Blind multi-microphone noise reduction and dereverberation algorithms for speech communication applications

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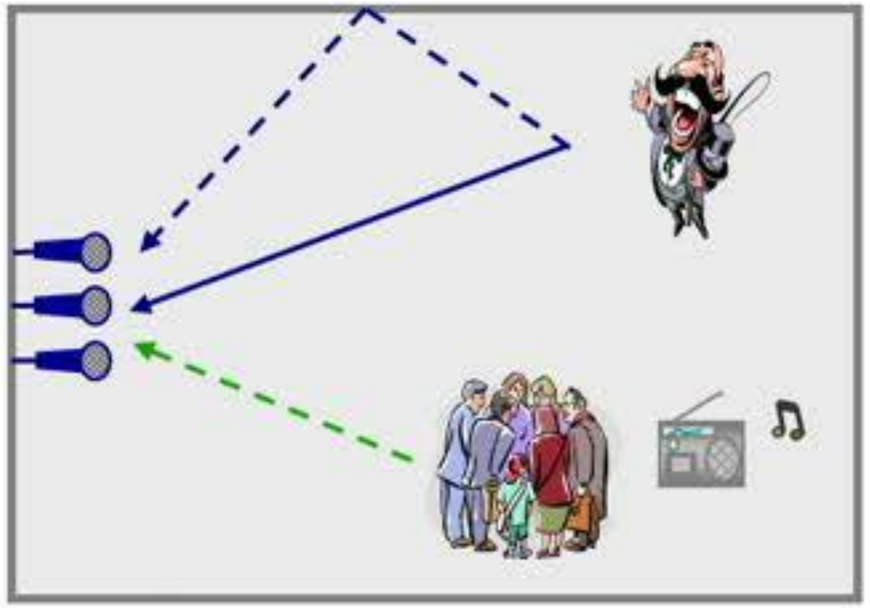
Introduction

- **Problem**
  - **Ambient noise and reverberation** jointly present in typical acoustic environments
  - **Speech quality and intelligibility** degradation for speech communication applications
  - Performance degradation of voice-controlled systems



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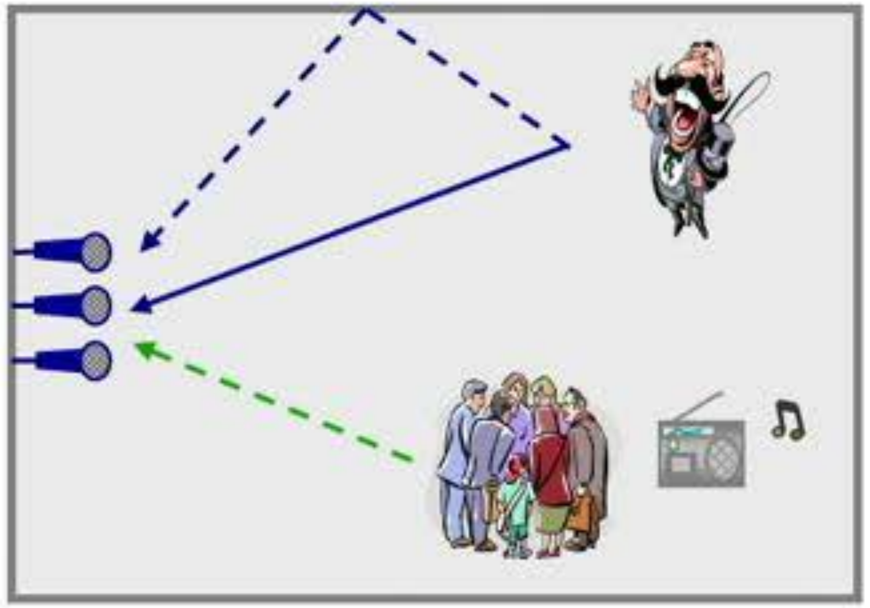

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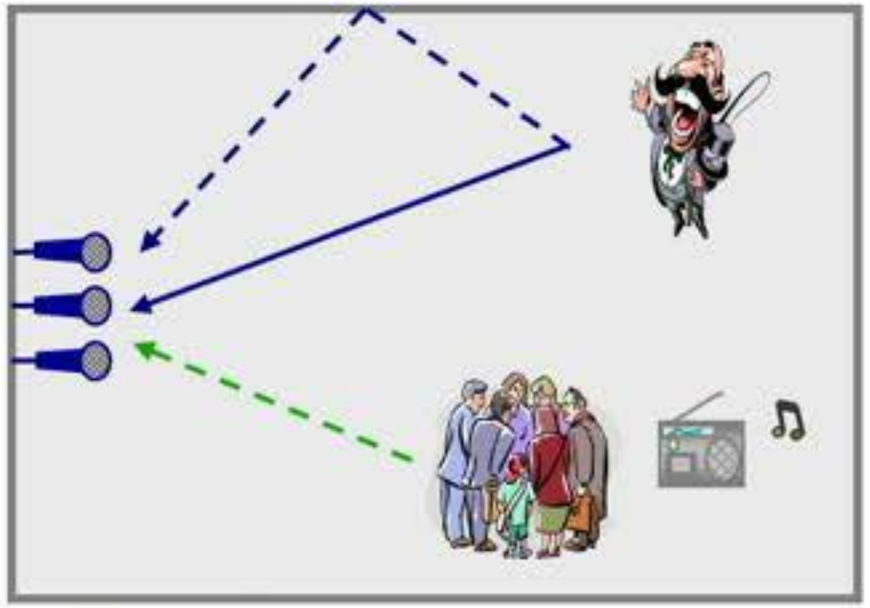

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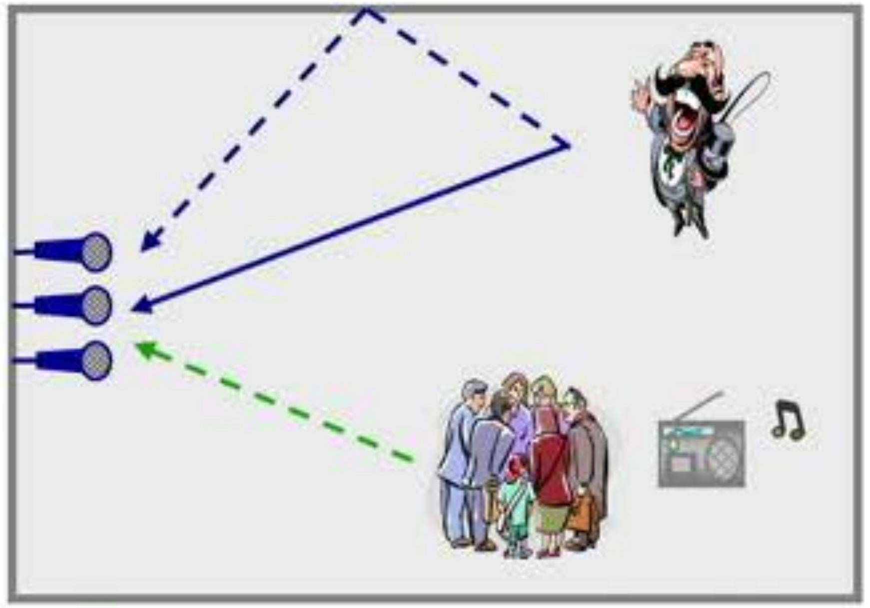

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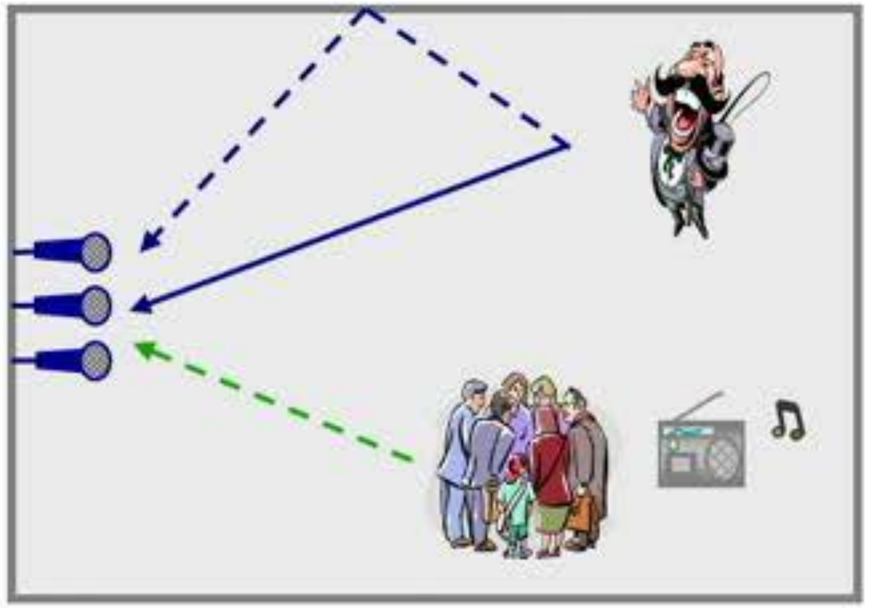
  - Single- and **multi-microphone joint noise reduction and dereverberation** algorithms
  - Speech communication applications: **blind and on-line processing** for time-varying dynamic acoustic scenarios
  - Exploit knowledge or (statistical) models of speech signals and room acoustics



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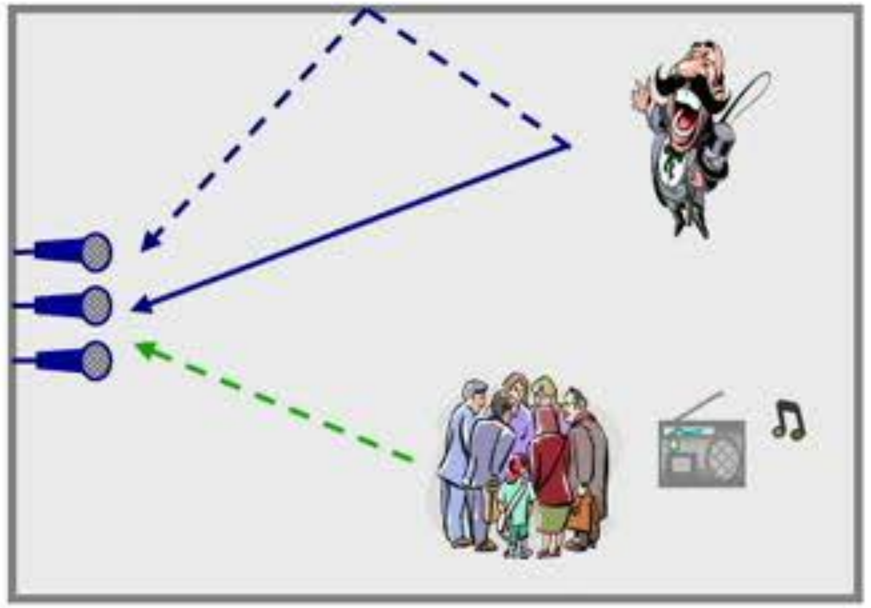

- **This presentation**
  1. **Joint estimation of (time-varying) spatial and spectral variables** for multi-microphone speech enhancement
  2. **Binaural hearing devices:** combination of speech enhancement and preservation of auditory scene
  3. **Extension to acoustic sensor networks** with spatially distributed microphones

1. Joint dereverberation and noise reduction

Signal model

- **Scenario:** speech source in noisy and reverberant environment, *M* microphones
- **Model in Short-Time Fourier Transform (STFT) domain:**

$$
\begin{aligned}
y_m(k,l) &= h_m(k,l) \star s(k,l) + v_m(k,l) \\
&= \underbrace{a_m(k,l) x_1(k,l)}_{\text{direct and early reverberation}} + \underbrace{x_{r,m}(k,l)}_{\text{late reverberation}} + \underbrace{v_m(k,l)}_{\text{ambient noise}}
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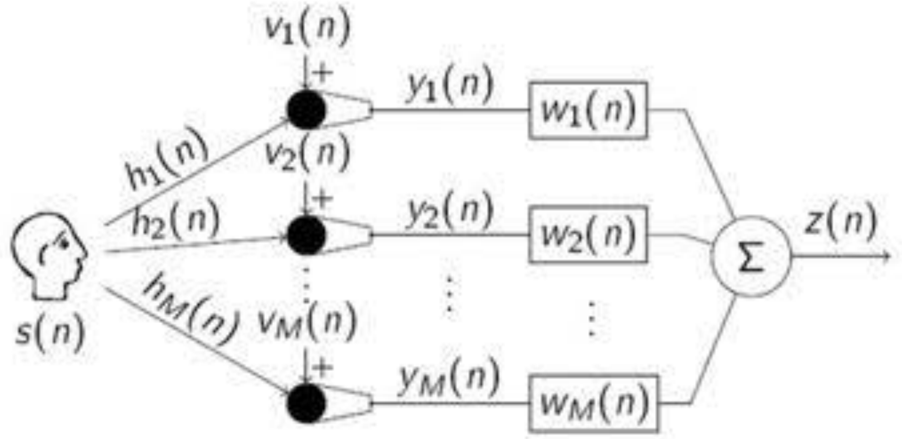

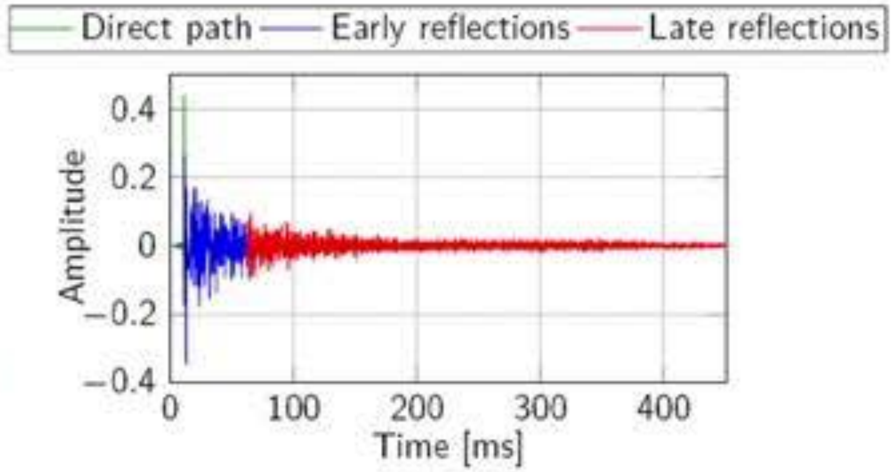

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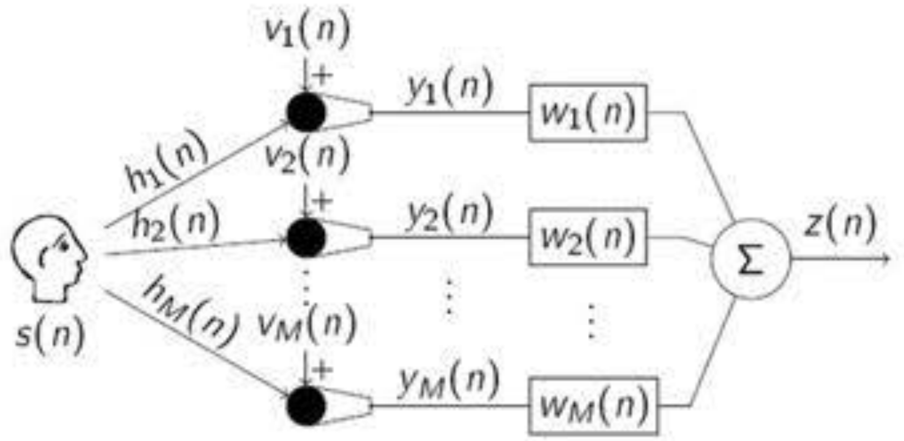
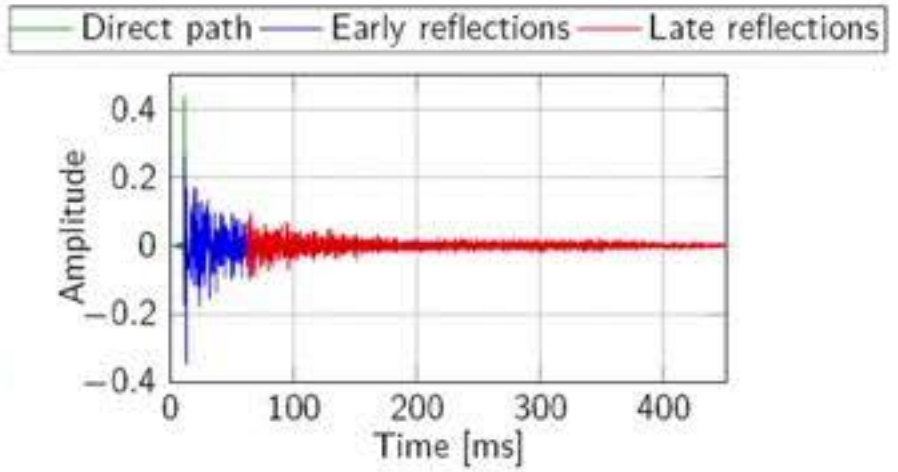
$$\boxed{\mathbf{y}(k,l) = \mathbf{a}(k,l)x_1(k,l) + \mathbf{x}_r(k,l) + \mathbf{v}(k,l)}$$

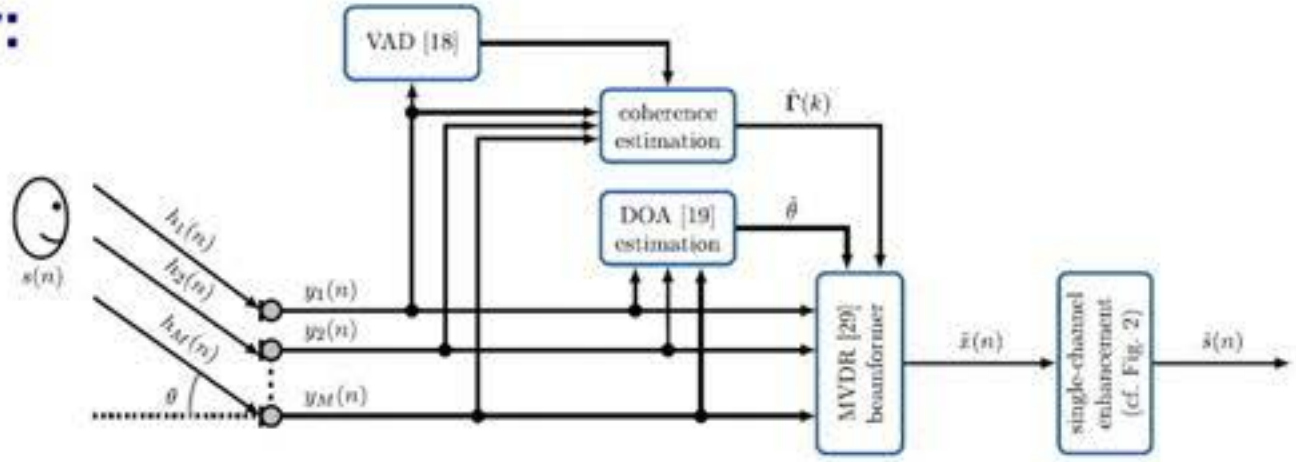
a(*k*,*l*) = vector of **relative early transfer functions (RETFs)** of target source





Multi-microphone dereverberation and noise reduction

1. **Beamforming + spectral postfilter:**
   multiply each time-frequency bin with *real-valued* gain



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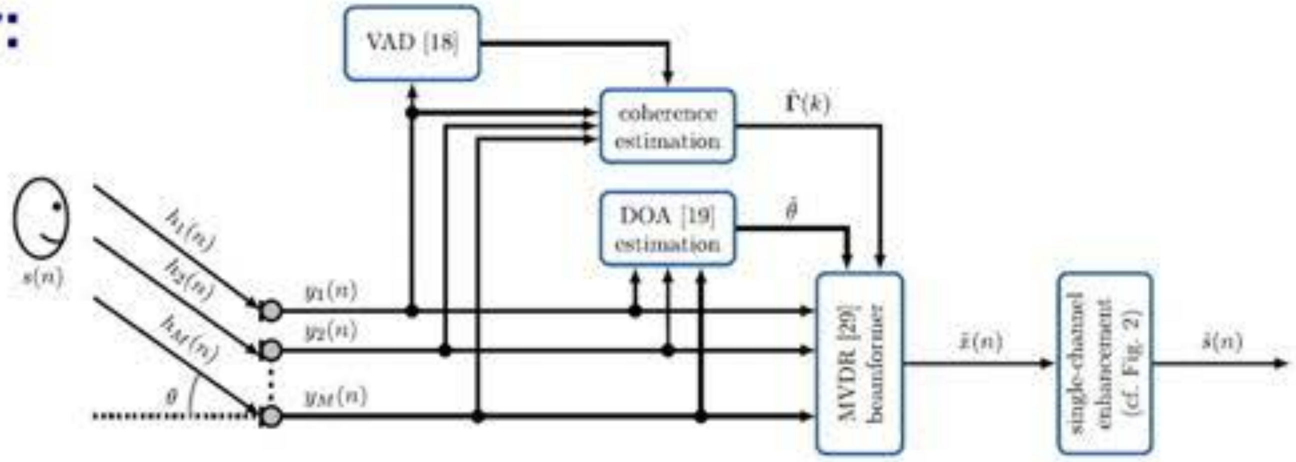

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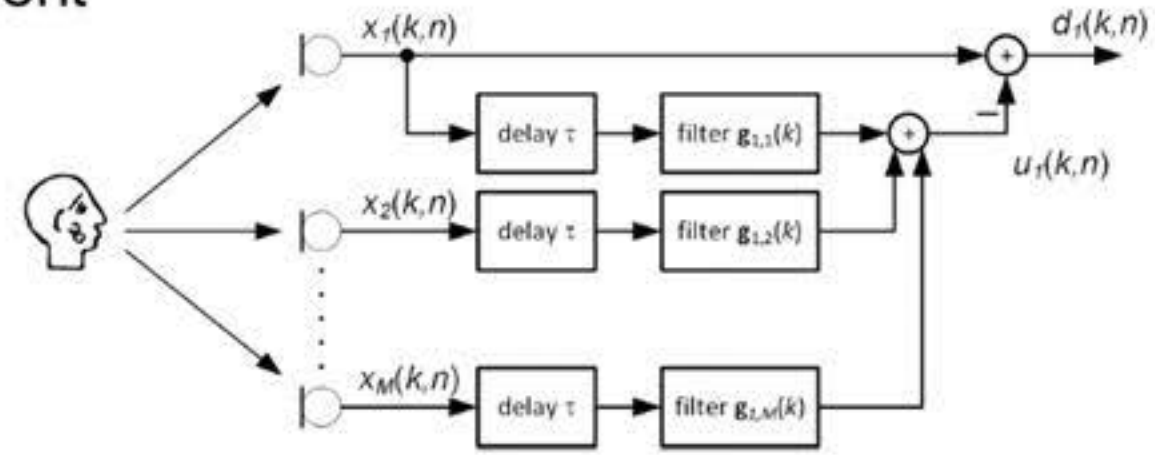
2. **Reverberation and noise suppression:** *subtract complex-valued* estimate of late reverberant and noise component



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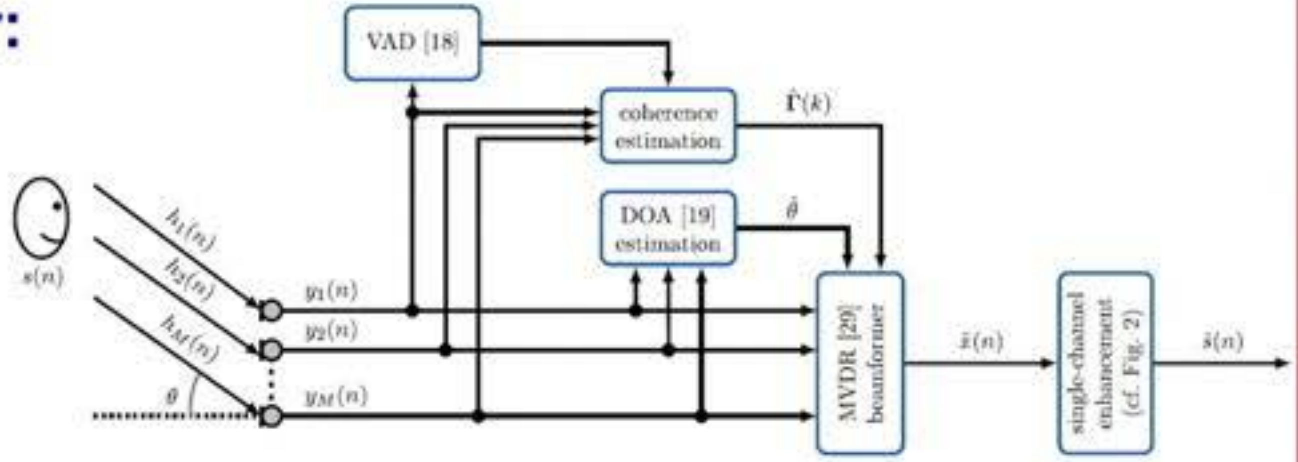

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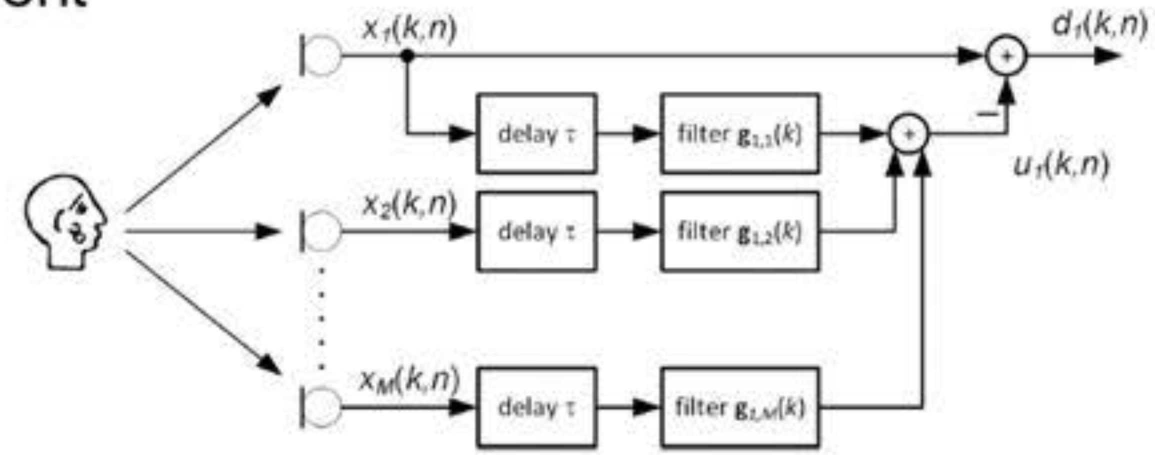

Beamforming + spectral postfilter

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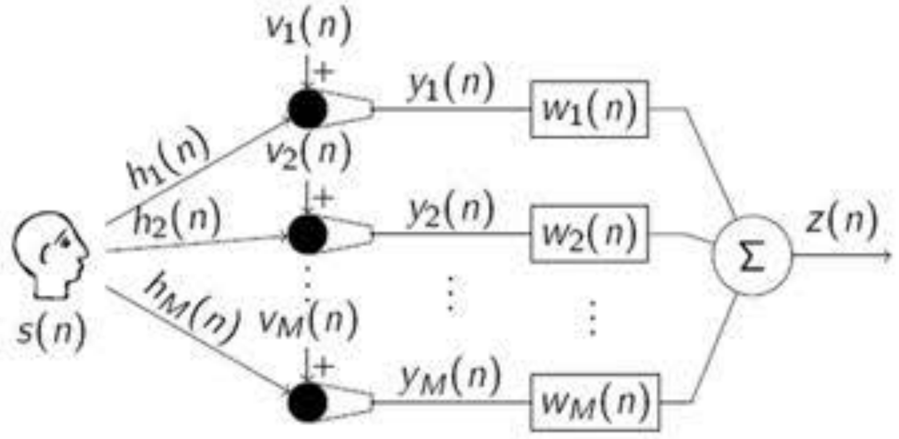

[Doclo, Kellermann, Makino, Nordholm, *IEEE Signal Processing Magazine*, Mar. 2015]
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  Goal: estimate desired speech component in reference microphone + trade off interference (*noise and/or reverberation*) reduction and speech distortion

$$\min_{\mathbf{w}} \mathcal{E}\{|\mathbf{w}^H \mathbf{x} - x_1|^2\} + \mu \mathcal{E}\{|\mathbf{w}^H \mathbf{n}|^2\} \quad \Rightarrow \quad \mathbf{w}_{MWF} = (\mathbf{\Phi}_x + \mu \mathbf{\Phi}_n)^{-1} \mathbf{\Phi}_x \mathbf{e}$$

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Beamforming + spectral postfilter

- **Signal model**

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Late reverberation: model as diffuse sound field $\mathbf{\Phi}_{x_r}(l) = \phi_d(l)\mathbf{\Gamma}$

with $\phi_d(l)$ *time-varying* diffuse PSD and $\mathbf{\Gamma}$ *time-invariant* coherence matrix (also incorporating diffuse noise !)

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- **Key estimation tasks:**
  - **RETF vector a**(*l*): *anechoic* (based on DOA estimate) or *reverberant*
  - **Diffuse/late reverberant PSD** $\phi_d(l)$: using single-channel *temporal model* (exponential decay) or based on multi-channel *diffuse sound field model*
  - **Noise covariance matrix** $\mathbf{\Phi}_v(l)$**:** *estimate* (based on SPP) or *model* (e.g., spatially white noise)

Estimation of PSDs

- **Requiring estimate of RETF vector and noise covariance matrix**

$$\hat{\mathbf{\Phi}}_x(l) = \hat{\mathbf{\Phi}}_y(l) - \hat{\mathbf{\Phi}}_v(l) = \phi_{x_1}(l)\mathbf{a}(l)\mathbf{a}^H(l) + \phi_d(l)\mathbf{\Gamma}$$

  – *Maximum-likelihood estimators,* requiring iterative optimisation procedure
  – Closed-form *least-squares estimators*, based on Frobenius norm

$$\min_{\phi_{x_1}(l),\phi_d(l)} ||\hat{\mathbf{\Phi}}_x(l) - \phi_{x_1}(l)\mathbf{a}(l)\mathbf{a}^H(l) - \phi_d(l)\mathbf{\Gamma}||_F^2$$

[Braun, Kuklasinski, Schwartz, Thiergart, Habets, Gannot, Doclo, Jensen, *IEEE/ACM Trans. Audio, Speech and Language Processing*, June 2018.]

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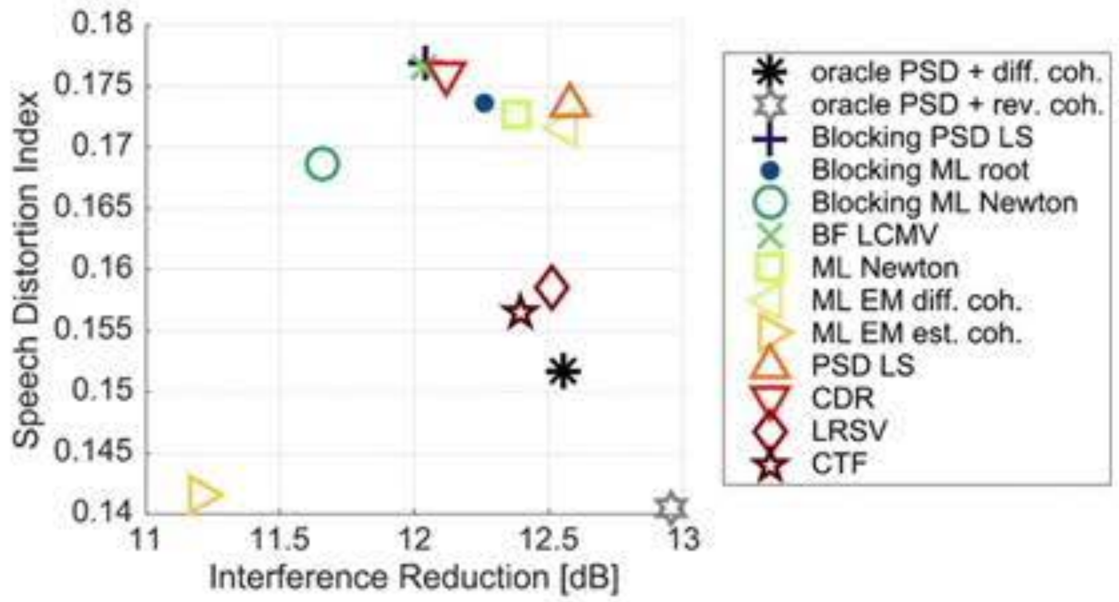

Fig. 9. Speech distortion vs. interference reduction for RSNR = 15 dB.

[Braun, Kuklasinski, Schwartz, Thiergart, Habets, Gannot, Doclo, Jensen, *IEEE/ACM Trans. Audio, Speech and Language Processing*, June 2018.]

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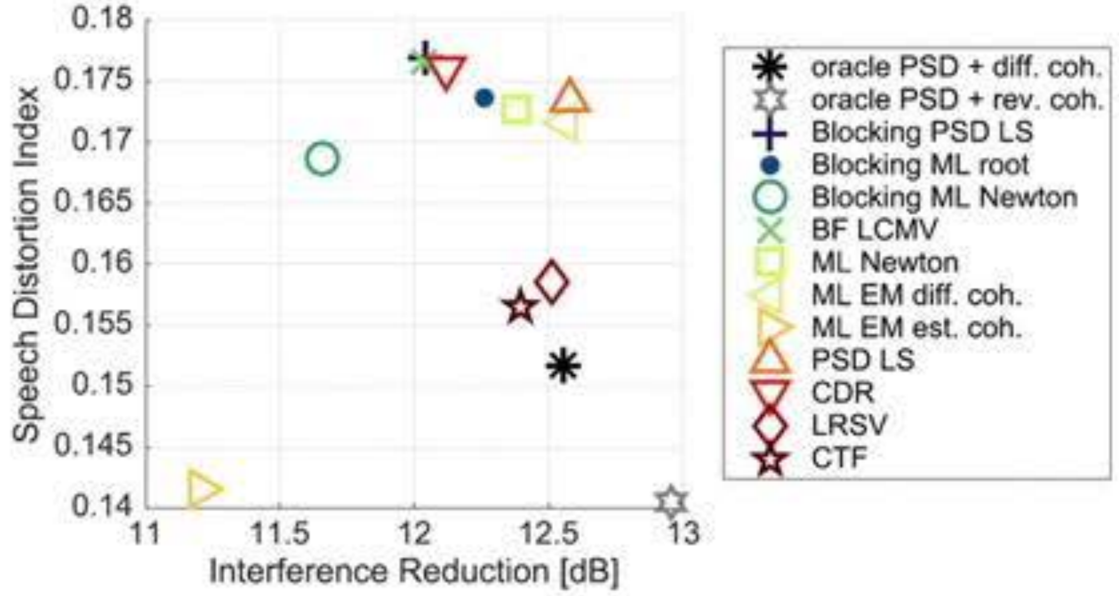

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Similar performance for most methods…

[Braun, Kuklasinski, Schwartz, Thiergart, Habets, Gannot, Doclo, Jensen, *IEEE/ACM Trans. Audio, Speech and Language Processing*, June 2018.]

Joint Estimation of RETF vector and PSDs

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   - **Eigenvalue decomposition** of prewhitened signal correlation matrix

$$\hat{\mathbf{\Phi}}_x^w(l) = \mathbf{\Gamma}^{-1/2}\hat{\mathbf{\Phi}}_x(l)\mathbf{\Gamma}^{-H/2} = \phi_{x_1}(l)\mathbf{b}(l)\mathbf{b}^H(l) + \phi_d(l)\mathbf{I}$$

Joint Estimation of RETF vector and PSDs

1. **Covariance whitening (CW) method:**
   - **Requires estimate of noise covariance matrix**

$$\hat{\mathbf{\Phi}}_x(l) = \hat{\mathbf{\Phi}}_y(l) - \hat{\mathbf{\Phi}}_v(l) = \phi_{x_1}(l)\mathbf{a}(l)\mathbf{a}^H(l) + \phi_d(l)\mathbf{\Gamma}$$

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     - **Principal eigenvector $\mathbf{u}(l)$: estimate of RETF vector**

$$\hat{\mathbf{a}}(l) = \frac{\mathbf{\Gamma}^{1/2}\mathbf{u}(l)}{\mathbf{e}^T\mathbf{\Gamma}^{1/2}\mathbf{u}(l)}$$

     - **Eigenvalues: estimate of PSDs**

$$\hat{\phi}_d(l) = \lambda_2\{\hat{\mathbf{\Phi}}_x^w(l)\} \qquad \hat{\phi}_{d,\mu}(l) = \frac{1}{M-1}\left(\mathrm{tr}\{\hat{\mathbf{\Phi}}_x^w(l)\} - \lambda_1\{\hat{\mathbf{\Phi}}_x^w(l)\}\right)$$

$$\hat{\phi}_{x_1}(l) = \lambda_1\{\hat{\mathbf{\Phi}}_x^w(l)\}/||\hat{\mathbf{b}}||_2^2$$

[Markovich-Golan, Gannot, *ICASSP 2015*] [Kodrasi, Doclo, *HSCMA 2017*]
[Kodrasi, Doclo, *IEEE/ACM Trans. Audio, Speech and Language Processing*, June 2018]

Joint Estimation of RETF vector and PSDs

2. **Alternating least squares (ALS) method,** minimizing Frobenius norm
   - **Model noise covariance matrix + estimate noise PSD**

$$\min_{\phi_{x_1}(l),\phi_d(l),\phi_v(l),\mathbf{a}(l)} ||\hat{\mathbf{\Phi}}_y(l) - \phi_{x_1}(l)\mathbf{a}(l)\mathbf{a}^H(l) - \phi_d(l)\mathbf{\Gamma} - \phi_v(l)\mathbf{\Psi}||_F^2$$

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   - **No closed-form solution → two-step alternating procedure** (least-squares problem for PSDs, eigenvalue problem for RETF vector)

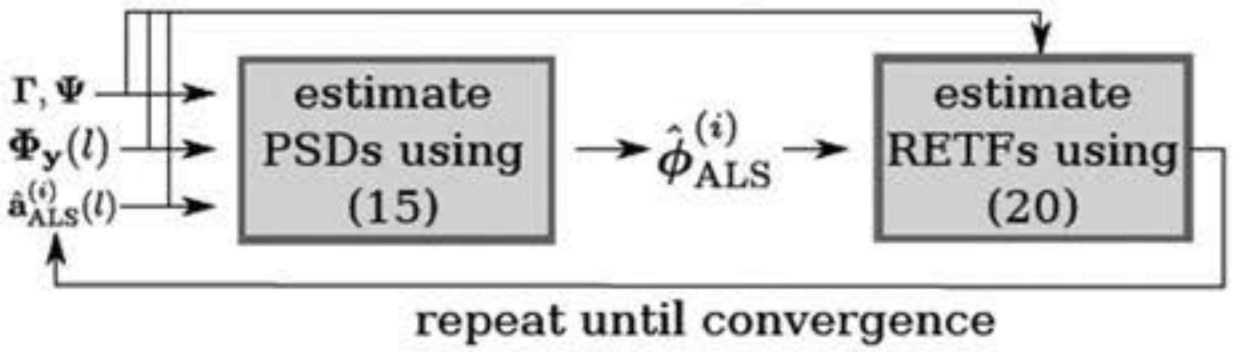

Fig. 1: Block diagram of ALS-based RETF vector and PSD estimation.

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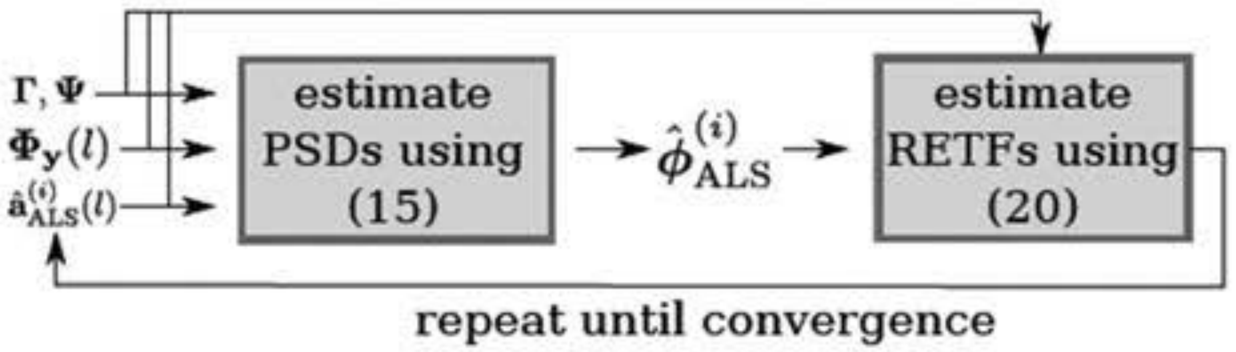

Fig. 1: Block diagram of ALS-based RETF vector and PSD estimation.

Algorithm 1: ALS method to jointly estimate the RETF vector and PSDs.

Input: $\mathbf{\Gamma}(k)$, $\mathbf{\Psi}(k)$, $\hat{\mathbf{\Phi}}_{\mathbf{y}}(k,l)$, iterations N, init. $\hat{\mathbf{a}}^{(0)}(k,1)$
Output: $\hat{\mathbf{a}}_{\mathrm{ALS}}(k,l)$, $\hat{\phi}_{\mathrm{ALS}}(k,l)$
for all (k,l) **do**
  for $i=1:N$ **do**
    compute $\mathbf{A}^{(i-1)}(k,l)$ using (16) and $\mathbf{b}^{(i-1)}(k,l)$ using (17)
    $\hat{\phi}_{\mathrm{ALS}}^{(i)}(k,l) = \left(\mathbf{A}^{(i-1)}(k,l)\right)^{-1}\mathbf{b}^{(i-1)}(k,l)$ (15)
    constrain $\hat{\phi}_{\mathrm{ALS}}^{(i)}(k,l)$ using (25)
    $\hat{\mathbf{\Phi}}_{\mathbf{x}}^{(i)}(k,l) =$
      $\hat{\mathbf{\Phi}}_{\mathbf{y}}(k,l) - (\hat{\phi}_{d,\mathrm{ALS}}^{(i)}(k,l)\mathbf{\Gamma}(k) + \hat{\phi}_{v,\mathrm{ALS}}^{(i)}(k,l)\mathbf{\Psi}(k))$
    $\hat{\mathbf{\Phi}}_{\mathbf{x}}^{(i)}(k,l) = \hat{\mathbf{N}}^{(i)}(k,l)\hat{\mathbf{\Lambda}}^{(i)}(k,l)\hat{\mathbf{N}}^{(i),H}(k,l)$ (EVD)
    $\hat{\mathbf{a}}_{\mathrm{ALS}}^{(i)}(k,l) = \sqrt{\hat{\lambda}_1^{(i)}(k,l)/\hat{\phi}_{s,\mathrm{ALS}}^{(i)}(k,l)}\,\hat{\boldsymbol{\nu}}_1^{(i)}(k,l)$ (20)
  end
  $\hat{\mathbf{a}}_{\mathrm{ALS}}^{(1)}(k,l+1) = \hat{\mathbf{a}}_{\mathrm{ALS}}^{(N)}(k,l)/(\mathbf{e}^T\hat{\mathbf{a}}_{\mathrm{ALS}}^{(N)}(k,l))$ (for next frame)
end

[Tammen, Kodrasi, Doclo, *ICASSP 2019*]

Simulation results

1. **Simulated stationary source (ACE)**
   - Linear microphone array (M=6, d=6cm)
   - Target source at 15° (measured room impulse responses, $T_{60} \approx 1.25$ s)
   - Simulated diffuse babble noise (SDR=10 dB)

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2. **Recorded moving source (varechoic lab)**
   - Linear microphone array (M=6, d=1cm)
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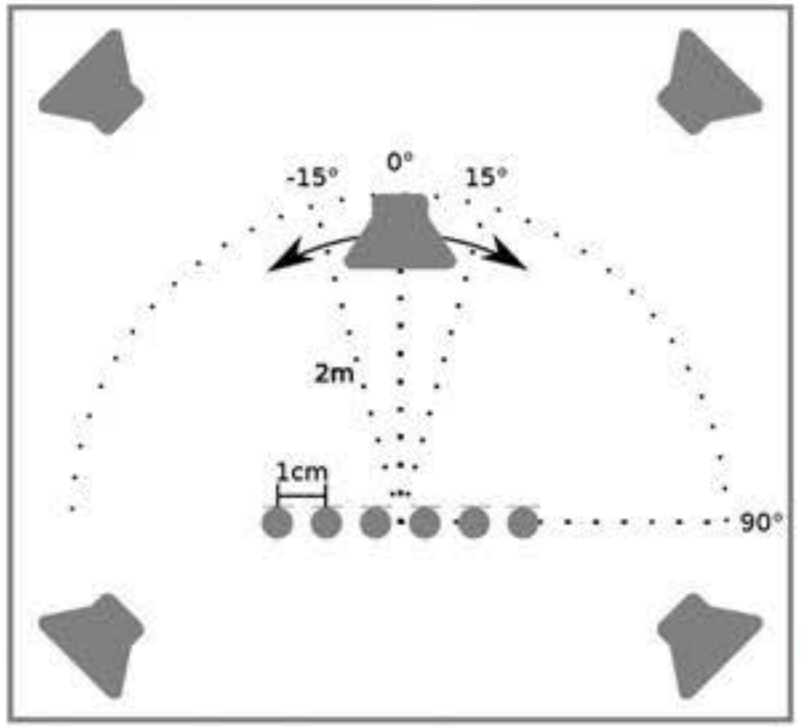

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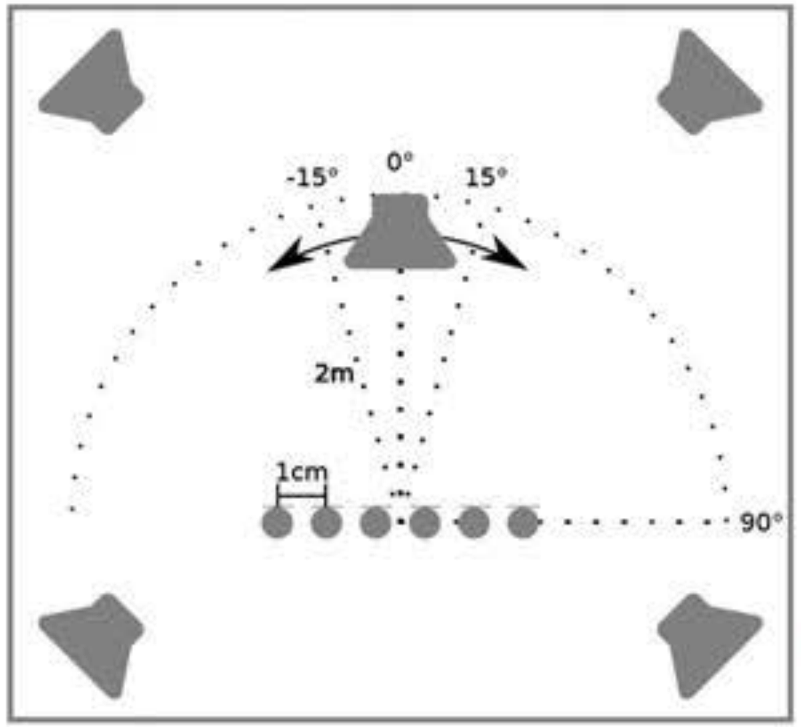
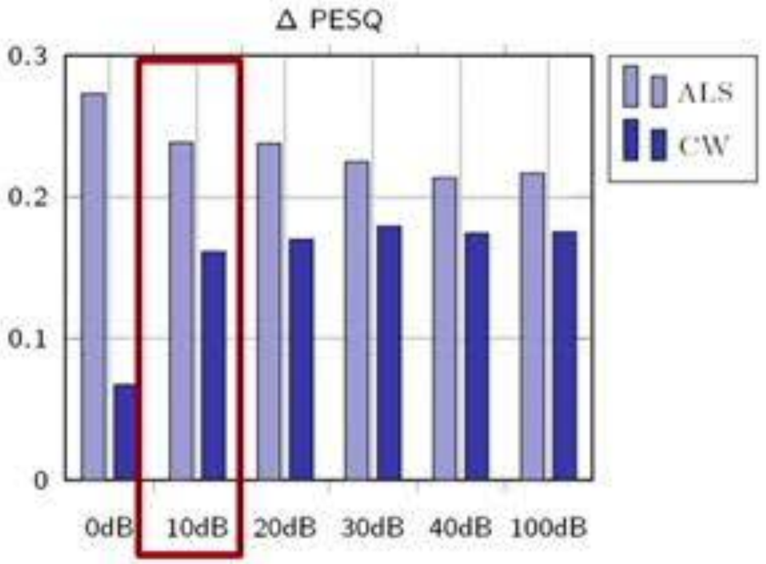


Simulation parameters:

- f_s = 16 kHz, STFT: 64 ms, 75% overlap, Hamming window
- Γ: spherically diffuse; smoothing: 40 ms; speech PSD estimated using decision-directed approach, G_{min} = -10 dB
- CW: noise covariance matrix estimated during first second; ALS: 5 iterations

Simulation results (PESQ improvement)

1. Simulated stationary source

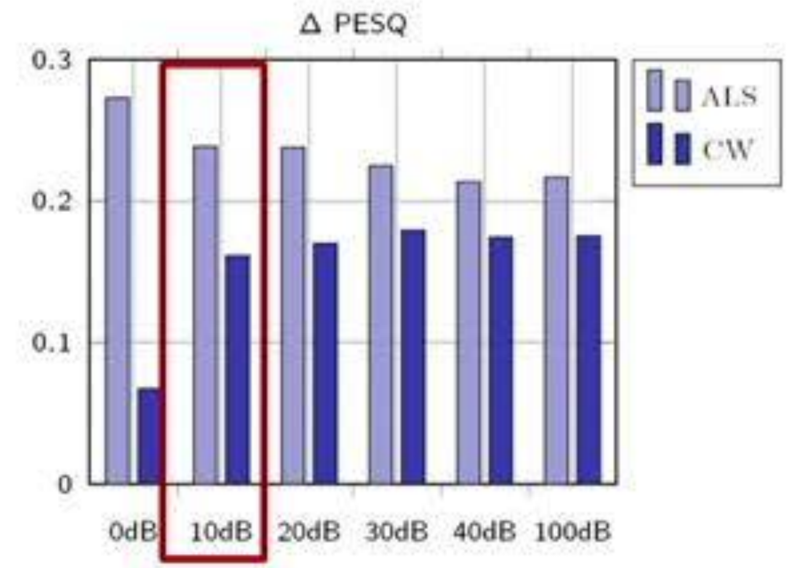


Input	MWF CW	MWF ALS

Linear array (M=6, d=6cm), fs=16kHz, stationary source at $\theta=15^{o}$, perfectly diffuse babble noise (SDR=10dB), sensor noise (DNR=10dB)

Simulation results (PESQ improvement)

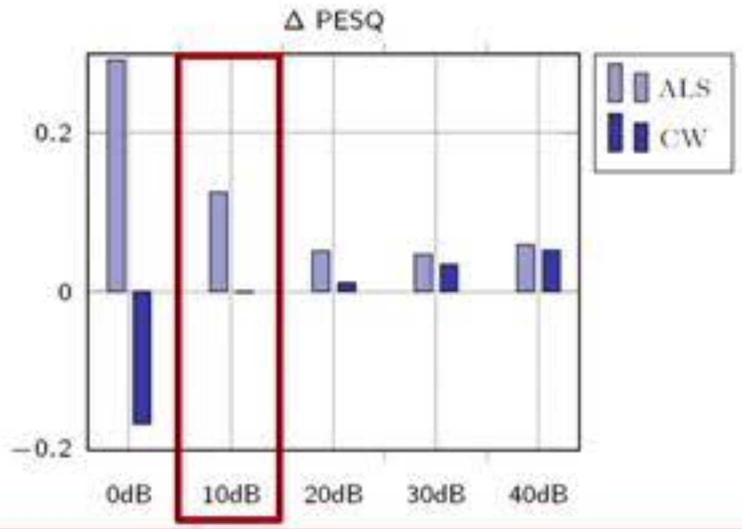
1. Simulated stationary source



Input	MWF CW	MWF ALS

Linear array (M=6, d=6cm), fs=16kHz, stationary source at $\theta=15^\circ$, perfectly diffuse babble noise (SDR=10dB), sensor noise (DNR=10dB)

2. Recorded moving source



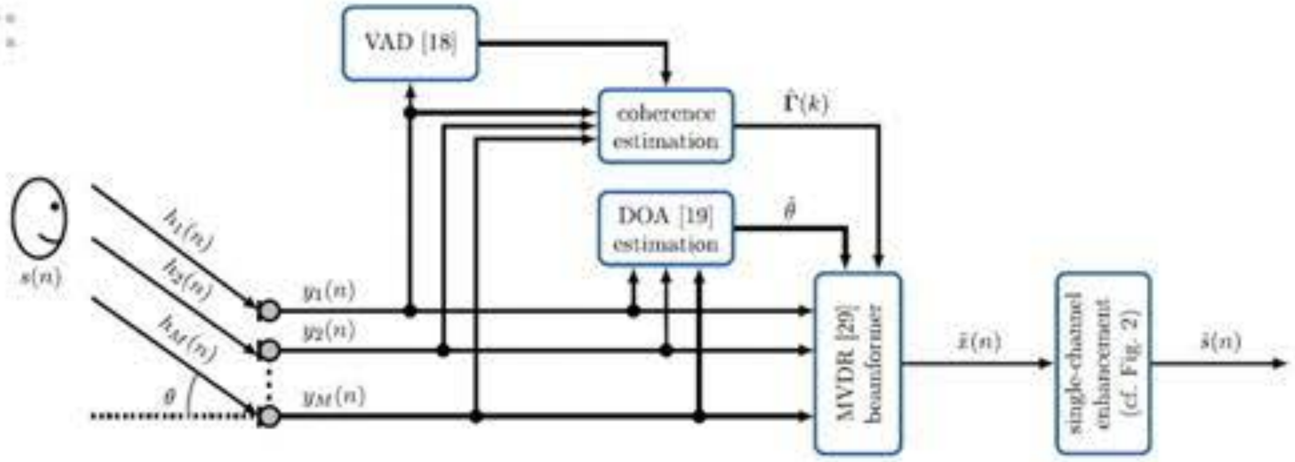
Input	MWF CW	MWF ALS

Linear array (M=6, d=1cm), fs=16kHz, moving source $\theta=0^\circ$ to $\theta=90^\circ$ pseudo-diffuse babble noise (SDR=10dB), sensor noise (DNR=10dB)

Multi-microphone dereverberation and noise reduction

1. **Beamforming + spectral postfilter:** *multiply* each time-frequency bin with *real-valued* gain

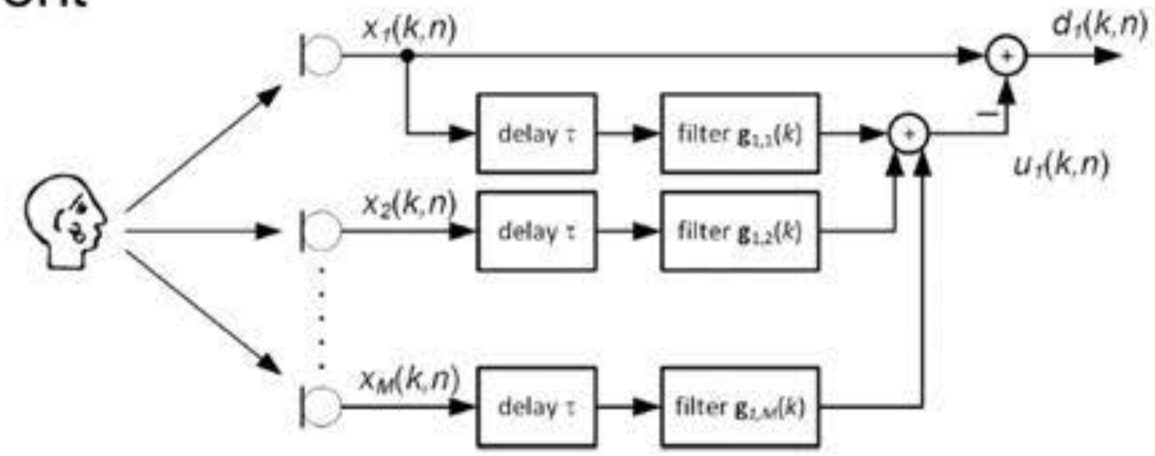
$$\mathbf{y}(l) = \mathbf{a}(l)x_1(l) + \mathbf{x}_r(l) + \mathbf{v}(l)$$



2. **Reverberation and noise suppression:** *subtract complex-valued* estimate of late reverberant and noise component

$$y_m(l) = h_m(l) \star s(l) + v_m(l)$$

$$\hat{x}_{e,1}(l) = y_1(l) - \mathbf{Y}_\tau(l)\mathbf{g}(l)$$

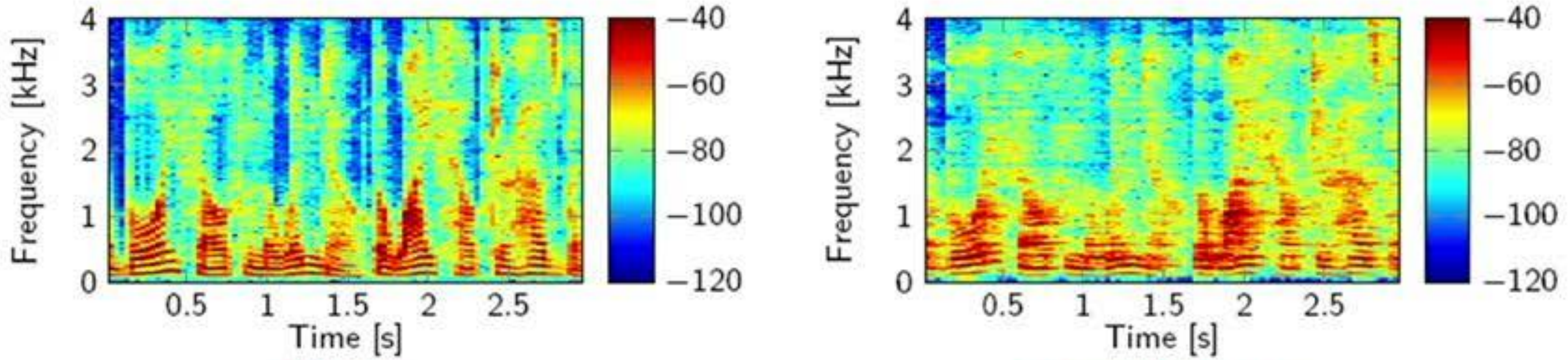


Reverberation suppression

- **Goal**: estimate clean speech STFT coefficients $s(k,l)$ from reverberant (and noisy) STFT coefficients $y_m(k,l)$ by subtracting late reverberant component

$$y_m(k,l) = \underbrace{h_m(k,l) \star s(k,l)}_{x_m(k,l)} + v_m(k,l)$$

  - Probabilistic estimation using (statistical) **models of desired speech signal and reverberation**
  - Exploit **sparsity properties** of speech in STFT-domain



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- **Approach**: transform to equivalent AR model → sparse **multi-channel linear prediction (MCLP)**

$$x_1(k,l) = d(k,l) + \sum_{m=1}^{M} \sum_{n=0}^{L_g-1} g_m(k,n) x_m(k,l-\tau-n)$$

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$$x_1(k,l) = \underbrace{d(k,l)}_{\substack{\uparrow \\ \text{clean signal} \\ \text{(incl. early reflections)}}} + \sum_{m=1}^{M} \sum_{n=0}^{L_g-1} g_m(k,n) x_m(k,l-\underbrace{\tau}_{\substack{\uparrow \\ \text{delay} \\ \text{(early reflections)}}}-n)$$

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prediction filters

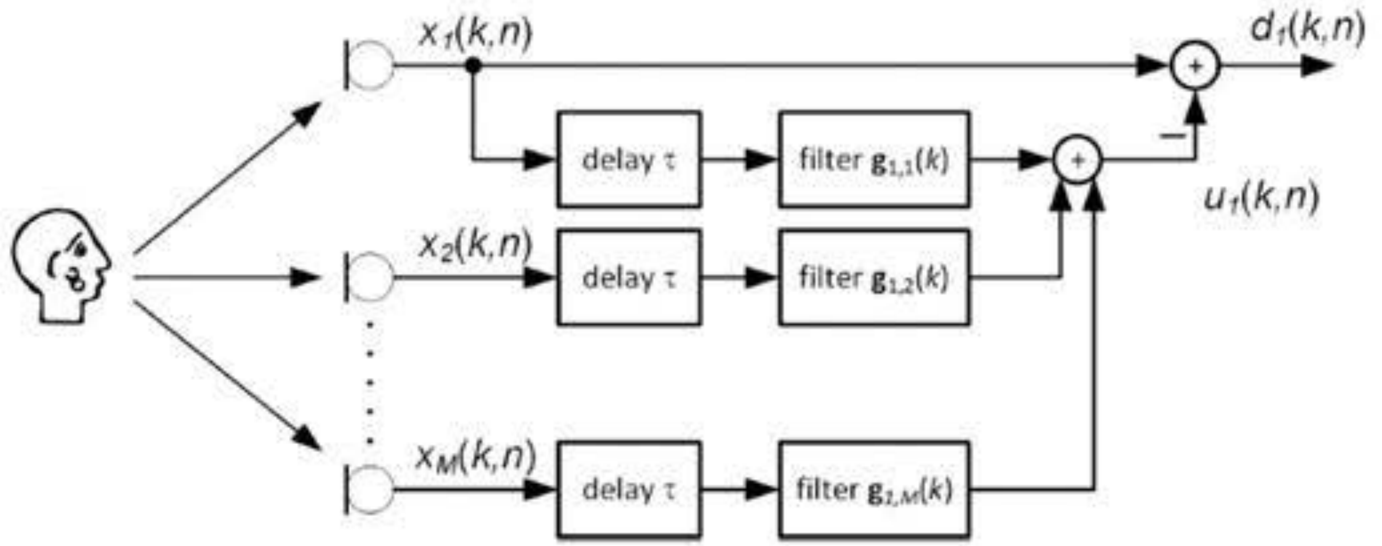
Multi-channel linear prediction

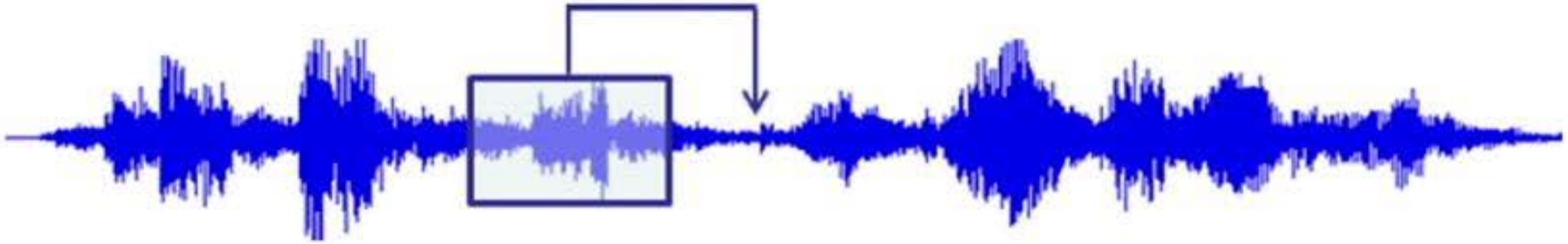
- **AR model of reverberant speech**

$$\mathbf{x_1}(k) = \mathbf{d}(k) + \mathbf{X}_\tau(k)\mathbf{g}(k)$$

$$\hat{\mathbf{d}}(k) = \mathbf{x_1}(k) - \mathbf{X}_\tau(k)\hat{\mathbf{g}}(k)$$

predicted reverberation





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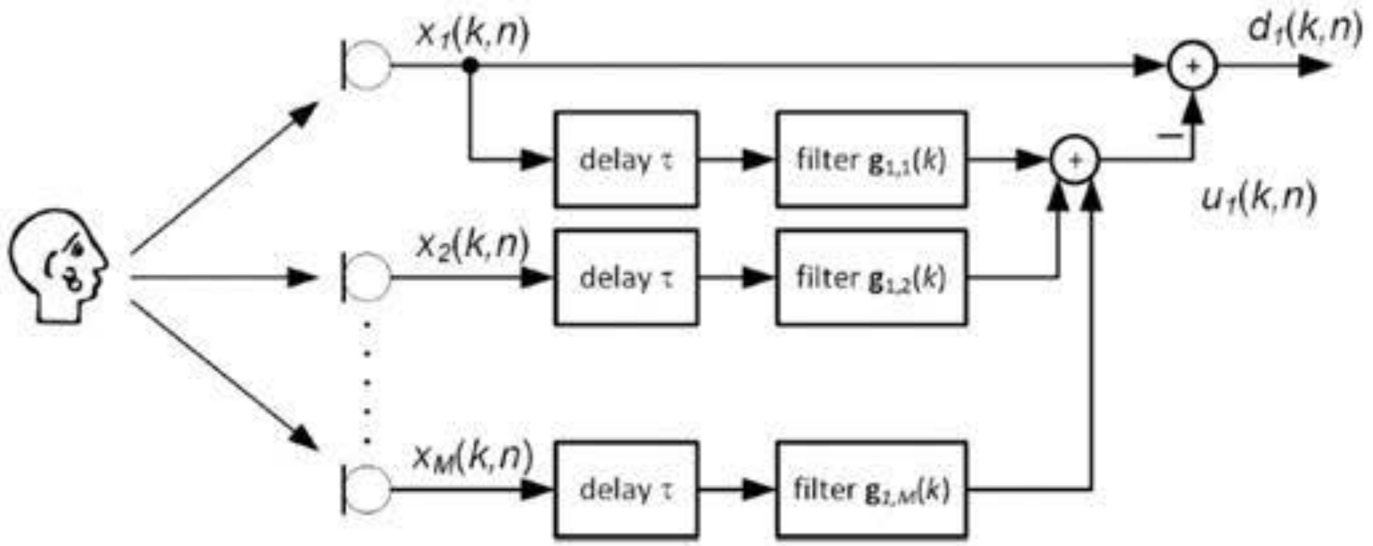

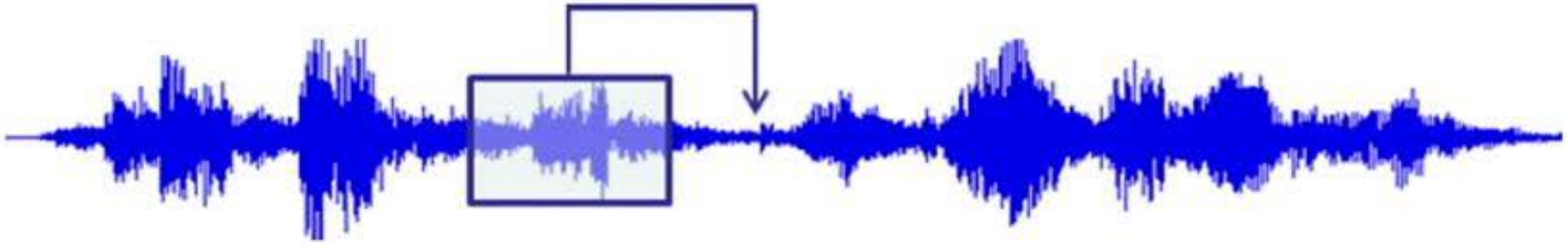

How to select suitable cost function for prediction filters ?

Multi-channel linear prediction

- **Approach:**
  - STFT coefficients of desired signal are modelled using **circular sparse/super-Gaussian prior with time-varying variance** $\lambda(n)$

$$\rho(d(n)) = \max_{\lambda(n)>0} \mathcal{N}_{\mathbb{C}}(d(n); 0, \lambda(n)) \boxed{\psi(\lambda(n))}$$

Scaling function $\psi(.)$ can be interpreted as **hyper-prior on variance**

[Nakatani, Yoshioka, Kinoshita, Miyoshi, Juang, *IEEE/ACM Trans. Audio Speech Language Proc.*, Sep. 2010.]
[Jukić, van Waterschoot, Gerkmann, Doclo, *IEEE/ACM Trans. Audio Speech Language Proc.*, Sep. 2015.]

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  - **Maximum-Likelihood Estimation** (batch, per frequency bin)

$$\mathcal{L}(\mathbf{g}) = \prod_{n=1}^{N} \rho\left(d(n)\right) \Rightarrow \min_{\boldsymbol{\lambda}>0,\mathbf{g}} \sum_{n=1}^{N} \left(\frac{|d(n)|^2}{\lambda(n)} + \log \pi\lambda(n) \boxed{- \log \psi(\lambda(n))} \right)$$

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  - **Alternating optimization procedure**
    1. Estimate **prediction vector** (assuming fixed variances)

$$\hat{\mathbf{g}}^{(i+1)} = \left(\mathbf{X}_\tau^H \mathcal{D}_{\hat{\boldsymbol{\lambda}}^{(i)}}^{-1} \mathbf{X}_\tau \right)^{-1} \mathbf{X}_\tau^H \mathcal{D}_{\hat{\boldsymbol{\lambda}}^{(i)}}^{-1} \mathbf{x}_1$$

    2. Estimate **variances** (assuming fixed prediction vector)

$$\hat{\lambda}^{(i+1)}(n) = \arg\min_{\lambda(n)>0} \frac{|\hat{d}^{(i+1)}(n)|^2}{\lambda(n)} + \log \pi\lambda(n) \boxed{- \log \psi(\lambda(n))}$$

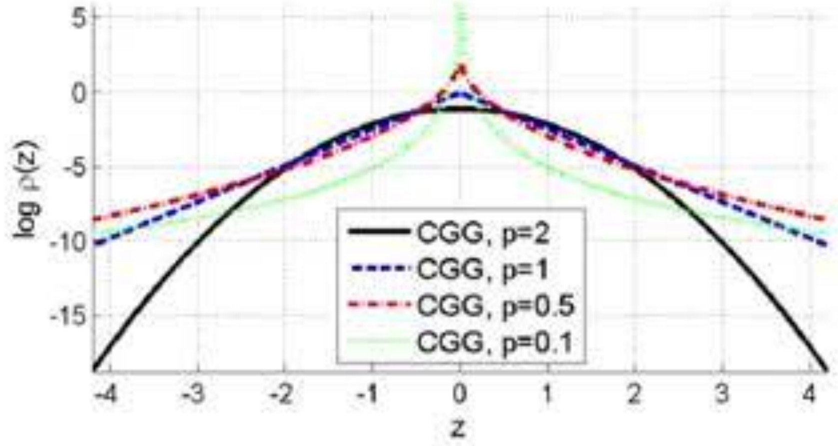
[Nakatani, Yoshioka, Kinoshita, Miyoshi, Juang, *IEEE/ACM Trans. Audio Speech Language Proc.*, Sep. 2010.]
[Jukić, van Waterschoot, Gerkmann, Doclo, *IEEE/ACM Trans. Audio Speech Language Proc.*, Sep. 2015.]

Multi-channel linear prediction

- **Example:** complex generalized Gaussian (CGG) prior with shape parameter *p*

$$\rho(z) = \frac{p}{2\pi\gamma\Gamma(2/p)} e^{-\frac{|z|^p}{\gamma^{p/2}}}$$

$$\boxed{\hat{\lambda}^{(i+1)}(n) = \left|\hat{d}^{(i+1)}(n)\right|^{2-p},}$$



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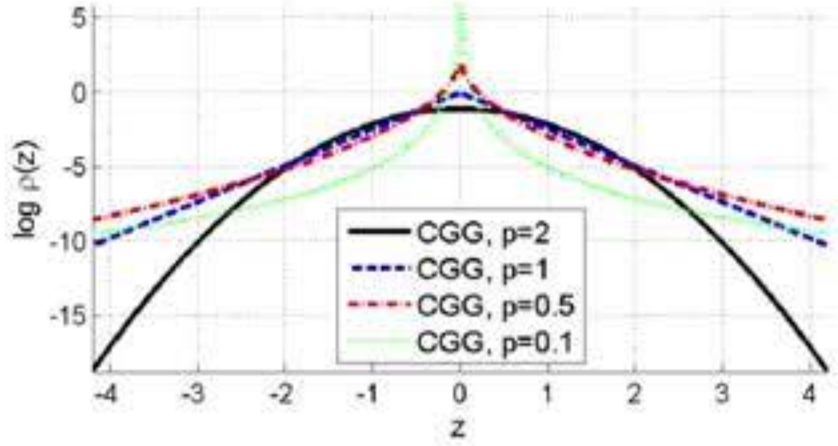


- **Remarks:**

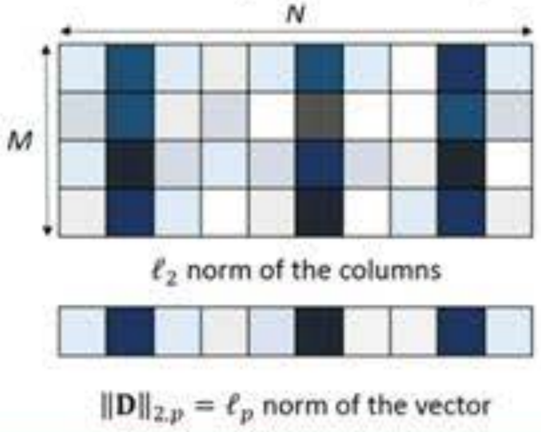
1. ML estimation using CGG prior is equivalent to ***l_p*-norm minimization** → **promotes sparsity of TF-coefficients across time** (for p < 2)

$$\boxed{\min_{\mathbf{g}} \|\mathbf{d}\|_p^p,}$$

2. Incorporate additional knowledge of speech signal, e.g. **low-rank structure** (NMF)

$$|\mathbf{D}|^2 \approx \underbrace{\mathbf{W}}_{\text{spectral dictionary}} \mathbf{H}$$

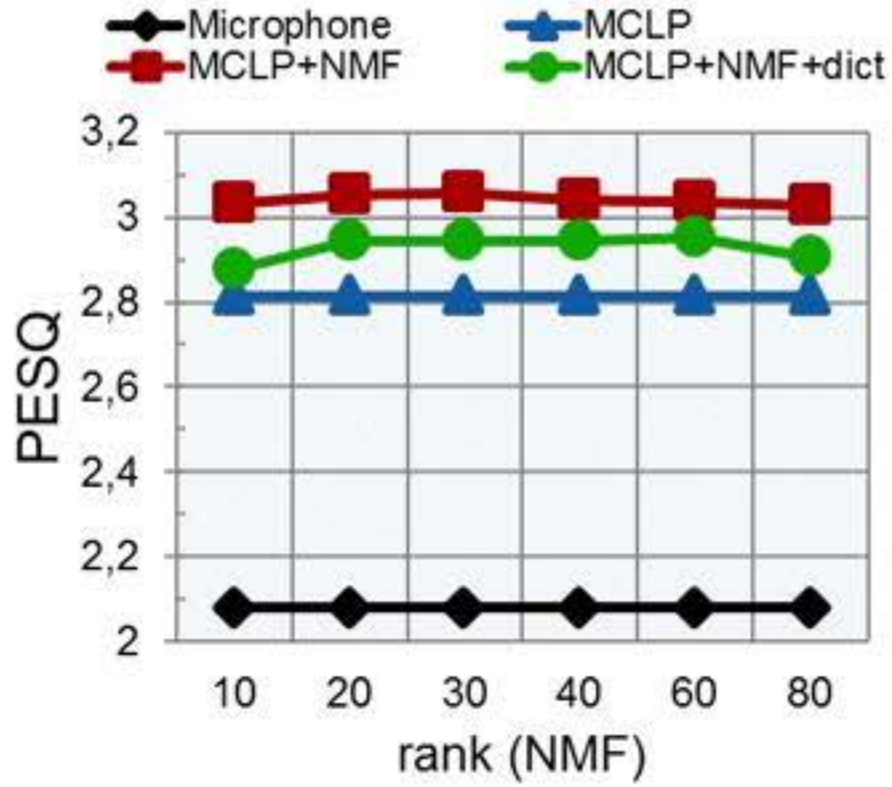
3. **Group sparsity** for MIMO speech dereverberation → mixed norms
4. **Recursive version** by constraining MCLP-based estimate of undesired component

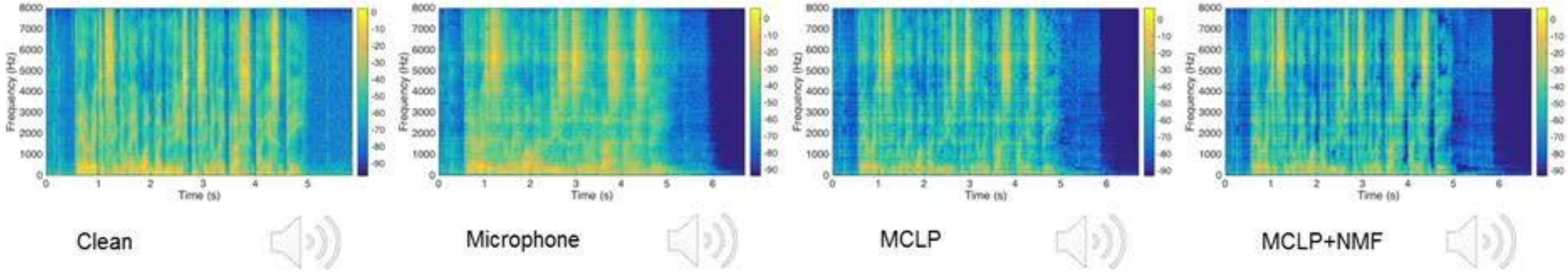


[Jukić, van Waterschoot, Gerkmann, Doclo, *IEEE/ACM Trans. Audio Speech Language Proc.*, Sep. 2015.]
[Jukić, van Waterschoot, Doclo, *IEEE Signal Processing Letters*, Jan. 2017.]

Multi-channel linear prediction

- **Instrumental validation (noiseless, batch)**
  - MCLP exploits sparsity
  - NMF introduces speech structure (unsupervised vs. supervised NMF)

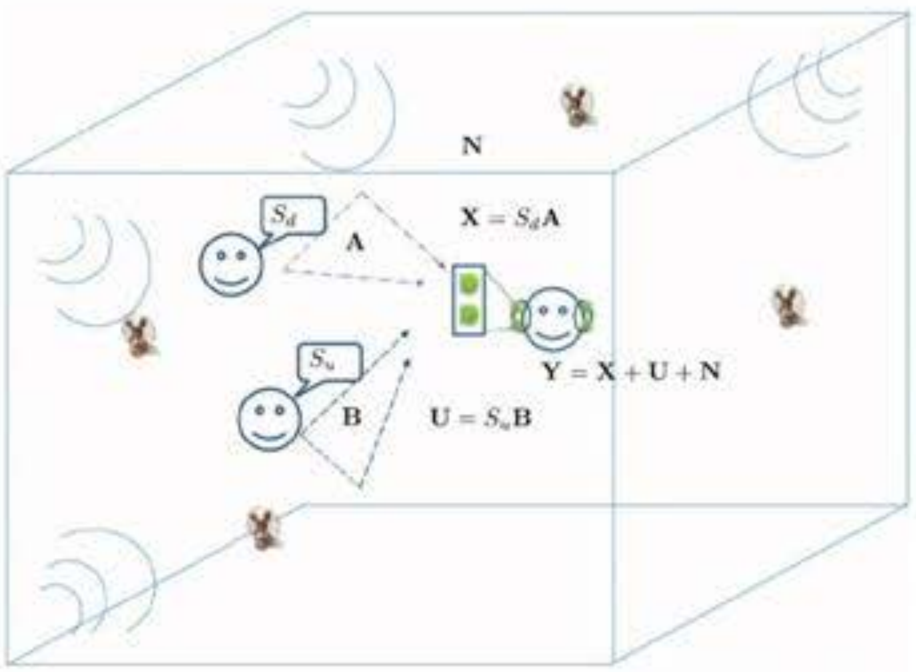




T_{60} ~ 700ms, M=4, fs=16 kHz; STFT: 64ms (overlap 16ms); MCLP: L_g=8, τ=2, p=0

Current/future work

- Estimation of RETF vectors and PSDs for **multi-speaker scenarios** (e.g. based on Procrustes problem)
- **Joint noise reduction and dereverberation:** integration of multi-channel linear prediction and generalized sidelobe canceller



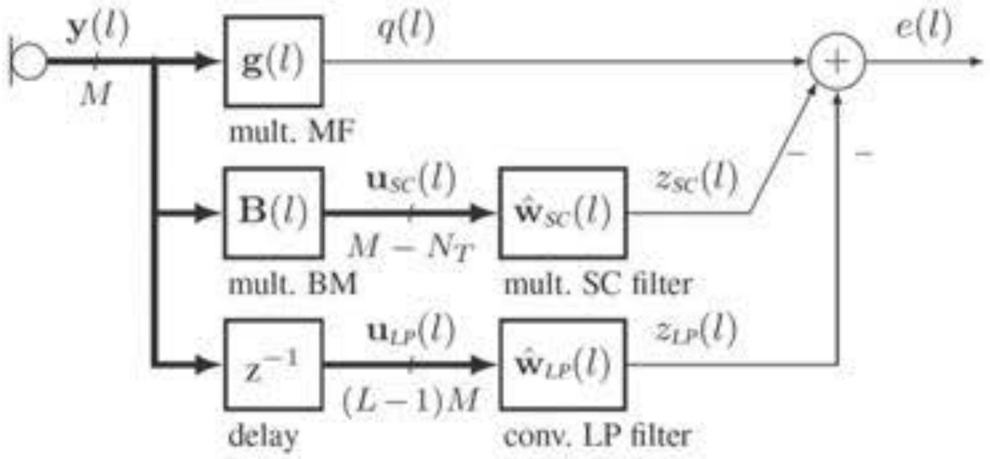


Fig. 1. The integrated sidelobe cancellation and linear prediction (ISCLP) architecture.

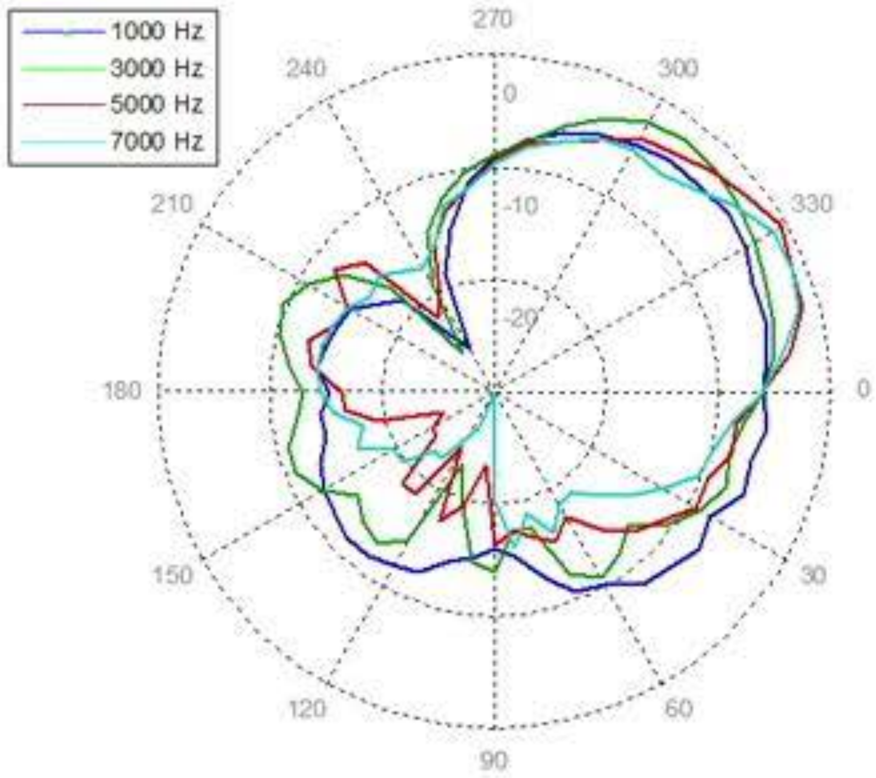
[Dietzen, Doclo, Moonen, van Waterschoot, *IEEE/ACM Trans. Audio Speech Language Proc.*, in review.]
[Dietzen, Doclo, Moonen, van Waterschoot, *IWAENC 2018.*]

2. Acoustic signal processing for binaural hearing devices

Hearing devices / hearables

- Hearing devices generally have multiple microphones available and allow for advanced acoustical signal pre-processing

Monaural (2-3)



[S. Doclo, W. Kellermann, S. Makino, S. Nordholm, *Multichannel signal enhancement algorithms for assisted listening devices*, *IEEE Signal Processing Magazine*, Mar. 2015.]

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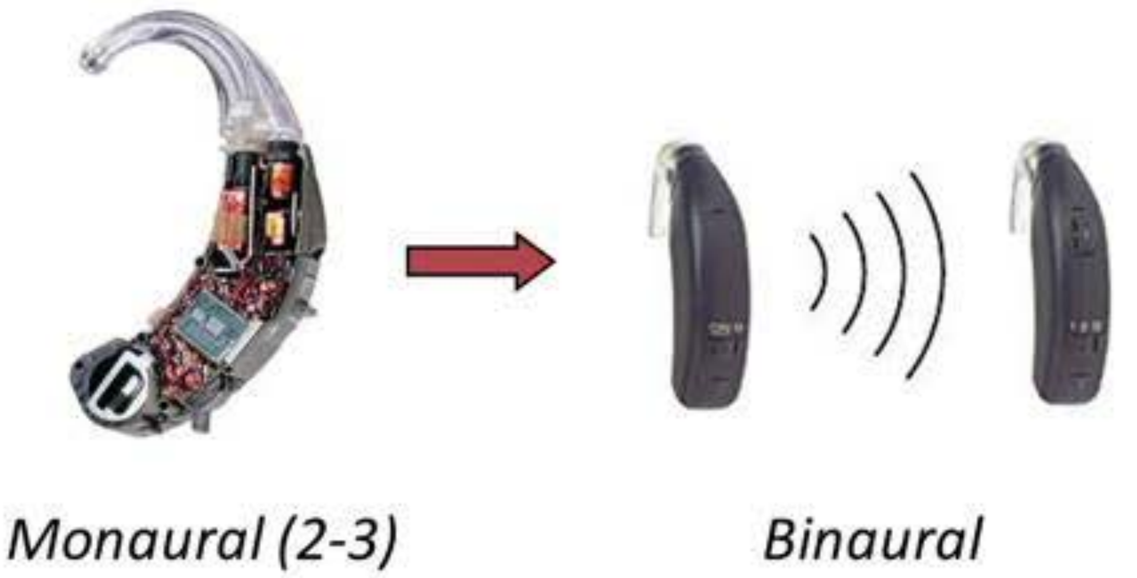

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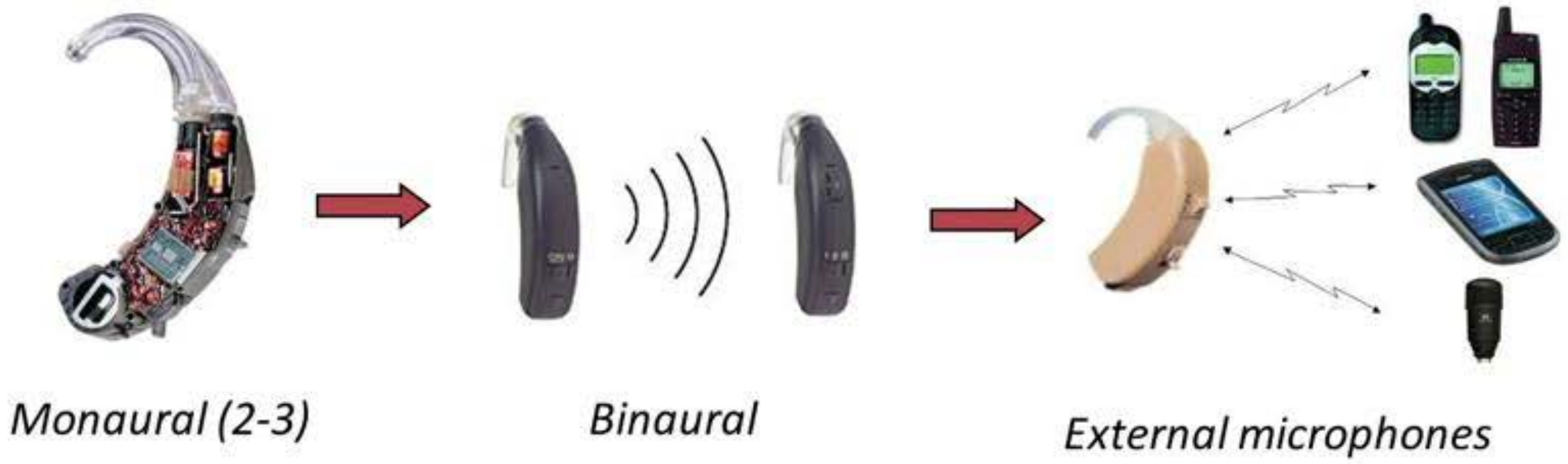

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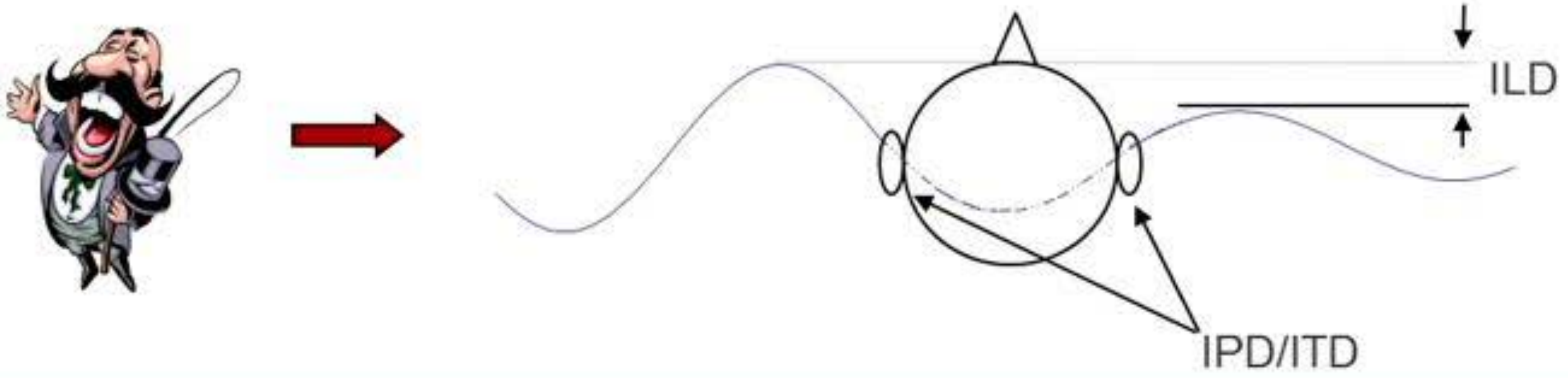
Monaural (2-3) *Binaural* *External microphones*

- Main objectives of binaural speech enhancement algorithms: improve speech intelligibility + **preserve spatial awareness (binaural cues)**

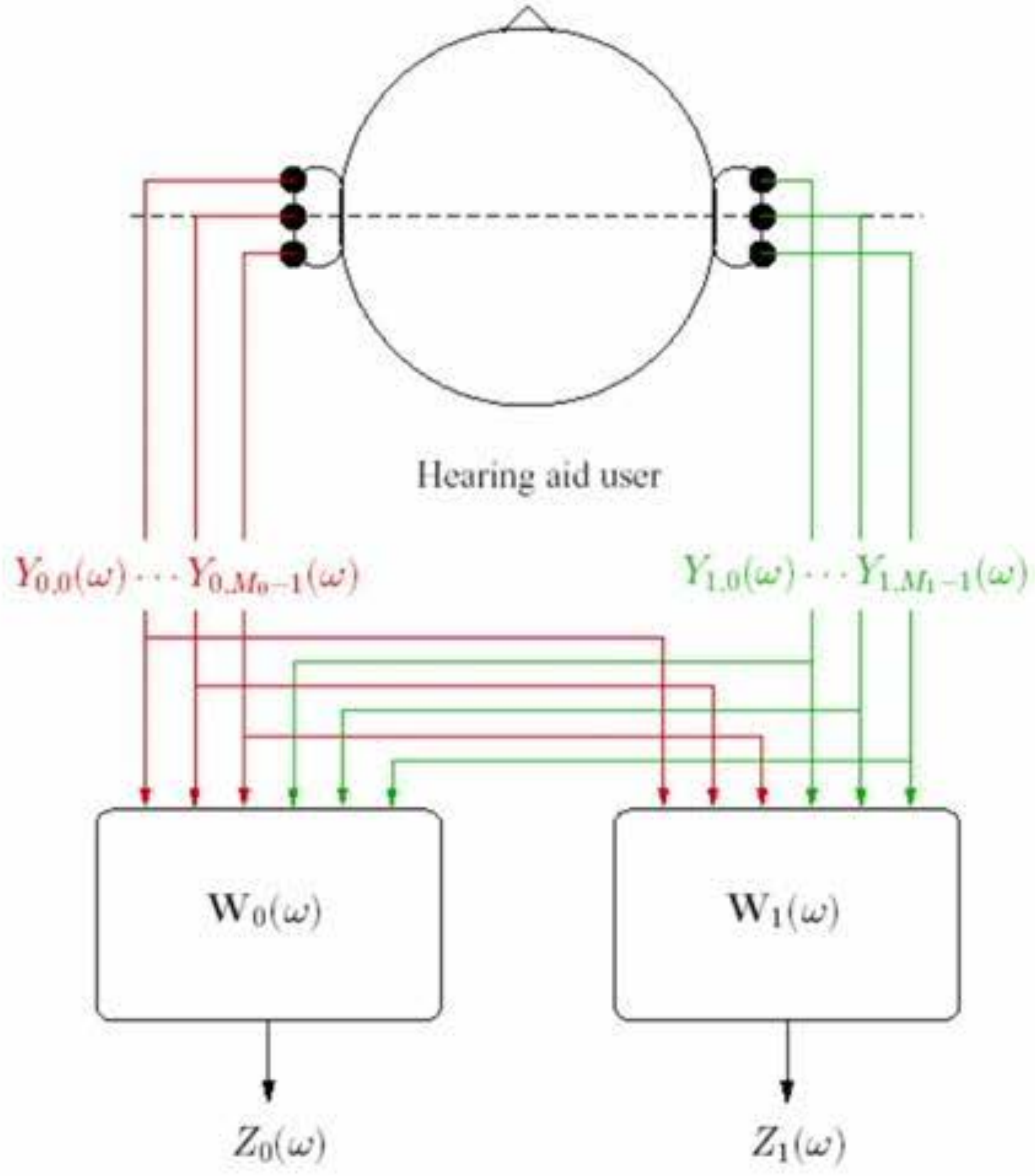
[S. Doclo, W. Kellermann, S. Makino, S. Nordholm, *Multichannel signal enhancement algorithms for assisted listening devices*, *IEEE Signal Processing Magazine*, Mar. 2015.]

Binaural auditory cues

- **Interaural Time/Phase Difference (ITD/IPD)**
  Interaural Level Difference (ILD)
  Interaural Coherence (IC)
  - ITD: f < 1500 Hz, ILD: f > 2000 Hz
  - IC: describes spatial characteristics, e.g. perceived width, of diffuse noise, and determines when ITD/ILD cues are *reliable*
- Binaural cues, in addition to spectro-temporal cues, play an important role in auditory scene analysis (source segregation) and speech intelligibility



Binaural noise reduction: Configuration



- Binaural hearing aid configuration:
  - Two hearing aids with in total *M* microphones
  - All microphone signals **Y** are assumed to be available at both hearing aids (perfect wireless link)

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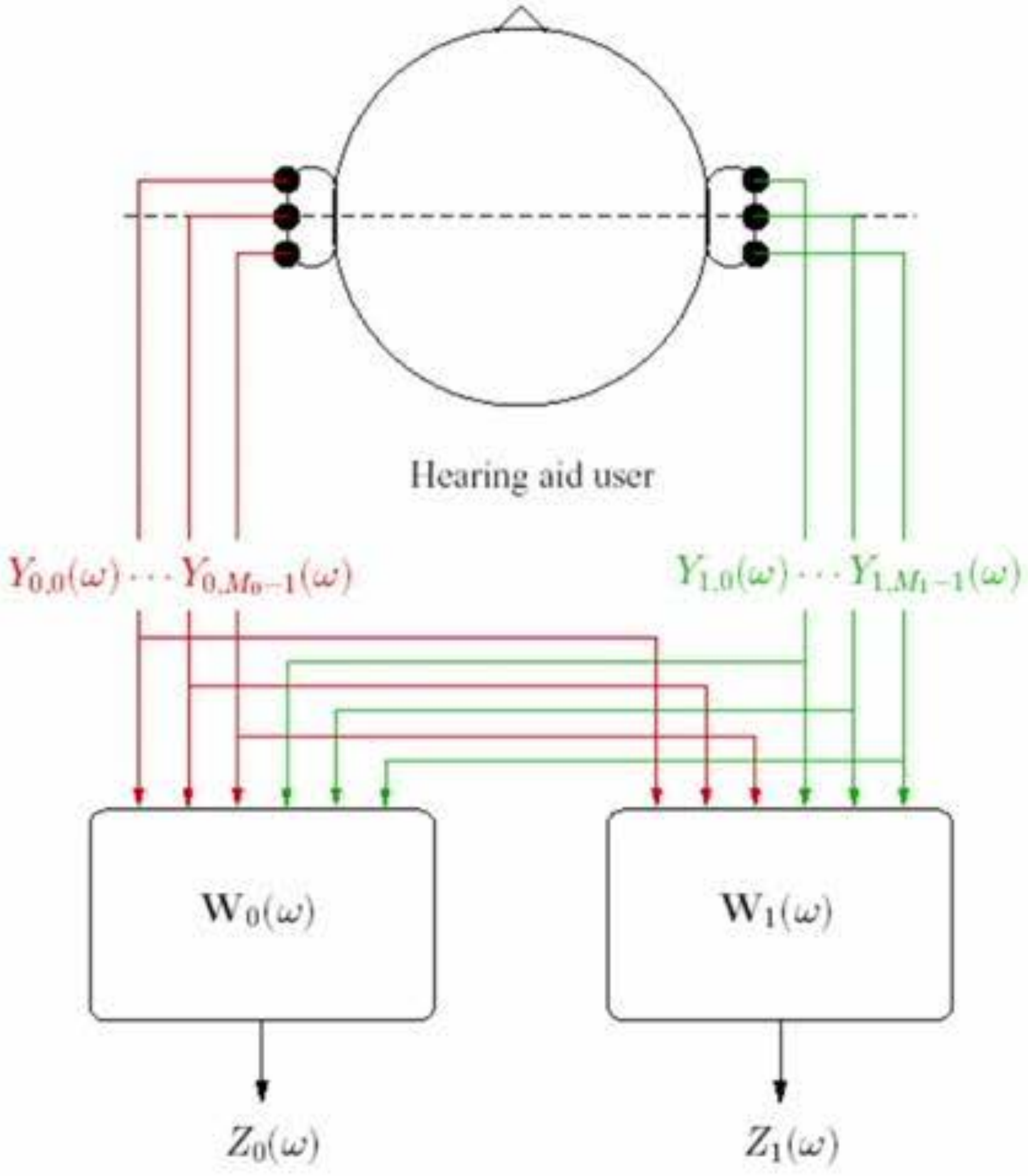


- Binaural hearing aid configuration:
  - Two hearing aids with in total *M* microphones
  - All microphone signals **Y** are assumed to be available at both hearing aids (perfect wireless link)
- Apply a filter $\mathbf{W}_0$ and $\mathbf{W}_1$ at the left and the right hearing aid, generating binaural output signals Z_0 and Z_1

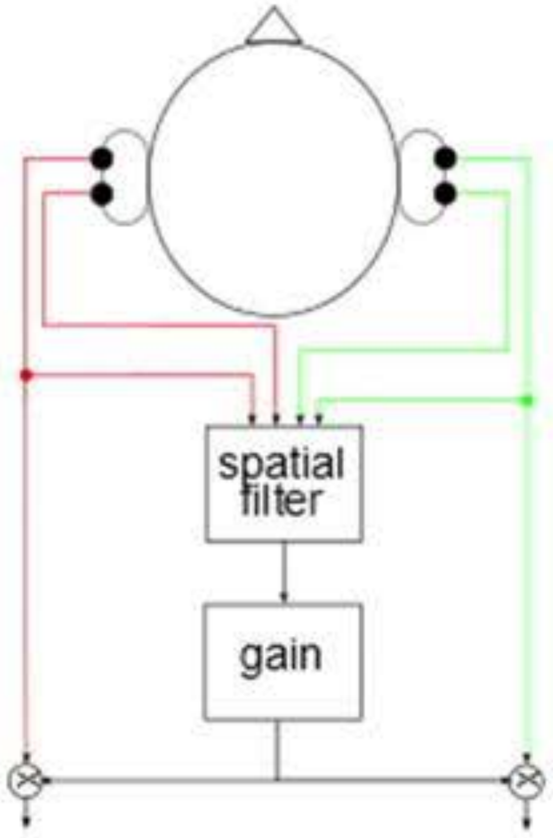
$$\boxed{Z_0(\omega) = \mathbf{W}_0^H(\omega)\mathbf{Y}(\omega), \quad Z_1(\omega) = \mathbf{W}_1^H(\omega)\mathbf{Y}(\omega)}$$

[S. Doclo, W. Kellermann, S. Makino, S. Nordholm, *Multichannel signal enhancement algorithms for assisted listening devices*, *IEEE Signal Processing Magazine*, Mar. 2015.]

Binaural noise reduction: Two main paradigms

Spectral post-filtering (based on multi-microphone noise reduction)

[Wittkop 2003, Lotter 2006, Rohdenburg 2008, Grimm 2009, Kamkar-Parsi 2011, Reindl 2013, Baumgärtel 2015, Enzner 2016]



- ⊕ Binaural cue preservation
- ⊖ Possible single-channel artifacts

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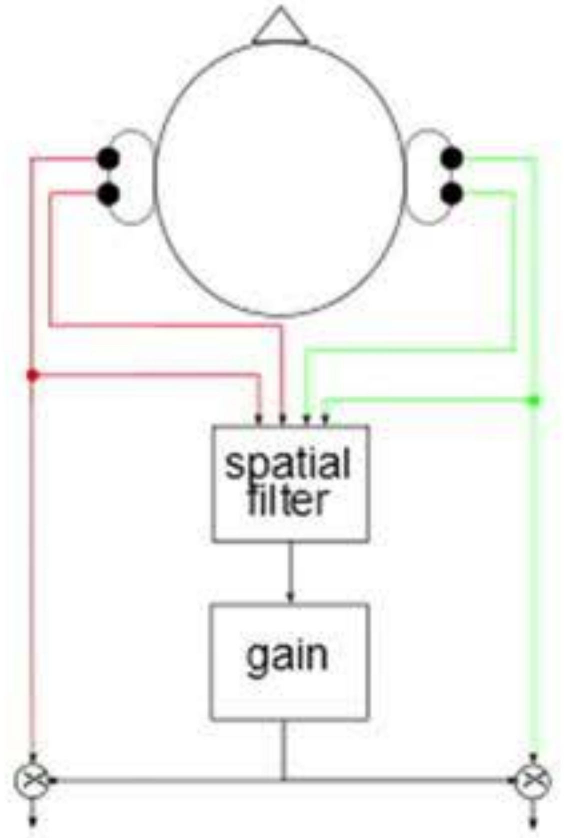

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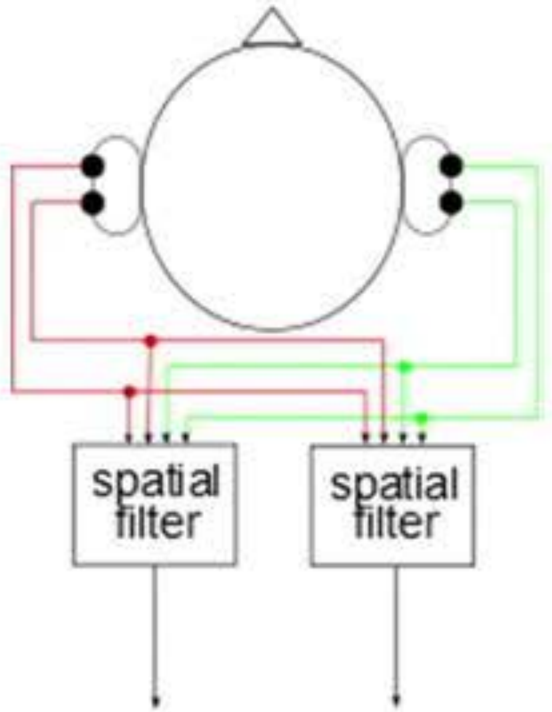
Binaural spatial filtering techniques

[Welker 1997, Aichner 2007, Doclo 2010, Cornelis 2012, Hadad 2015-2016, Marquardt 2015-2018, Koutrouvelis 2017-2019]



- ⊕ Larger noise reduction performance
- ⊕ Merge spatial and spectral post-filtering
- ⊖ Binaural cue preservation not guaranteed

Binaural MVDR and MWF

Minimum-Variance-Distortionless-Response (MVDR) beamformer

Goal: minimize output noise power without distorting speech component in reference microphone signals

$$\min_{\mathbf{W}_0} \mathbf{W}_0^H \mathbf{R}_v \mathbf{W}_0 \quad \text{subject to} \quad \mathbf{W}_0^H \mathbf{A} = A_0$$

$$\min_{\mathbf{W}_1} \underbrace{\mathbf{W}_1^H \mathbf{R}_v \mathbf{W}_1}_{\text{noise reduction}} \quad \text{subject to} \quad \underbrace{\mathbf{W}_1^H \mathbf{A} = A_1}_{\text{distortionless constraint}}$$

Requires estimate/model of noise coherence matrix (e.g. diffuse) and estimate/model of relative transfer function (RTF) of target speech source

Multi-channel Wiener Filter (MWF)

Goal: estimate speech component in reference microphone signals + trade off noise reduction and speech distortion

$$J_{\mathrm{MWF}}(\mathbf{W}) = \mathcal{E}\left\{ \underbrace{\left\| \begin{bmatrix} X_0 - \mathbf{W}_0^H \mathbf{X} \\ X_1 - \mathbf{W}_1^H \mathbf{X} \end{bmatrix} \right\|^2}_{\text{speech distortion}} + \mu \underbrace{\left\| \begin{bmatrix} \mathbf{W}_0^H \mathbf{V} \\ \mathbf{W}_1^H \mathbf{V} \end{bmatrix} \right\|^2}_{\text{noise reduction}} \right\}$$

Requires estimate of speech and noise covariance matrices, e.g. based on SPP

Can be decomposed as binaural MVDR beamformer and spectral postfilter

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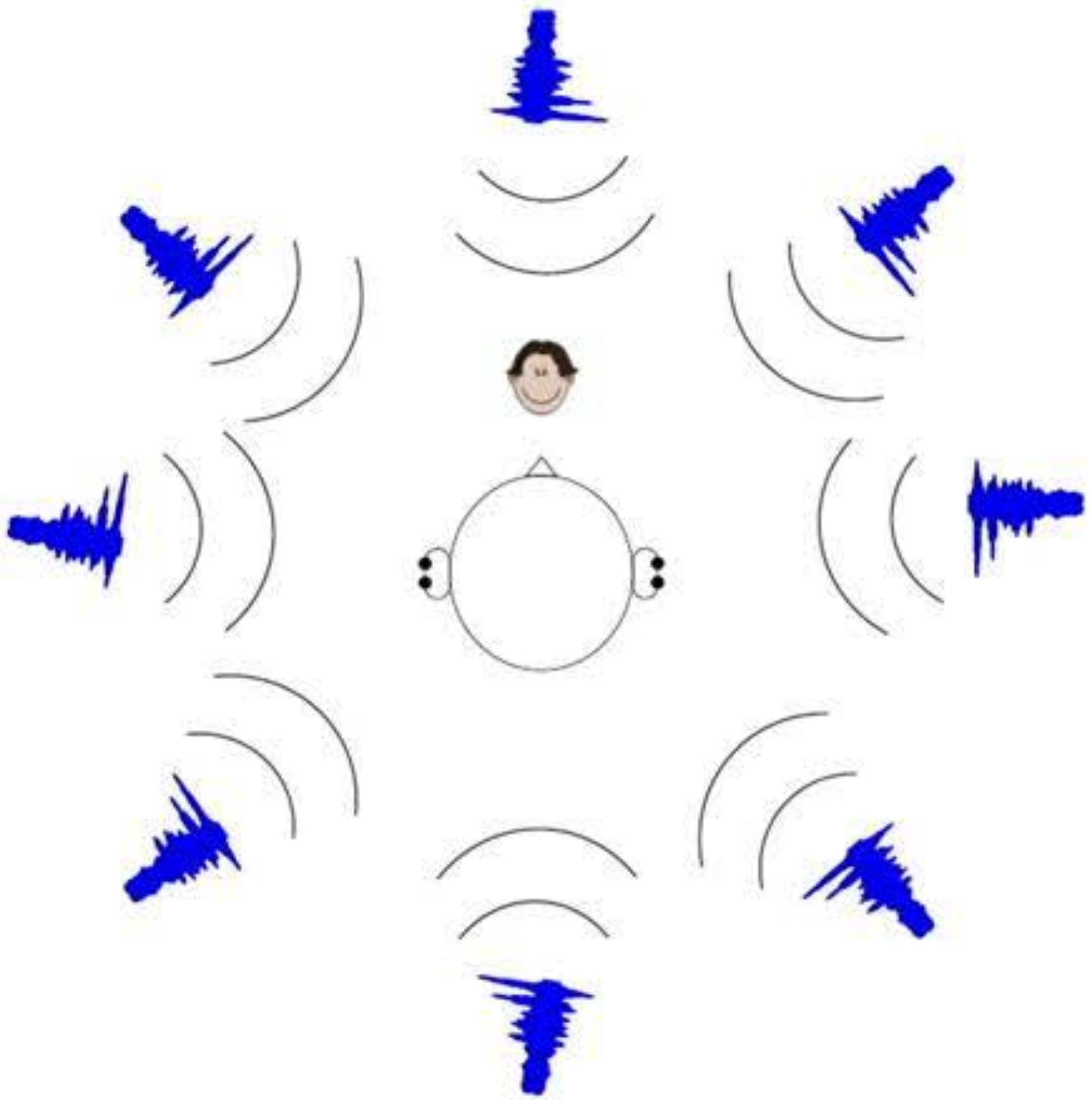
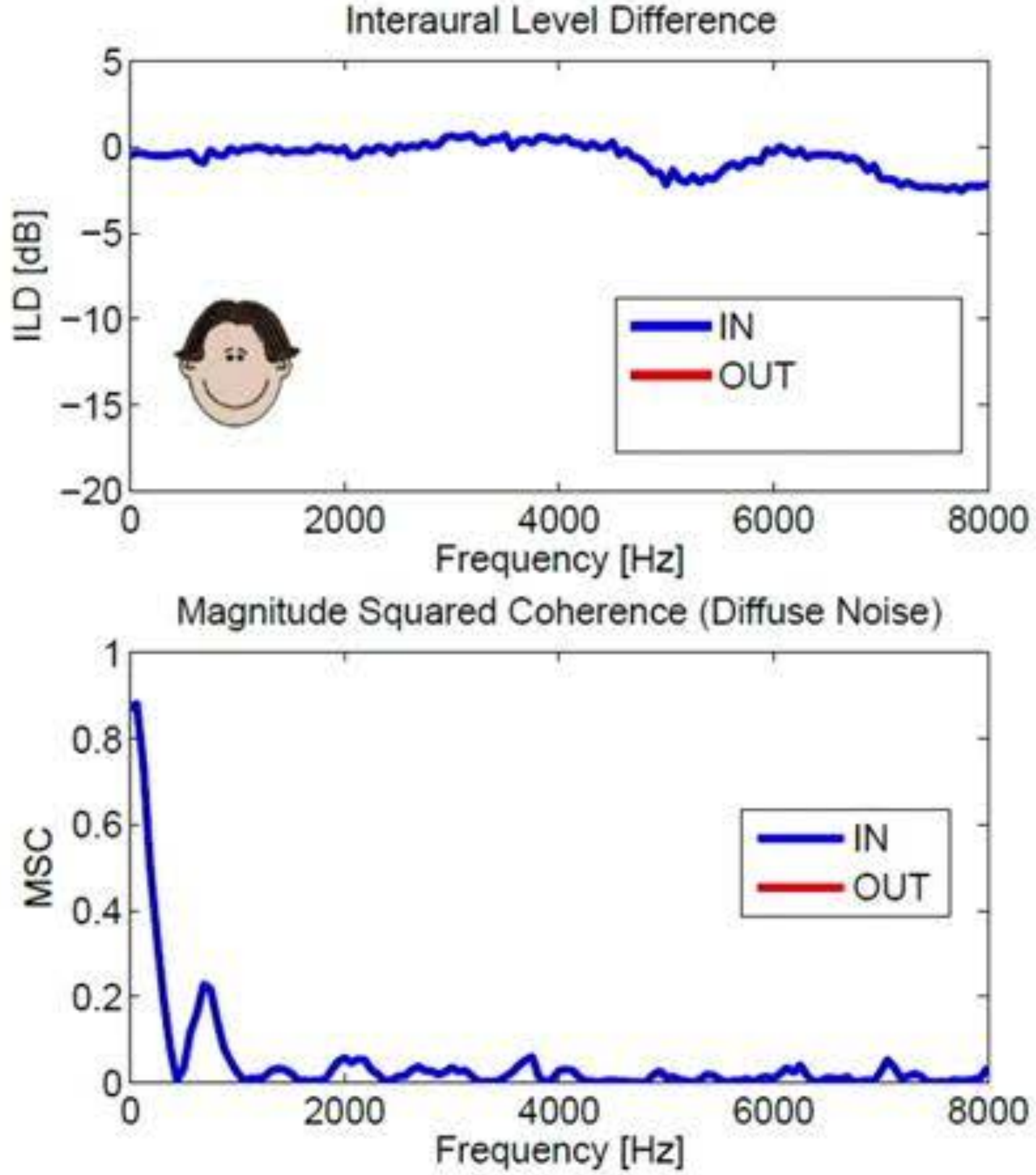
Good noise reduction performance, what about binaural cues ?

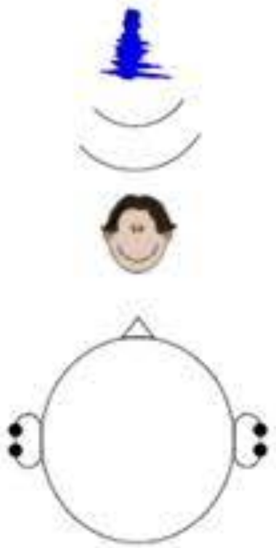
Binaural MVDR/MWF: binaural cues

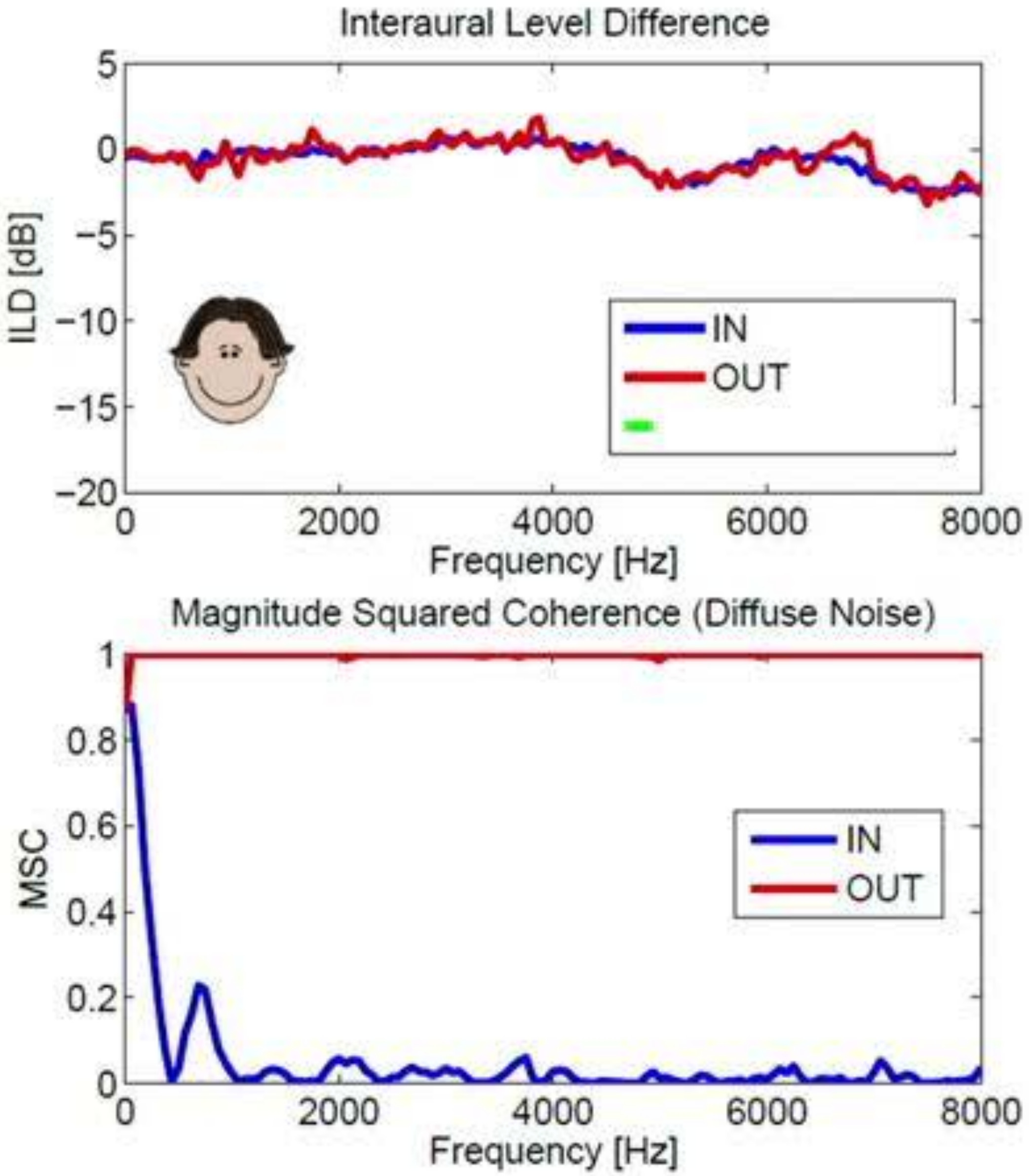




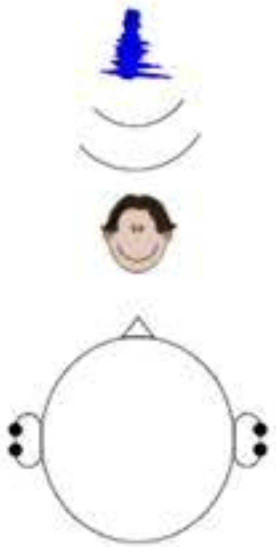
Note: MSC = Magnitude Squared Coherence

Binaural MVDR/MWF: binaural cues

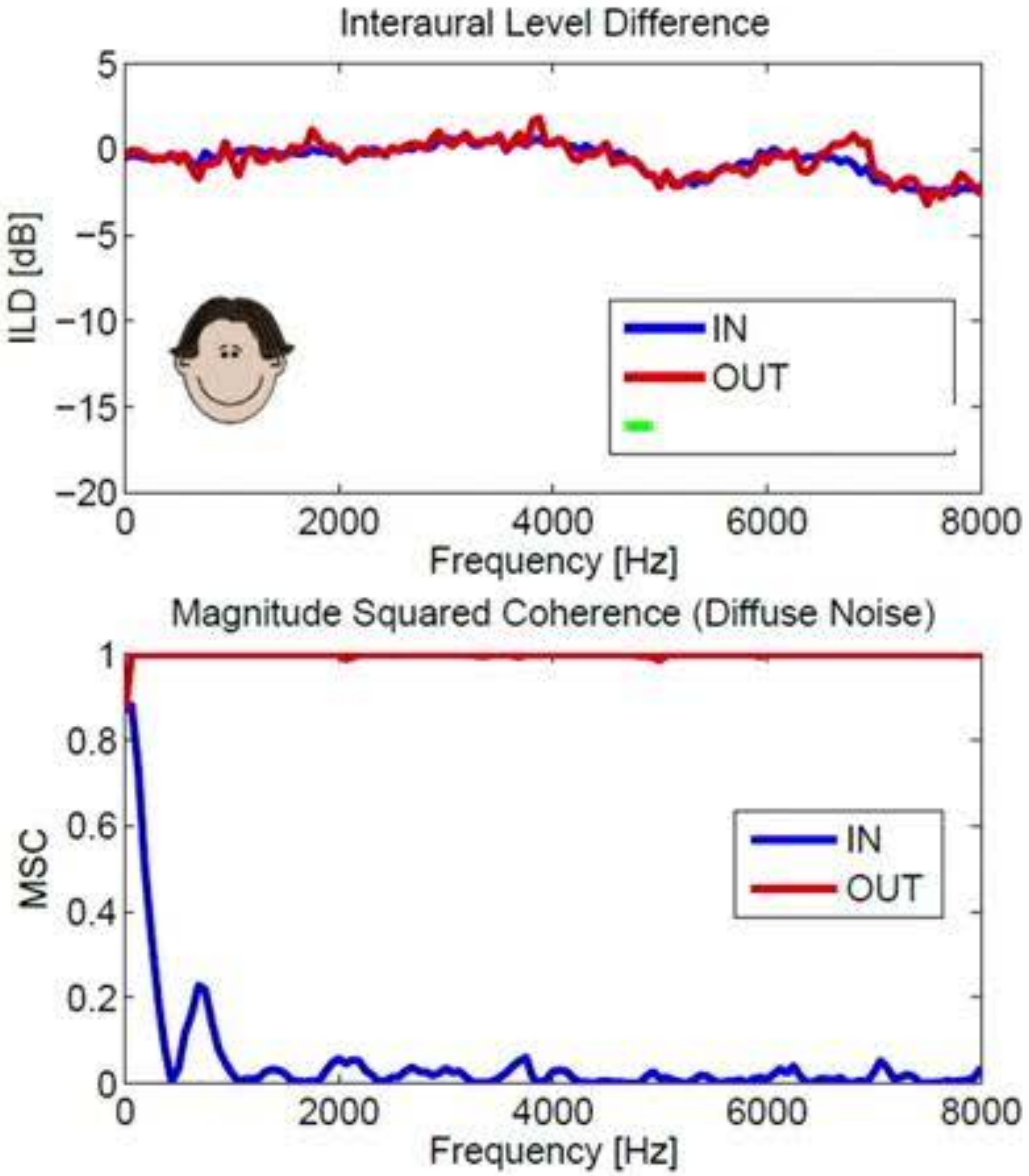




Binaural MVDR/MWF: binaural cues



Binaural cues for residual noise/interference in binaural MVDR/MWF not preserved



Binaural MWF: Extensions for diffuse noise

Binaural MWF

- ⊕ SNR improvement
- ⊕ Binaural cues of speech source
- ⊖ Binaural cues of noise

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- ⊕ SNR improvement
- ⊕ Binaural cues of speech source
- ⊖ Binaural cues of noise

Interaural coherence preservation (MWF-IC)

$$J_{MWF-IC}(\mathbf{W}) = J_{MWF}(\mathbf{W}) + \lambda \left| \frac{\mathbf{W}_0^H \mathbf{R}_v \mathbf{W}_1}{\sqrt{\mathbf{W}_0^H \mathbf{R}_v \mathbf{W}_0 \mathbf{W}_1^H \mathbf{R}_v \mathbf{W}_1}} - IC_v^{des} \right|^2$$

⊖ No closed-form solution, iterative optimization procedures required

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Binaural MWF

- ⊕ SNR improvement
- ⊕ Binaural cues of speech source
- ⊖ Binaural cues of noise

Interaural coherence preservation (MWF-IC)	Partial noise estimation (MWF-N)
$J_{MWF-IC}(\mathbf{W}) = J_{MWF}(\mathbf{W}) + \lambda \left\| \frac{\mathbf{W}_0^H \mathbf{R}_v \mathbf{W}_1}{\sqrt{\mathbf{W}_0^H \mathbf{R}_v \mathbf{W}_0 \mathbf{W}_1^H \mathbf{R}_v \mathbf{W}_1}} - IC_v^{des} \right\|^2$	$J_{\mathrm{MWF-N}}(\mathbf{W}) = \mathcal{E}\left\{ \left\| \begin{bmatrix} X_0 - \mathbf{W}_0^H \mathbf{X} \\ X_1 - \mathbf{W}_1^H \mathbf{X} \end{bmatrix} \right\|^2 + \mu \left\| \begin{bmatrix} \eta V_0 - \mathbf{W}_0^H \mathbf{V} \\ \eta V_1 - \mathbf{W}_1^H \mathbf{V} \end{bmatrix} \right\|^2 \right\}$
⊖ No closed-form solution, iterative optimization procedures required	⊕ Closed-form solution (mixing with reference microphone signals)

Binaural MWF: Extensions for diffuse noise

SNR improvement

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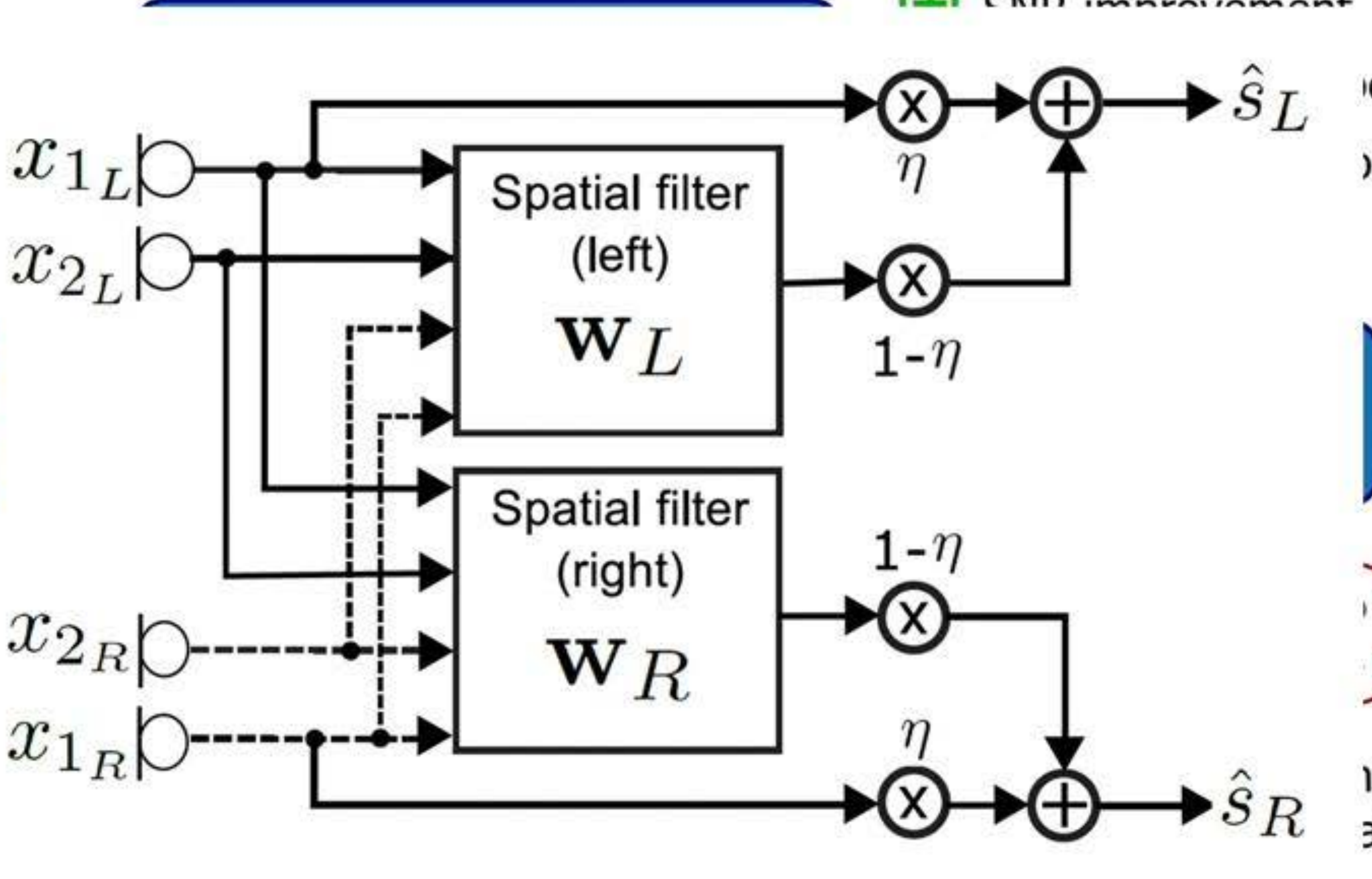
$J_{MWF-IC}(\mathbf{W}) = J_{\mathrm{M}}$

$-\mathbf{W}_0^H\mathbf{V}\Big]\Big\|^2$
$-\mathbf{W}_1^H\mathbf{V}\Big]\Big\|\Big\}$



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[Marquardt, Hohmann, Doclo, *IEEE/ACM Trans. Audio, Speech and Language Processing*, Dec. 2015.]
[Marquardt, Doclo, *IEEE/ACM Trans. Audio, Speech and Language Processing*, Jul. 2018.]

Binaural MWF: Extensions for diffuse noise

- ⊕ SNR improvement
- ⊕ Binaural cues of speech source
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Binaural MWF

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⊖ No closed-form solution, iterative optimization procedures required

Partial noise estimation (MWF-N)

$$J_{\mathrm{MWF-N}}(\mathbf{W}) = \mathcal{E}\left\{ \left\| \begin{bmatrix} X_0 - \mathbf{W}_0^H \mathbf{X} \\ X_1 - \mathbf{W}_1^H \mathbf{X} \end{bmatrix} \right\|^2 + \mu \left\| \begin{bmatrix} \eta V_0 - \mathbf{W}_0^H \mathbf{V} \\ \eta V_1 - \mathbf{W}_1^H \mathbf{V} \end{bmatrix} \right\|^2 \right\}$$

⊕ Closed-form solution (mixing with reference microphone signals)

⊜ **Trade-off** between SNR improvement and binaural cue preservation, depending on **parameters** (η and λ)

[Marquardt, Hohmann, Doclo, *IEEE/ACM Trans. Audio, Speech and Language Processing*, Dec. 2015.]
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Trade-off parameters for binaural MVDR/MWF

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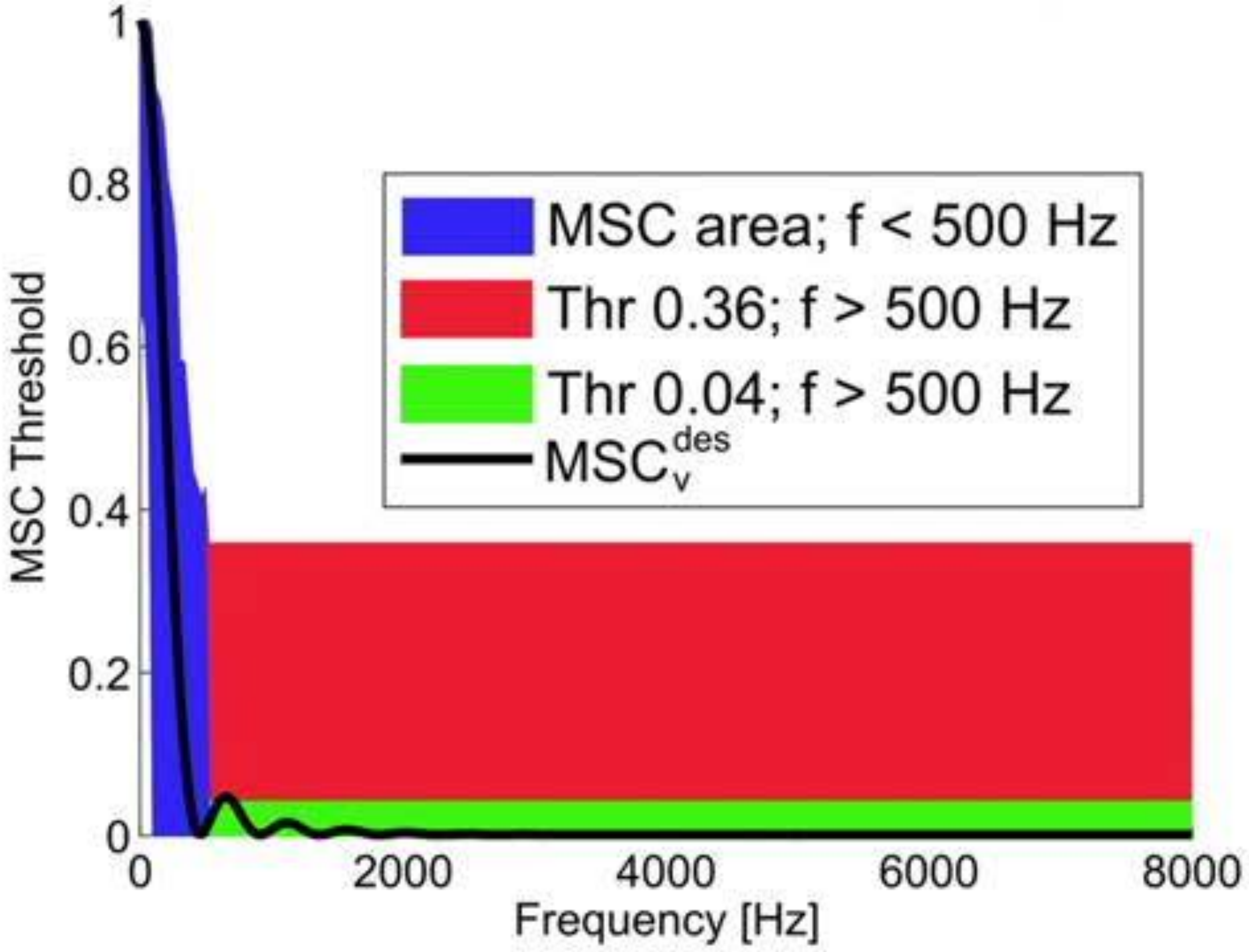

- IC discrimination ability depends on magnitude of reference IC
- **Boundaries on Magnitude Squared Coherence** (MSC=$|IC|^2$) :
  - For f < 500 Hz ("large" IC): frequency-dependent MSC boundaries (**blue**)
  - For f > 500 Hz ("small" IC): fixed MSC boundary, e.g. 0.36 (**red**) or 0.04 (**green**)

[Marquardt, Doclo, *IEEE/ACM Trans. Audio, Speech and Language Processing*, Jul. 2018.]

Trade-off parameters for binaural MVDR/MWF

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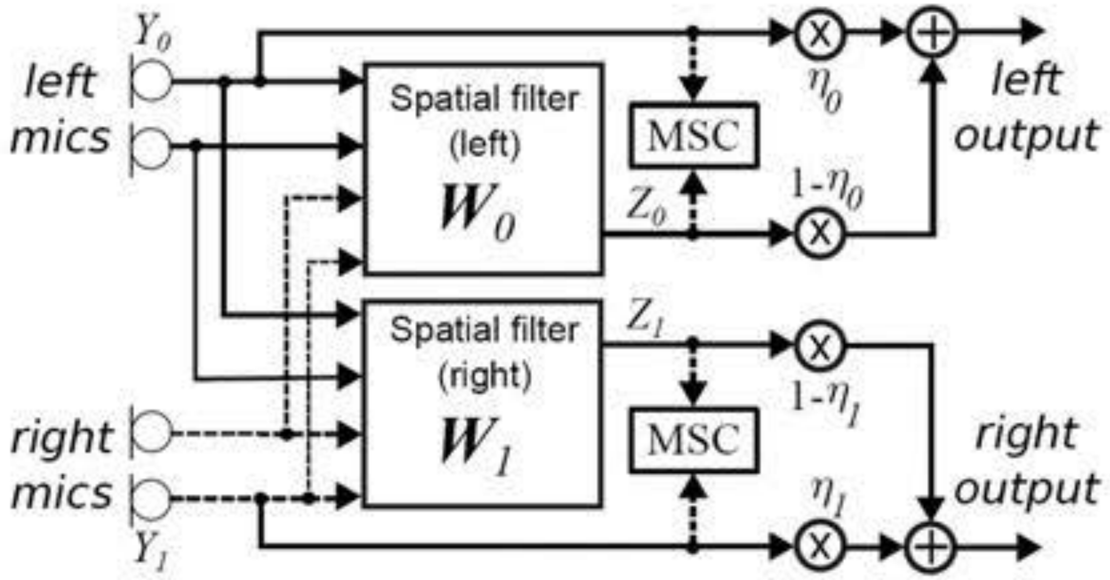
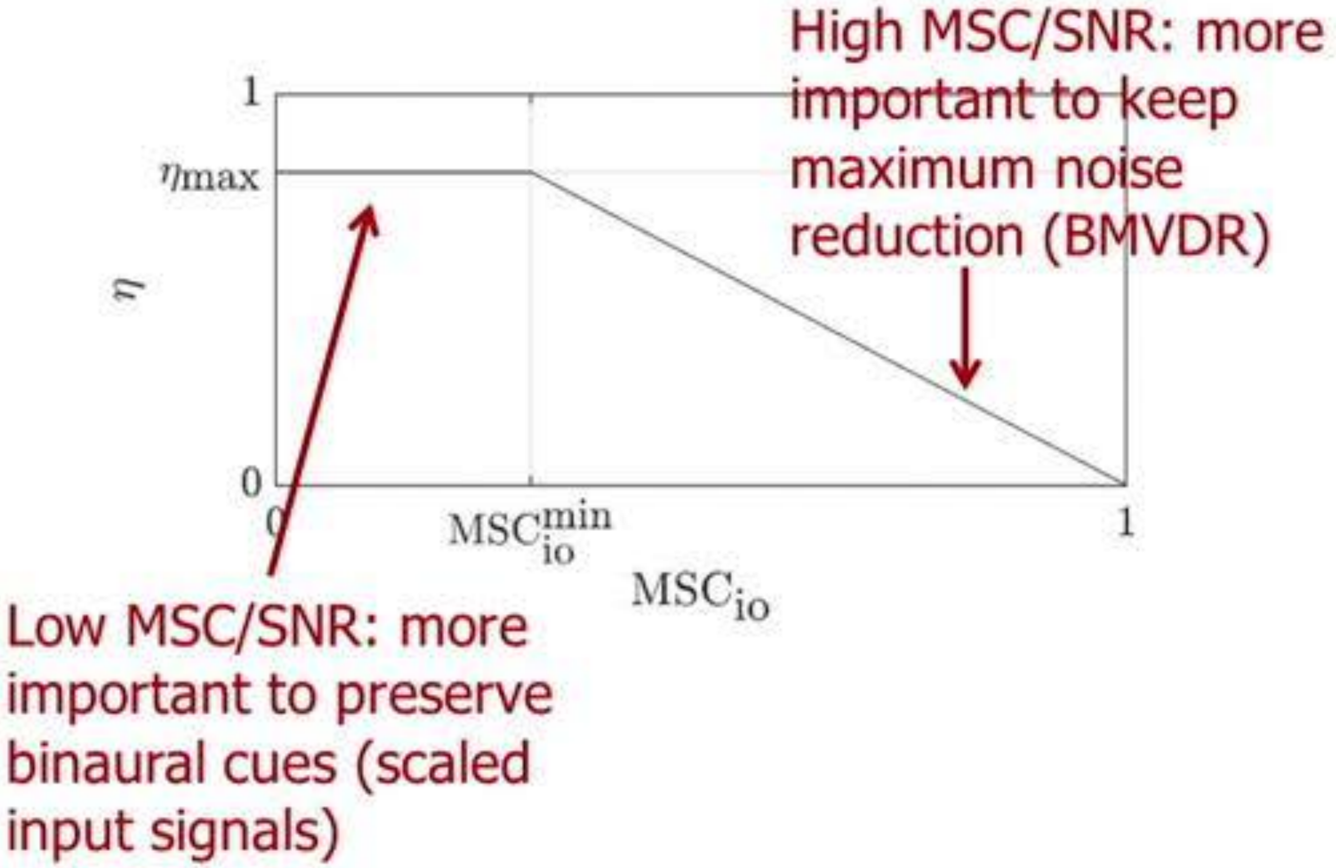
- **Frequency-dependent function** of MSC between noisy reference microphone signals and output signals of BMVDR beamformer





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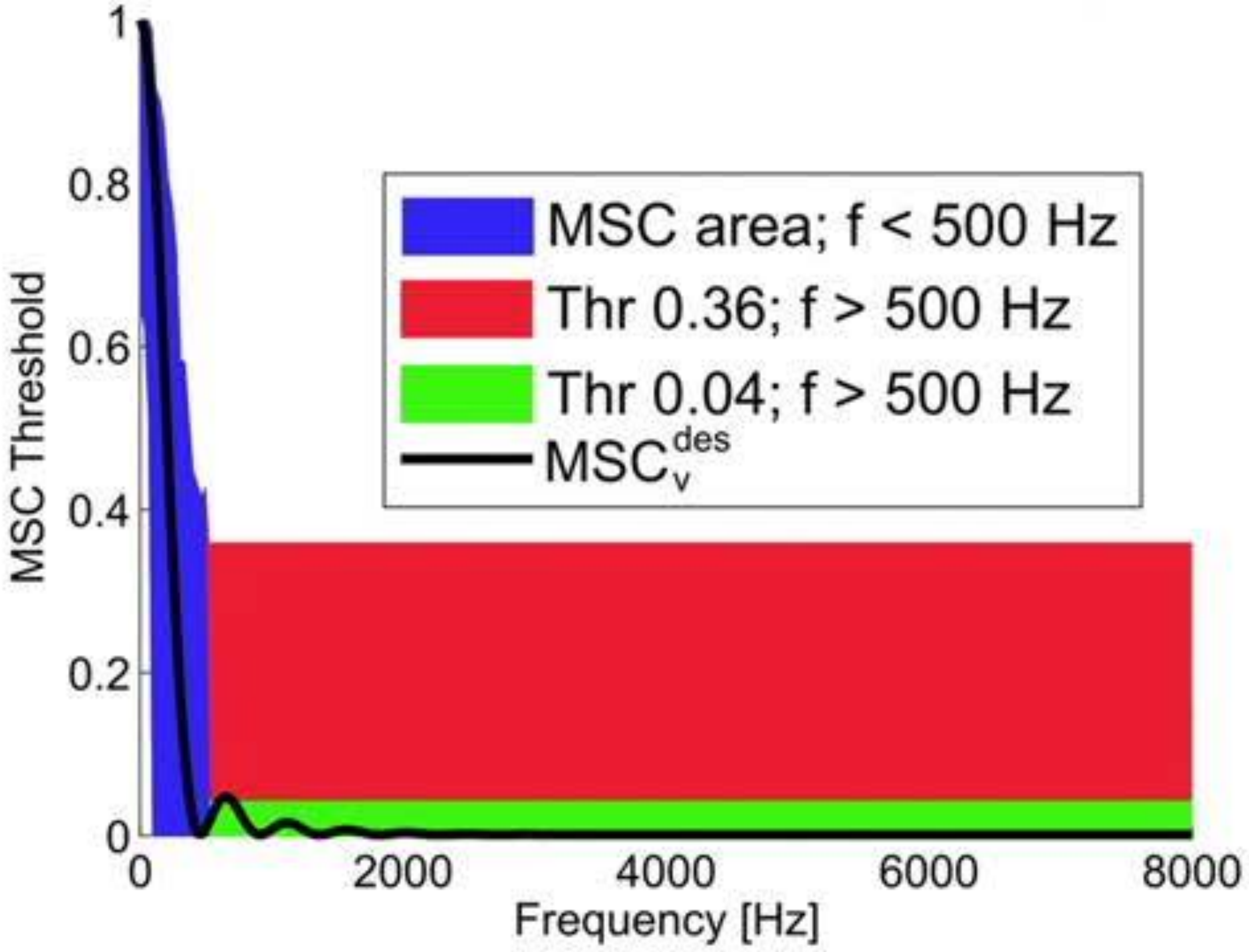

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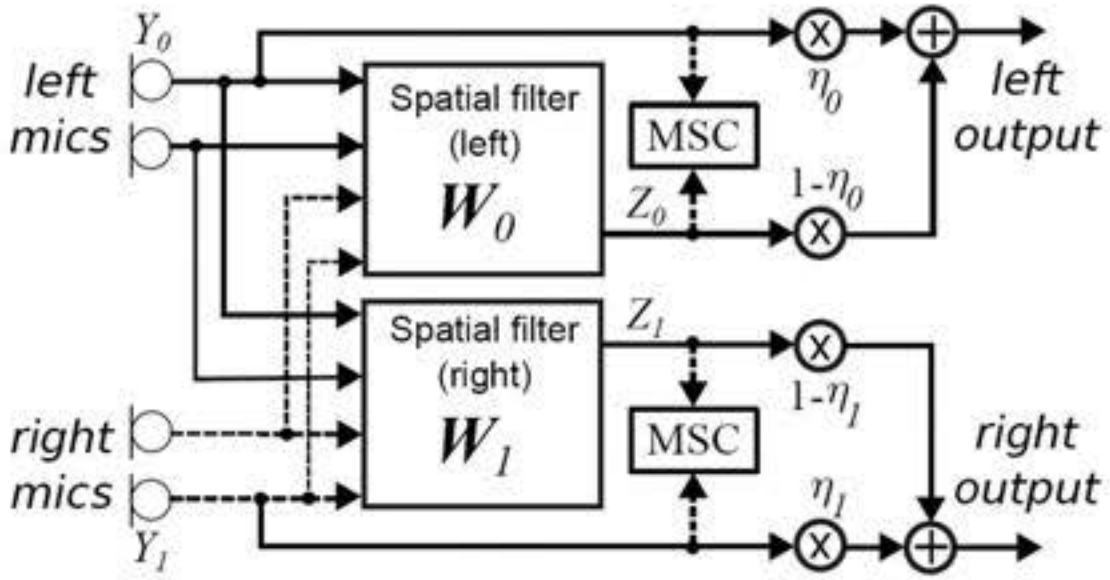

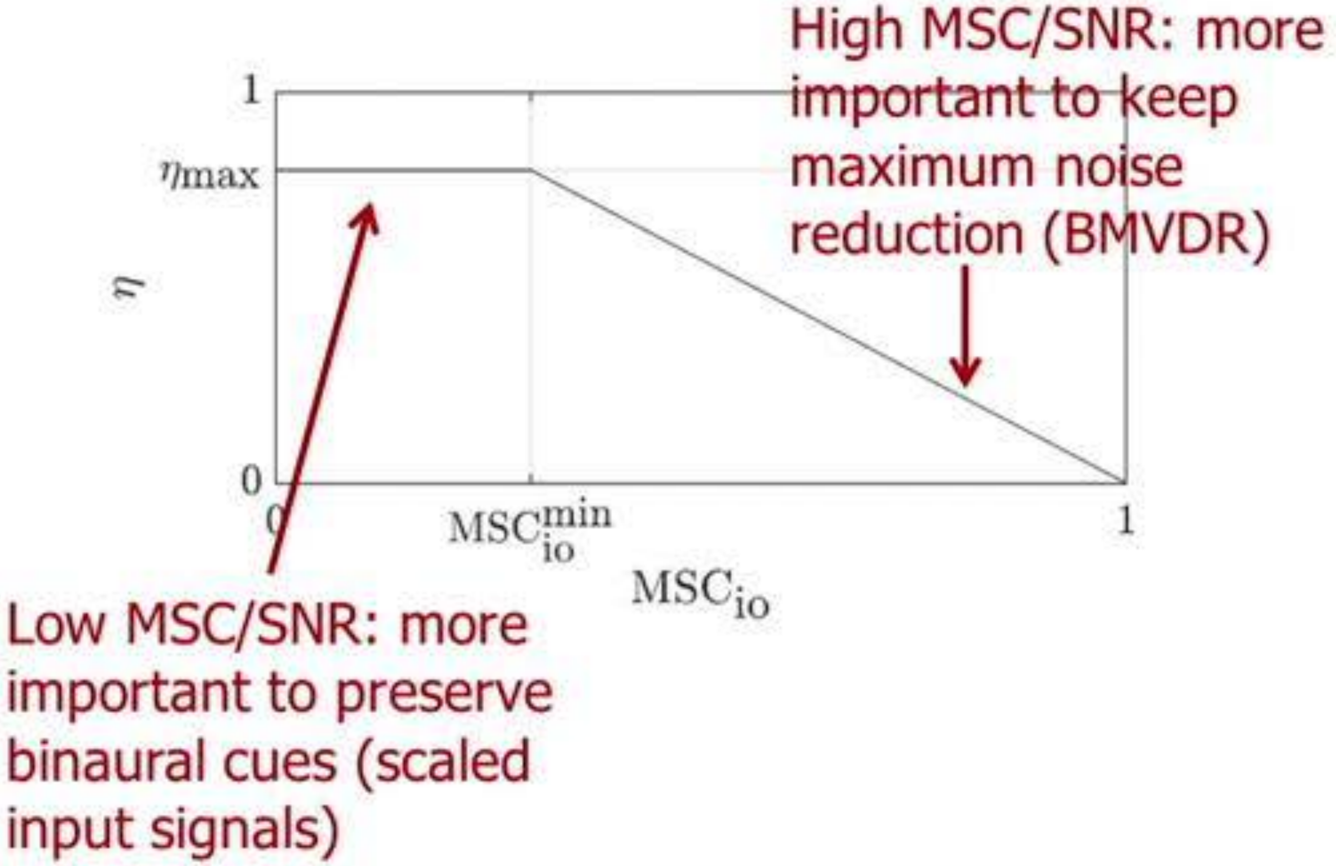

[Marquardt, Doclo, *IEEE/ACM Trans. Audio, Speech and Language Processing*, Jul. 2018.]
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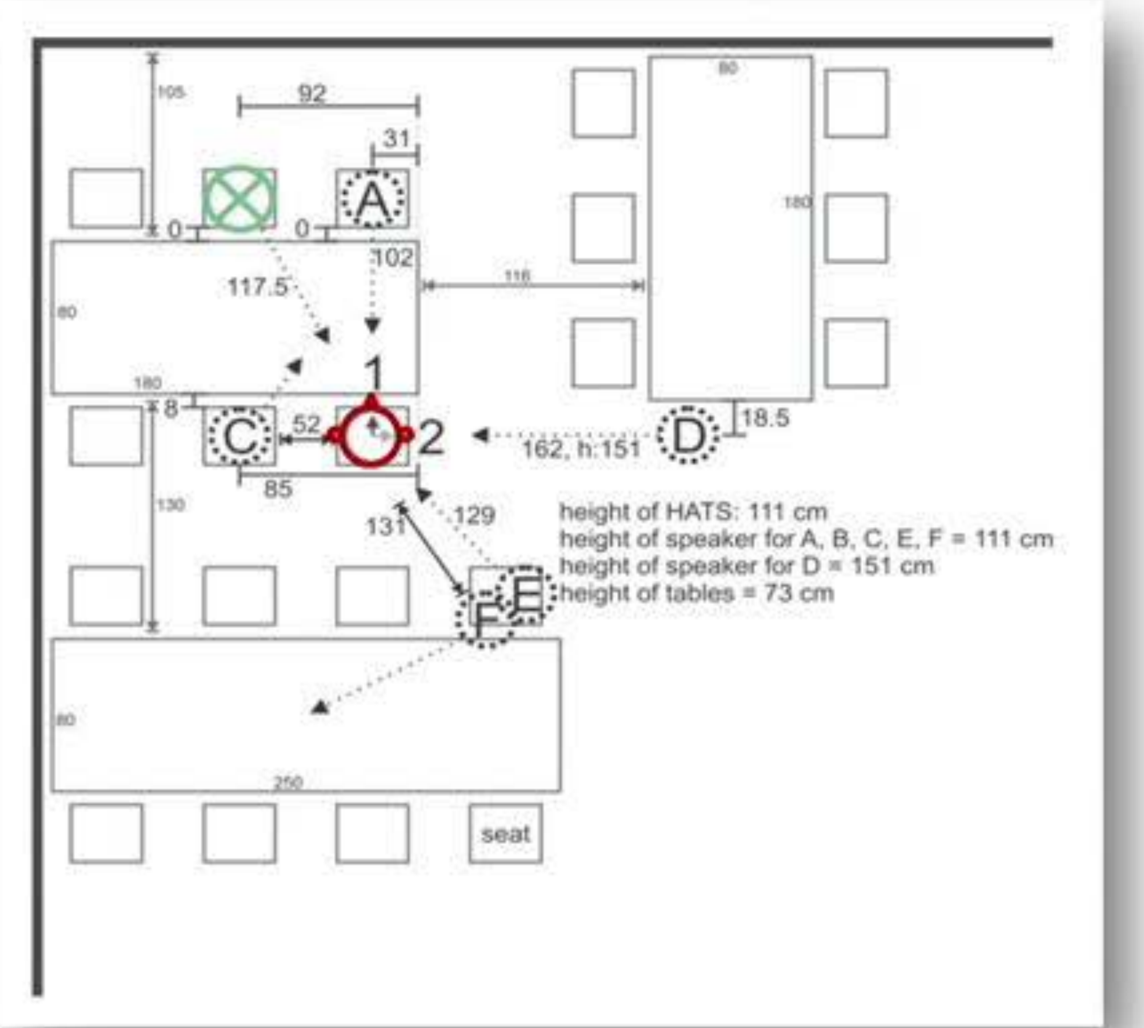
Evaluation: Test setup



- Binaural hearing aid recordings (M=4 mics) in **cafeteria** ($T_{60} \approx 1250$ ms)
  - Target speaker at -35°
  - Realistic cafeteria ambient noise
- **Algorithms**: binaural MVDR and binaural MVDR-N with different trade-off parameters:
  - MVDR-IC
  - MVDR-MSC1: $\eta_{max}=0.7$, $MSC_{min}=0$
  - MVDR-MSC2: $\eta_{max}=1.0$, $MSC_{min}=0.1$

[Klug, Marquardt, Gößling, Doclo, *ITG Conference Speech Communication*, Oct. 2018.]
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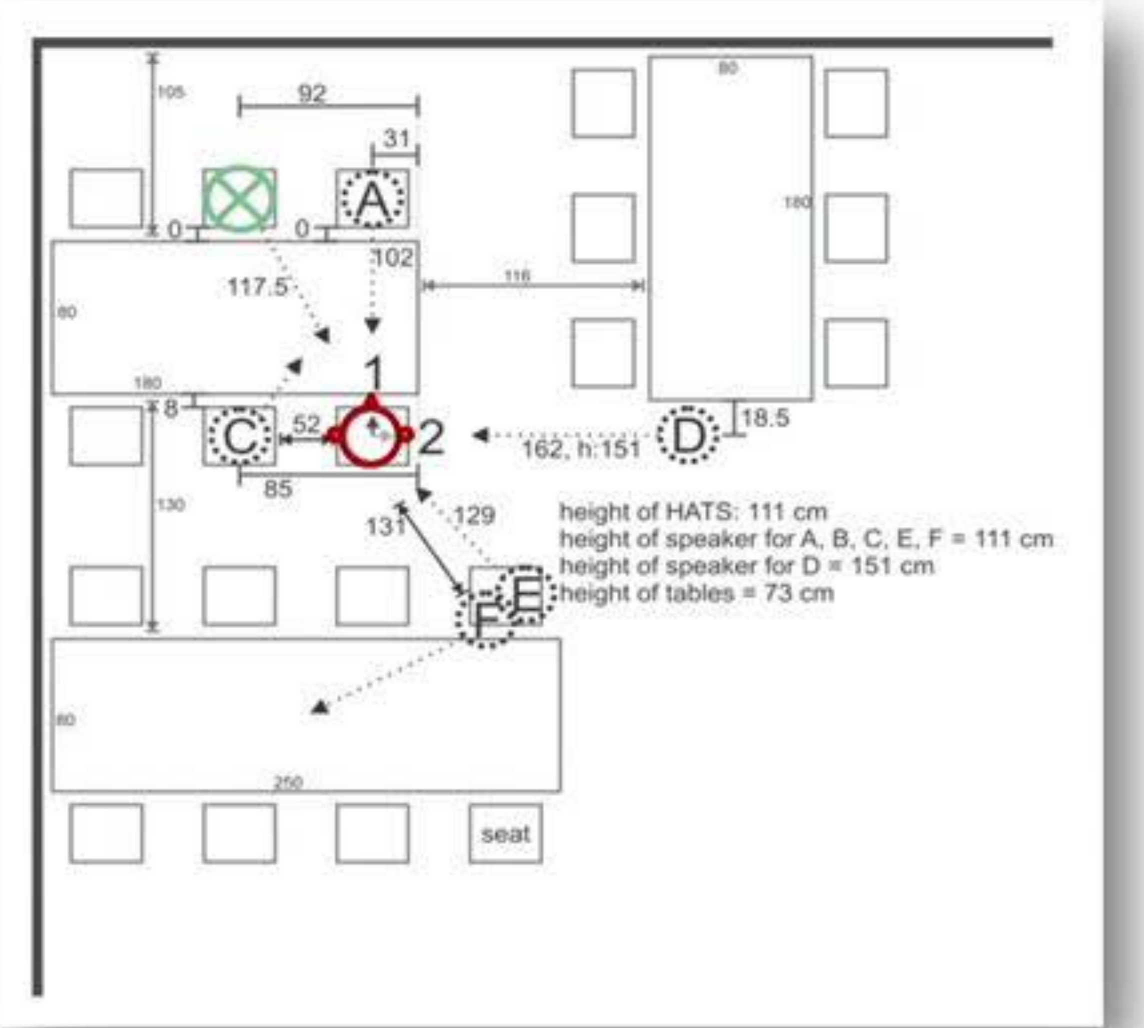

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  - **Spatial quality (diffuseness)** using MUSHRA

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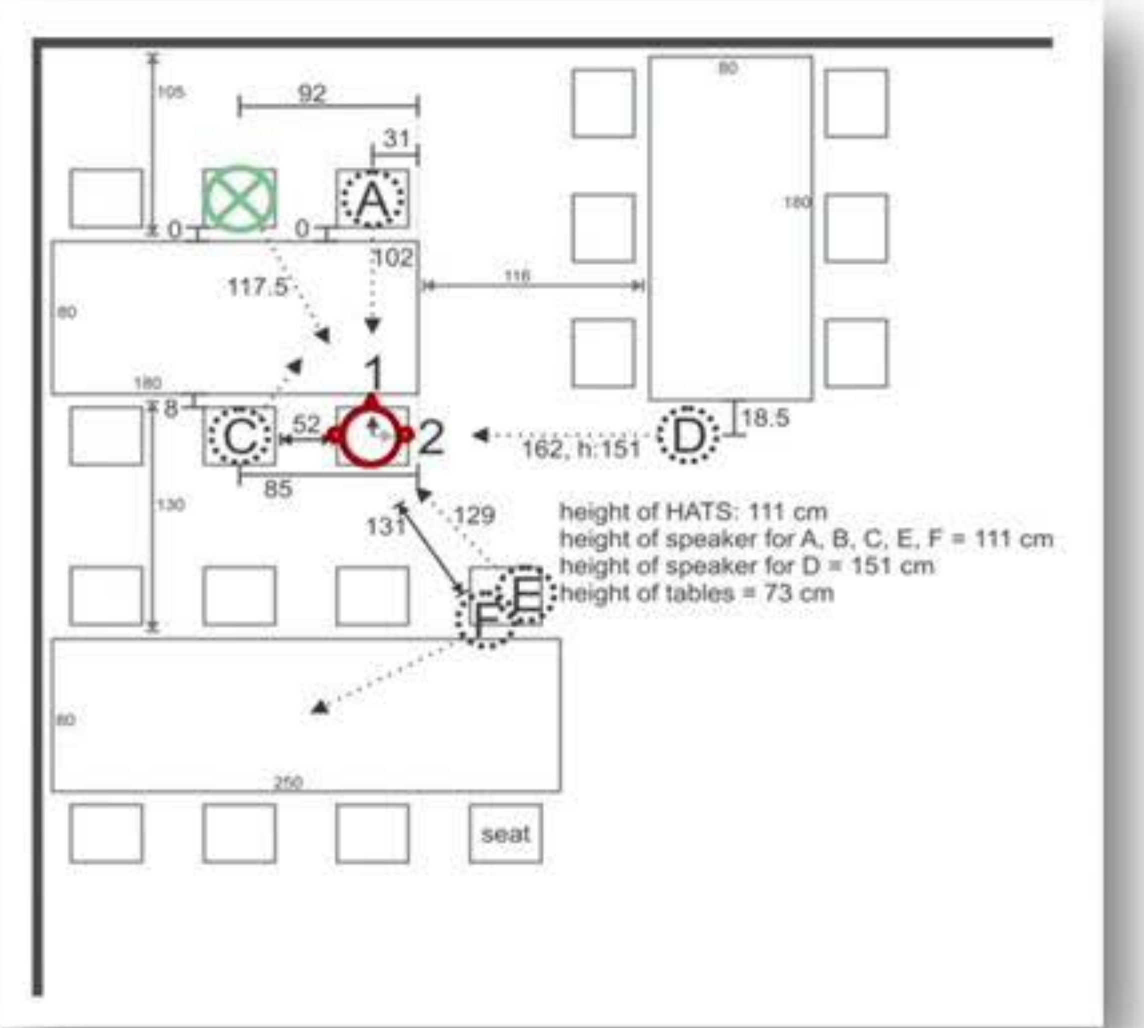

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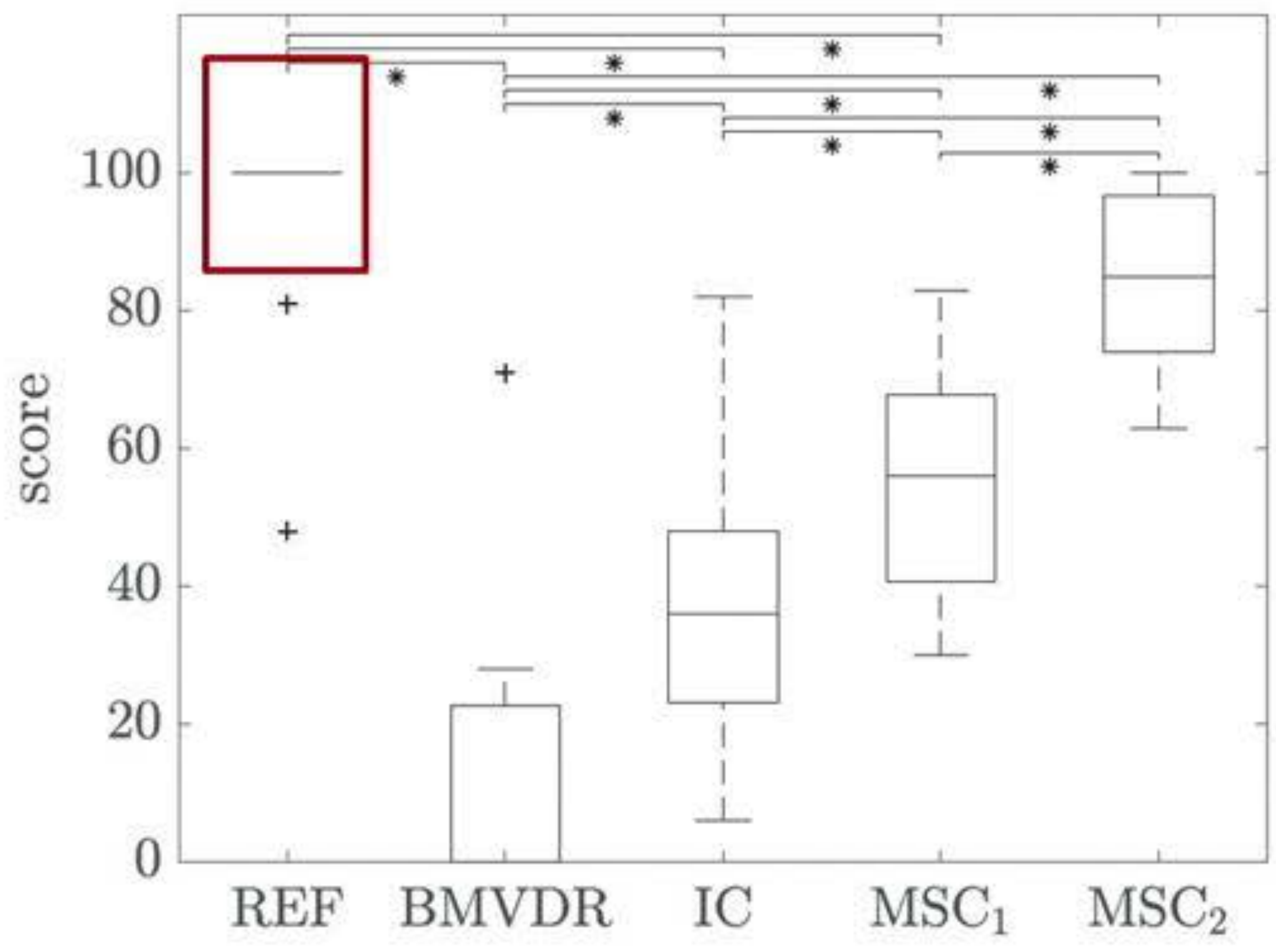
Does binaural unmasking compensate for SNR decrease of cue preservation algorithms (MVDR-N) ?

[Klug, Marquardt, Gößling, Doclo, *ITG Conference Speech Communication*, Oct. 2018.]
[Gößling, Marquardt, Doclo, *Trends in Hearing, in revision*.]

Evaluation: Spatial quality (MUSHRA)

- Evaluate spatial difference between reference microphone signals and binaural output signals



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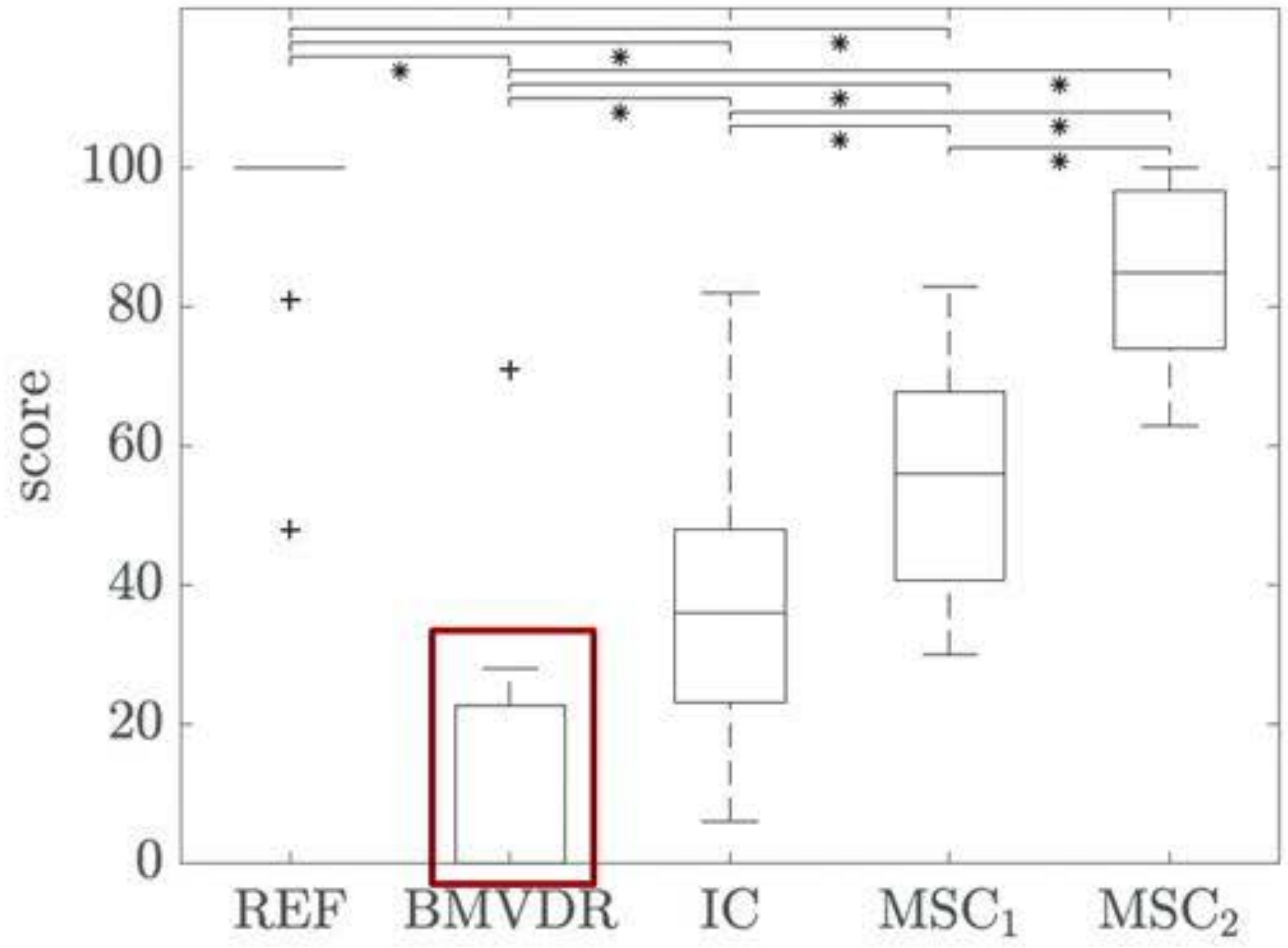
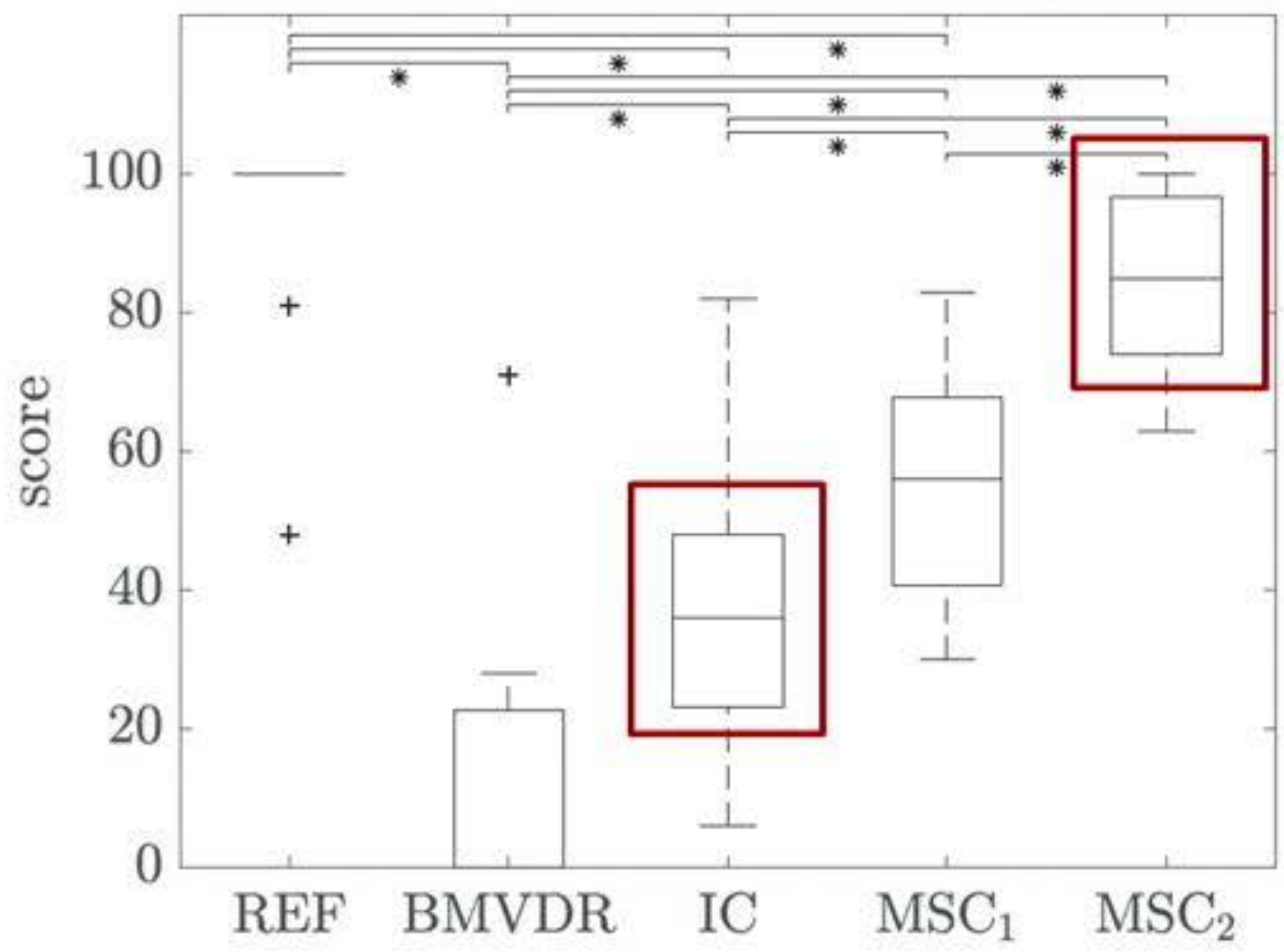


Evaluation: Spatial quality (MUSHRA)

- Evaluate spatial difference between reference microphone signals and binaural output signals
- **MVDR-N outperforms BMVDR**
  - Trade-off parameters: MSC-based better than IC-based
  - Using MSC2 hardly any difference to input !



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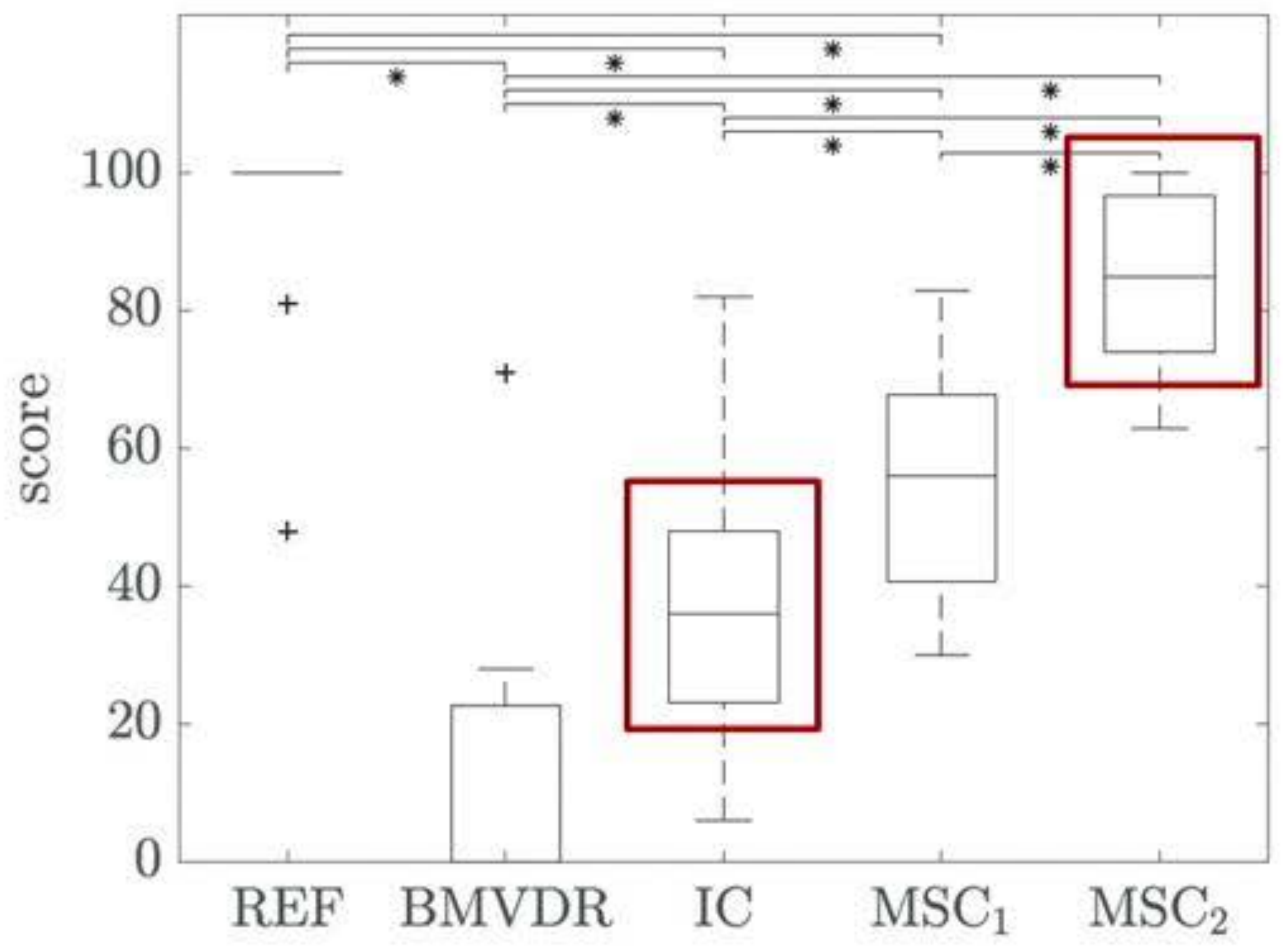
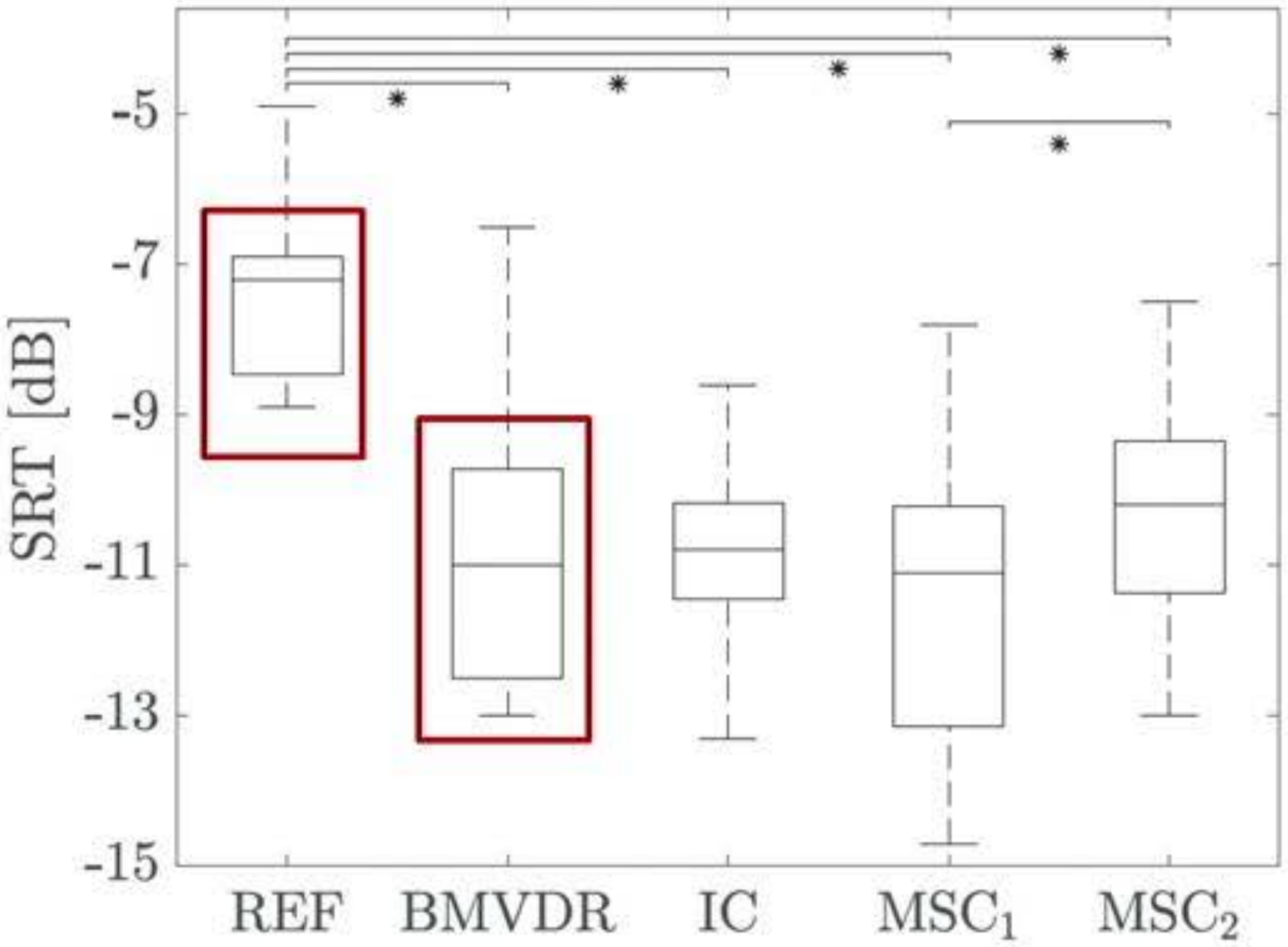


Binaural cue preservation for diffuse noise significantly improves spatial quality

[Klug, Marquardt, Gößling, Doclo, *ITG Conference Speech Communication*, Oct. 2018.]
[Gößling, Marquardt, Doclo, *Trends in Hearing, in revision*.]

Evaluation: Speech intelligibility (SRT)

- All algorithms show a highly significant speech reception threshold (SRT) improvement



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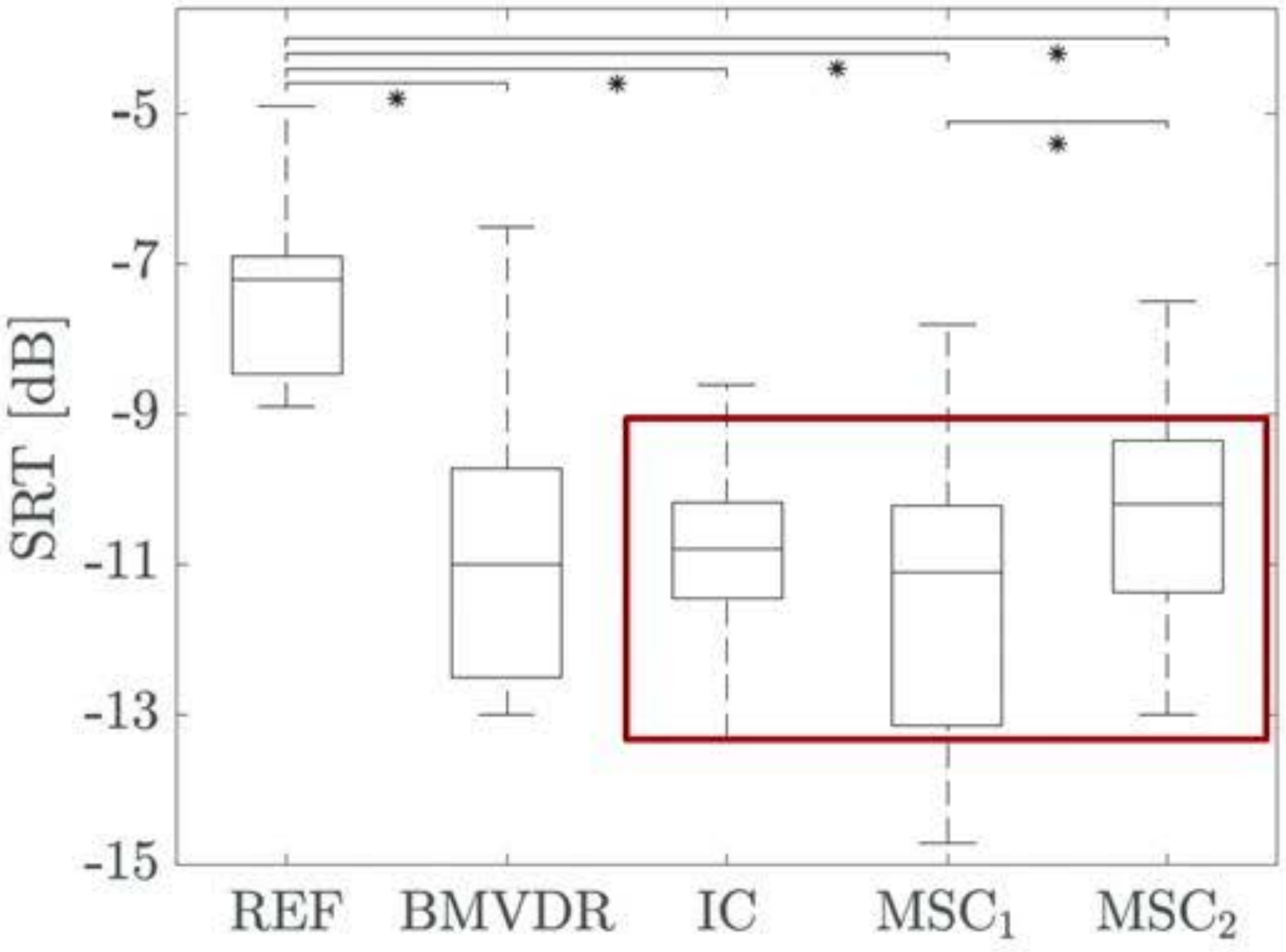

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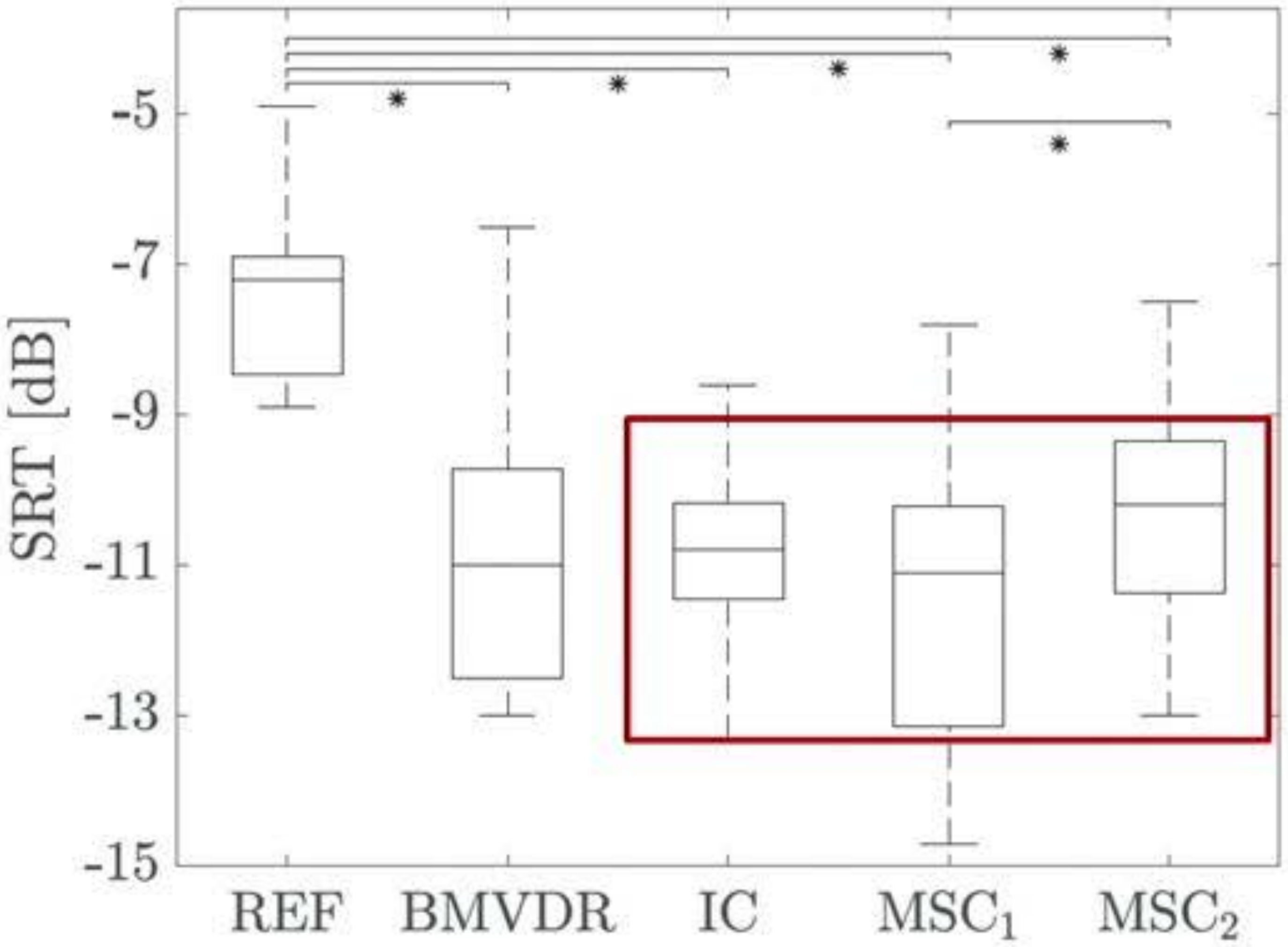
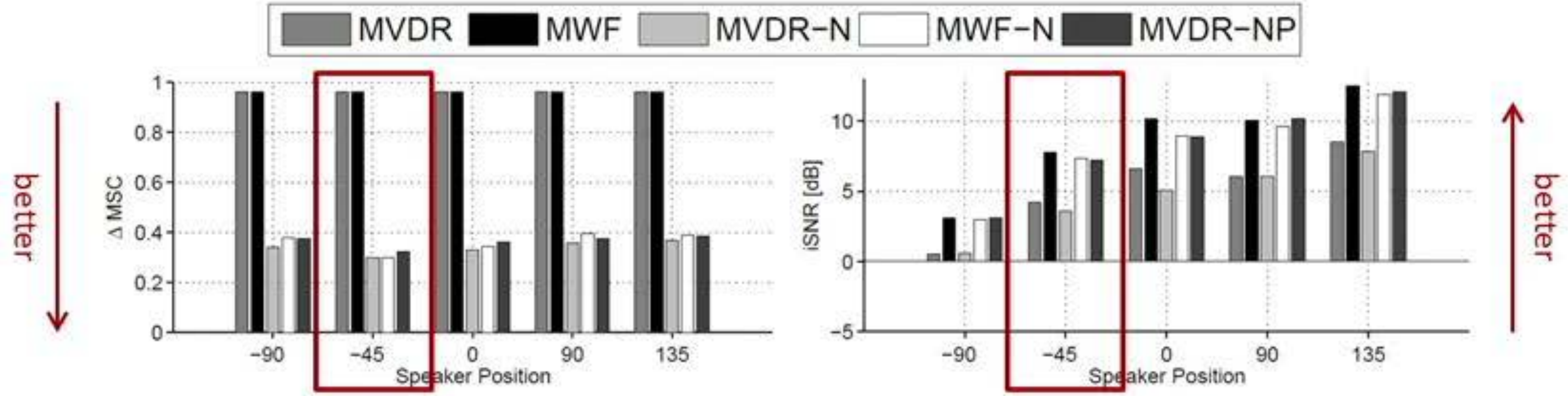


Binaural cue preservation for diffuse noise does not affect speech intelligibility

[Klug, Marquardt, Gößling, Doclo, *ITG Conference Speech Communication*, Oct. 2018.]
[Gößling, Marquardt, Doclo, *Trends in Hearing, in revision*.]

Binaural MVDR/MWF: Sound samples

Input	MVDR	MWF	MVDR-N	MWF-N	MVDR-NP



(a) $\Delta\mathrm{MSC}_{\mathrm{v}}$ (b) $\mathrm{iSNR}_{\mathrm{be}}^{\mathrm{out}}$

Cafeteria with recorded ambient noise, speaker at -45°, 0 dB input iSNR (left hearing aid)
MVDR: anechoic ATF, DOA known, spatial coherence matrix calculated from anechoic ATFs / MWF = MVDR + postfilter (SPP-based)

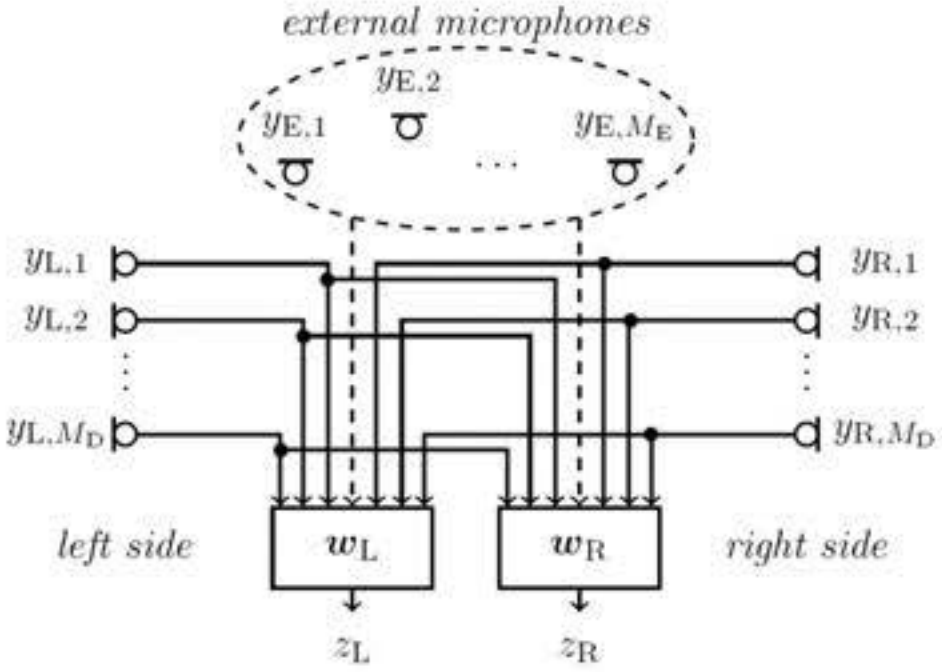
3. Acoustic sensor networks

External microphones

- Exploit the availability of one or more external microphones **(acoustic sensor network)** with hearing aids
  [Bertrand 2009, Szurley 2016, Yee 2018, Farmani 2018, Kates 2018, Ali 2019, Gößling 2019]

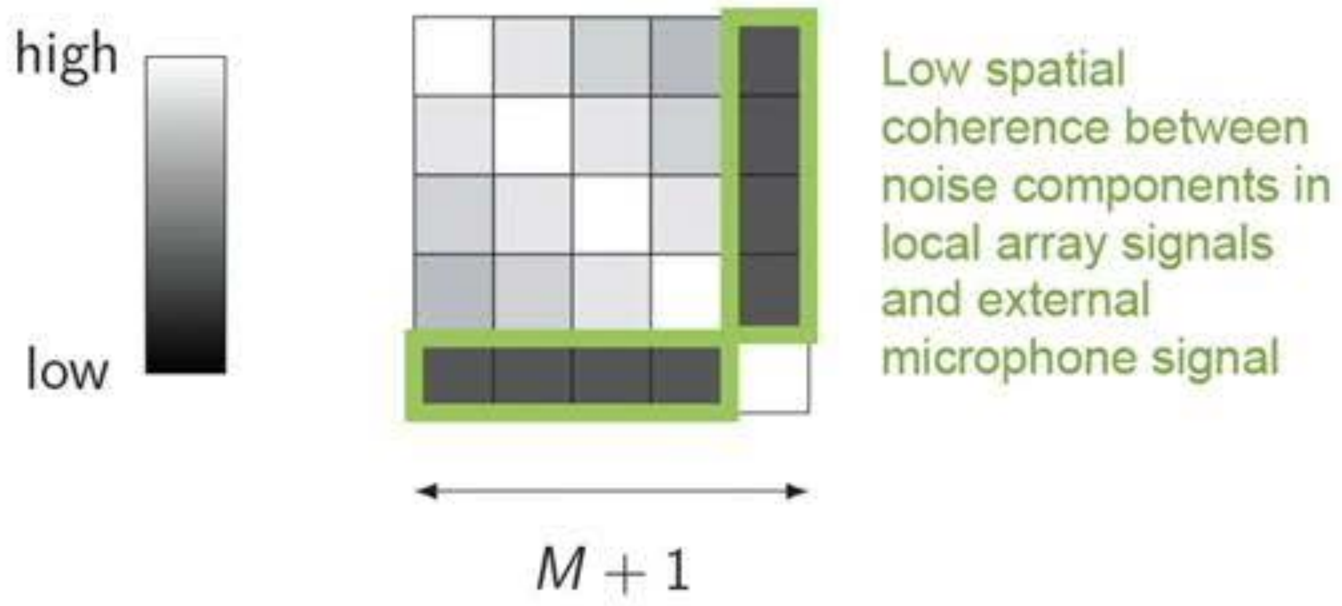
- Integrating external microphone(s) with hearing aid microphones may lead to:
  - Low-complexity method to **estimate relative transfer function (RTF)** vector of target speaker
  - Improved **noise reduction** and **binaural cue preservation** performance

$$\mathbf{w}_L = \frac{\mathbf{R}_v^{-1}\mathbf{a}_L}{\mathbf{a}_L^H\mathbf{R}_v^{-1}\mathbf{a}_L}, \quad \mathbf{w}_R = \frac{\mathbf{R}_v^{-1}\mathbf{a}_R}{\mathbf{a}_R^H\mathbf{R}_v^{-1}\mathbf{a}_R}$$



One external microphone: RTF estimation

- **Estimate RTF vector of target speaker** to steer binaural MVDR beamformer
- **Spatial coherence (SC) method:** assume that noise components in external microphone and HA microphones are uncorrelated, e.g., when external microphone is spatially separated from HA microphones + diffuse noise field



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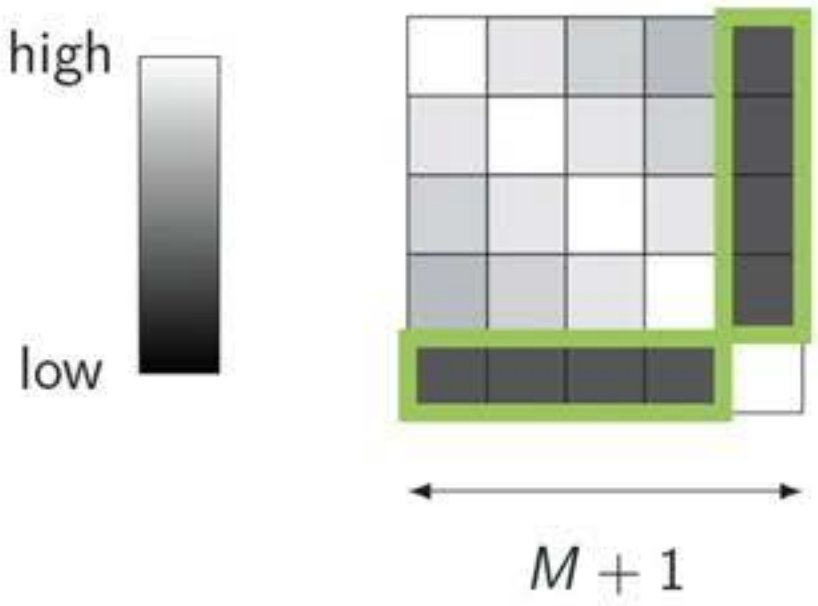
  → correlate HA microphone signals with external microphone signals and normalize by reference element



Low spatial coherence between noise components in local array signals and external microphone signal

$$\bar{\mathbf{a}}_{\mathrm{L}}^{\mathrm{SCE}} = \frac{\bar{\mathbf{R}}_{\mathrm{y}}\mathbf{e}_{\mathrm{E}}}{\mathbf{e}_{\mathrm{L}}^{T}\bar{\mathbf{R}}_{\mathrm{y}}\mathbf{e}_{\mathrm{E}}}, \quad \bar{\mathbf{a}}_{\mathrm{R}}^{\mathrm{SCE}} = \frac{\bar{\mathbf{R}}_{\mathrm{y}}\mathbf{e}_{\mathrm{E}}}{\mathbf{e}_{\mathrm{R}}^{T}\bar{\mathbf{R}}_{\mathrm{y}}\mathbf{e}_{\mathrm{E}}}$$

$$\bar{\mathbf{w}}_{\mathrm{L}}^{\mathrm{SCE}} = \begin{bmatrix} \alpha \cdot [\mathbf{I}_{2M},\, \mathbf{0}_{2M\times 1}]\,\bar{\mathbf{w}}_{\mathrm{L}} \\ \alpha(1+\beta)\cdot \mathbf{e}_{\mathrm{E}}^{T}\bar{\mathbf{w}}_{\mathrm{L}} \end{bmatrix}$$

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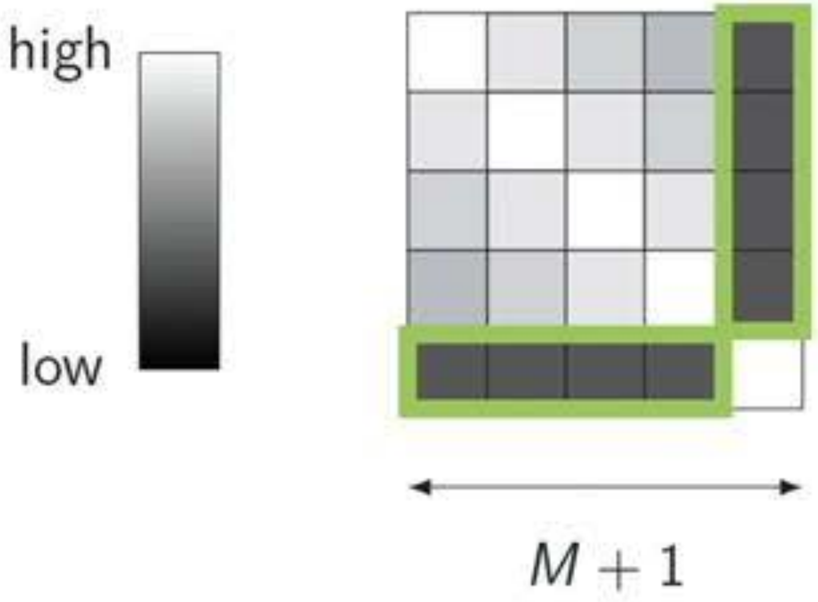

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real-valued bias

One external microphone: RTF estimation

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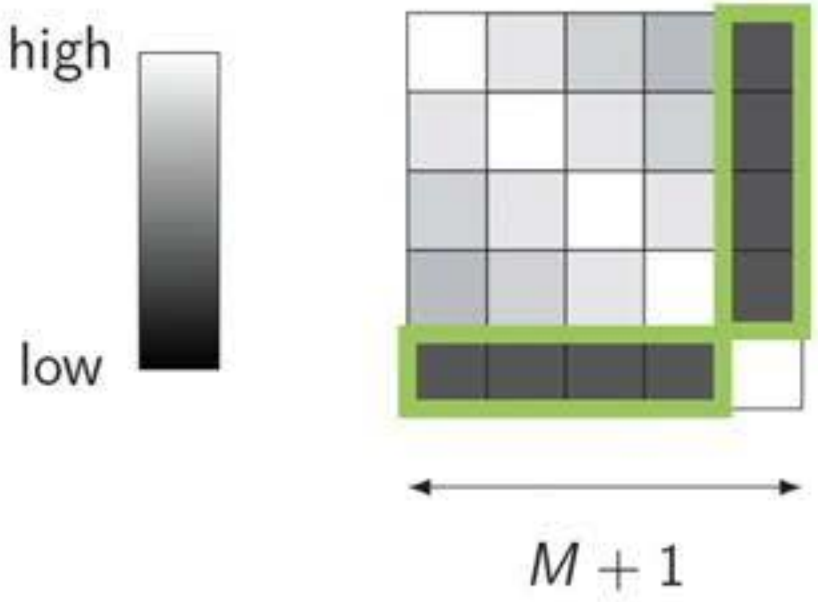
- **Spatial coherence (SC) method:** assume that noise components in external microphone and HA microphones are uncorrelated, e.g., when external microphone is spatially separated from HA microphones + diffuse noise field

  → correlate HA microphone signals with external microphone signals and normalize by reference element
- **Low computational complexity** with similar (even better in practice) performance than state-of-the-art covariance whitening (CW) approach



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One external microphone: Simulation results

Oldenburg Varechoic Lab ($T_{60} \approx 350$ms), M=4 + 1 external mic (1.5m/0.5m), moving speaker, pseudo-diffuse babble noise, iSNR=0dB (right HA)
STFT: 32 ms, 50% overlap, sqrt-Hann; SPP in external microphone; smoothing: 100 ms (speech), 1 s (noise)

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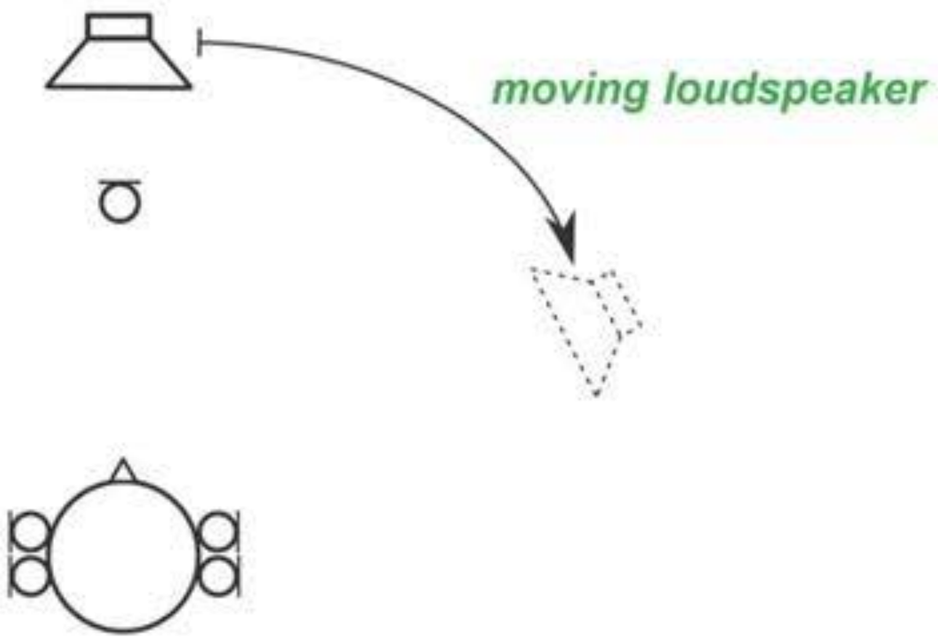

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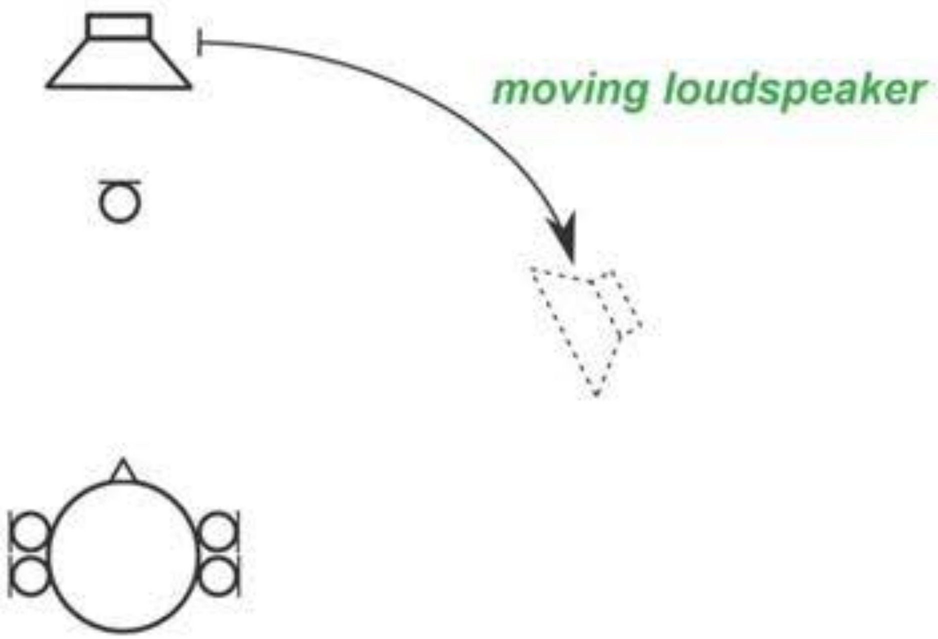

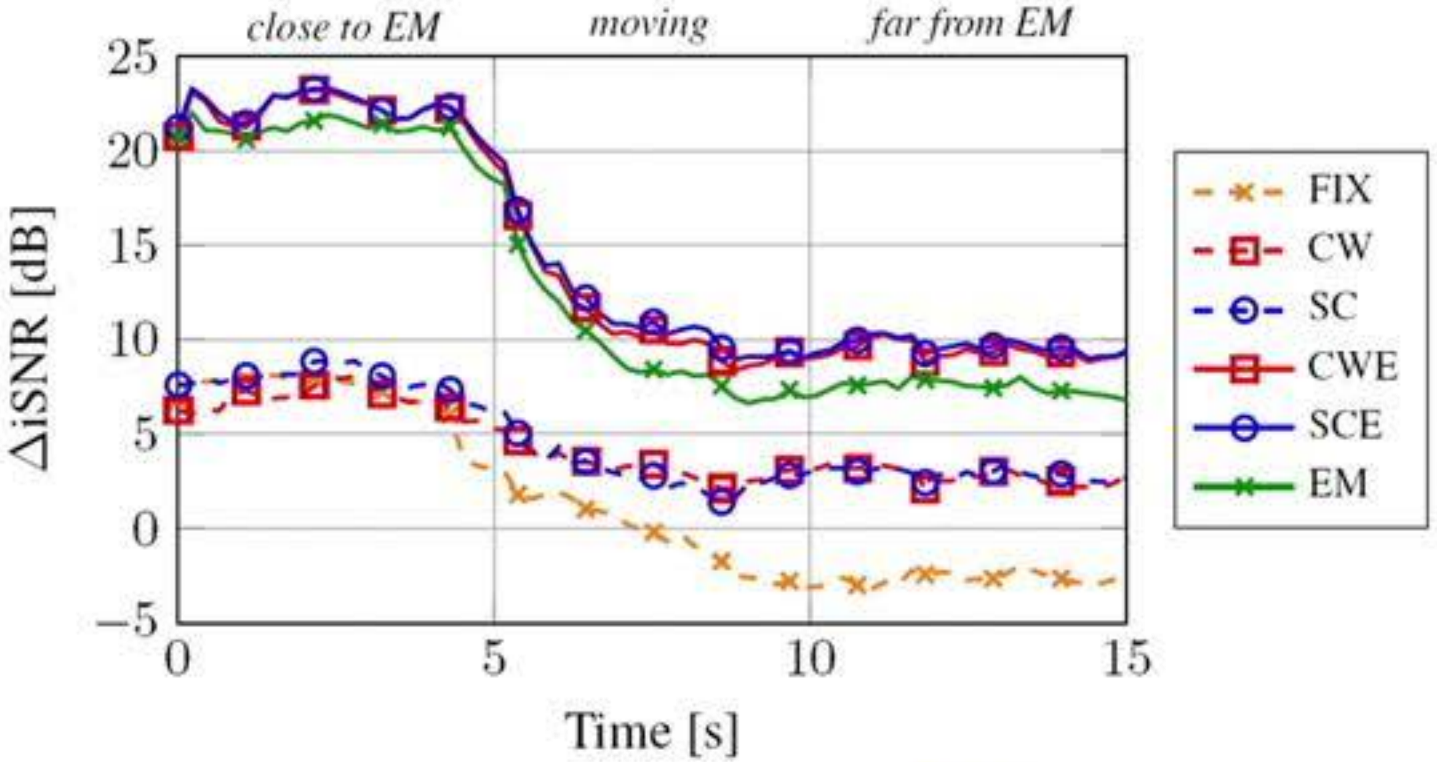

- MVDR with external microphone (SCE) leads to **better SNR** compared to MVDR using only HA microphones (SC,FIX) and external microphone (EM)

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[Gößling, Doclo, *Proc. IWAENC* 2018] [Gößling, Doclo, *Proc. ICASSP 2019*]

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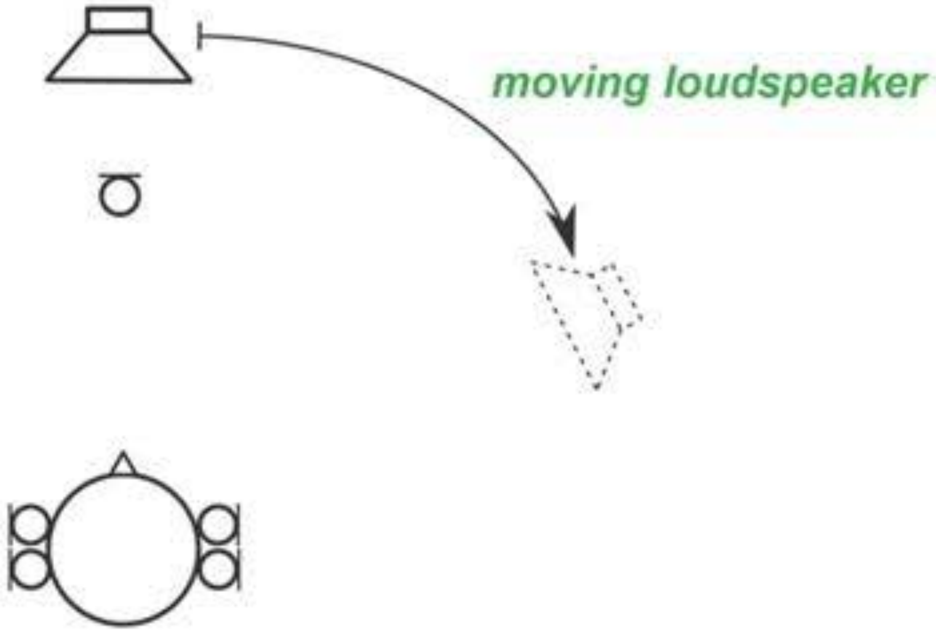
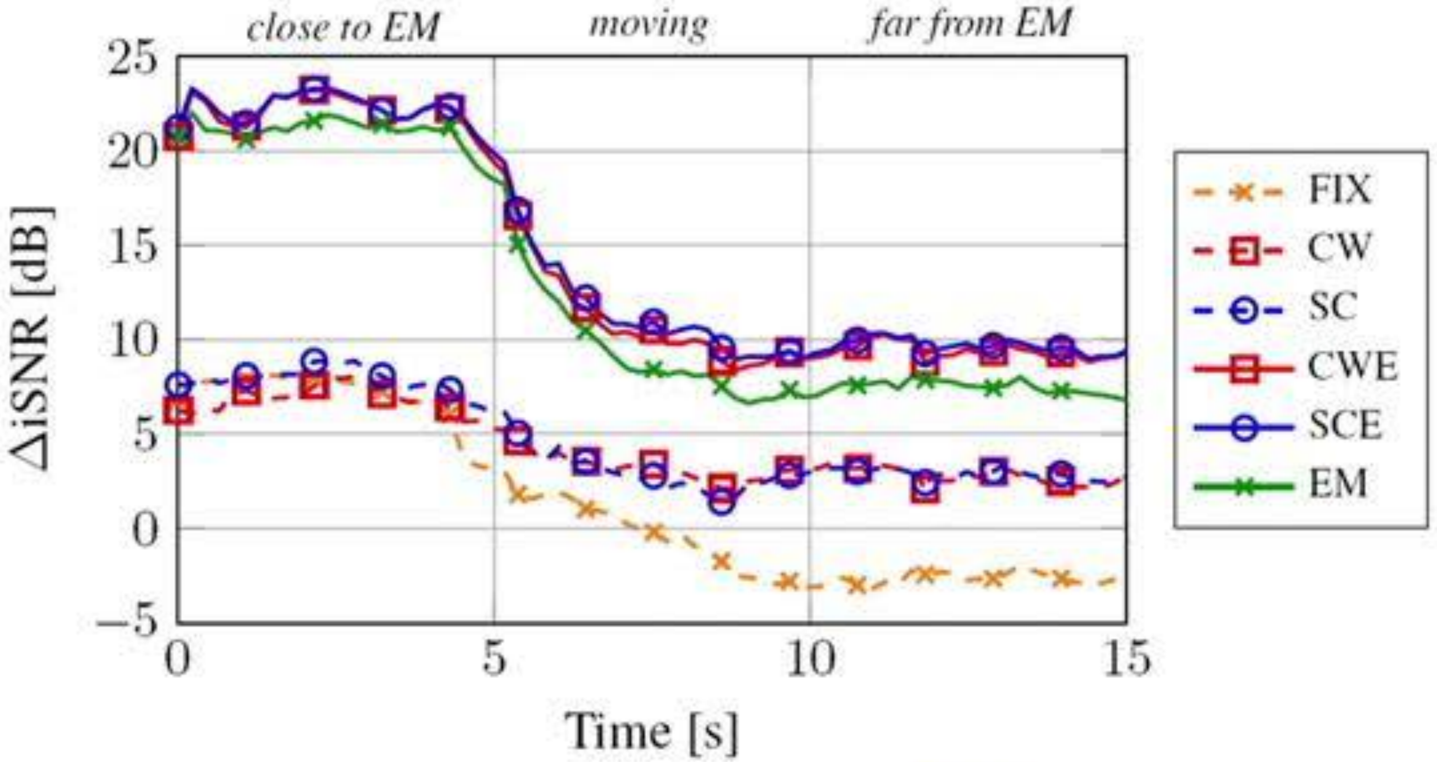
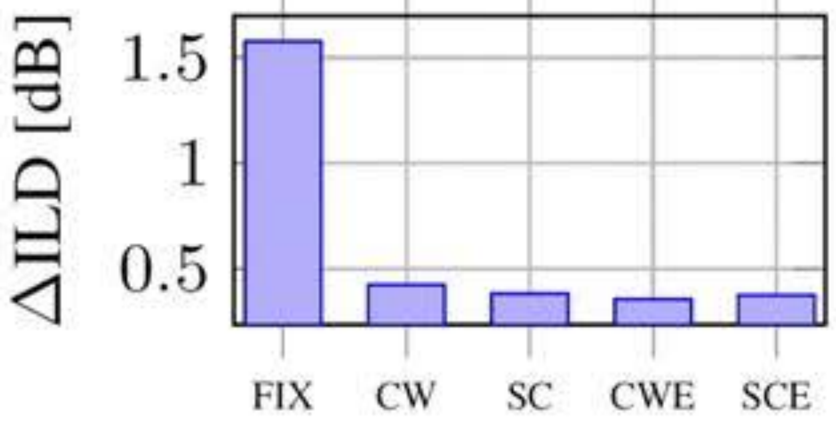






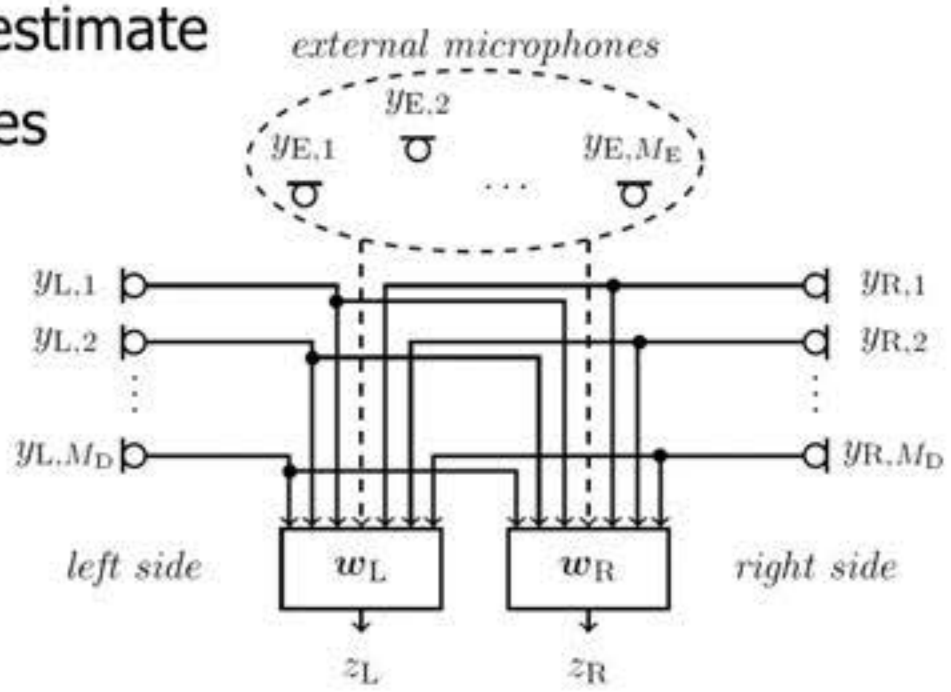
- MVDR with external microphone (SCE) leads to **better SNR** compared to MVDR using only HA microphones (SC,FIX) and external microphone (EM)
- MVDR using estimated RTFs (SCE, SC) **preserves binaural cues of target speaker** compared to fixed MVDR (FIX) and external microphone (EM)

Oldenburg Varechoic Lab ($T_{60} \approx$ 350ms), M=4 + 1 external mic (1.5m/0.5m), moving speaker, pseudo-diffuse babble noise, iSNR=0dB (right HA)
STFT: 32 ms, 50% overlap, sqrt-Hann; SPP in external microphone; smoothing: 100 ms (speech), 1 s (noise)

Multiple external microphones

- Each external microphone yields (different) RTF estimate
- **Linear combination/selection** of RTF estimates (per frequency)

$$\boxed{\boldsymbol{a}_{\mathrm{L}}^{\mathrm{SC-C}} = \frac{\boldsymbol{A}_{\mathrm{L}}^{\mathrm{SC}}\boldsymbol{c}}{\boldsymbol{e}_{\mathrm{L}}^{T}\boldsymbol{A}_{\mathrm{L}}^{\mathrm{SC}}\boldsymbol{c}}}$$



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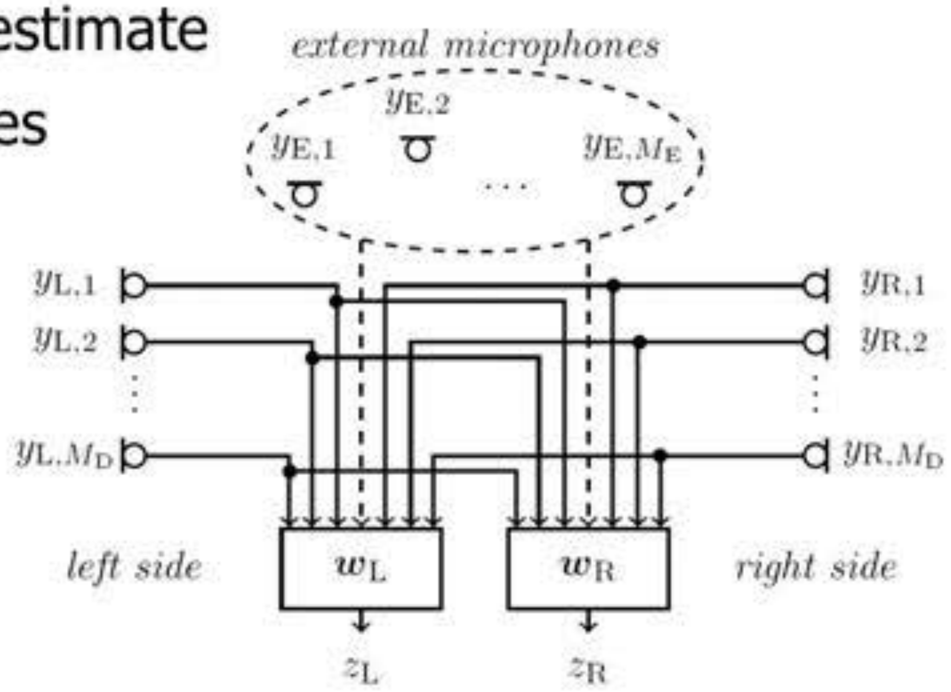

1. Input SNR-based selection

$$\boldsymbol{c}^{\mathrm{iSNR}} = \boldsymbol{e}_{\mathrm{E},\hat{i}}\,, \quad \hat{i} = \arg\max_{i}\ \frac{\boldsymbol{e}_{\mathrm{E},i}^{T}\boldsymbol{R}_{\mathrm{y}}\boldsymbol{e}_{\mathrm{E},i}}{\boldsymbol{e}_{\mathrm{E},i}^{T}\boldsymbol{R}_{\mathrm{n}}\boldsymbol{e}_{\mathrm{E},i}}$$

2. Simple averaging

$$\boldsymbol{c}^{\mathrm{AV}} = \left[\frac{1}{M_{\mathrm{E}}}, \ldots, \frac{1}{M_{\mathrm{E}}}\right]^{T}$$

3. Output SNR-maximizing combination

$$\boxed{\boldsymbol{c}^{\mathrm{mSNR}} = \arg\max_{\boldsymbol{c}}\ \mathrm{SNR}_{\mathrm{BMVDR,L}}^{\mathrm{out}} = \mathcal{P}\{\boldsymbol{\Lambda}_2^{-1}\boldsymbol{\Lambda}_1\}}$$

[Gößling, Middelberg, Doclo, *Proc. WASPAA 2019*]

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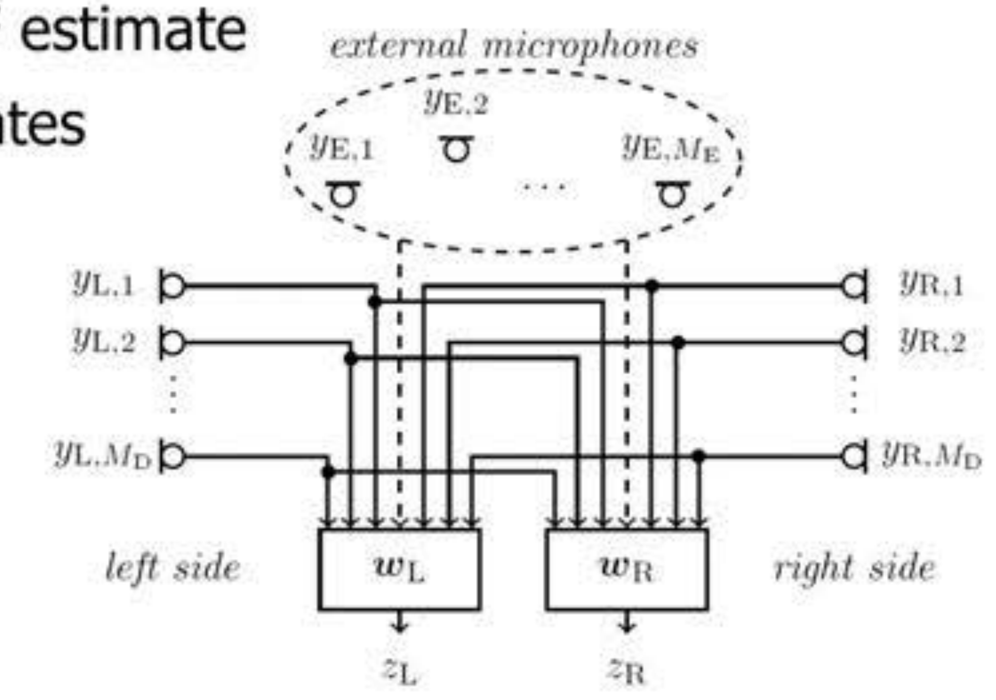

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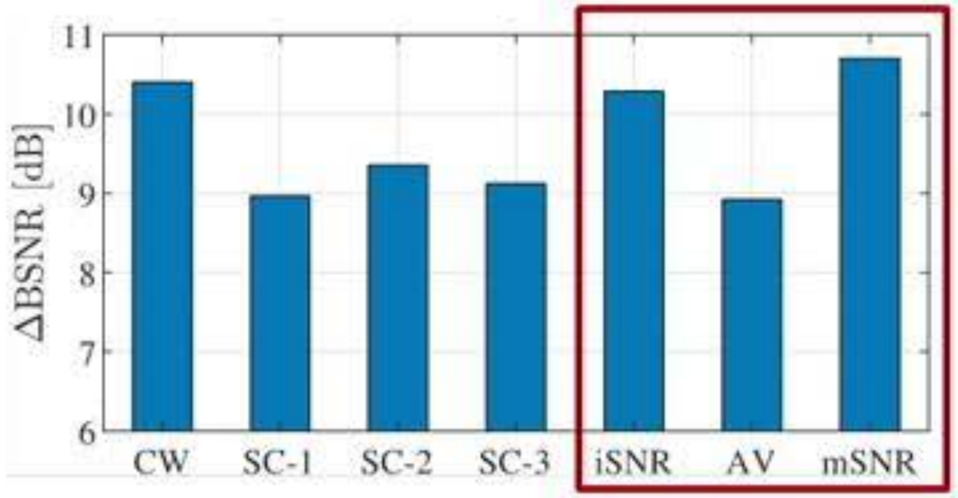


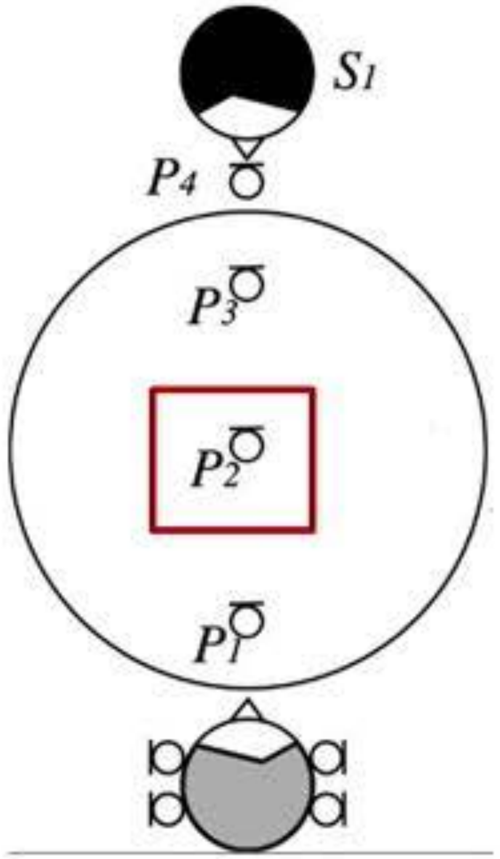
Audio Demo

- Real-world recordings ($T_{60} \approx 300$ ms), **moving speaker**
- KEMAR with **two BTE hearing aids** (2 mics each) and **one external mic**
- Pseudo-diffuse babble noise

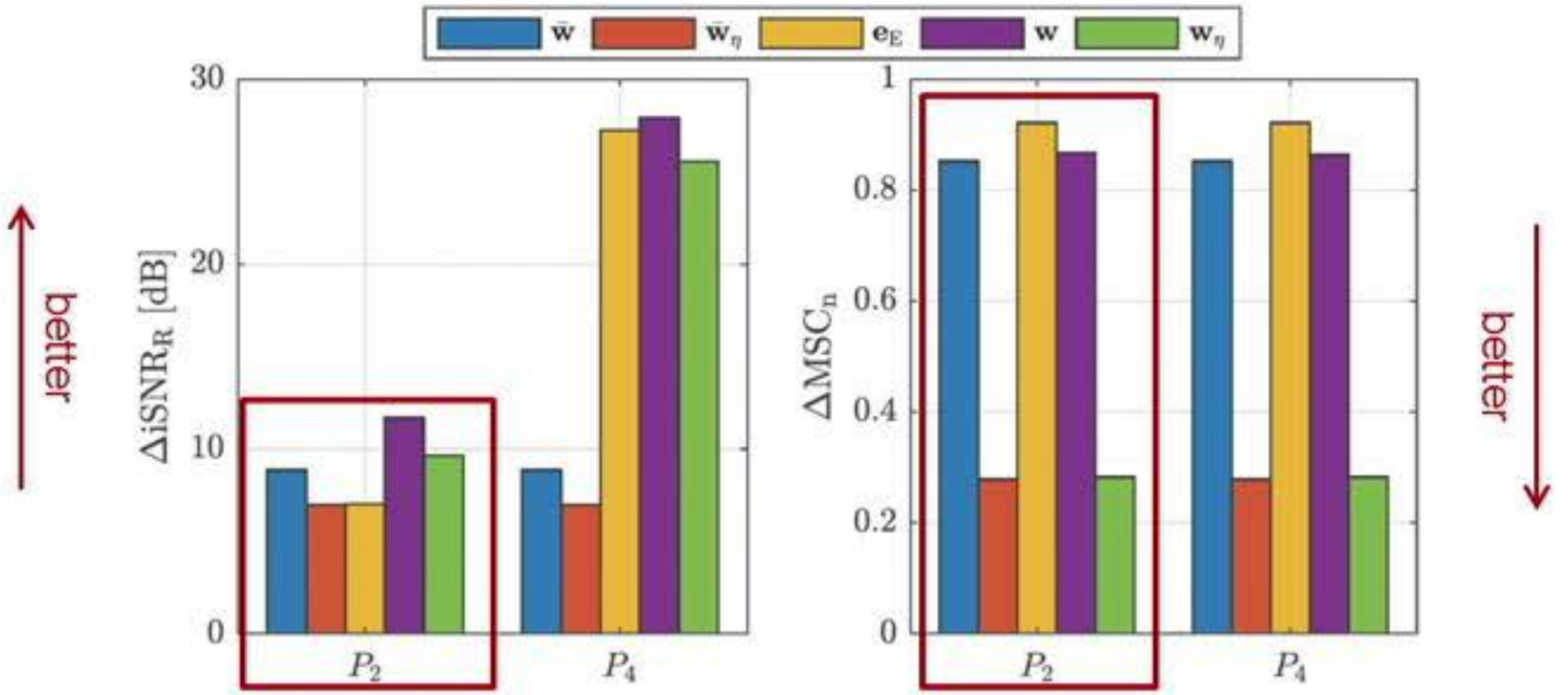
Audio Demo

Binaural MVDR-N beamformer

- Including external microphone in **binaural MVDR-N beamformer** leads to:
  - **Larger output SNR** for same trade-off parameter η
  - Same output SNR with larger trade-off parameter η → **better cue preservation**



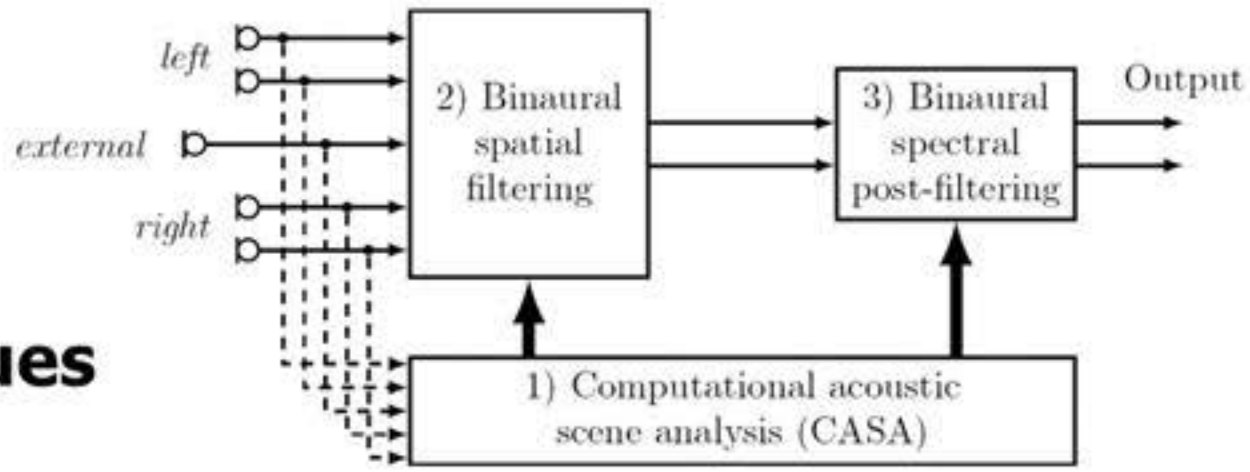
MVDR (HA) | MVDR-N (HA) | External | eMVDR (HA+ext) | eMVDR-N (HA+ext)

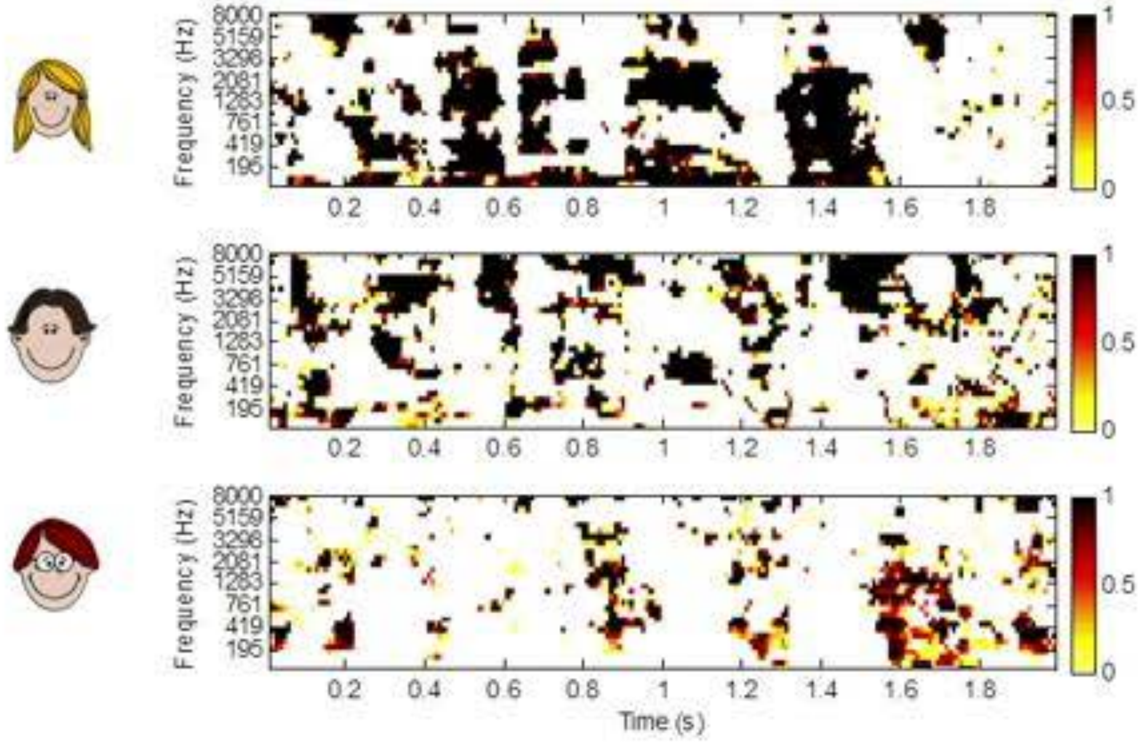


Starkey database with real-world recordings (T_{60} ≈ 620ms), M=4, target speaker S_1, multi-talker babble noise, 0 dB input iSNR (right hearing aid)
MVDR: perfectly estimated noise correlation matrix, RTF of target speaker estimated using covariance whitening method

Current/future work

- **Performance analysis** for different acoustic scenarios (interfering speakers)
- **Synchronization/latency issues**
- **Complex and time-varying scenarios**: incorporate computational acoustic scene analysis (CASA) into control path of developed algorithms
- **Subjective evaluation** of binaural speech enhancement algorithms with **HA/CI users** ongoing





Conclusions

- **Speech communication applications:** on-line speech enhancement algorithms for dynamic acoustic scenarios required

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  - Reverberation suppression: multi-channel linear prediction

Conclusions

- **Speech communication applications:** on-line speech enhancement algorithms for dynamic acoustic scenarios required
- **Joint noise reduction and dereverberation** using multiple microphones:
  - MVDR beamformer + spectral postfiltering: estimates of time-varying spatial and spectral variables (RETF vector, PSDs)
  - Reverberation suppression: multi-channel linear prediction
- **Binaural hearing devices** with binaural output signals:
  - Extensions of binaural MVDR/MWF enable to improve speech intelligibility while preserving spatial awareness (binaural cues)
  - Improved performance when integrating external microphones (acoustic sensor networks)

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DREAMS

DFG Deutsche Forschungsgemeinschaft

VolkswagenStiftung

GIF German-Israeli Foundation for Scientific Research and Development

Questions ?

House of Hearing, Oldenburg