Recent advances in noise reduction and dereverberation algorithms for binaural hearing aids

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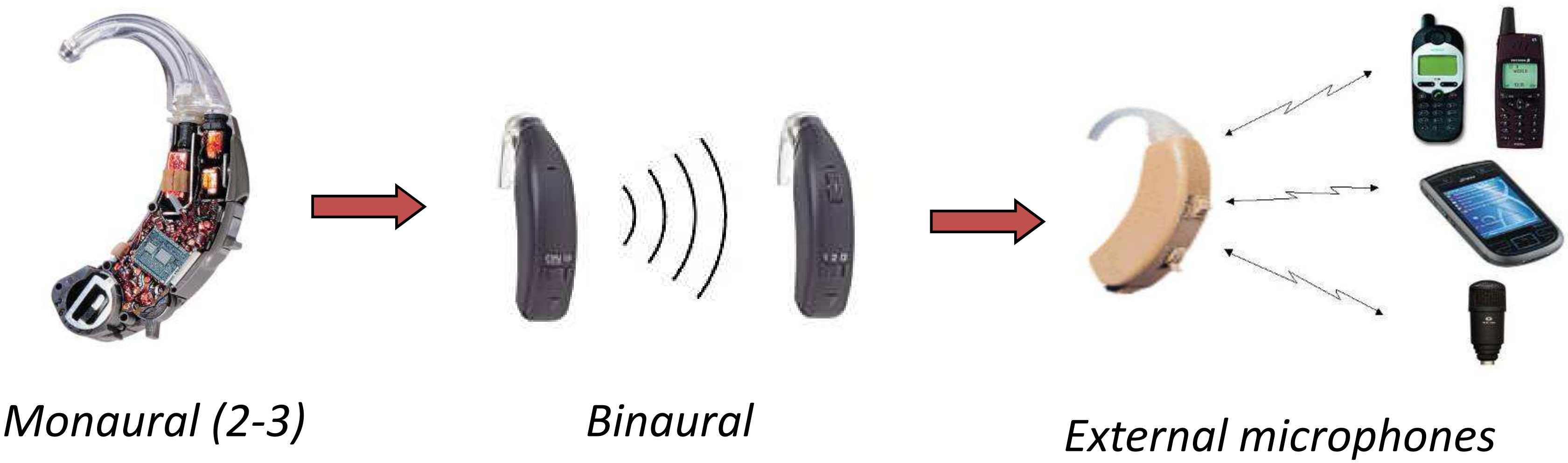
Introduction

- Hearing impaired suffer from a loss of speech understanding in adverse acoustic environments with competing speakers, background noise and reverberation

Apply **acoustic signal pre-processing techniques** in order to improve speech quality and intelligibility

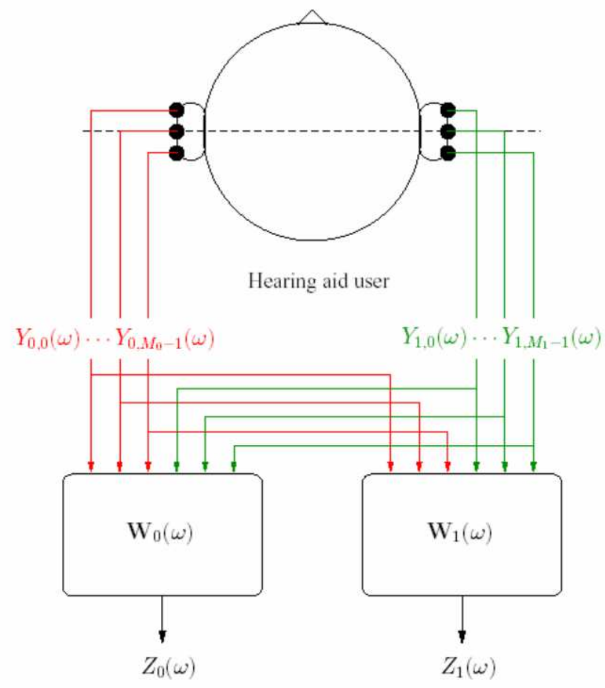
Introduction

- Digital hearing aids allow for advanced acoustical signal pre-processing
  - Multiple microphones available $\rightarrow$ spatial + spectral processing
  - Speech enhancement (noise reduction, beamforming, dereverberation), computational acoustic scene analysis (source localisation, environment classification)



Introduction

- **This presentation:**
  - Instrumental and subjective evaluation of recent **binaural noise reduction algorithms** based on MVDR/MWF
  - Recent advances in **blind multi-microphone dereverberation algorithms**

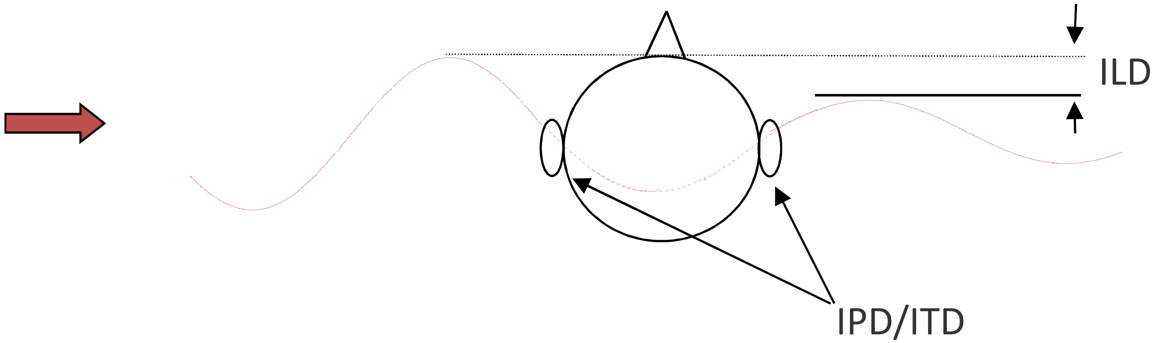


- **Main objectives of algorithms:**
  - Improve speech intelligibility and avoid signal distortions
  - Preserve spatial awareness and directional hearing (binaural cues)

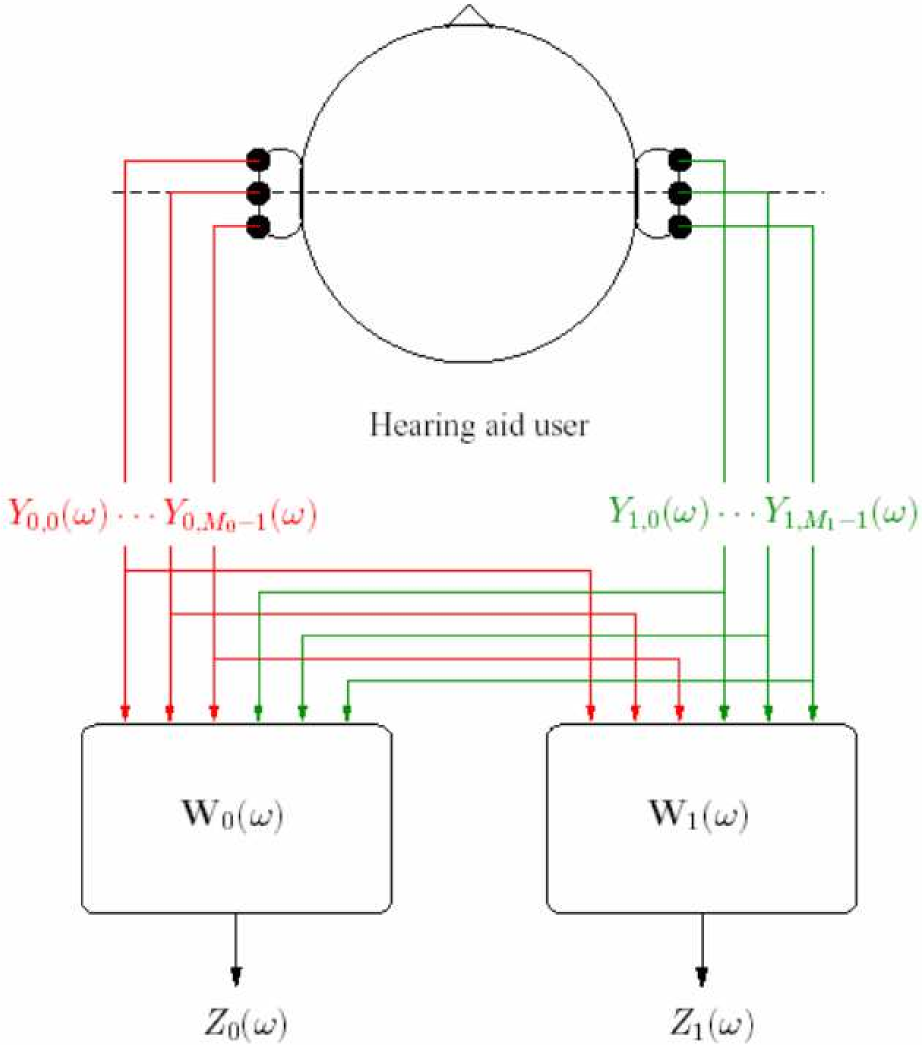
I. Binaural noise reduction

Binaural 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)
- 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

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

Binaural noise reduction: Acoustic scenario

- The microphone signals **Y** are composed of
  - (desired) speech component $\mathbf{X} = S_d\mathbf{A}$
  - (undesired) directional interference component $\mathbf{U} = S_u\mathbf{B}$
  - (undesired) background noise component **N**

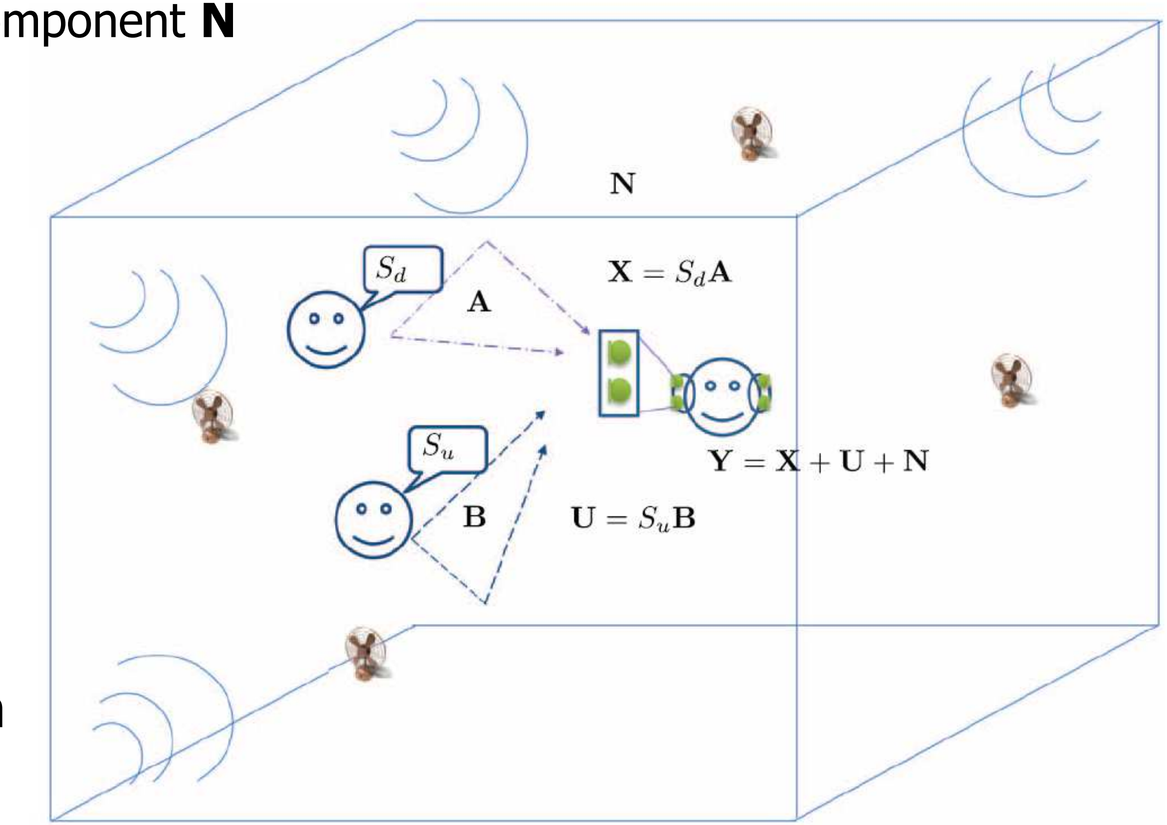
Acoustic Transfer Functions (ATFs)

- Correlation matrices:

$$\mathbf{R}_y = \mathbf{R}_x + \underbrace{\mathbf{R}_u + \mathbf{R}_n}_{\mathbf{R}_v}$$

$$\mathbf{R}_x = \mathcal{E}\left\{\mathbf{X}\mathbf{X}^H\right\} = P_s\mathbf{A}\mathbf{A}^H$$
$$\mathbf{R}_u = \mathcal{E}\left\{\mathbf{U}\mathbf{U}^H\right\} = P_u\mathbf{B}\mathbf{B}^H$$
$$\mathbf{R}_n = \mathcal{E}\left\{\mathbf{N}\mathbf{N}^H\right\},$$

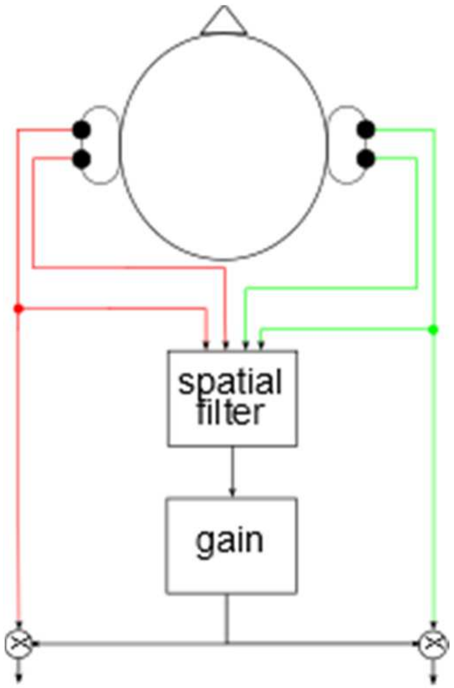
- All **binaural cues** can be written in terms of these matrices



Binaural noise reduction: Two main paradigms

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

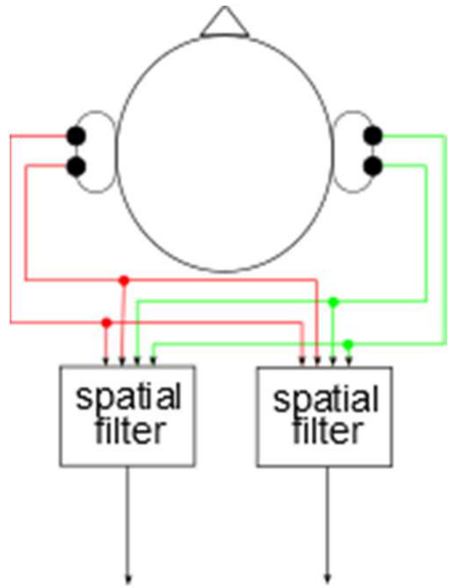
[Dörbecker 1996, Wittkop 2003, Lotter 2006, Rohdenburg 2008, Grimm 2009, Kamkar-Parsi 2011, Reindl 2013, Baumgärtel 2015]



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

Binaural spatial filtering techniques

[Merks 1997, Welker 1997, Aichner 2007, Doclo 2010, Cornelis 2012, Hadad 2014-2016, Marquardt 2014-2016]



- ⊕ 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

$$\min_{\mathbf{W}_0} \underbrace{\mathbf{W}_0^H \mathbf{R}_v \mathbf{W}_0}_{\text{noise reduction}} \quad \text{subject to} \quad \underbrace{\mathbf{W}_0^H \mathbf{A} = A_0}_{\text{distortionless constraint}}$$

$$\min_{\mathbf{W}_1} \mathbf{W}_1^H \mathbf{R}_v \mathbf{W}_1 \quad \text{subject to} \quad \mathbf{W}_1^H \mathbf{A} = A_1$$

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

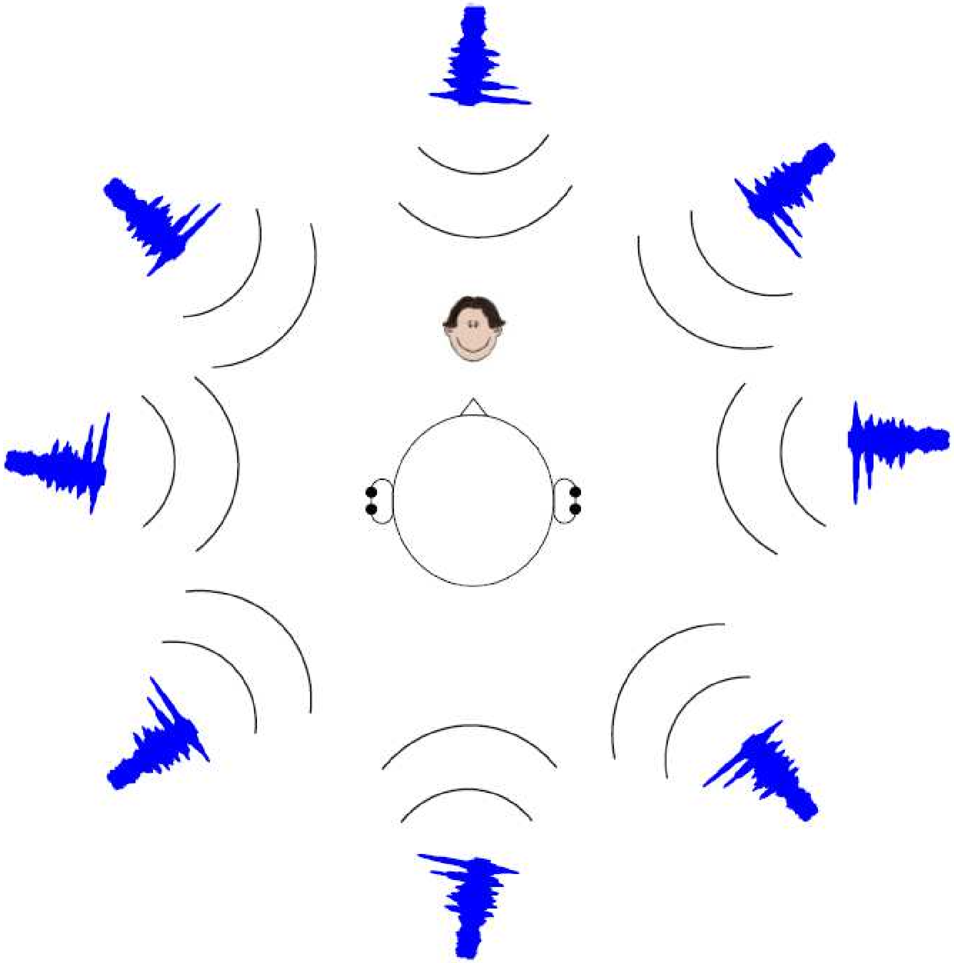
$$J_{\mathrm{MWF}}(\mathbf{W}) = \mathcal{E}\left\{ \underbrace{\left\| \begin{bmatrix} X_0 - \mathbf{W}_0^H \mathbf{X} \\ X_1 - \mathbf{W}_1^H \mathbf{X} \end{bmatrix} \right\|^2}_{\text{speech distortion}} + \mu \underbrace{\left\| \begin{bmatrix} \mathbf{W}_0^H \mathbf{V} \\ \mathbf{W}_1^H \mathbf{V}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

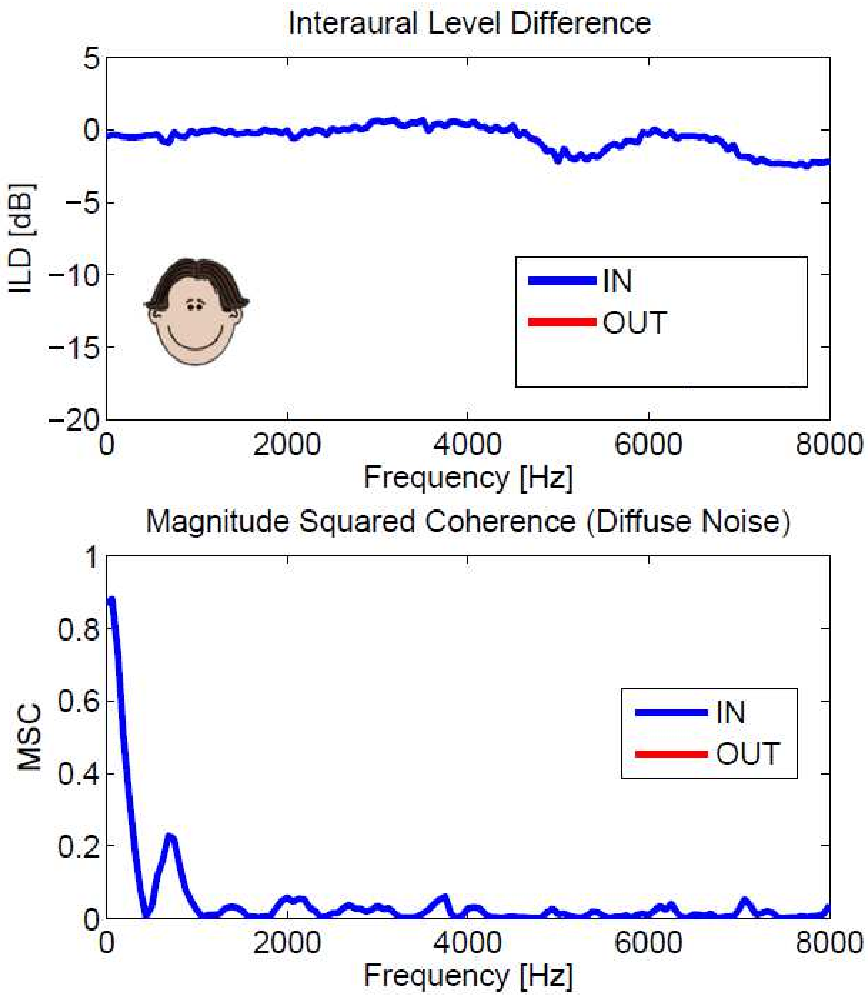
Requires estimate of speech and noise covariance matrices, e.g. based on VAD

Can be decomposed as binaural MVDR beamformer and spectral postfilter

Good noise reduction performance, what about binaural cues ?

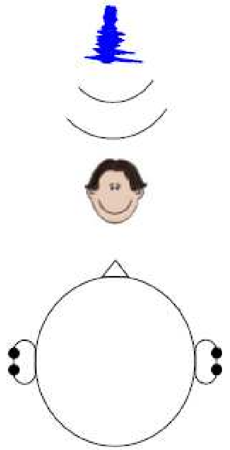
Binaural MVDR and MWF Binaural cues (diffuse noise)

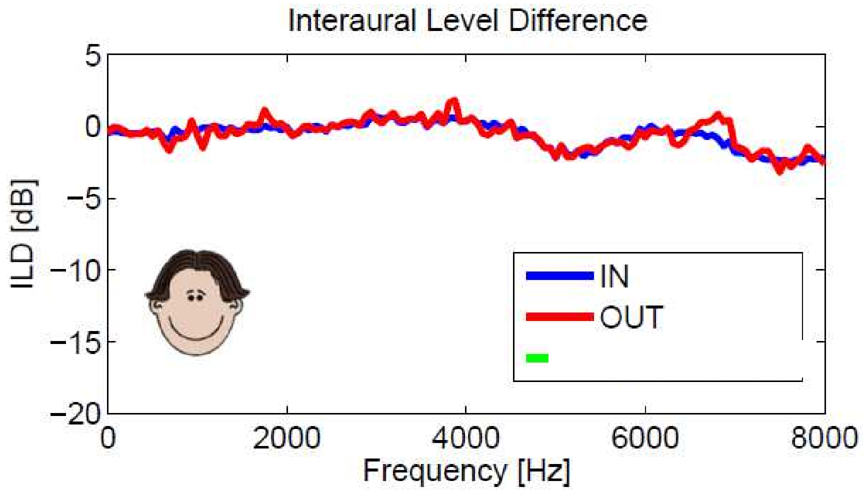


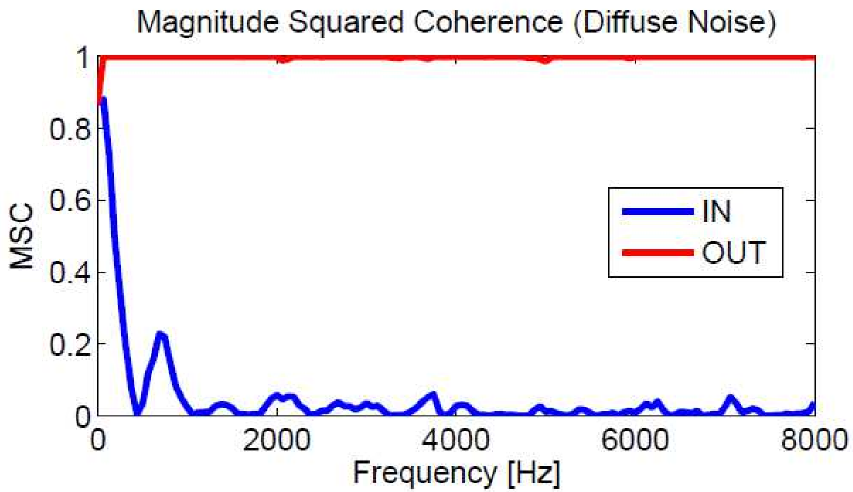


Note: MSC = Magnitude Squared Coherence

Binaural MVDR and MWF
Binaural cues (diffuse noise)







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

Binaural noise reduction
Extensions for diffuse noise

Binaural MWF: Extensions for diffuse noise

Binaural MWF

- ⊕ 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

Partial noise estimation (MWF-N)

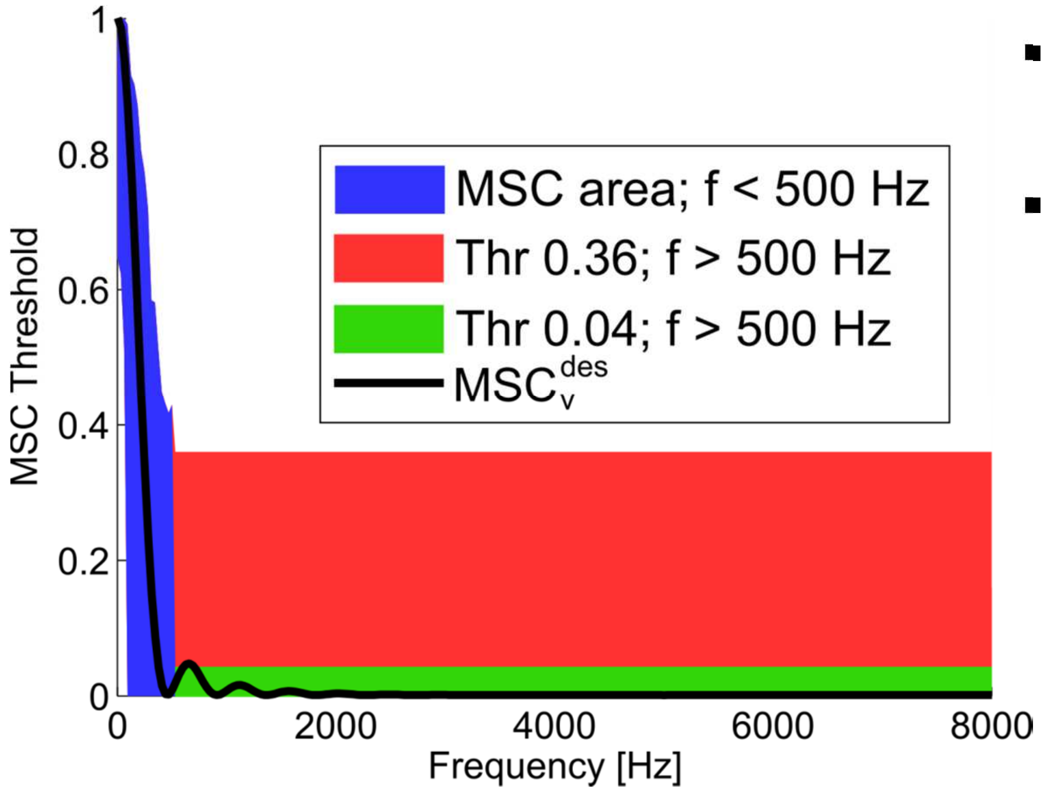
$$J_{\mathrm{MWF-N}}(\mathbf{W}) = \mathcal{E}\left\{ \left\| \begin{bmatrix} X_0 - \mathbf{W}_0^H \mathbf{X} \\ X_1 - \mathbf{W}_1^H \mathbf{X} \end{bmatrix} \right\|^2 + \mu \left\| \begin{bmatrix} \eta V_0 - \mathbf{W}_0^H \mathbf{V} \\ \eta V_1 - \mathbf{W}_1^H \mathbf{V} \end{bmatrix} \right\|^2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

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

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

Binaural MWF: Extensions for diffuse noise

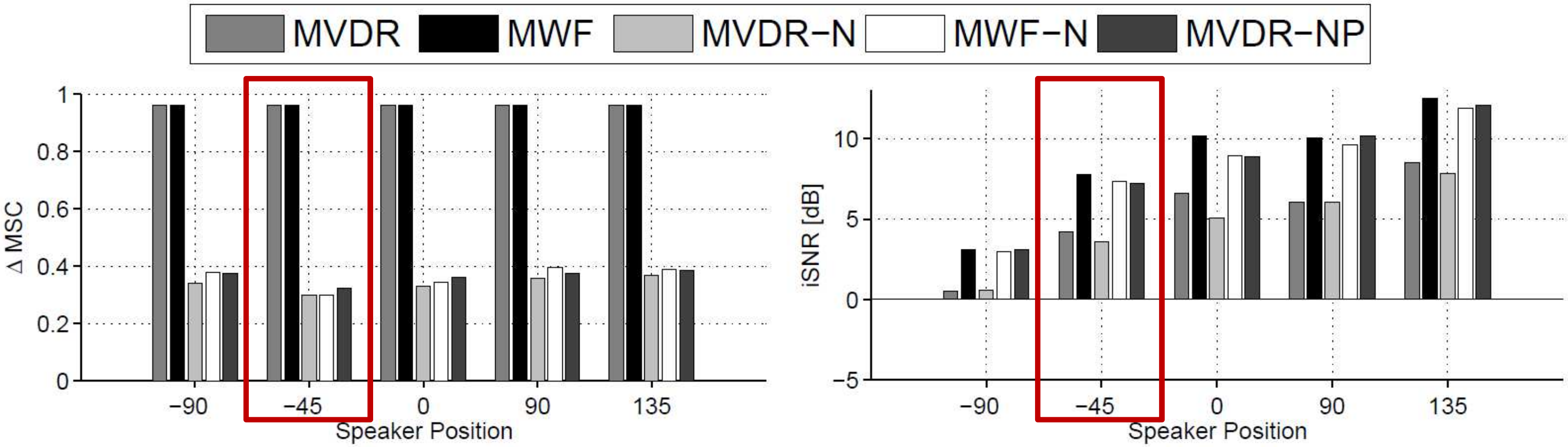
- **Determine (frequency-dependent) trade-off parameters based on psycho-acoustic criteria**
  - Amount of IC preservation based on subjective listening experiments evaluating the IC discrimination abilities of the human auditory system



- 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**)

Binaural MWF: Extensions for diffuse noise

❑ Instrumental evaluation / sound samples



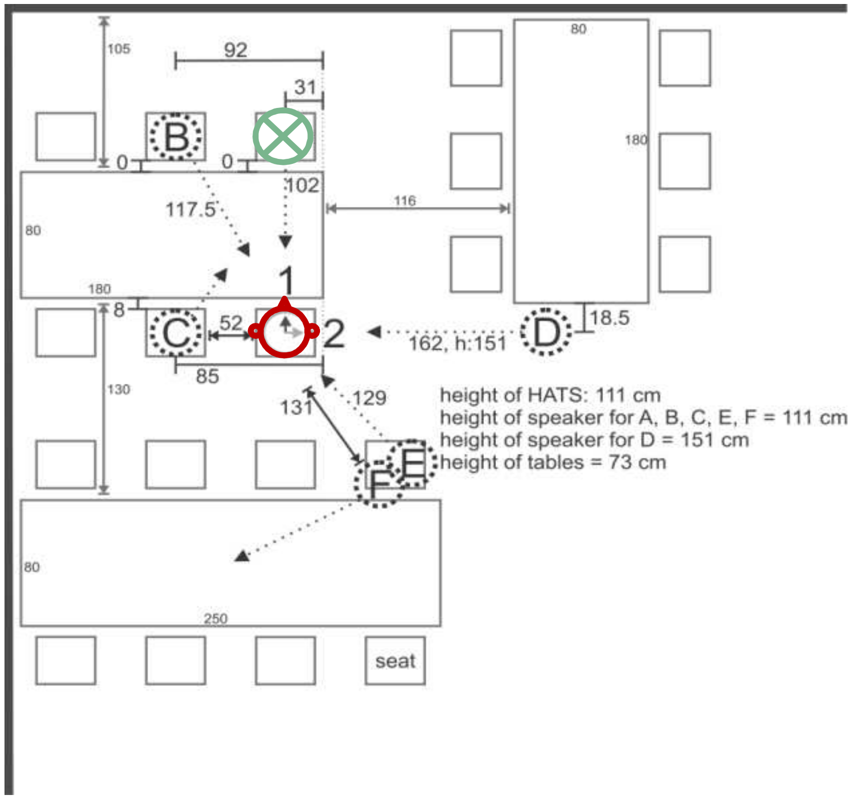
(a) $\Delta\mathrm{MSC_v}$ (b) $\mathrm{iSNR_{be}^{out}}$

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

Office ($T_{60} \approx$ 700ms), M=4 (BRIR), 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)

[Marquardt 2016]

Subjective Evaluation: Test setup

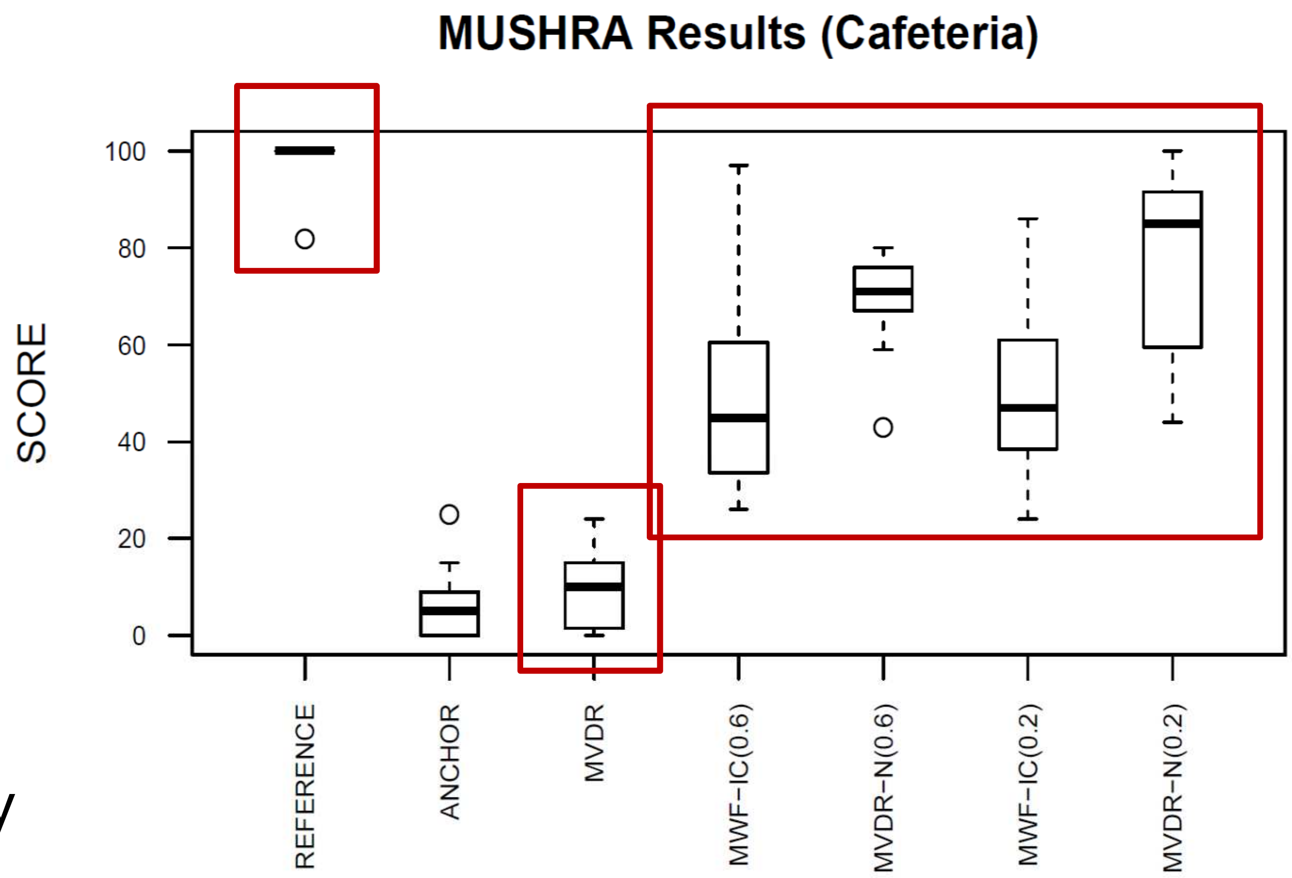


- Binaural hearing aid recordings (M=4 mics) in **cafeteria** (T_{60} ≈ 1250 ms) [Kayser 2009]
- **Noise:** realistic cafeteria ambient noise
- **Algorithms**: binaural MVDR + cue preservation extensions (MWF-IC, MVDR-N) with different MSC boundaries
- **Subjective listening experiments**:
  - 15 normal-hearing subjects
  - **SRT** using Oldenburg Sentence Test (OLSA)
  - **Spatial quality (diffuseness)** using MUSHRA

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

Subjective Evaluation: Spatial quality (MUSHRA)

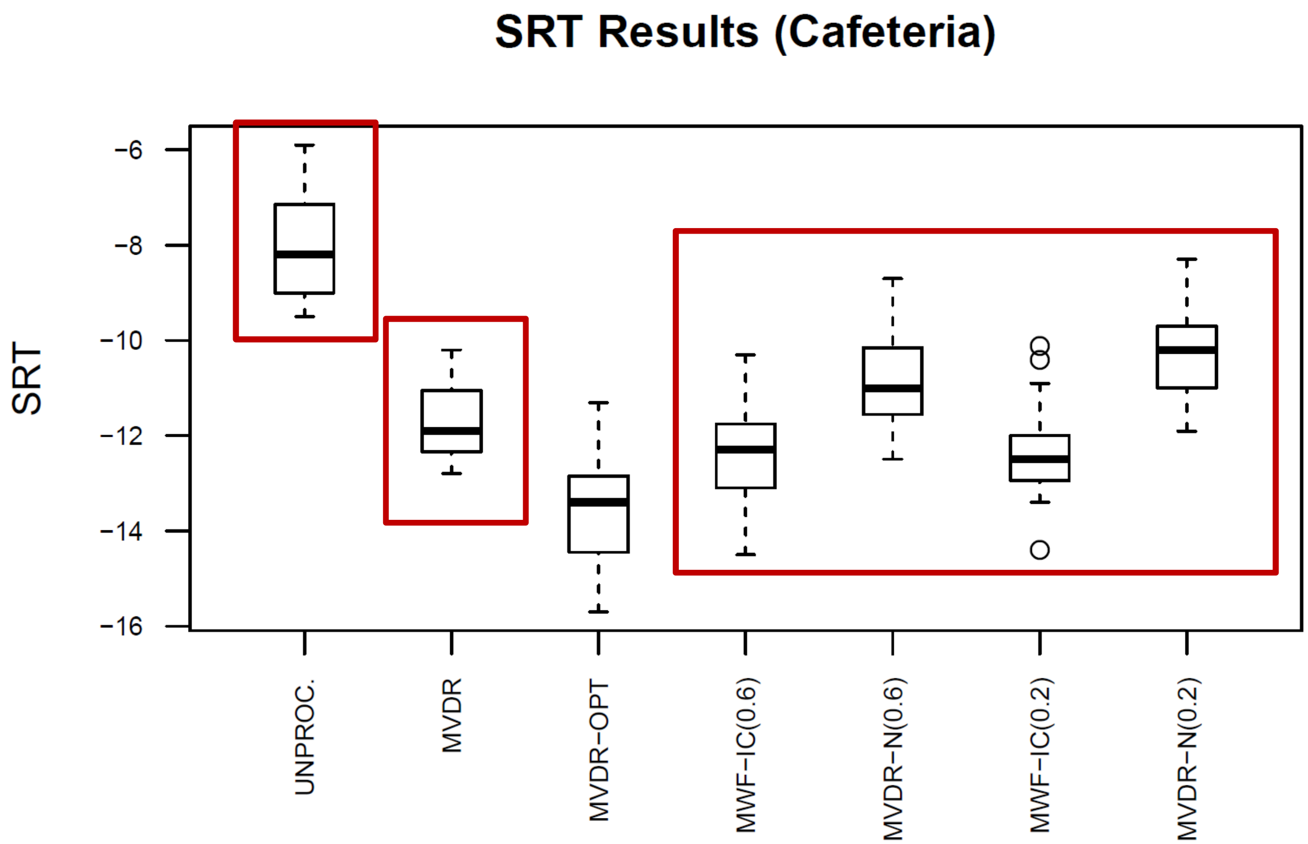
- Evaluate spatial difference between reference and output signal
- **MWF-IC and MVDR-N outperform MVDR**
  - MVDR-N shows better results than MWF-IC
  - Decreasing the MSC threshold slightly improves spatial quality



Binaural cue preservation for diffuse noise improves spatial quality

Subjective Evaluation: Speech intelligibility (SRT)

- All algorithms show a highly significant SRT improvement
- The SRT results mainly reflect the SNR differences between algorithms: MWF-IC outperforms MVDR-N
- **No significant SRT difference between MVDR and MWF-IC**



Binaural cue preservation for diffuse noise does not/hardly affect speech intelligibility

Binaural noise reduction

Extensions for interfering sources

Binaural MVDR: Extensions for interfering source

Binaural MVDR

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

Relative transfer function (BMVDR-RTF)

$$\min_{\mathbf{W}_0,\mathbf{W}_1} \left\{\mathbf{W}_0^H \mathbf{R}_v \mathbf{W}_0 + \mathbf{W}_1^H \mathbf{R}_v \mathbf{W}_1\right\}$$

$$\text{s.t. } \mathbf{W}_0^H \mathbf{A} = A_0, \mathbf{W}_1^H \mathbf{A} = A_1, \frac{\mathbf{W}_0^H \mathbf{B}}{\mathbf{W}_1^H \mathbf{B}} = \frac{B_0}{B_1}.$$

Interference rejection (BMVDR-IR)

$$\min_{\mathbf{W}_0} \left\{\mathbf{W}_0^H \mathbf{R}_v \mathbf{W}_0\right\} \text{ s.t. } \mathbf{W}_0^H \mathbf{A} = A_0, \mathbf{W}_0^H \mathbf{B} = \eta B_0$$

$$\min_{\mathbf{W}_1} \left\{\mathbf{W}_1^H \mathbf{R}_v \mathbf{W}_1\right\} \text{ s.t. } \mathbf{W}_1^H \mathbf{A} = A_1, \mathbf{W}_1^H \mathbf{B} = \eta B_1$$

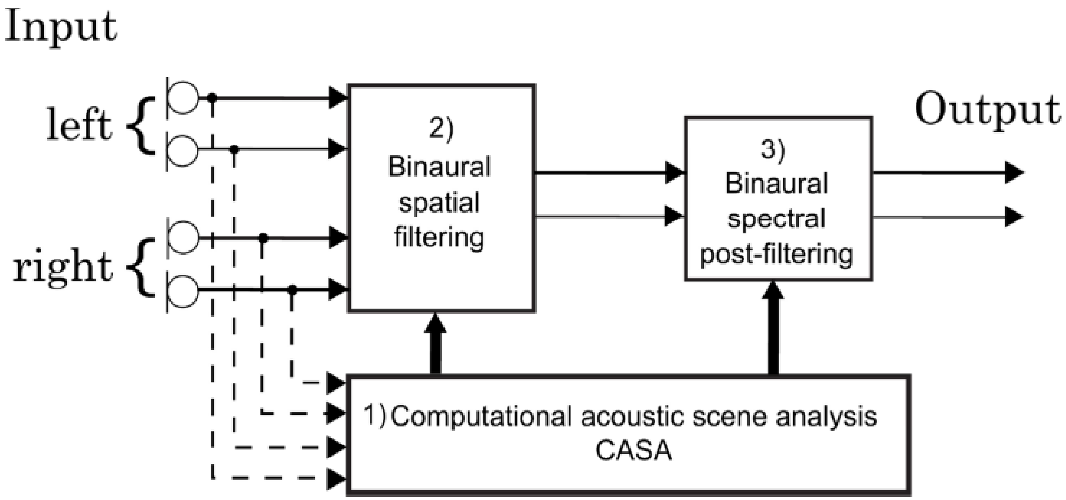
- ⊕ Binaural cues of speech source **and** interfering source preserved
- ⊕ Also binaural MWF-based versions (incl. spectral filtering) can be derived
- ⊖ Background noise: MSC not exactly preserved, possible noise amplification

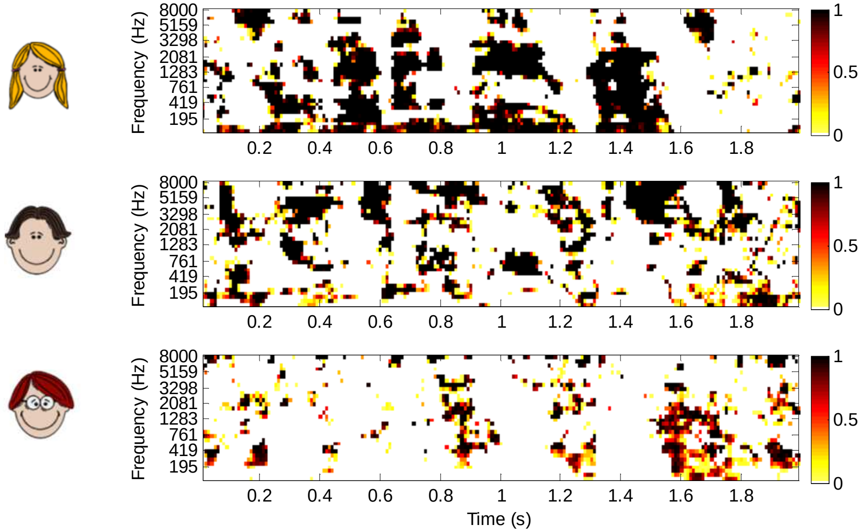
[Hadad 2014/2015/2016, Marquardt 2014/2015]

Current research: Integration with CASA

- For all discussed binaural noise reduction and cue preservation algorithms **several quantities need to be estimated**:
  - Steering vector (RTF/DOA) of desired source (and interfering sources)
  - Correlation matrix of background noise

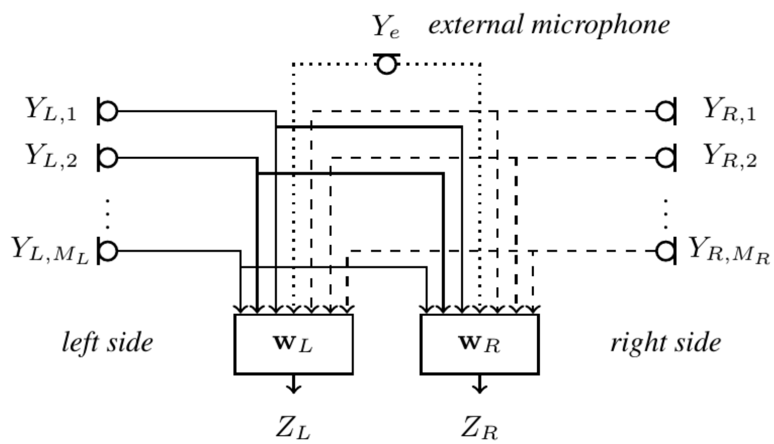
- Non-trivial task for **complex and time-varying acoustic scenarios** → **integration with computational acoustic scene analysis (CASA)** in the control path of speech enhancement algorithms





Current research: External microphone(s)

- Exploit the availability of one or more external microphones **(acoustic sensor network)** with hearing aids [Bertrand 2009, Yee 2016]
- **Objective:** improve noise reduction and/or binaural cue preservation performance
- For **binaural MVDR-N beamformer** with external microphone: trade-off between noise reduction performance and binaural cue preservation for
  - Interfering source [Szurley, 2016]
  - Diffuse noise [Gößling, 2017]



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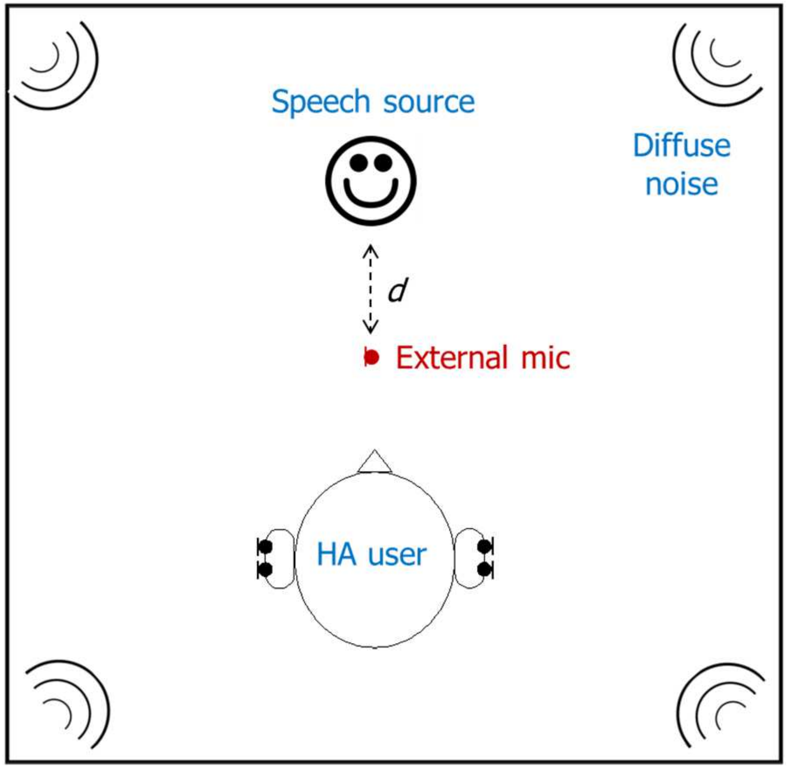
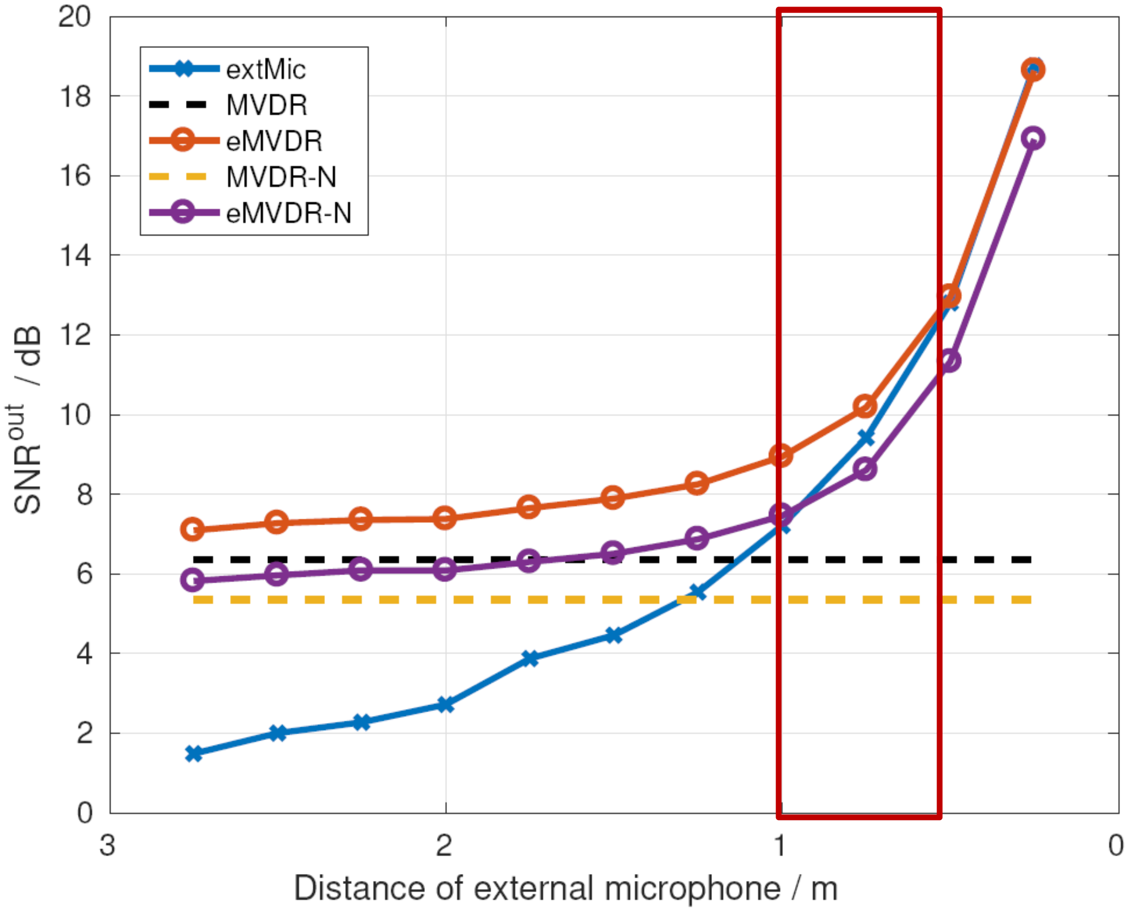




- Using external microphone may lead to **significant SNR improvement**
- **eMVDR-N is able to preserve binaural cues of both speech source + residual noise**

[Gößling, HSCMA 2017]

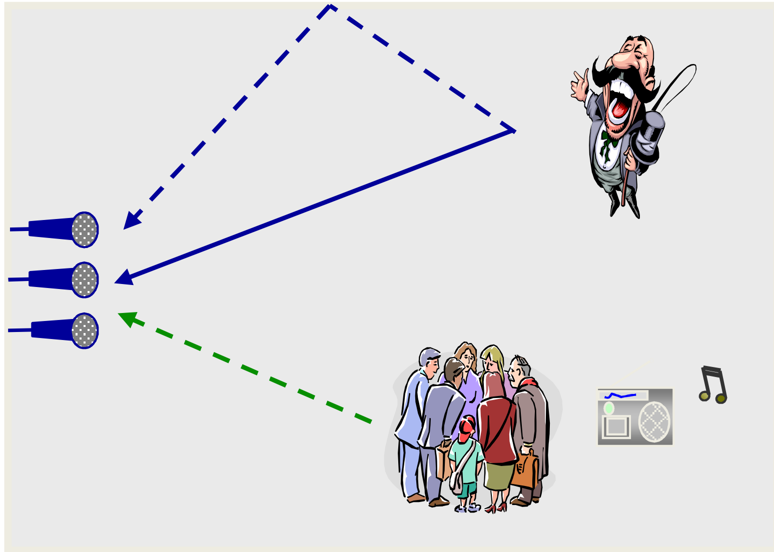
Summary

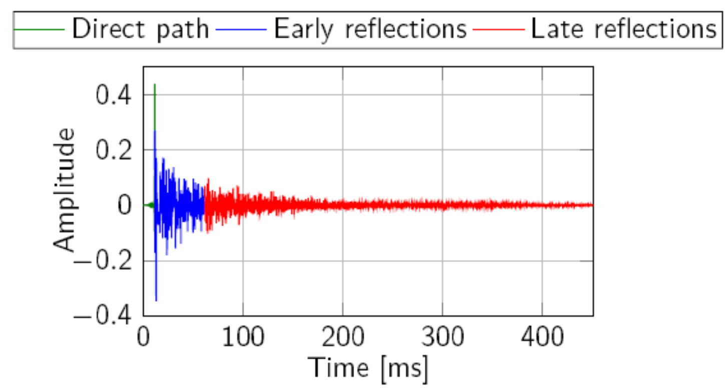
- **Binaural noise reduction algorithms**: 2 main paradigms
  - Spectral post-filtering
  - "True" binaural spatial filtering
- **Extensions of binaural MVDR/MWF** for diffuse noise and interfering speaker, preserving binaural cues of residual noise/interference
- Evaluation of **binaural MVDR extensions for diffuse noise**
  - Binaural cue preservation improves **spatial quality**
  - Binaural cue preservation does not/hardly affect **speech intelligibility**
  - MVDR-N : best spatial quality, MWF-IC : best SRT
- Extensions with **external microphone** possible

II. Joint dereverberation and noise reduction

Dereverberation and noise reduction

- **Problem**
  - Noise and reverberation jointly present in typical acoustic environments
  - Speech quality and intelligibility degradation
  - Performance degradation of ASR systems
- **Objectives**
  - Single- and multi-channel joint noise reduction and dereverberation algorithms
  - Exploit **knowledge / statistical models of room acoustics and speech signals**
- **Approaches**
  1. Single- and multi-microphone **spectral enhancement**
  2. **Multi-channel linear prediction**: probabilistic estimation using statistical model of desired signal

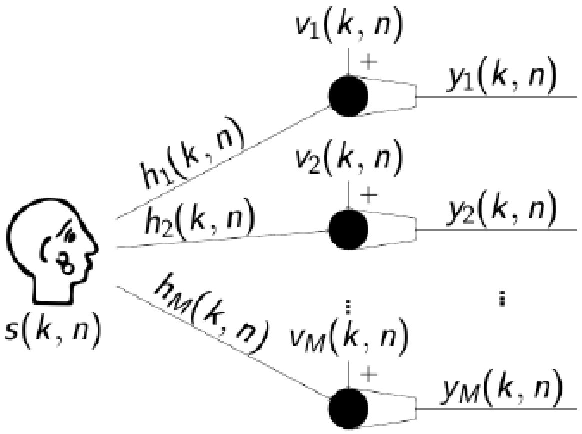


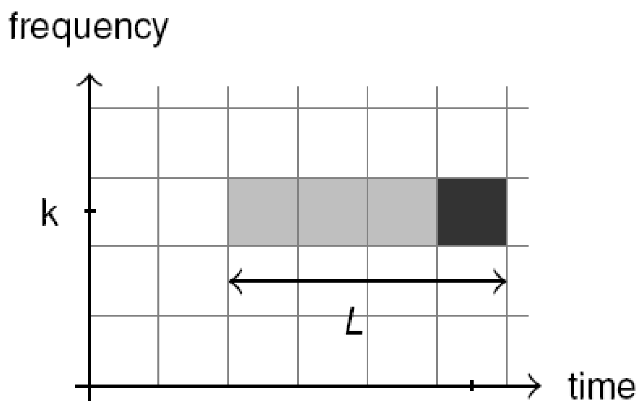


Dereverberation and noise reduction

- **Scenario:** speech source in noisy and reverberant environment, *M* microphones
- **STFT-domain:**
  - approximation of time-domain convolution using convolutive transfer function (CTF)

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





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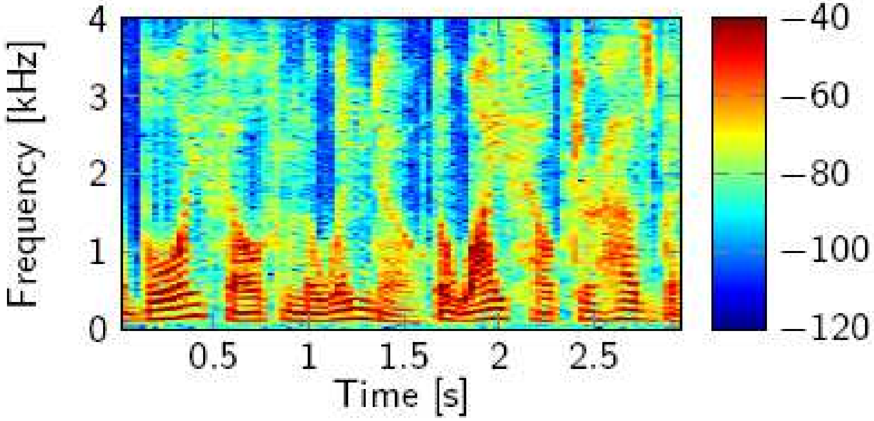
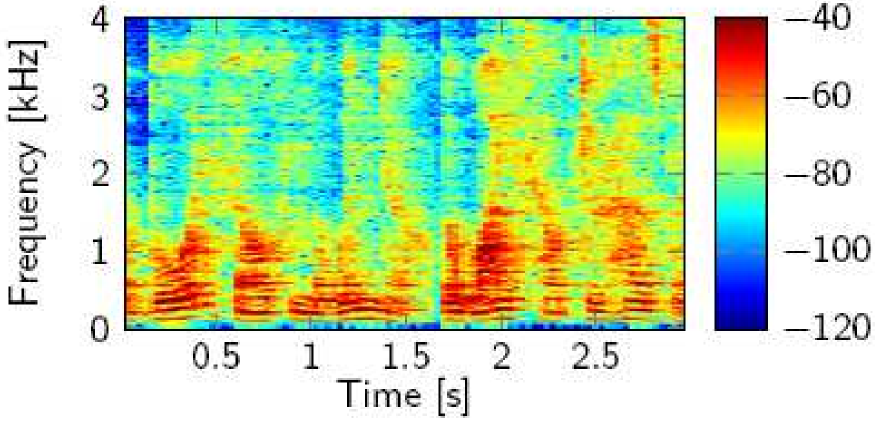
$$y_m(k,n) = \underbrace{h_m(k,n) * s(k,n)}_{x_m(k,n)} + v_m(k,n)$$

  - clean speech is **more sparse** than reverberant speech



Clean



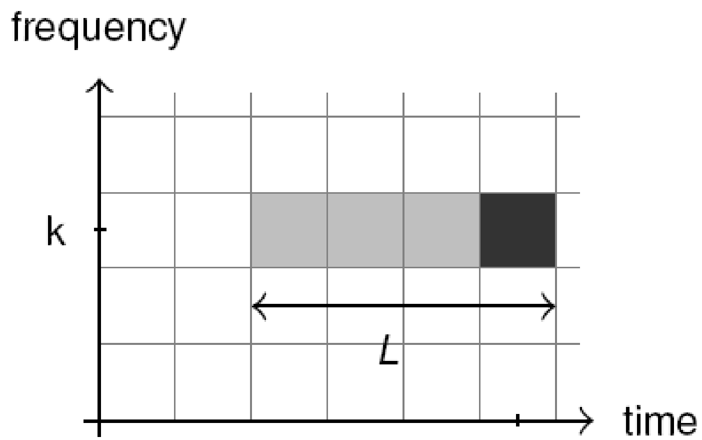
Reverberant

Dereverberation and noise reduction

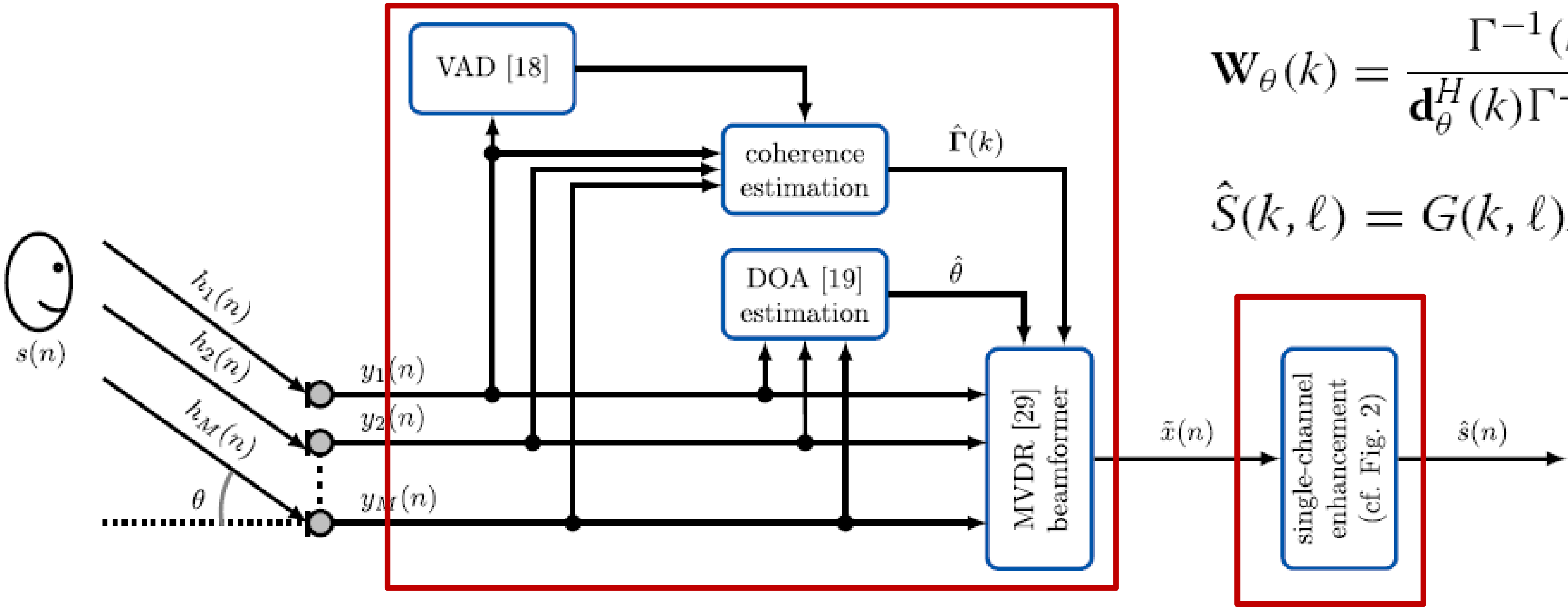
- **Scenario:** speech source in noisy and reverberant environment, *M* microphones
- **STFT-domain:**
  - approximation of time-domain convolution using convolutive transfer function (CTF)

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

  - clean speech is **more sparse** than reverberant speech
- **Dereverberation methods:**
  - **Spatial filtering / beamforming**
  - **Spectral enhancement:** apply real-valued gain to each time-frequency bin
  - **Reverberation suppression:** subtract (complex-valued) estimate of late reverberant component



1. Beamforming + spectral post-filtering



$$\mathbf{W}_\theta(k) = \frac{\Gamma^{-1}(k)\mathbf{d}_\theta(k)}{\mathbf{d}_\theta^H(k)\Gamma^{-1}(k)\mathbf{d}_\theta(k)}$$

$$\hat{S}(k,\ell) = G(k,\ell)\tilde{X}(k,\ell),$$

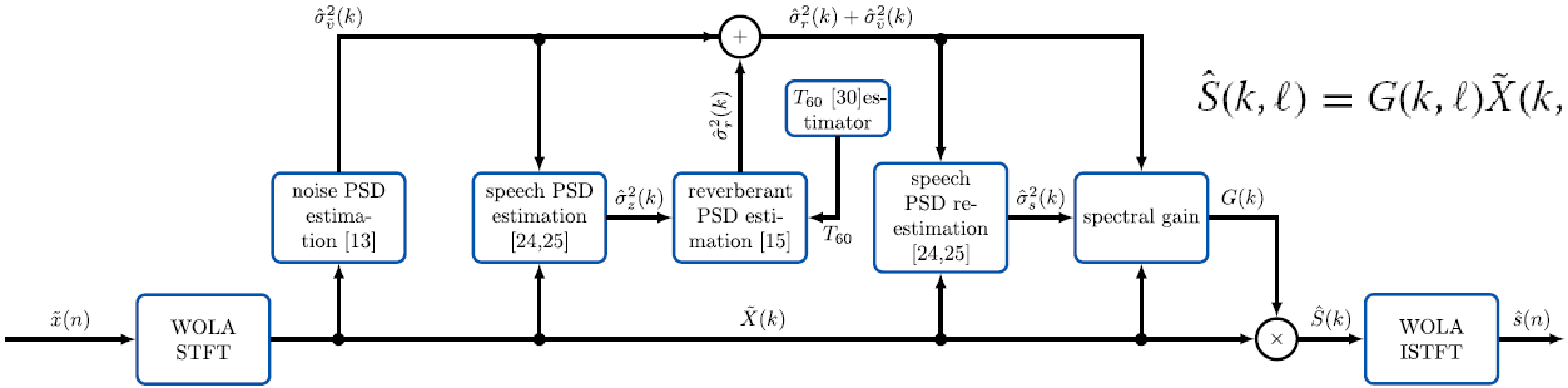
- **MVDR beamformer,** requiring assumption about spatial coherence of late reverberation + direction-of-arrival (DOA) estimate of speech source
- **Spectral post-filter: estimate of late reverberant PSD**
  - **Single-channel estimator,** requiring estimate of reverberation time T_{60}
  - **Multi-channel estimator**, requiring assumption about spatial coherence of late reverberation (+ DOA estimate of speech source)

[Cauchi et al., JASP 2015]

1. Beamforming + spectral post-filtering

- **Spectral post-filter: single-channel estimator**
  1. **Noise PSD**: minimum statistics approach (longer window as usual)
  2. **Reverberant speech PSD**: ML estimate + cepstro-temporal smoothing
  3. **Late reverberant PSD**: assuming exponential decay (requiring T60 estimate)
  4. **Clean speech PSD**: ML estimate + cepstro-temporal smoothing

$$\hat{\sigma}_r^2(k,\ell) = e^{-2\Delta T_d f_s} \hat{\sigma}_z^2(k,\ell - T_d/T_s)$$

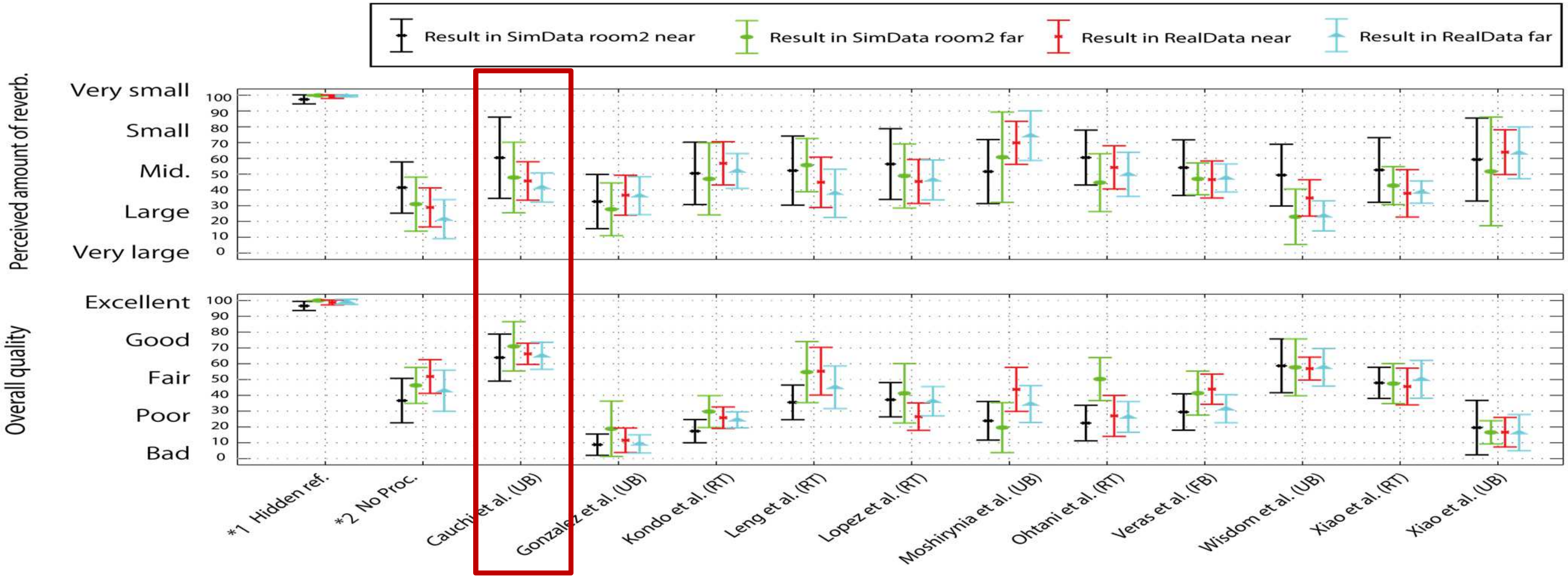


$$\hat{S}(k,\ell) = G(k,\ell)\tilde{X}(k,\ell),$$

1. Beamforming + spectral post-filtering

- **Subjective evaluation (evaluation set of REVERB challenge)**

Anchor | Unprocessed | SE_3 | MVDR | MVDR+SE_3



Circular array (M=8, d = 20 cm), fs = 16 kHz, SNR = 20 dB; S2: T60 = 500 ms (0.5m, 2m), R1: T60 = 700 ms (1m, 2.5m)
STFT: 32 ms, 50% overlap, Hann; MVDR: WNGmax = -10 dB; Postfilter: β=0.5, μ=0.5, Gmin = -10dB, Td = 80 ms, MS window = 3s

[Cauchi et al., JASP 2015] [Cauchi et al., REVERB 2015]

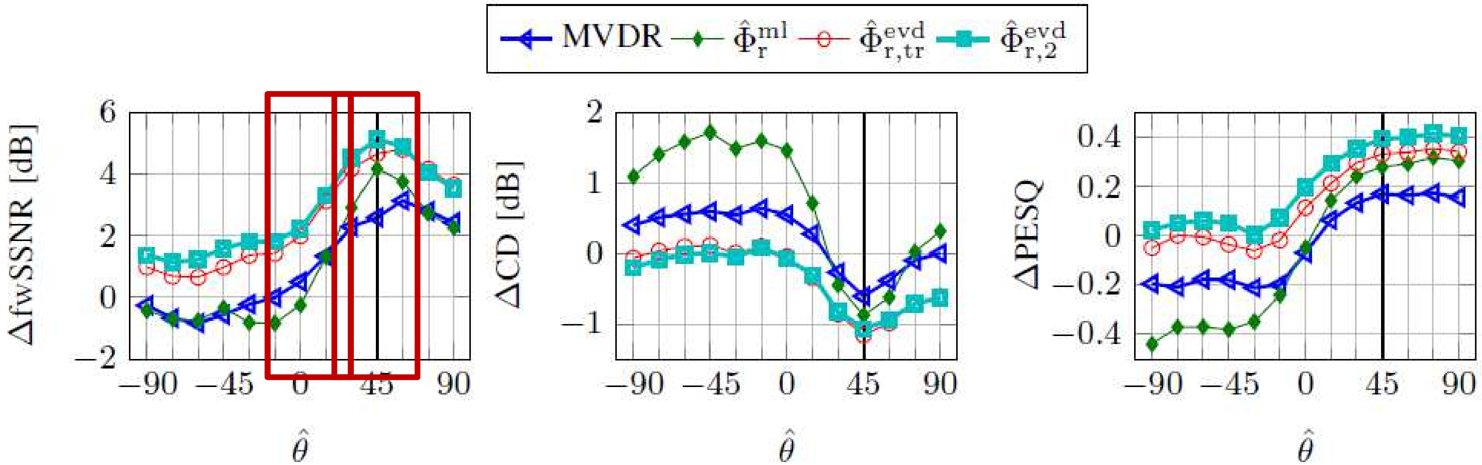
1. Beamforming + spectral post-filtering

Spectral post-filter: multi-channel estimator

- Requires assumption about spatial coherence Γ of late reverberant sound field, e.g. spherically isotropic (diffuse)
- Different estimators have been recently proposed:
  - ML estimator, requiring DOA estimate of speech source [Braun 2013, Kuklasinksi 2016]
  - Estimator based on eigenvalue decomposition, **not** requiring DOA estimate of speech source

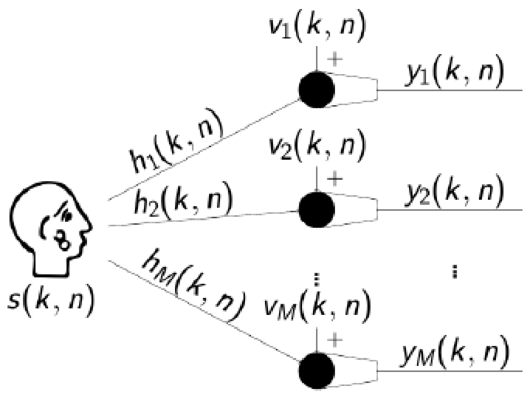
$$\hat{\Phi}_{\mathrm{r}}^{\mathrm{evd}} = \lambda_2\{\mathbf{\Phi}_{\mathrm{x}}\mathbf{\Gamma}^{-1}\} = \cdots = \lambda_M\{\mathbf{\Phi}_{\mathrm{x}}\mathbf{\Gamma}^{-1}\} = \frac{1}{M-1}\left(\mathrm{tr}\left\{\mathbf{\Phi}_{\mathrm{x}}\mathbf{\Gamma}^{-1}\right\} - \lambda_1\left\{\mathbf{\Phi}_{\mathrm{x}}\mathbf{\Gamma}^{-1}\right\}\right)$$

- Robustness against DOA estimation errors (M=4, T_{60}=610 ms, θ=45°)



2. Multi-channel linear prediction

- **Direct STFT-based approach:**
  - directly estimate clean speech STFT coefficients *s(k,n)* from reverberant (and noisy) STFT coefficients $y_m(k,n)$
  - Speech properties (e.g., sparsity) can be modelled naturally in STFT-domain
  - Low computational complexity



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

1. *Using convolutive transfer function (CTF) model*
2. Transform to equivalent AR model → **multi-channel linear prediction (MCLP)**

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

clean signal (incl. early reflections) **prediction filters** **delay (early reflections)**

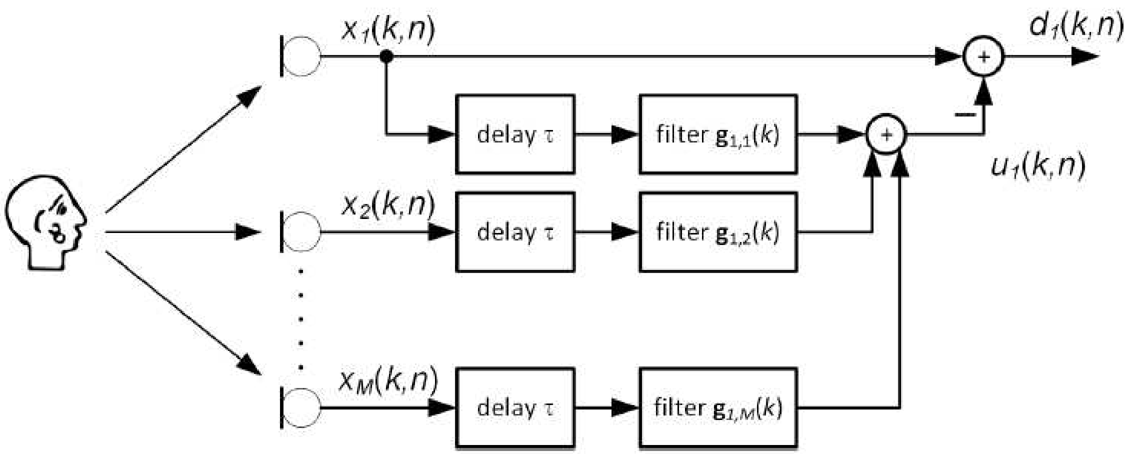
2. Multi-channel linear prediction

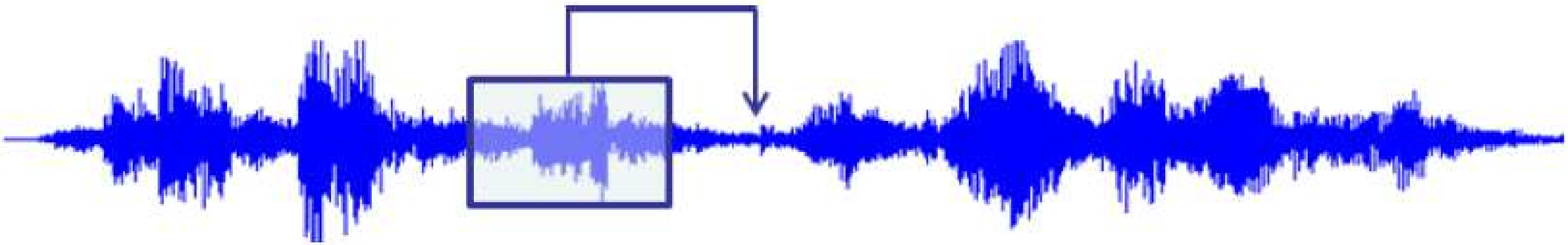
- **AR model of reverberant speech**

$$\mathbf{x}_1(k) = \mathbf{d}(k) + \mathbf{X}_\tau(k)\mathbf{g}(k).$$

$$\hat{\mathbf{d}}(k) = \mathbf{x}_1(k) - \mathbf{X}_\tau(k)\hat{\mathbf{g}}(k)$$

predicted reverberation





How to select suitable cost function for prediction filters ?

2. Multi-channel linear prediction

- **Generalization of original MCLP approach** [Nakatani et al., 2010]
  - STFT coefficients of desired signal are assumed to be independent and modelled using **circular sparse/super-Gaussian prior with time-varying variance** $\lambda(n)$

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

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

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

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

  - **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)

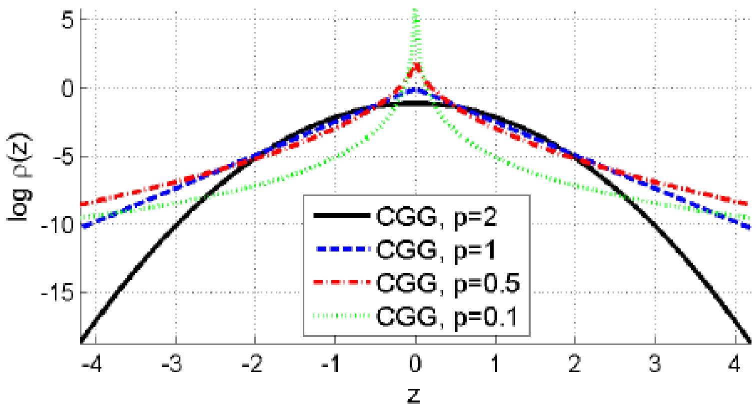
$$\hat{\lambda}^{(i+1)}(n) = \arg\min_{\lambda(n)>0} \frac{|\hat{d}^{(i+1)}(n)|^2}{\lambda(n)} + \log \pi\lambda(n) - \log \psi(\lambda(n))$$

2. Multi-channel linear prediction

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

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

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



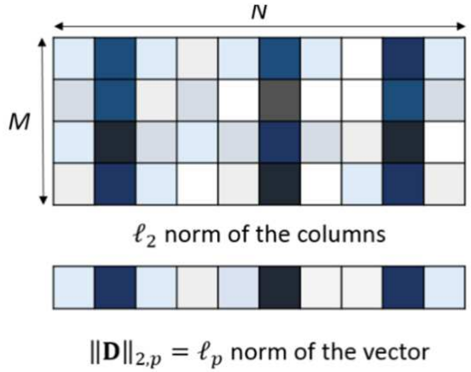
- **Remarks:**
  1. ML estimation using CGG prior is equivalent to **l_p-norm minimization**
     → **promotes sparsity of TF-coefficients across time** (for p < 2)

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

  2. Original approach [Nakatani et al. 2010] corresponds to **p=0:**
     - **Strong sparse prior**, strongly favoring values of desired signal close to zero

2. Multi-channel linear prediction: extensions

1. **Group sparsity for MIMO dereverberation**
   - Maximize sparsity of TF-coefficients across time and simultaneously keep/discard TF-coefficients across microphones → mixed $l_{2,p}$-norm
   - **Multiple outputs** → possibility to apply spatial filtering

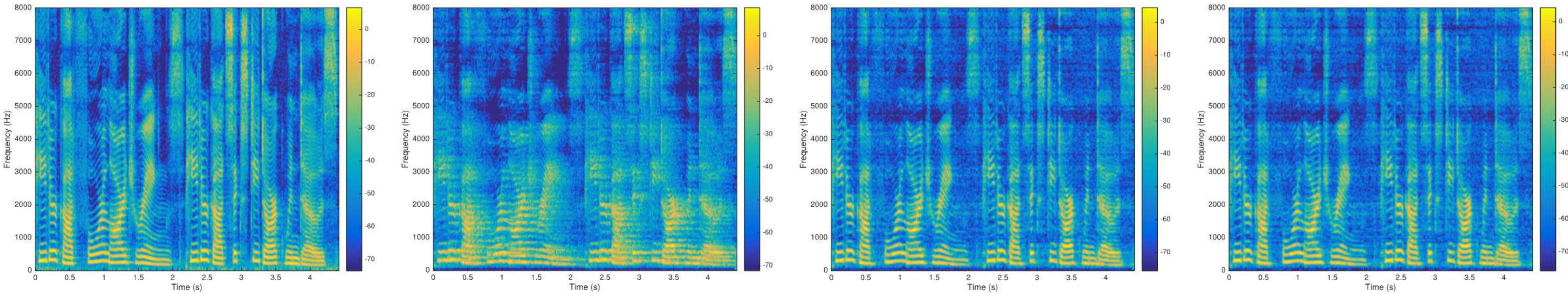


2. Incorporate **low-rank structure** of speech spectrogram
   - Combination with learned/pre-trained spectral dictionaries (NMF)
3. Batch processing → **adaptive processing**
   - Incorporate exponential weighting in cost function
   - **Problem:** overestimation of late reverberation for small forgetting factors γ (dynamic scenarios) → severe distortion in output signal
   - **Solution**: constrain MCLP-based estimate of late reverberation using PSD estimate

$$\check{\mathbf{G}}(n) = \arg\min_{\mathbf{G}(n)} \sum_{t=1}^{n} \gamma^{n-t} w(t) \|\mathbf{d}(t)\|_2^2 \quad \boxed{\text{subject to} \quad |\mathbf{G}^{\mathsf{H}}(n)\tilde{\mathbf{x}}_\tau(n)|^2 \leq \hat{\boldsymbol{\sigma}}_u^2(n)}$$

2. Multi-channel linear prediction: results

- **Instrumental validation (binaural, noiseless, batch)**



Clean | Microphone | MCLP | MCLP+NMF

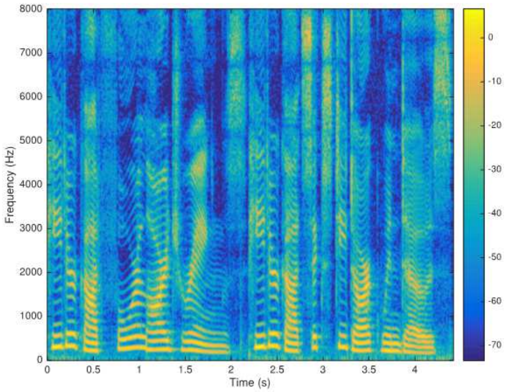
	PESQ	CD	FWSSNR	LLR	SRMR
Microphone	**1.21**	4.27	**3.61**	0.93	2.05
MCLP	2.40	3.15	7.92	0.60	3.83
MCLP+NMF	**2.42**	3.16	**7.84**	0.60	3.88

$T_{60} \approx 700$ms, M=2 (BRIR), distance 4m, fs=16 kHz; STFT: 64ms (overlap 16ms); MCLP: L_g=30, τ=2, p=0

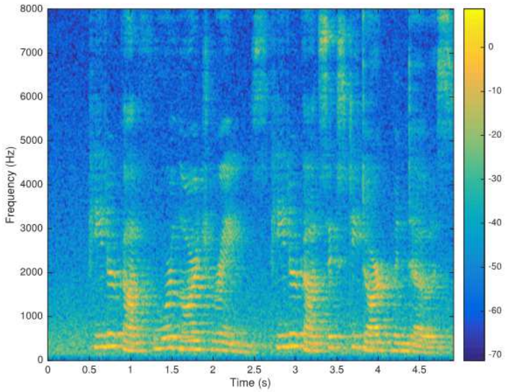
[Jukić et al., ICASSP 2015]

2. Multi-channel linear prediction: results

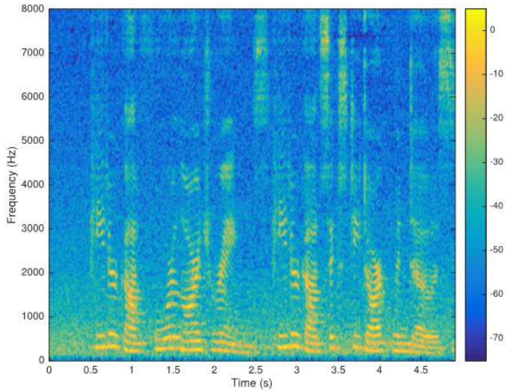
- **Instrumental validation (binaural, noisy 15dB, batch)**



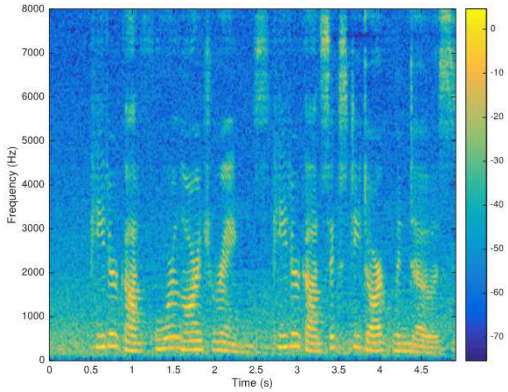
Clean



Microphone



MCLP



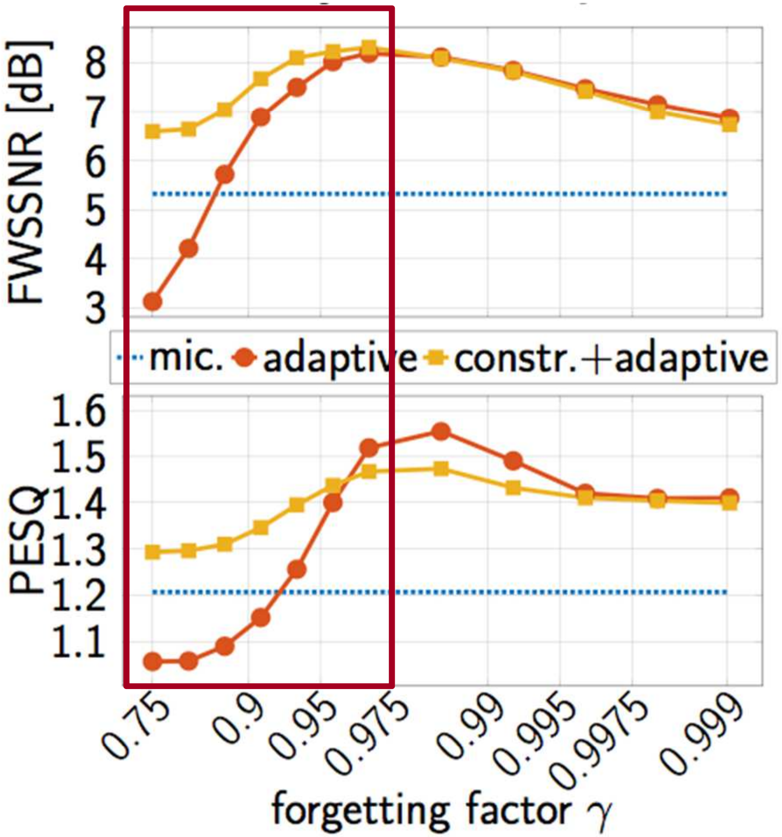
MCLP+NMF

$T_{60} \approx$ 700ms, M=2 (BRIR), distance 4m, fs=16 kHz; STFT: 64ms (overlap 16ms); MCLP: L_g=30, τ=2, p=0

[Jukić et al., ICASSP 2015]

2. Multi-channel linear prediction: results

- **Instrumental validation (noiseless, adaptive)**



clean **microphone**

	ADA	Constr. +ADA
γ=0.98		
γ=0.88		

Constrained MCLP much less sensitive to forgetting factor (especially for small values)

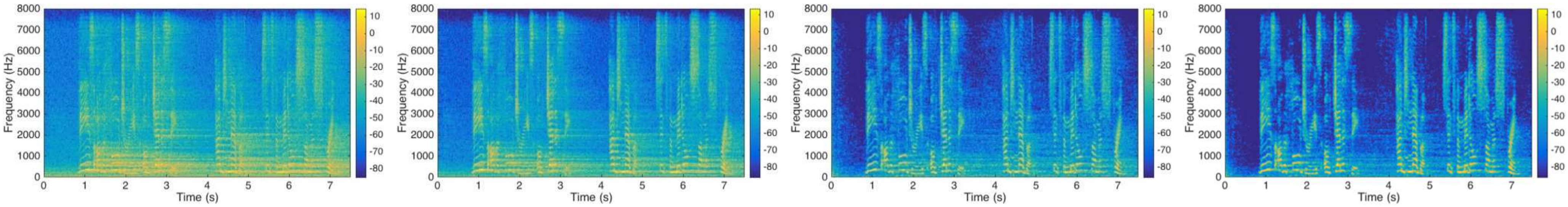
$T_{60} \approx$ 700ms, M=2, distance 2m, **source switching between +45 and -45,** fs=16 kHz; STFT: 64ms (overlap 16ms); L_g=20, τ=2, p=0

[Jukić et al., SPL 2017]

2. Multi-channel linear prediction: results

- **Instrumental validation (high reverberation + noisy, adaptive)**

d ~ 2m



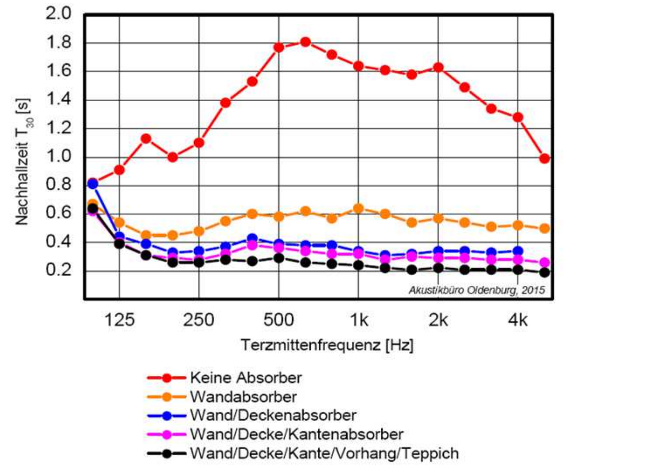
Microphone | 1ch SE [REVERB] | Adaptive MCLP | Adaptive MCLP + SE

T60 ~ 6s (St Alban The Martyr Church, London), M=2 (spacing~1m), fs=16 kHz, **real recordings**
STFT: 64ms (overlap 16ms); MCLP: L_g=30, τ=2, p=0, adaptive (γ=0.96)

Current/future research

- **Combined dereverberation and noise reduction**
  - Extension of multi-channel EVD-based PSD estimator and
  - Extension of blind probabilistic model-based approach
- **Instrumental measures**: prediction of perceived level of reverberation, by optimizing/redesigning SRMR measure (joint project with Prof. Tiago Falk)
- Database in new **varechoic lab**

Abbildung 1: In Raum E10 in den in Tabelle 1 angegebenen Raumzuständen gemessenen Nachhallzeiten in Terzbändern im Vergleich



Summary

- **Blind methods for combined dereverberation and noise reduction**
  - Spectral enhancement by applying real-valued gain to each time-frequency bin (single- and multi-channel PSD estimators)
  - Reverberation suppression by estimating late reverberant component using multi-channel linear prediction
- **Good dereverberation performance possible**, even for moving source and moderate noise
- Application to binaural hearing aids (combination with binaural noise reduction and cue preservation) to be further investigated

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DFG Deutsche Forschungsgemeinschaft

VolkswagenStiftung

GIF German-Israeli Foundation for Scientific Research and Development

Questions ?

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- A. Jukić, T. van Waterschoot, T. Gerkmann, S. Doclo, *A general framework for incorporating time-frequency domain sparsity in multi-channel speech dereverberation*, *Journal of the Audio Engineering Society*, Jan-Feb 2017.
- I. Kodrasi, B. Cauchi, S. Goetze, S. Doclo, *Instrumental and perceptual evaluation of dereverberation techniques based on robust acoustic multi-channel equalization*, *Journal of the Audio Engineering Society*, Jan-Feb 2017.
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