

# Spatial Voice Conversion: Voice Conversion Preserving Spatial Information and Non-target Signals



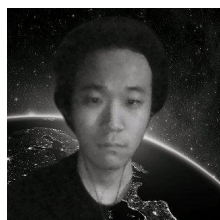
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# Overview of This Talk

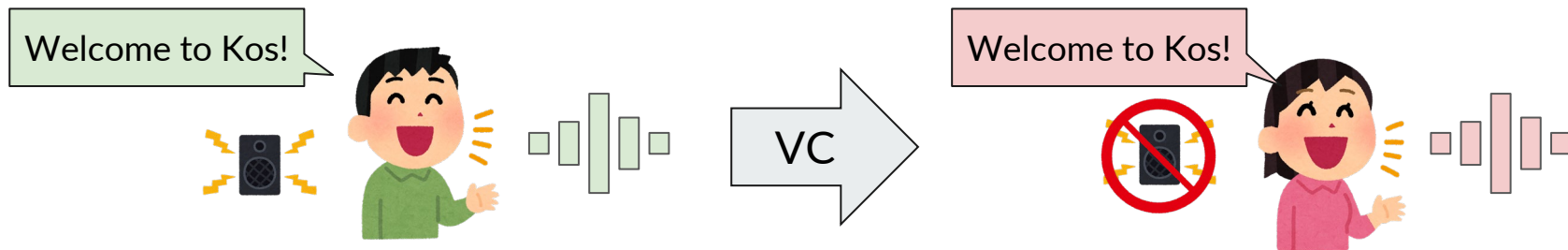
- We propose **a new task: Spatial Voice Conversion (Spatial VC)**
  - VC preserving spatial Information and non-target signals
- We propose **a baseline method** for spatia VC
  - **Combining BSS and VC** (BSS: blind source separation)
- We identify **key challenges** inherent in Spatial VC
  - Preserving spatial information may degrade audio quality

# Outline

1. **Background**
2. Problem description
3. Method
4. Experimental results and Analysis

# Background: Voice Conversion (VC)

- Convert speech to another speaker's speech (same linguistic content)
- Conventional studies tend to ...
  - Deal with **monaural** signal (single channel)
  - **Remove non-target audio** (e.g., background noise) [1]



# Background: Human Hearing

- **Stereo** hearing (not monaural)
  - Recognize **spatial information** (e.g., direction of the speaker)
- Even while focusing on a specific speech, **other signals are still processed**
  - For example, if an accident happens, we can recognize it
  - Non-target signals should not always be removed



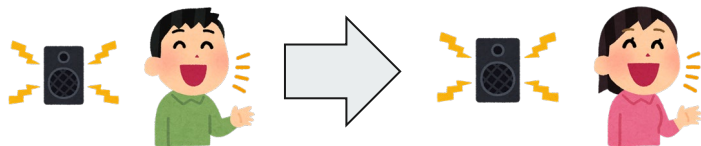
Recognize spatial information



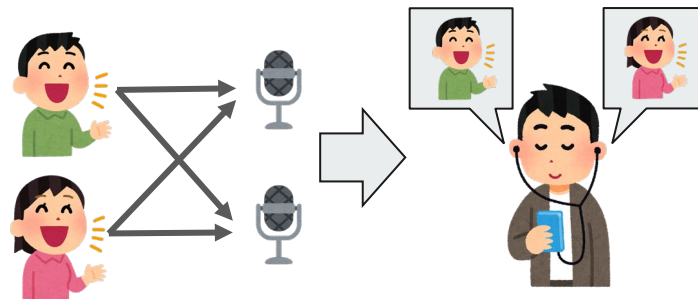
Process non-target signals

# Related works

- **Example 1: Noisy-to-noisy VC [2]**
  - Preserve noise in input signal (not removed)
- **Example 2: Stereo speech enhancement preserving spatial-cue [3]**
  - Apply speech enhancement to two speakers's mixed speech
  - Output left speaker's speech to left-ch (maintain spatial cue)
- **These studied are based on spatial information and non-target signals**



Noisy-to-noisy VC



Stereo speech enhancement

# Outline

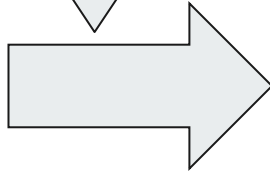
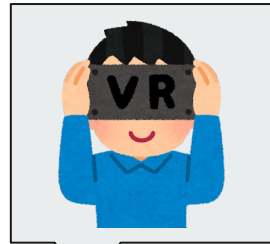
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# Goal: Spatial VC enables

- Talk with **virtual avatar** in **Mixed Reality** (MR)



Real world



Convert to **virtual avatar**

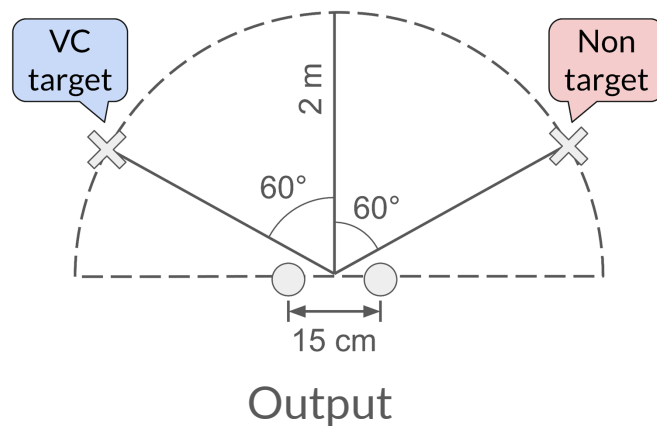
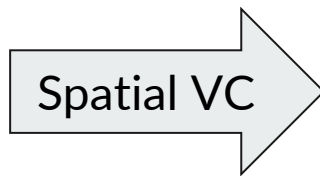
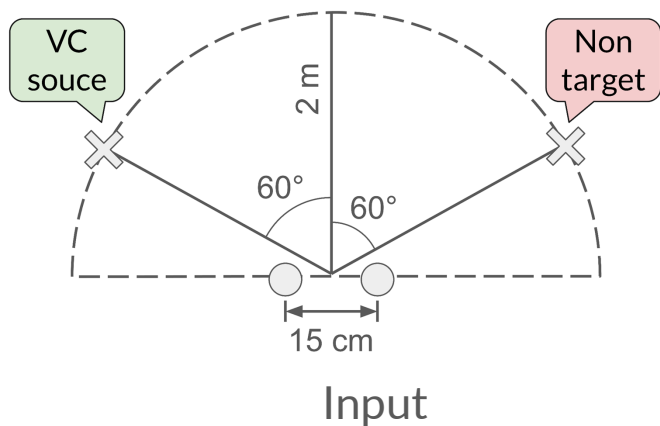


Mixed Reality



# Task Description

- **Input:** Recording of mixed speech (VC source + non target)
  - Multi-channel signal (containing spatial information)
- **Output:** Recording of mixed speech (VC target + non target)



# Problem Formulation

- **Input:** Sum of VC source speech and non-target signals

$$y_j(t) = h_{1j}(t) * x_1(t) + \sum_{i=2}^N h_{ij}(t) * x_i(t) \quad (j = 1, \dots, N)$$

- $x_1(t)$  : VC source speech,  $x_2(t), \dots, x_N(t)$ : Non-target signals
  - $h_{ij}(t)$ : Transfer function from i-th source to j-th microphone
- **Output:** Applying VC exclusively to VC source speech

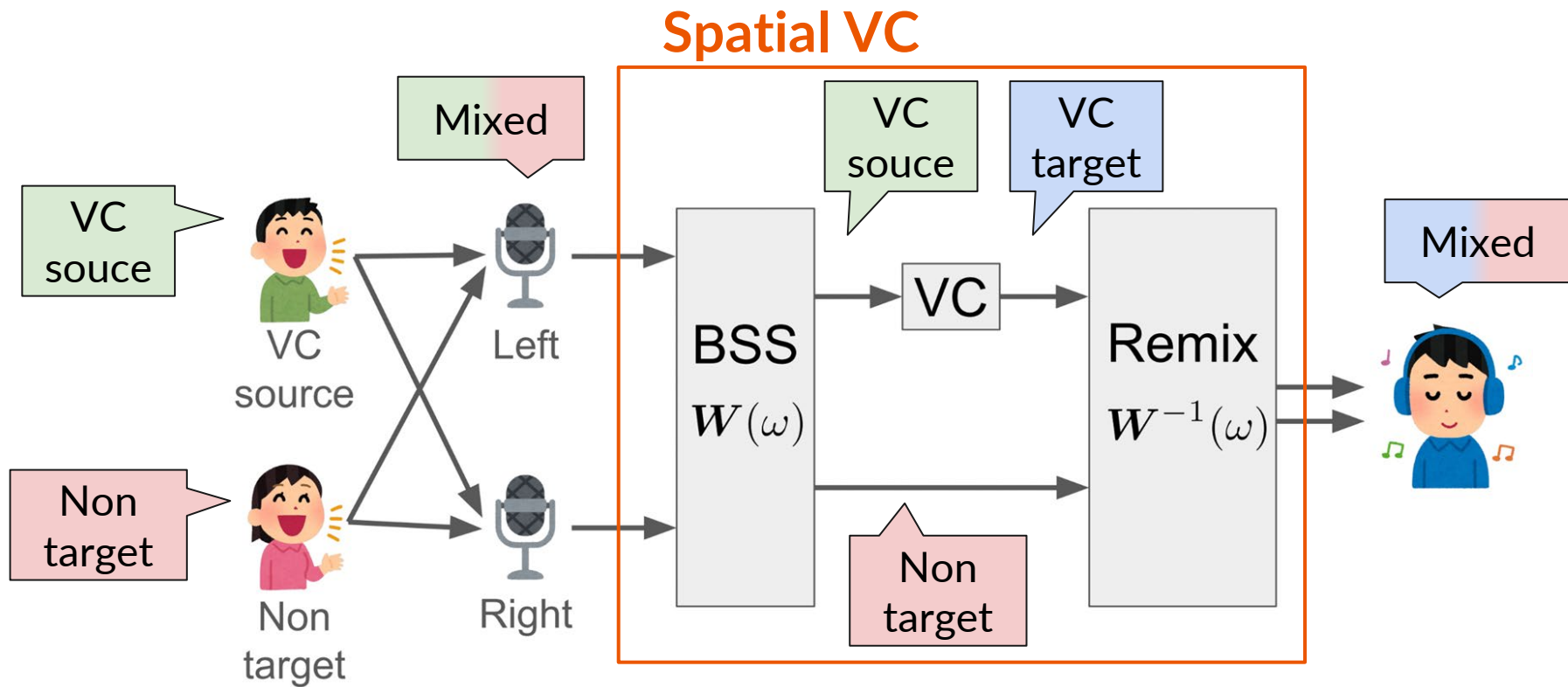
$$z_j(t) = h_{1j}(t) * \text{VC}[x_1(t)] + \sum_{i=2}^N h_{ij}(t) * x_i(t) \quad (j = 1, \dots, N)$$

- $\text{VC}[\cdot]$ : Voice Conversion

# Outline

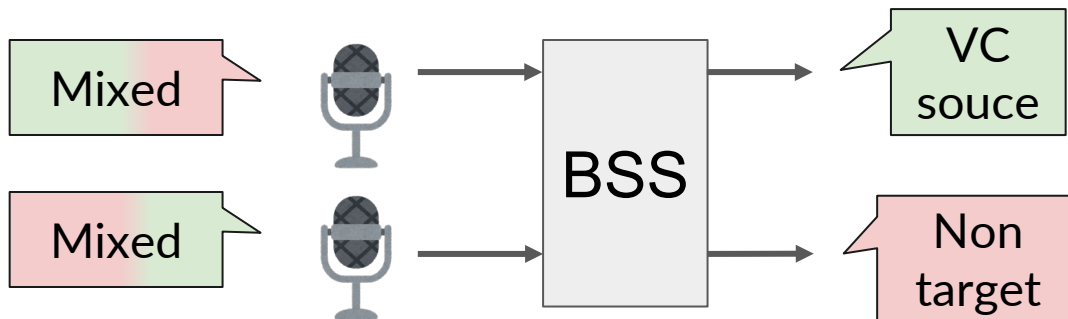
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# Method: Overview



# Method: Blind Source Separation (BSS)

- Purpose of this step
  - Enhance VC-source speaker's voice
  - Extract non-target signals (to preserve non-target information)
- Apply BSS to obtain each signal separately



# Method: Projection Back (in BSS)

- BSS is based on statistical independence, but cannot determine scale
- BSS output introduces a constant scaling factor (resulting in **distortion**)
- Projection Back: Determine scaling factor to reproduce microphone signal

By PB, we update separation matrix  $\mathbf{W}(\omega)$

minimize  $\mathbf{W}(\omega)$

New separation matrix

STFT of observed signals

STFT of 1st microphone

$$\mathbb{E} \left[ \left\| \mathbf{1}_N^\top \mathbf{W}(\omega) \mathbf{Y}(\omega, t) - Y_1(\omega, t) \right\|^2 \right],$$

Summation of separated signals

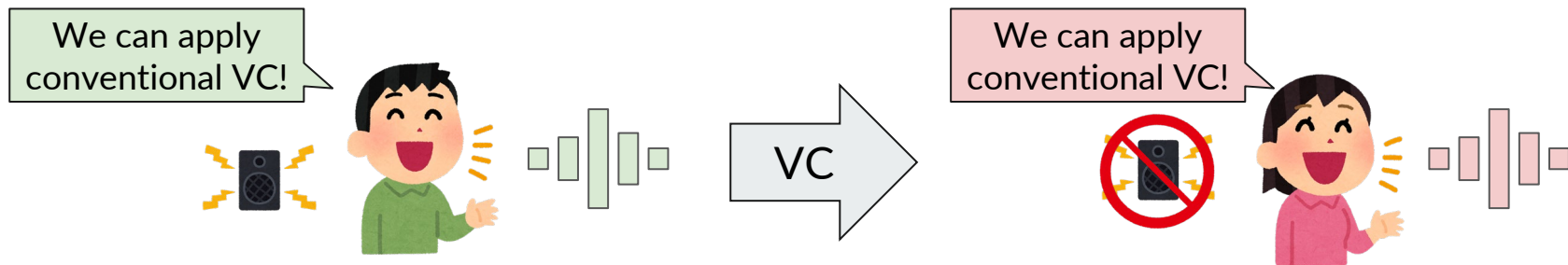
Separation matrix determined by BSS

subject to  $\exists k_1(\omega), \dots, k_N(\omega),$

$$\mathbf{W}(\omega) = \text{diag}\{k_1(\omega), \dots, k_N(\omega)\} \mathbf{V}(\omega)$$

# Method: Voice Conversion (VC)

- Apply VC to extracted VC source speaker's speech
- This step: noisy-to-clean setting
  - Non-target signals are extracted in another channel
  - This channel can remove non-target signal



# Method: Remix 1

- Simple approach: Apply **inverse matrix of separation matrix** ( $\hat{\mathbf{A}}(\omega) := \mathbf{W}(\omega)^{-1}$ )
  - “Mixing” is inverse process of “Separation”
  - Each component of  $\hat{\mathbf{A}}(\omega)$  is expected to be transfer function

$$\hat{\mathbf{Z}}(\omega, t) = \hat{\mathbf{A}}(\omega) \begin{bmatrix} \text{VC}[\hat{X}_1(\omega, t)] \\ \hat{\mathbf{X}}_{2:N}(\omega, t) \end{bmatrix}$$

- In reality, this may **degrade audio quality** of VC output!
  - After PB procedure,  $\hat{\mathbf{A}}(\omega)$  correspond to relative transfer function
    - From PB-target microphone to another microphone)
  - This implicitly include unstable inverse filter



# Method: Remix 2

- Another approach: Direct estimation of transfer function
  - We use **steering vector** as estimation
    - This model is based on the **direction of arrival** (DoA)
  - This model does **not account for other spatial factors**, (e.g., reverberation)
- For non-target signals, we apply inverse of separation matrix

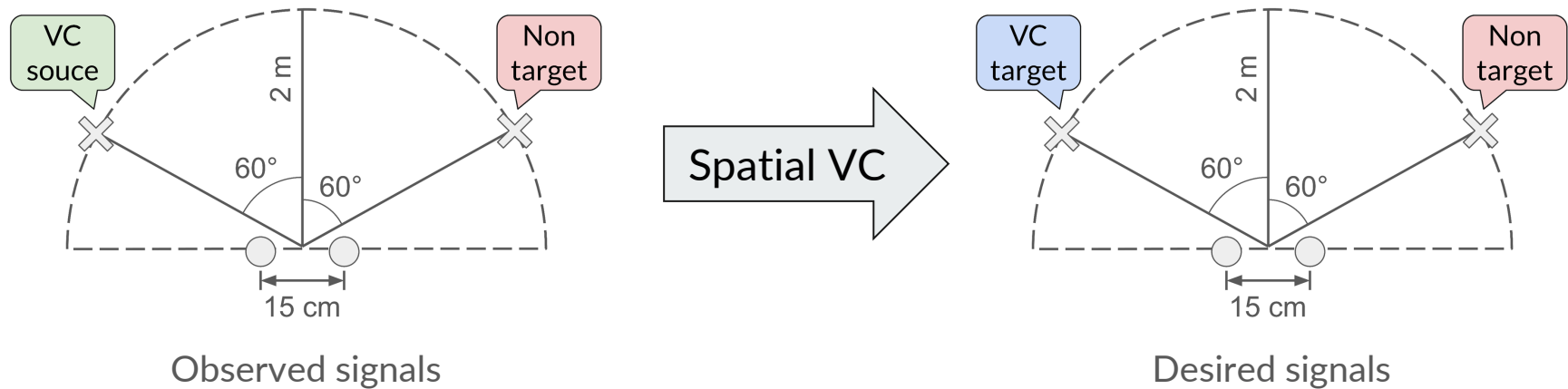
$$\hat{\mathbf{Z}}(\omega, t) = \begin{matrix} \text{Steering vector} \\ \boxed{\mathbf{d}(\omega)} \end{matrix} \hat{\mathbf{A}}_{2:N}(\omega) \begin{bmatrix} \text{VC}[\hat{\mathbf{X}}_1(\omega, t)] \\ \hat{\mathbf{X}}_{2:N}(\omega, t) \end{bmatrix}$$

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# Settings: Test Data

- Simulated with pyroomacoustics [4]
  - Reverberation time ( $RT_{60}$ ): Approx. 200ms
  - Speaker: Randomly sampled from 10 speakers in JVS corpus [5]



# Settings: Proposed Method

- **BSS: Geometrically Constrained Independent Vector Analysis (GC-IVA) [6]**
  - Features of GC-IVA:
    - Based on statistical independence of source signals
    - Utilize spatial regularization to specify VC-source speaker
  - Challenges in “Remixing” with inverse matrix:
    - Issues also arise with other BSS methods (e.g., ILRMA [7])
    - This problem is due to PB (common in linear BSS methods)
- **VC: DDSP-SVC [8]**
  - Open-source many-to-many voice conversion model

# Compared Methods

- Ideal: **Simulated** desired signal (for comparison)
- Inverse: **Spatial VC** using **inverse matrix** for remixing
  - Preserve spatial information, but degrade quality
- Steering: **Spatial VC** using **steering vector** for remixing
  - Maintain audio quality, but discard spatial information except DoA.

$$\hat{\mathbf{Z}}(\omega, t) = \hat{\mathbf{A}}(\omega) \begin{bmatrix} \text{VC}[\hat{\mathbf{X}}_1(\omega, t)] \\ \hat{\mathbf{X}}_{2:N}(\omega, t) \end{bmatrix}$$

Inverse

$$\hat{\mathbf{Z}}(\omega, t) = \mathbf{d}(\omega) \hat{\mathbf{A}}_{2:N}(\omega) \begin{bmatrix} \text{VC}[\hat{\mathbf{X}}_1(\omega, t)] \\ \hat{\mathbf{X}}_{2:N}(\omega, t) \end{bmatrix}$$

Steering

# Results: Acoustic Quality

- Calculated Mean Opinion Score (MOS) on naturalness
- “Inverse” exhibited a significantly lower score
  - Attributed to right channel (=other than PB target)
- **Indicating: Inverse matrix degrade audio quality**

Methods	Stereo	Monaural-Left (PB target)	Monaural-Right
Ideal	$4.254 \pm 0.060$	$4.062 \pm 0.060$	$4.102 \pm 0.058$
Inverse	$1.992 \pm 0.064$	$4.142 \pm 0.060$	$1.388 \pm 0.042$
Steering	$3.405 \pm 0.062$	$3.975 \pm 0.066$	$3.132 \pm 0.070$

MOS (↑)

# Results: Spatial Information

- Calculated Log-determinant divergence (LDD) [9] of spatial covariance matrix from “Ideal” to “Inverse” and “Steering”
  - Indicator for **accuracy of spatial information reproduction**
- “Inverse” is better than “Steering”
- **Indicating: Steering discards spatial information** (e.g., reverberation)

Methods	$RT_{60} \simeq 70 \text{ ms}$	$RT_{60} \simeq 200 \text{ ms}$	$RT_{60} \simeq 400 \text{ ms}$
Inverse	<b><math>0.468 \pm 0.074</math></b>	<b><math>0.979 \pm 0.147</math></b>	<b><math>2.058 \pm 0.270</math></b>
Steering	$1.990 \pm 0.367$	$3.097 \pm 0.552$	$4.666 \pm 0.535$

LDD (↓)

# Conclusion

- We proposed **a new task: Spatial Voice Conversion (Spatial VC)**
  - VC preserving spatial Information and non-target signals
- We proposed **a baseline method** for spatia VC
  - **Combining BSS and VC** (BSS: blind source separation)
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# Reference

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