NLMS (SC-IPNLMS) Algorithm:

Initialization:

$$\hat{h}_l(0) = 0, l = 0,1,\dots L-1$$

Parameters:

$$\alpha_{SC-IP} = -0.75$$

$$0 < \alpha < 2$$

$$\delta_{SC-IPNLMS} = cst.\sigma_x^2/L$$

Error:

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

Update:

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

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

$$q_l(n) = \left[\frac{1-0.5\xi(n)}{L}\right]\frac{(1-\alpha_{SC-IP})}{2L} + \left[\frac{1-0.5\xi(n)}{L}\right]\frac{(1-\alpha_{SC-IP})|h_l(n)|}{2\|h(n)\|_1+\delta_{IP}}$$

$$q_l(n) = \frac{(1-\alpha_{SC-IP})}{2L} + \frac{(1+\alpha_{SC-IP})|\boldsymbol{h}_l\hat{}(n)|}{2\|h(n)\|_1 + \delta_{SC-IPNLMS}} \quad for\, n \leq L$$

6. EXPERIMENTALS RESULTS

Experimental Setup:

Throughout the simulations, algorithms were tested using a zero mean WGN and a male speech signal as inputs while another WGN sequence w(n) was added to give an SNR of 20 dB. The length of the adaptive filter L = 1024 was assumed to be equivalent to that of the unknown system. The sparseness measure of these AIRs are computed by giving ξ(n) = 0.83 and ξ(n) = 0.59 respectively.

Convergence Performance of SC-MPNLMS for AEC:

Figure 8 and 9 illustrates the performance of NLMS, MPNLMS and SC-MPNLMS using WGN as the input signal. Step sizes are adjusted to achieve the same steady state misalignment for all algorithms. This corresponds to μNLMS=0.3, μMPNLMS=0.25, μSC-MPNLMS=0.35. The value of λ=6 was used for SC-MPNLMS. As can be seen from the result, the SC-MPNLMS algorithm attains approximately 9 dB improvement in normalized misalignment during initial convergence compared to NLMS and same initial performance followed by approximately 2.5 dB improvement over MPNLMS for the sparse AIR and SC-MPNLMS achieves approximately 2.7 dB improvement compared to MPNLMS and about 5 dB better performance than NLMS for dispersive AIR.

During Sparse Impulse response:

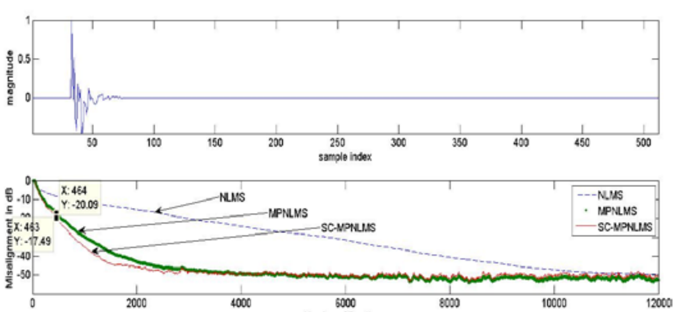

Fig 8: Relative Convergence of NLMS, MPNLMS and SC-MPNLMS when impulse response is Sparse

During Dispersive Impulse response:

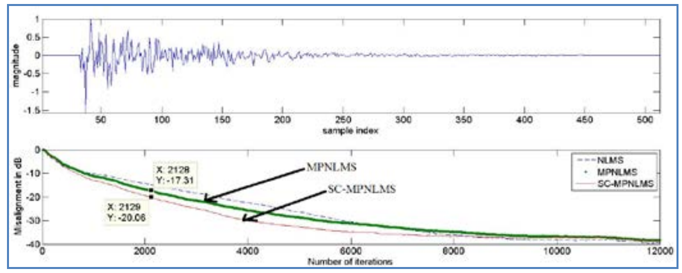

Fig 9: Relative Convergence of NLMS, MPNLMS and SC-MPNLMS when impulse response is Dispersive

The sparseness-controlled algorithms (SC-PNLMS, SC-MPNLMS and SCIPNLMS) give the overall best performance compare to their conventional methods across the range of sparseness measure. This is because the proposed algorithms take into account the sparseness measure of the estimated impulse response at each iteration.

7. MODIFIED SPARSENESS CONTROLLED IPNLMS (MSC-IPNLMS):

In the earlier algorithms like SC-IPNLMS and SC-MPNLMS, the sparseness measure used to measure the time varying sparseness of the impulse response to be identified is based on the l1 and l2 norms. But this sparseness measure is the good representation of sparse impulse response only. So, we can
improve the performance of SC-IPNLMS by incorporating another sparseness measure which is good representation of both sparse and dense impulse response. The new sparseness measure is the average of ζ12 (i.e. sparseness measure based on l1 and l2 norms) and ζ2∞ (i.e. sparseness measure based on l2 and l∞ norms). ζ12 is a good representation of sparse impulse response where as ζ2∞ is a good representation of dense impulse response. Hence ζ12∞ is good representation of both sparse impulse response and dense impulse response.

$$\xi_{12\infty} = \frac{\xi_{12} + \xi_{2\infty}}{2}$$

Convergence Performance of MSC-IPNLMS for AEC:

Figure 10 and 11 illustrates the performance of IPNLMS, SC-IPNLMS and MSC-IPNLMS using WGN as the input signal. Step sizes are adjusted to achieve the same steady state misalignment for all algorithms. This corresponds to IPNLMS =0.3, SC-IPNLMS =0.7, MSC-IPNLMS =0.9.

So by including ζ12∞ in the above SC-IPNLMS algorithm in the place of ζ^, this new MSC-IPNLMS algorithm showing the improvement of 4 dB over SC-IPNLMS when impulse response is more sparse and it is showing the improvement of 8 dB when impulse response is less sparse or dense.

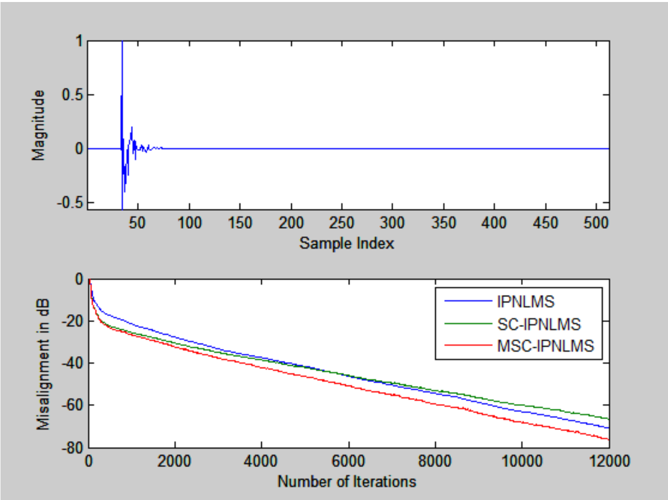

Fig10: Relative Convergence of IPNLMS, SC-IPNLMS and MSC-IPNLMS when impulse response is Sparse

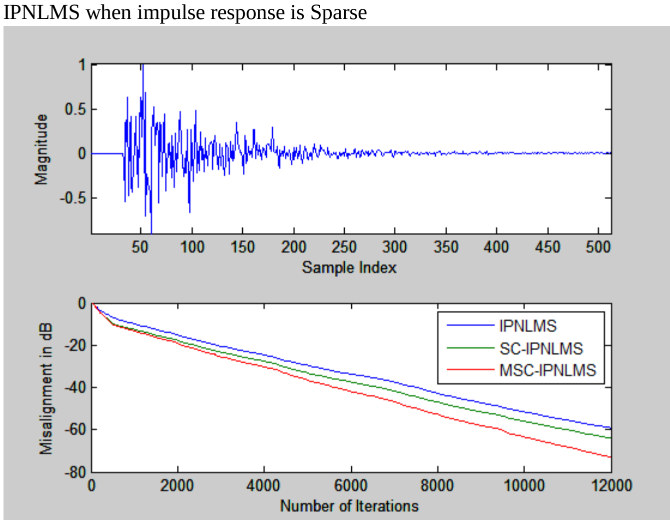

Fig11: Relative Convergence of IPNLMS, SC-IPNLMS and MSC-IPNLMS when impulse response is Dispersive

Conclusions:

This paper has addressed the significant problem caused by undesirable echoes that result from coupling between the loud speakers and microphones in the near end room. The research for this work focuses on the development of the adaptive filtering algorithms for sparse and non-sparse systems, emphasizing on the achievement of fast convergence rate with relatively low computational cost. The trade-off between convergence speed and the steady state misalignment is an important issue in this context, and can be balanced by choosing a sensible step size for the adaptive processes.

A series of experiments carried out both within and across NLMS, as well as a few other proportionate techniques, namely PNLMS, IPNLMS and MPNLMS, help to investigate their strengths and weaknesses. NLMS gives better performance in non-sparse system, whereas MPNLMS performs well in sparse impulse response. The combination of non-sparse and sparse technique, IPNLMS, exhibits an overall of better performance in all sparse levels. This identified an important factor, the sparseness measure (ξ), which affects their convergence speed.

By introducing ξ in both MPNLMS and IPNLMS, adaptive algorithms for acoustic echo cancellation can achieve fast convergence and robustness to sparse impulse response. The algorithms, known as SC-MPNLMS and SC-IPNLMS, take into account this factor differently via the coefficient update function. Simulation results show that the SC-IPNLMS exhibits more robustness to sparse systems than the other techniques. And the sparseness measure ζ12 used by the SC-IPNLMS and SC-MPNLMS is a good representation of sparse impulse response, so we have replaced this with ζ12∞ which is a good representation of both sparse and dense impulse response. And the algorithm with this sparseness measure showing better performance over SC-IPNLMS in the both sparse and dense impulse response, though its computational complexity is slightly higher than the existing main stochastic algorithms, this modified algorithms perform better in all ξ levels.

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