

Sparseness-Controlled Affine Projection Algorithm for Echo Cancellation

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Abstract—Affine projection algorithms (APAs) are popular in echo cancellation due to its fast convergence. Proportionate APA (PAPA) and improved APAP (IPAPA) have been proposed recently to enhance the performance of APAs based on the concept of assigning different effective step-sizes to the tap coefficients. Conventional IPAPA is found to be able to outperform PAPA by using a proper control parameter. In this paper, two sparseness controlled IPAPAs (SC-IPAPAs) are proposed to further improve the convergence of IPAPA, namely, SC-IPAPA-I and SC-IPAPA-II. Unlike conventional IPAPA, the control parameter is a function of the sparseness measure of the estimated impulse response in the proposed SC-IPAPA-I and SC-IPAPA-II, rather than a predefined constant. The contribution of our proposed SC-IPAPA-II is to remove the need to decide on a predefined control parameter as well as achieving high rate of convergence that is robust to the sparseness of the impulse response. Simulation results show that SC-IPAPA-I and SC-IPAPA-II have higher rate of convergence than that of IPAPA.

I. INTRODUCTION

The use of adaptive filters for system identification has found applications in both network and acoustic echo cancellation. Such adaptive filters are employed to estimate the unknown impulse response of the system and algorithms developed for such applications require fast convergence as well as good tracking performance. Although these requirements are similar, it is important to note that network impulse responses (NIRs) and acoustic impulse responses (AIRs) have different characteristics and hence adaptive algorithms developed for such applications differ.

Impulse responses of network hybrids are typically of length 64-128 ms. These NIRs possess an active region of large amplitudes with a duration of 8-12 ms [1] and as a consequence, are often considered sparse. Development of adaptive algorithms for network echo cancellation (NEC) revolves around the use of proportionate-type algorithms, such as in proportionate normalized least-mean-square (PNLMS) [2], where the step-size of each filter coefficient is made proportional to the corresponding magnitude of the estimated filter coefficient. It was subsequently found that the convergence of PNLMS degrades considerably with time due to the small step-sizes used for filter coefficients with smaller magnitudes. To address this, the improved PNLMS (IPNLMS) [3] algorithm

incorporates the proportionate (PNLMS) as well as the non-proportionate (NLMS) terms. It was found in [4] that the IPNLMS algorithm perform better than PNLMS for sparse and in some cases for non-sparse acoustic impulse responses.

In contrast to NIRs, AIRs are comparatively more dispersive in nature. This dispersive nature is brought about by the early as well as late reflections of an enclosed environment. This effect becomes more prominent especially for applications including hands-free telephony and/or robotic control where the acoustic coupling between the loudspeaker and the microphone is significant due to multipath effects of the enclosure. Since such multipath propagation contributes to the late reflections of the AIR, it is therefore foreseeable that the AIR will become comparatively sparse when these reflections are reduced. Such sparse AIRs can occur in, for example, an outdoor environment.

In this work, we develop adaptive algorithms that are robust to the sparseness of the impulse responses. We start by reviewing adaptive algorithms in the context of the affine projection algorithm (APA) [5] framework developed originally for NEC whereby the system is sparse. One of the first APA for sparse system identification in NEC is the proportionate APA (PAPA) [6]. The PAPA jointly utilizes the APA and proportionate step-size technique which was proposed in [2]. In the PAPA, each filter coefficient is updated with an independent step-size that is proportional to the magnitude of the estimated filter coefficient. Similar to PNLMS, the PAPA algorithm achieves fast initial convergence but slows down subsequently due to the slow convergence of the coefficients having significantly small magnitude [4]. The improved PAPA (IPAPA) [7] combines a weighted APA and PAPA such that the proportionate term associated with PAPA is aimed at enhancing the convergence speed of the coefficients in the active region while the non-proportionate term from APA is to improve the convergence speed for the coefficients having small magnitude in the non-active region.

The contribution of this work is to further enhance the performance of IPAPA by utilizing the sparseness measure [8] of an impulse response. As will be discussed in Section II-C, the success of IPAPA depends on the value of a control parameter. Therefore, it is foreseeable that an appropriate value of this control parameter differs from system to system. In view of this, we propose to incorporate the sparseness measure of the estimated impulse response in order to compute the weighting

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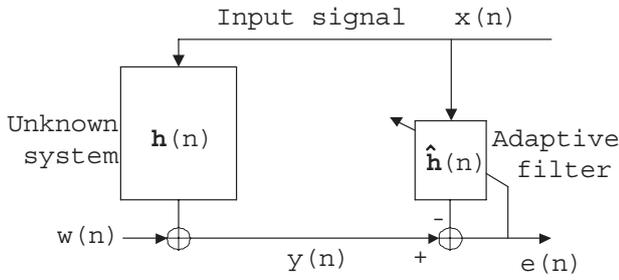


Fig. 1. Schematic diagram of a general echo canceller.

assigned to the proportionate and non-proportionate terms adaptively. We propose two mechanisms to achieve this. In the first proposed SC-IPAPA-I algorithm, additional weighting terms obtained by taking into account the sparseness measure of estimated impulse response are multiplied to the proportionate and non-proportionate terms in the conventional IPAPA algorithm. In the second proposed SC-IPAPA-II algorithm, the constant control parameter in conventional IPAPA is replaced by a sparseness-dependent control parameter. This reduces the need to determine the control parameter prior to adaptation. Results presented in Section IV show that the proposed SC-IPAPA-I and SC-IPAPA-II algorithms outperform the IPAPA as they achieve a higher rate of convergence.

II. REVIEW OF AFFINE PROJECTION ALGORITHMS FOR SPARSE SYSTEM IDENTIFICATION

We review adaptive algorithms in the context of sparse system identification by defining, as shown in Fig. 1, the tap-input vector $\mathbf{x}(n)$ and the unknown impulse response $\mathbf{h}(n)$ given by

$$\mathbf{x}(n) = [x(n) \ x(n-1) \ \cdots \ x(n-L+1)]^T, \quad (1)$$

$$\mathbf{h}(n) = [h_0(n) \ h_1(n) \ \cdots \ h_{L-1}(n)]^T, \quad (2)$$

where L is the filter length and $[\cdot]^T$ represents the transpose operator. The near-end signal $y(n)$ is the convolution between $h(n)$ and $x(n)$, i.e.,

$$y(n) = \mathbf{x}^T(n)\mathbf{h}(n) + w(n), \quad (3)$$

where $w(n)$ is the observation noise. For simplicity, we shall temporarily ignore the effects of $w(n)$ in description of algorithms. The adaptive filter $\hat{\mathbf{h}}(n)$ is an estimate of the unknown impulse response $\mathbf{h}(n)$.

A. Affine projection algorithm

The APA [5] with projection order p , $p \leq L$, is derived based on an optimization subject to multiple equality constraints. This optimization leads to the minimum-norm solution of the following simultaneous equations

$$\begin{aligned} y(n) &= \mathbf{x}^T(n)\hat{\mathbf{h}}(n), \\ y(n-1) &= \mathbf{x}^T(n-1)\hat{\mathbf{h}}(n), \\ &\vdots \\ y(n-p+1) &= \mathbf{x}^T(n-p+1)\hat{\mathbf{h}}(n). \end{aligned}$$

To compute $\hat{\mathbf{h}}(n)$ iteratively, this optimization problem can be formulated, based on the principle of minimal disturbance [9], as

$$\min_{\hat{\mathbf{h}}(n)} \|\hat{\mathbf{h}}(n) - \hat{\mathbf{h}}(n-1)\|, \quad (4)$$

subject to

$$\mathbf{e}(n) = \mathbf{y}(n) - \mathbf{X}^T(n)\hat{\mathbf{h}}(n) = \mathbf{0}, \quad (5)$$

where $\mathbf{y}(n) = [y(n) \ y(n-1) \ \cdots \ y(n-p+1)]^T$ and $\mathbf{X}(n) = [\mathbf{x}(n) \ \mathbf{x}(n-1) \ \cdots \ \mathbf{x}(n-p+1)]$.

The solution of $\hat{\mathbf{h}}(n)$ can be achieved by taking the Lagrangian for (4) and (5) such that

$$\mathcal{L}(\hat{\mathbf{h}}(n), \Lambda) = \|\hat{\mathbf{h}}(n) - \hat{\mathbf{h}}(n-1)\|^2 + \Lambda^T [\mathbf{y}(n) - \mathbf{X}^T(n)\hat{\mathbf{h}}(n)], \quad (6)$$

where $\Lambda = [\lambda_0, \lambda_1, \dots, \lambda_{p-1}]^T$ is a vector of Lagrange multipliers. Differentiating (6) with respect to $\hat{\mathbf{h}}(n)$ gives

$$\hat{\mathbf{h}}(n) = \hat{\mathbf{h}}(n-1) + \frac{1}{2}\mathbf{X}(n)\Lambda. \quad (7)$$

Combining (5) and (7), the Lagrange multipliers can be solved as

$$\Lambda = 2[\mathbf{X}^T(n)\mathbf{X}(n)]^{-1}\mathbf{e}(n) \quad (8)$$

and therefore, substituting (8) to (7) the update equation for APA can be written as

$$\hat{\mathbf{h}}(n) = \hat{\mathbf{h}}(n-1) + \mu\mathbf{X}(n)[\mathbf{X}^T(n)\mathbf{X}(n) + \delta\mathbf{I}]^{-1}\mathbf{e}(n),$$

where μ is the step-size and δ is a positive regularization parameter to overcome the numerical instability and the singularity caused by the data matrix $\mathbf{X}(n)$ [9].

B. The proportionate affine projection algorithm

Extending APA for sparse system identification and in order to update the coefficients proportionally to their magnitude, a proportionate APA update equation can be rewritten as [6]

$$\hat{\mathbf{h}}(n) = \hat{\mathbf{h}}(n-1) + \frac{1}{2}\mathbf{G}(n)\mathbf{X}(n)\Lambda', \quad (9)$$

where Λ' is the new Lagrange multiplier and $\mathbf{G}(n)$ is a diagonal proportionate step-size matrix of dimension $L \times L$. The diagonal elements of $\mathbf{G}(n)$ are related to the magnitude of the coefficients in $\hat{\mathbf{h}}(n-1)$ and can be expressed as [2]

$$\begin{aligned} g_l(n) &= \frac{\kappa_l(n)}{\sum_{i=0}^{L-1} \kappa_i(n)}, \\ \kappa_l(n) &= \max \left\{ \rho \times \right. \\ &\quad \left. \max [\gamma, |\hat{h}_0(n)| \cdots |\hat{h}_{L-1}(n)|], |\hat{h}_l(n)| \right\}, \end{aligned} \quad (10)$$

with $l = 0, \dots, L-1$ being the tap-indices. The parameter γ is included in (11) to prevent $\hat{h}_l(n)$ from stalling during initialization stage with $\hat{\mathbf{h}}(0) = \mathbf{0}_{L \times 1}$ while ρ prevents coefficients from stalling when they are much smaller than the largest coefficient [2].

Solving (9) and (5), we obtain the new Lagrange multiplier as

$$\Lambda' = 2\mathbf{e}(n)[\mathbf{X}^T(n)\mathbf{G}(n)\mathbf{X}(n)]^{-1}. \quad (12)$$

Therefore, the update equation of a general PAPA is given as

$$\hat{\mathbf{h}}(n) = \hat{\mathbf{h}}(n-1) + \mu \mathbf{G}(n) \mathbf{X}(n) \mathbf{R}_{xx}^{-1}(n) \mathbf{e}(n),$$

where $\mathbf{R}_{xx}^{-1}(n) = [\mathbf{X}^T(n) \mathbf{G}(n) \mathbf{X}(n)]^{-1}$.

C. The improved PAPA algorithm

Similar to PNLMS algorithm, the major drawback of PAPA is that it suffers from slow convergence due to the small step-size allocated to coefficients with small magnitude. In order to address this, an improved PAPA (IPAPA) algorithm was proposed in [7]. This algorithm is a combination of weighted PAPA and APA where elements of the control matrix in (10) and (11) are now defined, similar to IPNLMS [3], as

$$g_l(n) = \frac{1-\alpha}{2L} + \frac{(1+\alpha)|\hat{h}_l(n)|}{2\|\hat{\mathbf{h}}(n)\|_1 + \epsilon}, \quad l = 0, 1, \dots, L-1, \quad (13)$$

where α is the control parameter and ϵ is a small positive value to prevent division by zero during initialization when $\hat{\mathbf{h}}(0) = \mathbf{0}_{L \times 1}$ and $|\cdot|_1$ is the l_1 -norm operator. The control parameter α determines the relative significance of APA and PAPA. As can be seen from (13), when $\alpha = -1$,

$$g_l(n) = \frac{1}{L}, \quad l = 0, 1, \dots, L-1, \quad (14)$$

and as a consequence, the IPAPA is equivalent to the APA algorithm. On the other hand, when $\alpha = 1$,

$$g_l(n) = \frac{|\hat{h}_l(n)|}{\|\hat{\mathbf{h}}(n)\|_1 + \epsilon}, \quad l = 0, 1, \dots, L-1, \quad (15)$$

the estimated taps are normalized by the l_1 -norm of $\hat{\mathbf{h}}(n)$ such that the effective step-size of IPAPA is proportional to the magnitude of the estimated filter coefficients. Therefore, the performance of IPAPA converges to APA when $\alpha \rightarrow -1$ while for $\alpha \rightarrow 1$, IPAPA performs similar to PAPA. When $-1 \leq \alpha \leq 1$, a fast convergence of IPAPA is achieved by combining an APA term $(1-\alpha)/(2L)$ and a proportionate term $(1+\alpha)(|\hat{h}_l(n)|)/(2\|\hat{\mathbf{h}}(n)\|_1 + \epsilon)$. Results presented in [7] showed that a good choice of α value is 0.5.

III. THE SPARSENESS CONTROLLED APA ALGORITHMS

One of the main weaknesses of the IPAPA algorithm is to find a control parameter α offering a highest rate of convergence for different impulse responses. When the estimated impulse response $\hat{\mathbf{h}}(n)$ is adapted to the desired impulse response, this α value may vary from iteration to iteration. In view of this, we propose to assign weighting to the proportionate and non-proportionate terms in IPAPA adaptively according to the sparseness measure of $\hat{\mathbf{h}}(n)$, rather than using a predefined constant control parameter.

A. Sparseness measure

The sparseness of an impulse response of length L is measured as [8]

$$\xi(n) = \frac{L}{L - \sqrt{L}} \left[1 - \frac{\|\mathbf{h}(n)\|_1}{\sqrt{L}\|\mathbf{h}(n)\|_2} \right]. \quad (16)$$

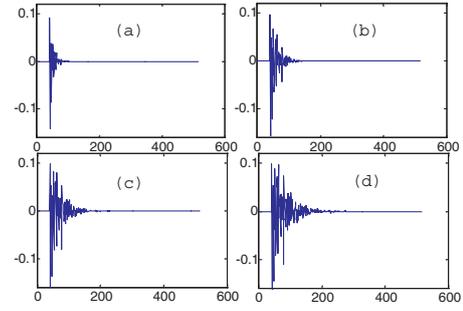


Fig. 2. Impulse response generate using (a) $\tau = 10$, (b) $\tau = 20$, (c) $\tau = 30$, (d) $\tau = 40$ with $\sigma_b^2 = 1$.

As shown in [4] a perfectly sparse system with a single non-zero coefficient has a sparseness measure $\xi = 1$ while a perfectly dispersive system with constant magnitude has a sparseness measure $\xi = 0$.

In order to further illustrate this concept, we generate synthetic impulse responses with various sparseness using an exponential model that is excited by a random input sequence [4]. This is achieved by first defining a $L \times 1$ vector

$$\mathbf{u} = [\mathbf{0}_{L_p \times 1} \ 1 \ e^{-1/\tau} \ e^{-2/\tau} \ \dots \ e^{-(L_u-1)/\tau}], \quad (17)$$

where L_p is the length of leading zeros and $L_u = L - L_p$ is the length of decaying window while τ is the decay constant. Defining a $L_u \times 1$ vector \mathbf{b} as a zero mean white Gaussian noise (WGN) sequence with variance σ_b^2 , the impulse response is subsequently generated as

$$\mathbf{B}_{L_u \times L_u} = \text{diag}\{\mathbf{b}\}, \quad \mathbf{h}(n) = \begin{bmatrix} \mathbf{0}_{L_p \times L_p} & \mathbf{0}_{L_p \times L_u} \\ \mathbf{0}_{L_u \times L_p} & \mathbf{B}_{L_u \times L_u} \end{bmatrix} \mathbf{u} + \mathbf{v}, \quad (18)$$

where \mathbf{v} is a $L \times 1$ vector generated using a zero mean WGN sequence with variance σ_v^2 . This vector \mathbf{v} ensures the elements in the ‘inactive’ region are small but non-zero. Figure 2 shows an example of impulse responses generated using (18) with $\sigma_b^2 = 1$, $\sigma_v^2 = 1 \times 10^{-5}$, $L = 512$ and $L_p = 40$, in which the decay constant in (a) $\tau = 10$, (b) $\tau = 20$, (c) $\tau = 30$ and (d) $\tau = 40$. The sparseness measures of the impulse responses are (a) $\xi = 0.8898$, (b) $\xi = 0.8162$, (c) $\xi = 0.7614$ and (d) $\xi = 0.7171$, respectively. Therefore, it can be observed that a higher ξ value corresponds to a more sparse impulse response.

B. Proposed sparseness controlled IPAPA (SC-IPAPA) algorithms

We propose a sparseness controlled IPAPA (SC-IPAPA) to improve the performance of IPAPA by taking into account the sparseness measure of the estimated impulse response $\hat{\mathbf{h}}(n)$ given by

$$\hat{\xi}(n) = \frac{L}{L - \sqrt{L}} \left[1 - \frac{\|\hat{\mathbf{h}}(n)\|_1}{\sqrt{L}\|\hat{\mathbf{h}}(n)\|_2} \right]. \quad (19)$$

The significance of the SC-IPAPA algorithm is its ability to control the relative significance of the non-proportionate

term $(1 - \alpha)/(2L)$ and the proportionate term $(1 + \alpha)|\hat{h}_l(n)|/(2\|\hat{\mathbf{h}}\|_1 + \epsilon)$ according to the sparseness measure of the estimated impulse response defined in (19). The improved convergence speed is achieved by assigning a higher weighting to the proportionate term if the estimated impulse response is sparse. On the other hand, for a dispersive impulse response, a higher weighting will be allocated to the APA term.

1) *SC-IPAPA-I*: Similar to [4], we first propose to control the weighting of the non-proportionate and proportionate term by using $1 - \hat{\xi}(n)$ and $1 + \hat{\xi}(n)$, respectively. It is worthwhile to note that if $\hat{\mathbf{h}}(n)$ is initialized as a null vector, i.e., $\hat{\mathbf{h}}(0) = \mathbf{0}_{L \times 1}$, the l_2 -norm of the impulse filter coefficient $\|\hat{\mathbf{h}}(0)\|_2 = 0$. Hence, in order to prevent division by zero, and in contrast to [4], we propose to incorporate a small positive number ϵ_{sc} in (19), such that

$$\hat{\xi}_{sc}(n) = \frac{L}{L - \sqrt{L}} \left[1 - \frac{\|\hat{\mathbf{h}}(n)\|_1}{\sqrt{L}\|\hat{\mathbf{h}}(n)\|_2 + \epsilon_{sc}} \right]. \quad (20)$$

By incorporating ϵ_{sc} , the proposed sparseness measure (20) can be applied from $n = 0$. Similar to α in [7] and $\xi(n)$ in [4], the computation of $g_l(n)$ for the SC-IPAPA-I can be expressed as

$$g_l(n) = \left[\frac{1 - 0.5\hat{\xi}_{sc}}{L} \right] \frac{1 - \alpha}{2L} + \left[\frac{1 + 0.5\hat{\xi}_{sc}}{L} \right] \frac{(1 + \alpha)|\hat{h}_l(n)|}{2\|\hat{\mathbf{h}}\|_1 + \epsilon}, \quad (21)$$

for $n \geq 0$ and $l = 0, 1, \dots, L - 1$. It can be seen from (22) that, when $\hat{\xi}(n)$ is high such as for a sparse impulse response, a higher weighting is assigned to the proportionate term. In the adaptation, when $\hat{\xi}(n)$ varies against the iterations, the weighting to the proportionate and non-proportionate terms changes correspondingly.

2) *SC-IPAPA-II*: The PAPA algorithm achieves fast initial convergence speed but slows down subsequently due to small step-sizes allocated to coefficients with small magnitude. The control parameter α in IPAPA [7] addresses this issue efficiently. It has been shown in [7] that IPAPA with a proper chosen α value can improve the convergence speed of PAPA. Although it is shown in [7] that a choice of $\alpha = 0.5$ achieves fast convergence in IPAPA, the performance of IPAPA may differ for different α values when adaptating in different impulse responses.

Unlike [7] where a fixed value of α is used for IPAPA, we propose to adopt a new time varying mechanism of $\alpha(n)$ which is a function of the estimated sparseness $\hat{\xi}_{sc}(n)$ such that

$$\alpha(n) = \psi\{\hat{\xi}_{sc}\}, \quad (22)$$

where $\psi\{\cdot\}$ is a non-linear scaling function. Similar to our proposed SC-IPAPA-I, the motivation of including the sparseness measure in the control matrix is to assign the weighting to the non-proportionate and proportionate terms adaptively. When the impulse response is with sparse measure $\hat{\xi}_{sc}(n) = 1$, it is

desirable to have the proportionate term in (13)

$$\frac{[1 + \alpha(n)]|\hat{h}_l(n)|}{2\|\hat{\mathbf{h}}(n)\|_1 + \epsilon} = 0, \quad (23)$$

and on the other hand, when $\hat{\xi} = 0$ for a dispersive impulse response, it is desirable to have

$$\frac{1 - \alpha(n)}{L} = 0. \quad (24)$$

From (23) and (24), we therefore define two conditions

$$\psi\{\hat{\xi}_{sc} = 0\} = -1, \quad (25)$$

$$\psi\{\hat{\xi}_{sc} = 1\} = 1. \quad (26)$$

There are various non-linear functions can fulfill the conditions of (25) and (26). It is also important to note that impulse responses often follow an exponentially decay model [10]. Therefore, we propose to assign weightings to different tap coefficients following the distribution of an exponential model according to the sparseness measure $\hat{\xi}_{sc}(n)$. However, to obtain the time constant of an impulse response is computationally expensive. For this reason, we propose to use a 3rd-order power function of $\hat{\xi}_{sc}(n)$ to model the exponentially varying weighting as

$$\alpha(n) = \psi\{\hat{\xi}_{sc}(n)\} = \beta[\hat{\xi}_{sc}(n) - 0.5]^3, \quad (27)$$

where β is a scalar. We note that $\beta = 8$ satisfies conditions (25) and (26).

Figure 3 illustrates how $\alpha(n)$ changes with $\hat{\xi}_{sc}(n)$ in our proposed model. It can be seen that the value of the control parameter increases exponentially when the sparseness of the impulse response increases. This implies that the proportionate term gains higher weighting when $\hat{\xi}(n) \rightarrow 1$. On the other hand, the non-proportionate term gains higher weighing when $\hat{\xi}(n) \rightarrow 0$. Similar to (13), the elements in the control matrix for our proposed SC-IPAPA-II can be expressed as

$$g_l(n) = \frac{1 - \psi\{\hat{\xi}_{sc}(n)\}}{2L} + \frac{[1 + \psi\{\hat{\xi}_{sc}(n)\}]|\hat{h}_l(n)|}{2\|\hat{\mathbf{h}}(n)\|_1 + \epsilon}, \quad (28)$$

where $l = 0, 1, \dots, L - 1$ and $\psi\{\hat{\xi}_{sc}(n)\}$ is defined in (27). It is important to note that, unlike [7] where the diagonal elements in the control matrix is dependent on a predefined control parameter α , the relative proportionate/non-proportionate weighting in our proposed SC-IPAPA-II is calculated based on the sparseness of estimated impulse response $\hat{\mathbf{h}}(n)$ at every iteration.

To better understand how (28) allocates step-sizes to different coefficients, we plot the diagonal elements of the control matrix $g_l(n)$ defined in (28) against normalized value of $|h_l(n)|/\max\{|h_l(n)|\}$. It can be seen that the effective step-size increases with the magnitude of the impulse response. It is also important to note that the gradient of the slope increases with sparseness. This implies that the large filter coefficients for a sparse system will adapt with a larger step-size compared to a dispersive system. On the other hand, the

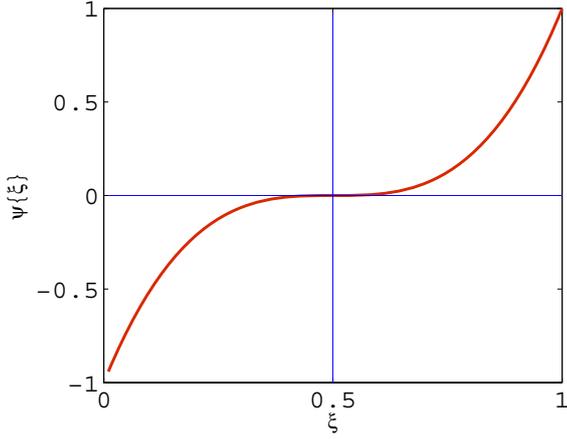


Fig. 3. Control parameter varies with sparseness measure $\hat{\xi}_{sc}(n)$.

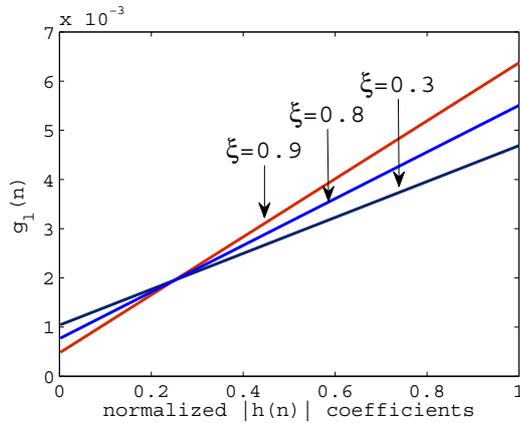


Fig. 4. Magnitude of the elements in the control matrix with different sparseness (ξ) values.

small filter coefficients in a sparse system is assigned with a smaller step-size compared to a dispersive system. Therefore, the contribution of our proposed SC-IPAPA-II is to remove the need to decide on a predefined control parameter as well as achieving high rate of convergence that is robust to the sparseness of the impulse response.

IV. SIMULATION RESULTS

The performance of the proposed SC-IPAPA-I and SC-IPAPA-II algorithm are compared with IPAPA using the normalized misalignment defined by

$$\eta(n) = \frac{\|\mathbf{h} - \hat{\mathbf{h}}(n)\|_2^2}{\|\mathbf{h}\|_2^2}. \quad (29)$$

We assumed throughout our simulation that the length of the adaptive filter is equivalent to that of the unknown system. It is studied in [11] that the amount of improvement in convergence diminishes with increasing p . In order to achieve an equilibrium between the convergence speed and computational load, the projection order is set as $p = 5$ throughout the following simulations.

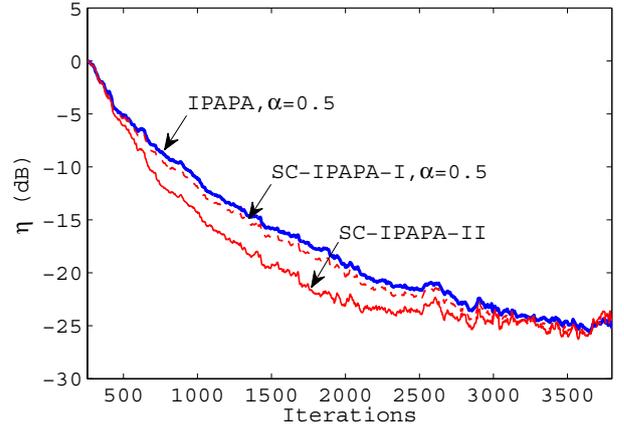


Fig. 5. Convergence of IPAPA, SC-IPAPA-I and SC-IPAPA-II using WGN input.

A. Simulations using WGN input

In the first simulation, we used an impulse response as shown in Fig. 2 (b) with $L = 512$ and $\xi = 0.8162$. The input signal is a zero mean WGN sequence while another zero mean WGN $w(n)$ is added to $y(n)$ as shown in Fig. 1 to achieve signal-to-noise ratio (SNR) of 20 dB. The step-sizes for IPAPA and SC-IPAPA-I are chosen to be $\mu_{IPAPA} = \mu_{SC-IPAPA-I} = 0.1$ while the step-size for SC-IPAPA-II is chosen as $\mu_{SC-IPAPA-II} = 0.2$ in order to achieve the same steady-state normalized misalignment as that for IPAPA and SC-IPAPA-I. We have also used $\alpha_{IPAPA} = \alpha_{SC-IPAPA-I} = 0.5$ [7]. The relative convergence performance of IPAPA, SC-IPAPA-I and SC-IPAPA-II in terms of normalized misalignment are shown in Fig. 5. As can be seen, our proposed SC-IPAPA-I and SC-IPAPA-II achieve faster convergence than that of IPAPA. We can also note that SC-IPAPA-II outperforms SC-IPAPA-I by offering an improvement of approximate 3 dB normalized misalignment. As compared to IPAPA, SC-IPAPA-II achieves improved normalized misalignment of approximately 4 dB.

In the second simulation, we assume that there is an echo path change midway through the simulation where the impulse response is changed from a sparse to one which is less sparse as shown in Fig. 2 (a) and (b). Similar to the input signal used to generate Fig. 5, a zero mean WGN sequence is used as the input signal and the SNR is set as 20 dB in this simulation. The step-sizes are $\mu_{IPAPA} = \mu_{SC-IPAPA-I} = 0.1$ and $\mu_{SC-IPAPA-II} = 0.2$. The control parameter for IPAPA and SC-IPAPA-I are $\alpha_{IPAPA} = \alpha_{SC-IPAPA-I} = 0.5$ as before. It can be observed from Fig. 6 the converged normalized misalignment curves of IPAPA, SC-IPAPA-I and SC-IPAPA-II increase at the 4×10^4 th iteration corresponding to the echo path change. It is important to note that before and after the echo path change, the proposed SC-IPAPA-I and SC-IPAPA-II algorithms achieve higher rate of convergence which implies that SC-IPAPA-I and SC-IPAPA-II have better tracking

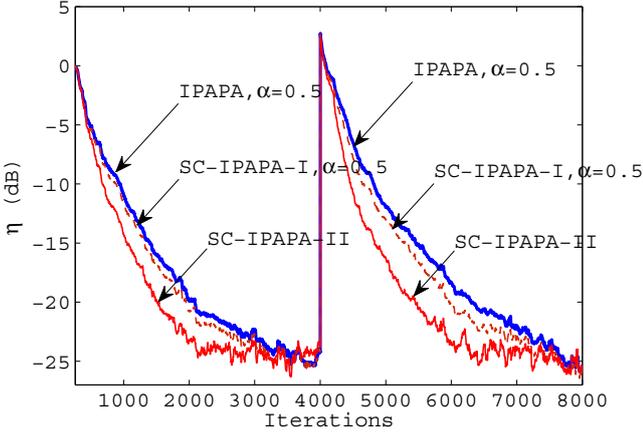


Fig. 6. Convergence of IPAPA, SC-IPAPA-I and SC-IPAPA-II using WGN input with echo path changed at the 4000th iteration.

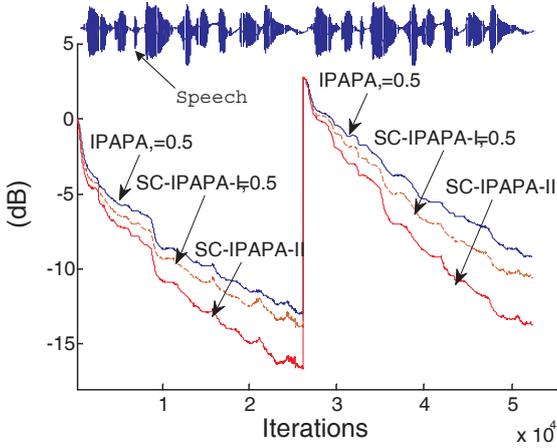


Fig. 7. Convergence of IPAPA, SC-IPAPA-I and SC-IPAPA-II using speech input with echo path changed at the 2.65×10^4 th iteration.

capability compared to IPAPA.

B. Simulation using speech input

In this simulation, we verify the performance of our proposed SC-IPAPA-I and SC-IPAPA-II algorithms using a male speech input. In order for the algorithms to achieve the same steady-state normalized misalignment performance, the step-sizes for IPAPA, SC-IPAPA and SC-IPAPA-II are kept the same as in Section IV-A corresponding to $\mu_{\text{IPAPA}} = \mu_{\text{SC-IPAPA-I}} = 0.1$ and $\mu_{\text{SC-IPAPA-I}} = 0.2$. The control parameter for IPAPA and SC-IPAPA-I are also the same as Section IV-A, $\alpha_{\text{IPAPA}} = \alpha_{\text{SC-IPAPA-I}} = 0.5$. Similar to the results shown in Section IV-A, the proposed SC-IPAPA-I achieves the highest rate of convergence. Compared to IPAPA, the proposed SC-IPAPA-I and SC-IPAPA-II algorithms achieve improvement of approximately 2 dB and 4 dB normalized misalignment, respectively.

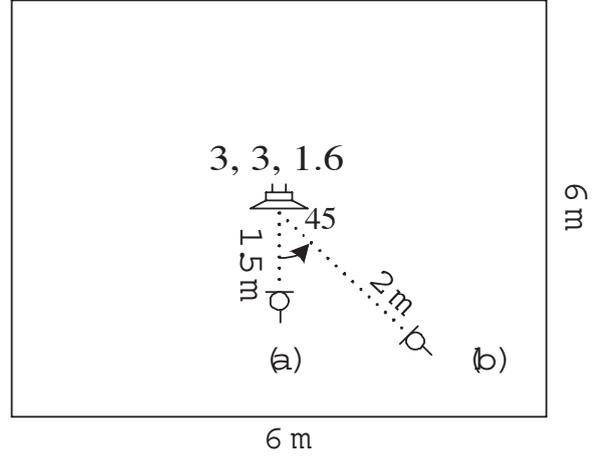


Fig. 8. Experiment setup used in image model to generate room impulse response.

C. Simulation using impulse responses generated by the image model

In the next experiment, we verify the performance of the proposed SC-IPAPA-I and SC-IPAPA-II algorithms using the impulse response generated by the image model [12]. Similar to Figs. 6 and 7, we assume that there is an echo path change midway through the simulation. The dimension of the room adopted in the image model is $(6 \text{ m} \times 6 \text{ m} \times 5 \text{ m})$ and loudspeaker is placed at the center of the room $\{3 \text{ m}, 3 \text{ m}, 1.6 \text{ m}\}$. The sampling frequency f_s is 8 kHz and reverberation time $T_{60} = 300 \text{ ms}$. The RIR is subsequently truncated to a length of $L = 512$ samples. The position of the receiver before the echo path change was $\{2.5 \text{ m}, 4 \text{ m}, 1.6 \text{ m}\}$ while the receiver moves to $\{4.41 \text{ m}, 1.6 \text{ m}, 1.6 \text{ m}\}$ after the echo path change. The experiment setup for this image model is shown in Fig. 8. Figure 9 (a) and (b) show the room impulse responses generated at position ‘a’ and ‘b’ labeled in Fig. 8. The sparseness measure of these impulse responses are $\xi_a=0.8162$ and $\xi_b=0.7768$, respectively. In this simulation, the input signal is generated by a WGN sequence and SNR is set as 20 dB. Similar to Section IV-A and IV-B, the step-sizes are $\mu_{\text{IPAPA}} = \mu_{\text{SC-IPAPA-I}} = 0.1$ and $\mu_{\text{SC-IPAPA-I}} = 0.2$ while the control parameter for IPAPA and SC-IPAPA-I is $\alpha_{\text{IPAPA}} = \alpha_{\text{SC-IPAPA-I}} = 0.5$. The convergence performance of IPAPA, SC-IPAPA-I and SC-IPAPA-II are shown in Fig. 10. As before, we can see that the proposed SC-IPAPA-I and SC-IPAPA-II algorithms achieve higher initial convergence compared to IPAPA before and after the echo path change. More importantly, the proposed SC-IPAPA-II algorithm achieves approximately 3 dB improvement in normalized misalignment while SC-IPAPA-I achieves approximately 1.5 dB improvement as compared to IPAPA, respectively.

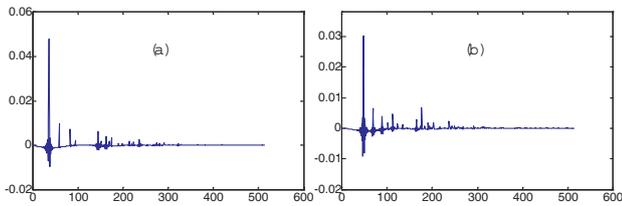


Fig. 9. Impulse responses generated using image model, $L = 512$.

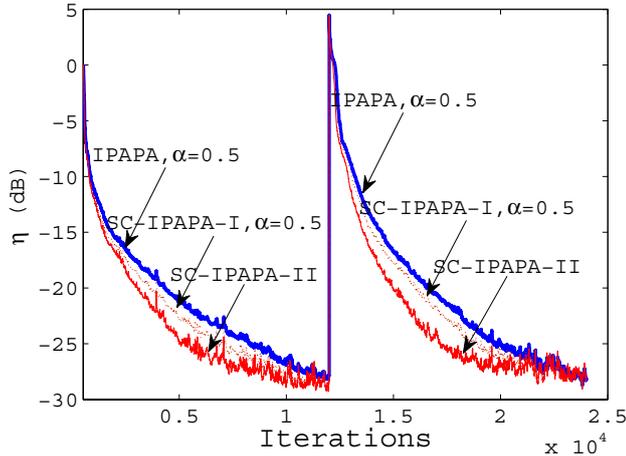


Fig. 10. Convergence of IPAPA, SC-IPAPA-I and SC-IPAPA-II using WGN input with impulse responses generated using image model.

V. CONCLUSION

We presented two sparseness-controlled affine projection algorithms for echo cancellation. Simulation results using impulse responses generated by exponentially decay model described in [4] and image method [12] have shown that our proposed SC-IPAPA-I and SC-IPAPA-II have faster convergence rate than that of IPAPA. More importantly, we have presented a time varying control parameter in SC-IPAPA-II by utilizing the sparseness measure of the estimated impulse response. In our proposed SC-IPAPA-II, the weighting of the proportionate and non-proportionate terms is determined by the sparseness measure of the estimated impulse response rather than a predefined constant in IPAPA algorithm. This sparseness-dependent weighting mechanism overcomes one of the major weaknesses of IPAPA since determination of α is no longer required for the proposed SC-IPAPA-II algorithm.

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