TRINICON: A Versatile Framework for Multichannel Blind Signal Processing

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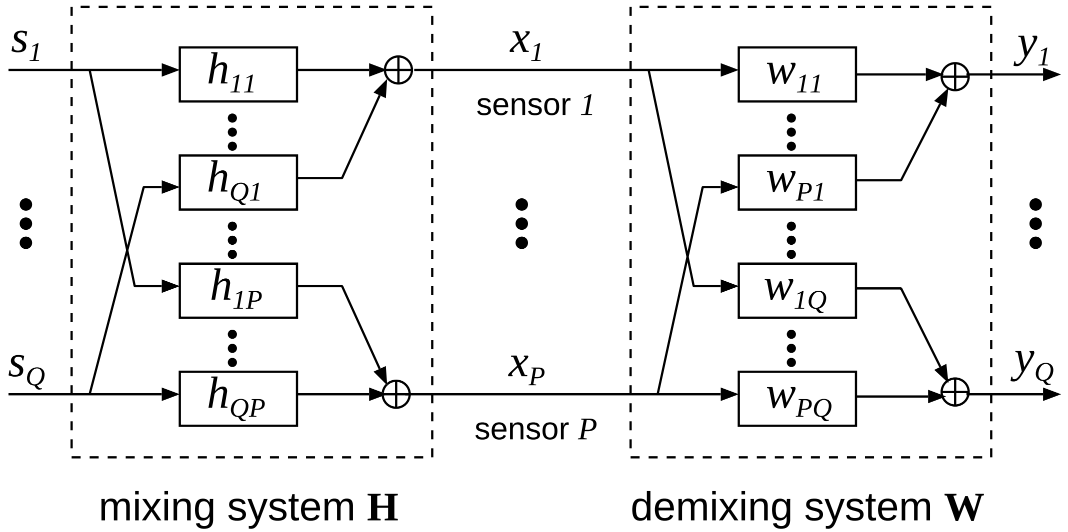
Contents

Introduction (1)

Scenario: **MIMO FIR model** (assuming number Q of sources $\leq$ number P of sensors)



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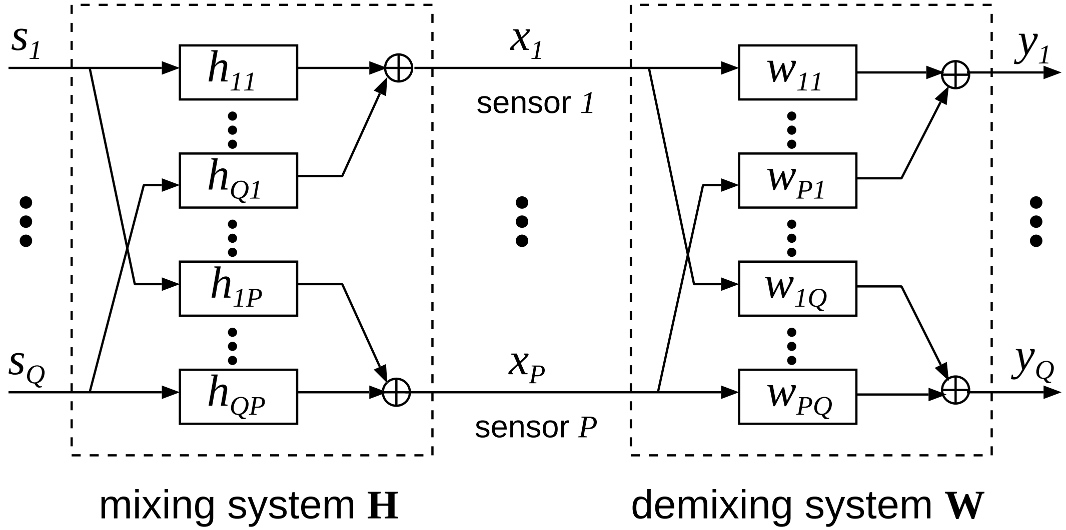

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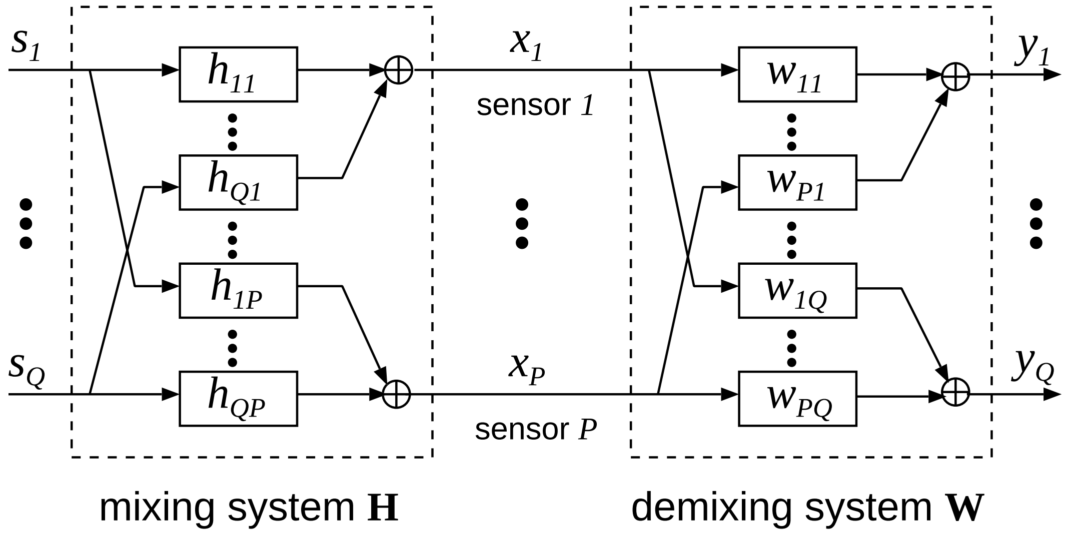

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- **Blind source separation (BSS) for convolutive mixtures**
  Separate signals by forcing the outputs to be mutually independent
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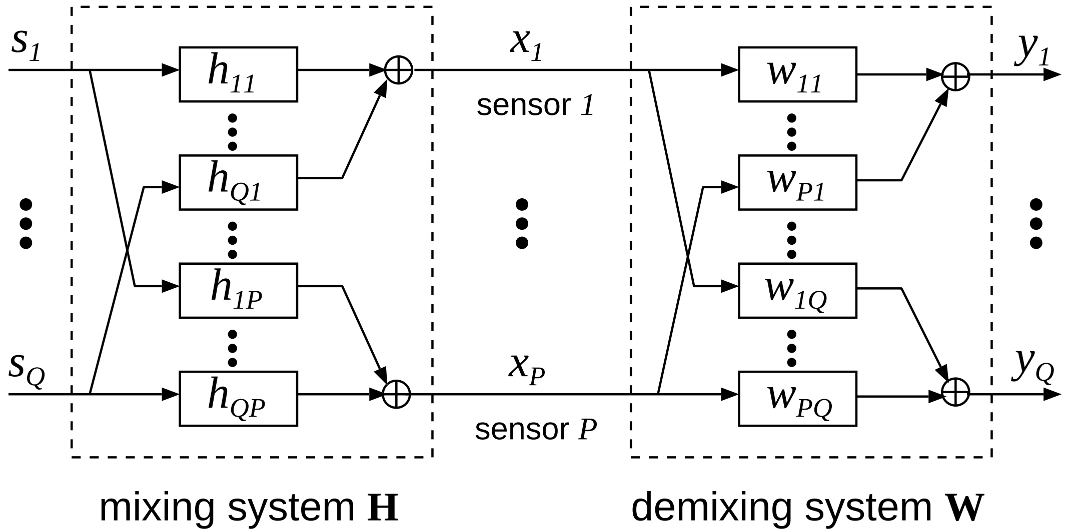

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- **Blind source separation (BSS) for convolutive mixtures**
  Separate signals by forcing the outputs to be mutually independent
  (output signals may be still filtered and channel-wise permuted)

- **Multichannel blind deconvolution $\Rightarrow$ dereverberation**
  In addition to BSS: recover original source signals up to *scaling* and permutation

Introduction (2)

How to estimate the $P \cdot Q \cdot L$ MIMO coefficients $w_{pq}(\kappa)$, $\kappa = 0, \dots, L-1$?

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Exploitation of

- Nonwhiteness
- Nonstationarity
- Nongaussianity

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• Nonwhiteness	• Second-order statistics (SOS) $\Rightarrow$ simultaneous output decorrelation for multiple time-lags
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Here: First rigorous derivation of a generic **broadband** adaptation algorithm

- exploiting all properties and
- avoiding problems of narrowband approaches (permutations, circularity, ...)

$\Rightarrow$ **TRINICON** ('**Tri**ple-**N** **I**CA for **Con**volutive Mixtures')

Optimization Criterion – Motivation (1)

Nongaussianity: higher-order statistics for Independent Component Analysis (ICA)

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Current ICA approaches for BSS of instantaneous mixtures
(or for independent application on individual frequency bins, i.e., **narrowband** approaches)

- Maximum likelihood (ML)
- Minimum mutual information (MMI)
- Maximum Entropy (ME) / 'Infomax'

It can be shown: **MMI is the most general approach** of these classes.

Mutual information [Shannon]:

$$I(Y_1, Y_2) = \int\int p(y_1, y_2) \mathrm{ld} \left(\frac{p(y_1, y_2)}{p(y_1)p(y_2)} \right) \mathrm{d}y_1 \mathrm{d}y_2$$

Optimization Criterion – Motivation (2)

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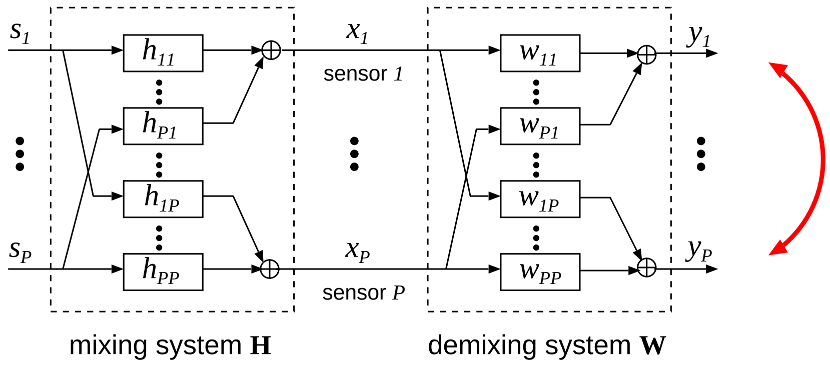
BSS for convolutive mixtures:



⇒ Minimize **mutual information** between the output channels

$$
\begin{aligned}
I(Y_1, Y_2) &= E\{\mathrm{ld}(p(y_1, y_2)) \\
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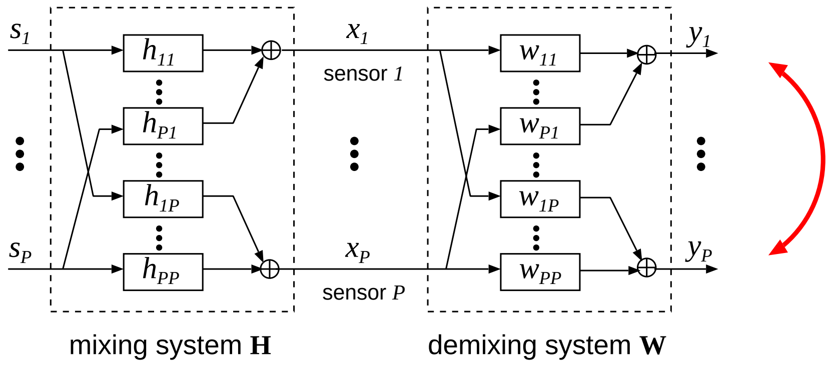

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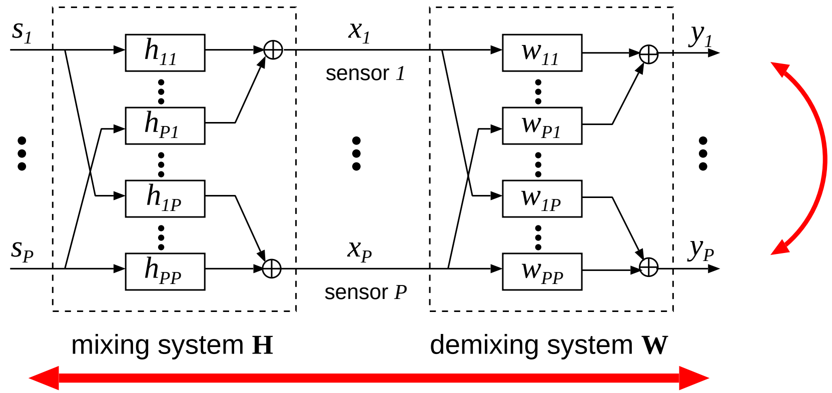
Multichannel Blind Deconvolution



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make outputs spatially *and temporally* independent

Problem for speech and audio:
i.i.d. assumption ⇒ whitening

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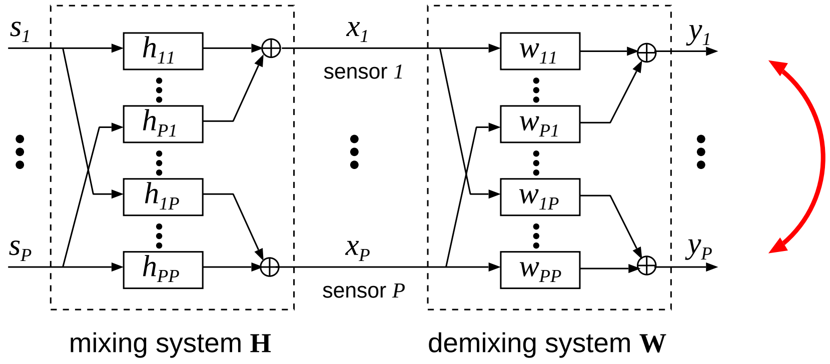

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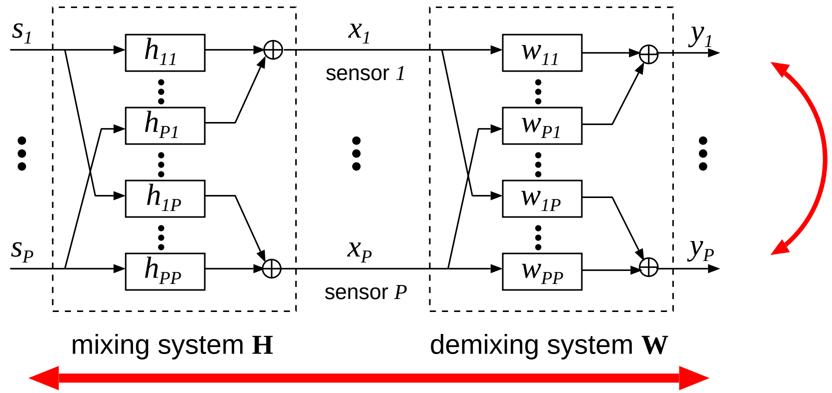

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Obvious **generalization**: factorization $p(y_1) \cdot p(y_2)$ ⇒ *arbitrary 'target pdf'*

⇒ Minimize **Kullback-Leibler distance** between a certain **source model** and output

Optimization Criterion

Nongaussianity: Kullback-Leibler distance between PDFs of source model and output.

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General TRINICON cost function

$$\mathcal{J}(m) = -\sum_{i=0}^{\infty} \beta(i,m) \frac{1}{N} \sum_{j=0}^{N-1} \{\log(\hat{p}_{s,PD}(\mathbf{y}(i,j))) - \log(\hat{p}_{y,PD}(\mathbf{y}(i,j)))\}$$

- β: window function for online, offline, and block-online algorithms
- $\hat{p}_{s,PD}(\cdot)$, $\hat{p}_{y,PD}(\cdot)$: assumed or estimated $multivariate$ source model PDF and output PDF, respectively.
- $\mathbf{y}(i,j)$: concatenated length-D output blocks of the P channels (i-th block, shifted by j samples), $\mathbf{y}_q(i,j) = [y_q(iL+j), \ldots, y_q(iL-D+1+j)]$

FIR model with multiple time lags – Matrix formulation

Nonwhiteness: simultaneously optimize MIMO coefficients for D **time lags**

Formulation of the **linear convolution in matrix notation**:

$$\mathbf{y}_q(m,j) = [y_q(mL+j),\ldots,y_q(mL-D+1+j)] = \sum_{p=1}^{P} \mathbf{x}_p(m,j)\mathbf{W}_{pq}(m)$$

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with the $2L \times D$ **Sylvester matrices**

$$\mathbf{W}_{pq}(m) = \begin{bmatrix} w_{pq,0} & 0 & \cdots & 0 \\ w_{pq,1} & w_{pq,0} & \ddots & \vdots \\ \vdots & w_{pq,1} & \ddots & 0 \\ w_{pq,L-1} & \vdots & \ddots & w_{pq,0} \\ 0 & w_{pq,L-1} & \ddots & w_{pq,1} \\ \vdots & & \ddots & \vdots \\ 0 & \cdots & 0 & w_{pq,L-1} \\ 0 & \cdots & 0 & 0 \\ \vdots & & \vdots & \vdots \\ 0 & \cdots & 0 & 0 \end{bmatrix}.$$

General Coefficient Update

Natural gradient $\mathbf{W}\mathbf{W}^H \nabla_{\mathbf{W}} \mathcal{J}$ of the cost function as **generic coefficient update**:

$$\Delta\mathbf{W}(m) \quad = \quad \frac{2}{N} \sum_{i=0}^{\infty} \beta(i,m) \sum_{j=0}^{N-1} \mathbf{W}(i)\mathbf{y}^H(i,j) \left\{ \Phi_{s,PD}(\mathbf{y}(i,j)) - \Phi_{y,PD}(\mathbf{y}(i,j)) \right\}$$

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To select a practical algorithm:

- 'desired' score function (hypothesized)

$$\Phi_{s,PD}(\mathbf{y}(i,j)) = -\frac{\partial \log \hat{p}_{s,PD}(\mathbf{y}(i,j))}{\partial \mathbf{y}(i,j)}$$

  where the model (i.e., desired) PDF is **factorized among the channels** ($\Rightarrow$ BSS) and/or **factorized among a certain number of time lags** ($\Rightarrow$ full or partial MCBD)

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How to obtain these sequences of high-dimensional multivariate PDFs?

Special Cases and Illustration – SOS case

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SOS case exploiting only non-stationarity and non-whiteness
by assuming **multivariate Gaussian** PDFs in both score functions:

$$\hat{p}_D(\mathbf{y}_p(i,j)) = \frac{1}{\sqrt{(2\pi)^D \det(\mathbf{R}_{\mathbf{y}_p\mathbf{y}_p}(i))}} e^{-\frac{1}{2}\mathbf{y}_p(i,j)\mathbf{R}^{-1}_{\mathbf{y}_p\mathbf{y}_p}(i)\mathbf{y}_p^H(i,j)}$$

$$\Delta\mathbf{W}(m) = 2\sum_{i=0}^{\infty}\beta(i,m)\mathbf{W}\left\{\hat{\mathbf{R}}_{\mathbf{yy}} - \hat{\mathbf{R}}_{\mathbf{ss}}\right\}\hat{\mathbf{R}}_{\mathbf{ss}}^{-1}$$

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- Generic SOS-based BSS: $\hat{\mathbf{R}}_{\mathbf{ss}} = \mathrm{bdiag}_D\, \hat{\mathbf{R}}_{\mathbf{yy}}$

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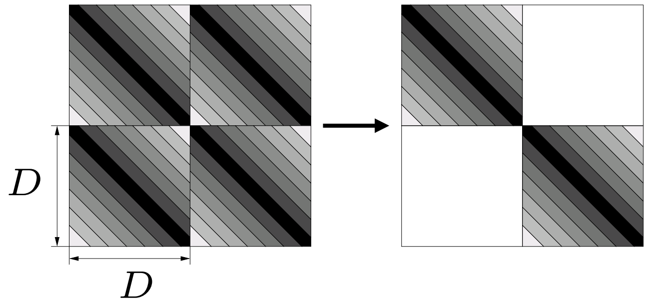

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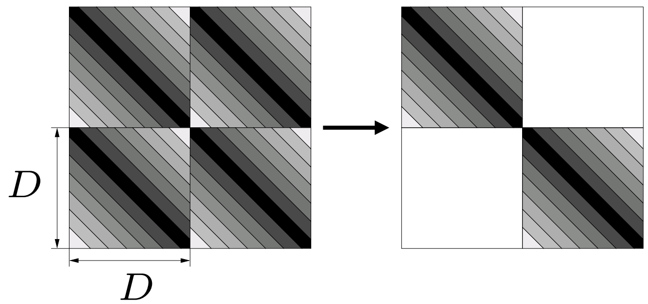

- Inherent RLS-like normalization $\Rightarrow$ Robust adaptation

Special Cases and Illustration – SOS case (2)

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Desired correlation matrices $\hat{\mathrm{R}}_{\mathrm{ss}}$ for BSS and dereverberation:

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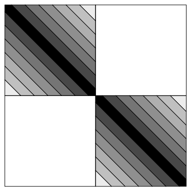

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spectral content untouched
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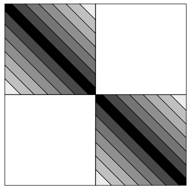

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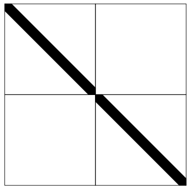

$$\hat{\mathbf{R}}_{\mathbf{ss}} = \mathrm{diag}_D\,\hat{\mathbf{R}}_{\mathbf{yy}}$$

output de-cross-correlated and de-auto-correlated
$\Rightarrow$ **undesirable for speech and audio**

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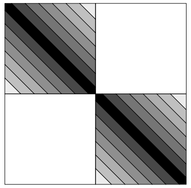

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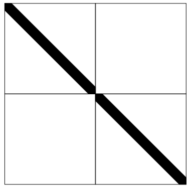

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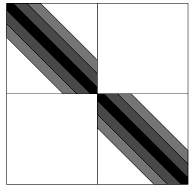
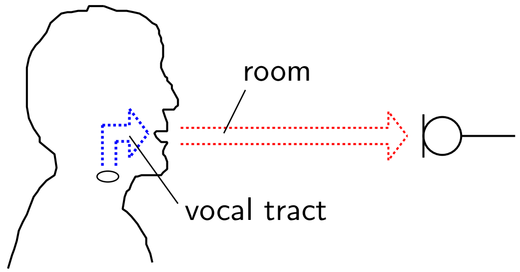
(c) **MCBPD**



remove only the influence of the room
$\Rightarrow$ **vocal tract untouched**



Models for Spherically Invariant Processes (SIRPs) in TRINICON

SIRPs are described by multivariate PDFs of the form (with suitable function f_D):

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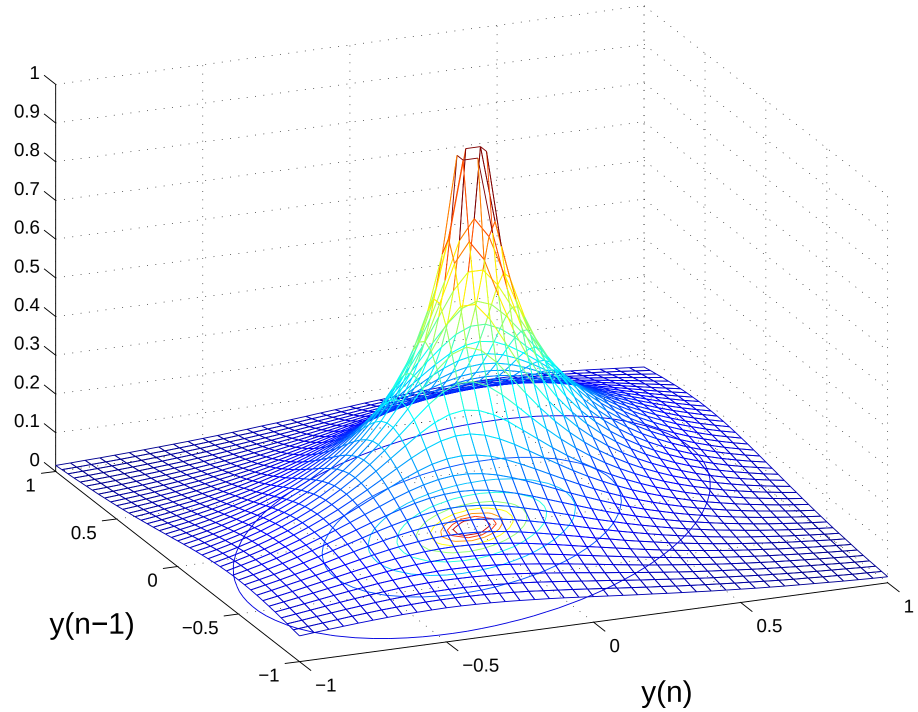

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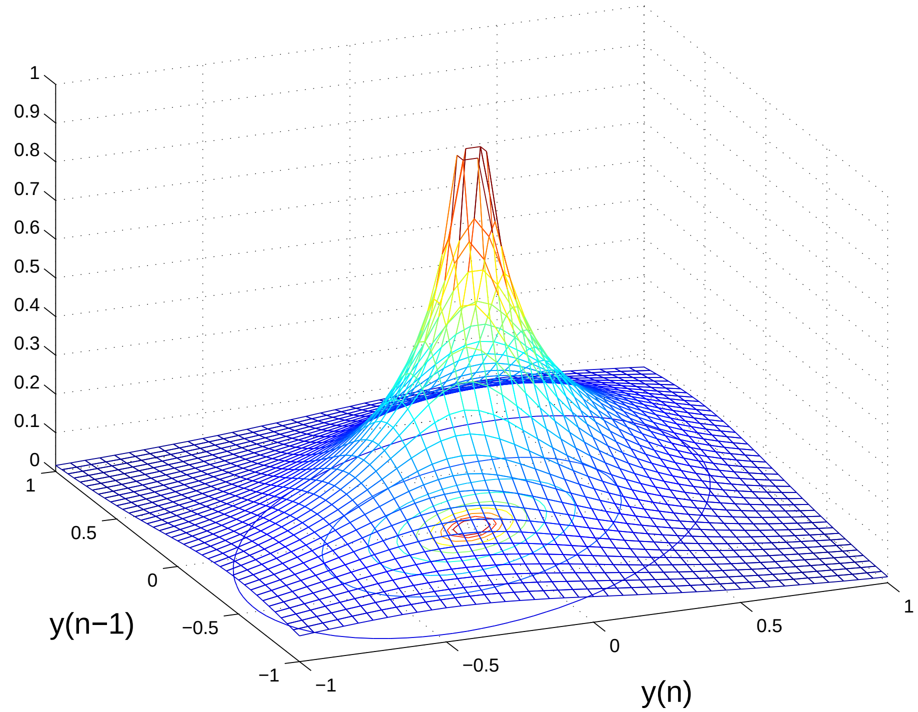

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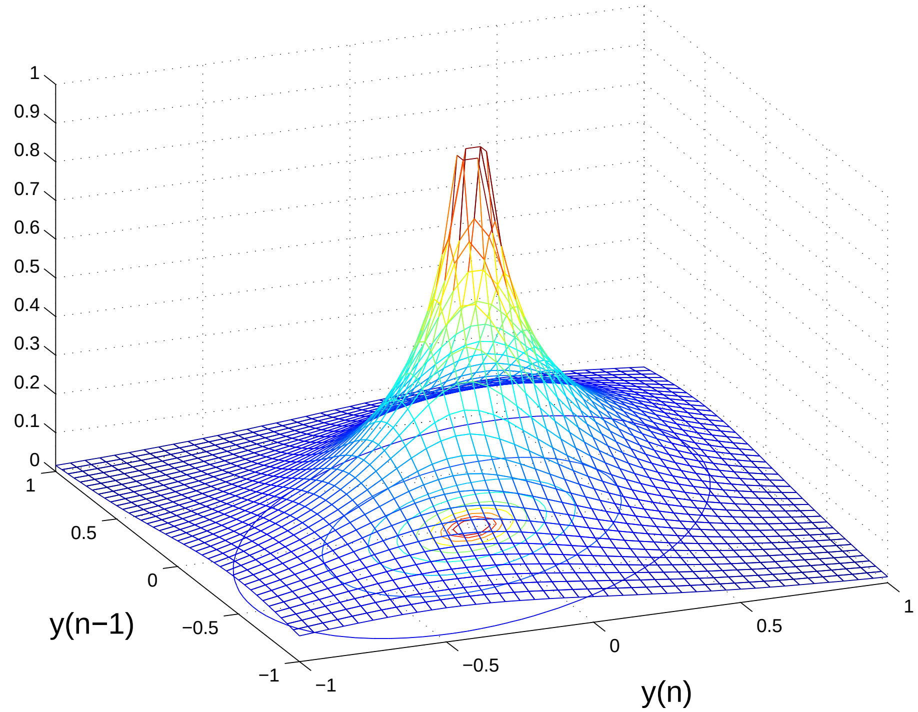

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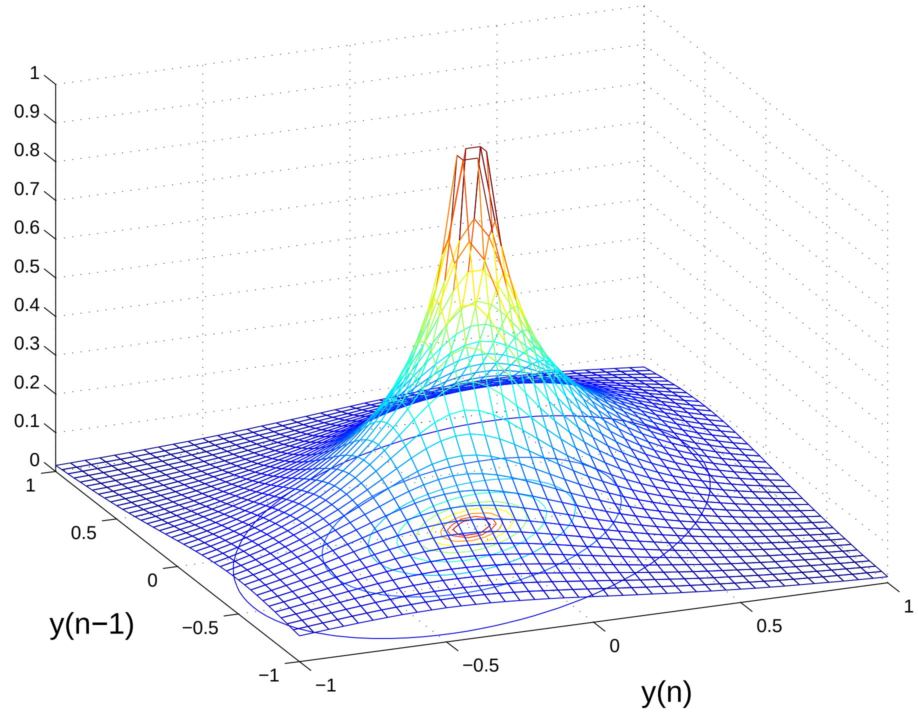

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- Reduced number of parameters to estimate for BSS or Dereverberation
- Multivariate PDFs can be derived analytically from corresponding univariate PDFs
- Incorporation into TRINICON leads to inherent stepsize normalization of the update equation

Incorporation of SIRPs into Generic BSS

BSS: coefficient update for 2 sources **with SIRPs** reads

$$\Delta \mathbf{W}(m) = \sum_{i=0}^{m} \beta(i,m)\mathbf{W}(i) \begin{bmatrix} \mathbf{0} & \tilde{\mathbf{R}}_{y_1 y_2}\mathbf{R}_{y_2 y_2}^{-1} \\ \tilde{\mathbf{R}}_{y_2 y_1}\mathbf{R}_{y_1 y_1}^{-1} & \mathbf{0} \end{bmatrix}$$

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BSS: coefficient update for 2 sources **with SIRPs** reads

$$\Delta \mathbf{W}(m) = \sum_{i=0}^{m} \beta(i,m)\mathbf{W}(i) \begin{bmatrix} \mathbf{0} & \tilde{\mathbf{R}}_{y_1 y_2} \mathbf{R}_{y_2 y_2}^{-1} \\ \tilde{\mathbf{R}}_{y_2 y_1} \mathbf{R}_{y_1 y_1}^{-1} & \mathbf{0} \end{bmatrix}$$

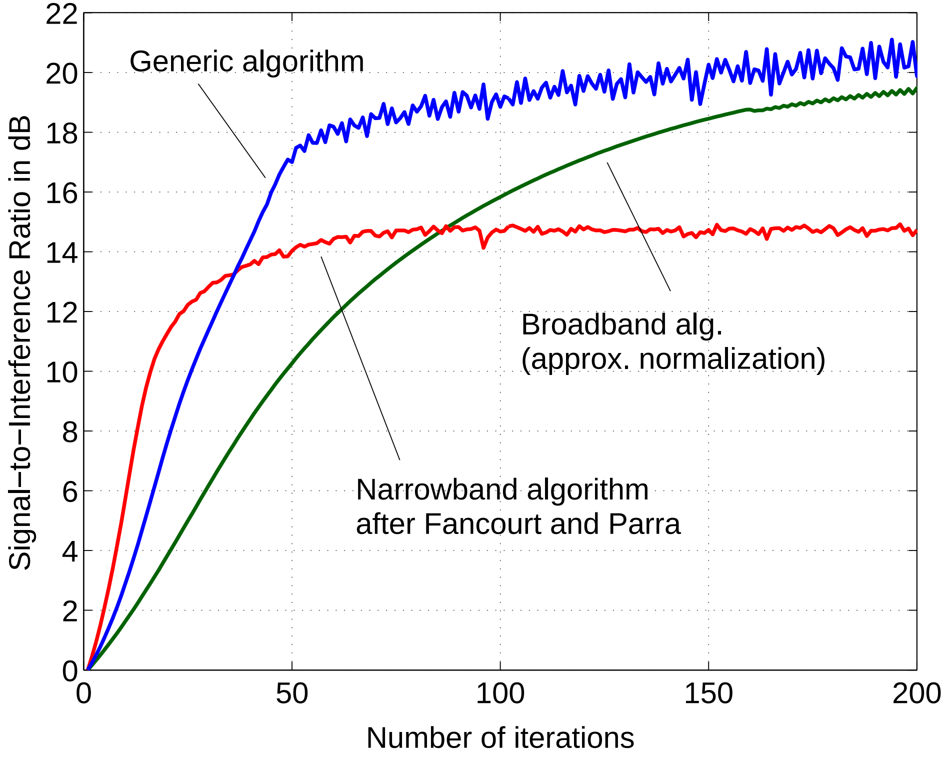
- **RLS-like normalization** (by lagged auto-correlation matrices $\mathbf{R}_{y_q y_q}$)
- Matrices $\tilde{\mathbf{R}}_{y_p y_q}$ of cross-relations include nonlinear terms derived from multivariate PDFs:

$$\begin{aligned} \tilde{\mathbf{R}}_{\mathbf{y}_p \mathbf{y}_q}(i) &= \frac{1}{N} \sum_{j=0}^{N-1} \phi_D \left(\mathbf{y}_q(i,j) \mathbf{R}_{\mathbf{y}_q \mathbf{y}_q}^{-1}(i) \mathbf{y}_q^H(i,j) \right) \mathbf{y}_p^H(i,j) \mathbf{y}_q(i,j), \\ \phi_D(s) &= -\frac{f_D'(s)}{f_D(s)} \end{aligned}$$

- **HOS-SIRP realizations**: $\phi_D(s)$ may be derived analytically from the univariate PDF

- **BSS performance:**
  Conditions: Reverberation time $T_{60} \approx 200ms$, 2×2 case, speech signals, microphone spacing $16cm$, sampling rate 16kHz, estimation of $\mathbf{R_{yy}}$ by correlation method

SOS Algorithms $(L = 1024)$



- **BSS performance:**
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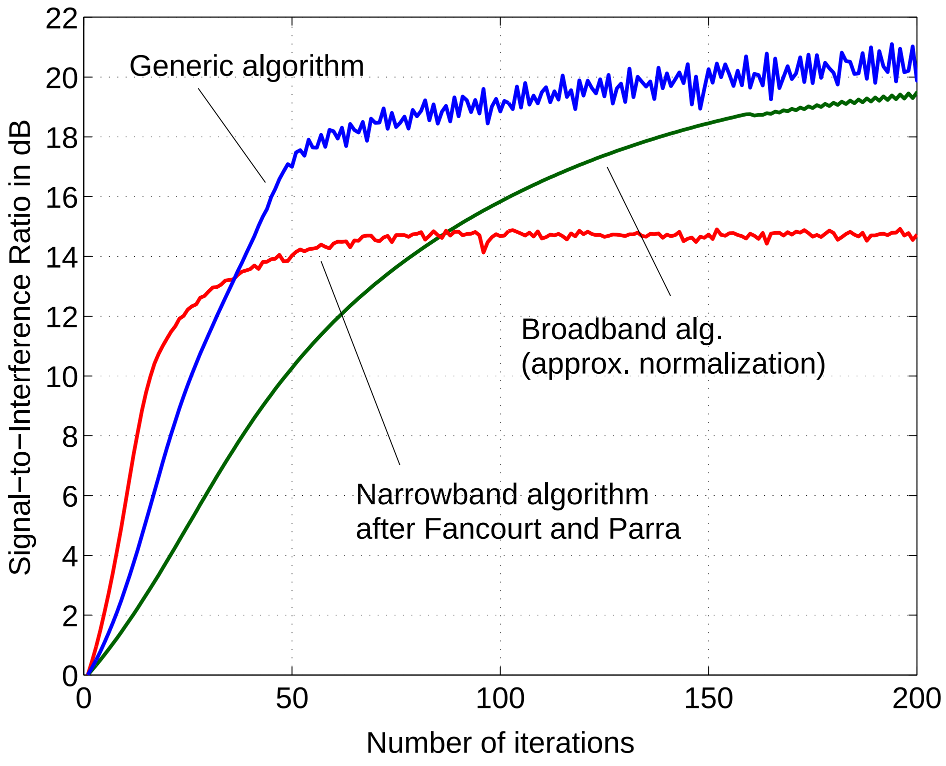
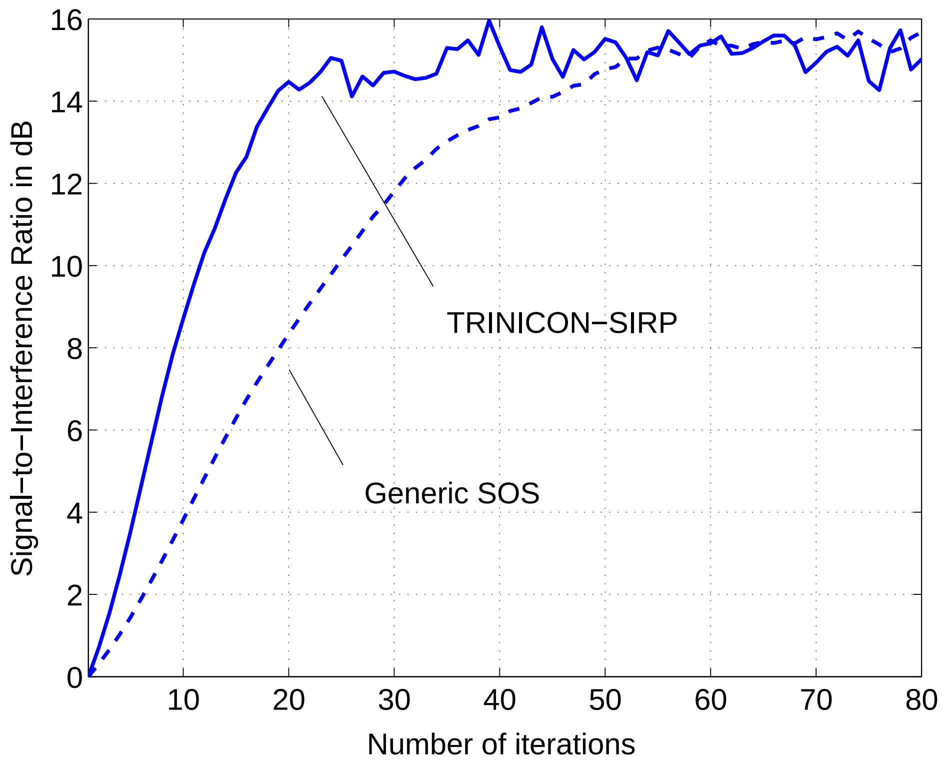
SOS Algorithms $(L = 1024)$

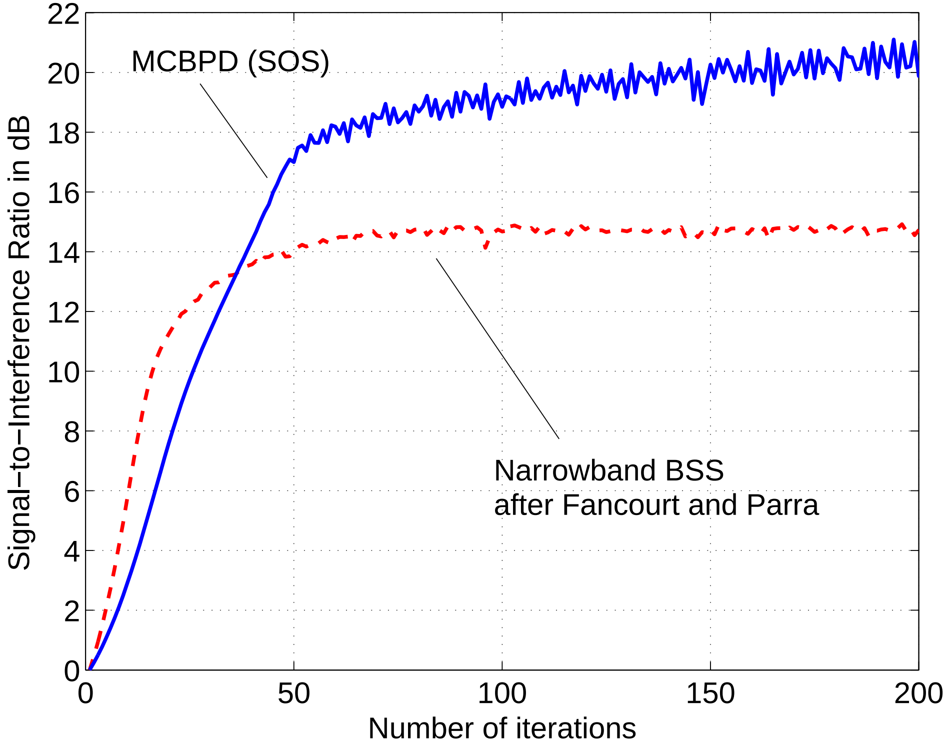


Generic SOS vs. TRINICON



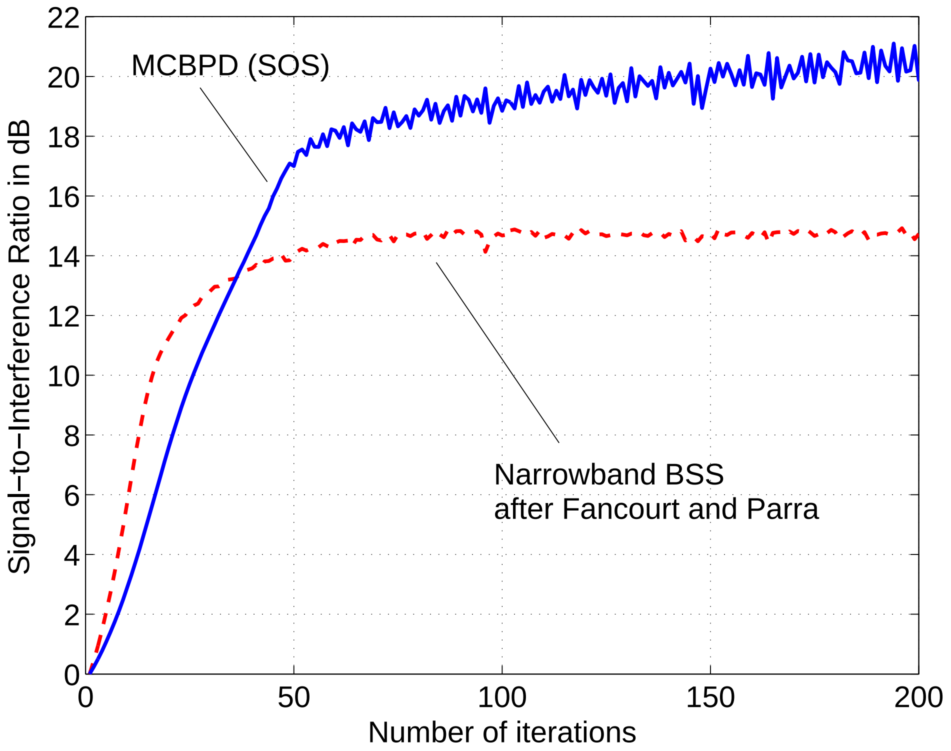
- **SOS-dereverberation performance:**
  Conditions: Reverberation time $T_{60} \approx 200ms$, 2×2 case, speech signals, microphone spacing $16cm$, unmixing filter length 1024 taps, sampling rate 16kHz, estimation of $\mathbf{R_{yy}}$ by correlation method

SIR improvement

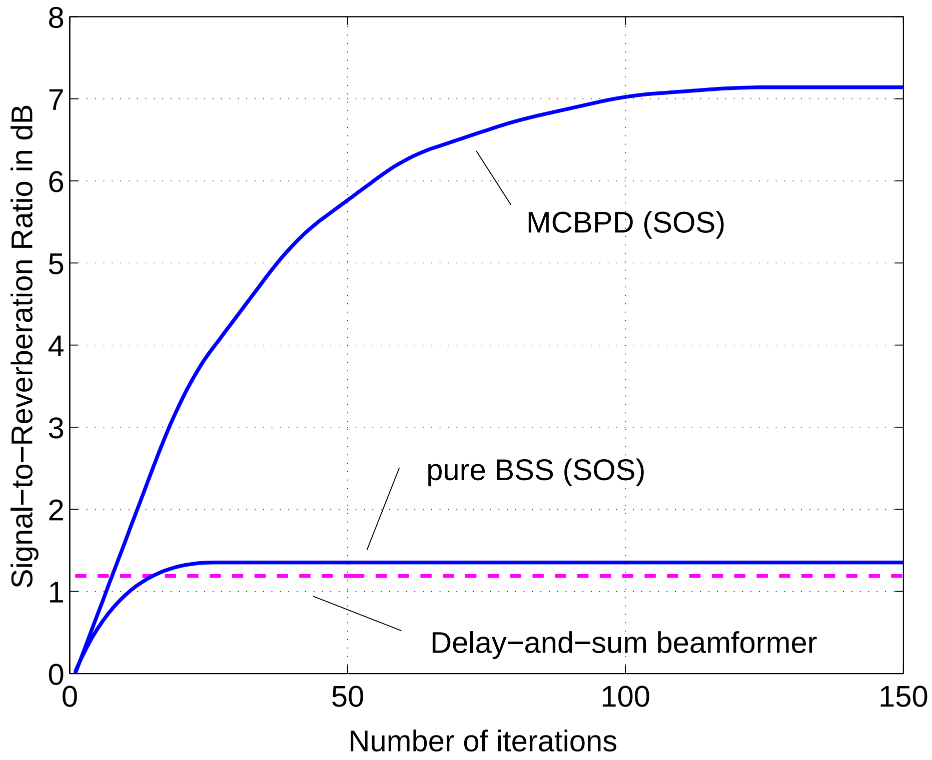


- **SOS-dereverberation performance:**
  Conditions: Reverberation time $T_{60} \approx 200ms$, 2×2 case, speech signals, microphone spacing $16cm$, unmixing filter length 1024 taps, sampling rate 16kHz, estimation of $\mathbf{R_{yy}}$ by correlation method

SIR improvement



SRR improvement



Summary and Outlook

- Versatile framework for blind MIMO signal processing exploiting **nongaussianity, nonwhiteness, and nonstationarity** in a rigorous way

- Various novel algorithms can be derived from it (time-domain and frequency-domain)

- Examples show: separation gain more than $20dB$,
dereverberation gain more than $7dB$

- This broadband approach has led to efficient realtime BSS on a laptop PC

- More sophisticated source models (e.g., HMM-based) may be incorporated in the framework