IEEE SPS Webinar, 07:30-09:00 EST, Nov. 14th, 2024

NTT

Enhancing Speech Quality: Modern Techniques in Dereverberation

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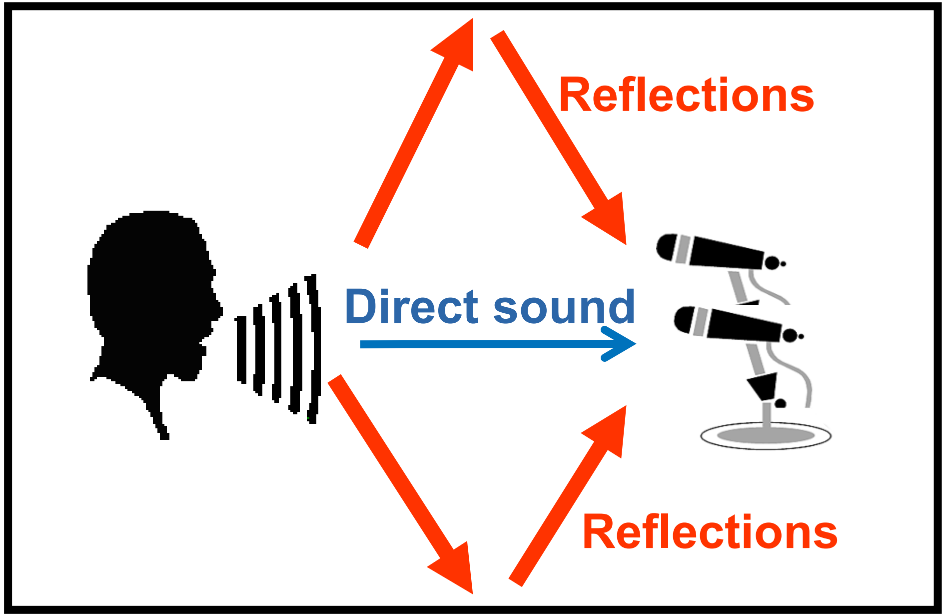
What is reverberation?

Reflections from walls, floors, and ceilings

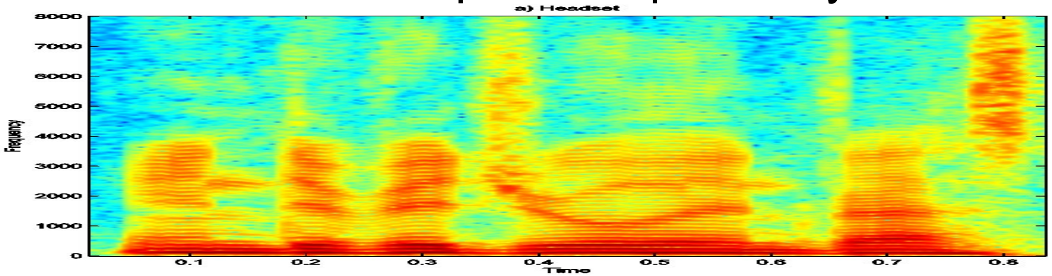


Omnipresent when using a distant mic in an enclosure

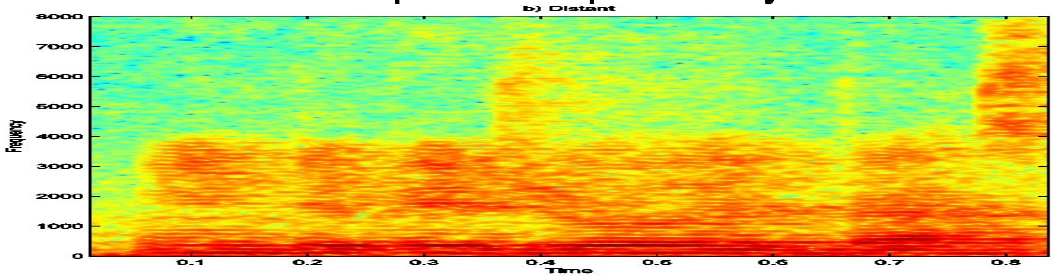
Effect of reverberation (1/2)

Largely modify spectral pattern

Non-reverberant speech captured by a headset



Reverberant speech captured by a distant mic

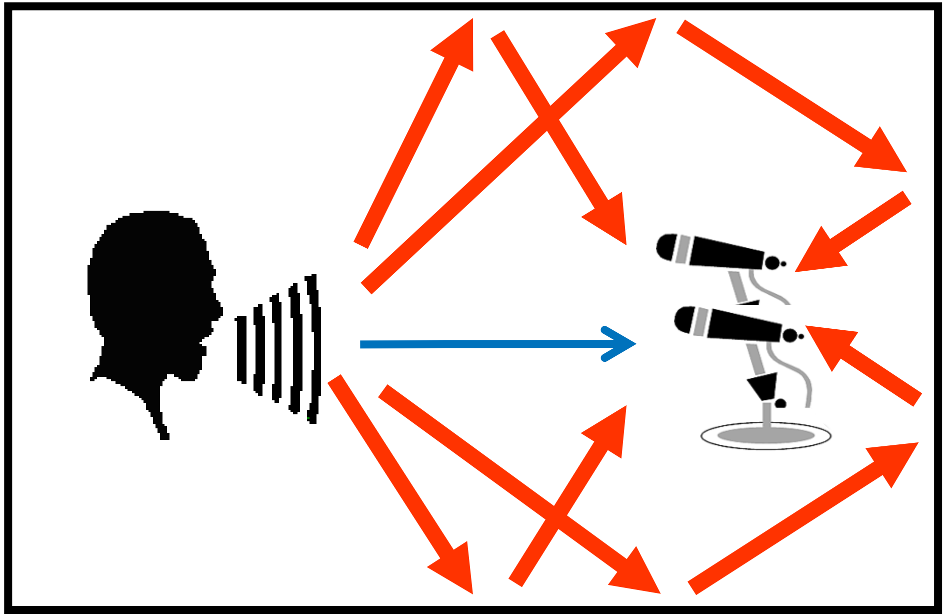


RT60≈0.6 s

- Speech becomes less intelligible for humans
- Automatic Speech Recognition (ASR) becomes very hard

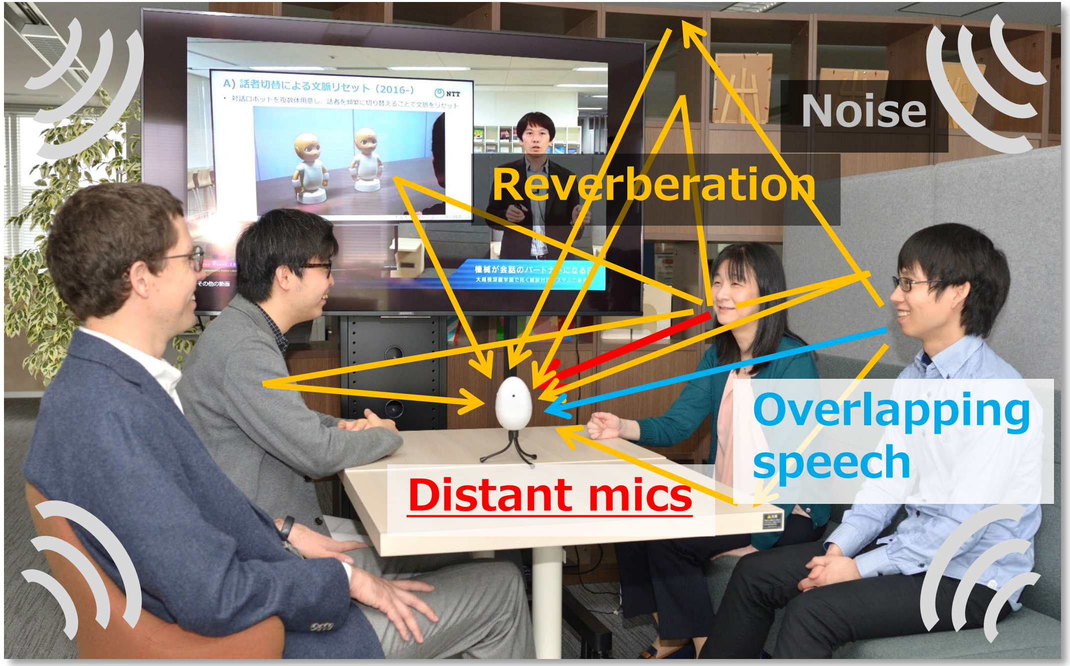
Effect of reverberation (2/2)

Speech arrives at mics from all directions



- Sound localization becomes unclear for humans
- Direction-of-arrival (DOA) estimation becomes challenging

More realistic scenario



Noise + Overlapping speech + Reverberation

Problemss caused by reverberation

- Degrades speech intelligibility and localization for humans
- Degrades performance of speech applications
- Hinders effectiveness of speech preprocessing

Noisy reverberant speech mixture → Speech preprocessing → Speech applications

Speech preprocessing

- Denoising
- Source separation
- Etc.

Degraded by reverberation

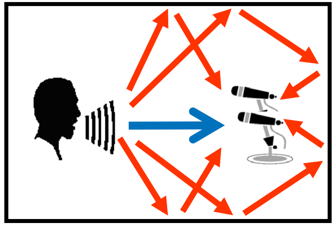
Speech applications

- ASR
- Remote conference
- Etc.

Degraded by reverberation

Role of dereverberation

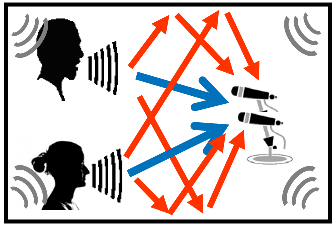
- Reduce reverberation in captured signals to mitigate its negative effects
  - To improve speech intelligibility and localization



Reverberant speech → Dereverb → ***Dereverberated*** speech

Improved intelligibility and localization

  - To improve speech preprocessing and applications



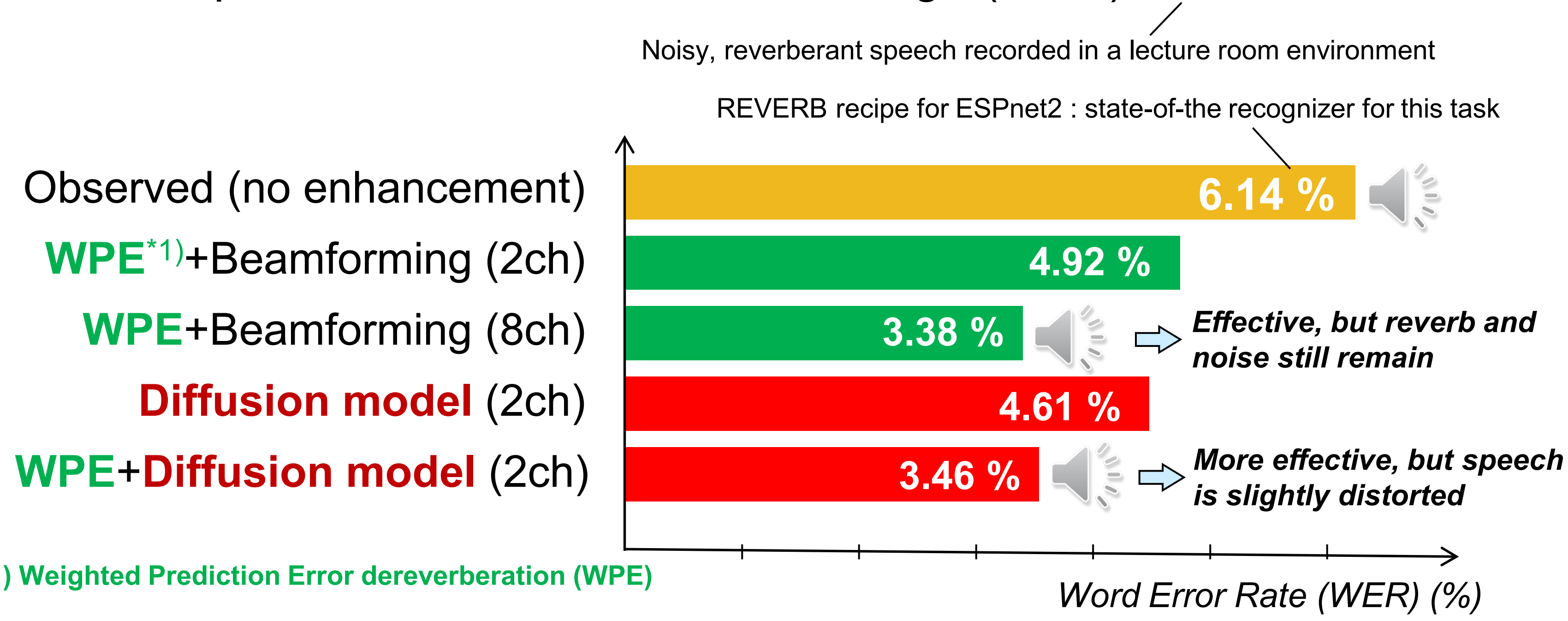
Noisy ***reverberant*** speech mixture → Dereverb → Noisy ***dereverberated*** speech mixture → Speech preprocessing (• Denoising • Source separation) → Speech applications (• ASR • Remote conference)

Improved accuracy

Improved performance

Quick overview of effectiveness

ASR improvement for REVERB Challenge (2014) Real dataset



*1) Weighted Prediction Error dereverberation (WPE)

This webinar puts particular focus on these techniques

Applications of speech dereverberation

A versatile technique to improve quality of speech applications

To enhance human listening

- Hearing aids
- Hands-free remote conference

For computers to understand human conversations

- Smart speaker
- Communication robot
- Meeting recognition

Hearing aids

Remote conference
Minutes generation

Smart speaker

Communication robot

Outline of this talk

1. Approaches to dereverberation
2. Blind inverse filtering-based dereverberation
   - Theoretical background
   - Weighted Prediction Error (WPE) method
   - Extension to joint denoising, dereverberation, and source separation
3. Neural network (NN)-based dereverberation
   - Diffusion model-based joint denoising and dereverberation
   - Integration with WPE and other SE techniques
4. Future challenges and concluding remarks

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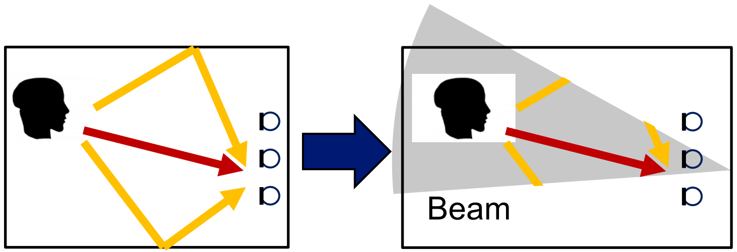
Signal model-based dereverberation

Beamforming (multi-ch) [Flanagan, 1985]

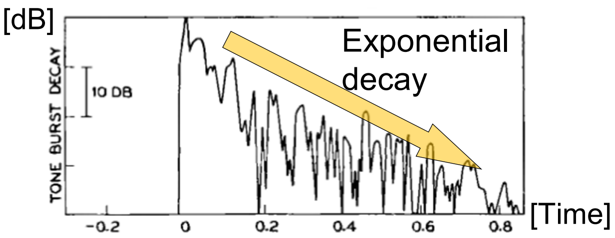
- Model: direct signal comes from source direction
- Solution: enhance signal coming from the source direction
- Requires many mics for large reverb reduction



Power spectral density (PSD) estimation (1-ch)

[Lebart+,2001], [Habets+,2004,2007,2009], [Löllman 2010]

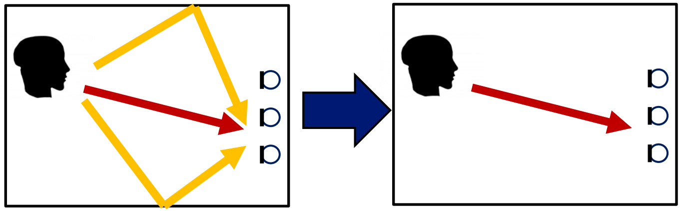
- Model: Energy of reverberation exponentially decays
- Solution: Suppress reverberation PSD in power domain
- Simple and efficient model with marginal effectiveness



Energy decay property of reverberation

Blind inverse filtering (multi-ch)

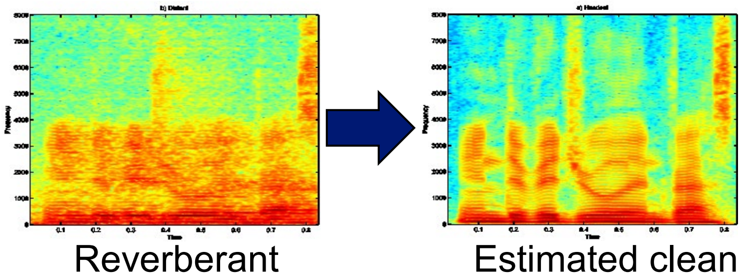
- Model: Convolution with room impulse response (RIR)
- Solution: Apply inverse filter to cancel RIR
  - **Weighted prediction error (WPE) method**
- **One of most effective techniques**



Neural Network (NN)-based dereverberation

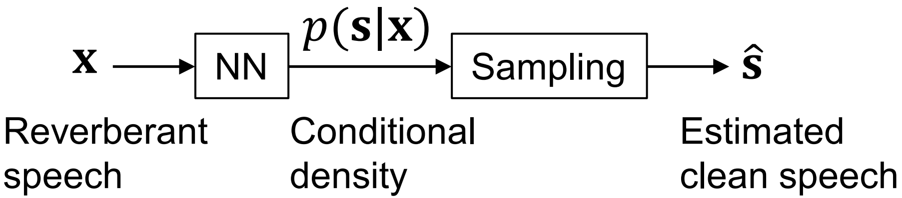
Deterministic prediction (1-ch/multi-ch)

- Train an NN to predict clean speech from reverberant obs. [Weninger+, 2014], [Xu, 2015]
- Use of U-Net [Ronneberger+, 2015] greatly improved the estimation accuracy [Wang, 2021]



Probabilistic prediction (1-ch/multi-ch)

- Train an NN to predict conditional density of clean speech (implicitly or explicitly) from reverberant observation.
- **Diffusion model-based denoising and dereverberation** [Serra+,2022],[Richter+, 2023]
  - An emerging speech enhancement (SE) technique
  - **Can be integrated with signal model-based dereverberation**



Key differences between approaches

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	Blind inverse filtering (Section 2)	NN-based approach (Section 3)	Hybrid (Section 3, and future work)
Prior training	**Not necessary**	**Necessary**	**Necessary**
Adaptability to test condition	**High**	**Limited** (by training data)	**Medium**
Dereverb performance	**Limited** (by signal model)	**High** (Under matched conditions)	**Very high** (Yet depending on conditions)

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Time-domain model of reverberation

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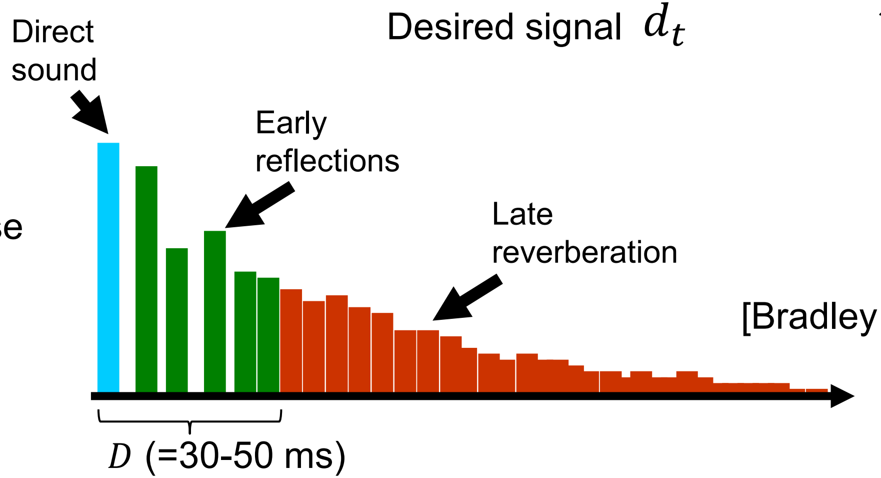
Preserve | Reduce

Reverberant speech $x_t = \sum_{\tau=0}^{L-1} a_\tau s_{t-\tau} = \boxed{\sum_{\tau=0}^{D-1} a_\tau s_{t-\tau}} + \boxed{\sum_{\tau=D}^{L-1} a_\tau s_{t-\tau}}$

Direct sound + Early reflections → Desired signal d_t

Late reverberation → r_t

Impulse response a_τ



[Bradley et al., 2003]

Matrix representation of RIR convolution

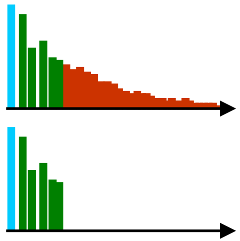
1-ch convolution at mth mic: $\mathbf{x}_{m,t} = \mathbf{H}_m \mathbf{s}_t = \underbrace{\mathbf{H}_m^d \mathbf{s}_t}_{\mathbf{d}_{m,t}} + \underbrace{\mathbf{H}_m^r \mathbf{s}_t}_{\mathbf{r}_{m,t}}$

$$\mathbf{x}_{m,t} = \begin{bmatrix} x_{m,t} \\ x_{m,t-1} \\ \vdots \\ x_{m,t-K} \end{bmatrix} \quad \mathbf{H}_m = \begin{bmatrix} a_{m,0} & a_{m,1} & \cdots & a_{m,L-1} & 0 & \cdots & 0 \\ 0 & a_{m,0} & a_{m,1} & \cdots & a_{m,L-1} & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & & \ddots & 0 \\ 0 & \cdots & 0 & a_{m,0} & a_{m,1} & \cdots & a_{m,L-1} \end{bmatrix} \in \mathbb{R}^{K \times K_0} \quad \mathbf{s}_t = \begin{bmatrix} s_t \\ s_{t-1} \\ \vdots \\ s_{t-K_0} \end{bmatrix}$$

$K_0 = L + K - 1$

Multi-ch convolution: $\mathbf{x}_t = \mathbf{H}\mathbf{s}_t = \underbrace{\mathbf{H}^d \mathbf{s}_t}_{\mathbf{d}_t} + \underbrace{\mathbf{H}^r \mathbf{s}_t}_{\mathbf{r}_t}$

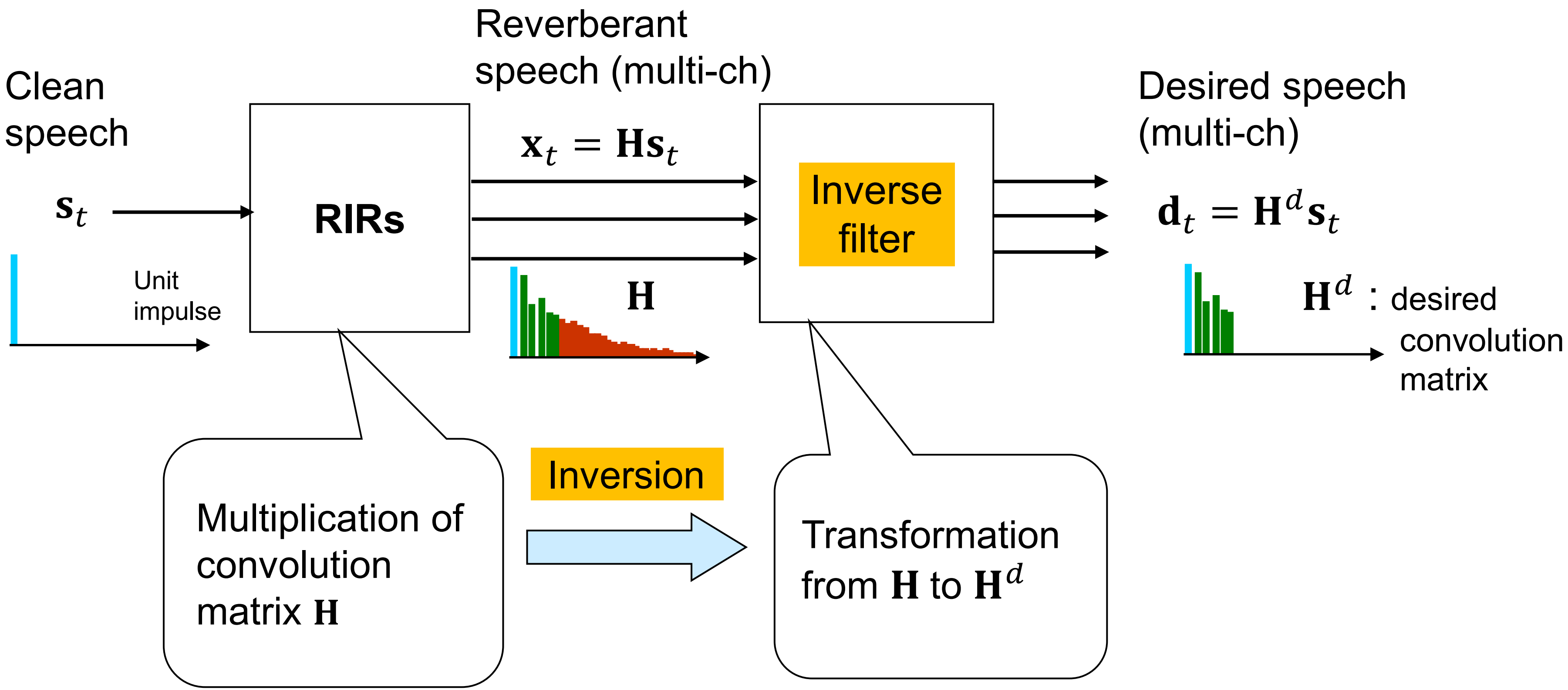
$$\mathbf{x}_t = \begin{bmatrix} \mathbf{x}_{1,t} \\ \vdots \\ \mathbf{x}_{M,t} \end{bmatrix} \quad \mathbf{H} = \begin{bmatrix} \mathbf{H}_1 \\ \vdots \\ \mathbf{H}_M \end{bmatrix} \in \mathbb{R}^{MK \times K_0}$$



$\mathbf{H}$: convolution matrix

$\mathbf{H}^d$: ***desired*** convolution matrix

What is inverse filtering?



Exact inverse filter for given RIR

[Miyoshi and Kaneda, 1988]

- Given $\mathbf{H}$, the inverse filter $\mathbf{W}$ should transform $\mathbf{H}$ to $\mathbf{H}^d$:

$$\mathbf{W}^{\mathsf{H}}\mathbf{H} = \mathbf{H}^d$$

- Solution is obtained using the pseudo-inverse of $\mathbf{H}$ denoted by $\mathbf{H}^+$:

$$\mathbf{W}^{\mathsf{H}} = \mathbf{H}^d\mathbf{H}^+ \quad \text{where} \quad \mathbf{H}^+ = \left(\mathbf{H}^{\mathsf{H}}\mathbf{H}\right)^{-1}\mathbf{H}^{\mathsf{H}}$$

  – When $\mathbf{H}$ is **full column rank** (requiring **#mics**≥ 2)

$\mathbf{H}$ is not given in a blind inverse filtering scenario

The challenge is to estimate $\mathbf{W}$ without knowing $\mathbf{H}$

STFT-domain convolution model

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- For computational efficiency, we decompose time-domain convolution by STFT-domain convolution at each frequency

Time-domain convolution

$$\mathbf{x}_t = \mathbf{H}\mathbf{s}_t$$

Decompose

STFT-domain convolution

$$\left.\begin{aligned} \mathbf{x}_{t,f_1} &= \mathbf{H}_{f_1}\mathbf{s}_{t,f_1} \\ \mathbf{x}_{t,f_2} &= \mathbf{H}_{f_2}\mathbf{s}_{t,f_F} \\ &\vdots \\ \mathbf{x}_{t,f_F} &= \mathbf{H}_{f_F}\mathbf{s}_{t,f_F} \end{aligned}\right\} \text{for each frequency } f$$

  - Valid when frame shift << analysis window [Nakatani+, 2008]

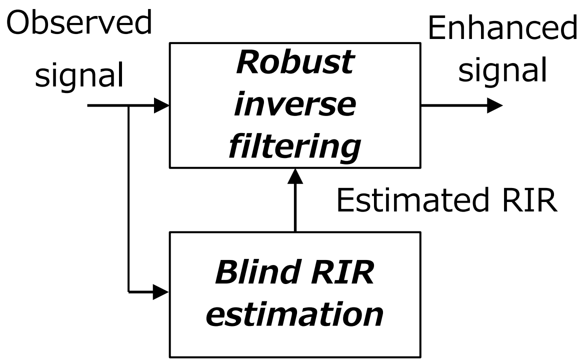
- Exact inverse filter can be defined in the same way as time-domain model

Inverse filtering can be performed separately in each frequency

Approaches to blind inverse filtering

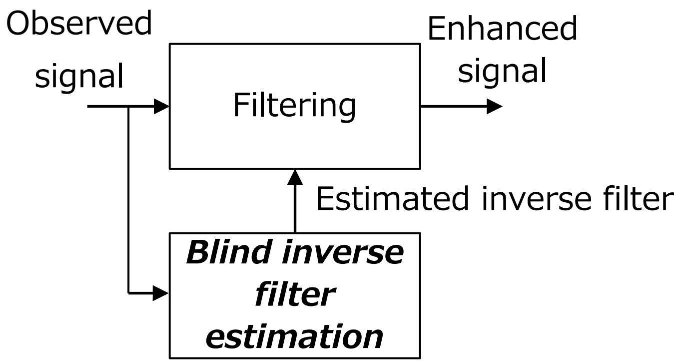
Blind RIR estimation + robust inverse filtering

- Blind RIR estimation is still a challenging problem
  - Eigenvalue decomposition-based [Gannot, 2010]
  - Rank-1 matrix lifting-based joint source and impulse response estimation [Yohena+, 2024]
- Robust inverse filtering for given RIR
  - Regularization [Hikichi+, 2007]
  - Partial multichannel equalization [Kodrasi+, 2013]



Blind and direct estimation of inverse filter

- Multichannel linear prediction (MCLP) based methods
  - Prediction Error (PE) method [Abed-Meraim+, 1997]
  - Delayed Linear Prediction [Kinoshita+, 2009]
  - Weighted Prediction Error (WPE) method [Nakatani+, 2010]
  - Multi-input multi-output (MIMO) WPE method [Yoshioka+, 2012]

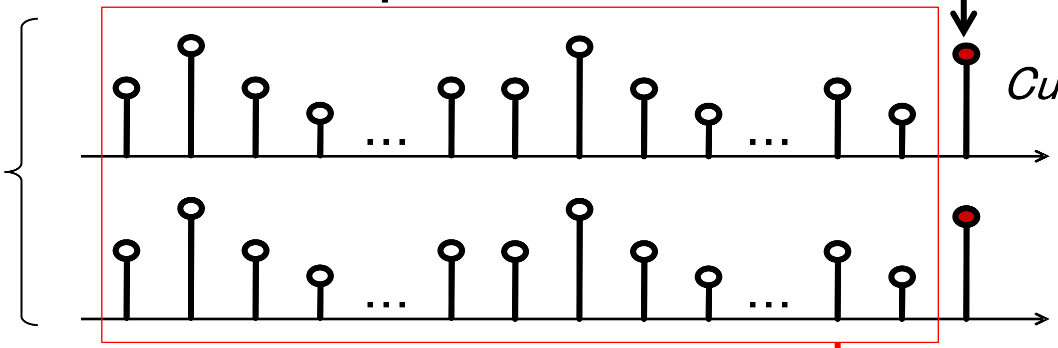


Vanilla MCLP [Abed-meraim+, 1997]

$\dot{\mathbf{d}}_{t,f}$: direct signal
$\dot{\mathbf{r}}_{t,f}$: reverberation

Predict $\sum_{\tau=1} \mathbf{G}_{\tau,f}^{H} \mathbf{x}_{t-\tau,f}$

Multi-ch



Current signal

$$\mathbf{x}_{t,f} = \dot{\mathbf{d}}_{t,f} + \underline{\dot{\mathbf{r}}_{t,f}}$$

Past signal

Predictable

Dereverberation: $\dot{\mathbf{d}}_{t,f} = \mathbf{x}_{t,f} - \underbrace{\sum_{\tau=1} \mathbf{G}_{\tau,f}^{H} \mathbf{x}_{t-\tau,f}}_{\textit{Predicted signal}}$

Subtract predicted signals from observation

Formal definition of vanilla MCLP

Multichannel autoregressive model

$$\mathbf{x}_{t,f} = \sum_{\tau=1}^{L} \mathbf{G}_{\tau,f}^{H} \mathbf{x}_{t-\tau,f} + \dot{\mathbf{d}}_{t,f}$$

$\mathbf{G}_{\tau,f} \in \mathbb{C}^{M \times M}$: prediction matrices.

- Assuming $\dot{\mathbf{d}}_{t,f}$ stationary white noise, Maximum Likelihood (ML) solution becomes

$$\hat{\mathbf{G}}_{\tau,f} = \underset{\{\mathbf{G}_{\tau,f}\}}{\arg\min} \sum_{t=1}^{T} \left\| \mathbf{x}_{t,f} - \sum_{\tau=1}^{L} \mathbf{G}_{\tau,f}^{H} \mathbf{x}_{t-\tau,f} \right\|_2^2$$

- With estimated $\hat{\mathbf{G}}_{\tau,f}$, $\dot{\mathbf{d}}_{t,f}$ is estimated (= inverse filtering) as

$$\hat{\dot{\mathbf{d}}}_{t,f} = \mathbf{x}_{t,f} - \sum_{\tau=1}^{L} \hat{\mathbf{G}}_{\tau,f}^{H} \mathbf{x}_{t-\tau,f}$$

Problems in vanilla MCLP

Speech is not stationary white noise

- » MCLP assumes the desired signal to be temporally uncorrelated
- » Speech signal exhibits short-term correlation (30-50 ms)

→ MCLP distorts the short-time correlation of speech

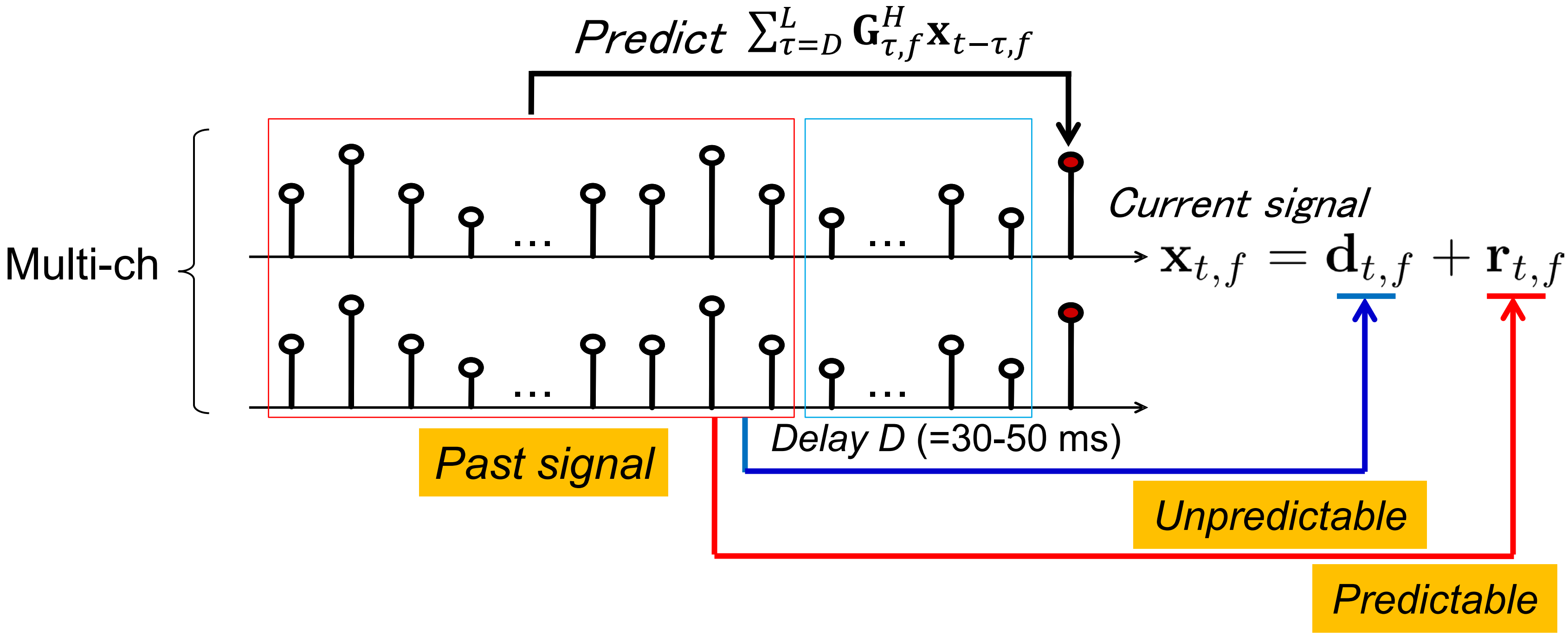
- » MCLP assumes the target signal d to be stationary
- » Speech is not stationary for long-time duration (200-1000 ms)

→ MCLP disrupts the temporal structure of speech

Solutions:

- Use of a prediction delay [Kinoshita+, 2009]
- Use of a non-stationary speech model [Nakatani+, 2010]

Delayed MCLP [Kinoshita+, 2009]



Delayed MCLP can reduce late reverberation $\mathbf{r}_{t,f}$ without distorting temporal correlations of speech

Use of non-stationary source model

[Nakatani+, 2010, Yoshioka+, 2011]

Model of desired signal: time-varying Gaussian (local Gaussian)

$$p(\mathbf{d}_{t,f};\theta) = N_c(\mathbf{d}_{t,f}; 0, \sigma_{t,f}^2 \mathbf{I}) \quad \text{where} \quad \theta = \{\sigma_{t,f}^2\} : \text{source PSD}$$

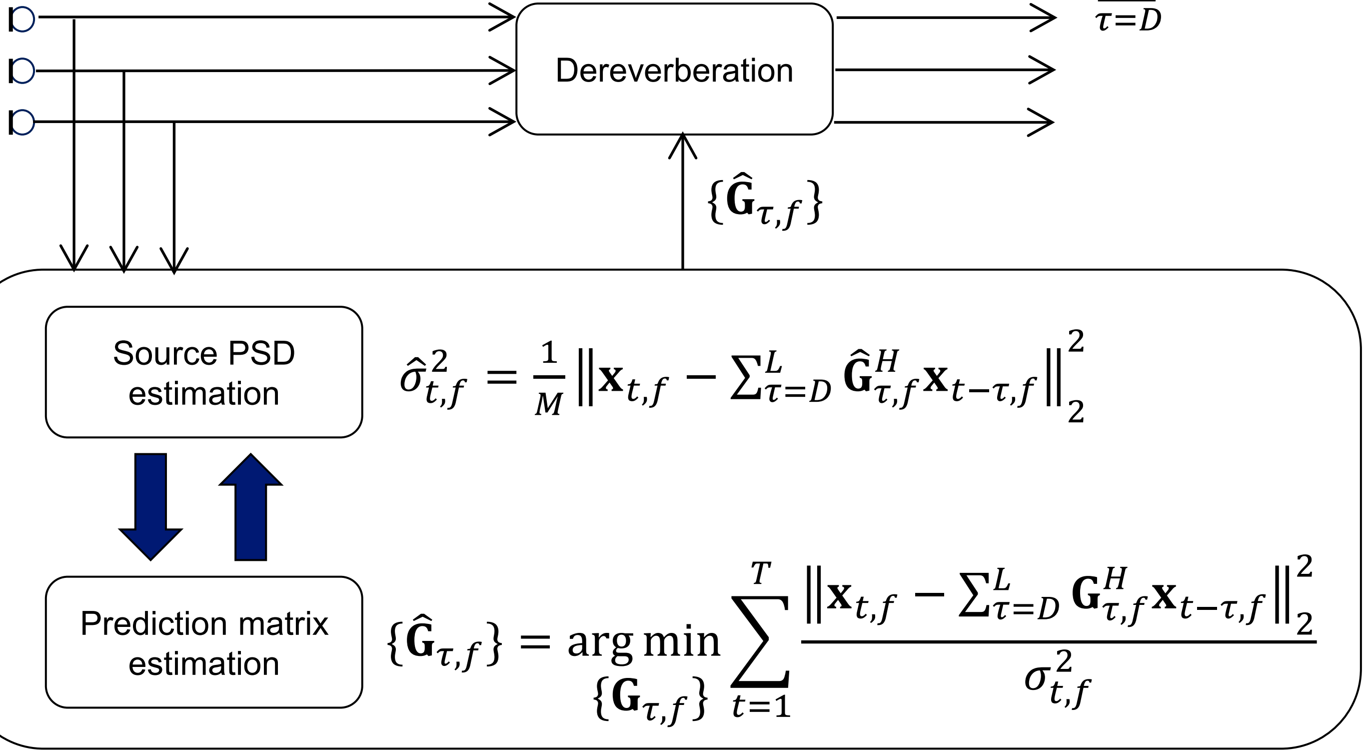
Maximum Likelihood (ML) estimation:

$$\{\hat{G}_{\tau,f}, \hat{\sigma}_{t,f}^2\} = \underset{\{\mathbf{G}_{\tau,f}, \sigma_{t,f}^2\}}{\arg\max} \prod_{t=1}^{T} \frac{1}{\pi \sigma_{t,f}^2} \exp\left(\underbrace{\frac{-\left\| \mathbf{x}_{t,f} - \sum_{\tau=D}^{L} \mathbf{G}_{\tau,f}^H \mathbf{x}_{t-\tau,f} \right\|_2^2}{\sigma_{t,f}^2}}_{\text{Weighted prediction error (WPE)}} \right)$$

→ Can perform dereverberation ***based only on a few seconds of observation***

Processing flow of WPE

$$\hat{\mathbf{d}}_{t,f} = \mathbf{x}_{t,f} - \sum_{\tau=D}^{L} \mathbf{G}_{\tau,f}^{H} \mathbf{x}_{t-\tau,f}$$



$$\{\hat{\mathbf{G}}_{\tau,f}\}$$

$$\hat{\sigma}_{t,f}^{2} = \frac{1}{M} \left\| \mathbf{x}_{t,f} - \sum_{\tau=D}^{L} \hat{\mathbf{G}}_{\tau,f}^{H} \mathbf{x}_{t-\tau,f} \right\|_2^2$$

$$\{\hat{\mathbf{G}}_{\tau,f}\} = \underset{\{\mathbf{G}_{\tau,f}\}}{\arg\min} \sum_{t=1}^{T} \frac{\left\| \mathbf{x}_{t,f} - \sum_{\tau=D}^{L} \mathbf{G}_{\tau,f}^{H} \mathbf{x}_{t-\tau,f} \right\|_2^2}{\sigma_{t,f}^{2}}$$

Does WPE perform inverse filtering?

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$$E\left\{\frac{\left\|\mathbf{x}_{t,f}-\sum_{\tau=D}^{L}\mathbf{G}_{\tau,f}^{H}\mathbf{x}_{t-\tau,f}\right\|_2^2}{\sigma_{t,f}^2}\right\}$$

$$=E\left\{\frac{\left\|\mathbf{d}_{t,f}\right\|_2^2}{\sigma_{t,f}^2}\right\}+E\left\{\frac{\left\|\mathbf{r}_{t,f}-\sum_{\tau=D}^{L}\mathbf{G}_{\tau,f}^{H}\mathbf{x}_{t-\tau,f}\right\|_2^2}{\sigma_{t,f}^2}\right\}$$

Assumption

$\mathbf{d}_{t,f}$ and $\mathbf{r}_{t,f}$ are mutually uncorrelated

$$\geq E\left\{\frac{\left\|\mathbf{d}_{t,f}\right\|_2^2}{\sigma_{t,f}^2}\right\}$$

Minimized when $\underbrace{\mathbf{r}_{t,f}}_{\text{Reverb}}=\sum_{\tau=D}^{L}\underbrace{\mathbf{G}_{\tau,f}^{H}\mathbf{x}_{t-\tau,f}}_{\text{Prediction}}$

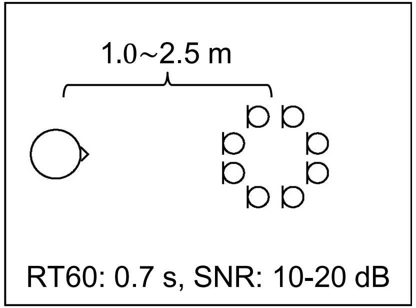
Yes, WPE performs inverse filtering when the inverse filter exists

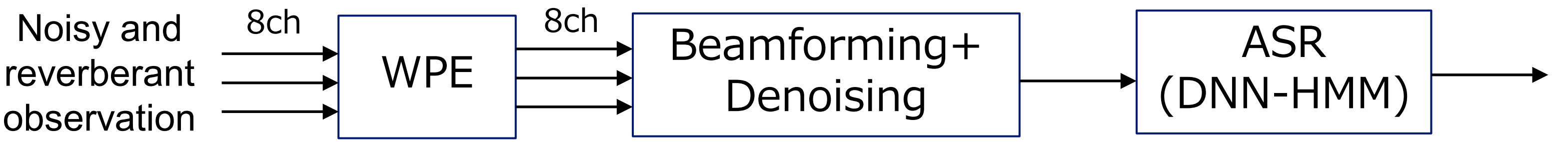
REVERB Challenge : improvement in ASR (2014)

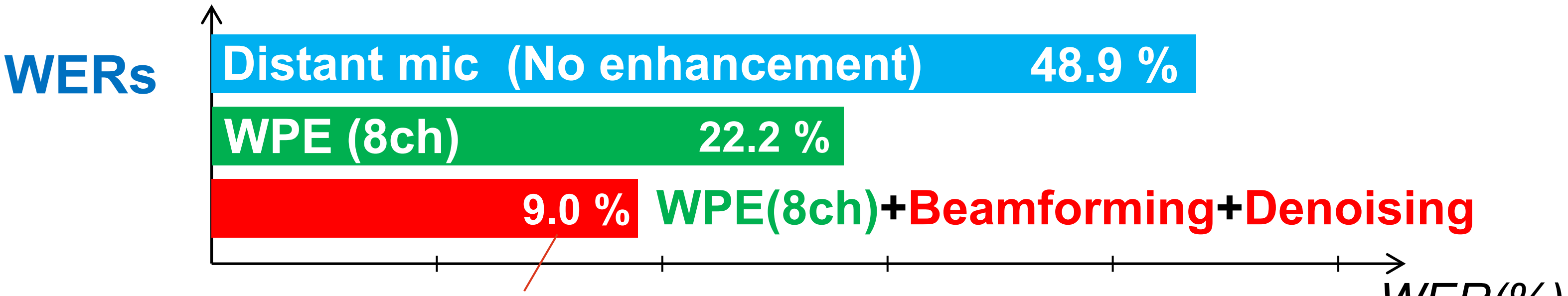
[Kinoshita+, 2016]

- Acoustic conditions
  - Real recordings of read speech
  - Noisy and reverberant lecture rooms
- Processing flow [Delcroix+., 2015]

8ch circular-array scenario







This was the best score at the 2014 challenge

Demonstration（8-mics, Real data）

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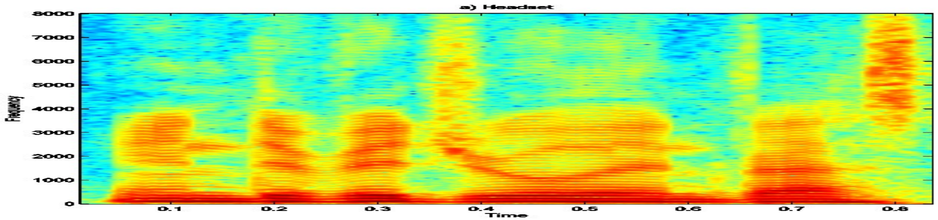
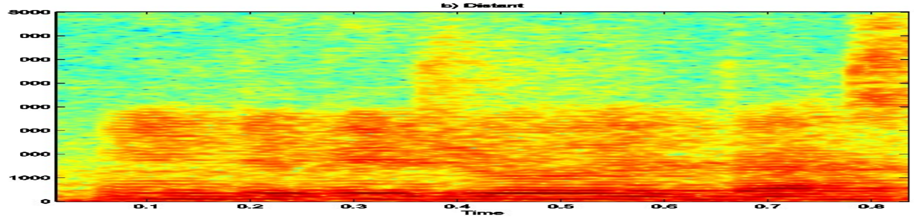
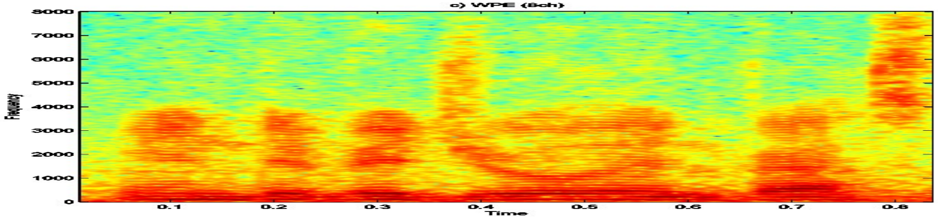
No reverberation
（headset）



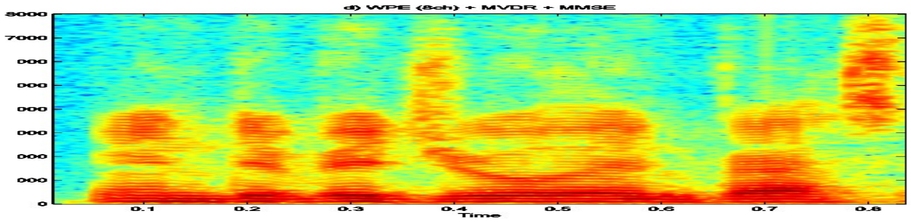
With reverberation
（distant mic）



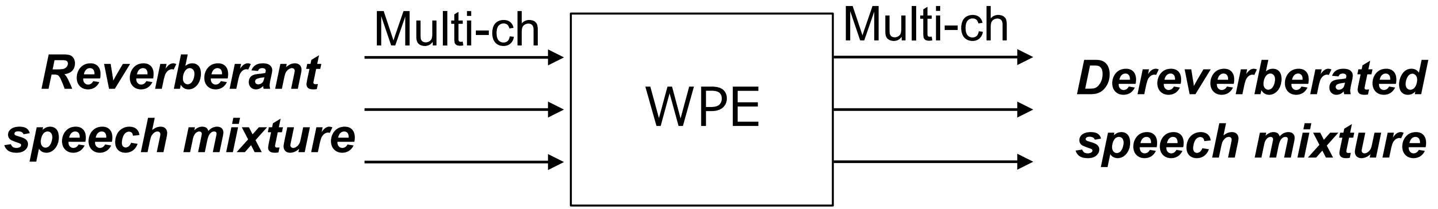
WPE
dereverberation



WPE+beamforming
+denoising



Dereverberation of speech mixture by WPE
[Yoshioka+, 2012]



Existence of such an inverse filter for mixture dereverberation is guaranteed [Miyoshi+, 1988] when

- #mics > #sources
- Convolution matrix for mixture is full column rank

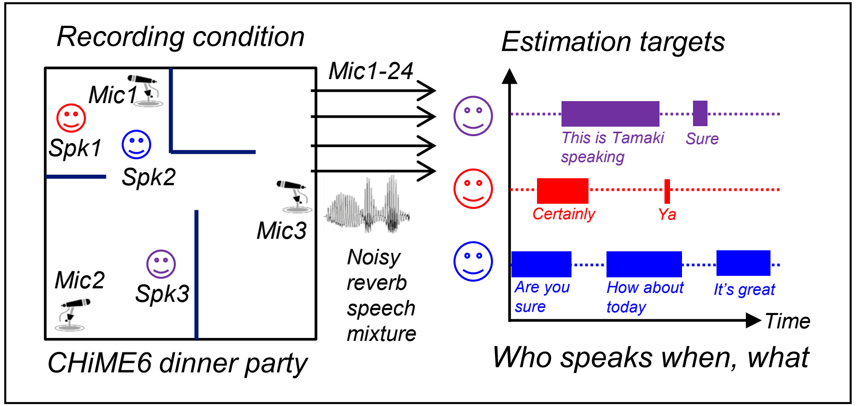
➡ WPE : *versatile dereverberation preprocessor*

Distant ASR challenge CHiME-8 task1 (2024)

[Cornell+, 2024]

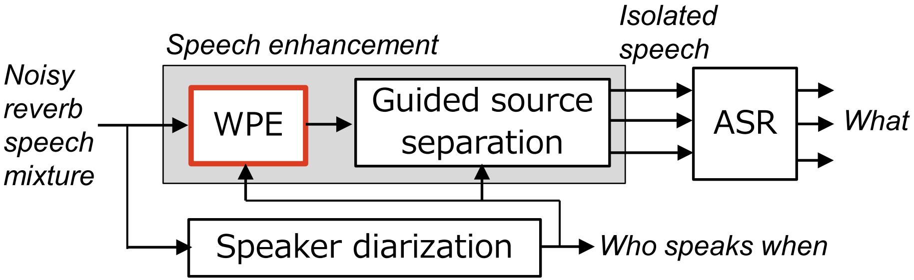
Goal: Estimate who speaks when and what

- In four different conversation scenarios
- Recorded by ***distant distributed mic-arrays***
  - ***Noisy reverberant speech mixture*** with ***unknown number of speakers***



Complex and challenging ASR task

Processing pipeline of baseline system



Results (Dev set): tcpWER*1) of NTT system [Kamo+, 2024]

Scenario (Dataset)	Dinner party1 (CHiME6)	Dinner party2 (DiPCo)	1-to-1 Interview (Mixer 6)	Office meeting (NotSoFar1)	Ave-rage
w/o WPE	21.63	31.22	11.62	9.31	17.52
w/ WPE	**19.80**	**27.33**	**10.13**	**8.93**	**15.85**

*1) Time-constrained minimum permutation WER

Demonstrates effectiveness of WPE for mixture derev.
Further improvement should be included in future work

Extensions of WPE (1/2)

NTT

Elaboration of probabilistic source models

- Sparse prior for speech PSD [Jukic et al., 2015]
- Bayesian estimation with student-T speech prior [Chetupalli+, 2019]

Frame-by-frame online estimation

- Recursive least square [Yoshioka+, 2009], [Caroselli+, 2017]
- Kalman filter for joint denoising and dereverberation [Togami+, 2013], [Braun+, 2018], [Dietzen+, 2018]

Extensions of WPE (2/2)

Dereverberation of more sources than microphones (***under-determined situation***)

- Switching WPE [Ikeshita+, 2021-1, 2021-2]

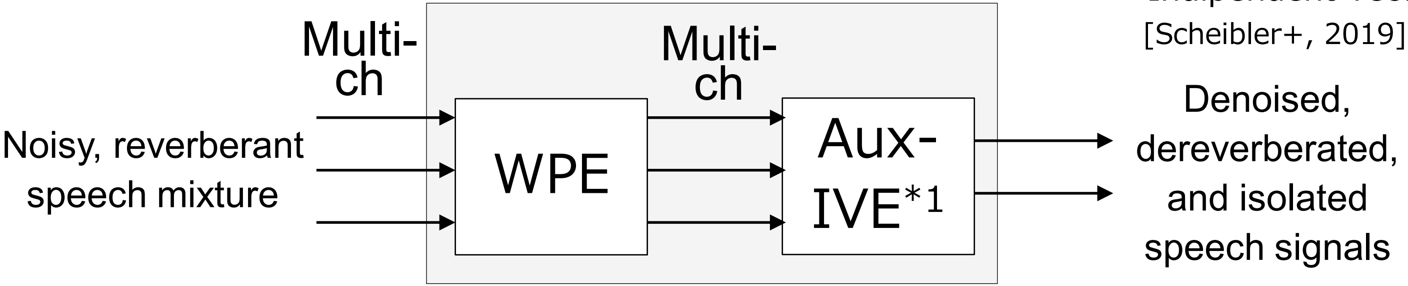
Joint optimization of dereverberation and beamforming

1. Maximum likelihood convolutional beamformer that can jointly perform denoising and dereverberation [Dietzen+, 2018], [Nakatani+, 2019]
2. Integration of WPE and blind source separation (BSS)/extraction (BSE) [Yoshioka+, 2010], [Ikeshita+, 2021], [Nakatani+, 2021]
3. Extension to switching convolutional beamformer [Nakatani+, 2022]

Joint optimization of WPE and BSS/BSE

[Yoshioka+, 2010], [Ikeshita+, 2021], [Nakatani+, 2021]

*1) Auxiliary-function-based Independent Vector Extraction [Scheibler+, 2019], [Ikeshita+, 2020]



Jointly optimize both blocks

Assumptions:

Signals estimated by overall system satisfy:

1. Each speech is time-varying Gaussian
2. Noise is stationary Gaussian
3. Speech signals and noise are mutually independent

Optimiza-tion	fwsSNR↑	STOI↑	WER↓
Separate	5.86 dB	0.83	19.54 %
Joint	**6.16 dB**	**0.84**	**16.31 %**

Results on REVERB-2Mix [Nakatani+, 2021]

Summary of WPE

Advantages:

- Versatile dereverberation preprocessing
  - Applicable to mixed signals
  - Require no prior training or knowledge on recording conditions
    - Highly adaptive to unknown environments

Limitations:

- Performance degrades in high noise conditions
- Relatively a large number of microphones are required for achieving highly accurate processing
- Unable to reduce early reflections

→ Overcome these limitations by using diffusion model-based approach

Outline of this talk

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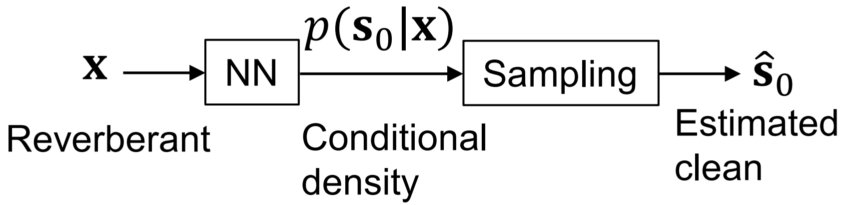
4. Future challenges and concluding remarks

Diffusion model-based joint denoising and dereverberation

Probabilistic prediction [Serra+,2022],[Richter+, 2023]

- Model $p(\mathbf{s}_0|\mathbf{x})$, i.e., conditional distribution of a clean speech, $\mathbf{s}_0$, given the observed signal, $\mathbf{x}$
- Perform **speech enhancement (SE) by sampling $\mathbf{s}_0$ from $p(\mathbf{s}_0|\mathbf{x})$**
- Score-based Generative Model for Speech Enhancement (SGMSE) [Welker+ 22] [Richter+, 23]



Multi-stream SGMSE (MS-SGMSE) [Nakatani+, 2024]:

- Platform to integrate SE methods using SGMSE
- By conditioning the model with **pre-enhanced signals** by the SE methods

⇒ further improve the SE performance

Conditional density modeled by MS-SGMSE

$$p(\underbrace{\mathbf{s}_0}_{\text{Clean speech}}|\underbrace{\mathbf{x}}_{\text{Observation}},\underbrace{\boldsymbol{X}}_{\text{Pre-enhanced signals}})$$

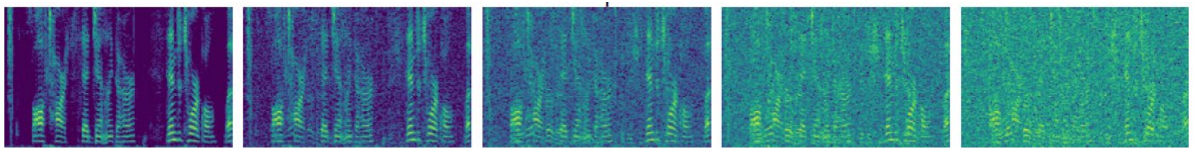
SE using conditional diffusion model

[Song+, 2021],[Richter+,2023]

Forward process

Intermediate state at step *n*

$$\boxed{\mathbf{s}_0 \sim p(\mathbf{s_0}|\mathbf{x},\mathbf{c})} \longrightarrow d\boxed{\mathbf{s}_n} = \mathbf{f}(\mathbf{s}_n,\mathbf{y})dn + g(n)d\mathbf{w} \longrightarrow \mathbf{s}_N = \mathbf{x}+\mathbf{v}$$



$$\mathbf{s}_0 \longleftarrow d\mathbf{s}_n = [-\mathbf{f}(\mathbf{s}_n,\mathbf{y})dt + g(n)^2 \boxed{\nabla_{\mathbf{s}_n} \log p(\mathbf{s}_n|\mathbf{x},\boldsymbol{c})}]dn + g(n)d\bar{\mathbf{w}} \longleftarrow \mathbf{s}_N = \mathbf{x}+\mathbf{v}$$

Score
(modeled by Neural network)

Reverse process

- SE is achieved by the reverse process.

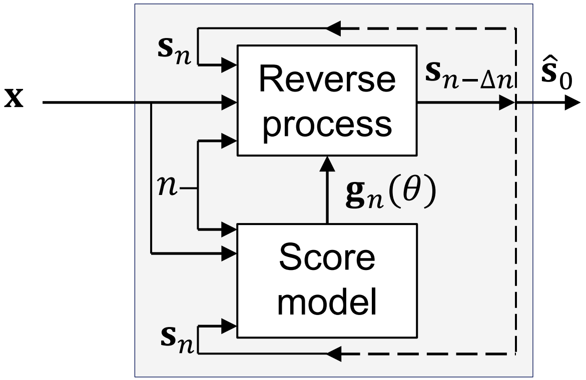
Score model $\mathbf{g}_n(\mathbf{s}_n,\mathbf{x},\boldsymbol{c},n\,;\theta) \simeq \nabla_{\mathbf{s}_t} \log p(\mathbf{s}_n|\mathbf{x},\mathbf{c})$ is all we need.

Loss: $\mathcal{J}^{\text{score}}(\theta) = E\left\|\nabla_{\mathbf{s}_n} \log p(\mathbf{s}_n|\mathbf{x},\boldsymbol{c}) - \mathbf{g}_t\,(\mathbf{s}_n,\mathbf{x},\boldsymbol{c},n;\theta)\right\|_2^2$

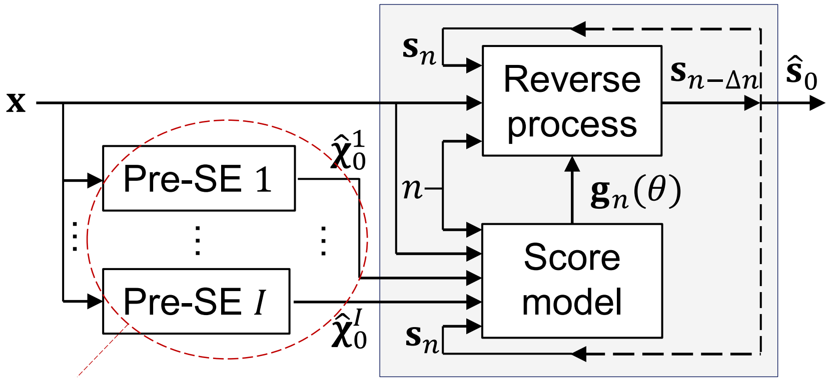
- **MS-SGMSE incorporates X as condition c for integration**

SGMSE and MS-SGMSE

SGMSE



MS-SGMSE



SE methods to be integrated

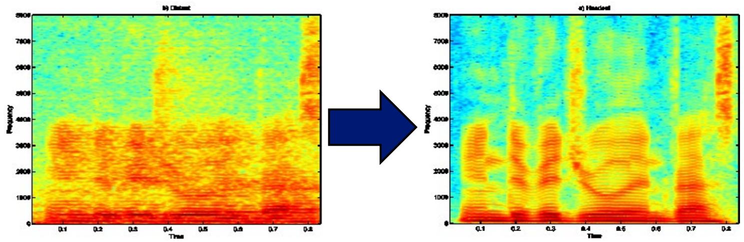
$\boldsymbol{X} = \{\hat{\chi}_0^1, \ldots, \hat{\chi}_0^I\}$: pre-enhanced signals

MS-SGMSE models $p(\mathbf{s}_0|\mathbf{x}, X)$ and improve the accuracy of SE

PRE-SE methods to be integrated

1. **Weighted Prediction Error: WPE**
2. **Complex Spectral Mapping: CSM**

   A deterministic prediction approach



Reverberant　　Predicted clean

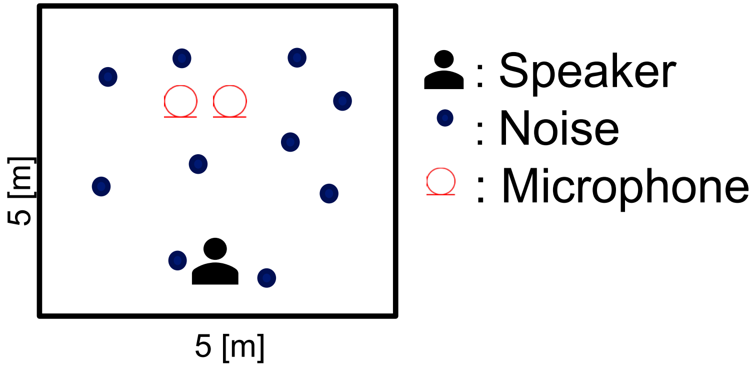
   Training objective:

$$L(\theta) = E[\|\mathrm{Re}(\mathbf{s} - \hat{\mathbf{s}}_0)\|_1 + \|\mathrm{Im}(\mathbf{s}_0 - \hat{\mathbf{s}}_0)\|_1] + \||\mathbf{s}_0| - |\hat{\mathbf{s}}_0|\|_1]$$

3. **Cascade configuration of the above two: WPE-CSM**

Experimental setting

- Experimental conditions
  - Training data: WSJ-CHiME3



# of speakers (WSJ0)	1
# of noises (CHiME3)	10
# of microphones	2
Speaker-mic. Distance [m]	0.5~1.5
Distance between microphones [m]	**0.02~0.14**
Reverberation time [s]	0.2~1.0
SNR [dB]	10~14

- Clean targets: Simulated using room impulse responses truncated at 2 ms.
  - Evaluation data
    - Matched condition: WSJ0-CHiME3 (the same as training data)
    - Mismatched condition: REVERB challenge

Experimental results

SE method	Input stream(s)	Simulated data			Real data
		SI-SDR*2) [dB]	PESQ *3)	ESTOI *4)	WER*5) [%]
Obs	–	-3.5	1.24	0.47	6.14
WPE	Obs	-0.8	1.32	0.55	4.97
CSM	Obs	7.3	2.58	0.86	4.30
WPE-CSM*1)	Obs	8.5	2.75	0.88	4.00
SGMSE	Obs	7.8	2.68	0.86	4.61
Multi-stream SGMSE	Obs, WPE	8.3	2.83	0.88	**3.46**
	Obs, CSM	8.5	2.67	0.87	4.30
	Obs, WPE-CSM	9.3	2.81	0.88	3.92
	Obs, WPE, CSM	9.4	2.84	**0.89**	3.81
	Obs, WPE, CSM, WPE-CSM	**9.8**	**2.85**	**0.89**	3.84

*1) Cascade of WPE and CSM, *2) Scale-Invariant Signal-to-Distortion Ratio,
*3) Perceptual Evaluation of Speech Quality, *4) Extended Short-Time Objective Intelligibility,
*5) Word Error Rate

Summary of diffusion model-based approach

Pros

- Highly accurate joint denoising and dereverberation
  - Direct signal can be recovered
- Further improvement with integration with other SE methods
  - Outperform not only blind inverse filtering approach, but also NN-based deterministic prediction approach

Cons

- Require prior training
  - Still sensitive to mismatch between training and test conditions

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Future challenges

Satisfactory speech quality is not yet achieved for real conversation recordings like CHiME-8 challenge

Challenges	Inverse filtering	NN-based approach
Distributed microphone array scenarios	**Under progress**	-
Mismatches between training and test conditions	-	**Under progress**
Unknown and varying number of speakers and ambient noises	Tighter integration with ***speaker diarization*** and ***audio event detection*** may be the key	
Moving speakers	Not yet well studied	

WPE-SD for spatially distributed microphones

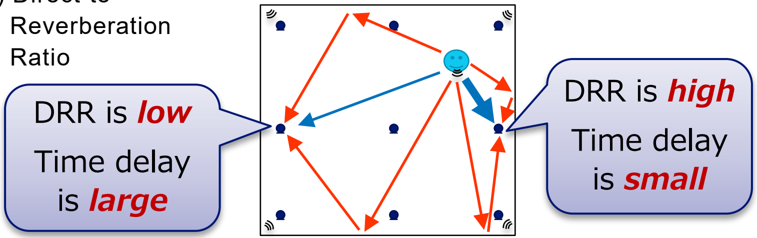
[Lohmann+, 2024]

Problems for distributed microphone scenario:

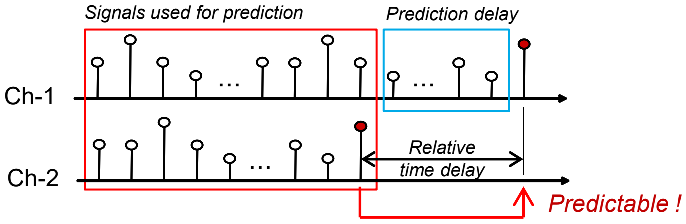
- DRR*1) largely differs depending on mic. locations
  - Performance depends largely on reference microphones

*1) Direct-to-Reverberation Ratio

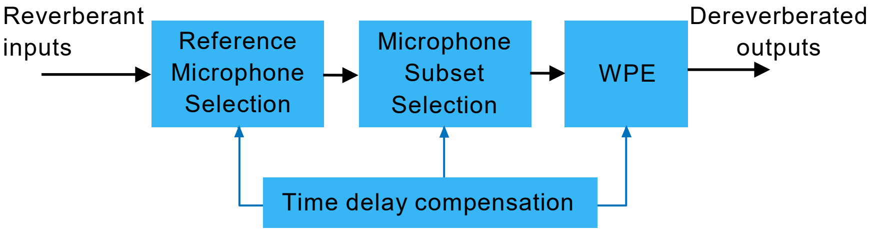
Distributed array

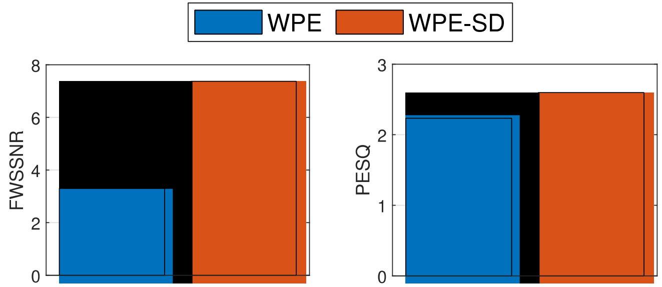


- Time delay between mics may exceed prediction delay
  - Direct signal can be predicted and distorted by WPE



WPE-SD (spatially distributed) [Lohmann+, 2024]





WPE-SD achieves ***large improvement***

⇨ **Future work: extension to more realistic scenarios with noisy reverberant mixtures**

Buddy: unsupervised dereverb with diffusion model (DM)

[Moliner+, 2024]

Jointly estimate clean speech and reverb

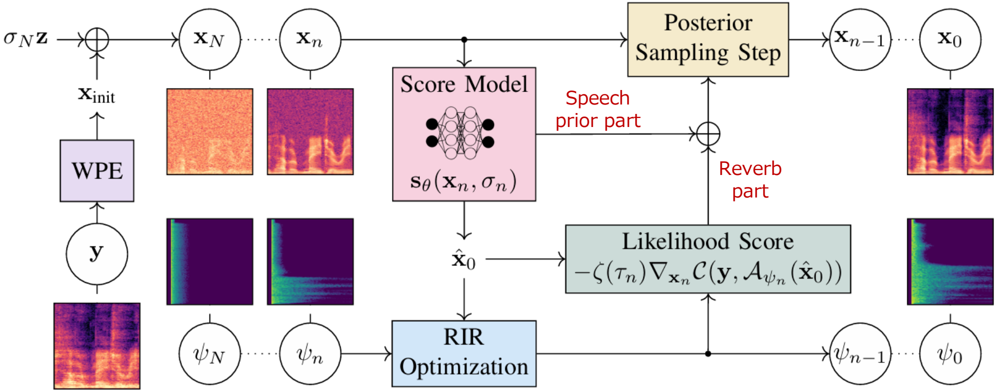
- Modeling clean speech prior $p(\mathbf{x}_0)$ using DM, and
- Reverb by exponential energy-decay model $\mathcal{A}_\psi(\mathbf{x}_0)$

Conditional score of DM

$$\begin{aligned}\nabla_{\mathbf{x}_t} \log p(\mathbf{x}_\tau|\mathbf{y}) &= \nabla_{\mathbf{x}_t} \log p(\mathbf{x}_\tau) + \nabla_{\mathbf{x}_t} \log p(\mathbf{y}|\mathbf{x}_\tau) \\ &\approx \underbrace{\mathbf{s}_\theta(x_t, \sigma_t)}_{\text{Speech prior part}} - \underbrace{\zeta(\tau)\nabla_{\mathbf{x}_t} \mathcal{C}(\mathbf{y}, \mathcal{A}_\psi(\hat{\mathbf{x}}_0))}_{\text{Reverb part}}\end{aligned}$$

Speech prior part (Environment independent)

Reverb part (Environment dependent)



	Matched			Mismatched		
	DNS-MOS	PESQ	ESTOI	DNS-MOS	PESQ	ESTOI
WPE	3.24	1.81	0.57	3.10	1.74	0.54
Buddy (w/ WPE)	**3.76**	**2.30**	**0.66**	**3.74**	**2.24**	**0.65**

Task: Single channel dereverberation (with no noise)

Future work: extension to more realistic scenarios with noisy reverberant mixtures

Concluding remarks

Dereverberation is now a solvable problem:

- Blind inverse filtering is applicable to unknown recording conditions
- NN can perform highly accurate dereverberation when training and test conditions well align

Future work:

- Enhancement of real conversation recordings is still challenging
  - Developing new techniques overcoming current limitations, and integrating various approaches could be the key to the solution

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