A SPARSENESS CONTROLLED PROPORTIONATE ALGORITHM FOR ACOUSTIC ECHO CANCELLATION

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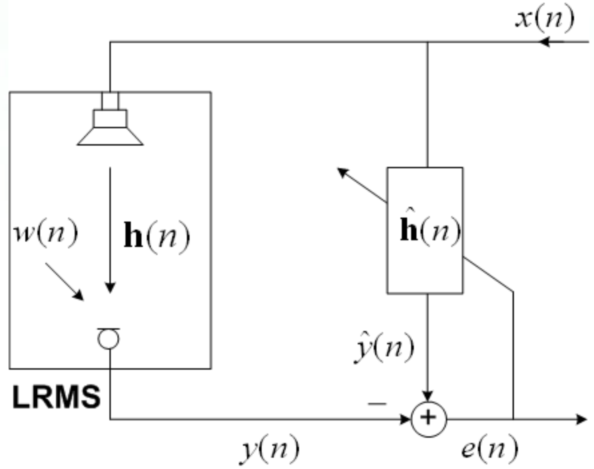
Introduction

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

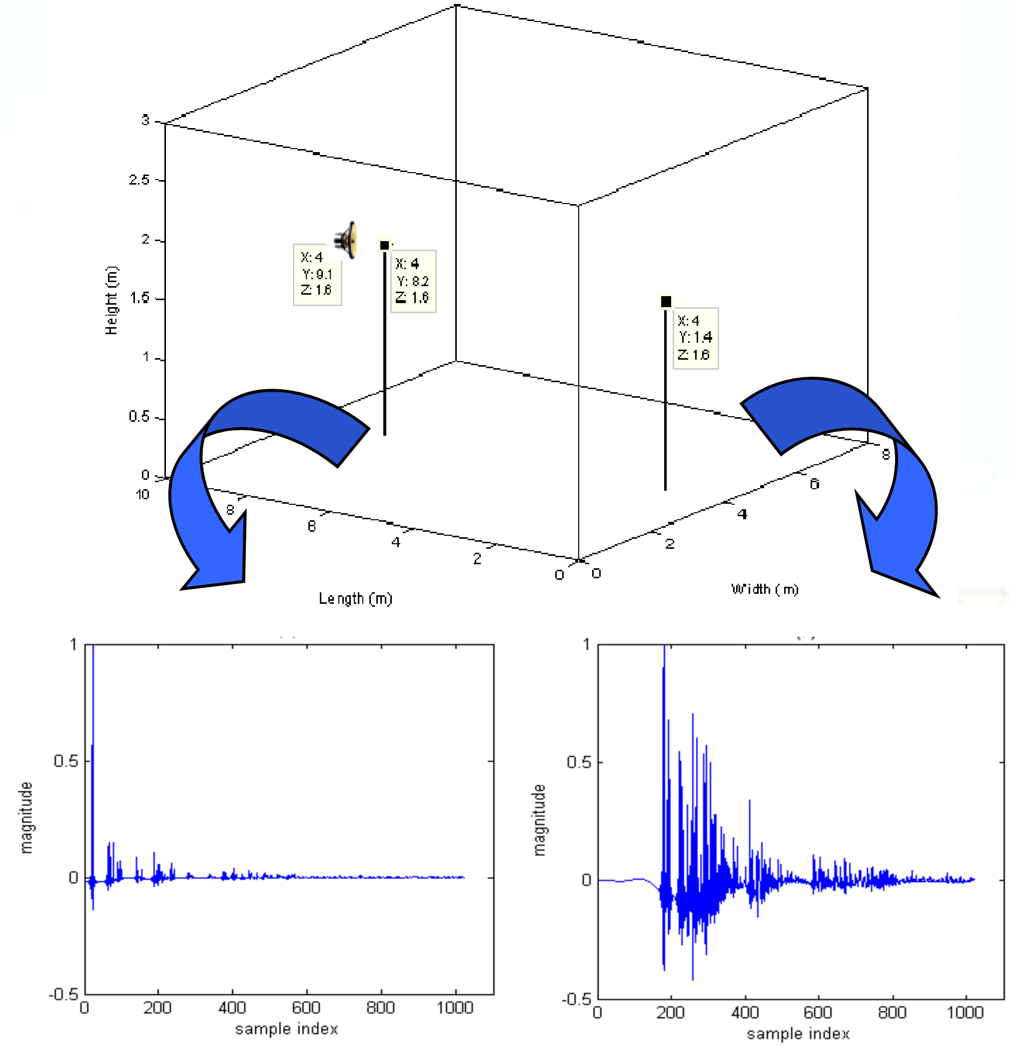


- Acoustic echo cancellation (AEC) applications:
  - Hands-free car phone systems
  - Standard speakerphone
  - Teleconferencing systems

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

Motivation

- Loudspeaker-Room-Microphone system (LRMS)
  - room dimension of $8 \times 10 \times 3$ m
  - loudspeaker fixed at $4 \times 9.1 \times 1.6$ m
  - microphone positioned at
    - a) $4 \times 8.2 \times 1.6$ m
    - b) $4 \times 1.4 \times 1.6$ m



- Sparse reduces with increasing separation between loudspeaker and microphone.

$\Rightarrow$ **Algorithms for AEC are required to be robust to the variations in the sparseness of the impulse response.**

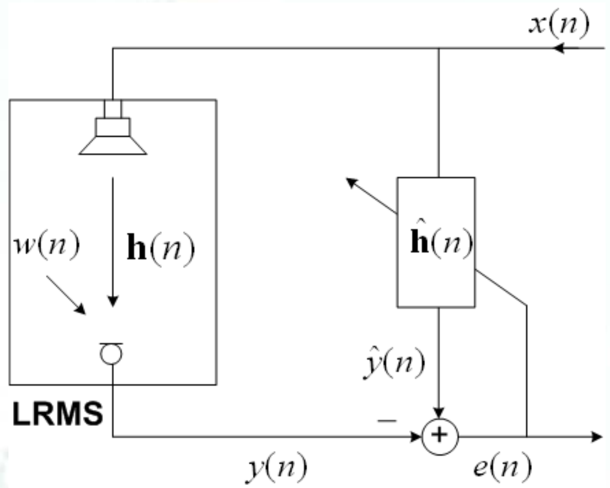
Adaptive filtering framework (NLMS)

- General formulation

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

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

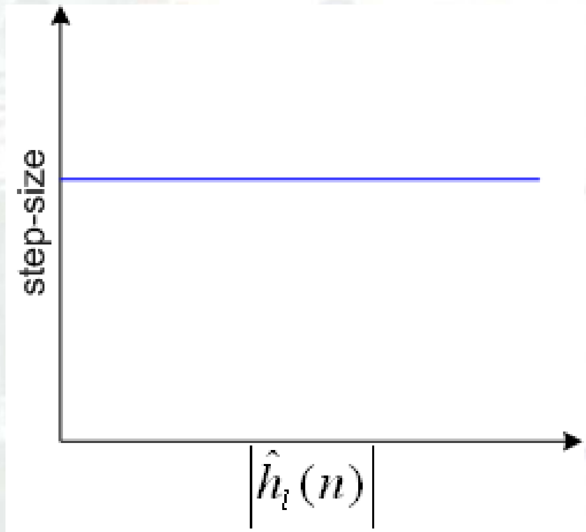
$$\mathbf{Q}(n-1) = \mathrm{diag}\left\{q_0(n-1), q_1(n-1), \ldots, q_{L-1}(n-1)\right\}$$



- NLMS: $\mathbf{Q}(n) = \mathbf{I}_{L\times L}$, $\delta_{\mathrm{NLMS}} = \sigma_x^2$

  + straight forward implementation, low complexity

  − slow convergence for sparse impulse response



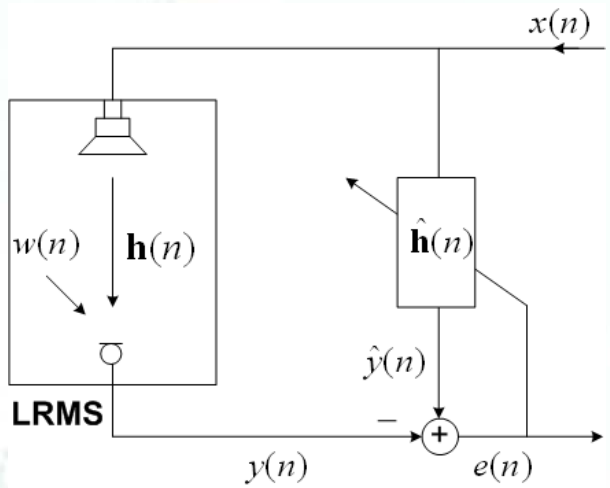
Adaptive filtering framework (PNLMS)

- General formulation

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

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

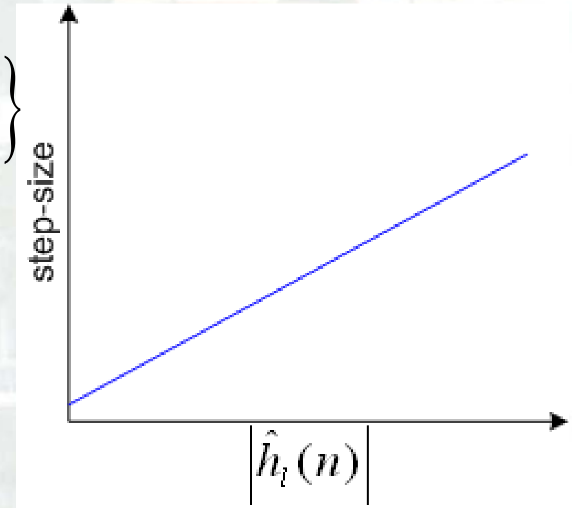
$$\mathbf{Q}(n-1) = \mathrm{diag}\left\{q_0(n-1), q_1(n-1), \ldots, q_{L-1}(n-1)\right\}$$



- PNLMS: $q_l(n) = \dfrac{\kappa_l(n)}{\sum_{i=0}^{L-1}\kappa_i(n)}, \quad l = 0, 1, \ldots, L-1$

$$\kappa_l(n) = \max\left\{\rho \times \max\left\{\gamma, |\hat{h}_0(n)|, \ldots, |\hat{h}_{L-1}(n)|\right\}, |\hat{h}_{L-1}(n)|\right\}$$

$$\gamma = 0.01, \quad \rho = 5/L$$

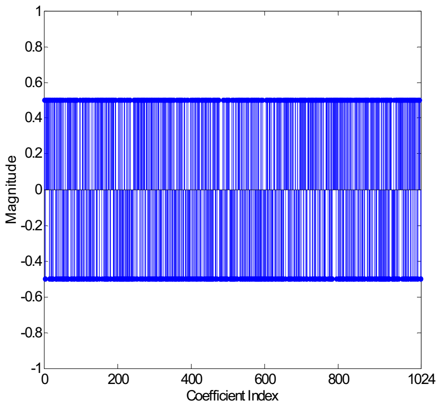


+ faster convergence for sparse impulse response
− slower convergence for dispersive impulse response

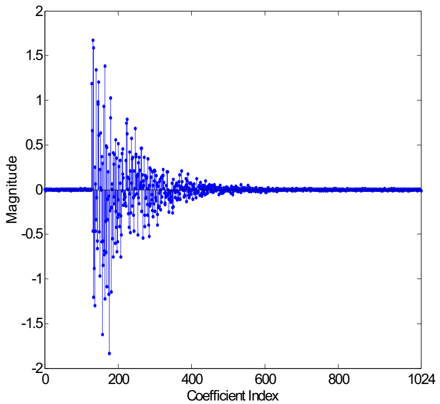
Sparseness measure

- Qualitative measure: ranging from strongly dispersive to strongly sparse

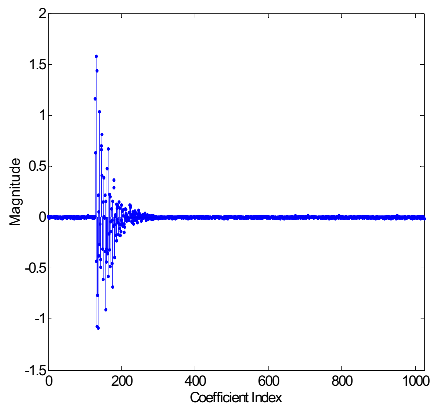
- Quantitative measure: $$\xi(n) = \frac{L}{L\text{-}\sqrt{L}}\left[1 - \frac{\|\mathbf{h}(n)\|_1}{\sqrt{L}\,\|\mathbf{h}(n)\|_2}\right]$$



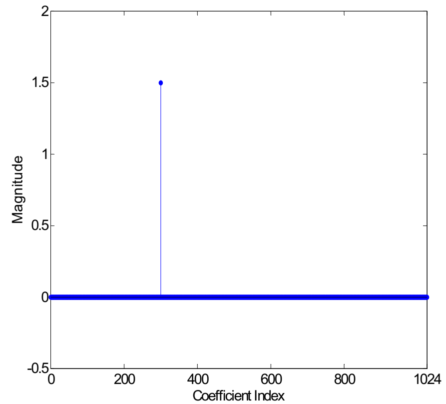
$\xi(\mathbf{h}) = 0$



$\xi(\mathbf{h}) = 0.655$



$\xi(\mathbf{h}) = 0.7885$



$\xi(\mathbf{h}) = 1$

← More dispersive

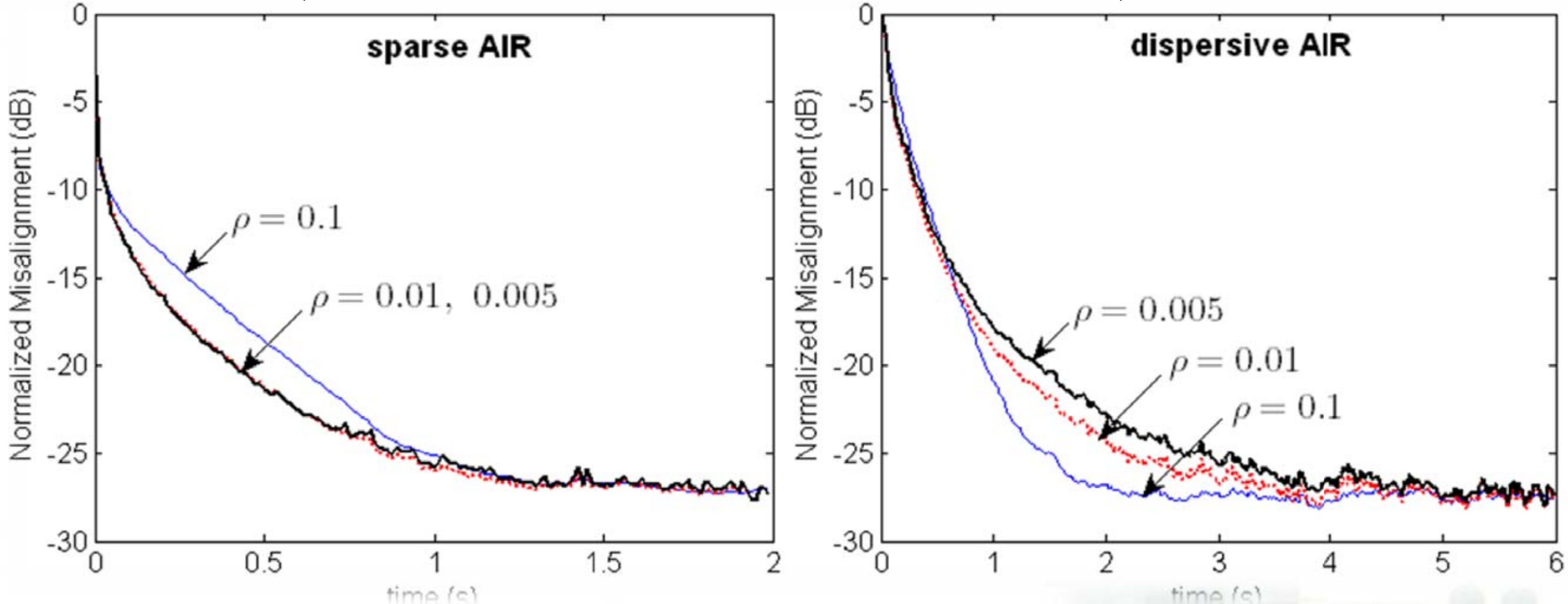
More sparse →

Improving the performance of PNLMS

PNLMS:

$$q_l(n) = \frac{\kappa_l(n)}{\sum_{i=0}^{L-1} \kappa_i(n)}, \quad l = 0,1,\ldots,L-1$$

$$\kappa_l(n) = \max\left\{ \rho \times \max\left\{ \gamma, |\hat{h}_0(n)|, \ldots, |\hat{h}_{L-1}(n)| \right\}, |\hat{h}_{L-1}(n)| \right\}$$

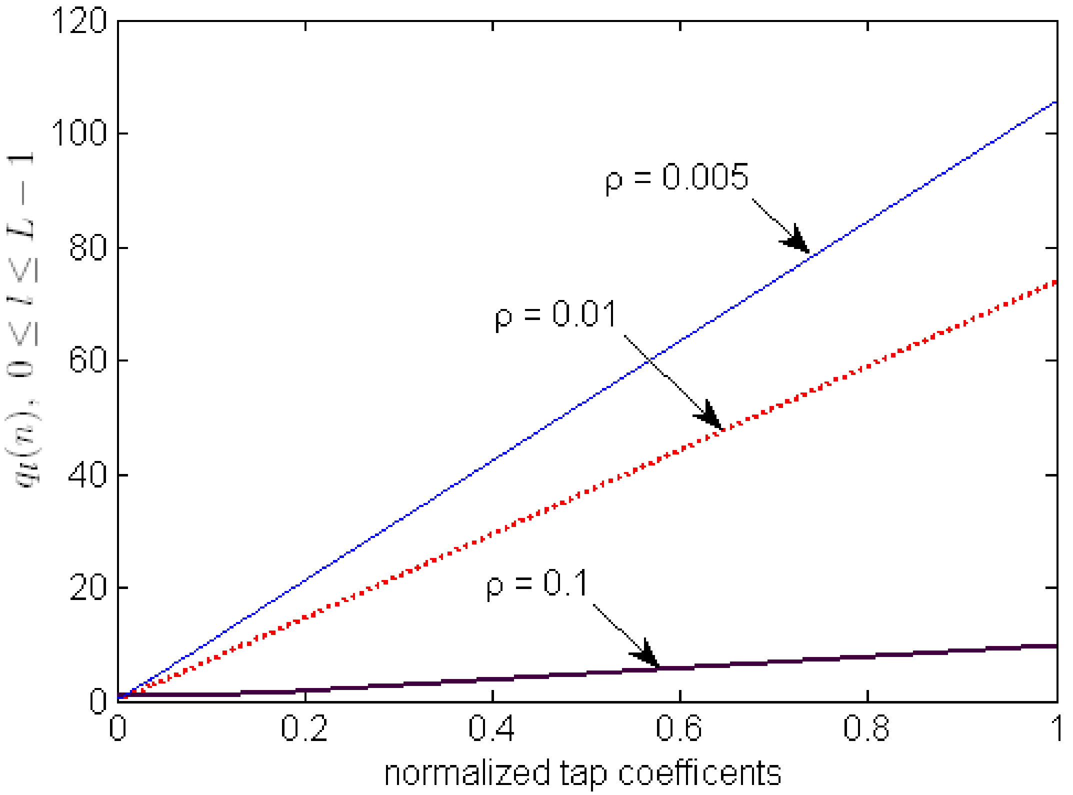


- **Sparse → low value of ρ**
- **Dispersive → high value of ρ**

Normalized misalignment:

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

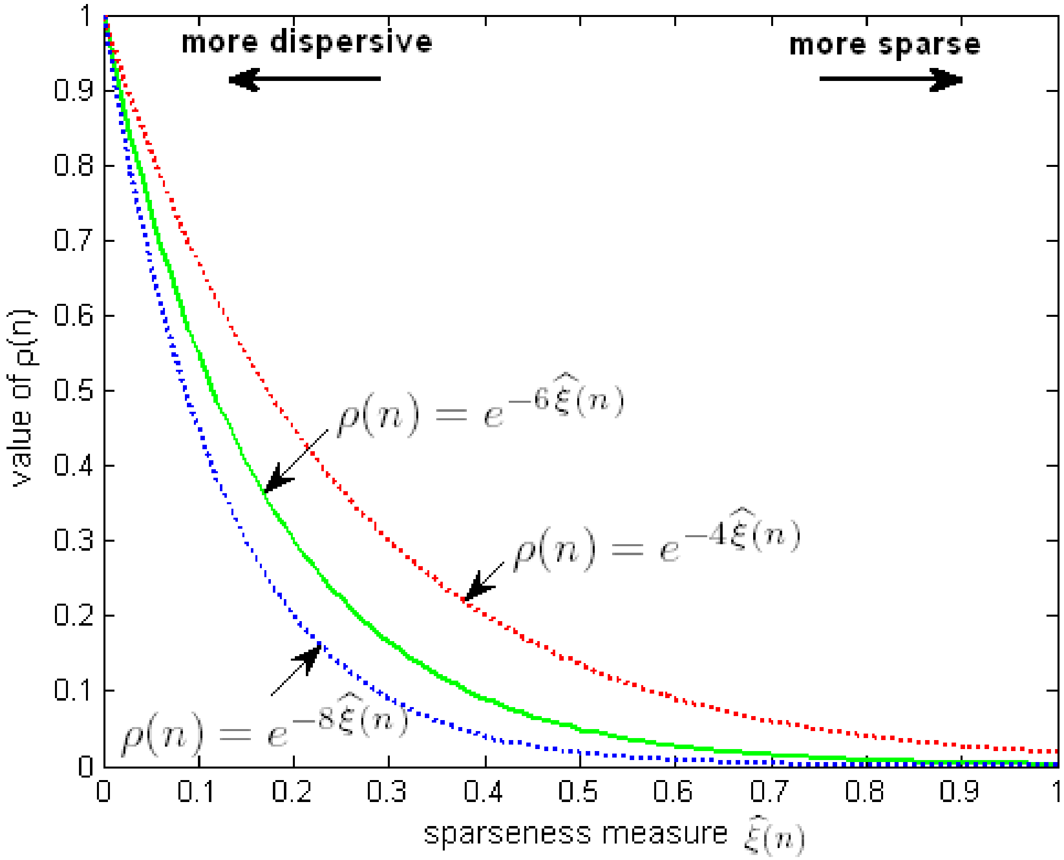
The SC-PNLMS formulation



- low value of ρ → step-size α magnitude of coefficient → good for sparse
- high value of ρ → step-size = constant → good for dispersive

The SC-PNLMS formulation

- Desired: low ρ for high $\hat{\xi}(n)$
  high ρ for low $\hat{\xi}(n)$
- Exponential function allows SC-PNLMS to inherit proportionality step-size control over large range of $\hat{\xi}(n)$



The SC-PNLMS formulation

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

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

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

$$q_l(n) = \frac{\kappa_l(n)}{\sum_{i=0}^{L-1}\kappa_i(n)}, \quad l = 0,1,\ldots,L-1$$

$$\kappa_l(n) = \max\left\{\rho \times \max\left\{\gamma, |\hat{h}_0(n)|, \ldots, |\hat{h}_{L-1}(n)|\right\}, |\hat{h}_{L-1}(n)|\right\}, \gamma = 0.01,$$

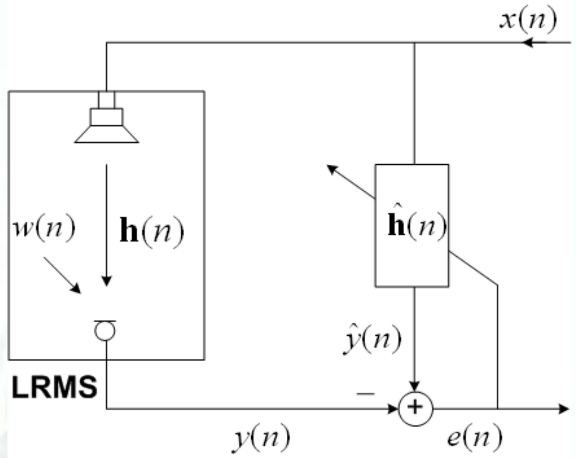
standard PNLMS

- For $n < L, \quad \rho(n) = 5/L$
- For $n \geq L, \quad \rho(n) = e^{-\lambda\hat{\xi}(n)}, \ \lambda = 6$

$$\hat{\xi}(n) = \frac{L}{L-\sqrt{L}}\left\{1 - \frac{\|\hat{\mathbf{h}}(n)\|_1}{\sqrt{L}\,\|\hat{\mathbf{h}}(n)\|_2}\right\}$$

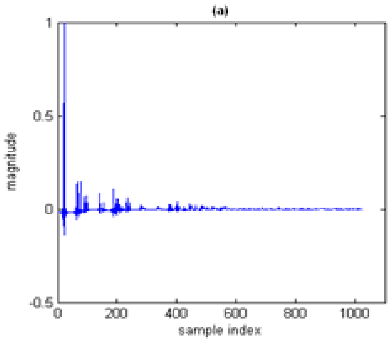
modification

Simulation set-up



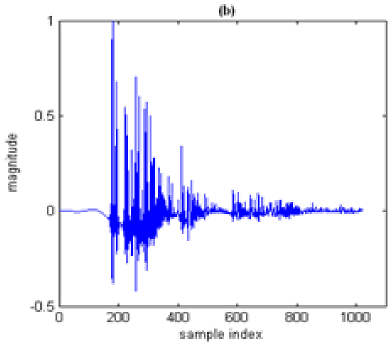
- $x(n)$ – White Gaussian Noise (WGN)
  – Male speech signal
- $\mathbf{h}(n)$ – $L = 1024$

  – Sparse



sparseness measure, $\xi(n) = 0.83$

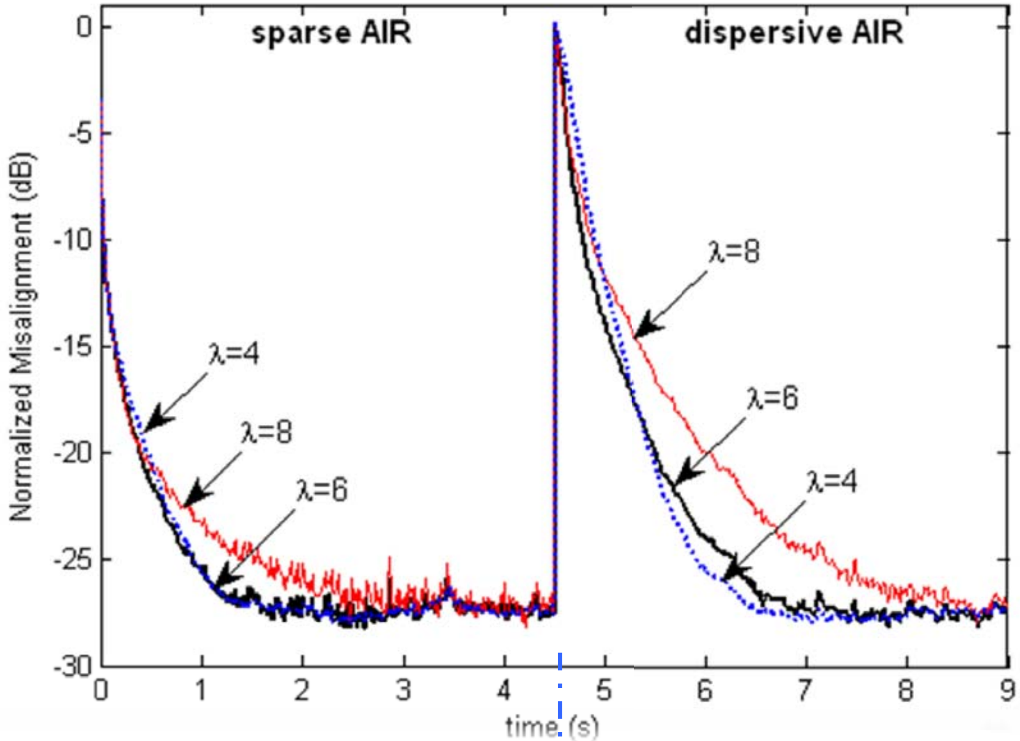
  – Dispersive



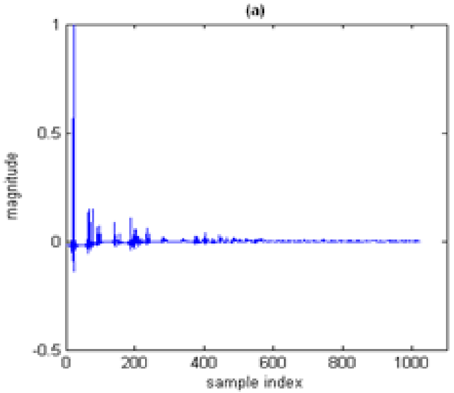
sparseness measure, $\xi(n) = 0.59$

- $w(n)$ – WGN to give an SNR = 20dB
- Step-sizes: $\mu_{\text{NLMS}} = \mu_{\text{PNLMS}} = \mu_{\text{SC-PNLMS}} = 0.3$

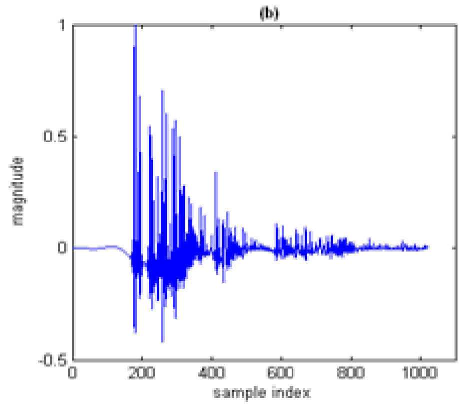
Simulation results of SC-PNLMS for different λ



- large λ → inherit more PNLMS
- small λ → inherit more NLMS

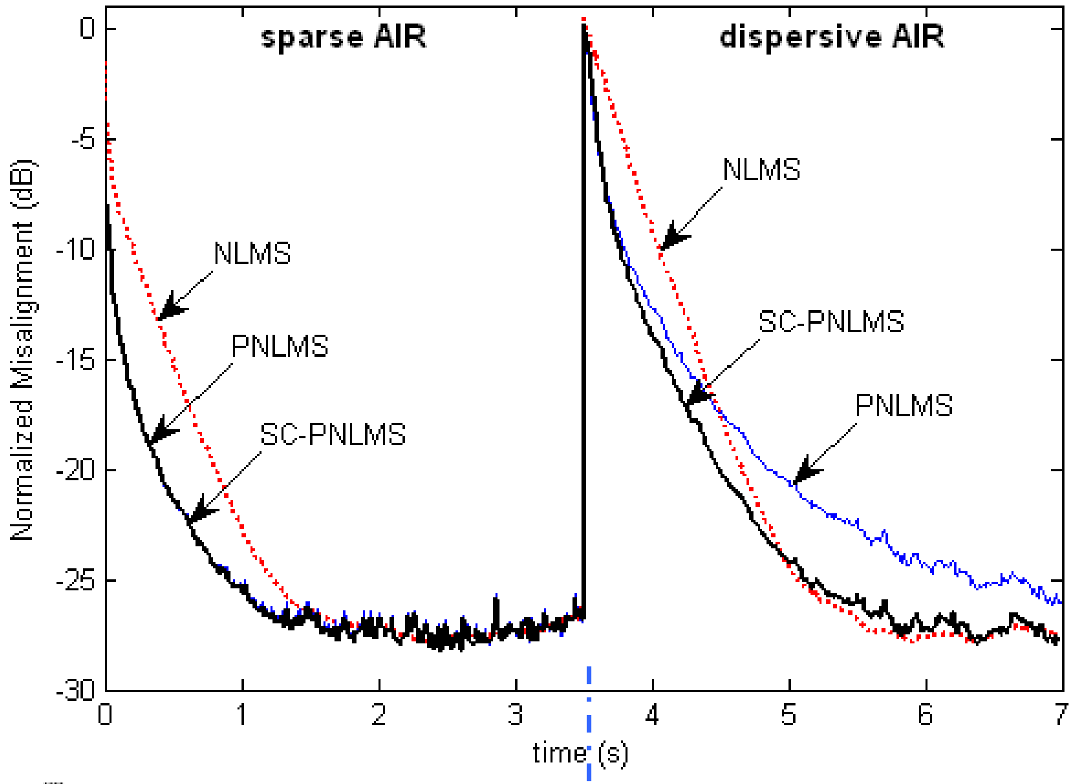


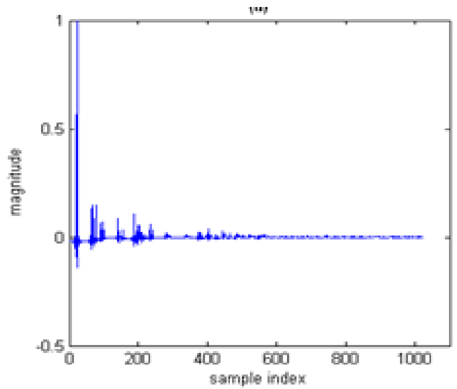
$\hat{\xi}(n) = 0.83$



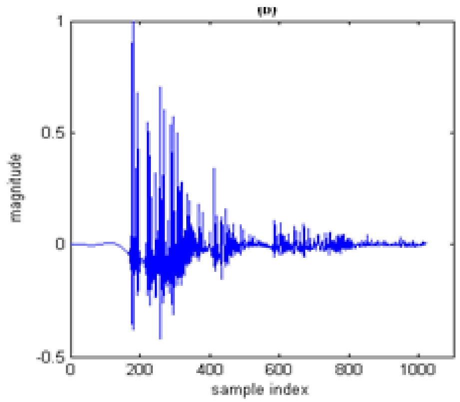
$\hat{\xi}(n) = 0.59$

Simulation results using WGN



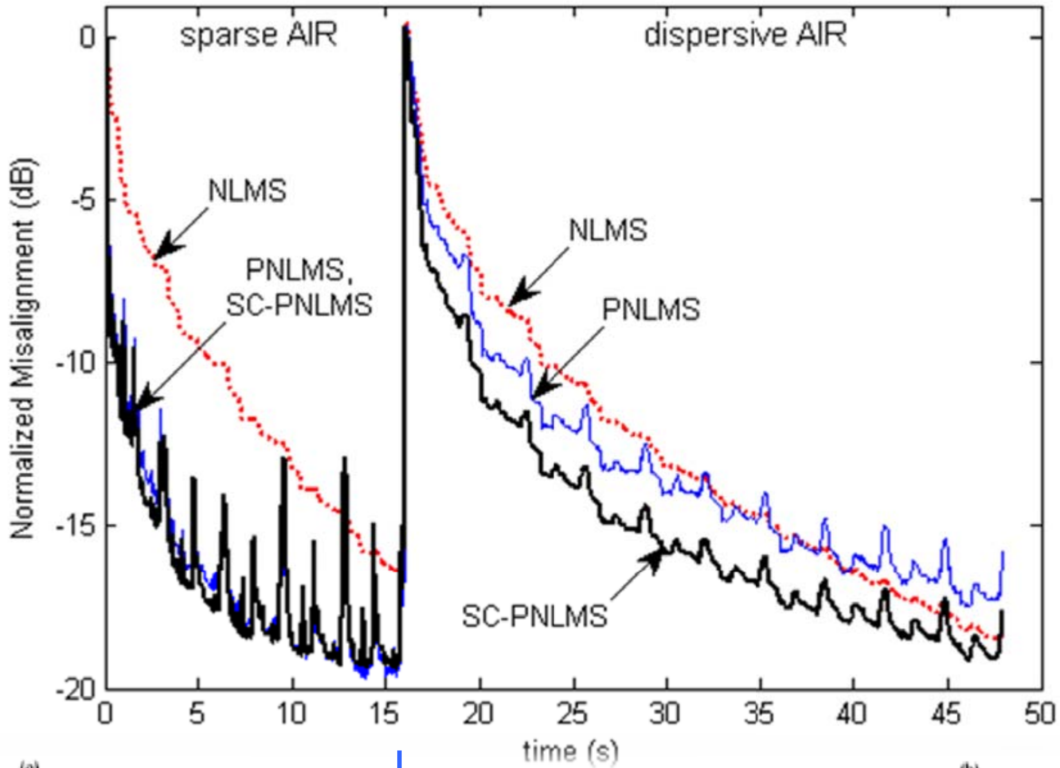


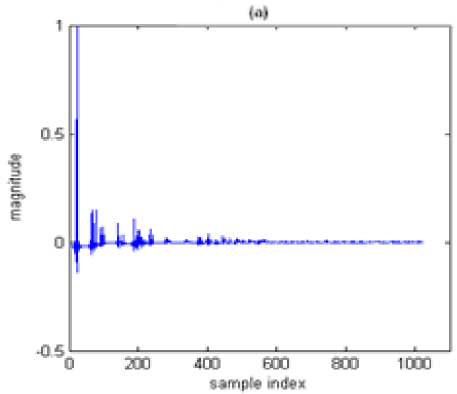
$\hat{\xi}(n) = 0.83$



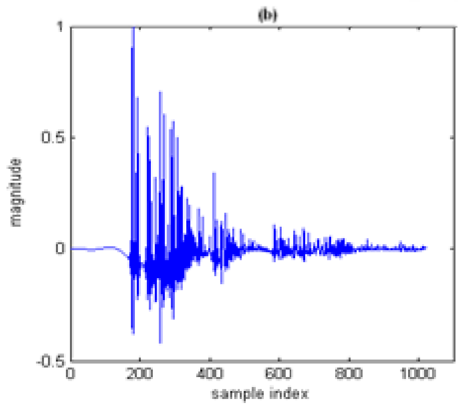
$\hat{\xi}(n) = 0.59$

Simulation results using speech signal





$\hat{\xi}(n) = 0.83$



$\hat{\xi}(n) = 0.59$

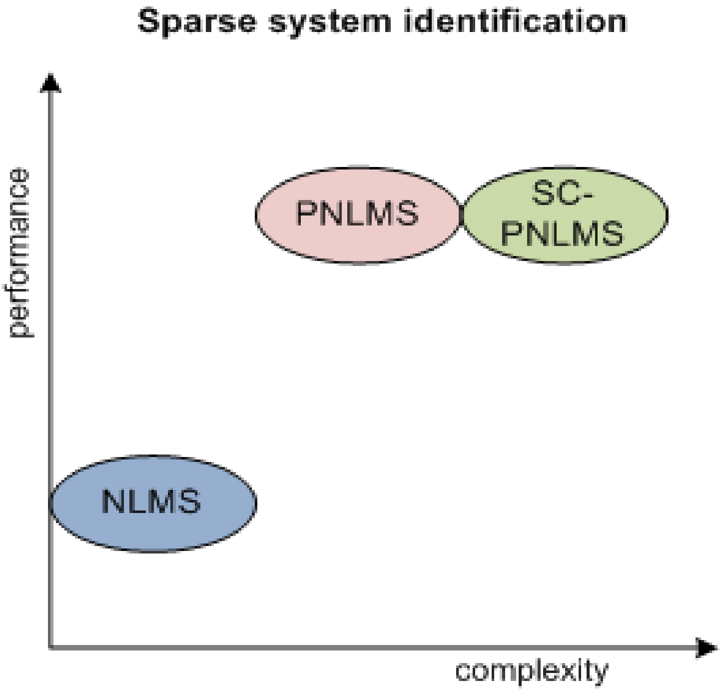
Complexity

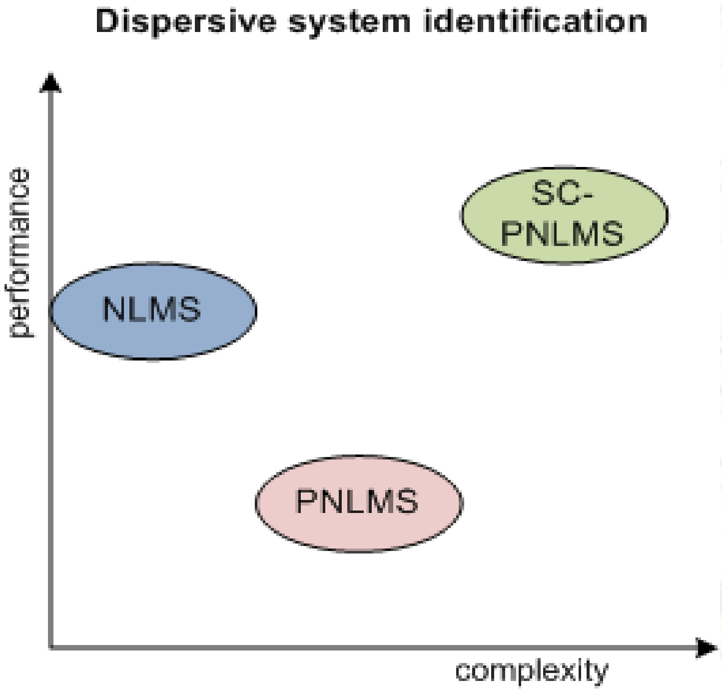
$$\hat{\xi}(n) = \frac{L}{L-\sqrt{L}}\left[1 - \frac{\|\hat{\mathbf{h}}\|_1}{\sqrt{L}\,\|\hat{\mathbf{h}}\|_2}\right]$$

Compute offline

Complexity for the case of L=1024

Algorithms	(+)	(x)	(/)
NLMS	1027	2051	1
PNLMS	2051	5124	1025
SC-PNLMS	4100	6150	1026





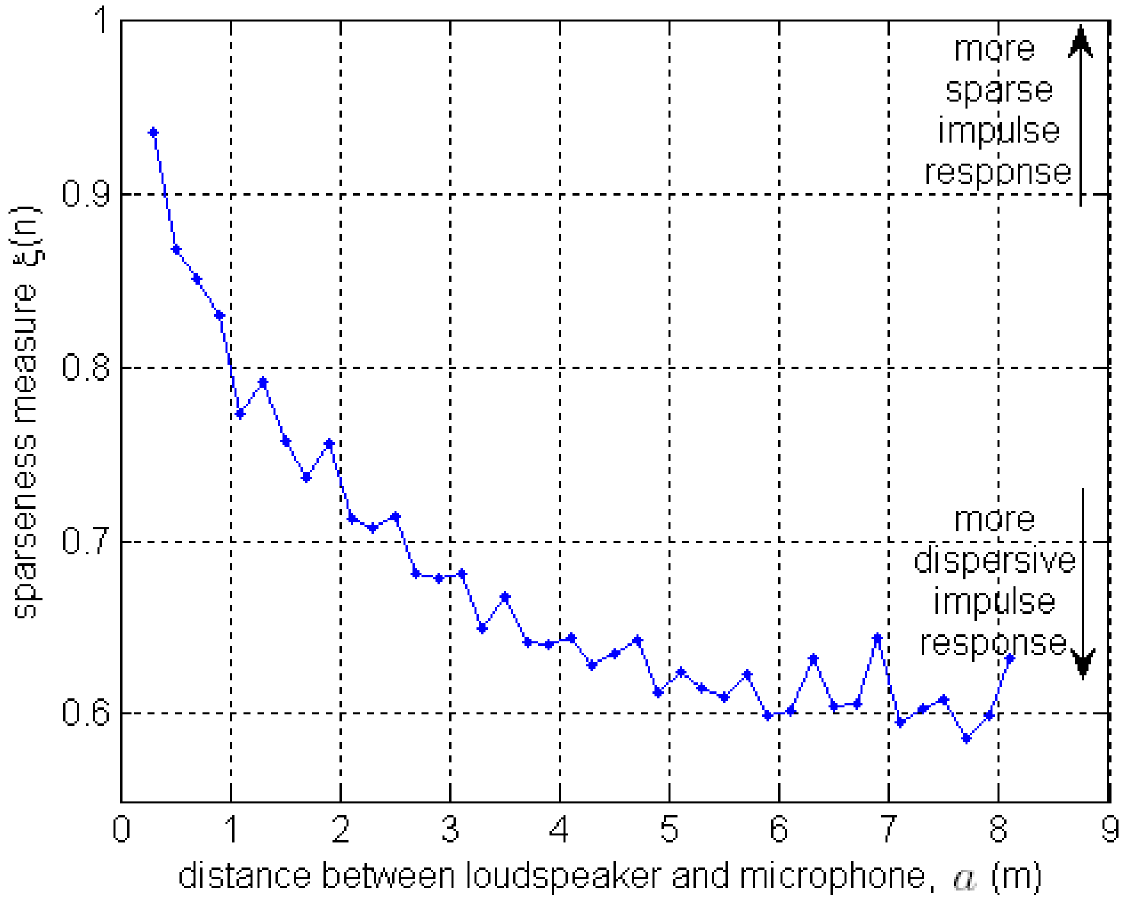
Conclusion

- Algorithms developed for mobile hands-free terminals are required to be robust to the variations in the sparseness of the acoustic path.

- SC-PNLMS: Sparseness measure has been incorporated into PNLMS.
  - Sparseness measured using estimated impulse response.
  - Modest increase in computational complexity
  - Outperformed across all sparseness levels.

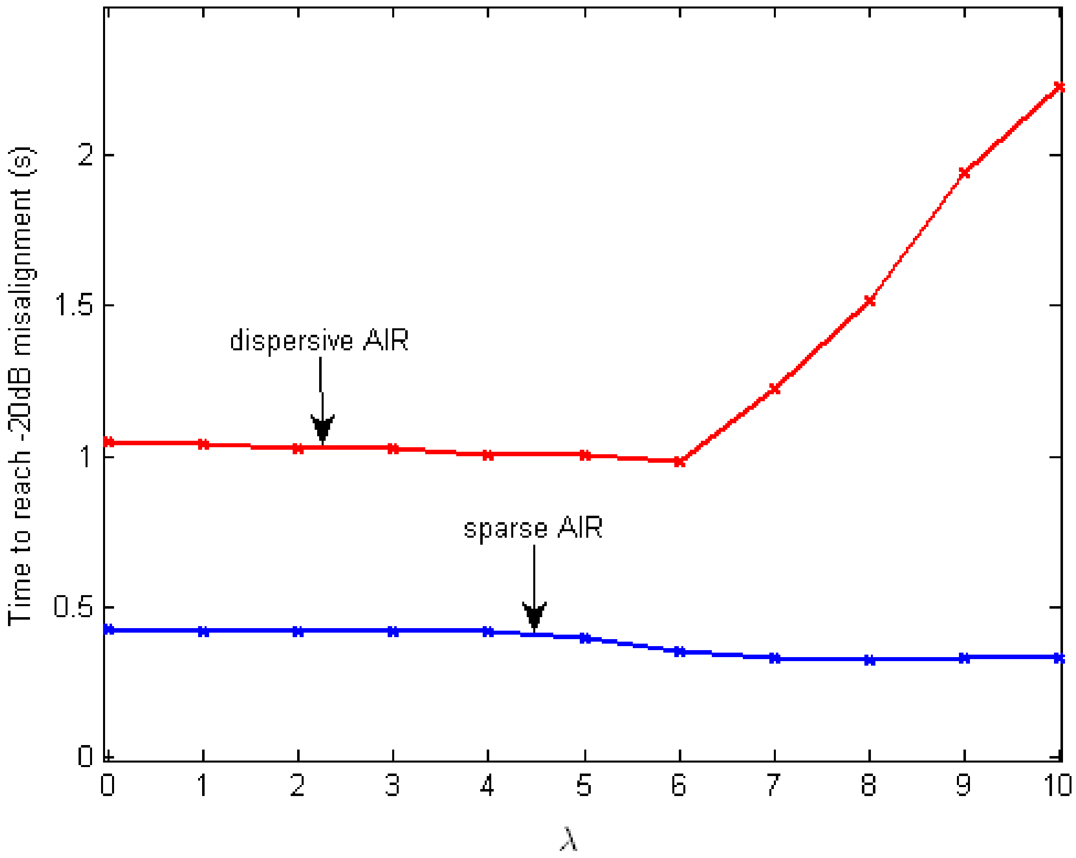
Additional slide 1

- Sparseness measure Vs. Distance between loudspeaker and microphone – room dimensions of 8x10x3 m



Additional slide 2

- Sensitivity of λ in ρ(n)



Additional slide 3

- Linear function for ρ(*n*)