A BIASED MULTICHANNEL ADAPTIVE ALGORITHM FOR ROOM EQUALIZATION

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ABSTRACT

The use of adaptive algorithms in multichannel equalization has become essential to compensate room effects of real sound reproduction systems. Due to the high complexity and number of compensation filters that involve these multiple-input multiple-output (MIMO) systems, a compromise has to be taken to provide good equalization without increasing the complexity of the adaptive algorithm. The impulse responses of a multichannel equalizer are usually long and exhibit a high (or unknown) degree of sparsity, which results in least-mean-square (LMS) type algorithms showing slow convergence speed. Recently, proportionate adaptive schemes have been introduced to accelerate filter convergence and to exploit sparsity in echo cancellation and active noise control systems. Moreover, it is possible to reduce the error of the adaptive filters by biassing the weights, specially under low signal-to-noise ratio condition. In this paper we propose a biased proportionate adaptive algorithm for multichannel room equalization in several scenarios. Experimental results show that the proposed adaptive algorithm significantly outperforms the traditional LMS based ones.

Index Terms— Multichannel equalization, proportionate adaptive filters, biased adaptive filtering.

1. INTRODUCTION

In sound reproduction systems, a sound travels through an acoustic medium before reaching a listener or a microphone. The behavior of the acoustic system at a particular listening position is characterized by its impulse response. In some applications equalization may be usually required to compensate for the listening room response. The goal is to make the global impulse response of the sound reproduction channel as close as possible to a desired one. Fig.1 illustrates the equalization system arrangement. The input source signal $x(n)$ is filtered through the equalization filter previously to feed the loudspeaker. Thus, the combined effect of the equalizer and the acoustic path $\mathbf{h}$ will allow to obtain a good approximation of the desired signal, $z(n)$, at the microphone.

Sound equalization systems have primarily focused on the simplified case of a single source and a single receiver (see Fig.1). Such a setup is the most straightforward to analyze, but real world systems with multiple inputs and multiple outputs (MIMO) are much more complex. They include a wide number of possibilities: from single to multiple sources and/or listeners, sparse or non-so-sparse acoustic channels, or time-varying characteristics are some of them.

Those equalization filters can be implemented in two different forms: fixed or adaptive. Fixed equalization techniques have been used for years to compensate for these room effects (see as example [1] and [2], in time and frequency domain respectively). In these methods, filters are computed once, and usually in a previous stage to the rendering one. However, real systems imply time-varying scenarios.

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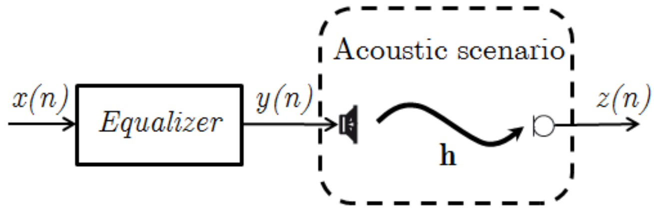


Fig. 1. Sound equalization system.

For this purpose, the equalization filter must be adaptively designed [3],[4]. In the adaptive equalization (AE) context, literature contains several interesting algorithms, which usually consider a least-mean-square (LMS) algorithm, in time or frequency domains. However, these works only present results for a single-input multiple-output (SIMO) system, that is, an AE that computes only one adaptive filter for all the microphone signals (see as example [5]-[7]).

Since long adaptive filters are required for AE, LMS type algorithms (such as the LMS and the normalized LMS (NLMS)) suffer from slow convergence speed. As a solution to this, time-invariant weighted stepsize algorithms are proposed for system identification [8]. However, this method is not straightforward to apply in equalization scenarios. The proportionate adaptive filters (especially the improved proportionate NLMS (IPNLMS) [9]) have been introduced to accelerate filter convergence in scenarios where the optimal solution presents a high (but unknown) degree of sparsity. Those adaptive filters have been successfully applied to system identification [10], acoustic echo cancellation [11] and active noise control (ANC) [12]. The IPNLMS algorithm spends more energy on adapting the active coefficients, and it converges faster than the NLMS. However, the IPNLMS requires to know the degree of sparsity of the optimal solution, which rarely occurs in practical systems. To improve the robustness of the IPNLMS to these channels, in [13] was presented the convex combination of IPNLMS filters for echo cancellation. In the context of ANC, the combination of LMS filters was successfully applied in [14] and the combination of IPNLMS filters in [12].

Recently, a new scheme has been proposed to reduce the error of the adaptive filters [15] by means of including a bias. This method uses a scaling factor $\lambda(n)$ that multiplies the estimator, providing a bias estimator of the optimal solution that can outperform the unbiased one, especially when the signal-to-noise ratio (SNR) is low. The suitable selection of the scaling factor to bias the weights is a key issue of this scheme. In [15], $\lambda(n)$ is effectively adapted by considering this scheme as the convex combination of the output of a standard filter and that of a virtual filter with constant output equal to zero. In this contribution, the bias adaptive scheme will be considered to improve robustness of the IPNLMS filters for multichannel AE, mainly when the SNR changes over time. This strategy is more computationally efficient than the standard convex combination structure, which requires at least a double number of adaptive filters.

In this paper, the IPNLMS algorithm with the conventional filtered-x scheme [3] embedded (IPNLMS-FX), previously introduced for ANC [12], is extended to multichannel AE applications. This extension is not straightforward and requires some modifications. However, we have undertaken one step further and propose a biased multichannel IPNLMS-FX algorithm that can satisfactorily work in the AE context. Simulation results illustrate the ability of the derived biased algorithm to improve the steady-state error and robustness against unknown or time-varying degrees of sparsity and low SNR. This algorithm has been compared with both the IPNLMS-FX algorithm and the NLMS algorithm based on the conventional filtered-x structure (NLMS-FX).

In Section 2 of this paper, a brief description of the single-channel and multichannel IPNLMS-FX (MIPNLMS-FX) algorithms for AE will be presented. Section 3 will describe the algorithms that result from the biasing of the IPNLMS-FX algorithms: the biased IPNLMS-FX and its multichannel version (the biased MIPNLMS-FX). Simulations are performed in Section 4 for a single-channel and a multichannel AE with different SNR and room channels with different degrees of sparsity. Finally, Section 5 summarizes the main conclusions of this work.

2. IMPROVED PROPORTIONATE ADAPTIVE FILTERS FOR MULTICHANNEL EQUALIZATION

In this section we extend the IPNLMS algorithm described in [9] to multichannel AE.

2.1. Single-channel IPNLMS-FX

First, we will describe the single-channel improved proportionate NLMS algorithm that has been adapted to room equalization application with the conventional filtered-x structure embedded (IPNLMS-FX). The block diagram of a single-channel AE system is shown in Fig. 2. The output of the adaptive filter $y(n)$ can be expressed as:

$$y(n) = \mathbf{w}^T(n-1)\mathbf{x}_{L_w}(n), \tag{1}$$

where $\mathbf{w}(n) = [w_0(n), w_1(n), \ldots, w_{L_w-1}(n)]^T$ is the weight vector of L_w-length, and $\mathbf{x}_{L_w}(n) = [x(n), x(n-1), \ldots, x(n-(L_w-1))]^T$ includes the last L_w samples of the input signal $x(n)$. The signal measured at the microphone ($z(n)$) is subtracted from the desired signal in order to obtain the error signal ($e(n)$), which will be used to update the adaptive filter weights,

$$z(n) = \mathbf{h} * y(n) \tag{2}$$

$$e(n) = d(n) - z(n). \tag{3}$$

The desired signal $d(n)$ corresponds to the input signal with a suitable source-microphone delay $x(n-\tau)$ and $\mathbf{h}$ is assumed to be stationary during the convergence of the algorithm.

The IPNLMS-FX weights are updated at each iteration according to

$$w_l(n) = w_l(n-1) + \mu_l(n)e(n)x_f(n-l),\ l = 0, \ldots, L_w-1, \tag{4}$$

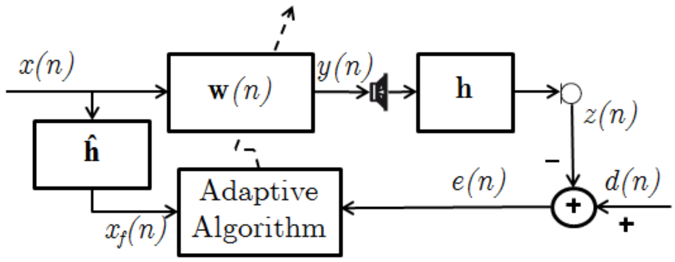


Fig. 2. Single-channel IPNLMS-FX system.

where $x_f(n)$ is the input signal $x(n)$ filtered through the estimated impulse response $\hat{\mathbf{h}}$. Furthermore, the adaptation speed for each filter weight, with μ being the step size for the IPNLMS filter, is computed for the IPNLMS-FX algorithm as:

$$\mu_l(n) = \frac{\mu g_l(n)}{\delta + \sum_{k=0}^{L_w-1} g_k(n) x_f^2(n-k)}, \tag{5}$$

with the adaptation gain factors given by

$$g_l(n) = (1-\kappa)\frac{1}{2L} + (1+\kappa)\frac{|w_l(n)|}{\varepsilon + 2\sum_k |w_k(n)|}, \tag{6}$$

where δ and ε are small constants to avoid division by zero, and $\kappa \in [-1, 1]$ arranges from an NLMS-FX algorithm ($\kappa = -1$) to $\kappa = 1$, where the adaptation is proportional to the absolute value of each filter weight.

2.2. Multichannel IPNLMS-FX

A generic multichannel AE (with J loudspeakers and M microphones) is considered and illustrated in Fig. 3 to extend the IPNLMS-FX algorithm to the multichannel case (MIPNLMS-FX). This system presents $J \times M$ room responses, multiple error signals and multiple adaptive filters to simultaneously be updated. The management of those signals become the main difficulty in extending the IPNLMS-FX to the multichannel case. Thus, the equations of the IPNLMS-FX algorithm can be rewritten as follows.

The rendering signal of each loudspeaker $y_j(n)$ can be expressed as,

$$y_j(n) = \mathbf{w}_j^T(n-1)\mathbf{x}_{L_w}(n), \quad j = 1, \ldots, J, \tag{7}$$

where $\mathbf{w}_j(n)$ denotes the jth adaptive filter. The signal measured at each microphone and its corresponding error are given, respectively, by (8) and (9),

$$z_m(n) = \sum_{j=1}^{J} \mathbf{h}_{m,j} * y_j(n), \quad m = 1, \ldots, M, \tag{8}$$

$$e_m(n) = d_m(n) - z_m(n), \tag{9}$$

where $\mathbf{h}_{m,j}$ is the room channel response between loudspeaker j and microphone m, and the desired signal $d_m(n)$ corresponds to the input signal with its corresponding source-microphone delay $x(n-\tau_m)$.

Each single adaptive filter follows its own update equation, thus, among the different possibilities, the L_w weights of each adaptive filter are updated according to

$$\mathbf{w}_j(n) = \mathbf{w}_j(n-1) + \boldsymbol{\mu}_j(n) \sum_{m=1}^{M} e_m(n)\mathbf{x}_{f_{(m,j)}}(n), \tag{10}$$

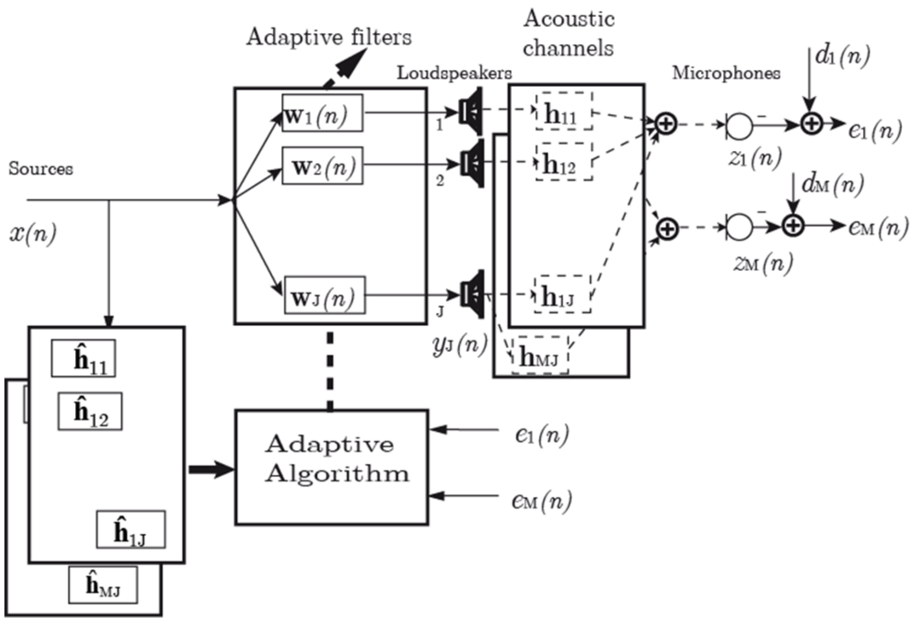


Fig. 3. Block diagram of a multichannel AE system.

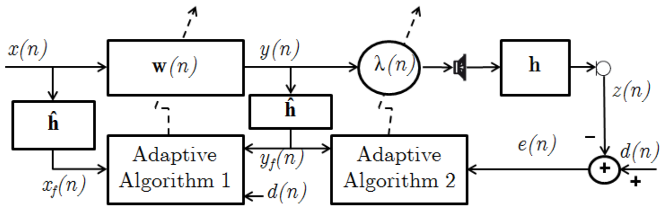


Fig. 4. Block diagram of a biased single-channel AE system.

being $\mathbf{w}_j(n) = [w_{j,0}(n), w_{j,1}(n), \ldots, w_{j,L_w-1}(n)]^T$, and $\mathbf{x}_{f_{(m,j)}}(n)$ the last L_w samples of the source signal filtered through the estimated room channel from loudspeaker j to microphone m. Similarly to (5) and (6), it is obtained,

$$\boldsymbol{\mu}_j(n) = \frac{\mu \mathbf{g}_j(n)}{\delta + \sum_{k=0}^{L_w-1} g_{j,k}(n) x^2_{f_{(m,j)}}(n-k)} \quad \text{and} \tag{11}$$

$$\mathbf{g}_j(n) = (1-\kappa)\frac{1}{2L} + (1+\kappa)\frac{|\mathbf{w}_j(n)|}{\varepsilon + 2\sum_k |w_{j,k}(n)|}. \tag{12}$$

3. BIASED IPNLMS-FX ADAPTIVE FILTERS

A novel scheme that biases the weights of the adaptive filter was introduced in [15] for channel identification in order to reduce the adaptive filter mean-square error, mainly when working in SNR situations. In this section we will adaptively bias the weights of the IPNLMS-FX algorithm providing the biased IPNLMS-FX algorithm. Fig. 4 shows the block diagram of a biased single-channel AE system. This strategy requires to rewrite (2) and (4) as:

$$z(n) = \lambda(n)[\mathbf{h} * y(n)] \tag{13}$$

$$w_l(n) = w_l(n-1) + \mu_l(n) e'(n) x_f(n-l), \quad l = 0, \ldots, L_w - 1. \tag{14}$$

where $e'(n) = d(n) - y_f(n)$ is the error due to the output of the adaptive filter $y(n)$ filtered by $\hat{\mathbf{h}}$ (adaptive block 1 in Fig. 4).

The scaling factor of the algorithm $[\lambda(n)]$ is defined by using a sigmoid activation function

$$\lambda(n) = \frac{sgm[a(n)] - sgm[-4]}{sgm[4] - sgm[-4]}, \tag{15}$$

where $a(n)$ is updated according to the following expression, similarly to [12],

$$a(n+1) = a(n) - \frac{\overline{\mu}_a}{p(n)} \frac{\partial e^2(n)}{\partial a(n)}, \tag{16}$$

where $\overline{\mu}_a$ is the adaptation speed, $p(n)$ the normalizing factor and $e(n)$ is given in (3).

The biased IPNLMS-FX strategy can be extended to the multichannel case, providing the biased MIPNLMS-FX. According to the notation in section 2.2, this algorithm is described by **Algorithm 1**.

4. EXPERIMENTAL RESULTS

For the study of the algorithms proposed (the IPNLMS-FX, the biased IPNLMS-FX and their multichannel versions), several experiments have been carried out with different scenarios. Moreover these algorithms have been compared with the NLMS-FX algorithm. In a first experiment we consider the single-channel case with one loudspeaker and one microphone (1:1:1 AE system). A second experiment considers a more complex configuration, specifically a MIMO system with two loudspeakers and two microphones (1:2:2 AE system).

Some changes in the channel response (including different degrees of sparsity and time-varying SNR) have been implemented to study the robustness of the algorithms and to take into account that $\mathbf{h}$ could be non-stationary in practical systems. These acoustic channels have been measured in a real audio room, with a reverberation time, τ_{60}, of approximately 250 ms. Fig. 5(a) shows an example of these impulse responses (with 256 taps) of the 1:2:2 system. The simulations start with non-sparse impulse responses and commute to different ones in the second part of the simulations. The new impulse responses have been artificially obtained from the previous paths by taking the first 50 samples and zero-padding to length 256

Algorithm 1 Biased MIPNLMS-FX.

Require: Source signal $x(n)$ and microphone signals $z_m(n)$, $m = 1, \ldots, M$

Ensure: Output of the adaptive filters $y_j(n), \quad j = 1, \ldots, J$

1: Update the vector $\mathbf{x}_{L_w}(n)$ and $\mathbf{x}_{f_{(m,j)}}(n)$

2: $y_j(n) = \mathbf{w}_j^T(n-1)\mathbf{x}_{L_w}(n), \quad j = 1, \ldots, J$

3: $e_m(n) = d_m(n) - z_m(n), \quad m = 1, \ldots, M$

4: Update vector $\mathbf{y}(n)$ and $y_{f_{(m,j)}}$

5: $\overline{\mu}_{a_j} = \frac{\mu_{a_j}}{sgm[4] - sgm[-4]}$

6: $p_j(n) = \beta p_j(n-1) + (1-\beta) y^2_{f_{(m,j)}}(n)$

7: $a_j(n) = a_j(n-1) +$
$+\frac{\overline{\mu}_{a_j}}{p_j(n)} \sum_{m=1}^{M} [e_m(n) y_{f_{(m,j)}}(n)] sgm[a_j(n-1)]\{1 - sgm[a_j(n-1)]\}$

8: $\lambda_j(n) = \frac{sgm[a_j(n)] - sgm[-4]}{sgm[4] - sgm[-4]}$

9: $e'_{m,j}(n) = d_m(n) - \Sigma_{j=1}^{J} y_{f_{(m,j)}}(n)$

10: $\mathbf{g}_j(n) = (1-\kappa)\frac{1}{2L} + (1+\kappa)\frac{|\mathbf{w}_j(n)|}{\varepsilon + 2\sum_k |w_{j,k}(n)|}$

11: $\boldsymbol{\mu}_j(n) = \frac{\mu \mathbf{g}_j(n)}{\delta + \sum_{k=0}^{L_w - 1} g_{j,k}(n) x^2_{f_{(m,j)}}(n-k)}$

12: $\mathbf{w}_j(n) = \mathbf{w}_j(n-1) + \boldsymbol{\mu}_j(n) \sum_{m=1}^{M} e'_{m,j}(n) \mathbf{x}_{f_{(m,j)}}(n)$

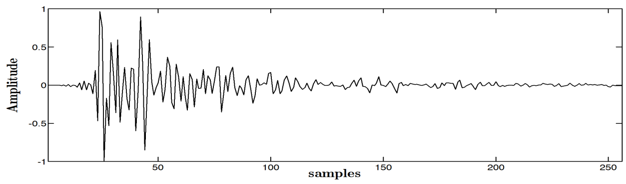
(see Fig. 5(b)). An uncorrelated noise signal has been added to the microphones to simulate a real scenario. The power of the additive noise has been set to get two different SNR (5 and -5dB).

The adaptive filters have a length of $L_w = 256$ taps, same length as the room responses. A step size $\mu = 0.2$ and an asymmetry factor $\kappa = -0.5$ (as recommended in [9]) have been fixed for the IPNLMS type algorithms. Other parameters for the biased method have been set to $\mu_a = 0.1$ and $\beta = 0.9$.

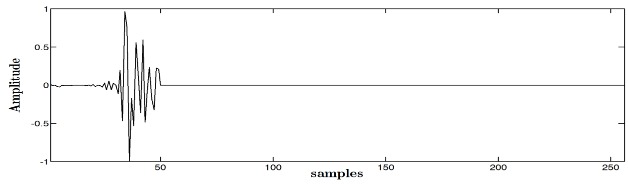
The evaluation of the algorithms behavior is based on the system distance (D) index [16] with a lower value implying a better performance, $\mathrm{D}(n) = 20\log_{10}[\|(\mathbf{w}(n) * \mathbf{h}) - \delta(n-\tau)\|_2 / \|\delta(n-\tau)\|_2]$, being $\|\cdot\|_2$ the 2-norm. The results have been obtained by averaging 100 independent runs.

First we illustrate the performance of the IPNLMS-FX, the biased IPNLMS-FX and the NLMS-FX algorithms for a single-channel system. Fig. 6(a) represents the D of the three algorithms. As can be observed, the IPNLMS-FX and its biased version exhibit faster convergence especially after $n = 200,000$ where the degree of sparsity of the room channel increases. For high SNR, both algorithms follow the same behavior independently of the sparsity of the system. However, the biased IPNLMS-FX performs better than both, the IPNLMS-FX and the NLMS-FX, when the SNR worsens from $100,000 < n < 200,000$ and within the last $100,000$ iterations. In Fig. 6(b) the evolution of $\lambda(n)$ is displayed. With higher values of SNR, the IPNLMS-FX algorithm has a good convergence and consequently $\lambda \simeq 1$ for the biased IPNLMS-FX algorithm; for lower SNR, the IPNLMS-FX convergence worsens and the biased method exhibits an improved behavior with $\lambda < 1$. Furthermore, it can be noticed that the scaling factor tends towards zero when the algorithm has to re-converge.

In the second experiment we consider a 1:2:2 MIMO system where the performance of the MIPNLMS-FX and the biased MIPNLMS-FX has been compared. As expected, a behavior similar to the single-channel case is obtained. Fig. 7 shows the D evolution at the two microphones. The convergence performance



(a) Non-sparse impulse response



(b) Sparse impulse response

Fig. 5. Room impulse responses.

of both algorithms is very similar when SNR $=$ 5dB, independently of the degree of sparsity of the impulse responses. However, when SNR $= -5$dB the biased approach clearly outperforms the MIPNLMS-FX algorithm (between $n = 100,000$ and $n = 300,000$). The evolution of $\lambda(n)$ in Fig. 8 evidences the advantage of including a bias different to zero when the SNR is low. Moreover, the evolution of the two bias parameters is slightly different between $n = 200,000$ and $n = 300,000$, due to the different D performance obtained at both microphones.

5. CONCLUSIONS

This work presents an adaptive equalization algorithm to compensate for the room effects in MIMO systems. The new algorithm proposed (the biased IPNLMS-FX and its multichannel version) is based on both the proportionate adaptation implemented with the IPNLMS algorithm and the biasing of the adaptive filter weights. First, the proportionate adaptation with a suitable configuration provides improve convergence with respect to the standard NLMS-FX algorithm, especially when the impulse responses involved have a high (or unknown) degree of sparsity. Moreover, a scaling factor has been introduced to bias the adaptive filter weights to improve the robustness of the algorithms, mainly with low SNR. The scaling factor has been effectively adapted by considering the convex combination of adaptive filters, providing a reduction in the adaptive filter error.

Simulations in stationary and non-stationary conditions have been carried out with different configurations (single and multiple channels, time-varying room responses with different degrees of sparsity and different SNR). The experimental results have shown good convergence properties of the proposed approach and its ability to reconverge when the SNR or the impulse response suddenly change, validating the proposed biased IPNLMS-FX algorithm for equalization of MIMO systems.

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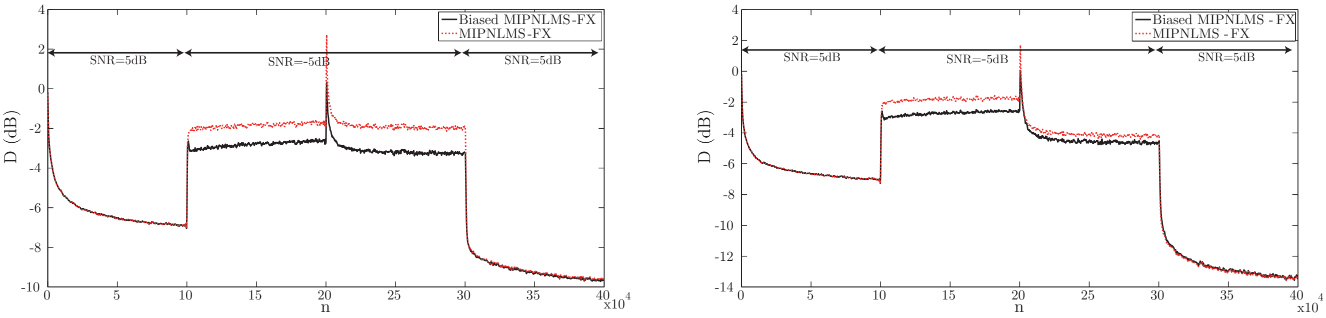
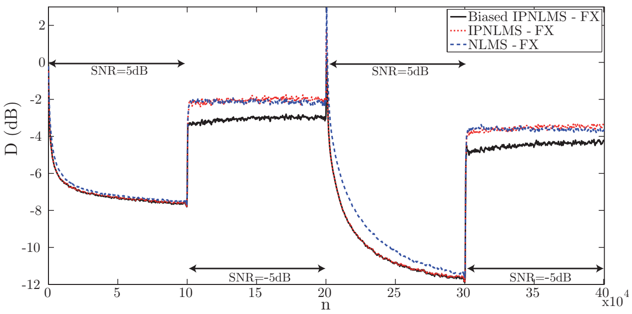
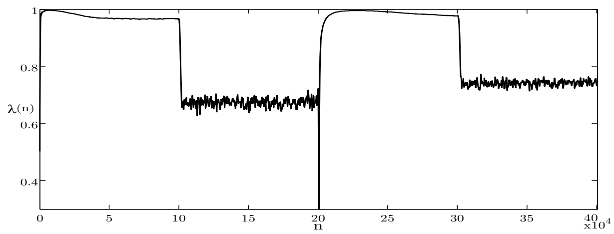


(a) (b)

Fig. 7. D(n) evolution for the 1:2:2 configuration for: (a) microphone 1, and (b) microphone 2.



(a)



(b)

Fig. 6. (a) D(n) and (b) $\lambda(n)$ evolution for the single-channel case.

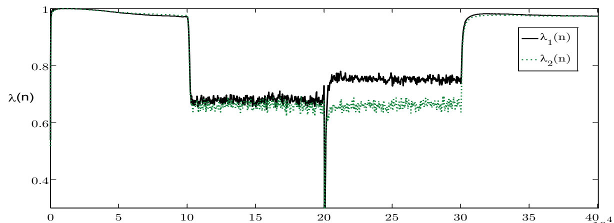


Fig. 8. Scaling factor evolution for the 1:2:2 AE system.

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