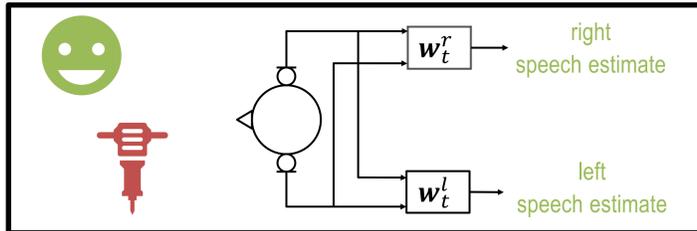


PROBLEM STATEMENT

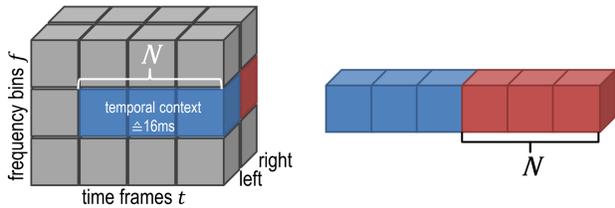
- microphone signals on hearing aids degraded by **ambient noise**
→ decreased speech quality and intelligibility
- multi-frame speech enhancement algorithms** have been shown to yield good noise reduction and low speech distortion [1]
- multi-frame filter coefficients are difficult to estimate** using traditional approaches

this poster: supervised learning-based approaches to estimate binaural multi-frame filter coefficients: should filter structure be imposed?



SIGNAL MODEL

- apply complex-valued **multi-frame filter** to N frames in STFT domain:
$$\mathbf{y}_{t,f} = [Y_{t,f}^l \dots Y_{t-N+1,f}^l \ Y_{t,f}^r \dots Y_{t-N+1,f}^r]^T = \mathbf{x}_{t,f} + \mathbf{n}_{t,f}$$



- assumptions:**
 - independent speech and noise components:
$$\Phi_{\mathbf{y},t} = \mathcal{E}\{\mathbf{y}_t \mathbf{y}_t^H\} = \Phi_{\mathbf{x},t} + \Phi_{\mathbf{n},t} \in \mathbb{C}^{2N \times 2N}$$
 - decompose speech into spatio-temporally correlated and uncorrelated components [1]:
$$\mathbf{x}_t = \boldsymbol{\gamma}_{x,t}^l X_t^l + \mathbf{x}_t^l = \boldsymbol{\gamma}_{x,t}^r X_t^r + \mathbf{x}_t^r$$

with $\boldsymbol{\gamma}_{x,t}^{\{l,r\}}$ the **speech correlation vectors**

- relation to beamforming approaches:

binaural multi-frame filtering	binaural beamforming
exploits spatio-temporal correlations	exploits spatial correlations
spatio-temporal correlation vector: signal-dependent → highly time-varying	steering vector: room- and geometry-dependent → quasi-stationary

MULTI-FRAME MVDR FILTER

- minimizes output noise power spectral density while leaving correlated speech component undistorted:

$$\begin{aligned} \mathbf{w}_t &= \underset{\tilde{\mathbf{w}}_t}{\operatorname{argmin}} \tilde{\mathbf{w}}_t^H \Phi_{n,t} \tilde{\mathbf{w}}_t \text{ s.t. } \tilde{\mathbf{w}}_t^H \boldsymbol{\gamma}_{x,t} = 1 \\ &= \frac{\Phi_{n,t}^{-1} \boldsymbol{\gamma}_{x,t}}{\boldsymbol{\gamma}_{x,t}^H \Phi_{n,t}^{-1} \boldsymbol{\gamma}_{x,t}} \end{aligned}$$

- requires estimate of
 - inverse noise covariance matrix $\Phi_{n,t}^{-1}$
 - speech correlation vectors $\boldsymbol{\gamma}_{x,t}$ (left / right, **highly time-varying**)

DATASET

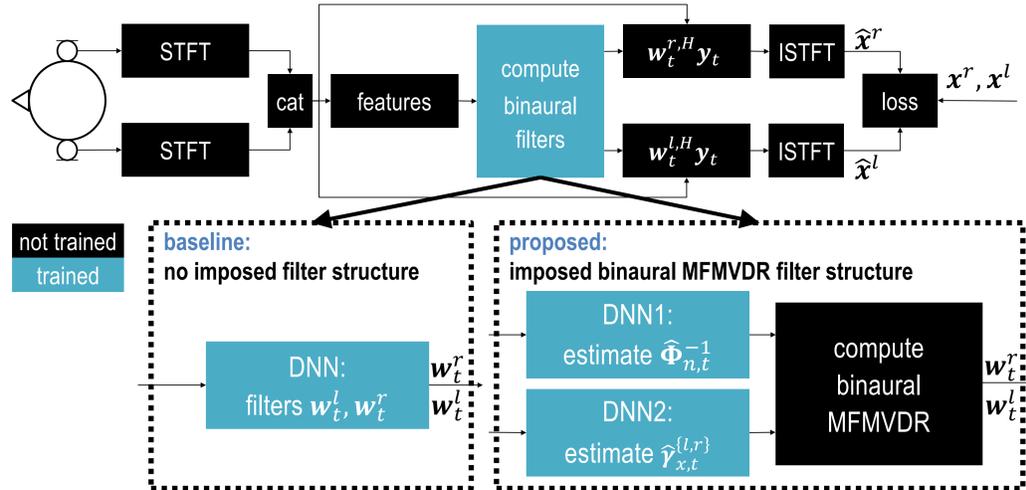
	training	evaluation
hearing aids	BTE hearing aids	
binaural room impulse responses (speech and noise)	simulated ; from Clarity Enhancement Challenge [2]	measured ; daily-life communication scenarios [3]
clean speech	deep noise suppression (DNS) challenge 1 training set	DNS challenge 3 test set
noise		
SNR	[0, 15] dB	[-5, 20] dB
speech azimuth	[-30, 30]°	[-180, 180]°

REFERENCES

- [1] Y. A. Huang and J. Benesty, "A Multi-Frame Approach to the Frequency-Domain Single-Channel Noise Reduction Problem," *IEEE Trans. Audio, Speech, and Language Processing*, vol. 20, no. 4, pp. 1256–1269, May 2012.
- [2] S. Graetzer et al., "Clarity-2021 Challenges: Machine Learning Challenges for Advancing Hearing Aid Processing," in *Proc. Interspeech*, Brno, Czech Republic, Aug. 2021, pp. 686–690.
- [3] H. Kayser, S. D. Ewert, J. Anemüller, T. Rohdenburg, V. Hohmann, and B. Kolmeier, "Database of Multichannel In-Ear and Behind-the-Ear Head-Related and Binaural Room Impulse Responses," *EURASIP J. Adv. Signal Process.*, vol. 2009, no. 1, Dec. 2009.

SUPERVISED LEARNING-BASED FILTER ESTIMATION

- integrate **fully-differentiable binaural MFMVDR filter** into **end-to-end supervised learning framework** [4]
 - all parameters estimated using DNNs
 - training is guided using binaural speech enhancement loss function



SIMULATIONS

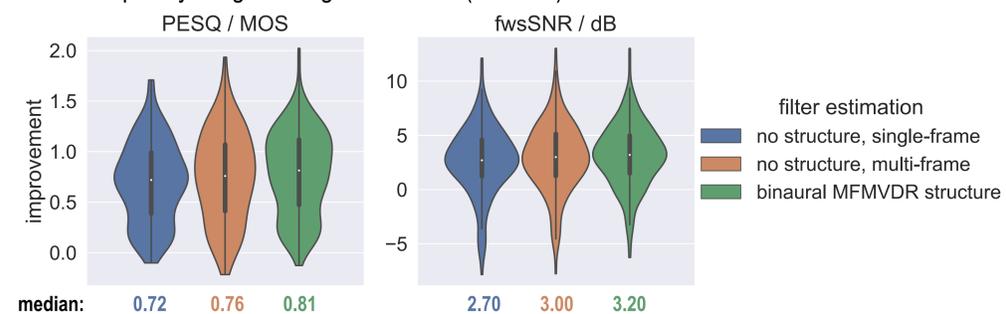
Settings

- $f_s = 16$ kHz; **STFT**: $\sqrt{\text{Hann}}$ window, 8 ms frame length, 75 % overlap
- filter length $N = 5$ → temporal context of 16 ms
- features**: log-magnitude, cosine and sine of phase of microphone signals
- DNN architecture**: causal temporal convolutional networks [5]
 - 2 stacks of 6 layers; hidden dimensions chosen to yield similar number of parameters across compared algorithms
 - temporal receptive field size: 512 ms
- loss function**: combined complex and magnitude absolute spectral error [6]
- trained using **AdamW optimizer** for ≤ 150 epochs (with early stopping)
- minimum gain** of -20 dB during evaluation

Results

- Speech Enhancement Performance** (averaged across left / right):

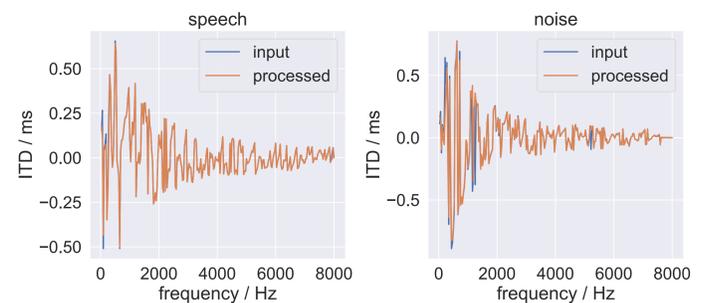
- perceptual evaluation of speech quality (PESQ)
- frequency-weighted segmental SNR (fwsSNR)



- all algorithms yield **considerable speech quality improvements**
- multi-frame filters outperform single-frame filter

imposing binaural MFMVDR structure yields highest improvements

- Preservation of Interaural Time Differences:**



both speech and noise cues are well preserved

OUTLOOK

- reduce complexity** of binaural MFMVDR filter by assuming, e.g., slowly varying *spatial* correlations, with final goal of **real-time implementation**
- evaluation of binaural MFMVDR filters using **listening test**

check out audio demos:



- [4] M. Tammen and S. Doclo, "Deep Multi-Frame MVDR Filtering for Single-Microphone Speech Enhancement," in *Proc. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Toronto, Canada, Jun. 2021, pp. 8443–8447.
- [5] Y. Luo and N. Mesgarani, "Conv-TasNet: Surpassing Ideal Time-Frequency Magnitude Masking for Speech Separation," *IEEE/ACM Trans. on Audio, Speech, and Language Processing*, vol. 27, no. 8, pp. 1256–1266, Aug. 2019.
- [6] Z.-Q. Wang, P. Wang, and D. Wang, "Complex Spectral Mapping for Single- and Multi-Channel Speech Enhancement and Robust ASR," *IEEE/ACM Trans. on Audio, Speech, and Language Processing*, vol. 28, pp. 1778–1787, Jan. 2020.
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