Joint Multi-Channel Dereverberation and Noise Reduction Using a Unified Convolutional Beamformer With Sparse Priors

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Introduction

- **Reverberation** and **noise degrades speech quality**.
- The weighted power minimization distortionless response **(WPD) beamformer unifies** weighted prediction error **(WPE) dereverberation** and the minimum power distortionless response **(MPDR) beamformer** [1, 2].
- In the STFT-domain reverberation and noise lead to a **less sparse representation** of a signal compared to its clean version.

IN THIS POSTER

- Similar as in [3] for WPE we introduce a shape parameter p to **control the sparsity** of the cost function for WPD.
- Additionally we investigate the effect of **single- and multi-channel initialization** of the iterative optimization.

Convolutional Beamformer

Convolutional Signal Model (multi-frame) in STFT-domain

$$\mathbf{y}_t = \sum_{l=0}^{L_a-1} \mathbf{a}_l s_{t-l} + \mathbf{n}_t = \underbrace{\sum_{l=0}^{\tau-1} \mathbf{a}_l s_{t-l}}_{\text{direct/early } \mathbf{d}_t} + \underbrace{\sum_{l=\tau}^{L_a-1} \mathbf{a}_l s_{t-l}}_{\text{late reverb } \mathbf{r}_t} + \underbrace{\mathbf{n}_t}_{\text{noise}}$$

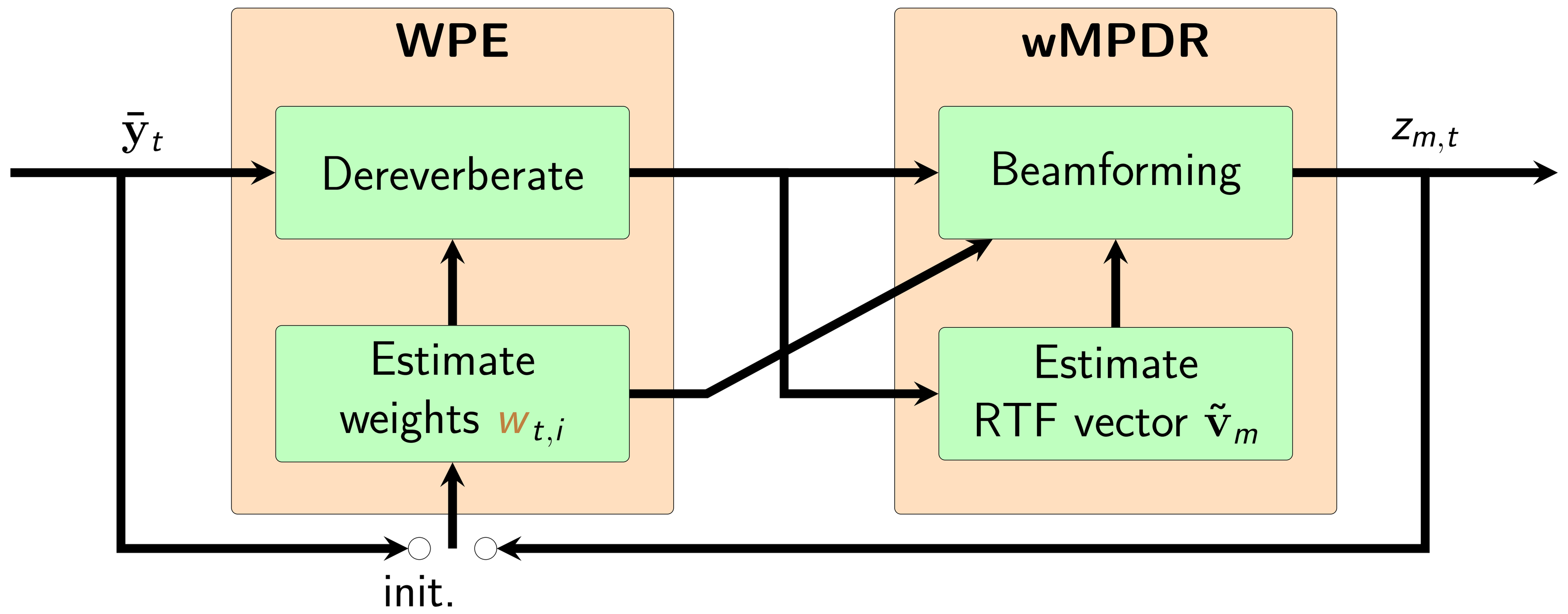
- Prediction delay τ separates early reflections and late reverberation
- Desired component $\mathbf{d}_t$ can be approximated by: $\mathbf{d}_t \approx \mathbf{v} s_t = \tilde{\mathbf{v}}_m d_{m,t}$ with the **relative transfer function (RTF)** vector $\tilde{\mathbf{v}}_m$

Convolutional Filter (multi-frame) $\bar{\mathbf{h}}_m$

$$z_{m,t} = \bar{\mathbf{h}}_m^{\mathrm{H}} \bar{\mathbf{y}}_t \quad \text{with} \quad \bar{\mathbf{y}}_t = \left[\mathbf{y}_t^{\mathrm{T}} \mid \mathbf{y}_{t-\tau}^{\mathrm{T}} \cdots \mathbf{y}_{t-L_h+1}^{\mathrm{T}}\right]^{\mathrm{T}} \in \mathbb{C}^{M(L_h-\tau+1)\times 1}$$

- Stacked signal vector $\bar{\mathbf{y}}_t$ contains the current frame and the past frames corresponding to late reverberation $\rightarrow$ **Gap of $\tau - 1$ frames** to keep early reflections

Iterative WPD algorithm unifying WPE dereverberation and MPDR beamformer [2]



Filter Optimization

Distortionless Constraint

Distortionless constraint for desired component using RTF vector

$$\bar{\mathbf{h}}_m^{\mathrm{H}} \bar{\mathbf{v}}_m = 1 \quad \text{with} \quad \bar{\mathbf{v}}_m = \left[\tilde{\mathbf{v}}_m^{\mathrm{T}} \ \mathbf{0}^{\mathrm{T}}\right]^{\mathrm{T}}$$

- **Conventional WPD** uses time-varying circular Gaussian model for STFT coefficients as objective function
- **Proposed generalization**: ℓ_p-norm reformulation of the generalized Gaussian prior from [3], which introduces a shape parameter p.

Conventional Objective Function

Time-varying Gaussian model

- Variances $\lambda_t = \mathbb{E}\left[|d_{m,t}|^2\right]$
- $\boldsymbol{\Lambda} = \mathrm{diag}\left(\left[\lambda_1 \cdots \lambda_T\right]^{\mathrm{T}}\right)$

$$\mathcal{L}\left(\bar{\mathbf{h}}_m, \boldsymbol{\Lambda}\right) \propto \left(\mathrm{tr}\left(\ln \boldsymbol{\Lambda}\right) + \mathbf{z}_m \boldsymbol{\Lambda}^{-1} \mathbf{z}_m^{\mathrm{H}}\right)$$

$\rightarrow$ iterative optimization scheme

Proposed Objective Function

ℓ_p-norm cost function

$$\mathcal{L}\left(\bar{\mathbf{h}}_m\right) \propto \|\mathbf{z}_m\|_p^p \propto \sum_{t=1}^{T} |z_{m,t}|^p$$

$\rightarrow$ iterative reweighted optimization scheme using ℓ_2-norm

$$\mathcal{L}\left(\bar{\mathbf{h}}_{m,i}, \mathbf{W}_i\right) \propto \sum_{t=1}^{T} w_{t,i} |z_{m,t}|^2 \propto \mathbf{z}_{m,i} \mathbf{W}_i \mathbf{z}_{m,i}^{\mathrm{H}}$$

Iterative Algorithms

1. Optimize and update the beamformer $\bar{\mathbf{h}}_{m,i}$ (iteration index i)
2. Optimize and update the variances $\boldsymbol{\Lambda}_i$ and weights $\mathbf{W}_i$

Conventional

$$\bar{\mathbf{h}}_{m,i}^{\mathrm{opt}} = \frac{\bar{\mathbf{R}}_{y,i}^{-1} \bar{\mathbf{v}}_m}{\bar{\mathbf{v}}_m^{\mathrm{H}} \bar{\mathbf{R}}_{y,i}^{-1} \bar{\mathbf{v}}_m}$$

with noisy power-weighted multi-frame covariance matrix

$$\bar{\mathbf{R}}_{y,i} = {}^{1}/_{T} \bar{\mathbf{Y}} \boldsymbol{\Lambda}_i^{-1} \bar{\mathbf{Y}}^{\mathrm{H}}$$

Variance update

$$\lambda_{t,i+1} = |z_{m,t,i}|^2 = \left|\bar{\mathbf{h}}_{m,i}^{\mathrm{opt,H}} \bar{\mathbf{y}}_t\right|^2$$

Proposed

$$\bar{\mathbf{h}}_{m,i}^{\mathrm{opt}} = \frac{\left(\bar{\mathbf{R}}_{y,i}^{\mathbf{W}}\right)^{-1} \bar{\mathbf{v}}_m}{\bar{\mathbf{v}}_m^{\mathrm{H}} \left(\bar{\mathbf{R}}_{y,i}^{\mathbf{W}}\right)^{-1} \bar{\mathbf{v}}_m}$$

with noisy **reweighted** multi-frame covariance matrix

$$\bar{\mathbf{R}}_{y,i}^{\mathbf{W}} = {}^{1}/_{T} \bar{\mathbf{Y}} \mathbf{W}_i \bar{\mathbf{Y}}^{\mathrm{H}}$$

Weight update

$$w_{t,i+1}^{-1} = |z_{m,t,i}|^{2-p} = \left|\bar{\mathbf{h}}_{m,i}^{\mathrm{opt,H}} \bar{\mathbf{y}}_t\right|^{2-p}$$

$\longrightarrow$ **Proposed method equals conventional method for $p = 0$**

Initialization of Variances/Weights

No output signal power available in first iteration $\rightarrow$ Use input signal power

Single-channel initialization: $\lambda_{t,1} = |y_{m,t}|^2$ and $w_{t,1}^{-1} = |y_{m,t}|^{2-p}$

Multi-channel initialization: $\lambda_{t,1} = \frac{\|\mathbf{y}_t\|_2^2}{M}$ and $w_{t,1}^{-1} = \frac{\|\mathbf{y}_t\|_2^{2-p}}{M}$

Experimental Evaluation

Reverb Challenge development dataset [4]

- Reverberation time $T_{60} \in \{0.3\,\mathrm{s}, 0.6\,\mathrm{s}, 0.7\,\mathrm{s}\}$, SNR of about 20 dB
- Circular array with 8 microphone channels (speaker-to-mic distance 50 cm or 200 cm)

Algorithm parameters

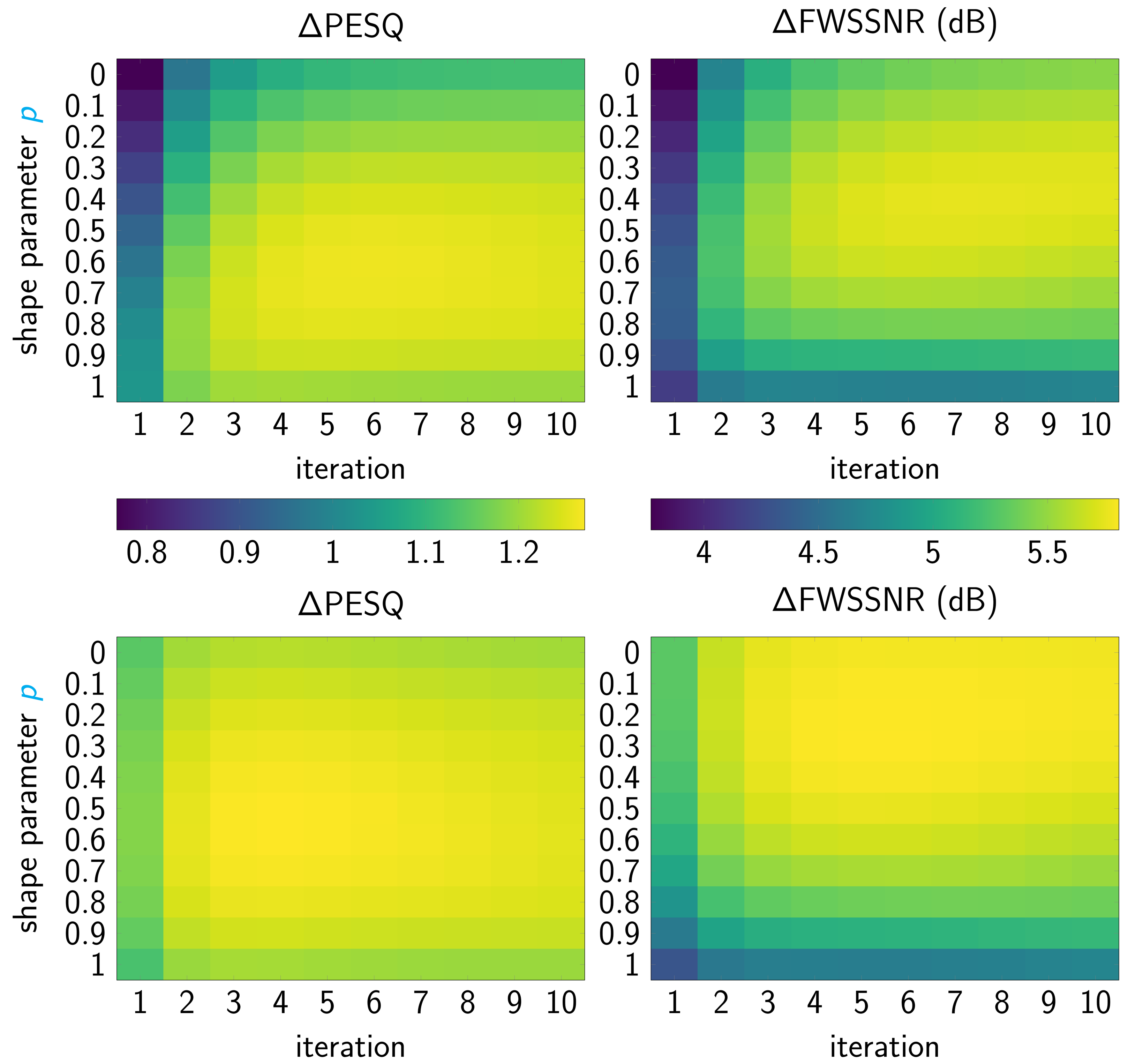
- STFT: 32 ms frame length with 25% overlap and square-root-Hann window
- Prediction delay $\tau = 4$ and prediction filter length $L_h = 12$

RTF estimation

- RTF vector $\tilde{\mathbf{v}}_m$ is estimated using covariance whitening
- Assuming only-noise period in the first 225 ms $\rightarrow$ noise covariance matrix

Results

Influence of shape parameter p, initialization and number of iterations



- ✓ **Multi-channel initialization outperforms single-channel initialization (higher performance and faster convergence)**
- ✓ **Proposed beamformer with sparse priors outperforms conventional WPD beamformer (only slightly if multi-channel initialization is used)**
- ✓ **We extended the proposed method towards a weighted LCMP beamformer and participated in the Clarity Challenge** [5, 6]

References

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[6] S. Graetzer and T. Cox, "Clarity challenge."