FACTA UNIVERSITATIS
Series: **Electronics and Energetics** Vol. 36, Nº 4, December 2023, pp. 519 - 532
https://doi.org/10.2298/FUEE2304519M

Original scientific paper

SPARSE ECHO CANCELLATION USING VARIANTS OF LEAST MEAN FOURTH AND LEAST MEAN SQUARE ALGORITHMS

Swastika Mishra, Jibendu Sekhar Roy

School of Electronics Engineering, Kalinga Institute of Industrial Technology (KIIT) Deemed to be University, Odisha, India

Abstract. *Echo cancellation is the most essential and indispensable component of telephone networks. The impulse responses of most of the networks are sparse in nature; that is, the impulse response has a small percentage of its components with a significant magnitude (large energy), while the rest are zero or small. In these sparse environments, conventional adaptive algorithms like least mean square (LMS) and normalized LMS (NLMS) show substandard and inferior performances. In this paper, the performances of the normalized least mean square (NLMS) algorithm, the normalized least mean fourth (NLMF) and the proportionate normalized least mean fourth (PNLMF) are compared for sparse echo cancellation. The sparseness of both the echo response and the input signal is exploited in this algorithm to achieve improved results at a low computational cost. The PNLMF algorithm showed better results and faster convergence in sparse and non sparse systems, but its results in sparse environments are more impressive. The NLMF algorithm shows good results in sparse environments but not in non-sparse environments. The PNLMS algorithm can be considered superior to the NLMF and NLMS algorithms with respect to the error profile. A modified algorithm, the sparse controlled modified proportionate normalized LMF (SCMPNLMF) algorithm, is proposed, and its performances are compared with the other algorithms.*

Key words: *channel sparsity, echo cancellation, sparse echo, sparse adaptive algorithm, NLMF, PNLMF, SCMPNLMF*

1. INTRODUCTION

A requisite requirement of a telecommunications infrastructure is to effectively and constructively remove hybrid and acoustic echoes to achieve improved and upgraded voice quality standards [1]. Adaptive filtering has substantial applications not only in the field of telecommunication but also in a large number of emerging areas like geophysics, biomedical, radar, and sonar engineering [1, 2]. Adaptive filtering approaches are very prevalent in the

Received April 27, 2023; revised June 30, 2023 and July 30, 2023; accepted September 26, 2023
Corresponding author: Jibendu Sekhar Roy
School of Electronics Engineering, Kalinga Institute of Industrial Technology (KIIT) Deemed to be University, Bhubaneswar-751024, Odisha, INDIA
E-mail: drjsroy@kiit.ac.in

field of digital communications and have numerous utilization, such as noise cancellation, blind and semi-blind equalization, and adaptive beam formation in antenna systems. Echo cancellation is an explicit application of noise cancellation in telecommunication systems. To overcome the problems of echoes in wireless communication systems, researchers have come up with many adaptive filtering algorithms. Accurate data transmission and superior audio quality are the most essential and requisite requirements for digital voice and video communications, for example, in distance learning education via video-conferencing [3, 4]. Various algorithms are examined, and their effectiveness and potency are compared with each other with the aim of cancelling the echo on pragmatic test data. Nowadays, mostly in case of hands-free telephony systems where there is a large distance between the loudspeaker and a microphone, adaptive echo cancellers are used. High-speed digital signal processing techniques are used in this approach to replicate and remove the echo and therefore surpass the suppression-based technique [4, 5].

2. Related Work

Deep learning-based channel estimation uses channel sparsity, which is one of the characteristics of wireless channels. In most cases, like in acoustic echo, which is a feedback cancellation system, the impulse responses (IRs) are mostly sparse or quasi-sparse. Thus, it is very vital to design adaptive filters that can act effectively on the sparse nature of the system's IR [5, 6]. Sparsity means the number of non-zero elements in the signal, and for broadband transmission, the IR of the channel is mostly sparse [7]. To identify the echo path in the echo cancellation scheme, and to improve the performance of a filter, many adaptive filtering algorithms are developed. In a mobile environment, the degree of sparseness in acoustic IR can differ and fluctuate to a great extent. The convergence of standard or regular approaches is not adequate when the sparseness of the response is very strong [8]. So there is extensive study in sparsity-aware adaptive filtering research for successfully learning compact solutions to linear problems using sparse signal recovery (SSR) techniques [9]. System identification in an adaptive way is a demanding and difficult problem in a sparse impulse response system. When a substantial portion of energy is present in a minute fragment of a signal, then the input signal's impulse response is sparse in nature. [10, 11]. Qualitatively, a system's degree of sparseness can be calculated, ranging from highly dispersive to highly sparse. Adaptive filtering algorithms can also be developed to act on the sparseness in the input of the signal along with the sparseness of echo responses [12, 13]. Typically, in a system, the duration of the echo response is in the range of 64–128 ms and is associated with a large delay that is dependent on various factors [14, 15, 16]. As the length of the active region is very short (8–12 ms), the IR mostly consists of idle areas where coefficients are nearly equal to null, resulting in it being sparse in nature, and the echo cancellation algorithm must be strong enough to overcome this sparseness [17, 18, 19]. For improved adaptive identification of the above-mentioned systems, various sparse adaptive algorithms have been developed [20-22]. The NLMS Algorithm, which is sparse-aware set-membership in nature, is used for channel estimation and echo cancellation [22]. In this work, the performances of NLMS, PNLMS, and variants of the LMF algorithm, i.e., NLMF and PNLMF are compared in the scenario of sparse echo cancellations. Their performances are inspected in terms of various measures like mean square error (MSE), echo return lossless enhancement (ERLE), and normalized projection misalignment (NPM) using MATLAB. The adaptive echo cancellation process is shown in Fig. 1. Here, *x(n)* and e(n) are the input signal and error, respectively.

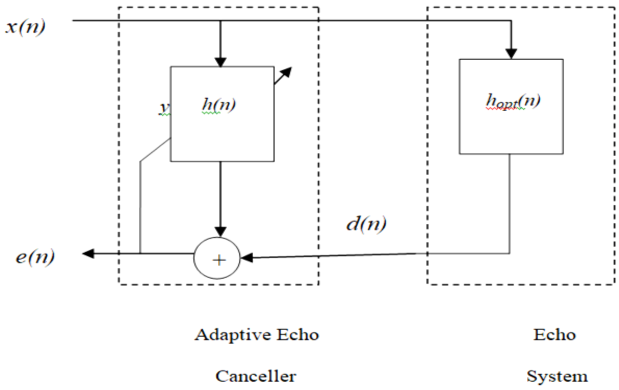


Fig. 1 Adaptive echo cancellation process

In this paper, in Section 3, different types of sparse algorithms used in this work are described with their mathematical backgrounds. In Section 4, the simulated results for sparse echo cancellation using variants of the LMS and LMF algorithms are presented. In Section 5, the conclusion of the present work and its future extension are presented.

3. SPARSENESS AND ALGORITHMS FOR SPARSE ECHO CANCELLATION

The impulse response of wireless telephone networks is mostly sparse in nature, where the magnitude of most of the components is either very small or zero. Only 8–10% of the path shows an active region, as bulk delays are present. Fig. 2 shows a common example of sparse impulse response.

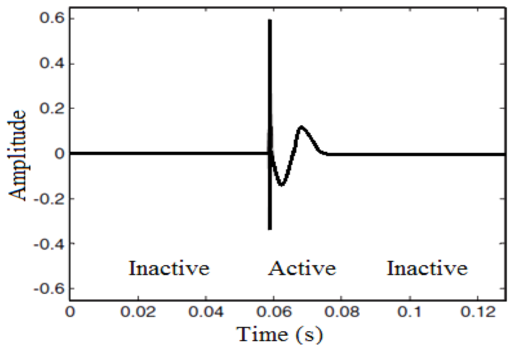


Fig. 2 Example of Sparse Impulse Response

3.1. Sparseness Measure

In a qualitative perspective, the degree of sparseness of the impulse response of an environment ranges from highly dispersive to firmly sparse. The equations to measure sparseness quantitatively are

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

$$\text{where } \; |h(n)\|_1 = \sum_{l=0}^{L-1}|h_l(n)| \tag{2}$$

$$|h(n)\|_2 = \sqrt{\sum_{l=0}^{L-1}h_l^2(n)} \tag{3}$$

and, L = length of filter , 0<L<1 ,Where the lower bound is acquired by uniform filter $[1\ ...1]^T$ and the upper limit by the Dirac filter $[1\ 0\ ...0]^T$.

3.2. Pulse Impulse Response Generator

Synthetic sparse impulses can be generated using random sequences with the help of a sparse impulse response generator, which can be obtained by describing an L×1 vector as

$$u_{Lx1} = \left[0_{Lpx1}\ 1\ e^{\frac{-1}{\Psi}}\ e^{\frac{-2}{\Psi}}\ ...\ e^{\frac{((L_u)-1)}{\Psi}}\right] \tag{4}$$

The length of the bulk delay is defined by leading zeros with length *Lp*. Decaying window length, *Lu* = *L* – *Lp*. This is controlled by ψ. System is more sparse when the ψ value is lower. Examples of non-sparse and sparse impulse responses are shown in Fig. 3.

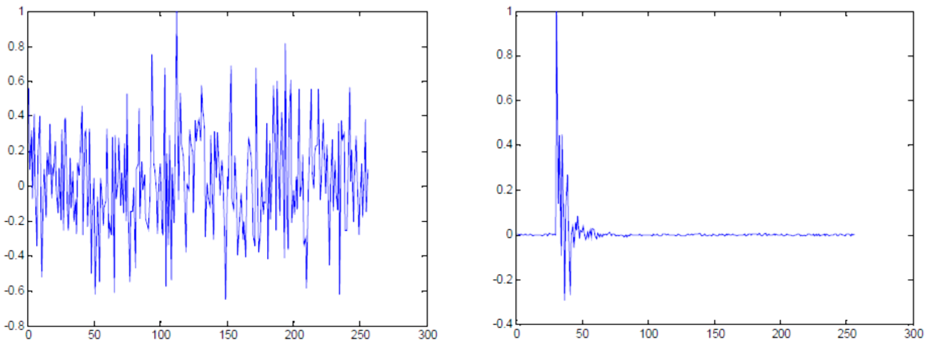


Fig. 3 Examples of non-sparse and sparse impulse responses using ψ =∞ and ψ =8

3.3. Normalized Least Mean Square (NLMS) Algorithm

The process of channel estimation using multipath sparse communication system is shown in Fig.4.

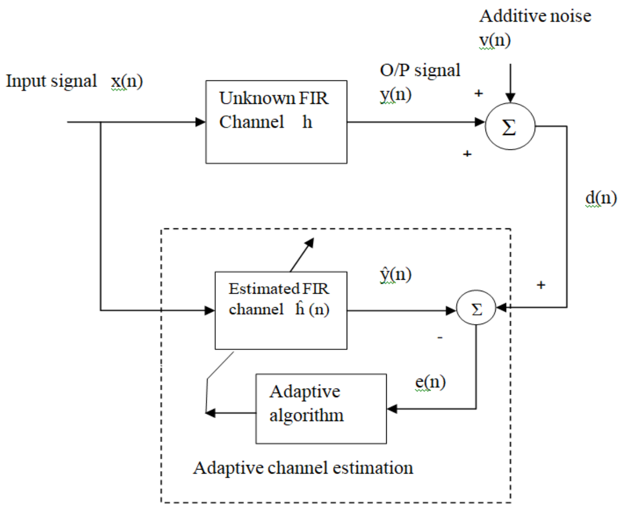


Fig. 4 Block diagram of Sparse Communication System

The input signal is

$$x(n) = \left[x(n), x(n-1), \dots \dots \dots, x(n-N+1)\right]^T \tag{5}$$

This contains the *N* most new samples that are transmitted over a FIR channel with channel IR is given by

$$h = \left[h_0,\ h_1,\ \dots \dots \dots ,\ h_{N-1}\right]^T \tag{6}$$

where $(\cdot)T$ = transposition operation. Then the output of the channel is

$$y(n) = h^T x(n) \tag{7}$$

where, h = sparse channel vector with K dominant active taps and $(N-K)$ inactive taps. $K > 0$, $(N-K) \approx 0$ and $K >> N$.

NLMS algorithm uses the input *x(n)*, the output *y(n)*, and the instantaneous estimation error *e(n)*, to estimate the unknown sparse channel h, which is

$$e(n) = d(n) - \hat{h}T(n)\ x(n) \tag{8}$$

where $\hat{h}(n)$ = NLMS adaptive channel estimator at instant n, $d(n) = y(n) + v(n)$, and $v(n)$ = additive noise at the receiver.

In the LMS, the weight adjustment and tap input vector, $x(n)$ is directly proportional to each other. As a result of which, for a larger value of $x(n)$ vector, the LMS deals with a gradient noise amplification problem. So at each iteration the adjustment applied to the tap weight vector is normalized with respect to the square of Euclidean norm of *x(n)* to control the amplification problem, which is

$$\hat{h}(n+1) = \hat{h}(n) + 2\mu \frac{x(n+1)\ e(n+1)}{\left\|x(n+1)\right\|^2 + \delta_{NLMS}} \tag{9}$$

$\delta_{NLMS} = \sigma_x^2$ = the input signal variance.

During initialization the regularization parameter δ_{NLMS} checks division by zero when $x(n) = 0$. The step size must be in the range as given below to ensure stability.

$$0 < \mu < 2\frac{E\left\{\left|x(n+1)\right|^2\right\}D(n+1)}{E\left\{\left|e(n+1)^2\right\}} \tag{10}$$

where E{|x(n)|^2} is the power of inputs tap, E{|e(n)|^2 } is the power error signal and D(n) is the mean square deviation.

3.4. Proportionate Normalized Least Mean Square (PNLMS) Algorithm

PNLMS was developed from the NLMS equation for tracking sparse IR at a faster rate. The step-size update matrix Q in the coefficient update equation makes it slightly different from NLMS, which is

$$\hat{h}(n+1) = \hat{h}(n) + \mu\frac{Q(n)\ x(n+1)\ e(n+1)}{x^T(n+1)\ Q(n)\ x(n+1) + \delta_{PNLMS}} \tag{11}$$

where $\delta_{PNLMS} = \delta_{NLMS} / L$, and the diagonal matrix,

$$Q(n) = \text{diag}\left\{q_0(n)\ q_1(n)\ \ldots\ \ldots\ \ldots\ \ldots\ \ldots\ \ldots\ q_{L-1}(n)\right\} \tag{12}$$

These control element is represented as

$$q_1(n) = \frac{k_l(n)}{\frac{1}{L}\sum_{i=0}^{L-1} k_i(n)} \tag{13}$$

$$k_l(n) = \max\left\{\rho \cdot \max\left\{\gamma, \left|\hat{h}_0(n)\right|\ \ldots\ \left|\hat{h}_{L-1}(n)\right|\right\}, \left|\hat{h}_l(n)\right|\right\} \tag{14}$$

with l = 0,1… L – 1.

Value of parameters $\rho = 5/L$ and the value of parameter $\gamma = 0.01$ which prevents $\hat{h}(n)$ from stalling during the initialization stage. The parameter $h(n)$ is the room impulse response and $\hat{h}(n)$ is the estimated room impulse response.

3.5. Least Mean Fourth (LMF) and Normalized Least Mean Fourth (NLMF) Algorithms

LMF algorithm evaluates the unknown channel vectors adaptively by using the training signal $x(n)$ and the output $y(n)$. The estimated coefficient vector is $W(n)$ at iteration n. For a standard LMF algorithm, the cost function $L(n)$ is

$$L(n) = \frac{1}{4}e^4(n) \tag{15}$$

$$e(n) = y(n) - W^T(n)\ x(n) \tag{16}$$

$e(n)$ = Instantaneous update estimation error at n-th step. The channel vector updating equation is

$$W(n+1) = W(n) - \mu \frac{\partial L(n)}{\partial W(n)} = W(n) + \mu e^3(n)\ x(n) \tag{17}$$

where, μ = step-size parameter.

Regular LMF algorithm in terms of impulse response is represented by

$$\hat{h}(n+1) = \hat{h}(n) + \beta e_n^3 x(n) \tag{18}$$

where, β = step-size. The stable NLMF algorithm is given by

$$\hat{h}(n+1) = \hat{h}(n) + \mu \frac{e_n^3 x(n)}{\|x(n)\|^2 (\|x(n)\|^2 + e_n^2)},\ 0 < \mu < 2 \tag{19}$$

which can be derived from the NLMS algorithm. Similarly the PNLMF Algorithm obtained from equation (19) is given by

$$\hat{h}(n+1) = \hat{h}(n) + 2\mu \frac{Q(n)\ x(n+1)\ e^3(n+1)}{x^T(n+1)\ Q(n)\ x(n+1) + \delta_{PNLMF}} \tag{20}$$

δ_{PNLMF} = Regularisation parameter.

4. Sparse Echo Cancellation Using Variants of LMF and LMS Algorithms

The various steps for the implementation of variants of LMS and LMF algorithms for sparse echo cancellation are given below.

Step 1: Implementation starts with recording a Speech signal which is named as *x(n)*.

Step 2: Then, to the input signal, the echo signal is added, which is the delayed version of the input. The distorted and corrupted signal along with the noise signal is named as d(n).

Step 3: Then the error signal $e(n)$ is derived by subtracting the output signal y(n) from $d(n)$, where $d(n)$ = Echo signal + Noise signal.

Step 4: Then the respective adaptive algorithm is implemented, and optimization is done for error minimization. Adaptive filter replicate the echo signal by estimating the echo path of the room and then adapt to the change in environment. Different adaptive algorithms show different convergence rates for estimating room acoustic paths.

Step 5: Steps 1–4 are repeated in four different sparse environments.

Step 6: The adaptive algorithms' performance is compared to each other using the three performance measures listed below.

The mean square error (MSE) measures the average of the squared difference between the estimated values and the actual value. It is given by

$$MSE(n) = E\{e^2(n)\} \tag{21}$$

In an acoustic echo cancellation system the echo signals attenuation is measured by echo return loss enhancement (ERLE) as given in equation below. Reduction in echo is more with increased ERLE.

$$ERLE(n) = \frac{10\log_{10} y^2(n)}{e^2(n)} \text{ dB} \tag{22}$$

Normalized Projection Misalignment (NPM) calculates the relation between $\hat{h}(n)$ to that of $h(n)$, i.e., how close they are to each other and $\hat{h}(n)$ = estimated IR and $h(n)$ = unknown IR. It can be expressed as

$$NPM(n) = 20\log_{10}\left(\frac{1}{\|h\|}\left\| h - \frac{h^T \hat{h}(n)}{\hat{h}^T(n)\,\hat{h}(n)}\hat{h}(n)\right\|\right) \text{ dB} \tag{23}$$

where the denominator is the squared 12-norm operator. The misalignment must be almost equal to zero for better results.

According to the above steps, in four different sparse environments (with increasing sparseness), echo cancellation is performed by implementing the NLMS, PNLMS, and PNLMF algorithms. The performance measures of the three methods, i.e., MSE, ERLE, and NPM, are simulated and their results are compared in Fig. 5, Fig. 6, Fig. 7, and Fig.8. In Fig. 5, Non Sparse environment with with Ψ=∞. In Fig. 6, Sparse environment with Ψ=100, in Fig. 7, Sparse environment with Ψ=40, and in Fig. 8, Ψ=40.

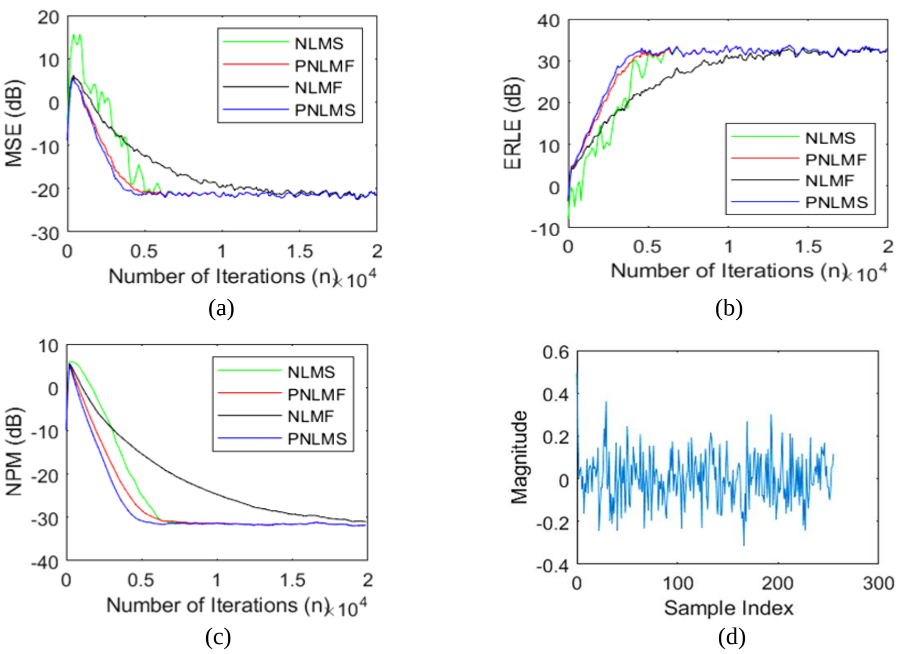


Fig. 5 Performances of algorithms in sparse environment with Ψ=∞

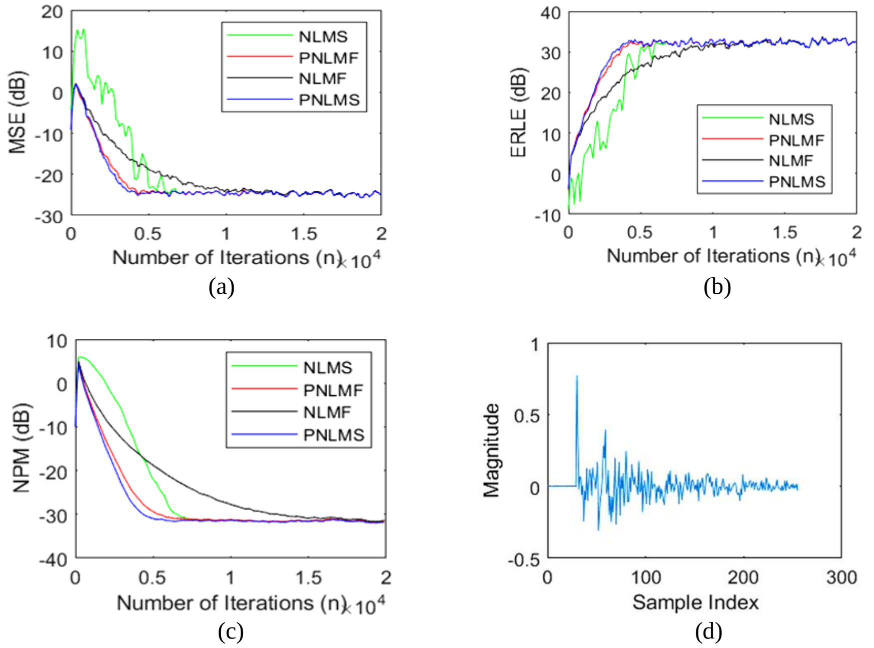


Fig. 6 Performances of algorithms in sparse environment with Ψ=100

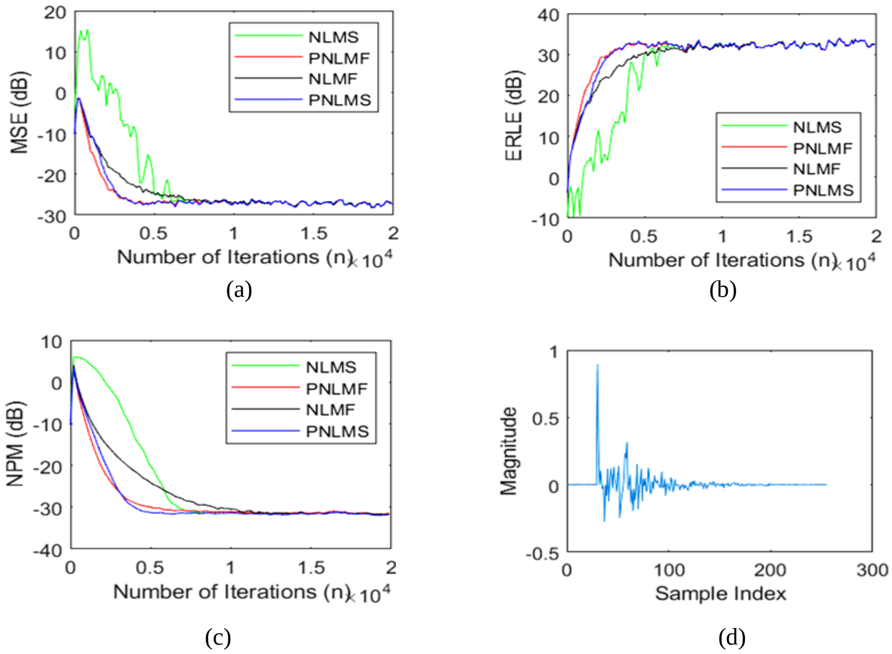


Fig. 7 Performances of algorithms in sparse environment with Ψ=40

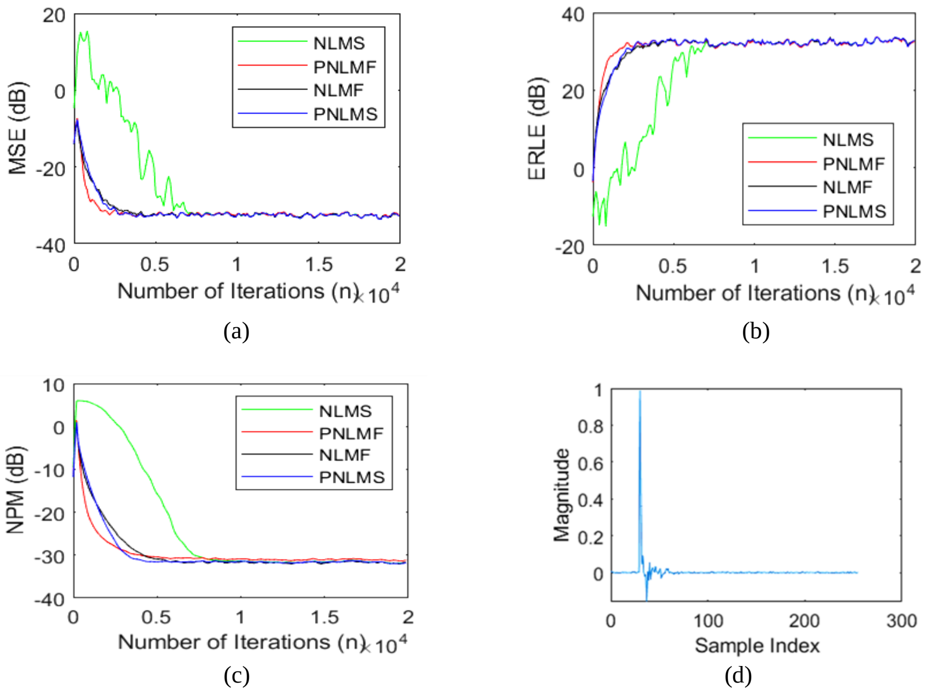


Fig. 8 Performances of algorithms in sparse environment with Ψ=8

It can be seen from the above graphical results that the PNLMF algorithm showed better results and faster convergence in sparse and non sparse systems, but its results in sparse environments are more impressive. The NLMF algorithm shows good results in sparse environments but not in non-sparse environments. The PNLMS algorithm can be considered superior to the NLMF and NLMS algorithms, but the results for PNLMF algorithm are more improved than PNLMS with respect to MSE, ERLE, NPM, and computational complexity.

Further, a new modified algorithm is proposed to obtain better performances in the sparse environment. This proposed algorithm is a sparse controlled modified proportionate normalized LMF (SCMPNLMF) algorithm. The SCMPNLMF algorithm demonstrates superior results and faster convergence in both sparse and non sparse systems. SCMPNLMF algorithm is derived from the sparse controlled modified proportionate normalized least mean square (SCMPNLMS) algorithm, also called µ-controlled algorithm which is the modified version of MPNLMS. It combines the benefits of sparsity and proportionate adaptation. It is designed to efficiently estimate sparse systems while providing improved convergence and tracking performance. The MPNLMS algorithm is derived from the PNLMS algorithm (11) but an additional weighting factor ρ ($0 < \rho < 1$) is used to control the step size adaptation. The introduction of ρ allows the MPNLMS algorithm to provide a trade-off between fast convergence (with larger step sizes) and steady-state maladjustment (with smaller step sizes).

The weight update equation in MPNLMS is:

$$W(n+1) = W(n) + \alpha(n).e(n).x(n) \tag{24}$$

$W(n)$ is the filter tap weights at time step n, and $\alpha(n)=\rho/(\lambda+||x(n)||^2)$ is the adaptation step size at time step n, which is determined based on the power of the input signal and the sparsity level of the system, and λ is the small positive constant for numerical stability.

The SCMPNLMS is an extension of the MPNLMS algorithm with an additional sparsity-induced term. The SCMPNLMS algorithm can be summarized by the following equation [14,21]

$$W(n+1) = \rho.(W(n) + \alpha(n).x(n).e(n)) - \mu.\lambda_S.\text{sign}(W(n)) \quad (25)$$

λ_s is the sparsity regularization parameter, and *sign*($W(n)$) is the element wise sign function that takes the sign of each element in the $W(n)$ vector. The sparsity induced term, $\mu.\lambda_s.sign(W(n))$ promotes sparsity in the adaptive filter by making many filter coefficients zero.

The weight update equation of SCMPNLMS with respect to channel impulse response derived from the PNLMS algorithm given in equation (11) is given by

$$\hat{h}(n+1) = \hat{h}(n) + \alpha(n)\frac{Q(n)\ x(n+1)\ e(n)}{x^T(n+1)\ Q(n)\ x(n+1) + \delta_{SCMPNLMS}} \quad (26)$$

where, $\alpha(n)$, used instead of μ, is the step size at iteration n, which controls the rate of updating of the filter coefficients and can be time-varying to enhance the performance according to the sparsity of the system. Here, Q is the step-size update matrix and $\delta_{SCMPNLMS}$ is the regularization parameter.

Similarly, the SCMPNLMF algorithm is an extension of the above algorithms where the robustness of LMF algorithm is incorporated. According to equations (15), (16), and (17), the weight update equation of LMF algorithm is

$$W(n+1) = W(n) + \mu e^3(n)\ x(n) \quad (27)$$

The SCMPNLMF algorithm combines the robustness of the LMF algorithm with the benefits of the SCMPNLMS algorithm, providing a sparse and robust adaptive filtering solution. The SCMPNLMF algorithm is derived from equations (25) and (27) and represented as

$$W(n+1) = \rho.(W(n) + \alpha(n).x(n).\eta(n)) - \mu.\lambda_S.\text{sign}(w(n)) \quad (28)$$

Here, η(n) is the updated error term of LMF algorithm and the channel impulse response is derived as

$$\hat{h}(n+1) = \hat{h}(n) + \alpha(n)\frac{Q(n)\ x(n+1)\eta(n)}{x(n+1)Q(n)\ x(n+1) + \delta_{SCMPNLMF}} \quad (29)$$

Here, Q is the step-size update matrix and $\delta_{SCMPNLMF}$ is the regularization parameter.

The SCMPNLMF algorithm operates iteratively, updating the filter tap weights based on the input signal, error signal, and the adapted step size. By adaptively adjusting step size based on the power of the input signal and incorporating sparsity measures, the SCMPNLMF algorithm can achieve faster convergence, improved tracking of the system, and efficient estimation of sparse systems.

The comparison of ERLE for the proposed SCMPNLMF algorithm with other algorithms is plotted in Fig. 9.

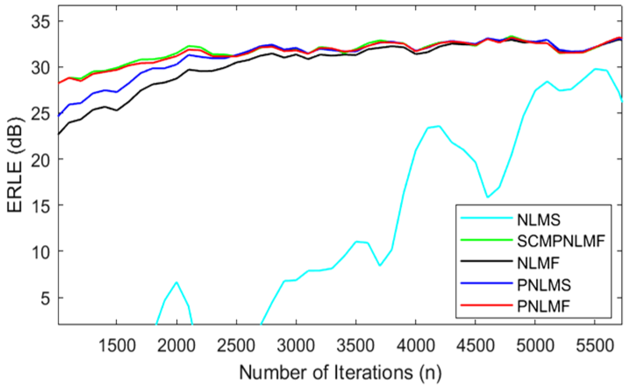
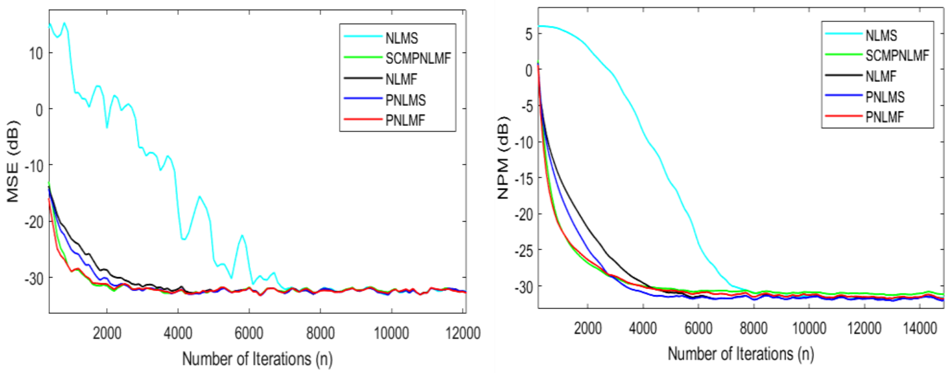


Fig. 9 Comparison of SCMPNLMF algorithm in sparse environment with Ψ=8

The comparisons of MSE and NPM for the proposed SCMPNLMF algorithm with other algorithms are plotted in Fig. 10.



(a)MSE (b)NPM

Fig. 10 Performances of SCMPNLMF algorithm in sparse environment

The simulated results for ERLE in sparse environment are compared in Table 1 with the reported results [4, 6, 14, 18] for Ψ = 8.

Table 1 Comparison of ELRE, obtained from different sparse adaptive algorithms

	Algorithm	ERLE (dB)
Ref. 4	PNLMS	31.6
Ref. 6	NLMS	11.1
Ref.14	NLMF	31.2
Ref.18	PNLMF	31.8
This paper	SCMPNLMF	32.0

It can be seen from the table that the value of ELRE is the largest in the PNLMF algorithm among all other algorithms with an equal iteration number and Ψ value. The reduction in echo is more pronounced as ERLE increases. The SCMPNLMF algorithm operates iteratively; updating the filter tap weights based on the input signal, error signal, and adapted step size.

5. Conclusion

In a non-sparse environment with scattered AIRs, the NLMS algorithm shows good convergence with a low response time. But in a sparse environment, its convergence is not impressive, whereas PNLMS shows better results than NLMS with respect to ERLE and MSE in sparse environments. But the computational complexity of PNLMS is high. The best result with respect to MSE, ERLE, and NPM is achieved in the case of the SCMPNLMF algorithm, as can be seen from the output graphs. The implementation of LMF and its variants will be further studied in real time and in light of recent scenarios like massive MIMO systems. By adaptively adjusting the step size, based on the power of the input signal and incorporating sparsity measures, the SCMPNLMF algorithm can achieve faster convergence, improved tracking of the system, and efficient estimation of sparse systems.

References

[1] W. H. Khong, J. Benesty and P. A. Naylor, "Stereophonic Acoustic Echo Cancellation: Analysis of the Misalignment in the Frequency Domain", *IEEE Signal Process. Lett*., vol. 13, no. 1, pp.33-36, 2006.

[2] S. Haykin, *Adaptive Filter Theory*, Prentice-Hall, Englewood Cliffs, NJ, 2002.

[3] P. A. Naylor, J. Cui and M. Brookes, "Adaptive Algorithms for Sparse Echo Cancellation", *J. Signal Process.*, vol. 86, pp. 1182-1192, 2006.

[4] C. H. Lee, B. D. Rao and H. Garudadri, "A Sparse Conjugate Gradient Adaptive Filter", *IEEE Signal Process. Lett*., vol.27, pp. 1000-1004, 2020.

[5] Y. Chen, Y. Gu and A. O. Hero, "Sparse LMS for System Identification", In Proceedins of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP),vol. 3, 2009, pp. 3125-3128.

[6] H-C. Shin, A. H. Sayed and W-J. Song, "Variable Step-Size NLMS and Affine Projection Algorithms", *IEEE Signal Process. Lett.*, vol.11, no. 2, pp. 132-135, 2004.

[7] S. Mishra and J. S. Roy, "Blind Channel Equalization Using Adaptive Signal Processing Algorithms", *IOSR J. Eng. (IOSR-JEN)*, vol. 9, no. 2, pp. 74-79, 2019.

[8] R. Chinaboina, D. S. Ramkiran, H. Khan, M. Usha, B. T. P. Madhav, K. P. Srinivas and G. V. Ganesh, "Adaptive Algorithms for Acoustic Echo Cancellation in Speech Processing", *Int. J. Res. Rev. Appl. Sci*., vol. 7, no. 1, pp. 38-42, 2011.

[9] C. Ye, K. Toyoda and T. Ohtsuki, "Improved Sparse Adaptive Algorithms for Accurate Non-contact Heartbeat Detection Using Time-Window-Variation Technique", In Proceedings of the 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Honolulu, HI, USA 18-21 July 2018, pp. 1-6.

[10] I. Hassani, A. Kedjar, M. A. Ramdane, M. Arezki and A. Benallal, "Fast Sparse Adaptive Filtering Algorithms for Acoustic Echo Cancellation", In Proceedings of the International Conference on Communications and Electrical Engineering (ICCEE), 17-18 Dec.,2018, El Oued, Algeria, pp. 1-5.

[11] A. Zhang, P. Liu, J. Sun and B. Ning , "Block-Sparsity Log-Sum-Induced Adaptive Filter for Cluster Sparse System Identification", *IEEE Access* , no. 8, pp. 175265-175276, 2020.

[12] C. Paleologu, J. Benesty and S. Ciochina, *Sparse Adaptive Filters for Echo Cancellation*, Springer, 2010.

[13] D.L. Duttweiler, "Proportionate Normalized Least-Mean Squares Adaptation in Echo Cancellers", *IEEE Trans. Speech Audio Process.*, vol. 8, no. 5 , pp. 508-518, 2002.

[14] E. Eweda, "A Stable Normalized Least Mean Fourth Algorithm with Improved Transient and Tracking Behaviors", *IEEE Trans. Signal Process.*, vol. 64, no. 18, pp. 4805-4816, 2016.

[15] W. H. Khong and P. A. Naylor, "Selective-tap Adaptive Algorithms in the solution of the Non-Uniqueness Problem for Stereophonic Acoustic Echo Cancellation", *IEEE Signal Process. Lett.*, vol. 12, no. 4, pp. 269-272, 2005.

[16] H. Zhang, K. Tan and D. Wang, "Deep Learning for Joint Acoustic Echo and Noise Cancellation with Nonlinear Distortions", In Proceedings of the 20th Annual Conference of the International Speech Communication Association (INTERSPEECH), Graz, Austria, 2019, pp.4255-4259.

[17] A. Akhbari and A. Ghaffar, "The Performance Comparison of Improved Continuous Mixed P-norm and Other Adaptive Algorithms in Sparse System Identification", *Int. J. Adv. Intell. Paradig.*, vol. 16, no. 1, pp. 65-74, 2020.

[18] M. O. Sayin, Y. Yilmaz, A. Demir and S. S. Kozat, "The Krylov-Proportionate Normalized Least Mean Fourth Approach: Formulation and Performance Analysis", *J. Signal Process.*, vol. 109, pp. 1-13, 2015.

[19] X. Zhang, Y. Liu and X. Wang, "A Sparsity Preestimated Adaptive Matching Pursuit Algorithm", *J. Electr. Comput. Eng.*, vol. 2021, pp. 1-8, 2021.

[20] Z. Habibi, H. Zayyani and Md. S. E. Abadi, "A Robust Subband Adaptive Filter Algorithm For Sparse And Block-Sparse Systems Identification", *J. Syst. Eng. Electron.*, vol.32, no. 2, pp.487-497, 2021.

[21] F. L. Perez, C. A. Pitz and R. Seara, "A Two-gain NLMS Algorithm for Sparse System Identification", *Signal Process.*, vol. 200, p. 108636, 2022.

[22] Y. Li, Y. Wang and T. Jiang, "Sparse-aware Set-membership NLMS Algorithms and Their Application for Sparse Channel Estimation and Echo Cancelation", *AEÜ-Int. J. Electron. Commun.*, vol. 70, pp. 895-902, 2016.