**CHiME-8 Task 3 - MMCSG**
**ASR for multimodal conversations in smart glasses**

# The SEUEE System for the CHiME-8 MMCSG Challenge – Neural Directional Speech Extraction for ASR on Smart Glasses

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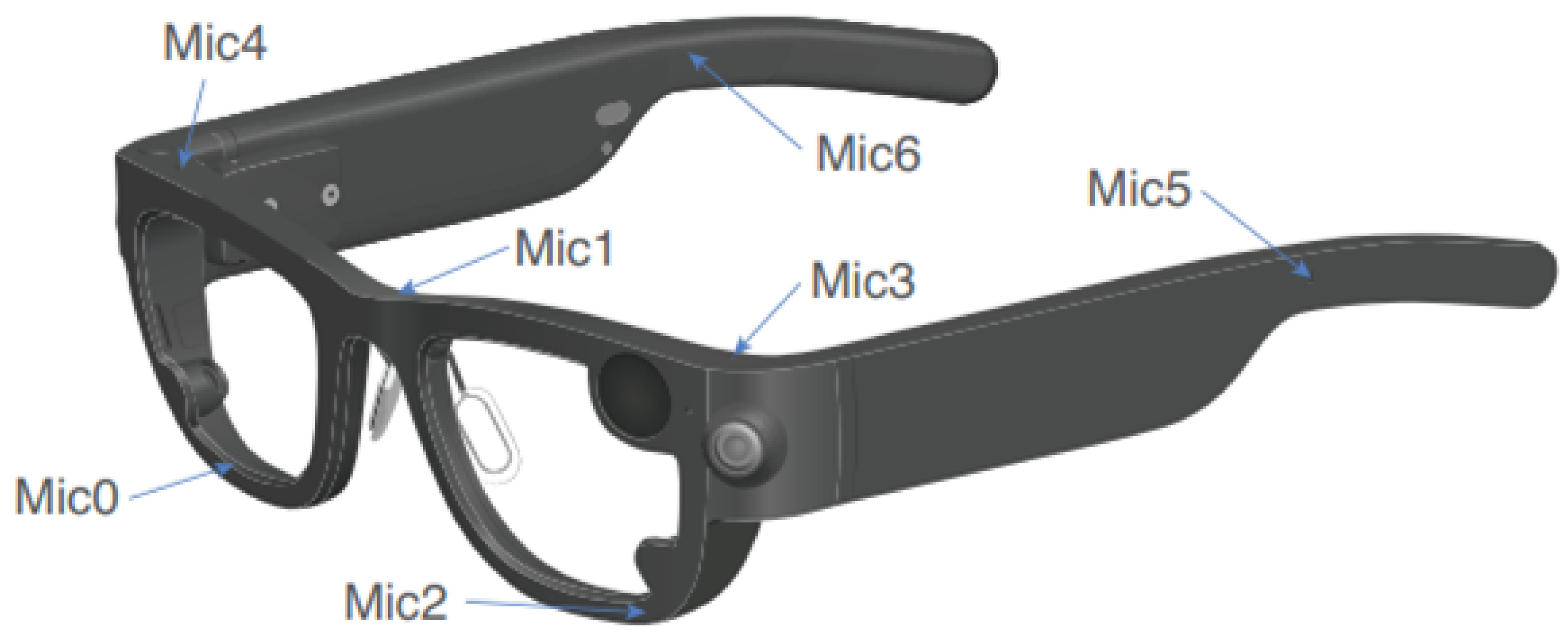
# 01 Introduction

The CHiME-8 MMCSG challenge focuses on transcribing both sides of a conversation where one participant is wearing smart glasses equipped with a microphone array and other sensors.



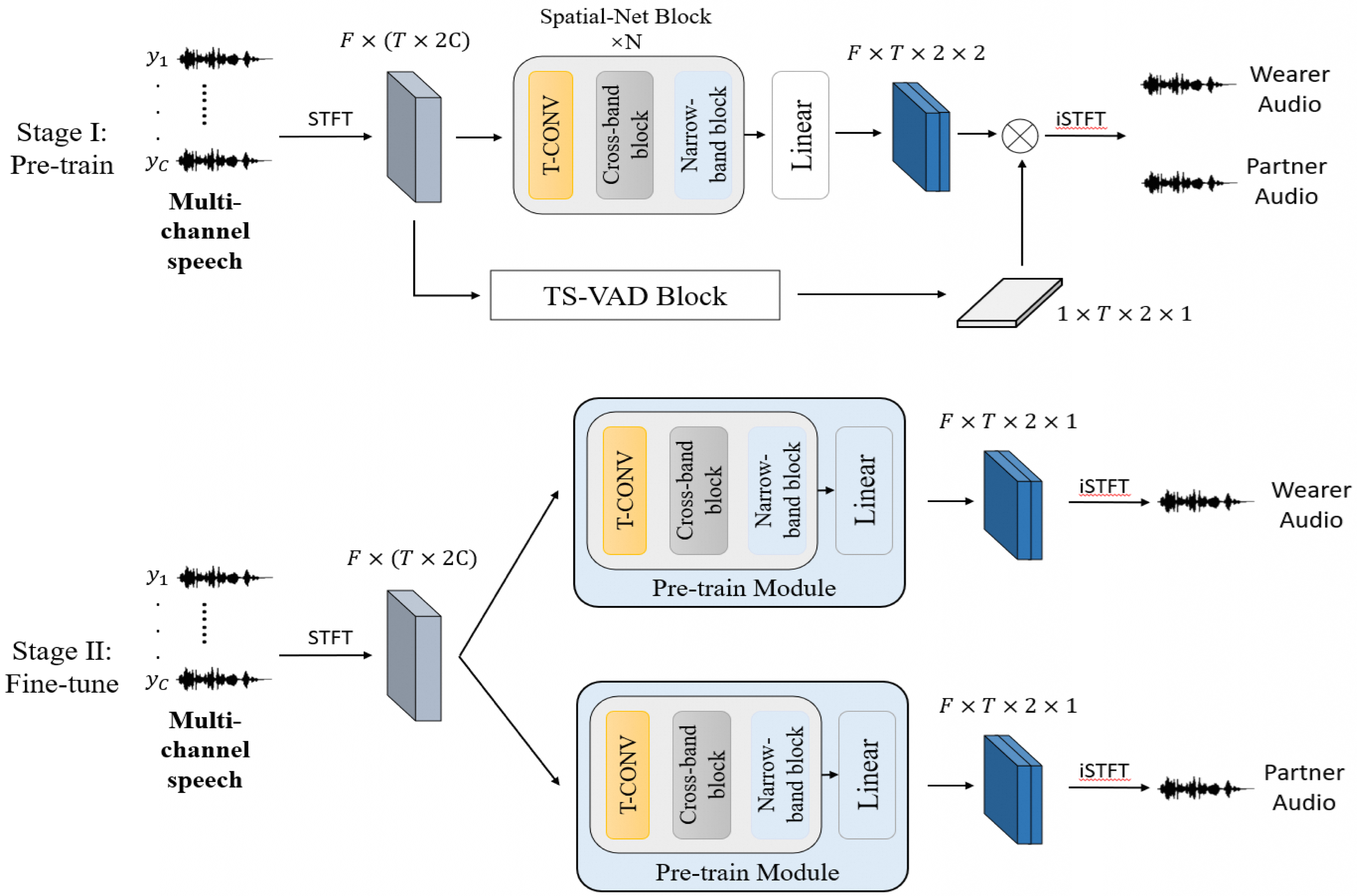

- We introduce our directional speech extraction (DSE) system for MMCSG task to extract the wearer and the partner audio

- *Submitted system*: based on SpatialNet [1] and target-speaker voice activity detection (TS-VAD) [2,3], we introduce a two-stage training strategy to stabilize the individual DSE models

- *Extension work*: we introduce direction features (DFs) and ASR-inspired loss function to constrain the DSE model

[1] C. Quan and X. Li, "SpatialNet: Extensively Learning Spatial Information for Multichannel Joint Speech Separation, Denoising and Dereverberation," in TASLP, 2024.
[2] M. Cheng, W. Wang, Y. Zhang, X. Qin, and M. Li, "TargetSpeaker Voice Activity Detection via Sequence-to-Sequence Prediction," in ICASSP, 2023.
[3] F. Liu, F. Xiong, Y. Hao, K. Zhou, C. Zhang, and J. Feng, "AS-pVAD: A Frame-Wise Personalized Voice Activity Detection Network with Attentive Score Loss," in ICASSP, 2023.

# 02 Submitted System for MMCSG




- **SpatialNet** exploit narrow-band and cross-band spatial information.
- **TS-VAD** is used to weight speech segments of different attributes. The entire module mainly includes multiple 2D convolutions and FT-LSTM blocks, and the module is trained jointly.
- **100h training dataset** is simulated[1,2,3]. Both wearer and partners' labeled speech are normalized to -25dBFS (16bits).
- **Two-stage training strategy** is introduced to stabilize the individual DSE models.
  - pre-train: obtain global spatial knowledge
  - fine tune: separating the one's speech from that of conversation others

[1]https://ai.meta.com/datasets/mcas-dataset/
[2]Librispeech: An ASR corpus based on public domain audio books
[3]ICASSP 2023 Deep Noise Suppression Challenge

# 03 Experiments

dev set

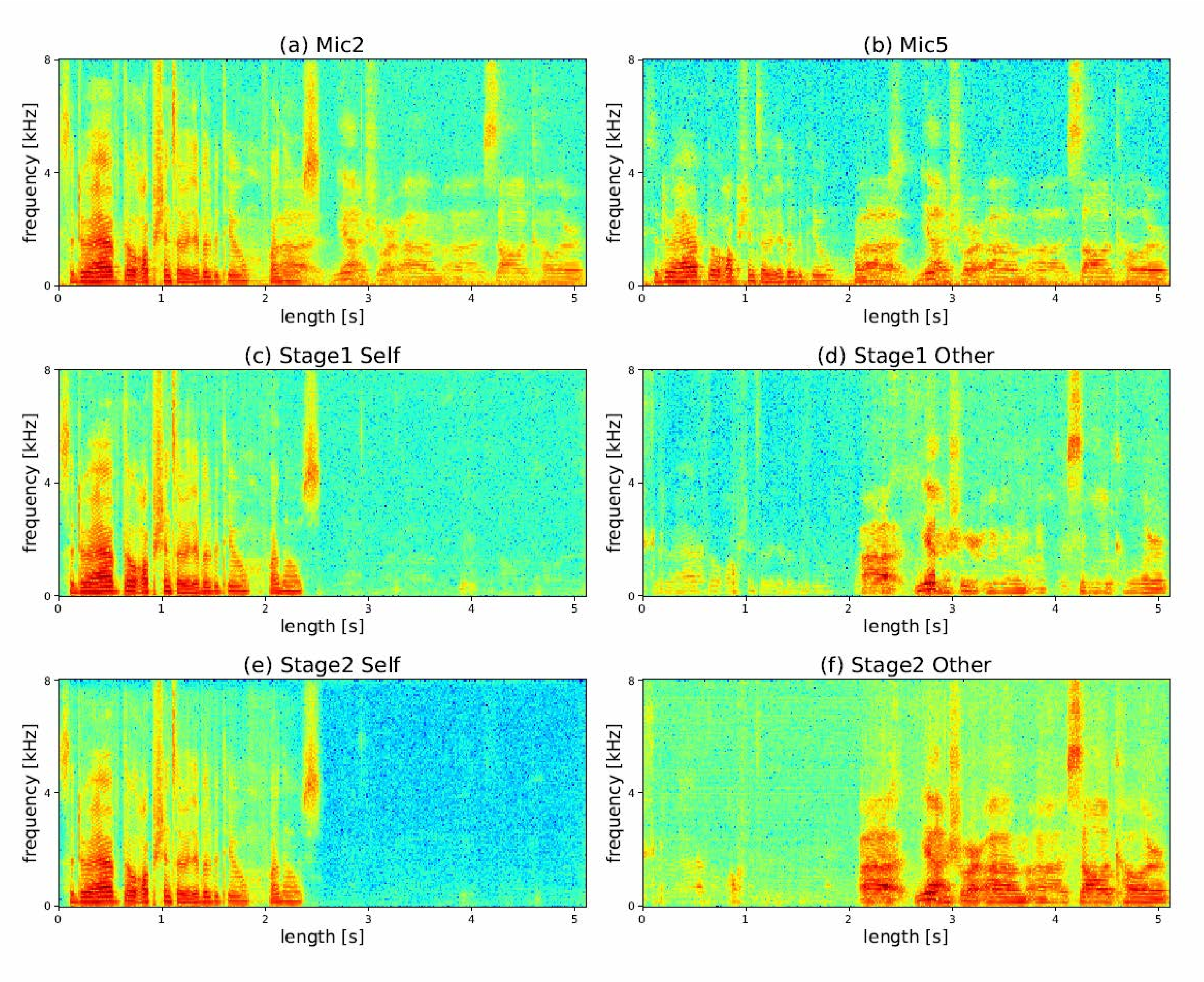
| Method | Latency [s] | SELF | | | | | OTHER | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | WER | INS | DEL | SUB | ATTR | WER | INS | DEL | SUB | ATTR |
| **Baseline** | 0.15 | 17.9 | 1.7 | 4.2 | 10.5 | 1.6 | 24.4 | 2.6 | 7.3 | 12.3 | 2.2 |
| | 0.34 | 15.0 | 1.4 | 3.9 | 8.4 | 1.4 | 21.4 | 2.2 | 7.2 | 10.1 | 1.8 |
| | 0.62 | 14.3 | 1.3 | 3.8 | 7.9 | 1.3 | 20.3 | 2.1 | 7.1 | 9.6 | 1.6 |
| **SEUEE** | >1.0 | **12.0** | 1.4 | 3.9 | 6.3 | 0.4 | **20.2** | 3.0 | 6.5 | 10.2 | 0.5 |

- Loss function:

$$\mathcal{L} = \alpha_1 \mathcal{L}_{\text{SiSNR}} + \alpha_2 \mathcal{L}_{STFT}(r).$$

- TS-VAD is helpful to obtain a robust pre-trained model
- SEUEE achieved a relative WER improvement of 16.43% (Self) and 0.49% (Other) over the baseline on development set

# 03 Experiments




Spectrograms of sample audio for the MMCSG task.

(a) Signal received by microphone 2.

(b) Signal received by microphone 5.

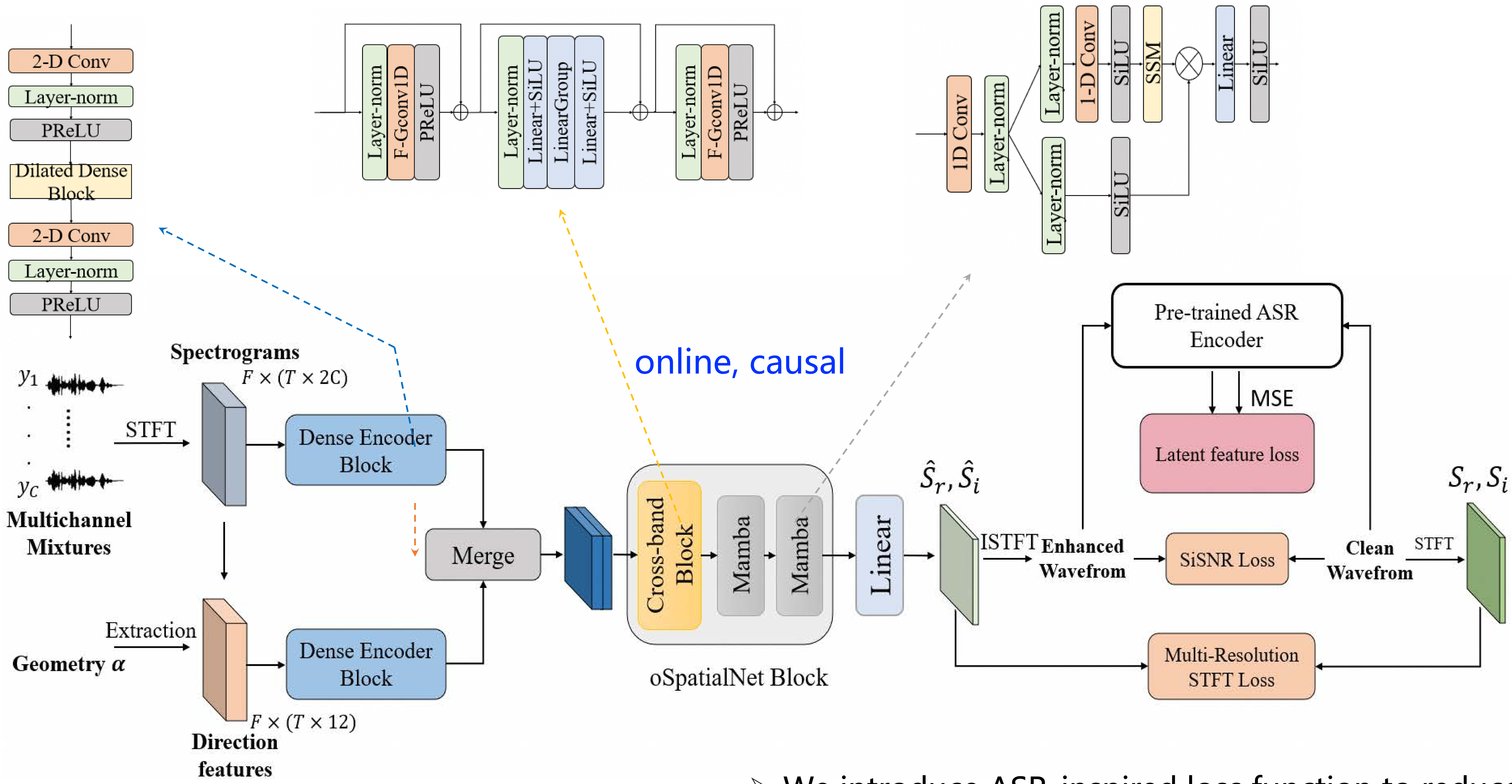
(c) The wearer's speech separated by the proposed model in stage 1.

(d) The partner's speech separated by the proposed model in stage 1.

(e) The wearer's speech separated by the proposed model in stage 2.

(f) The wearer's speech separated by the proposed model in stage 2.

# 04 Extension Work




- We introduce direction features (DFs) to enhance the spatial knowledge in feature dimension

- We introduce ASR-inspired loss function to reduce the distance between the clean and reconstructed latent representations from the pre-trained FastConformer Hybrid Transducer-CTC model [4]

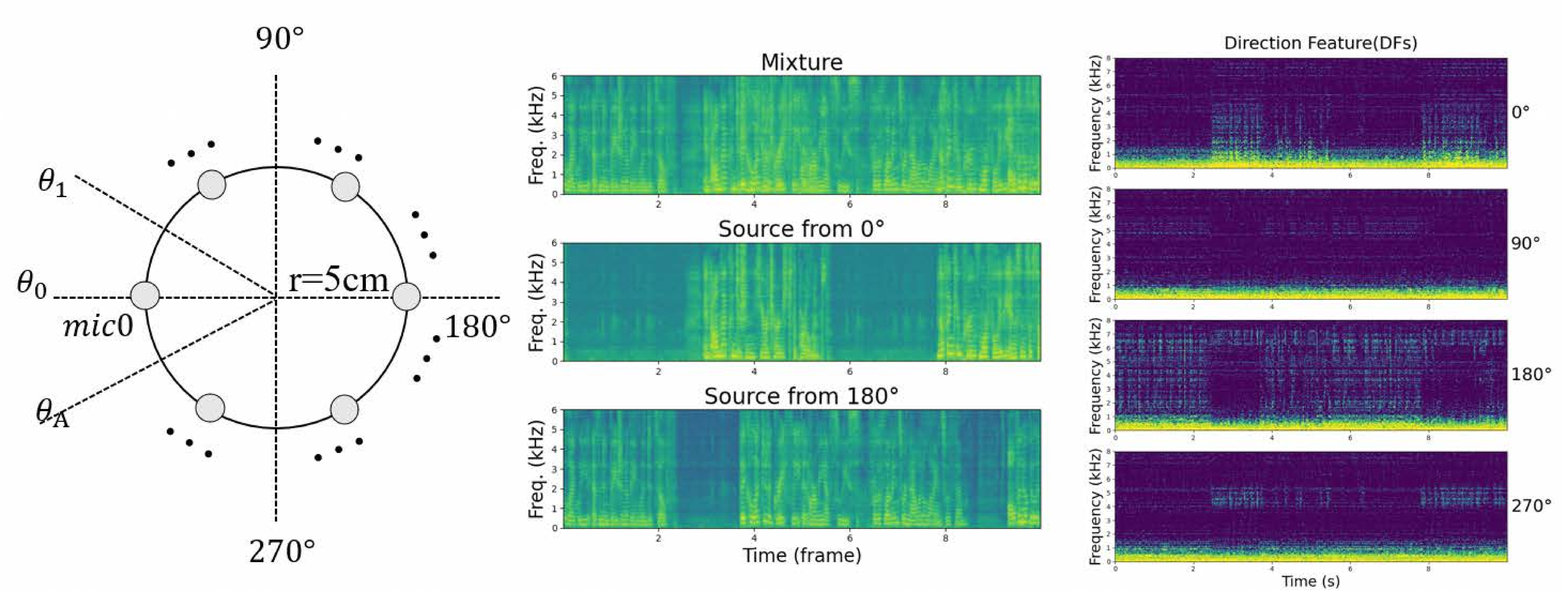
$$\mathcal{L}_{enc} = MSE(Enc_{ASR}(\hat{X}) - Enc_{ASR}(X))$$


[4] V. Bataev, R. Korostik, E. Shabalin, V. Lavrukhin, and B. Ginsburg, "Text-only domain adaptation for end-to-endasr using integrated text-to-mel-spectrogram generator," in INTERSPEECH 2023

# 04 Extension Work

- DFs trained to learn the directional knowledge representations to further assist the spectrograms to extract the speech from a specific direction (a-prior)

$$DF(\theta_i, t, f) = \sum_p \left\langle \mathrm{K}^{IPD^{(p)}(t,f)}, \mathrm{K}^{TPD^{(p)}(\theta,f)} \right\rangle, i = 1, 2, ..., M,$$




- cosine similarity between ideal phase difference and target-dependent phase difference
- target directions degree 0 and degree 180 more discriminative features from 1kHz – 8kHz

eval set

| Method | latency [s] | Overall WER | SELF WER | SELF ATTR | OTHER WER | OTHER ATTR |
|---|---|---|---|---|---|---|
| Baseline | 0.14 | 22.1 | 17.8 | 2.5 | 26.3 | 2.5 |
| | 0.33 | 18.9 | 15.0 | 2.4 | 22.9 | 2.2 |
| | 0.62 | 17.9 | 14.1 | 2.3 | 21.7 | 2.1 |
| **SEUEE** | >1.0 | 16.3 | 11.1 | 1.1 | 21.5 | **0.8** |
| **Extended** | 0.34 | **15.8** | **10.7** | **1.0** | **20.9** | 0.9 |

- Extended system: real-time, causal system, latency 0.34s
- Compared to our previously submitted system, a relative WER improvement of 3.6% (Self) and 2.8% (Other) is achieved on evaluation test set
- Overall WER: 15.8%; Self 10.7%, Other 20.9%
- Still very challenging for extracting partners' speech

# CHiME-8 Task 3 - MMCSG
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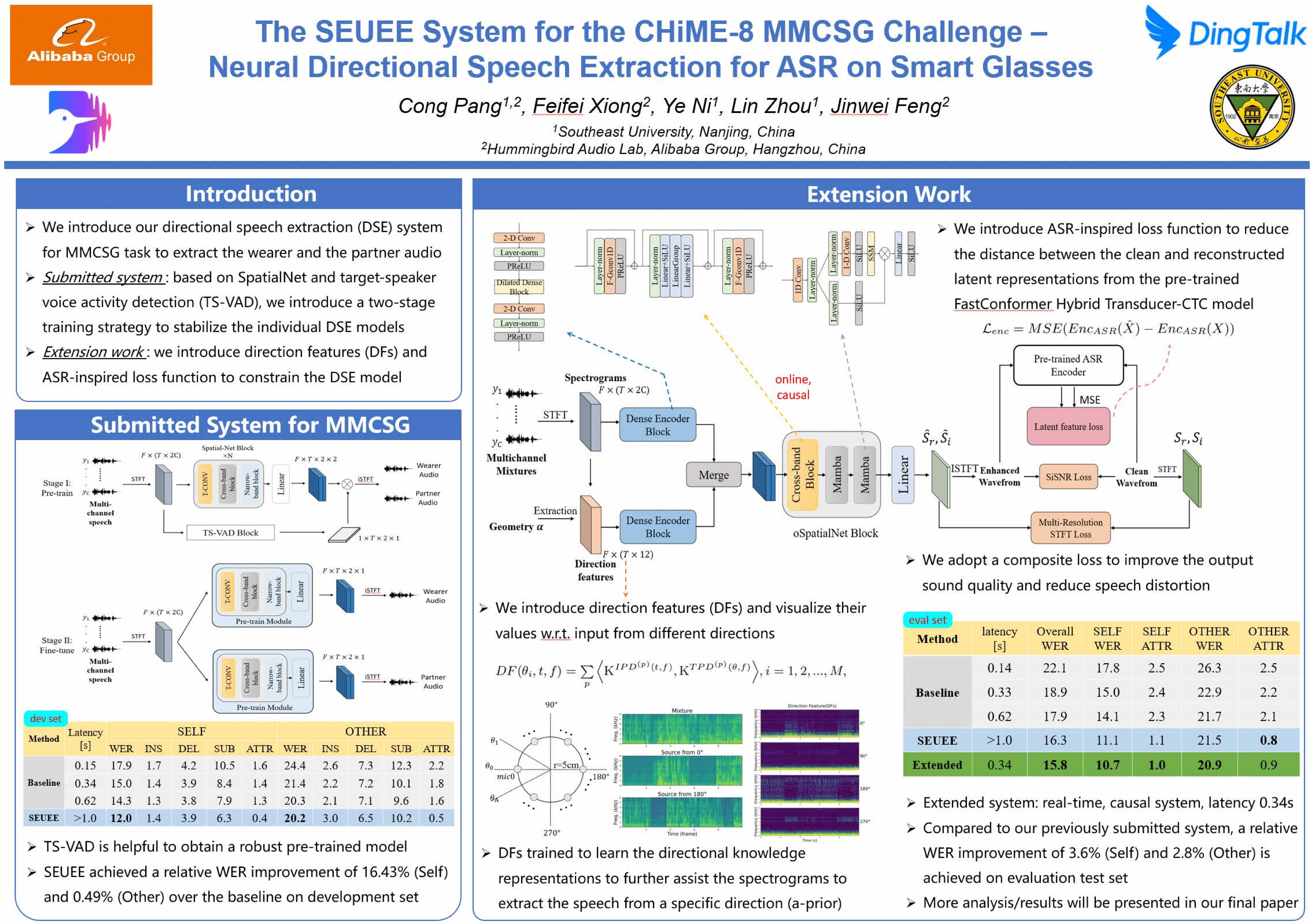
CHiME CHALLENGE

# Thank you for your listening!



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- *Submitted system*: based on SpatialNet and target-speaker voice activity detection (TS-VAD), we introduce a two-stage training strategy to stabilize the individual DSE models
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**Submitted System for MMCSG**

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- SEUEE achieved a relative WER improvement of 16.43% (Self) and 0.49% (Other) over the baseline on development set

**Extension Work**

- We introduce ASR-inspired loss function to reduce the distance between the clean and reconstructed latent representations from the pre-trained FastConformer Hybrid Transducer-CTC model

$$\mathcal{L}_{enc} = MSE(Enc_{ASR}(\hat{X}) - Enc_{ASR}(X))$$

- We adopt a composite loss to improve the output sound quality and reduce speech distortion
- We introduce direction features (DFs) and visualize their values w.r.t. input from different directions

$$DF(\theta_i, t, f) = \sum_p \left\langle K^{IPD^{(p)}(t,f)}, K^{TPD^{(p)}(\theta,f)} \right\rangle, i = 1, 2, ..., M,$$

- DFs trained to learn the directional knowledge representations to further assist the spectrograms to extract the speech from a specific direction (a-prior)

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- Extended system: real-time, causal system, latency 0.34s
- Compared to our previously submitted system, a relative WER improvement of 3.6% (Self) and 2.8% (Other) is achieved on evaluation test set
- More analysis/results will be presented in our final paper

Any questions please contact:

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