A Partitioned Block Proportionate Adaptive Algorithm for Acoustic Echo Cancellation

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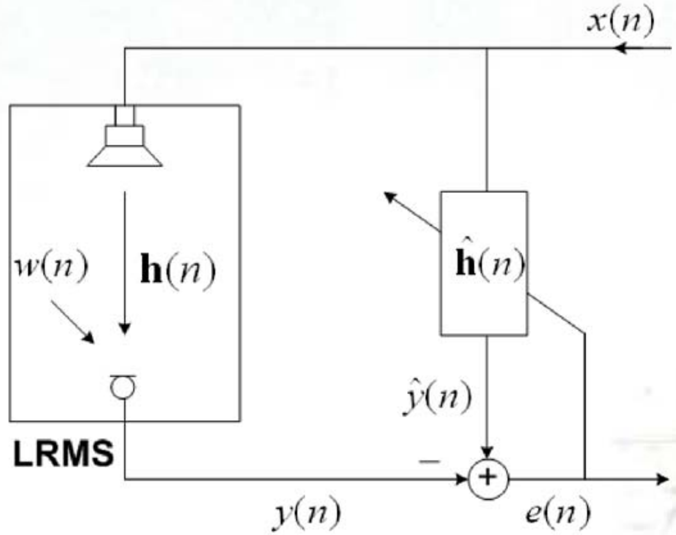
Introduction

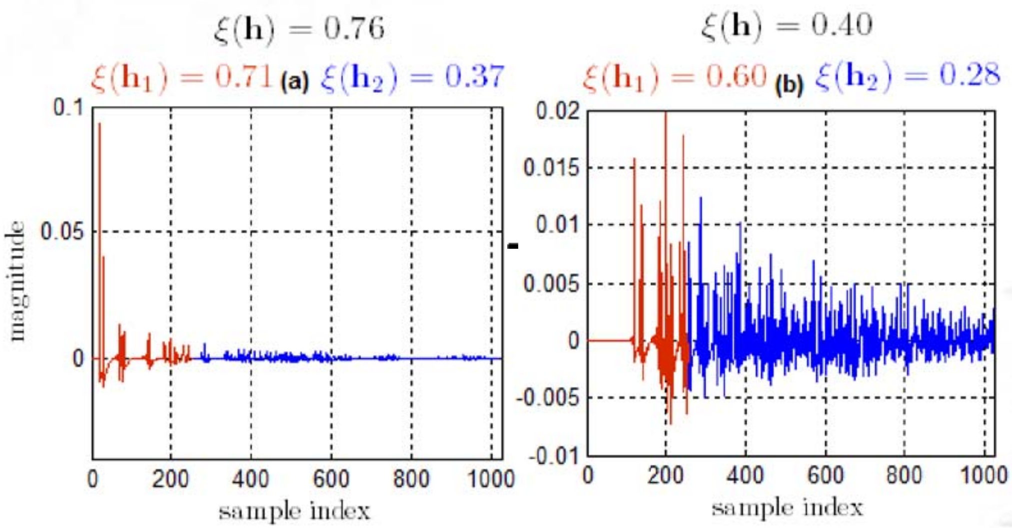
- Acoustic echo due to the coupling between the loudspeaker and microphone.



- Adaptive filters employed in AEC
  - Two signals are available:
    1. input signal to LRMS $x(n)$
    2. output signal from LRMS $y(n)$
  - Predict $\mathbf{h}(n)$ so that $e(n)$ is minimised at each iteration.

Motivation

- Partition the acoustic impulse response (of a LRMS) into 2 blocks
  - First block contains the direct path and early reflections of the AIR
  - Second block contains the late reverberant part of the AIR



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

i.e. : $\xi(\mathbf{w})=1 \Rightarrow$ highly sparse

$\xi(\mathbf{w})=0 \Rightarrow$ highly dispersive

$\Rightarrow$ **The first block is in both cases substantially sparser than the second block.**

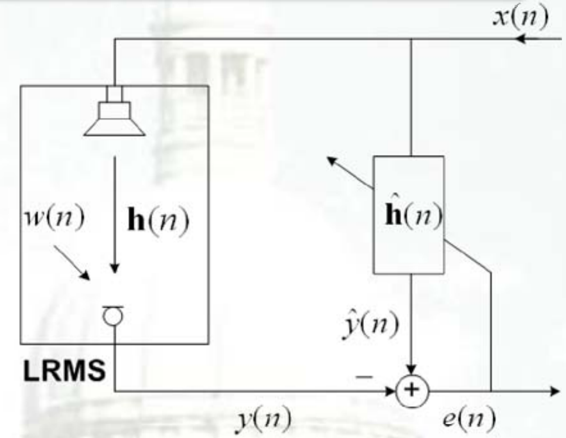
Review of IPNLMS

- General formulation

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

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

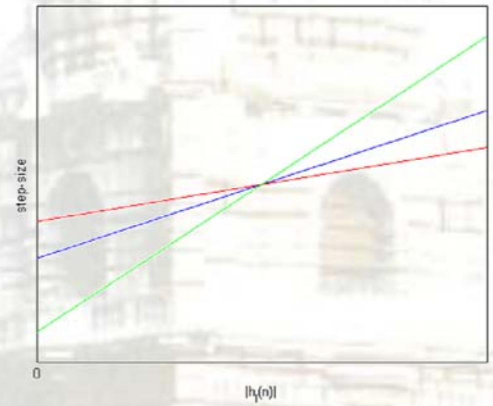
$$\mathbf{Q}(n-1) = \mathrm{diag}\left\{q_0(n-1), q_1(n-1), \ldots, q_{L-1}(n-1)\right\}$$



- IPNLMS:

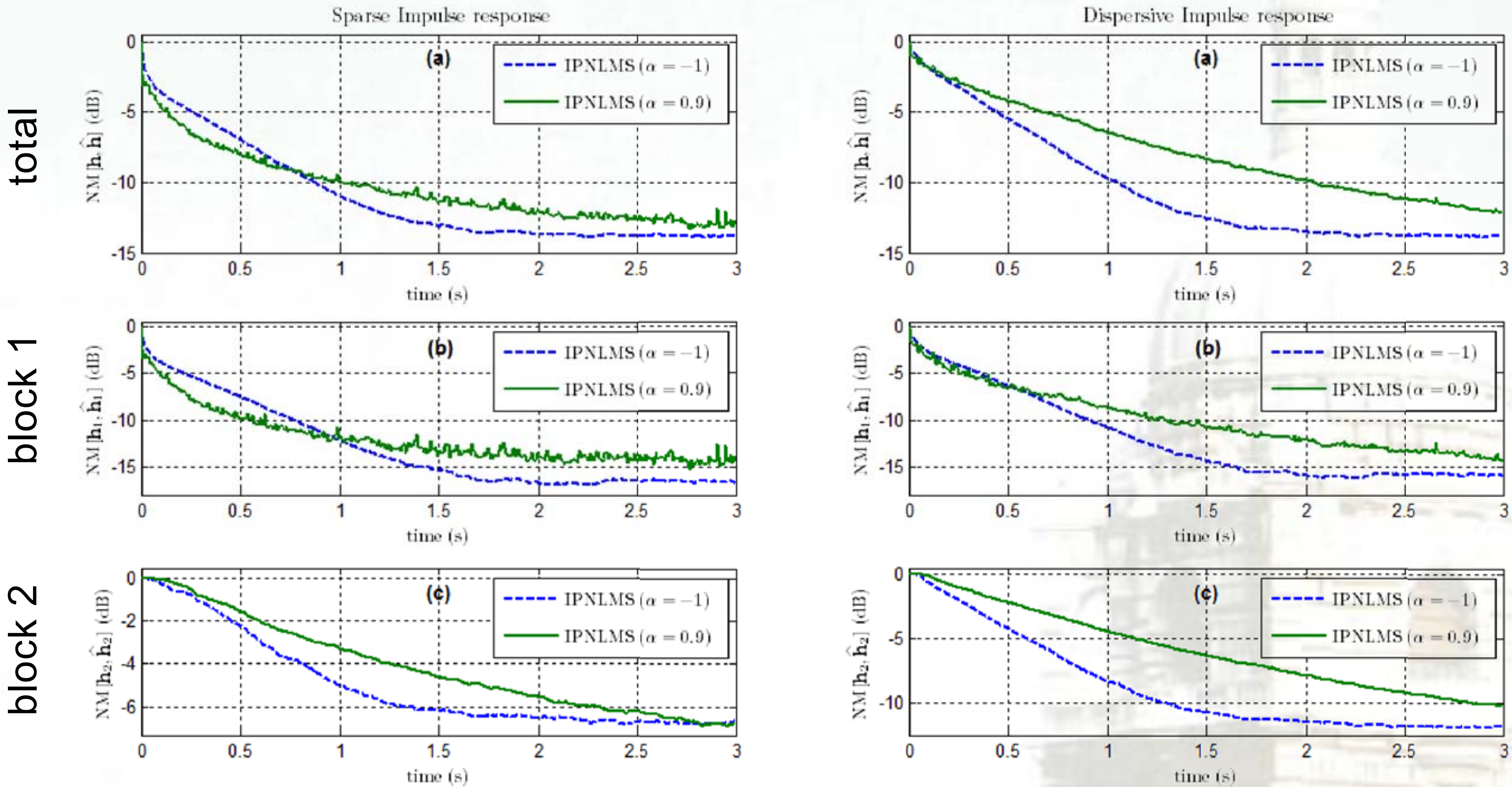
$$q_l(n) = \frac{1-\alpha}{2L} + \frac{(1+\alpha)|\hat{h}_l(n)|}{2\|\hat{h}_l(n)\|_1 + \delta}, \quad l = 0, 1, \ldots, L-1$$

$$\alpha = 0, -0.5, -0.75$$



+ faster convergence for sparse and dispersive impulse responses compared to NLMS and PNLMS.
− slower convergence for highly sparse impulse response compared to µ-law proportionate normalized least mean square (MPNLMS).

IPNLMS example



- Desired: IPNLMS with α=0.9 (i.e. sparse algorithm) for the first block, initially
  IPNLMS with α= -1 (i.e. dispersive algorithm) for the second block

The PB-IPNLMS algorithm

$$
\begin{aligned}
\widehat{\mathbf{h}}_1(n) &= [\widehat{h}_0(n) \ \ldots \ \widehat{h}_{L_1-1}(n)]^T \\
\widehat{\mathbf{h}}_2(n) &= [\widehat{h}_{L_1}(n) \ \ldots \ \widehat{h}_{L-1}(n)]^T \\
\widehat{\mathbf{h}}(n) &= [\widehat{\mathbf{h}}_1(n)^T \ \widehat{\mathbf{h}}_2(n)^T]^T
\end{aligned}
$$

(includes direct path and few early reflections)

(includes all other reflections)

The variable step-size for the first block of length L_1

$$
\begin{aligned}
q_l(n) &= \frac{(1-\alpha_1)}{2L_1} + \frac{(1+\alpha_1)|\widehat{h}_l(n)|}{2\|\widehat{\mathbf{h}}_1(n)\|_1+\delta_{\mathrm{IP}}}, \qquad 0 \le l \le L_1 - 1 \\
\mathbf{Q}_1(n-1) &= \mathrm{diag}\left\{q_0(n-1), \ldots, q_{L_1-1}(n-1)\right\}
\end{aligned}
$$

The variable step-size for the second block

$$
\begin{aligned}
q_l(n) &= \frac{(1-\alpha_2)}{2(L-L_1)} + \frac{(1+\alpha_2)|\widehat{h}_l(n)|}{2\|\widehat{\mathbf{h}}_2(n)\|_1+\delta_{\mathrm{IP}}}, \qquad L_1 \le l \le L - 1 \\
\mathbf{Q}_2(n-1) &= \mathrm{diag}\left\{q_{L_1}(n-1), \ldots, q_{L-1}(n-1)\right\}
\end{aligned}
$$

The PB-IPNLMS algorithm

- But, for IPNLMS the following holds:

$$\mathrm{diag}(\mathbf{Q}(n-1)) = \sum_{l=0}^{L-1} q_l(n-1) = 1$$

- Non-proportionate PB-IPNLMS

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

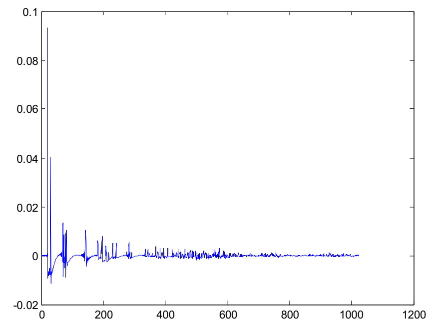
- Proportionate PB-IPNLMS

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

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

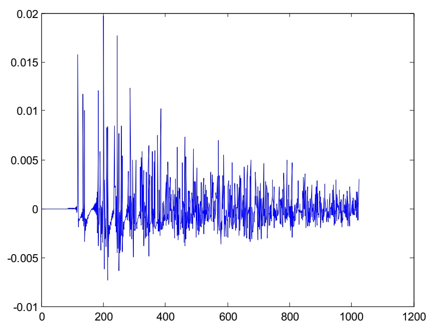
Simulation setup

- $x(n)$ – White Gaussian Noise (WGN)
- $\mathbf{h}(n)$ – $L = 1024$
  - Sparse

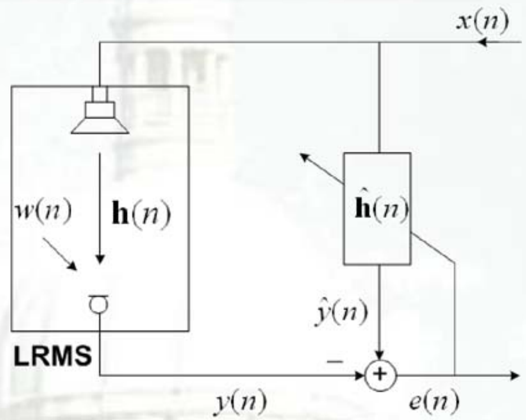


sparseness measure, $\xi(\mathbf{h}) = 0.76$

  - Dispersive



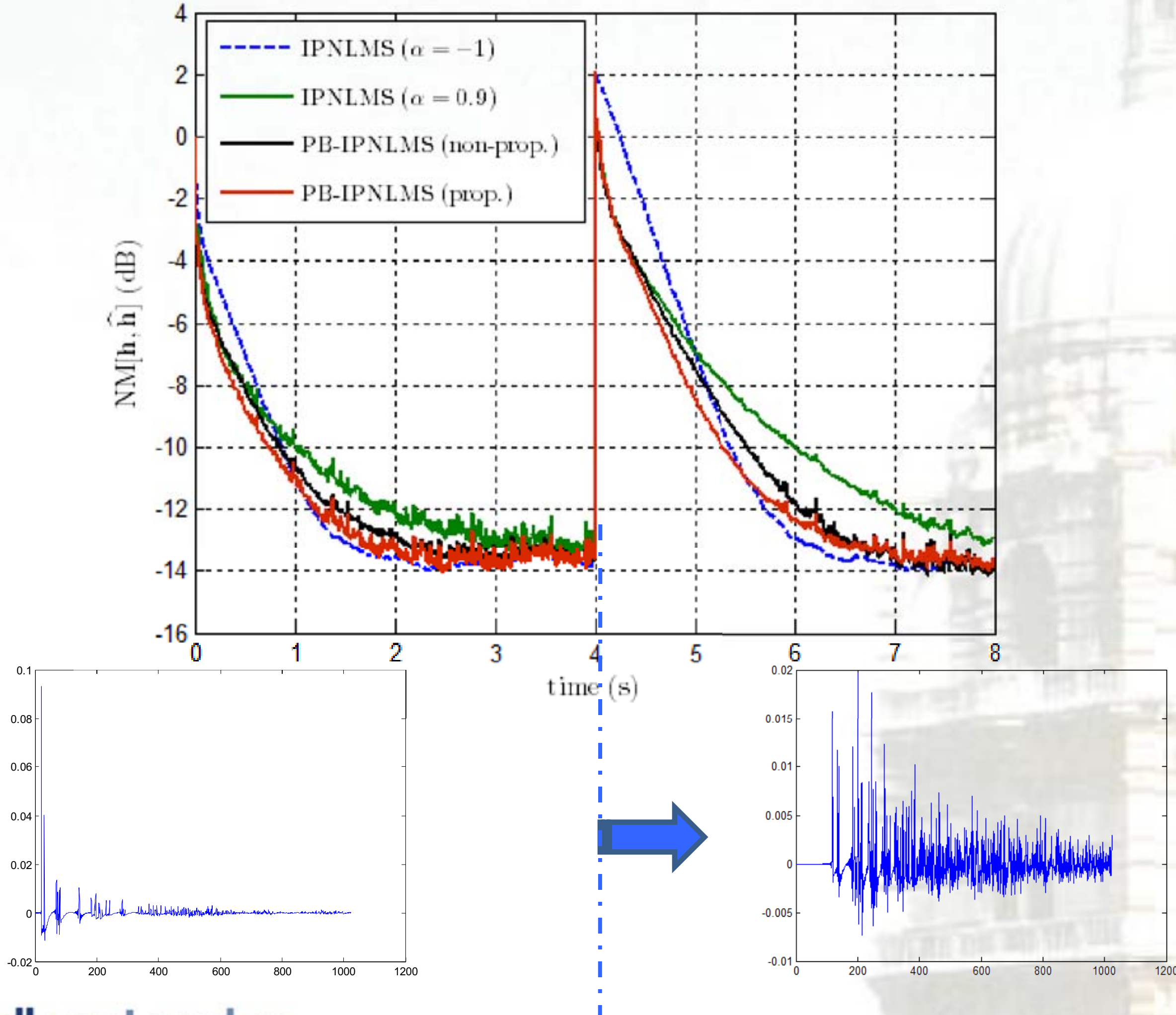
sparseness measure, $\xi(\mathbf{h}) = 0.40$



- $w(n)$ – WGN to give an SNR = 20dB
- Step-sizes: $\mu = 0.3$

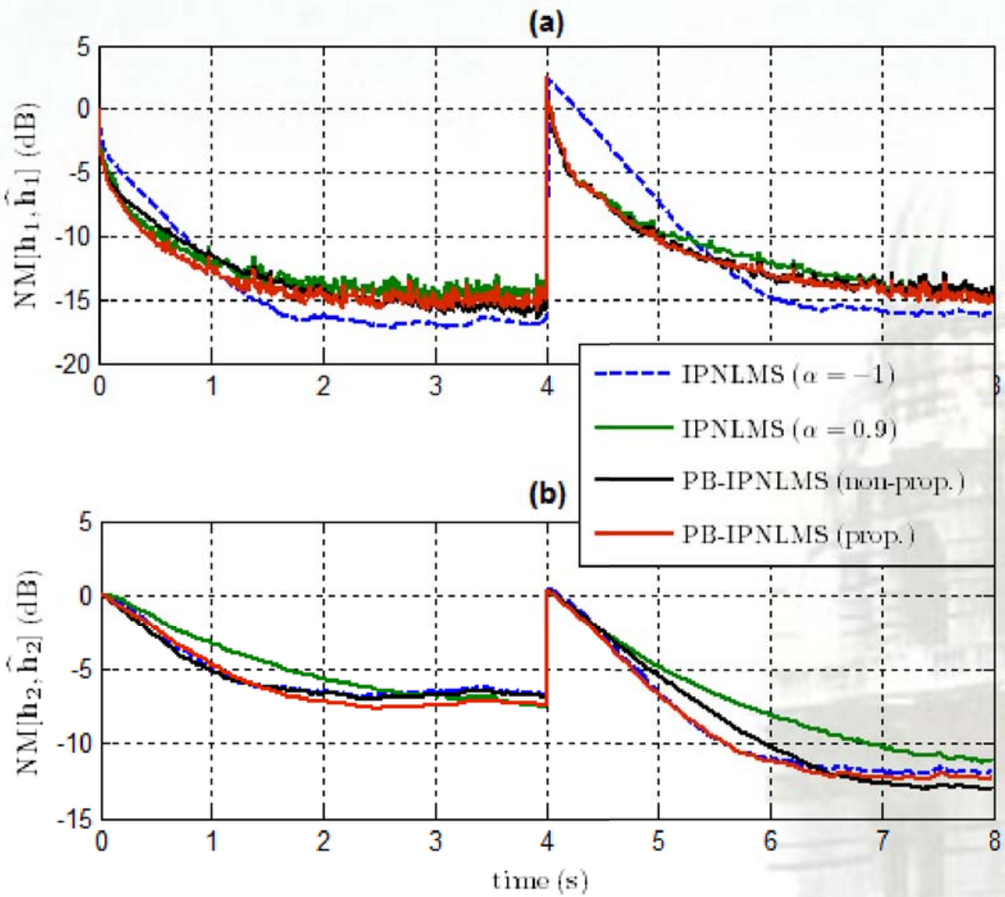
Simulation results using WGN

- Overall performance



Simulation results using WGN

- Performances for the first and second partitioned blocks



Conclusions

- For sparse and dispersive echo paths, the partitioned block of the echo path that consists of the direct path and a few early reflections is typically sparser than the second block.
  - a sparse algorithm is desired for the first block,
  - a non-sparse algorithm is desired for the second block.

- PB-IPNLMS is proposed with two IPNLMS with a different proportional/non-proportional factor
  - works well in both sparse and dispersive circumstances
  - in practical applications involving time-varying systems

Thank You …

Simulation results using a coloured input signal

- Using a coloured input signal

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

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