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Improved Proportionate Symmetric Backward Adaptive Speech Enhancement Approach

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Abstract— This research focuses on the development of speech enhancement techniques for two-channel audio systems. Specifically, we explore the utilization of an efficient sparseness recursive algorithm to tackle this challenge. The algorithm is designed to identify and attenuate noise components present in the audio signals, with the aim of improving the overall audio quality. In this investigation, we propose innovative approaches and enhancements to the sparseness recursive normalized least mean square (NLMS) algorithm, denoted Backward μ-law Proportionate NLMS (BMP_{NLMS}), making it more suitable and effective for two-channel speech enhancement. By capitalizing on the sparsity properties of the audio signals, techniques proposed in this paper aim to enhance the desired audio while suppressing unwanted noise. Performance of the presented algorithm was examined by rigorous experiments based on several criteria. The obtained results thoroughly confirm the effectiveness of the proposed approach in real-world situations.

Keywords— Backward μ-law proportionate algorithm; Backward normalized least mean square algorithm; Signal to noise ratio; Cepstral distance; System mismatch; Speech signal.

Nomenclature

BMP_{NLMS}	Backward μ-law proportionate NLMS	SNR	Signal to noise ratio
BNLMS	Backward NLMS	USASI	USA standards institute
BSS	Blind source separation	ε	Regularization parameter introduced to avoid division by zero
CD	Cepstral distance	μ_{12}, μ_{21}	two adaptation step-size
DIR	Dispersive impulse response	ρ	Small parameter introduced to prevent the freeze of adaptation process
NLMS	Normalized least mean square	δ	Initialization parameter to ensure the stability of the adaptation process
SegSNR	Segmental SNR	η	Positive number calculated from the noise power
SIR	Sparse impulse response	μ	Reciprocal of η, implying that $\mu = 1/\eta$
SM	System mismatch		

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1. INTRODUCTION

In the system of telecommunications, noise reduction techniques play a vital role in mitigating the presence of unwanted noise. Researchers have been actively exploring various ways to enhance the reliability and performance of noise cancellation systems [1, 2].

One approach that has garnered significant interest is the utilization of source separation techniques in two-channel convoluted dispersive systems, with the aim of separating speech signals from acoustic noise.

This method holds considerable promise in improving the effectiveness of noise cancellation. The fundamental objective of noise reduction techniques is to enhance the overall quality of transmitted or recorded audio by minimizing the impact of background noise.

Undesirable noise can infiltrate audio during the stages of capture, transmission, or playback, resulting in a degradation of speech intelligibility and audio clarity. To combat this issue, researchers have dedicated their efforts to devising innovative strategies for noise cancellation.

To further optimize the performance of noise cancellation systems, researchers have explored the integration of different adaptive algorithms. Among these approaches, the dual microphone backward technique has emerged as a crucial component for enhancing speech signals [3-5].

Extensive research has been conducted on this structure, providing comprehensive analyses and insights into its application in noise cancellation. However, it is important to acknowledge that the dual microphone backward normalized least mean square (NLMS) algorithm [3, 6, 7] is a well-known structure.

This latter exhibits poor performance when dealing with sparse impulse responses. This algorithm requires the adaptation of a relatively long filter, leading to adaptation noise in inactive tap weight regions. To overcome these limitations, it is essential to address the challenges associated with longer filters and mitigate adaptation noise during inactive tap weight regions [8-11].

In this research paper, we introduce a modification of the dual microphone backward NLMS algorithm based on μ-law proportionate approach, denoted BMP_{NLMS}. This algorithm incorporates specific normalized step sizes and employs a μ-law proportionate technique [12, 13] to enhance its performance. By utilizing these techniques, the proposed algorithm improves both convergence speed and misadjustment.

Our aim is to validate the effectiveness and advantages of the presented algorithm for two-channel backward NLMS noise reduction. Overall, this research aims to contribute to the field of noise cancellation by introducing a modified algorithm that addresses the limitations of the existing dual microphone backward NLMS algorithm.

The proposed algorithm has the potential to enhance the performance of noise reduction, particularly in scenarios involving sparse impulse responses.

The next organization of this paper is: In Section 2, we provide a detailed explanation of the two-channel convoluted system. Section 3 presents the conventional backward NLMS algorithm (BNLMS) which has been token as a reference. In Section 4, we introduce our proposed BMP_{NLMS} algorithm, outlining its methodology and modifications. We present the simulation part and discussion results obtained from extensive experiments in Section 5. Finally, we present the conclusion of our findings and contributions in last Section.

2. CONVOLUTIVE SYSTEM AND RELATED WORKS

2.1. The Problem of Two-Channel Convolutive System

In our system, we analyze two source signals: The first signal: s(n) is an acoustic speech signal, the second signal: b(n) is an acoustic punctual noise. These signals undergo convolution with impulse responses of the mixture system. Specifically, s(n) is convolved with $h_{12}(n)$, and b(n) is convolved with $h_{21}(n)$ [3, 5, 14, 15]. The output signals of this analysis model are:

$$p_1(n) = [h_{21}(n) * b(n)] + s(n) \tag{1}$$

$$p_2(n) = [h_{12}(n) * s(n)] + b(n) \tag{2}$$

where $*$ represents the operation of convolution. The convolutive model with two sources and two microphones is shown in Fig. 1.

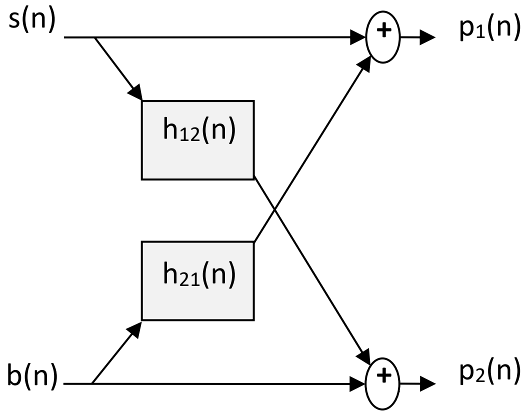

Fig. 1. Convolutive model with two sources and two microphones [3, 5, 14].

In our assumption, we consider the physical arrangement of the microphones in relation to the speaker and the noise source. We assume that the first microphone is located close to the speaker, while the second microphone is positioned near to the noise. Based on this setup, we can assume that the direct impulse response from two sources to respective microphones respectively can be approximated as the Kronecker unit impulse [3, 4, 8]. This implies that the direct acoustic signals arrive at the microphones instantaneously without significant delays or distortions caused by the propagation medium.

In various scenarios such as conference systems or hands-free systems for communication, there is a need for an acoustic noise canceler to estimate the acoustic impulse response. The duration of the acoustic impulse response is directly connected to reverberation in an enclosed area. The duration of reverberation is directly related to the size of the space and inversely related to the amount of surface area available for sound absorption [16]. When analyzing impulse responses, two distinct categories can be identified: Dispersive impulse response (DIR) and Sparse impulse response (SIR). To visually illustrate these impulse response types, Fig. 2, provides examples depicting the characteristics of both DIR and SIR with a length of 128 samples [17].

In the case of DIR, the energy is evenly distributed across all coefficients, meaning there is no concentration of energy in specific coefficients. On the other hand, SIR indicates that most of the energy is concentrated in a few coefficients, the residual coefficients are close to very small in magnitude or zero.

2.2. Related Works

Several techniques explore the application of the two-microphone technique to address the challenges posed by convolutive systems in acoustic noise reduction and speech enhancement. All these study aims to enhance the quality of speech signals in noisy environments by leveraging the information captured by two microphones. By employing this technique, the convolutive effects introduced by the acoustic environment can be mitigated. To enhance the speech quality by introducing an extended two-sensor sparse adaptive algorithm within sub-bands [17].

This algorithm is built upon the Forward structure. This extended version is developed to address challenges posed by the full-band sparse forward algorithm when faced with acoustical environments featuring dispersive impulse responses. In [18], the two-channel feedback normalized Decorrelation algorithms have been proposed to resolve two problems of noise reduction and speech enhancement when the acoustical mixing system. In this paper, three recent NLMS-based sparse adaptive filtering algorithms are implemented on two-channel feedback BSS structures. In [19], the authors propose a probe signal-based method for acoustic feedback cancellation in hearing aids. This method employs two adaptive filters: one quickly converges but can yield biased results, and the other is driven by an uncorrelated probe signal. Both filters are adapted using a delay-based normalized least mean square (NLMS) algorithm. Coefficient exchange ensures unbiased feedback estimation, and probe signal gain is adjusted to enhance performance during transient and steady states. Another research paper introduces a speech enhancement technique that relies on an adaptive filter using Recursive Least Squares (RLS) for processing speech signals. The authors proceed to evaluate the noise reduction capabilities of the proposed RLS algorithm by comparing it to the existing NLMS algorithm. This evaluation involves measuring Mean Squared Error (MSE), Signal to Noise Ratio (SNR), and SNR Loss metrics [20].

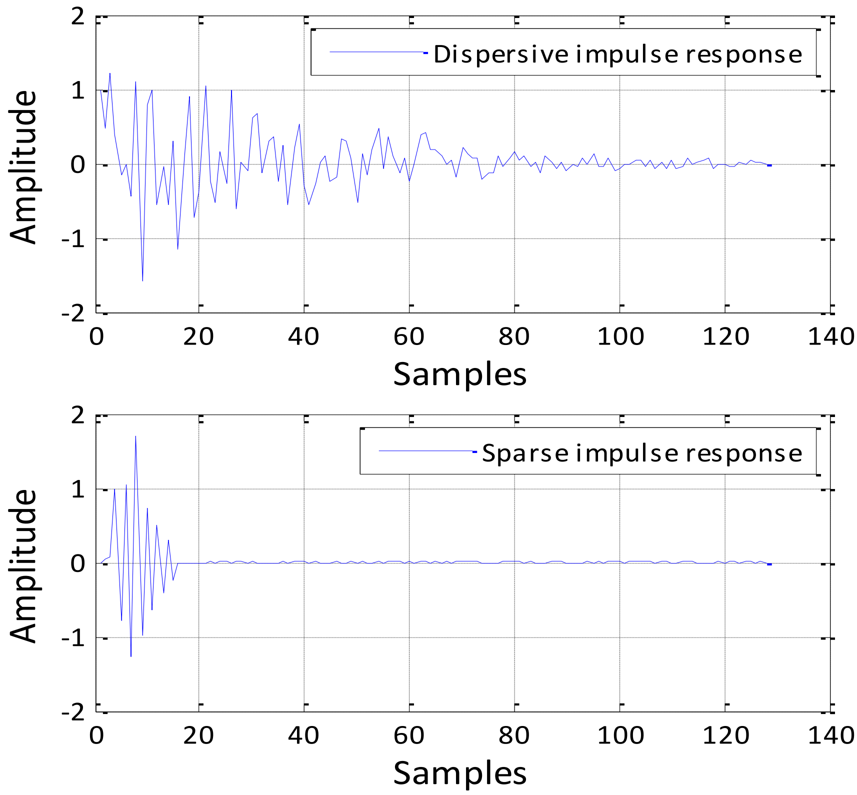

Fig. 2. a) DIR; b) SIR with L = 128.

In [21], they have presented a novel approach for enhancing speech quality through a dual channel double backward distributive weighted adaptive filtering algorithm. The method's effectiveness is assessed using objective measures such as Perceptual Evaluation of Speech Quality (PESQ) and Short Time Objective Intelligibility (STOI) across various noise conditions.

Other research studies capitalize on the sparse characteristics of acoustic path impulse responses within the mixing model, resulting in enhanced speech quality when contrasted with conventional methods.

3. BACKWARD BSS STRUCTURE BASED ON NLMS ALGORITHM

Firstly, we will be introducing the Backward Adaptive Filtering NLMS algorithm, commonly known as BNLMS [18, 17]. To provide context, we first present the dual backward blind source separation (BSS) structure, illustrated in Fig. 3. This structure serves as the foundation for our algorithm.

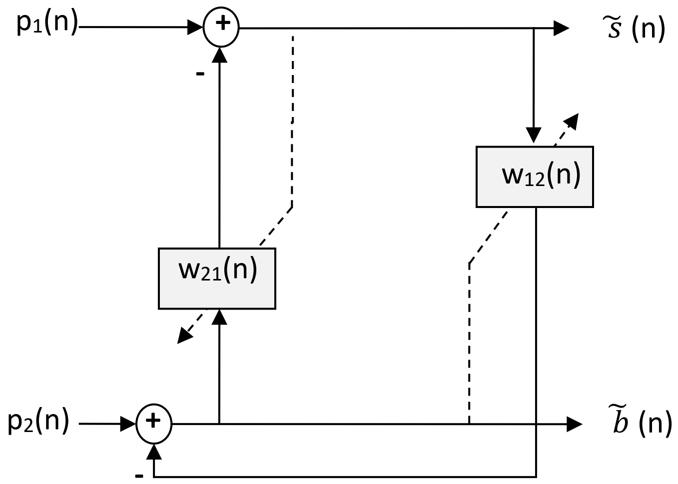

Fig. 3. Model of the BNLMS algorithm.

The backward structure yields outputs that provide estimates for both the speech signal and the acoustic noise signal.

$$\tilde{s}(n) = p_1(n) - \left[w_{21}(n) * \tilde{b}(n)\right] \tag{3}$$

$$\tilde{b}(n) = p_2(n) - \left[w_{12}(n) * \tilde{s}(n)\right] \tag{4}$$

The perfect solutions of two filters presented by: $w_{21}(n) = h_{21}(n)$ and $w_{12}(n) = h_{12}(n)$. By substituting these optimal solutions and inserting the Eqs. (1) and (2), into Eqs. (3) and (4), we obtain the following expressions for the output signal relations:

$$\tilde{s}(n) = s(n) \tag{5}$$

$$\tilde{b}(n) = b(n) \tag{6}$$

The adaptation relations by NLMS algorithm are:

$$\mathbf{w}_{12}(n+1) = \mathbf{w}_{12}(n) + \mu_{12} \frac{\tilde{\mathbf{s}}(n)\ \tilde{b}(n)}{[\tilde{\mathbf{s}}(n)]^{\mathbf{T}}\ \tilde{\mathbf{s}}(n) + \varepsilon_{nlms}} \tag{7}$$

$$\mathbf{w}_{21}(n+1) = \mathbf{w}_{21}(n) + \mu_{21} \frac{\tilde{\mathbf{b}}(n)\ \tilde{s}(n)}{\left[\tilde{\mathbf{b}}(n)\right]^{\mathbf{T}}\ \tilde{\mathbf{b}}(n) + \varepsilon_{nlms}} \tag{8}$$

The selection of an optimal step-size within the range of 0 to 2 is crucial to achieve the desired convergence.

4. THE PROPOSED BMP$_{NLMS}$ ALGORITHM

We introduce an enhanced variant of the backward NLMS that utilizes µ-law proportionate [12] and normalized step-sizes. The proposed efficient version incorporates two key enhancements: µ-law proportionate step-sizes and normalized step-sizes.

µ-law proportionate step-sizes: The concept of µ-law principle is applied to determine the step-size adaptation in the NLMS algorithm. This latter is a compression-expansion technique commonly used in telecommunications. By applying µ-law principle, we can emphasize smaller step-sizes for lower input amplitudes and larger step-sizes.

Normalized step-sizes: Another enhancement is the introduction of normalized step-sizes. These step-sizes are obtained by dividing the µ-law proportionate step-sizes by the input signal power. Normalization helps to counteract the effects of input signal variations, preventing excessively large step-sizes for high-power signals and ensuring stability and convergence for different input conditions.

The BMP$_{NLMS}$ algorithm aims to optimize the performance of adaptive filters by reducing the time required to converge to the desired solution. By implementing this algorithm, we can achieve faster and more efficient convergence compared to traditional approaches. The updating formula of the proposed algorithm are given by:

$$\mathbf{w}_{12}(n+1) = \mathbf{w}_{12}(n) + \mu_{12} \frac{\mathbf{Q}_{12}(n)\ \tilde{\mathbf{s}}(n)\ \tilde{b}(n)}{[\tilde{\mathbf{s}}(n)]^{\mathbf{T}}\ \mathbf{Q}_{12}(n)\ \tilde{\mathbf{s}}(n) + \varepsilon} \tag{9}$$

$$\mathbf{w}_{21}(n+1) = \mathbf{w}_{21}(n) + \mu_{21} \frac{\mathbf{Q}_{21}(n)\ \tilde{\mathbf{b}}(n)\ \tilde{s}(n)}{\left[\tilde{\mathbf{b}}(n)\right]^{\mathbf{T}}\ \mathbf{Q}_{21}(n)\ \tilde{\mathbf{b}}(n) + \varepsilon} \tag{10}$$

Here, we introduce the $Q_{12}(n)$ and $Q_{21}(n)$ matrices, which are diagonal matrices of size L x L. By incorporating these matrices, we approximate the optimal proportionate step-size, enabling faster convergence and low steady state.

The diagonal matrix $Q_{12}(n)$ and $Q_{21}(n)$ are given respectively by:

$$Q_{12}(n) = \begin{bmatrix} q_{12,1}(n) & 0 & \cdots & 0 \\ 0 & q_{12,2}(n) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & q_{12,L}(n) \end{bmatrix} \tag{11}$$

$$Q_{21}(n) = \begin{bmatrix} q_{21,1}(n) & 0 & \cdots & 0 \\ 0 & q_{21,2}(n) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & q_{21,L}(n) \end{bmatrix} \tag{12}$$

$Q_{12}(n)$ and $Q_{21}(n)$ are the matrix contains the coefficients $q_{12,l}(n)$ and $q_{21,l}(n)$ on its diagonal. The matrix $Q_{12}(n)$ and $Q_{21}(n)$ are used in the update equations to adjust the step size for all coefficients in the vectors $\mathbf{w}_{12}(n)$ and $\mathbf{w}_{21}(n)$ respectively.

The calculations for $q_{12,l}(n)$ and $q_{21,l}(n)$ are presented in Eqs. (13) and (14) respectively.

$$q_{12,l}(n) = \gamma_{12,l}(n) \Big/ \textstyle\sum_{i=1}^{L}\left[\gamma_{12,i}(n)\right] \tag{13}$$

$$q_{21,l}(n) = \gamma_{21,l}(n) \Big/ \textstyle\sum_{i=1}^{L}\left[\gamma_{21,i}(n)\right] \tag{14}$$

where

$$\gamma_{12,l}(n) = Max\{\rho \times F_{12}, F_{Log,12}\} \quad (15)$$

$$\gamma_{21,l}(n) = Max\{\rho \times F_{21}, F_{Log,21}\} \quad (16)$$

with

$$F_{12} = Max\{\delta, F_{Log}(|w_{12,1}(n)|), \dots, F_{Log}(|w_{12,\mathrm{N}}(n)|)\} \quad (17)$$

$$F_{21} = Max\{\delta, F_{Log}(|w_{21,1}(n)|), \dots, F_{Log}(|w_{21,N}(n)|)\} \quad (18)$$

The parameter ρ is set to a very small coefficient, specifically ρ = 5/L, to prevent stalling during the adaptation process. By choosing a small value for ρ relative to L, we ensure that the algorithm continues to update and adjust the filter coefficients even when progress towards convergence slows down. This helps to avoid situations where the adaptation process gets stuck or stalls. The regularization term, δ, helps to stabilize the updating process when the filter coefficients are initialized to zero. δ, typically set to 0.01, introduces a small non-zero value that helps to regulate and stabilize the update process, facilitating the convergence towards the desired solution.

The two logarithmic functions are given by:

$$F_{Log,12} = \frac{ln(\mu \times |w_{12,l}(n)| + 1)}{ln(\mu + 1)} \quad (19)$$

$$F_{Log,21} = \frac{ln(\mu \times |w_{21,l}(n)| + 1)}{ln(\mu + 1)} \quad (20)$$

η is a positive quantity that needs to be determined based on the level of noise. In the context of sparse impulse response identification, a common practical choice for η is 0.001, indicating an extremely small range of convergence. Moreover, μ represents the reciprocal of η, implying that μ = 1/η, which offers insight into the resolution or precision of the algorithm.

The detailed diagram, parameters, and instructions of the proposed backward μ-law proportionate algorithm (BMP_{NLMS}) are presented respectively in Fig. 4 and Algorithm 1.

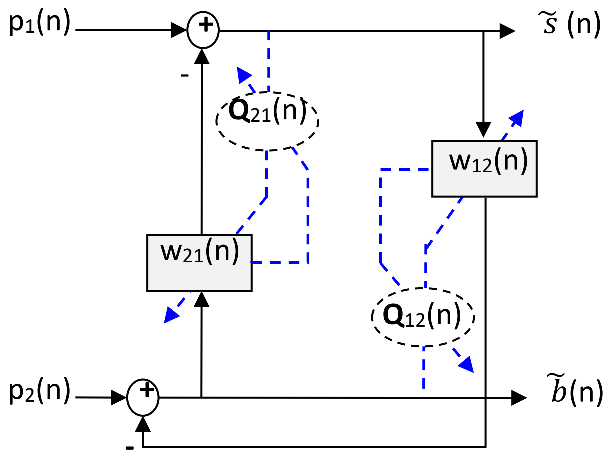

Fig. 4. Detailed diagram of the backward μ-law proportionate algorithm (BMP_{NLMS}).

5. ANALYSIS OF THE SIMULATION RESULTS

5.1. Measured Objective Criteria Used in Experiments

We present in this section the values of parameters and measured objective criteria used in simulations of two algorithms: backward NLMS and the proposed BMP_{NLMS}. Our primary focus is to thoroughly evaluate the performance of this proportionate algorithm, particularly in terms of its ability to estimate speech. This evaluation is conducted by examining all first output and second estimated filter. To conduct the evaluation, we employ a convolutive model illustrated in Fig. 1. The model incorporates a speech that has been phonetically equilibrated, along with an acoustic noise component. The entire model operates at Fs = 8 kHz. The input SNR for both noisy signals is set to -6 dB. It is worth noting that the real impulse responses length is specifically chosen as L = 512 to ensure accurate modelling of the system. By thoroughly examining all simulation results and comparing the real performance of classical backward NLMS with the proposed BMP_{NLMS} algorithm, we can gain valuable insights into the effectiveness and advantage of presented proportionate algorithm in accurately estimating speech signals under the given convolutive mixing model and challenging SNR conditions.

Algorithm 1. Parameters and instructions of the proposed BMP_{NLMS} algorithm.

Initialize symbols

$\varepsilon \leftarrow 10^{-6}$

$\eta \leftarrow 0.001$

$\mu \leftarrow 1/\eta$

$\rho \leftarrow 5/L$

$\delta \leftarrow 0.01$

for n = 1 to end-iteration do

$$\tilde{s}(n) \leftarrow p_1(n) - \left[\mathbf{w}_{21}(n) * \tilde{\mathbf{b}}(n)\right]$$

$$\tilde{b}(n) \leftarrow p_2(n) - \left[\mathbf{w}_{12}(n) * \tilde{\mathbf{s}}(n)\right]$$

$$F_{Log,12} \leftarrow ln\left(\mu \times \left|w_{12,l}(n)\right| + 1\right)/ln(\mu + 1)$$
$$F_{Log,21} \leftarrow ln\left(\mu \times \left|w_{21,l}(n)\right| + 1\right)/ ln(\mu + 1)$$

$$F_{12} \leftarrow Max\left\{\delta, F_{Log}\left(\left|w_{12,1}(n)\right|\right), \dots, F_{Log}\left(\left|w_{12,N}(n)\right|\right)\right\}$$
$$F_{21} \leftarrow Max\left\{\delta, F_{Log}\left(\left|w_{21,1}(n)\right|\right), \dots, F_{Log}\left(\left|w_{21,N}(n)\right|\right)\right\}$$

for l =1 to L do

$$\gamma_{12,l}(n) \leftarrow Max\left\{\rho \times F_{12}, F_{Log,12}\right\}$$
$$\gamma_{21,l}(n) \leftarrow Max\left\{\rho \times F_{21}, F_{Log,21}\right\}$$

$$q_{12,l}(n) \leftarrow \gamma_{12,l}(n) \Big/ \sum_{i=1}^{L}\left[\gamma_{12,i}(n)\right]$$

$$q_{21,l}(n) \leftarrow \gamma_{21,l}(n) \Big/ \sum_{i=1}^{L}\left[\gamma_{21,i}(n)\right]$$

end for

$$\mathbf{Q}_{12}(n) \leftarrow diag\left[q_{12,1}(n), q_{12,2}(n), \dots, q_{12,\mathrm{L}}(n)\right]$$

$$\mathbf{Q}_{21}(n) \leftarrow diag\left[q_{21,1}(n), q_{21,2}(n), \dots, q_{21,\mathrm{L}}(n)\right]$$

$$\mathbf{w}_{12}(n+1) \leftarrow \mathbf{w}_{12}(n) + \mu_{12}\left[\mathbf{Q}_{12}(n)\ \tilde{\mathbf{s}}(n)\ \tilde{b}(n)/[\tilde{\mathbf{s}}(n)]^{\mathbf{T}}\ \mathbf{Q}_{12}(n)\ \tilde{\mathbf{s}}(n) + \varepsilon\right]$$

$$\mathbf{w}_{21}(n+1) \leftarrow \mathbf{w}_{21}(n) + \mu_{21}\left[\mathbf{Q}_{21}(n)\ \tilde{\mathbf{b}}(n)\ \tilde{s}(n)/\left[\tilde{\mathbf{b}}(n)\right]^{\mathbf{T}} \mathbf{Q}_{21}(n)\ \tilde{\mathbf{b}}(n) + \varepsilon\right]$$

end for

a) For comparing a convergence time of proportionate algorithm with non-proportionate algorithm, we employ the System Mismatch criterion (SM) as an evaluation metric. The SM is calculated by Eq. (21). This criterion allows us to quantitatively measure and compare the performance in terms of convergence speed. By analyzing the System Mismatch criterion, we can gain insights into how quickly the proposed algorithm reaches convergence compared to the non-proportionate algorithm, providing valuable information for assessing the efficiency and effectiveness of the proposed approach.

b) Secondly, for the evaluation of the quality of all estimated speech, we conducted additional simulations using objective speech quality measures. One widely used measure is the Segmental signal-to-noise ratio (SegSNR) criterion, which provides effective assessment of the similarity between output enhanced speech and the clean speech. The SegSNR is computed using the formula presented in Eq. (22).

c) To further confirm a behaviour of proportionate algorithm in terms of distortion, we employed the Cepstral Distance (CD) as an evaluation metric. The CD measures the dissimilarity between output enhanced speech and the clean speech. It is estimated using the formulas of Eq. (23).

$$SM_{dB} = 10\ log_{10}\left[\frac{\|h_{21}(n) - w_{21}(n)\|}{\|h_{21}(n)\|}\right]^2 \tag{21}$$

$$SegSNR_{dB} = 10\ log_{10}\left[\sum_{i=1}^{B}|s(i)|^2 \Big/ \sum_{i=1}^{B}|s(i) - \tilde{s}(i)|^2\right] \tag{22}$$

$$CD_{dB} = \sum_{p}^{B} ISFT\left[log(|S(\omega,p)|) - log\left(\left|\tilde{S}(\omega,p)\right|\right)\right]^2 \tag{23}$$

It's important to acknowledge that adaptive filtering is intricate and achieving optimality hinges on factors like the problem's nature, data characteristics, and algorithm design. The non-convex nature of optimization problems in adaptive filtering often complicates the pursuit of global optimality. The suitability of these parameter values can vary based on the specific problem and data available. Striking a balance between convergence speed, steady-state performance, and computational complexity is a typical challenge in robust and optimal parameter selection. Numerous simulations employing varied parameters were conducted to observe the proposed algorithm's behavior across diverse conditions. Metrics such as convergence speed, steady-state error, and overall performance were assessed. Through these experiments, parameter values were identified that elicited the intended algorithm behavior, tailored to the algorithm's specific acoustic noise reduction application. Table 1 provides a summary of the optimal parameters selected for both the classical BNLMS and the proposed BMP_{NLMS} algorithms. It outlines the key parameter values chosen for each algorithm.

Table 1. Values of the algorithms simulation parameters.

Algorithms	Parameters values
Classical BNLMS	$\varepsilon_{nlms} = 10^{-6}$
Proposed BMP_{NLMS}	$\varepsilon = \varepsilon_{nlms}/L$, $\rho = 5/L$, $\delta = 0.01$, $\mu = 1000$

5.2. Experimental Results and Discussion

We will present the simulation results and discuss the findings obtained from the experiments conducted with the classical BNLMS and the proposed BMP_{NLMS} algorithms.

Fig. 5 displays the original speech signal along with all enhanced speech. This allows for a qualitative assessment of the algorithms' performance in accurately reproducing the original speech signal. Furthermore, Fig. 6 and Table 2 present the evolution of the SM with the length of the adaptive filters is 512 coefficients. The SM provides insights into convergence behavior and performance of all algorithms. As we have done other simulations with very large impulse response L = 1024 that are presented in Fig. 7.

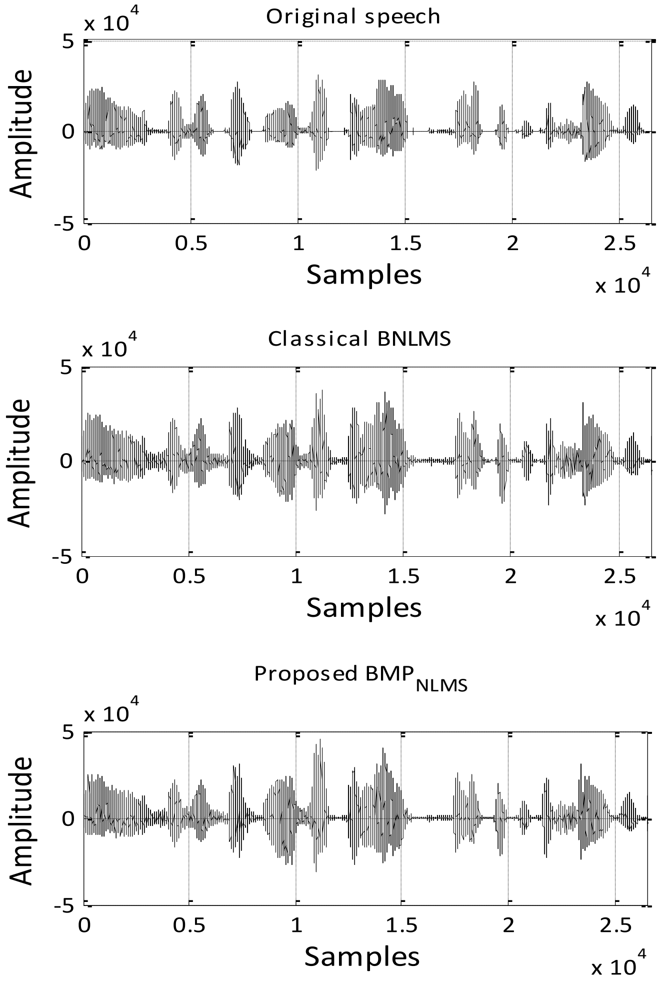

Fig. 5. Evolution of enhanced speech.

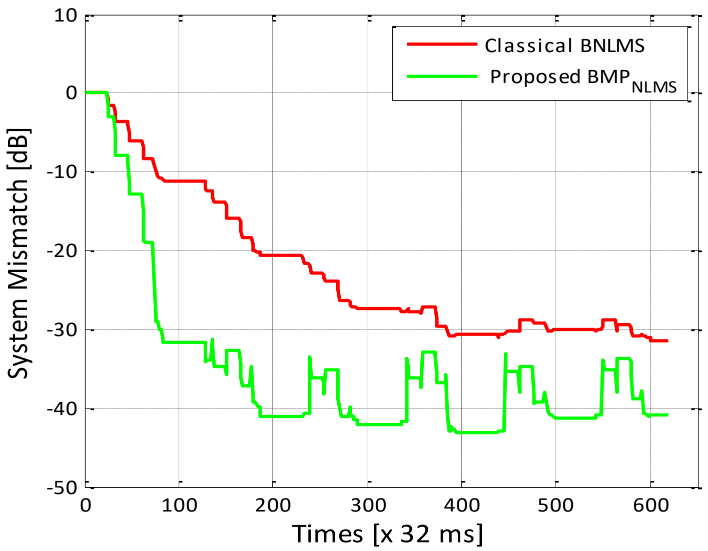

Fig. 6. Convergence speed of adaptive filter with L = 512.

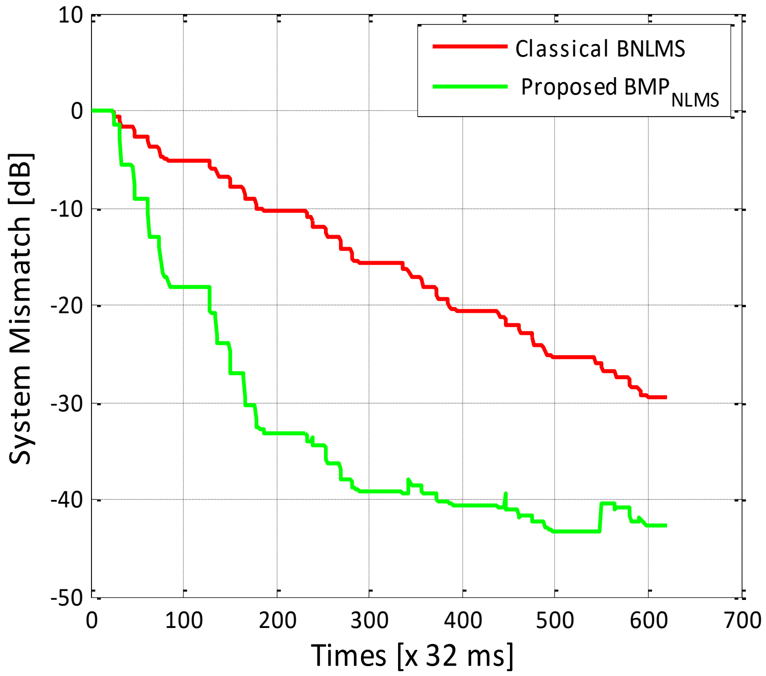

Fig. 7. Convergence speed of adaptive filter with L = 1024.

Table 2. Evolution of the final SM values.

Time [s]	SM [dB]	
	Classical BNLMS	Proposed BMP_{NLMS}
After 1.6 s	-11.05	-31.12
After 3.2 s	-20.21	-41.33
After 4.8 s	-27.53	-43.00
After 6.4 s	-30.95	-44.43
After 8.0 s	-30.00	-41.47
After 9.6 s	-32.41	-41.01

From Figs. 6 and 7, it is evident that the proposed backward μ-law proportionate NLMS algorithm demonstrates superior convergence speed compared to the classical non-proportionate backward NLMS algorithm, particularly in highly noisy environments with L equal 512 and 1024.

Table 2 shows that the BMP_{NLMS} algorithm achieves the lowest final SM values, indicating its ability to effectively lessen SM in sparse convolutive systems.

In addition to these visual representations, we show further experiments for evaluating the algorithms performance based on various criteria. These included output SNR and CD measures. Four acoustic noises (white, USASI, babble, and street) were considered during the experiments.

The real and adaptive filters lengths were set to a large value of L = 512 to ensure comprehensive analysis and robust evaluation of the algorithms. We present all obtained results of output SNR and CD measures in Table 3, Fig. 8, Table 4 and Fig. 9.

Table 3. Output SNR evaluation for the BNLMS and the proposed BMP_{NLMS} algorithms.

Noise type	Input-SNR [dB]	Segmental SNR [dB]	
		Classical BNLMS	Proposed BMP_{NLMS}
White	-6	46,75	50,92
	0	48,22	52,10
	6	50,02	54,80
USASI	-6	45,38	50,05
	0	48,69	51,77
	6	49,79	54,43
Babble	-6	44,01	50,23
	0	45,08	52,98
	6	48,89	53,71
Street	-6	45,03	50,22
	0	46,93	52,12
	6	49,25	54,99

Table 4. CD evaluation for the BNLMS and the proposed BMP_{NLMS} algorithms.

Noise type	Input SNR [dB]	CD [dB]	
		Classical BNLMS	Proposed BMP_{NLMS}
White	-6	-6.80	-7.30
	0	-7.01	-7.98
	6	-7.75	-8.53
USASI	-6	-5.95	-6.76
	0	-6.51	-7.21
	6	-6.96	-7.69
Babble	-6	-6.61	-6.98
	0	-6.69	-7.33
	6	-7.70	-8.76
Street	-6	-6.42	-7.00
	0	-7.09	-7.91
	6	-7.33	-8.24

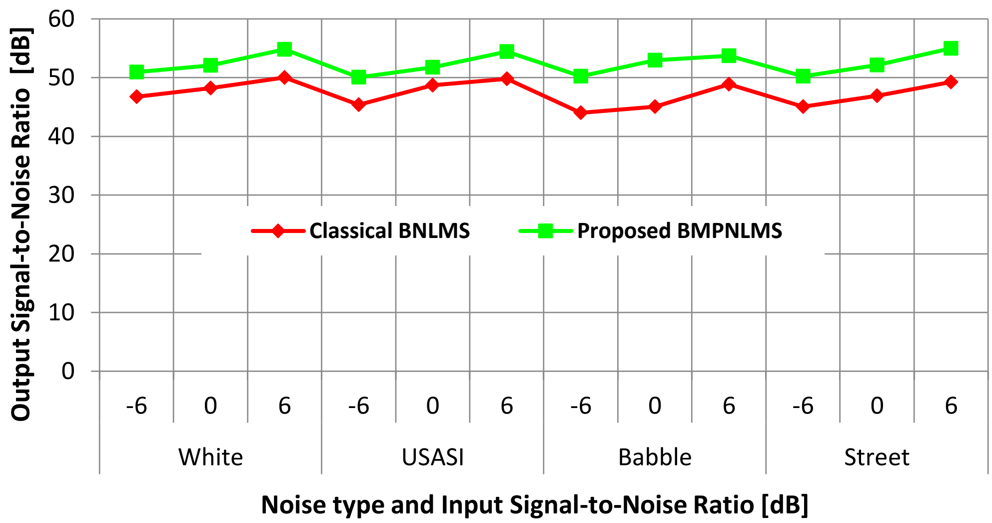

Fig. 8. Output SNR evaluation for the BNLMS and the proposed BMP_{NLMS} algorithms.

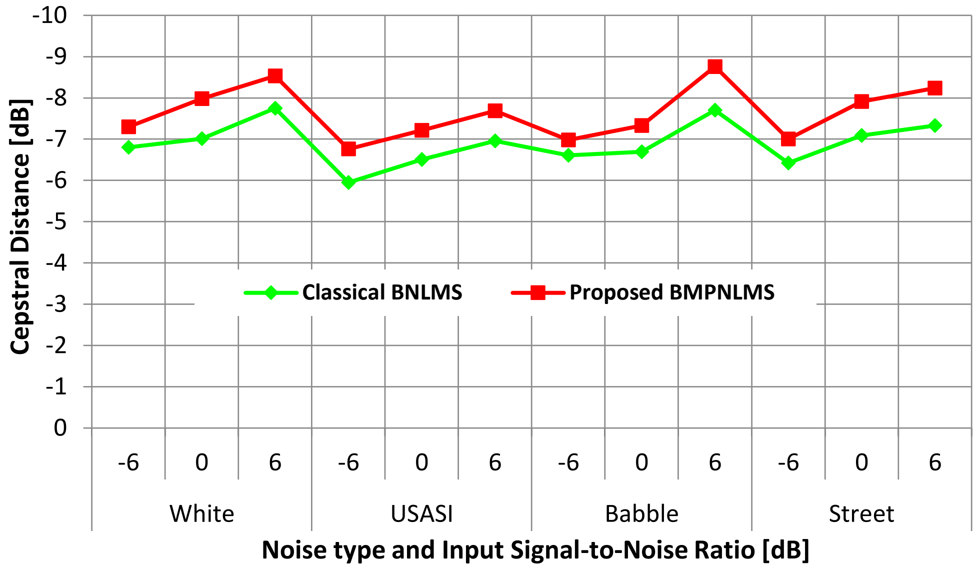

Fig. 9. CD evaluation for BNLMS and the proposed BMP_{NLMS} algorithms.

This observation highlights the strong performance of the BMP_{NLMS} algorithm, especially in challenging and noisy conditions. The algorithm combined with the μ-law adaptation, allows for improved convergence and better adaptation to the underlying system dynamics. These factors contribute to its ability to achieve lower system mismatch and enhance output speech. The results emphasize the potential of the proposed BMP_{NLMS} algorithm as a suitable choice for applications where accurate estimation of speech signals in sparse convolutive systems is crucial, particularly in the presence of high levels of noise.

Table 3 presents the SegSNR values obtained from the experiments conducted with the BNLMS and the proposed BMP_{NLMS} algorithms. These values provide a quantitative measure of SNR and serve as indicators of the quality and accuracy of the estimated speech signals.

On the other hand, Table 4 displays the CD values resulting from the evaluation of two algorithms. The CD values quantify the dissimilarity between the estimated speech signals and the clean speech signals. Lower CD values indicate reduced distortion and a closer resemblance to the original speech. By referring to this table, we can analyze and compare the performance of the classical BNLMS and the proposed BMP_{NLMS} algorithms based on their SegSNR and CD values. This allows for a comprehensive assessment of the algorithm ability to accurately estimate speech signals and minimize distortion under various conditions and noise levels.

Using the presented results in Fig. 8 and 9, it is evident that the BMP_{NLMS} outperforms the other algorithm BNLMS in various scenarios. This superior performance is observed across different noisy types, including white, USASI, babble, and street noise, as well as different input signal-to-noise ratios (SNR) such as -6 dB, 0 dB, and 6 dB. The BMP_{NLMS} algorithm consistently achieves higher output SNR values and lower CD values. This indicates that the proposed algorithm provides better speech signal estimation accuracy and lower distortion compared to the other algorithm.

These findings suggest that the BMP_{NLMS}, effectively mitigates the adverse effects of different noise types and improves the overall speech signal quality. The algorithm's ability to enhance the output SNR and reduce CD values indicates its suitability for various applications where accurate and high-quality speech signal estimation is essential.

6. CONCLUSIONS

This study aimed to investigate and evaluate the performance of a proposed BMP_{NLMS} for speech signal estimation in noisy environments. The algorithm was compared with the classical non-proportionate BNLMS algorithm across different scenarios, including various noisy types and input signal-to-noise ratios. The results obtained from the experiments conducted in this study have several noteworthy implications. Firstly, the BMP_{NLMS} algorithm exhibited a significant advantage in terms of convergence speed when compared to the BNLMS algorithm. It demonstrated faster convergence, reaching an optimal solution more quickly. This characteristic is particularly beneficial in real-time applications where prompt and accurate estimation of speech signals is required. Furthermore, the BMP_{NLMS} algorithm demonstrated superior performance in terms of output SNR and distortion reduction. It consistently yielded higher output SNR values, indicating improved estimation accuracy and noise suppression. Additionally, the algorithm yielded lower CD values, indicating reduced distortion and a closer resemblance to the original clean speech signal. These results highlight the effectiveness of BMP_{NLMS} in enhancing the quality of estimated speech signals, even in the presence of various types of noise.

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