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New Low-Complexity Selected Active Coefficients Adaptive Sparse Algorithm for Teleconferencing Systems and Identification

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***Abstract*—** Addressing the challenge of sparse acoustic channel is important in communication systems such as tele- and video-conferencing systems. Sparse impulse response plays an efficient role in acoustic identification systems, particularly in long acoustic rooms. This article presents an enhanced version of the Improved Proportionate Normalized Least-Mean-Squares (IP-NLMS) algorithm. It adapts only the active coefficients, thereby reducing the computational complexity of IP-NLMS algorithm. The selected active coefficients of the IP-NLMS algorithm (SAC-IP-NLMS) are proposed exactly in sparse impulse response (SIR) in order to reduce the computational complexity with faster convergence rate. Several simulations conducted across various sparse environments - based on the time evolution of error signals, the mean square error, the echo return loss enhancement and the computational complexity - validate the effectiveness of the proposed algorithm.

***Keywords*—** Adaptive filtering; Sparse impulse responses; Improved Proportionate Normalized Least-Mean-Squares algorithm; Communication system.

1. INTRODUCTION

Recently, the advancement in telecommunication systems have shown significant improvements in areas such as speech recognition [1, 2], noise reduction [3, 4], acoustic echo cancellation [5, 6], and speech enhancement [7]. However, noise in closed environments can disrupt conversations, leading to unclear communication. This noise, known as punctual noise, reduces the connection between users. Recently, numerous research papers have explored the use of adaptive filtering algorithms in various telecommunication systems, such as reducing acoustic echo and noise, to improve conversation quality and speed convergence [7].

Many research activities have attempted the identification problem both in the time and frequency domains. For instance, widely utilized techniques include the basic Least Mean Square (LMS) and its normalized version, for their simplicity [8]. Additionally, various filtering algorithms personalized for Acoustic Echo Cancellation (AEC) have been proposed [9-10].

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However, the challenge deteriorates in scenarios with strongly non-stationary excitation signals and variable echo paths. Echo cancellers, employing digital Finite Impulse Response (FIR) filters, offer a solution to these complexities. These include lengthy Impulse Response (IR) modeling of the echo channel and the presence of non-stationary input signals such as speech.

To resolve the sparse environment problem, several adaptive filtering algorithms have been developed, such as the proportionate NLMS algorithm (PNLMS) [11]. The improved proportionate NLMS algorithm (IP-NLMS) has been proposed to address dispersive or sparse environments [12]. These algorithms update a significant portion of adaptive filter coefficients to achieve best performance [11-13]. Based on real-time implementation of AEC systems, the algorithm complexity is important.

This paper introduces a novel approach to reduce the computational complexity of adaptive algorithms while ensuring fast convergence rates as IP-NLMS algorithm, particularly in SIR systems. Our proposed version involves including an averaging constant detection into the IP-NLMS algorithm for adapting the selected active coefficients. This method aims to dynamically adjust the detection thresholds to identify the active coefficients. The algorithm showcases excellent performance in terms of achieving low MSE values, all while maintaining very low computational complexity.

The paper is structured as follows. In section 2, we present the acoustic impulse response identification systems, detailing NLMS and improved P-NLMS algorithms. In section 3, the proposed selected active coefficients IP-NLMS (SAC-IP-NLMS) algorithm is introduced, focusing on its development. The experimental results are presented in the next section. Finally, a conclusion is done in the last section of this paper.

2. ACOUSTIC IMPULSE RESPONSE IDENTIFICATION SYSTEMS

We are considering a system of two conferencing rooms equipped by two microphones and two loudspeakers, as presented in Fig. 1. The channel between a microphone and loudspeaker in each room is characterized by acoustical impulse response. In the locale room, $s_1(n)$ is the first speech signal send to the second room, however, $s_2(n)$ presents the second speech signal send from the second room to the first ones that is coupled with the first acoustic impulse response $h_1(n)$. In the second room, the first speech signal $s_1(n)$ is filtered by the acoustic impulse response $h_2(n)$ [9]. We can define the two output signals $y_1(n)$ and $y_2(n)$ of adaptive filters $y_1(n)$ and $y_2(n)$, respectively by:

$$y_1(n) = s_2(n) * h_1(n) \quad (1)$$

$$y_2(n) = s_1(n) * h_2(n) \quad (2)$$

where (*) is the convolution operation. The two echo paths $h_1(n)$ and $h_2(n)$ represent impulse responses of two rooms. The Basic impulse response identification system is presented in Fig. 1 [14-16]. In any teleconferencing system, it is efficient to eliminate the two acoustic echoes, $y_1(n)$ and $y_2(n)$, added to the signals received by the microphones installed in the two rooms. For the AEC system, adaptive filters are employed to identify the room IR. The filter needs to be updated continuously, because the characteristics of the room vary in time with the movement of people and objects [14-16]. Noting that $s_2(n)$ is convoluted by $h_1(n)$. In other hand, $s_2(n)$ is convoluted by adaptive filter $w_1(n)$ that is used to estimate the $h_1(n)$, and subtracted from the $d(n)$. To update the filter $w_1(n)$, we use the error signal during silence periods of $s_1(n)$ [14]. This error is given by:

$$e(n) = d(n) - \hat{y}_1(n) \tag{3}$$
$$d(n) = s_1(n) + s_2(n) * h_1(n) \tag{4}$$

$$\hat{y}_1(n) = s_2(n) * w_1(n) \tag{5}$$

Inserting Eqs. (4) and (5) in Eq. (3), we obtain

$$e(n) = s_1(n) + s_2(n) * h_1(n) - s_2(n) * w_1(n). \tag{6}$$

$$e(n) = s_1(n) + s_2(n) * [h_1(n) * w_1(n)]. \tag{7}$$

In the optimal case [15, 16], $w_1(n)$ converges to $h_1(n)$, and the calculated error becomes:

$$e(n) = s_1(n) \tag{8}$$

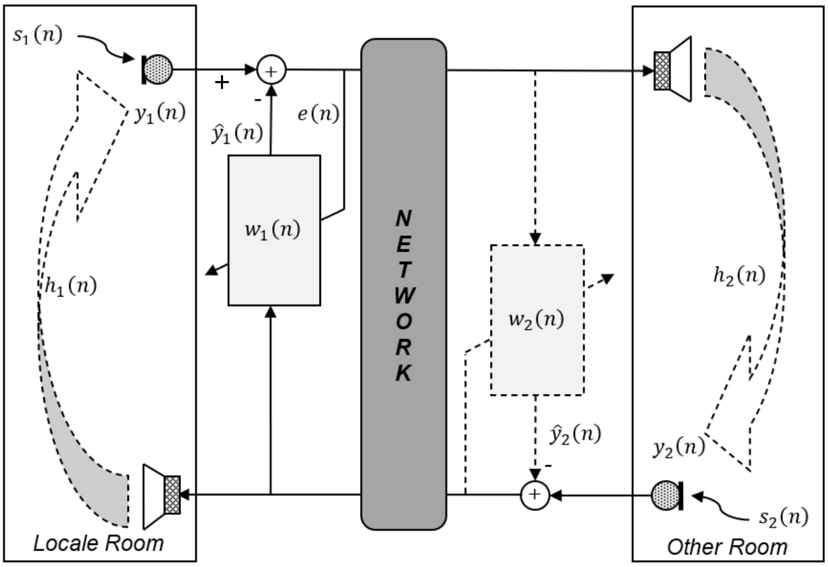


Fig. 1. Basic impulse response identification system.

2.1. Basic Non-Sparse NLMS Adaptation

Firstly, we are employing the estimation of the adaptive filter $\mathbf{w}_1(n)$, the *a priori* error signal e(n) at each iteration is determined as [6]:

$$e(n) = d(n) - \mathbf{s}_2(n) * \mathbf{w}_1(n) \tag{9}$$

By incorporating the *a priori* error signal e(n) from Eq. (9), the cost function $J(\mathbf{w}_1(n))$ is formulated as [9, 10]:

$$J(\mathbf{w}_1(n)) = E\{e(n)^2\} \tag{10}$$

Hence, the mean square error (MSE) cost function is quadratic in the adaptive filter vector $\mathbf{w}_1(n)$. The minimum of the error surface is achieved by setting the partial derivatives of $J(\mathbf{w}_1(n))$ with respect to each filter coefficient to zero. Therefore, the unique optimal adaptive filter is defined as [6, 9, 10]:

$$\mathbf{w}_{1,opt}(n) = \mathbf{R}^{-1}\mathbf{p} \tag{11}$$

where $\mathbf{p}$, the M × 1 cross-correlation vector between $\hat{y}(n)$ and $s_2(n)$, is defined as $\mathbf{p} = E\{\hat{y}(n)\mathbf{s}_2(n)\}$. And $\mathbf{R}$, the M × M auto-correlation matrix of the tap inputs in the transversal filter, is defined by $\mathbf{R} = E\{\mathbf{s}_2(n)\mathbf{s}_2^{\mathrm{T}}(n)\}$. This method, known as the Wiener-Hopf solution, provides the minimum MSE and can be used to estimate the unknown room impulse response. However, it is not suitable for non-stationary signals such as speech signals, and the autocorrelation and cross-correlation values are also unknown. To resolve this problem, we can use the steepest descent method that is an iterative gradient-based technique that optimizes cost function $J(\mathbf{w}_1(n))$ by iteratively adjusting filter coefficients in the direction of the steepest decrease, thereby approaching the minimum error point with each iteration. Therefore, the filter coefficient update equation of steepest descent is expressed as [8]:

$$\mathbf{w}_1(n+1) = \mathbf{w}_1(n) + \lambda[\mathbf{p} - \mathbf{R}\,\mathbf{w}_1(n)] \tag{12}$$

In Eq. (12), the adaptive step-size λ is designed to control the rate of convergence. The LMS algorithm is widely favored for its ease of implementation, low complexity, and numerical stability. The filter coefficient update equation for the LMS algorithm is expressed as [8]:

$$\mathbf{w}_1(n+1) = \mathbf{w}_1(n) + \lambda\ \mathbf{s}_2(n)e(n) \tag{13}$$

For stability it must be lie with the range $0 < \lambda < 2/\vartheta_{s,Max}$, with $\vartheta_{s,Max}$represents the largest eigen-value of the auto-correlation matrix R. The LMS algorithm represents as a first estimator for the Wiener-Hopf filter due to its approximation of the gradient vector. In Eq. (13), the adjustment of the filter coefficients is directly proportional to the tap input vector $\mathbf{s}_2(n)$. Consequently, when the $\mathbf{s}_2(n)$ vector is large, the LMS algorithm experiences gradient noise amplification. To address this issue, the adjustment applied to the tap weight vector at each iteration can be normalized by the squared Euclidean norm of $\mathbf{s}_2(n)$. So, the adaptation step-size λ of LMS algorithm has been changed by $[\mu/\mathbf{s}_2^{\mathrm{T}}(n)\mathbf{s}_2(n)]$. The NLMS algorithm is proposed to ensure convergence behavior independent of the input energy of the adaptive filter, and is widely adopted, particularly in AEC applications. Eq. (14) is the NLMS recursive update formula [8].

$$\mathbf{w}_1(n+1) = \mathbf{w}_1(n) + \frac{\mu\mathbf{s}_2(n)e(n)}{\mathbf{s}_2^{\mathrm{T}}(n)\mathbf{s}_2(n) + \xi_{nlms}} \tag{14}$$

where, a small parameter ξ_{nlms} is added in the denominator to overcome the problem of division by zero when the quantity $[\mathbf{s}_2^{\mathrm{T}}(n)\mathbf{s}_2(n)]$ takes small values or a zero value.

$\mathbf{w}_1(n) = [\mathrm{w}_{1,1}(n), \mathrm{w}_{1,2}(n), \dots, \mathrm{w}_{1,M}(n)]$, this vector is used for identifying the impulse response $\mathrm{h}_1(n)$. It contains the filter coefficients that are updated at each iteration to minimize the error signal.

$\mathbf{s}_2(n) = [\mathrm{s}_2(n-1), \mathrm{s}_2(n-2), \dots, \mathrm{s}_2(n-M)]$ represent the M recent values of the input signal $\mathbf{s}_2(n)$ at each iteration n. It is used to compute the output of the adaptive filter and the error signal.

μ represents the normalized adaptation step-size parameter that is takes its values between 0 and 2 [8]. In the context of the NLMS algorithm, the normalized parameter μ is important for ensuring the stability and convergence speed of the adaptive filter $\mathbf{w_1}(\boldsymbol{n})$. The value of μ typically ranges between 0 and 2 [8, 17]. Firstly, μ must be chosen such that the filter does not diverge, and this range is chosen to guarantee the stability of this adaptive NLMS algorithm. As we note that, the higher values of μ lead to faster convergence but can also increase the risk of instability and larger steady-state errors. Conversely, the smaller values provide better stability and lower steady-state errors but result in slower convergence rates.

One major drawback of the NLMS algorithm is its significantly reduced convergence rate when dealing with sparse impulse responses, which are common in network echo cancellation applications. To address this issue, several sparse adaptive algorithms have been specifically developed to effectively identify sparse impulse responses in such contexts [11-13].

2.2. Sparse NLMS versions

In teleconferencing AEC systems, the length of IR can extend up to 2048 filter taps, representing approximately 256 milliseconds. The acoustic system exhibits sparsity, meaning most of its taps are close to zero (inactive coefficients), while only a small subset of coefficients has significant magnitudes (active coefficients) [13]. Numerous sparsity-aware adaptive algorithms have been proposed to address the NLMS algorithm in teleconferencing systems, particularly its inability to accurately identify SIR. The filter coefficients update equation for numerous sparse adaptive algorithms can be represented by Eq. (15) along with the following set of generalized equations [11]:

$$\mathbf{w}_1(n+1) = \mathbf{w}_1(n) + \frac{\mu\, Q(n)\, \mathbf{s}_2(n)\, e(n)}{\mathbf{s}_2^{\mathrm{T}}(n)\, Q(n)\, \mathbf{s}_2(n) + \xi} \tag{15}$$

The diagonal control matrix $Q(n)$ is employed to precise the step-size value for each coefficient. It is defined as by:

$$Q(n) = \begin{bmatrix} q_1(n) & 0 & \cdots & 0 \\ 0 & q_2(n) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & q_M(n) \end{bmatrix} \tag{16}$$

The Proportionate NLMS algorithm [11], aims to enhance the initial convergence speed. This method assigns a high adaptation gain to large coefficients while providing minimal adaptation gain for small coefficients. The diagonal elements $q_m(n)$ of the step-size control matrix $Q(n)$ in Eq. (16) for the PNLMS algorithm can be expressed as [11-13]:

$$q_m(n) = \frac{\theta_m(n)}{\frac{1}{M}\sum_{i=0}^{M-1}\theta_i(n)}, \quad 0 \le m \le M-1 \tag{17}$$

$$\theta_m(n) = max\{\rho \times max\{\gamma, F(|w_{1,0}(n)|),, \dots, F(|w_{1,M-1}(n)|)\}, F(|w_{1,m}(n)|)\} \tag{18}$$

where, the function $F(|w_{1,m}(n)|)$ is personalized to the specific used algorithm. The parameter $\gamma = 0.01$ prevents the filter coefficients $w_{1,\mathrm{m}}(n)$ from stalling when $\mathbf{w}_1(n) = 0_{1\times M}$ at initialization. The parameter ρ, usually set to 0.01, ensures that the coefficients do not stall when they are much smaller than the largest coefficient. For the PNLMS algorithm [11], the elements $F(|w_{1,m}(n)|)$ are defined by:

$$F(|w_{1,m}(n)|) = |w_{1,m}(n)| \tag{19}$$

Therefore, PNLMS uses larger step-sizes for active coefficients, resulting in faster convergence than NLMS for sparse impulse responses. However, after a rapid initial convergence, PNLMS experiences a slower convergence in second phase.

The MPNLMS algorithm improves the convergence of PNLMS by computing the optimal proportionate step-size during adaptation. It ensures all coefficients converge to within a vicinity $\epsilon$of their optimal value in the same number of iterations. Consequently in [17], $F(|w_{1,m}(n)|)$ for MPNLMS is defined by:

$$F(|w_{1,m}(n)|) = ln(1 + \eta|w_{1,m}(n)|) \tag{20}$$

The MPNLMS algorithm adjusts the step-size with $\eta = 1/\epsilon$, where ϵ is a very small positive number [17]. A value of $\epsilon = 0.001$ is recommended for typical echo cancellation scenarios. The positive bias of 1 in Eq. (20) prevents numerical instability during initialization when $w_{1,\mathrm{m}}(0) = 0, \forall m$.

Both PNLMS and MPNLMS algorithms encounter slow convergence when dealing with dispersive unknown systems, such as those found in acoustic impulse responses (AIRs). This issue arises because the step-sizes become small for each large coefficient due to the significant enlargement of certain parameters in the algorithms when the impulse response is dispersive. This is attributed to the significant enlargement of $\theta_m(n)$in Eq. (18) for most $0 \leq m \leq M-1$ when the impulse response is dispersive.

In [12], the authors introduced the IP-NLMS algorithm, which combines elements of both non-sparse and sparse adaptation. The update formula of IP-NLMS is the same as presented previously in Eq. (15). Where the diagonal elements $q_m(n)$ are calculated as [12]:

$$q_m(n) = \frac{(1-\alpha)}{2M} + \frac{(1+\alpha)|w_{1,m}(n)|}{2\,\|\mathbf{w}_1(n)\|_1+\varphi} \quad (21)$$

where α is a control parameter must be fixed between –1 and 1 [12]. With φ is small number to prevent division by zero, particularly during the initial stages of adaptation when filter taps are initialized to zero. The IP-NLMS algorithm mirrors the non-proportionate NLMS algorithm when α equals -1.

Conversely, when α equals 1, the IP-NLMS and P-NLMS algorithms coincide. In practical applications like AEC systems, α= 0, -0.5, or -0.75 are commonly preferred choices [19]. $\|\mathbf{w}_1(n)\|_1$ is defined as the l_1-norm:

$$\|\mathbf{w}_1(n)\|_1 = \sum_{m=1}^{M} w_{1,m}(n) \quad (22)$$

In the next, we examine the computational complexity of NLMS, PNLMS, MPNLMS, and IPNLMS algorithms. In Table 1, we assess the relative computational complexity of four algorithms in terms of the total number of additions, multiplications, divisions, comparisons, and logarithms required per iteration for coefficient adaptation.

Table 1. Complexity of coefficients update filter using four algorithms [6, 11-13].

Algorithm	Addition	Multiplication	Division	Comparison	Logarithm
NLMS	3M + 3	6M + 4	1	0	0
P-NLMS	4M + 1	7M + 3	2	4M	0
MP-NLMS	4M + 2	8M + 3	2	4M	M
IP-NLMS	4M + 3	8M + 2	2	0	0

Table 1 demonstrates that the overall computational complexities of PNLMS, MPNLMS, and IPNLMS either increase or remain comparable to NLMS. Justifying these heightened complexities requires significantly improved convergence. Notably, the IP-NLMS presents a promising solution compared to others, as it updates all coefficients, both active and non-active of the sparse filter. In the next section, we will introduce our proposed algorithm, based on the IP-NLMS approach but engineered for very low complexity.

3. PROPOSED LOW-COMPLEXITY SAC-IP-NLMS ALGORITHM

In longer AEC applications, the complexity of the IP-NLMS algorithm becomes more pronounced compared to the basic NLMS. The adaptive filter comprises mostly small or nearzero inactive coefficients and only a few active coefficients with significant magnitudes. Hence, selecting the right number of active coefficients in the adaptive filter is important for efficiently handling SIR (see Fig. 2). For minimizing the computational complexity of the basic sparse IP-NLMS, we propose to adapt the active coefficients in the sparse adaptive filter. To achieve this goal, we propose a modified IP-NLMS adaptive filtering approach with significantly reduced complexity.

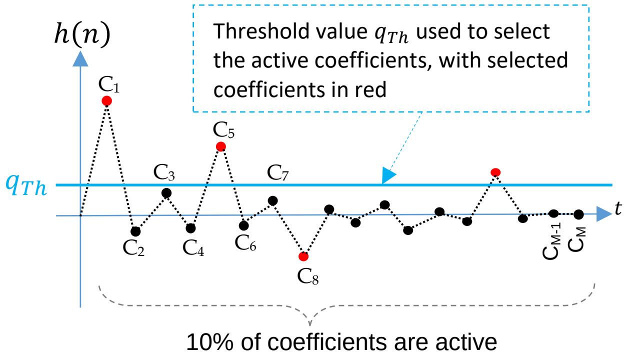


Fig. 2. Selection procedure of active coefficients.

We note that C_i represent the coefficients of the SIR. We propose to adapt only the active coefficients, employing a selection active coefficients bloc based on an averaging constant detection. In the proposed new AEC system, a novel bloc has been introduced to facilitate the selection of active coefficients within the adaptive filter. Following this stage, the adaptation process focuses solely on these active coefficients, thereby reducing the computational complexity load. The updating formula of the selected coefficients is expressed as follows:

$$\mathbf{w}_{1,S}(n+1) = \mathbf{w}_{1,S}(n) + \frac{\mu_S Q_S(n)\mathbf{s}_{2,S}(n)e(n)}{\mathbf{s}_{2,S}^T(n)Q_S(n)\mathbf{s}_{2,S}(n)+\xi_{IP}} \tag{23}$$

where $\xi_{IP} = ((1-\alpha)/2M)\xi_{nlms}$ and α is a control parameter must be fixed between –1 and 1. This formula updates only the active coefficients in $\mathbf{w}_{1,S}(n)$ based on the error signal and input signal, thereby reducing computational complexity by ignoring small and inactive coefficients. The new diagonal control matrix $Q_S(n)$ is written as:

$$Q_S(n) = \begin{bmatrix} q_{S,1}(n) & 0 & \cdots & 0 \\ 0 & q_{S,2}(n) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & q_{S,M}(n) \end{bmatrix} \tag{24}$$

where, $diag\{Q_S(n)\} = [q_{S,1}(n), q_{S,2}(n), \dots, q_{S,M}(n)]$. The modified diagonal coefficients $q_{S,j}(n)$ are estimated as

$$q_{S,j}(n) = \frac{(1-\alpha)}{2M} + \frac{(1+\alpha)|w_{1,S,j}(n)|}{2\left\|\mathbf{w}_{1,S}(n)\right\|_1+\varphi} \tag{25}$$

The new sparse impulse response identification systems and selected active coefficients bloc of proposed SAC-IP-NLMS algorithm are illustrated in Figs. 3 and 4.

Following the threshold calculation, the second step involves identifying the S active filter coefficients, new vector $\mathbf{w}_{1,S}(n)$. This is achieved by comparing each element of the step-size control matrix with the previously calculated threshold value. Any element in the matrix that larger or equals the threshold is considered an active coefficient.

To precisely determine the active coefficients, the important step involves calculating a threshold derived from the mean value of the matrix elements that is expressed as:

$$q_{Th} = \gamma \sum_{j=1}^{M} q_j(n) \tag{26}$$

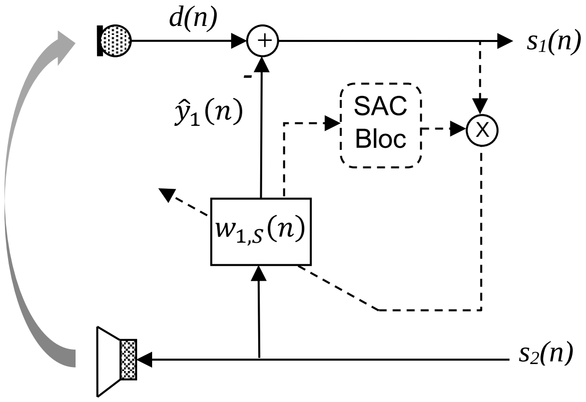


Fig. 3. AEC based on proposed algorithm with SAC presented in detail in Fig. 4.

In this context, if $q_j(n) \geq q_{Th}$, the coefficient $w_{1,j}(n)$ is considered an active coefficient. Conversely, if $q_j(n) < q_{Th}$, the coefficient $w_{1,j}(n)$ presents an inactive coefficient. The active coefficients are adapted and adjusted using the Sparse IP-NLMS. On the other hand, the inactive coefficients, are non-adapted and remain unchanged.

In the final step, we extract all *j* positions corresponding to the active coefficients. These positions are important for identifying the new vector of active coefficients for the SIR.

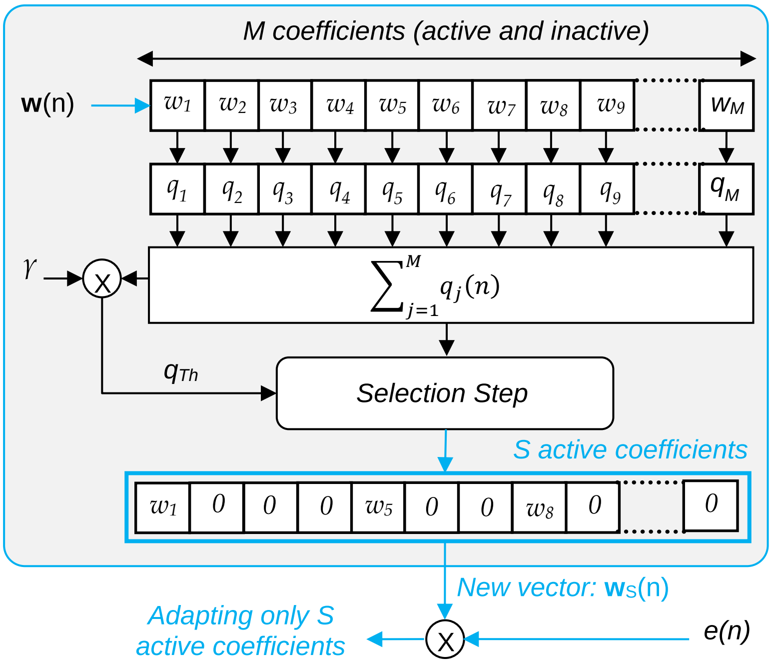


Fig. 4. Detailed steps of SAC bloc.

Based on the computational complexity presented in Table 1, we note that the standard IP-NLMS updates all filter coefficients regardless of their activity status [13]. However, the SAC-IP-NLMS focuses on updating only the active coefficients, which constitute a mere 10% of the total coefficients.

This selective updating mechanism significantly reduces the computational load, making the SAC-IP-NLMS algorithm less complex compared with other non-sparse and sparse algorithms. The proposed SAC-IP-NLMS algorithm demands 4Ms + 3 additions, 8Ms + 2 multiplications and 2 divisions with Ms represents the number of active coefficients of sparse impulse response, i.e., which constitute only 10% of the total coefficients.

4. SIMULATION RESULTS

In this experimental part, we evaluate the performance of the proposed SAC-IP-NLMS algorithm for impulse response identification process. In order to give a good evaluation of this algorithm by maintaining the original characteristics of the real rooms, we have used SIRs. We have used two types of signals, with a sampling frequency of 8 kHz, that are filtered by SIR which give desired signals. We evaluated the algorithm using three criteria: (i) Time evolution of error signals, (ii) Mean Square Error (MSE), and (iii) Echo Return Loss Enhancement (ERLE).

To show the performance of the proposed adaptive filtering algorithm, we have used in our experiments a stationary signal and a non-stationary signal, respectively: (i) the first one is the USASI-noise (USA Standards Institute) represented in Fig. 5, and (ii) the second is a speech signal of a male speaker (see Fig. 6) [18, 19]. Fig. 7 represents the SIR used in all simulations, with a) M = 64, b) M = 128 and c) M = 256.

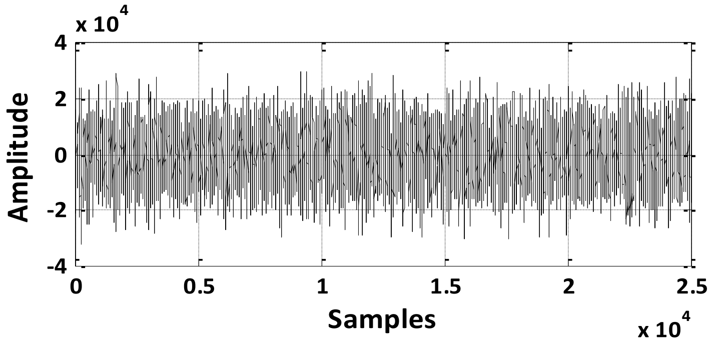


Fig. 5. Stationary USASI noise.

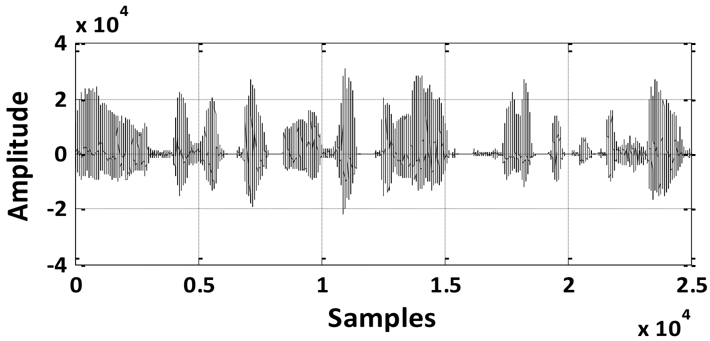


Fig. 6. Non-stationary speech signal.

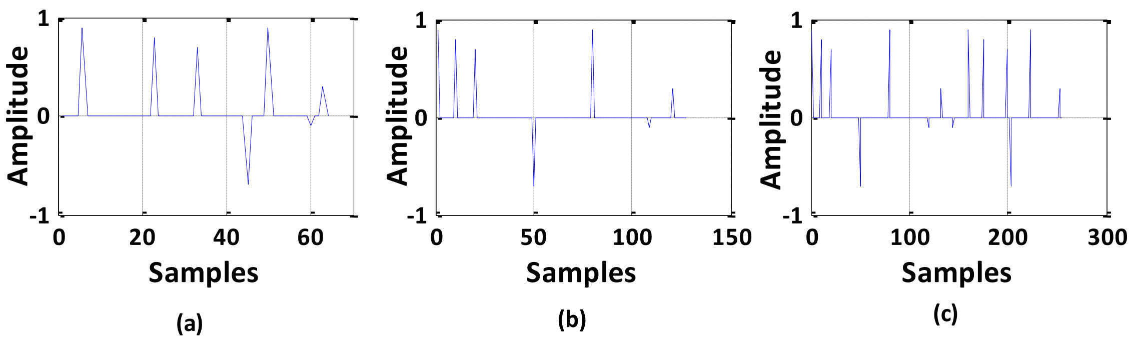


Fig. 7. Sparse impulse responses with a) M = 64; b) M = 128; c) M = 256.

4.1. Temporal Evolution

In this part of simulation, we present the time evolution of the error signal obtained by the proposed algorithm using the two signals, USASI noise and speech signal. The parameters values of three simulated algorithms are summarized in Table 2.

Table 2. Parameters of the simulated algorithms.

Algorithm	Parameter
Basic-NLMS	μ = 0.9, $\xi_{nlms} = 10^{-6}$,
IP-NLMS	μ = 0.9, $\xi_{IP} = 10^{-6}$, α = - 0.5, $\varphi = 10^{-6}$
Proposed	μ = 0.9, $\xi_{IP,S} = \xi_{IP}$, α = - 0.5, $\varphi = 10^{-6}$

During these experiments, the number of iterations is set to 52000 iterations and the input Signal to Noise Ratio (SNR) is chosen equal to 90 dB. The error signals for USASI noise and speech signal are presented in Fig. 8. We present in Fig. 9, all estimated sparse impulse responses obtained by the proposed algorithm using two input signals (USASI and speech) for three scenarios: M = 64, M = 128, and M = 256.

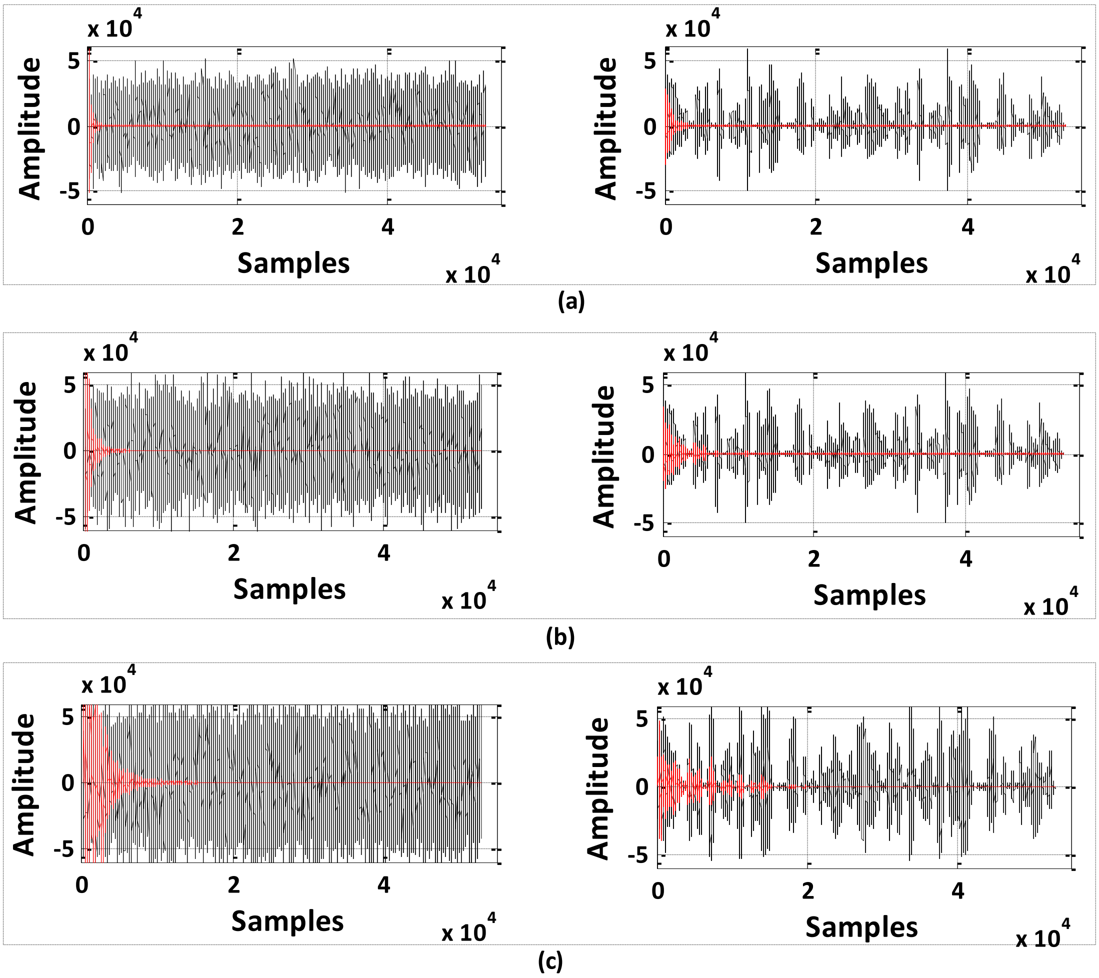
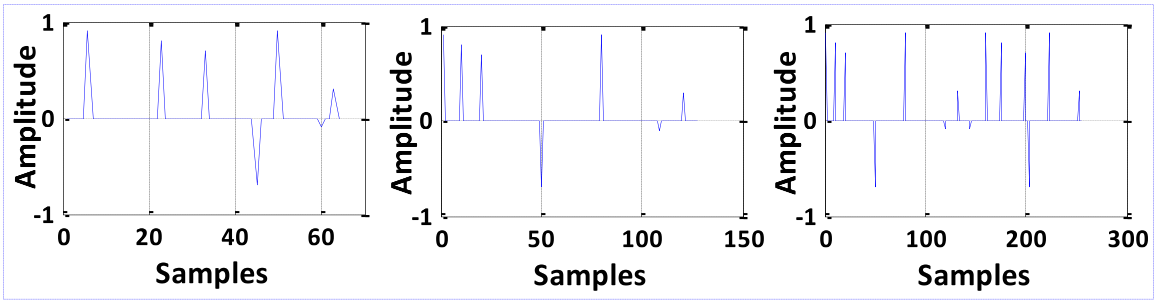


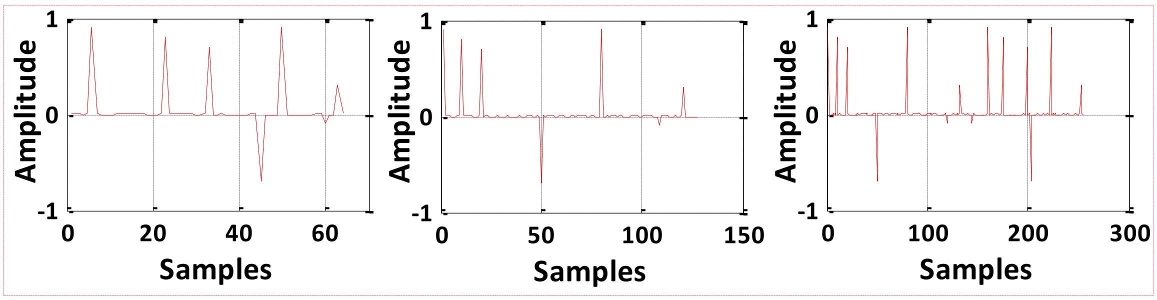
Fig. 8. Time evolution of echo signal (in Black) and error signal (in Red) with USASI to the left and speech to the right for a) M = 64; b) M = 128; c) M = 256.

From Fig. 8, we note that the proposed adaptive algorithm reduces error signals across different signal environments, including both stationary and non-stationary signals. Complementary, the time representations demonstrate the good performance by showing a visible reduction in echo signal intensity under varying conditions. This reduction is a positive indicator of the algorithm ability to improve signal quality and minimize the fluctuations, eventually enhancing the overall effectiveness in diverse situations.

Based on Fig. 9, we observe that all estimated coefficients by the proposed algorithm converge exactly to the original and real sparse impulse responses with M = 64, M = 128 and M = 256. We note that the proposed SAC-IP-NLMS algorithm presents the efficient solution for acoustical sparse identification systems.

By analyzing the same results presented in Fig. 9, we can observe significant conclusions about the performance of the proposed SAC-IP-NLMS algorithm in sparse acoustical environments with different filter lengths (M = 64, M = 128, and M = 256). Firstly, all estimated coefficients generated by the SAC-IP-NLMS algorithm converge precisely to the original and real sparse impulse responses. This convergence suggests that the algorithm precisely identifies and reconstructs the sparse characteristics of the impulse responses despite variations in filter length (M). Secondly, the observed convergence of estimated coefficients indicates that the SAC-IP-NLMS algorithm offers an efficient solution for acoustical sparse environments.





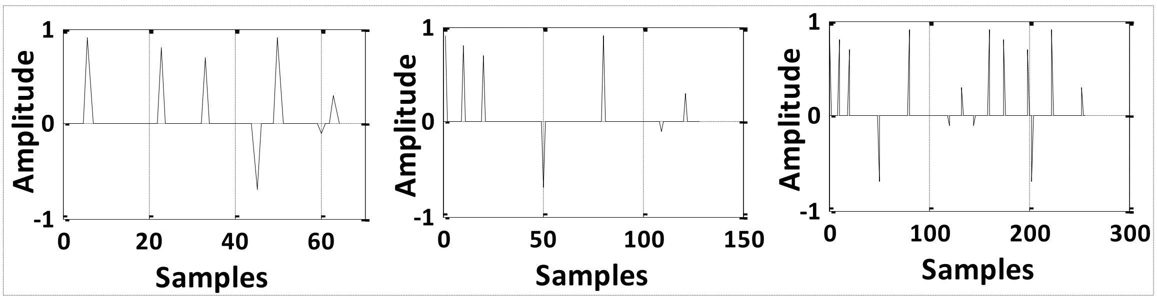


Fig. 9. Comparison between the real SIRs and the estimated one obtained by the proposed algorithm: a) real SIR with M = 64, 128 and 256; b) estimated SIR with M = 64, 128 and 256 for input USASI noise signal; c) estimated SIR with M = 64, 128 and 256 for input speech signal.

4.2. MSE Evaluation

This section mainly focuses on evaluating the convergence rate to identify sparse impulse response. We measure this convergence speed by looking at MSE values. Low MSE means high precision, showing small values between estimated and desired signals. Conversely, high MSE indicates significant errors and less effective algorithm performance. The expression of the MSE is presented by the next formula:

$$MSE_{dB} = 10 \log_{10}(E\|e(n)^2\|) \tag{27}$$

where, $e(n)$ is the normal linear filtering error and $E\| \,.\, \|$ denote the statistic expectation. We have tested the proposed selected active coefficients IP-NLMS algorithm (SAC-IP-NLMS) compared with its non-selected IP-NLMS algorithm [12]. The obtained MSE results with the two input signals USASI noise and speech signal are presented respectively in Figs. 10(a) and 10(b). We have done other simulations using only the proposed algorithm for presenting its performance in terms of coefficients number. Figs. 10(c) and 10(d) present respectively the obtained MSE result with USASI noise and speech signal for three filter lengths, M = 64, 128 and 256.

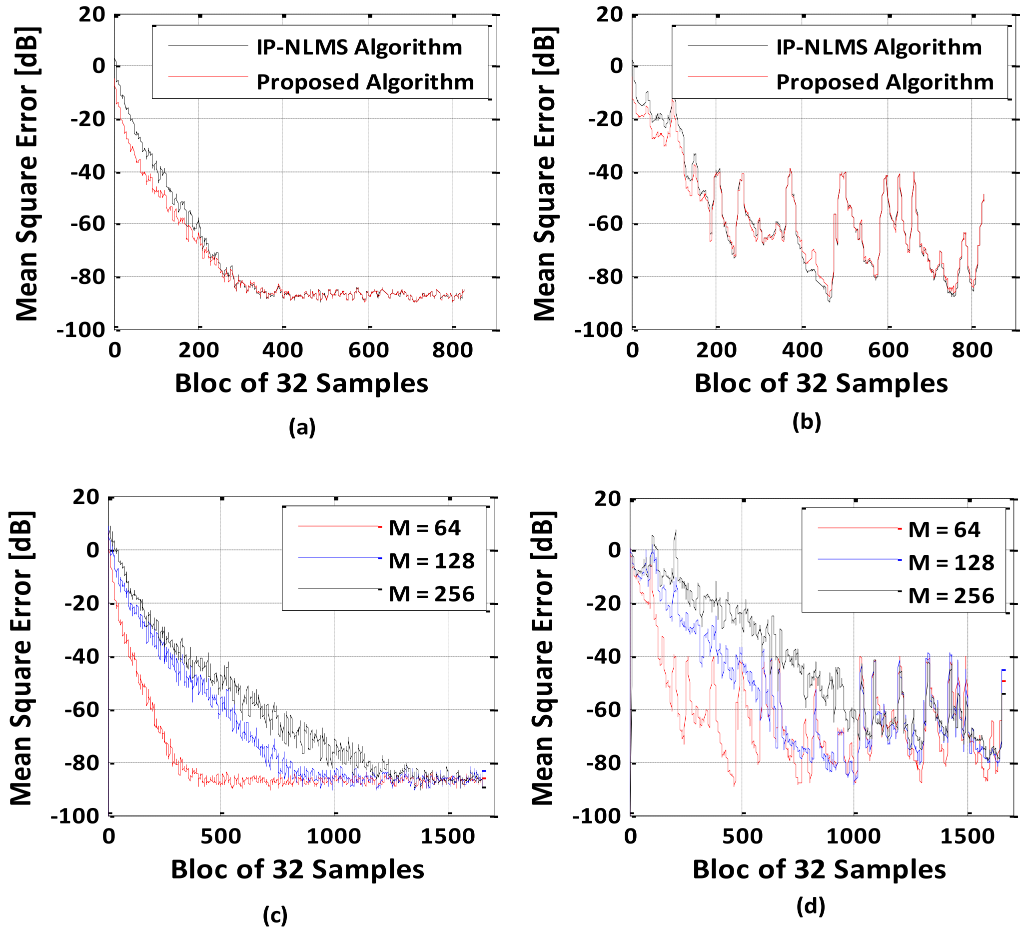


Fig. 10. Convergence speed test with: a) input USASI noise signal; b) input speech signal; c) three filter lengths with input USASI noise signal; d) three filter lengths with input speech signal.

Figs. 10(a) and 10(b) indicate that the proposed algorithm shows a similar convergence rate to basic IP-NLMS algorithm. This suggests that while the proposed algorithm performs comparably in terms of convergence speed, it achieves the highest MSE values in two different input signals but with a very low computational complexity (see section 4.4).

In Figs. 10(c) and 10(d), the simulation results based on MSE criteria highlight specific performance characteristics of the proposed SAC-IP-NLMS algorithm with selected active coefficients: the fast convergence in Sparse IR is noted with filter length M = 64.

The algorithm exhibits very fast convergence in environments characterized by small or moderate sparse impulse responses, particularly with high input signal-to-noise ratio (SNR) conditions. Conversely, when the acoustical environments are characterized by large sparse impulse responses, the algorithm demonstrates slower convergence rates.

4.3. ERLE Evaluation

We now present the performance of the proposed SAC-IP-NLMS algorithm and the classical ones using the ERLE criterion. We note that the higher values indicate more effective reducing signal interference, while lower values signify poor performance. The ERLE measures can be defined as the ratio of the power of far end signal to the power of the residual error signal after the identification process and it is expressed by:

$$ERLE_{dB} = 10\log_{10}\left(\frac{E\|d(n)^2\|}{E\|e(n)^2\|}\right) \tag{28}$$

The obtained results of ERLE criterion with the two input signals, USASI noise and speech signal are presented in Fig. 11. As we present in the same figure the comparative simulation results of the proposed algorithm using the ERLE criterion in term of coefficients length, M = 64, 128 and 256.

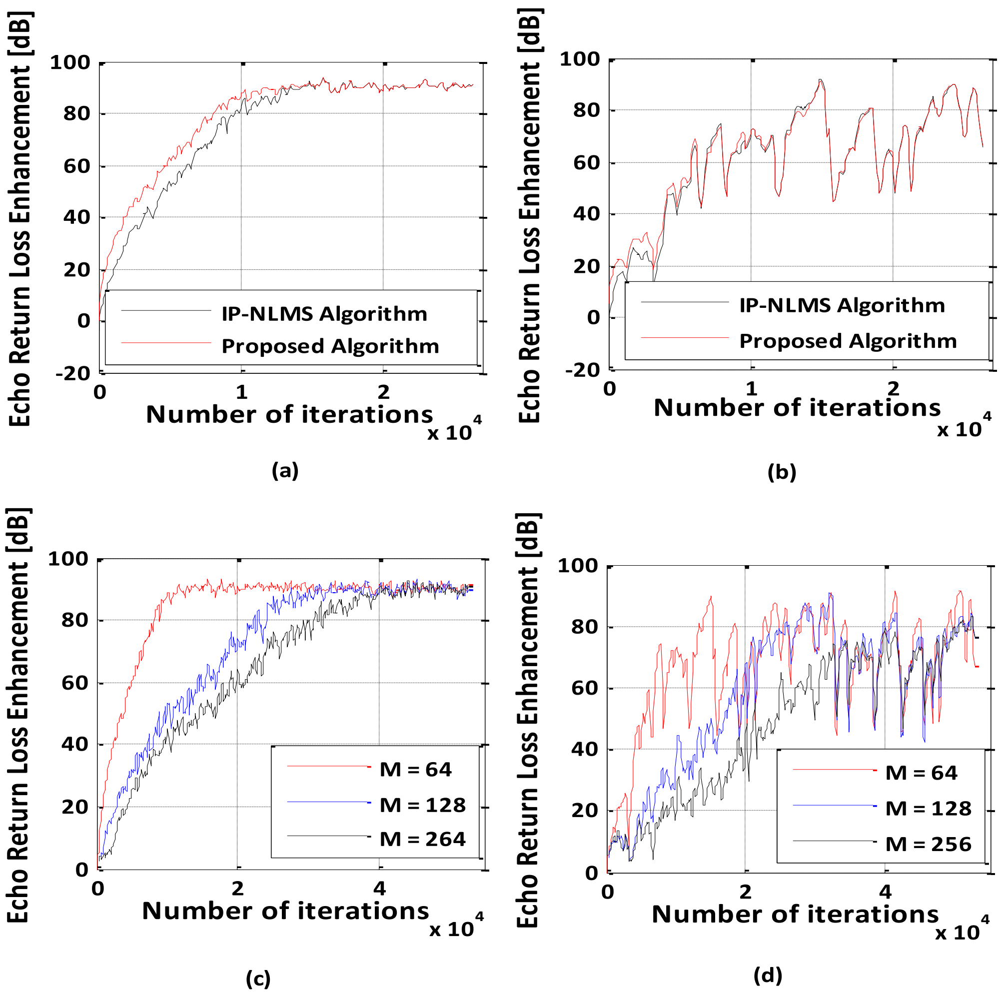


Fig. 11. ERLE evaluation with: a) input USASI noise signal; b) input speech signal; c) three filter lengths with input USASI noise signal; d) three filter lengths with speech input signal.

Based on objective evaluation criteria of Figs. 11(a) and 11(b), the obtained results indicate that the proposed algorithm achieves the highest ERLE values for both stationary and non-stationary input signals. This suggests that the proposed algorithm is efficient solution in reducing or cancelling out echo effects within the signal, leading to improve the quality. Another important observation from these figures is the similarity in ERLE achieved by the proposed algorithm compared to other sparse algorithm. This similarity indicates that the proposed algorithm achieves high ERLE.

The ERLE results shown in Figs. 11(c) and 11(d) expose that the proposed IP-NLMS algorithm exhibits a rapid response to ERLE, especially evident with a filter length (M) of 64. This rapid response highlights the algorithm effectiveness in reducing the impact for identifying acoustic systems, especially in scenarios with short sparse impulse responses.

4.4. Computational Complexity Study

This subsection examines the computational complexities of NLMS and IP-NLMS algorithms compared to the proposed one, focusing on the number of multiplications and additions necessary for each weight update. Through comparative simulations across SIR scenarios with varying coefficient lengths from 32 to 2048.

By concentrating on calculating and controlling the adapted active coefficients, which constitute only 10% of the total coefficients, the proposed algorithm significantly computational load. In Table 3, we present the numerical computational complexities for real filter length M = 32, 64, 128, 256, 512, 1024 and 2048 and selected active coefficients Ms = 3, 6, 12, 25, 51, 102 and 204.As we present the number of multiplications and additions per iteration for three algorithms in two Figs. 12 and 13, respectively.

Table 3. Numerical computational complexities with M = 32, 64, 128, 256, 512, 1024 and 2048, Mp is number of multiplications and Ad is number of additions.

Filter Length	M = 32 Ms = 3		M = 64 Ms = 6		M = 128 Ms = 12		M = 256 Ms = 25		M = 512 Ms = 51		M = 1024 Ms = 102		M = 2048 Ms = 204	
Algorithms	Mp	Ad	Mp	Ad	Mp	Ad	Mp	Ad	Mp	Ad	Mp	Ad	Mp	Ad
NLMS	196	99	388	195	772	387	1540	771	3076	1539	6148	3076	12292	6147
IP-NLMS	258	131	514	259	1026	515	2050	1027	4098	2051	8194	4098	16386	8195
Proposed	26	15	50	27	98	51	202	103	410	207	818	411	1226	819

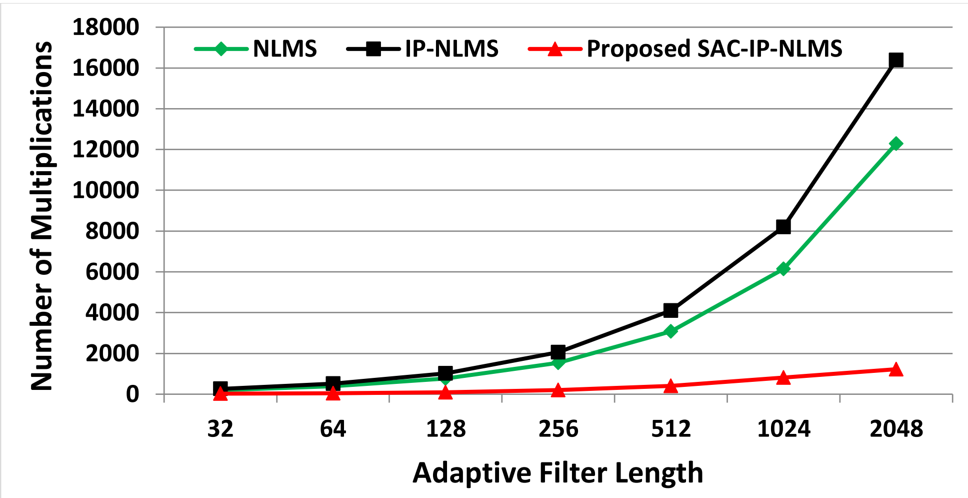


Fig. 12. Computational complexities of all algorithms in terms of multiplications.

Based on Table 3 and Figs. 12 and 13, the comparison between the three algorithms exposes the following insights regarding their computational complexities:

a) Firstly, we note that the NLMS algorithm demonstrates the lowest computational complexity across different filter lengths (M), requiring the fewest number of multiplications and additions compared to IP-NLMS.As first observation, the IP-NLMS algorithm exhibits higher computational complexity than NLMS for the same filter lengths (M).
b) Secondly, when the filter length (M) increases, the computational requirements of IP-NLMS also increase linearly. This increase is attributed to the additional computations needed to implement the intelligent processing features of IP-NLMS, which contribute to performance improvements such as faster convergence.
c) Finaly, the proposed SAC-IP-NLMS algorithm shows lower complexities compared to both NLMS and IP-NLMS with very faster convergence rate as IP-NLMS algorithm as presented previously in section 4.2.

For example, with a real filter length M = 2048 and a sparsity level Ms = 204, the proposed SAC-IP-NLMS algorithm demands 1226 multiplications and 819 additions. In comparison, the NLMS algorithm requires 12292 multiplications and 6147 additions. However, the IP-NLMS algorithm demands 16386 multiplications and 8195 additions. This shows that the proposed algorithm is efficient, delivering good performance with very low computational complexity compared to the basic sparse version (IP-NLMS).

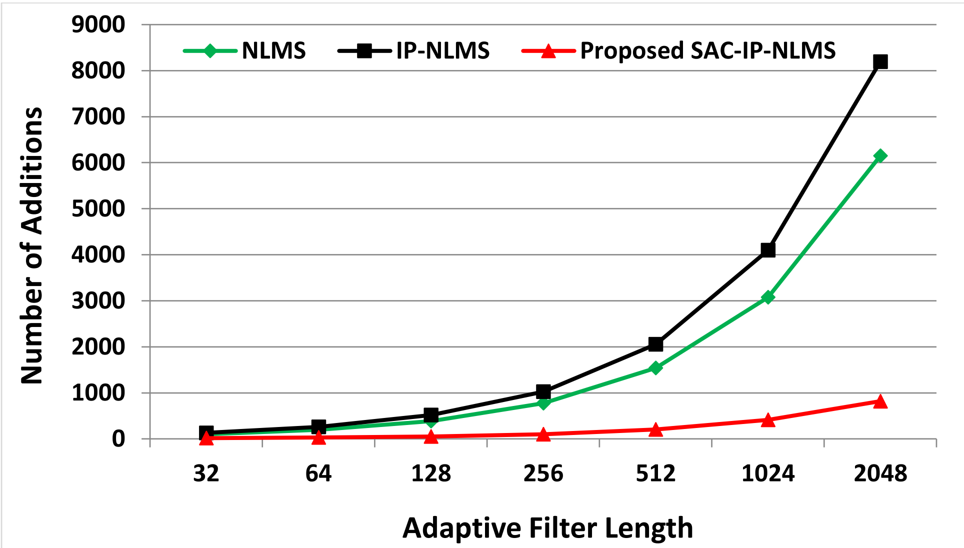


Fig. 13. Computational complexities of all algorithms in terms of additions.

5. CONCLUSIONS

In this study, we addressed the problem of identifying sparse acoustic impulse responses in telecommunications and conferencing systems. We proposed the SAC-IP-NLMS algorithm, which focuses on adapting only the active coefficients of the Sparse Impulse Response using efficient bloc of selection. Our simulations in various acoustic environments confirm its effectiveness in signal quality and convergence rate compared to the existing IP-NLMS algorithms. The proposed algorithm presents a good solution, particularly in reducing MSE values. In conclusion, the proposed algorithm offers a promising solution based on the active coefficients, reduces computational complexity without compromising performance and it requires very low computational complexity compared to other ones. Future research can be focusd on integrating selective partial updates with the SAC-IP-NLMS algorithm to enhance its efficiency and applicability in more complex multi-conferencing rooms. Furthermore, evaluating the algorithm's performance in diverse real-world scenarios will be important for understanding its broader impact and identifying areas for potential improvement.

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