A Partitioned Block Proportionate Adaptive Algorithm for Acoustic Echo Cancellation

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***Abstract*—Due to the properties of an acoustic enclosure, the early part (i.e., direct path and early reflections) of the acoustic echo path is sparse while the late reverberant part of the acoustic path is dispersive. In this contribution, an adaptive filter structure that consists of two time-domain partition blocks is used such that different adaptive algorithms can be used for each part. Specifically, the improved proportionate normalized least-mean-square (IPNLMS) algorithm is used for which the filter update is a combination of non-proportioned and proportionated updates. By properly controlling the mixing parameter for the partitioned blocks separately, the proposed partitioned block IPNLMS (PB-IPNLMS) algorithm works well in both sparse and dispersive circumstances and in practical applications involving time-varying systems. Simulation results using a white Gaussian noise (WGN) sequence show improved performance compared to using a single IPNLMS adaptive filter.**

I. Introduction

The acoustic impulse responses (AIRs), and hence the sparseness of AIRs, are time-varying and depend on factors such as air temperature and pressure and reflectivity of the acoustic environment [1]. The level of sparseness in AIR also varies with the location of the receiving device in an open or enclosed environment. Hence, algorithms developed for acoustic echo cancellation (AEC) are required to be robust to the variations in the sparseness of the acoustic path.

The normalized least-mean-square (NLMS) algorithm is traditionally used in adaptive filters to achieve AEC. One of the main drawbacks of the NLMS algorithm is that its convergence rate reduces significantly when the impulse response is sparse [2]. Sparse adaptive filtering algorithms, such as proportionate NLMS (PNLMS) [3], have been proposed to identify sparse impulse responses. However, PNLMS suffers from slow convergence when the unknown system is dispersive [2], [4]. Improved PNLMS (IPNLMS) [5] proposed to exploit the 'proportionate' idea by introducing a controlled mixture of proportionate (i.e., PNLMS) and non-proportionate (i.e., NLMS) adaptation controlled by a single proportionate/non-proportionate factor α. A sparseness measure has been exploited within IPNLMS in [6], [7], [8]. This adaptively detects the sparsity of the adaptive filter, therefore the factor α of the IPNLMS algorithm is adjusted accordingly.

For sparse and dispersive AIRs, the partitioned block of the echo path that consists of the direct path and a few early reflections is almost always sparse while the other partitioned block is always dispersive. To validate this, consider an example case where two AIRs of length $L = 1024$ were simulated using the

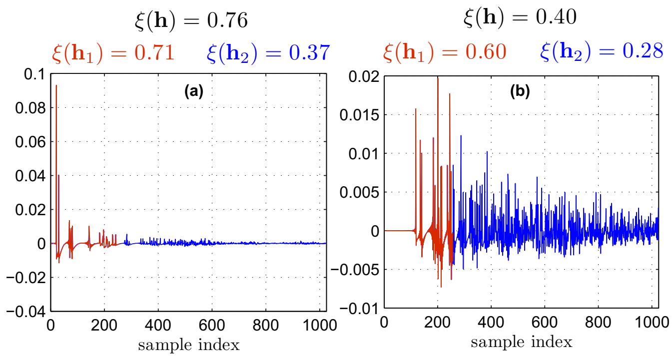

Fig. 1. Acoustic impulse responses obtained using the method of images [9]. $\xi(\mathbf{h}), \xi(\mathbf{h}_1)$ and $\xi(\mathbf{h}_2)$ respectively denote the sparseness measures [6], [10] of the full impulse response, the first block with size of 256 and the second block.

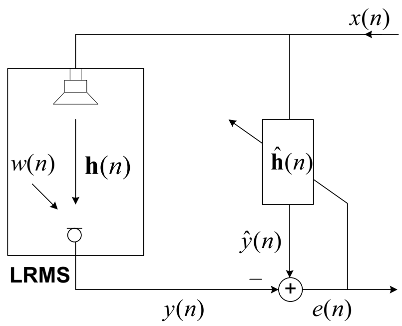

Fig. 2. Adaptive system for acoustic echo cancellation in a Loudspeaker-Room-Microphone system.

method of images [9] in a room of dimension $8 \times 10 \times 3$ m at a sampling frequency of 8 kHz. Figure 1(a) shows the AIR obtained when the loudspeaker-microphone distance is 0.85 m in the loudspeaker-room-microphone system (LRMS) with 0.3 reflection coefficient. Figure 1(b) illustrates the AIR attained when the loudspeaker-microphone distance is 5 m in the LRMS with 0.53 reflection coefficient. As can be seen from the figure and the sparseness measure [6], [10], the first block is always sparser than the second block. Hence, a sparse algorithm is desired for the first block, whereas a non-sparse algorithm is desired for the second block.

In this paper, we propose to use two IPNLMS algorithms each with a different proportionate/non-proportionate factor α for the two corresponding time-domain partitioned blocks and develop a fast tracking time-domain adaptive algorithm for AEC. The classic IPNLMS is first reviewed in Section II. We then show, in Section III, how the sparseness of AIRs varies when we partition the echo path into two blocks with different sizes. Incorporating the findings, the proposed partitioned block IPNLMS (PB-IPNLMS) algorithm is developed, using two different ways to compose the step-size control matrix of each block. Simulation results shown in Section IV, in the context of AEC, demonstrate a faster tracking performance for both sparse and dispersive AIRs compared to the IPNLMS algorithm with single mixing factor α.

II. Review of IPNLMS

Figure 2 shows a LRMS and an adaptive filter $\widehat{\mathbf{h}}(n) = [\widehat{h}_0(n)\ \widehat{h}_1(n) \dots \widehat{h}_{L-1}(n)]^T$, with L coefficients, deployed to cancel acoustic echo in, for example, a hands-free phone application. The output of the LRMS is expressed as

$$y(n) = \mathbf{h}^T(n)\mathbf{x}(n) + w(n), \tag{1}$$

where $\mathbf{x}(n) = [x(n)\ x(n-1)\ \dots\ x(n-L+1)]^T$ is the input signal, $\mathbf{h}(n) = [h_0(n)\ h_1(n)\ \dots\ h_{L-1}(n)]^T$ is the unknown impulse response and $w(n)$ is additive noise. The general computations of many adaptive algorithms can be described by the following equations:

$$e(n) = y(n) - \widehat{\mathbf{h}}^T(n-1)\mathbf{x}(n), \tag{2}$$

$$\widehat{\mathbf{h}}(n) = \widehat{\mathbf{h}}(n-1) + \frac{\mu\mathbf{Q}(n-1)\mathbf{x}(n)e(n)}{\mathbf{x}^T(n)\mathbf{Q}(n-1)\mathbf{x}(n)+\delta}, \tag{3}$$

$$\mathbf{Q}(n-1) = \mathrm{diag}\{q_0(n-1)\ \dots\ q_{L-1}(n-1)\}, \tag{4}$$

where μ is a step-size and δ is the regularization parameter. The diagonal step-size control matrix $\mathbf{Q}(n)$ determines the step-size of each filter coefficient and is dependent on the specific algorithm.

The NLMS algorithm is one of the most popular for AEC, with $\mathbf{Q}(n) = \mathbf{I}_{L\times L}$. The PNLMS [3] has been proposed for sparse system identification, with the diagonal elements of $\mathbf{Q}(n)$ proportional to the magnitude of the estimated impulse response coefficients.

The IPNLMS algorithm [5] employs a combination of non-proportionate (i.e., NLMS) and proportionate (i.e., PNLMS) adaptation, with the relative significance of each controlled by a factor α such that the diagonal elements of $\mathbf{Q}(n)$ are given by

$$q_l(n) = \frac{1-\alpha}{2L} + \frac{(1+\alpha)|\widehat{h}_l(n)|}{2\|\widehat{\mathbf{h}}(n)\|_1 + \delta_{\mathrm{IP}}}, \qquad 0 \le l \le L-1. \tag{5}$$

where $\|\cdot\|_1$ is the ℓ_1-norm. It can be seen that IPNLMS reduces to NLMS when $\alpha = -1$ and PNLMS when $\alpha = 1$. For most AEC applications, α = 0, -0.5 or -0.75 are favorable choices [5]. It is important to note that $\mathrm{tr}\{\mathbf{Q}(n)\}$, where $\mathrm{tr}\{\}$ is the trace operator, for IPNLMS is almost 1, when δ_{IP} is very small.

It has been shown that regardless of the impulse response nature, the IPNLMS algorithm has faster convergence than NLMS and PNLMS with the above choices of α [5]. However, we note from our simulations that the choice of α influences the tracking performance of IPNLMS for sparse and dispersive AIRs.

III. The Partitioned Block IPNLMS (PB-IPNLMS) Algorithm

In this Section, we provide an illustrative example to show how the sparseness of AIRs varies when we partitioned the echo path into two blocks with different sizes. This serves as a motivation for us to develop a new algorithm which improves the robustness and the tracking performance of IPNLMS. In addition, we also demonstrate how the sums of the composite diagonal elements of $\mathbf{Q}(n)$ for the two blocks affect the overall performance of the proposed algorithm.

A. Motivation

Let us first express the echo path as

$$\mathbf{h}(n) = [\mathbf{h}_1^T(n)\ \mathbf{h}_2^T(n)]^T, \tag{6}$$

with

$$\mathbf{h}_1(n) = [h_0(n)\ \dots\ h_{L_1-1}(n)]^T, \tag{7}$$
$$\mathbf{h}_2(n) = [h_{L_1}(n)\ \dots\ h_{L-1}(n)]^T. \tag{8}$$

Here, $\mathbf{h}_1(n)$ with length L_1 includes the direct path and a few early reflections, which is sparser than $\mathbf{h}_2(n)$ that includes all other reflections. The sparseness measures of these AIRs are computed using [6], [10]

$$\xi(\mathbf{w}) = \frac{N}{N-\sqrt{N}}\left\{1 - \frac{\|\mathbf{w}\|_1}{\sqrt{N}\ \|\mathbf{w}\|_2}\right\}, \tag{9}$$

where N is the length of the vector $\mathbf{w}$ and $\|\mathbf{w}\|_1$ and $\|\mathbf{w}\|_2$ represent ℓ_1 and ℓ_2-norms of $\mathbf{w}$. Figure 1(a) and (b) show illustrative AIRs for substantially sparse and dispersive cases respectively. With $L = 1024$, the sparseness measure, $\xi(\mathbf{h})$, of the AIR shown in Fig. 1(a) equals 0.76. The measures of the first and second blocks with $L_1 = \lceil \frac{L}{4} \rceil$ are $\xi(\mathbf{h}_1) = 0.71$ and $\xi(\mathbf{h}_2) = 0.37$. The AIR shown in Fig. 1(b) gives $\xi(\mathbf{h}) = 0.40$, $\xi(\mathbf{h}_1) = 0.60$ and $\xi(\mathbf{h}_2) = 0.28$. As can be seen, the first block is in both cases substantially sparser than the second block.

Figure 3 shows the convergence performance of IPNLMS measured using the normalized misalignment defined by

$$\mathrm{NM}[\mathbf{w}(n), \widehat{\mathbf{w}}(n)] = \frac{\|\mathbf{w}(n) - \widehat{\mathbf{w}}(n)\|_2^2}{\|\mathbf{w}(n)\|_2^2}, \tag{10}$$

for the sparse AIR shown in Fig. 1(a), with $\alpha = -1$ and 0.9. A zero mean white Gaussian noise (WGN) sequence is used as the input signal while another WGN sequence $w(n)$ is added to give an SNR of 20 dB and $\mu = 0.3$. It can be seen from Fig. 3(a)-(c) that, IPNLMS with $\alpha = 0.9$ is better for the first block during the initial phase and therefore giving an overall faster initial convergence, while $\alpha = -1$ (NLMS) is better for the second block and thus giving an improved overall steady-state performance. The same observation is seen from Fig. 4 for the dispersive AIR shown in Fig. 1(b), under the same experimental setup as before. As the first block of the AIR

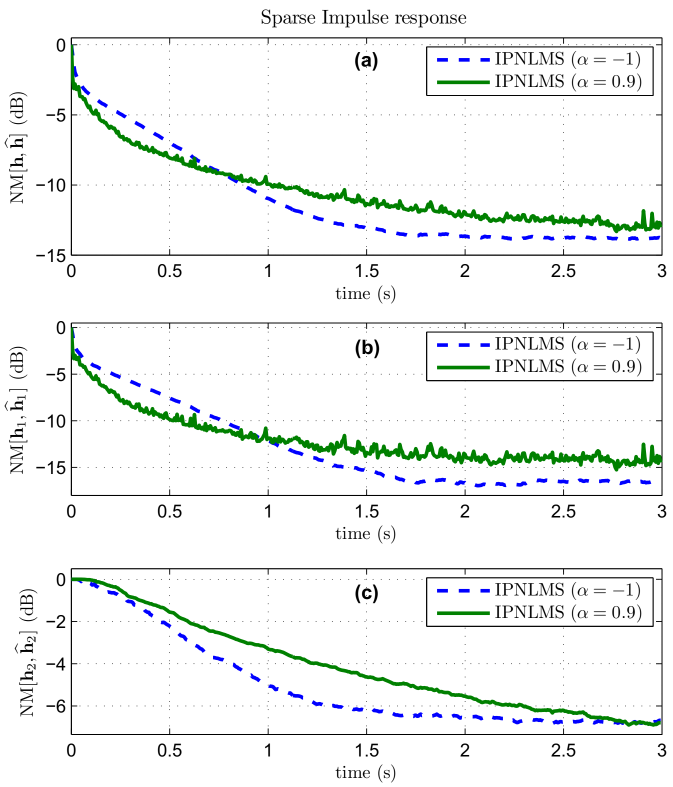

Fig. 3. Normalized misalignments (NM) of IPNLMS with different mixing parameters, α, for identification of a sparse impulse response.

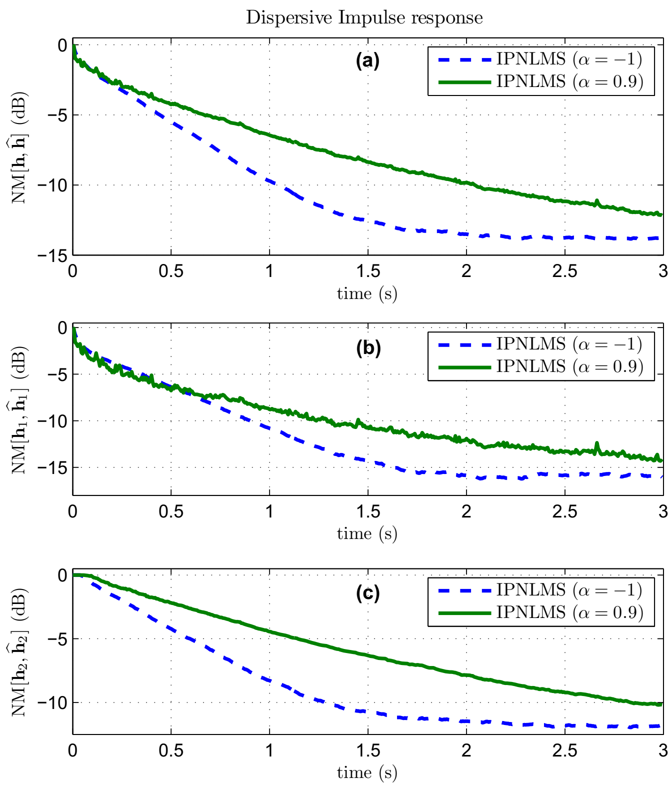

Fig. 4. Normalized misalignments (NM) of IPNLMS with different mixing parameters, α, for identification of a dispersive impulse response.

contains the dominant parts of the echo path, allocating larger individual step-sizes for the coefficients in the block gives faster initial convergence performance. Moreover, through our simulations, we found that distributing almost equal step-sizes for the second block gives better steady-state performance. As a consequence of this important observation, we propose a new adaptation approach for IPNLMS as described below.

B. Proposed algorithm

To achieve the desired effect explained in Section III-A, we propose IPNLMS with the mixing parameter α_1 close to 1 as the sparse algorithm for the first block of length L_1, where the diagonal elements q_l of the step-size control matrix of the first block $\mathbf{Q}_1(n)$ for the proposed partitioned block IPNLMS (PB-IPNLMS) algorithm can be expressed as

$$q_l(n) = \frac{(1-\alpha_1)}{2L_1} + \frac{(1+\alpha_1)|\widehat{h}_l(n)|}{2\|\widehat{\mathbf{h}_1}(n)\|_1 + \delta_{\mathrm{IP}}}, \quad 0 \le l \le L_1 - 1, \quad (11)$$

$$\mathbf{Q}_1(n-1) = \mathrm{diag}\{q_0(n-1), \ldots, q_{L_1-1}(n-1)\}, \quad (12)$$

where $\mathrm{diag}\{\}$ is the diagonal operator. For the second block, as it is more dispersive compared to the first block, we propose to employ IPNLMS with the mixing parameter α_2 ($\alpha_2 < \alpha_1$) close to -1, where q_l of the second block $\mathbf{Q}_2(n)$ for PB-IPNLMS can be formulated as

$$q_l(n) = \frac{(1-\alpha_2)}{2(L-L_1)} + \frac{(1+\alpha_2)|\widehat{h}_l(n)|}{2\|\widehat{\mathbf{h}_2}(n)\|_1 + \delta_{\mathrm{IP}}}, \quad L_1 \le l \le L - 1, \quad (13)$$

$$\mathbf{Q}_2(n-1) = \mathrm{diag}\{q_{L_1}(n-1), \ldots, q_{L-1}(n-1)\}. \quad (14)$$

When using different update rules, the constraint on $\mathrm{tr}\{\mathbf{Q}(n)\}$ of PB-IPNLMS, which is composed of $\mathbf{Q}_1(n)$ and $\mathbf{Q}_2(n)$, still needs to be 1 for very small values of δ_{IP}. Although this constraint can be satisfied in many ways, we propose the following two different approaches in this work.

1) PB-IPNLMS with non-proportionate block weighting: In the first approach, we allocate equal weights as

$$\mathbf{Q}(n-1) = \begin{bmatrix} 0.5\,\mathbf{Q}_1(n-1) & \mathbf{0}_{L_1 \times (L-L_1)} \\ \mathbf{0}_{(L-L_1)\times L_1} & 0.5\,\mathbf{Q}_2(n-1) \end{bmatrix}, \quad (15)$$

to satisfy the constraint on $\mathbf{Q}(n)$ of PB-IPNLMS. This approach has been dubbed the ‘non-proportionate PB-IPNLMS’. Thus, the non-proportionate PB-IPNLMS algorithm is described by (2), (3) and (11)-(15), as specified in Table I. It is worthwhile noting that the non-proportionate approach works well only if $\|\mathbf{h}_1(n)\|_1 \approx \|\mathbf{h}_2(n)\|_1$, but in practice this condition is seldom met.

2) PB-IPNLMS with proportionate block weighting: As $\mathbf{h}_1(n)$ and $\mathbf{h}_2(n)$ are unobservable, we propose to allocate weights proportional to the ratio between $\|\widehat{\mathbf{h}}_1(n)\|_1$ and $\|\widehat{\mathbf{h}}(n)\|_1$, while satisfying $\mathrm{tr}\{\mathbf{Q}(n)\}$ is close to 1 for very small values of δ_{IP}. We refer to this approach as the 'proportionate PB-IPNLMS'. It is noted that, for a sparse system identification with $\widehat{\mathbf{h}}(0) = \mathbf{0}$, the ratio between $\|\widehat{\mathbf{h}}_1(n)\|_1$ and $\|\widehat{\mathbf{h}}(n)\|_1$ is close to 1 during the initial stage and decays to a value κ $(0 \le \kappa \le 1)$, which on average is greater than 0.5, due to the fact that the first block contains almost all the dominant echo. However, for a dispersive AIR, the ratio quickly decays to a value less than κ, as the second block also has many weaker reflections. In this approach, the proportionality is controlled by $\beta(n)$ which is defined as follows, for $n > 1$, in order to calculate the composed step-size control matrix $\mathbf{Q}(n-1)$:

$$\beta(n) = \begin{cases} \lambda \frac{\|\widehat{\mathbf{h}}_1(n)\|_1}{\|\widehat{\mathbf{h}}(n)\|_1}, & \frac{\|\widehat{\mathbf{h}}_1(n)\|_1}{\|\widehat{\mathbf{h}}(n)\|_1} > \kappa, \\ \lambda^{-1} \frac{\|\widehat{\mathbf{h}}_1(n)\|_1}{\|\widehat{\mathbf{h}}(n)\|_1}, & \text{otherwise} \end{cases} \tag{16}$$

$$\mathbf{Q}(n-1) = \begin{bmatrix} \beta(n)\, \mathbf{Q}_1(n-1) & \mathbf{0}_{L_1 \times (L-L_1)} \\ \mathbf{0}_{(L-L_1)\times L_1} & [1-\beta(n)]\, \mathbf{Q}_2(n-1) \end{bmatrix}. \tag{17}$$

With the formulation of $\beta(n)$ in (16) for the first block, we allocate a weight that is directly proportional to the ratio between $\|\widehat{\mathbf{h}}_1(n)\|_1$ and $\|\widehat{\mathbf{h}}(n)\|_1$ when the ratio is above a threshold value κ, where λ $(0 < \lambda < 1)$ is introduced to allocate almost equal weights for the two blocks after the initial convergence. The factor λ also ensures that $1 - \beta(n)$ for the second block is always greater than zero, and therefore avoids stalling the adaptation of $\widehat{\mathbf{h}}_2$. Likewise, λ^{-1} (which is $\ge$ 1) ensures that $\beta(n)$ is never very small, thereby avoiding stalling the adaptation of $\widehat{\mathbf{h}}_1$. When the ratio is below or equal to κ, the first block gets higher weight during the initial stage of a dispersive system identification and gradually reduces such that the second block gets more weight. With the experimentally determined values of $\lambda = 0.8$ and $\kappa = 0.5$, proportionate PB-IPNLMS not only works well in both sparse and dispersive circumstances, but also performs well when the scenario involves a time-varying system. The proposed proportionate PB-IPNLMS algorithm is thus described by (2), (3), (11)-(14), (16) and (17), as specified in Table I.

TABLE I
PARTITIONED BLOCK IPNLMS (PB-IPNLMS) ALGORITHM

Initialisation

$$\widehat{\mathbf{h}}(0) = \mathbf{0}_{L\times 1}$$

General Computations

$$e(n) = y(n) - \widehat{\mathbf{h}}^T(n-1)\mathbf{x}(n)$$

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

PB-IPNLMS

$$\widehat{\mathbf{h}}_1(n) = [\widehat{h}_0(n) \ \ldots \ \widehat{h}_{L_1-1}(n)]^T$$

$$\widehat{\mathbf{h}}_2(n) = [\widehat{h}_{L_1}(n) \ \ldots \ \widehat{h}_{L-1}(n)]^T$$

$$\widehat{\mathbf{h}}(n) = [\widehat{\mathbf{h}}_1(n)^T \ \widehat{\mathbf{h}}_2(n)^T]^T$$

$$q_l(n) = \frac{(1-\alpha_1)}{2L_1} + \frac{(1+\alpha_1)|\widehat{h}_l(n)|}{2\|\widehat{\mathbf{h}}_1(n)\|_1 + \delta_{\mathrm{IP}}}, \quad 0 \le l \le L_1 - 1$$

$$\mathbf{Q}_1(n-1) = \mathrm{diag}\{q_0(n-1), \ldots, q_{L_1-1}(n-1)\}$$

$$q_l(n) = \frac{(1-\alpha_2)}{2(L-L_1)} + \frac{(1+\alpha_2)|\widehat{h}_l(n)|}{2\|\widehat{\mathbf{h}}_2(n)\|_1 + \delta_{\mathrm{IP}}}, \quad L_1 \le l \le L - 1$$

$$\mathbf{Q}_2(n-1) = \mathrm{diag}\{q_{L_1}(n-1), \ldots, q_{L-1}(n-1)\}$$

Non-proportionate PB-IPNLMS

$$\mathbf{Q}(n-1) = \begin{bmatrix} 0.5\, \mathbf{Q}_1(n-1) & \mathbf{0}_{L_1 \times (L-L_1)} \\ \mathbf{0}_{(L-L_1)\times L_1} & 0.5\, \mathbf{Q}_2(n-1) \end{bmatrix}_{L\times L}$$

Proportionate PB-IPNLMS

$$\beta(n) = \begin{cases} \lambda \frac{\|\widehat{\mathbf{h}}_1(n)\|_1}{\|\widehat{\mathbf{h}}(n)\|_1}, & \frac{\|\widehat{\mathbf{h}}_1(n)\|_1}{\|\widehat{\mathbf{h}}(n)\|_1} > \kappa, \\ \lambda^{-1} \frac{\|\widehat{\mathbf{h}}_1(n)\|_1}{\|\widehat{\mathbf{h}}(n)\|_1}, & \text{otherwise} \end{cases}$$

$$\mathbf{Q}(n-1) = \begin{bmatrix} \beta(n)\, \mathbf{Q}_1(n-1) & \mathbf{0}_{L_1 \times (L-L_1)} \\ \mathbf{0}_{(L-L_1)\times L_1} & [1-\beta(n)]\, \mathbf{Q}_2(n-1) \end{bmatrix}_{L\times L}$$

IV. PERFORMANCE EVALUATION

We present simulation results to evaluate the performance of the proposed PB-IPNLMS algorithm. Throughout our simulations, algorithms were tested using a zero mean WGN signal as input while another WGN sequence $w(n)$ was added to give an SNR of 20 dB. We assumed that the length of the adaptive filter $L = 1024$ is equivalent to that of the unknown system. Two receiving room impulse responses $\mathbf{h}(n)$ for AEC simulations have been used, with an echo path change at 4 s. The AIR is changed from that shown in Fig. 1 (a) to (b) and μ = 0.3. For PB-IPNLMS, L_1 was fixed to 256 such that the first partitioned block contained the direct path and early reflections and, $\alpha_1 = 0.9$ and $\alpha_2 = -1$ were used, while $\lambda = 0.8$ and $\kappa = 0.5$ were employed specifically for the proportionate PB-IPNLMS algorithm.

Figure 5 compares the overall performance of IPNLMS, in terms of normalized misalignment, with $\alpha = -1$ and 0.9 and PB-IPNLMS using the non-proportionate and proportionate weight allocation approaches, while Fig. 6 shows the normalized misalignments of the first and second blocks. As it can be seen that the proposed non-proportionate PB-IPNLMS achieves approximately 3 dB improvements over the IPNLMS with $\alpha = -1$, and performs similar to the IPNLMS with $\alpha = 0.9$ during the initial stage of the sparse system identification. After the echo path change, a similar

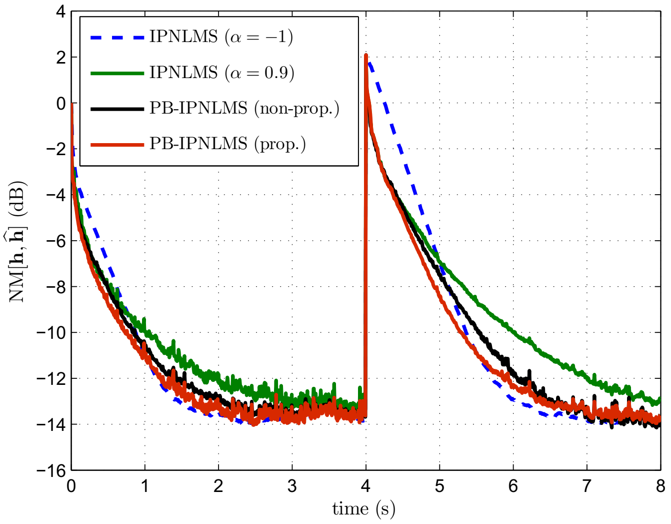

Fig. 5. Relative convergence of IPNLMS for $\alpha = -1$ and 0.9 and PB-IPNLMS with non-proportionate and proportionate weight allocation approaches, using WGN input signal with an echo path change at 4 s.Impulse response is changed from that shown in Fig. 1 (a) to (b) and $\mu = 0.3$, SNR = 20 dB.

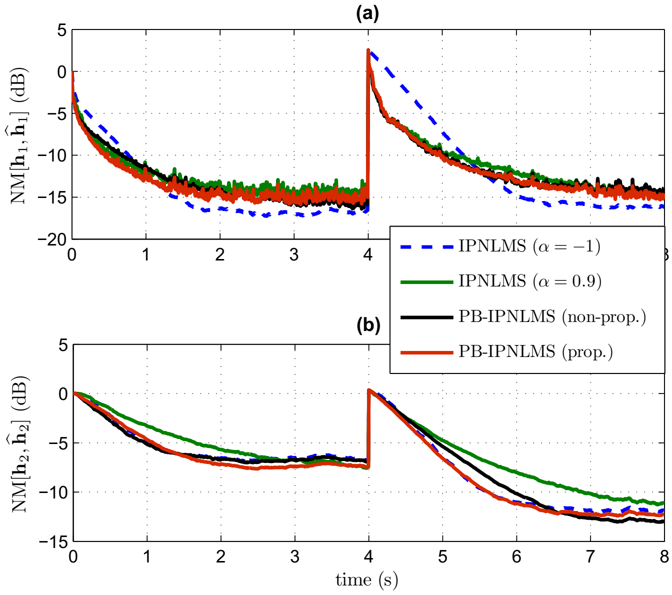

Fig. 6. The normalized misalignments (NM) for the overall convergence performance illustrated in Fig. 5

performance pattern was observed between $4-5$ s. However, below the -10 dB NM level, the non-proportionate PB-IPNLMS algorithm performs similar to the IPNLMS with $\alpha = -1$, and achieves approximately 3 dB better convergence performance over the IPNLMS with $\alpha = 0.9$. Moreover, the proportionate PB-IPNLMS gives better performance compared to all the algorithms, notably a 2 dB improvement over the non-proportionate PB-IPNLMS after the echo path changes to dispersive AIR. PB-IPNLMS achieves this better initial performance by exploiting the beneficial properties of the IPNLMS with $\alpha = 0.9$ for the first block and allocates step-sizes similar to the IPNLMS with $\alpha = -1$ for the second block, as illustrated in Fig. 6.

Figure 7 shows a detailed study on the evolution of β in (16), which is equivalent to $\|\widehat{\mathbf{h}}_1(n)\|_1$ for the IPNLMS algorithm with $\alpha = -1$ and $\alpha = 0.9$ and 0.5 for the non-proportionate PB-IPNLMS algorithm, throughout the simulation time for the overall performance illustrated in Fig. 5. As can be seen, the IPNLMS with $\alpha = -1$ gives a small weight, β, for the first block at all time, therefore gives higher weight, $(1-\beta)$, for the second block to achieve a better steady-state performance. While, the IPNLMS with $\alpha = 0.9$ allocates higher weight during the early stages of before and after the echo path change, giving faster convergence performance initially. The proportionate PB-IPNLMS exploits both of the beneficial properties and achieves the better overall performance.

The same experiment was repeated with the exact parameter settings using a correlated unity-variance AR(2) process given by [11]

$$x(n) = 0.73\,x(n-1) - 0.8\,x(n-2) + s(n), \qquad (18)$$

where $s(n)$ is a white Gaussian noise with $\sigma_s^2 = 0.3$, and

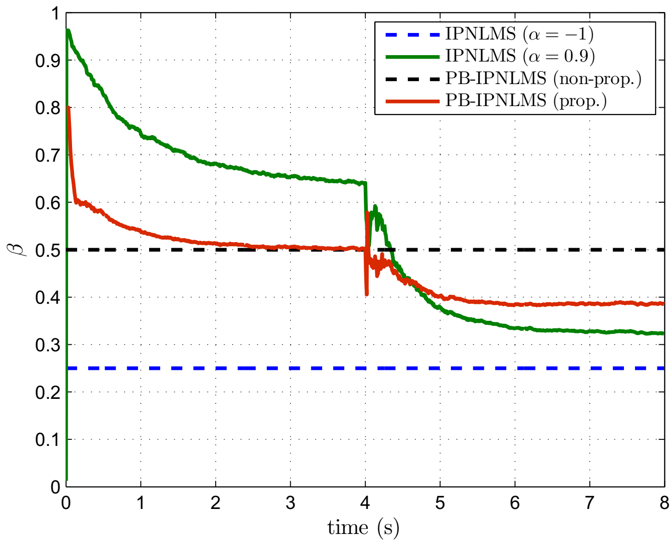

Fig. 7. Evolution of β in (16), which is equivalent to $\|\widehat{\mathbf{h}}_1(n)\|_1$ for the IPNLMS algorithm with $\alpha = -1$ and $\alpha = 0.9$ and 0.5 for the non-proportionate PB-IPNLMS algorithm.

the relative performances are shown in Fig. 8. As observed in the WGN input signal case, the proportionate PB-IPNLMS outperforms all the aforementioned algorithms before and after the echo path change.

V. Conclusion

We presented a partitioned block IPNLMS algorithm, with two different approaches to allocate weights for the composition of the step-size control matrix of the two blocks. The proposed algorithm achieves improved convergence compared to classical IPNLMS with fixed single proportional/non-proportionate factor α. For the proposed PB-IPNLMS algo-

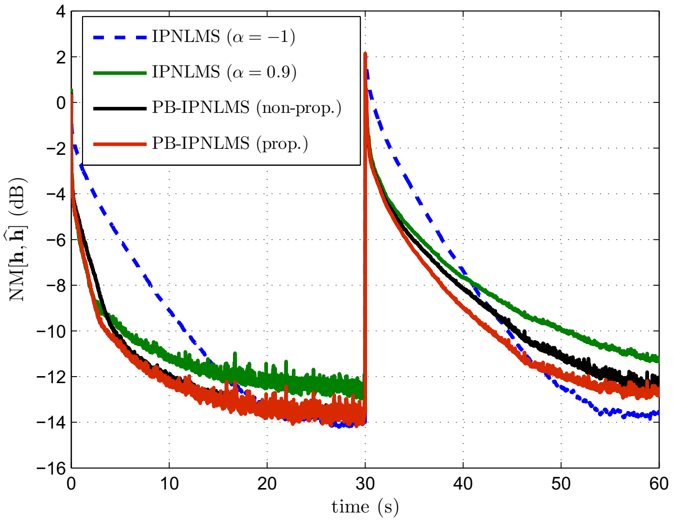

Fig. 8. Relative convergence of IPNLMS for $\alpha = -1$ and 0.9 and PB-IPNLMS with non-proportionate and proportionate weight allocation approaches, using the input signal generated by (18) with an echo path change at 4 s.Impulse response is changed from that shown in Fig. 1 (a) to (b) and μ = 0.3, SNR = 20 dB.

rithm with proportionate weighting, we incorporated the ratio between the ℓ_1-norm of the first block's estimated filter coefficients and that of the overall filter coefficient into IPNLMS for AEC to achieve fast convergence for both sparse and dispersive acoustic echo paths. As a future work, the length of the partitioned block (L_1) can be considered time-dependent to improve the robustness of PB-IPNLMS.

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