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Dual-branch Attention-In-Attention Transformer for single-channel speech enhancement

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Background

- In real acoustic environment, speech quality and intelligibility can be severely degraded by background noise.

- Supervised SE methods based on deep learning are mainly divided into time-frequency domain methods and time domain methods [1].

- The time-frequency domain methods mainly conduct masking and mapping on spectral magnitude or complex spectrum [2, 3].

- The time domain method directly map the clean waveform.

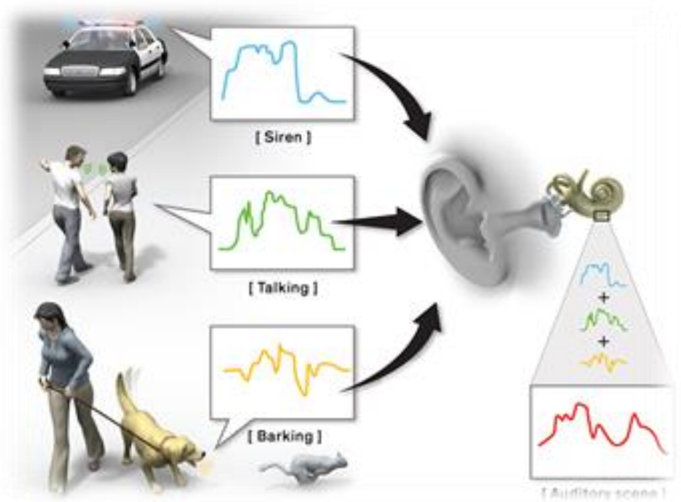

Figure 1: adverse acoustic environment

[1] D. L. Wang and J. Chen, “Supervised speech separation based on deep learning: An overview,” IEEE/ACM Trans. Audio. Speech, Lang. Process., , vol. 26, no. 10, pp. 1702–1726, 2018

[2] Y. Wang, A. Narayanan, and D. L. Wang, “On training targets for supervised speech separation,” IEEE/ACM Trans. Audio. Speech, Lang. Process., , vol. 22, no. 12, pp. 1849–1858, 2014

[3] Y. Xu, J. Du, L-R. Dai, and C-H. Lee, “A regression approach to speech enhancement based on deep neural networks,” IEEE/ACM Trans. Audio. Speech, Lang. Process., , vol. 23, no. 1, pp. 7–19, 2014.

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Background

The recovery of phase is important to improve speech perception quality. [4]

Complex spectrum based SE:
$$Y^{(r)}_{m,f} + iY^{(i)}_{m,f} = \left(S^{(r)}_{m,f} + N^{(r)}_{m,f}\right) + i\left(S^{(i)}_{m,f} + N^{(i)}_{m,f}\right),$$

1） complex ration mask （CRM）[5]

$$CRM = \frac{X_r S_r + X_i S_i}{X_r^2 + X_i^2} + j\frac{X_r S_i - X_i S_r}{X_r^2 + X_i^2} = \widetilde{M}_r + j\widetilde{M}_i$$

2） estimating real and imaginary components of complex spectrum [6]

[4] K. Paliwal, K. Wojcicki, and B. Shannon, “The importance of phase in speech enhancement,” Speech Commun, vol. 53, no.4, pp. 465–494, 2011.
[5] D. S. Williamson, Y. Wang, D. Wang, Complex ratio masking for monaural speech separation, IEEE/ACM Trans. Audio. Speech, Lang. Process., vol. 24, no. 3, pp. 483–492, 2015
[6] K. Tan and D. L. Wang, “Learning complex spectral mapping with gated convolutional recurrent networks for monaural speech enhancement,” IEEE/ACM Trans. Audio. Speech, Lang. Process., vol. 28, pp. 380–390, 2019

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Related works

Decoupling-style phase-aware SE methods:

Decouple the original complex spectrum optimization into magnitude and phase estimation, and two sub-network are utilized in a step-wise manner [7].

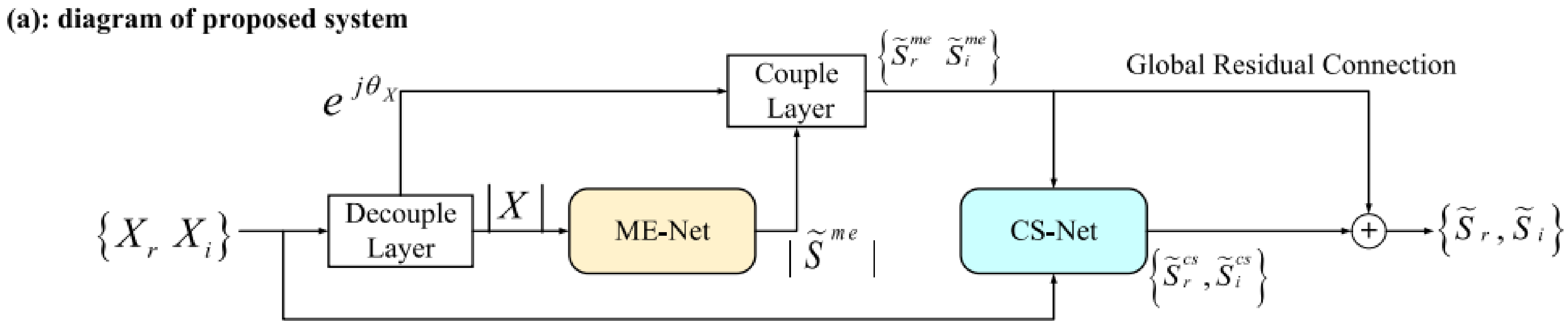

Fig 2：The diagram of CTS-Net [5], which consist of a magnitude estimation network (ME-Net) and a complex spectrum refine network (CS-Net)

[7] A. Li, W. Liu, C. Zheng, C. Fan, and X. Li, “Two Heads are Better Than One: A Two-Stage Complex Spectral Mapping Approach for Monaural Speech Enhancement,” IEEE/ACM Trans. Audio. Speech, Lang. Process., vol. 29, pp. 1829–1843, 2021.

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Related works

Transformer-based SE approaches:

Dual-path transformer has been developed for sequence modelling in speech area [8].

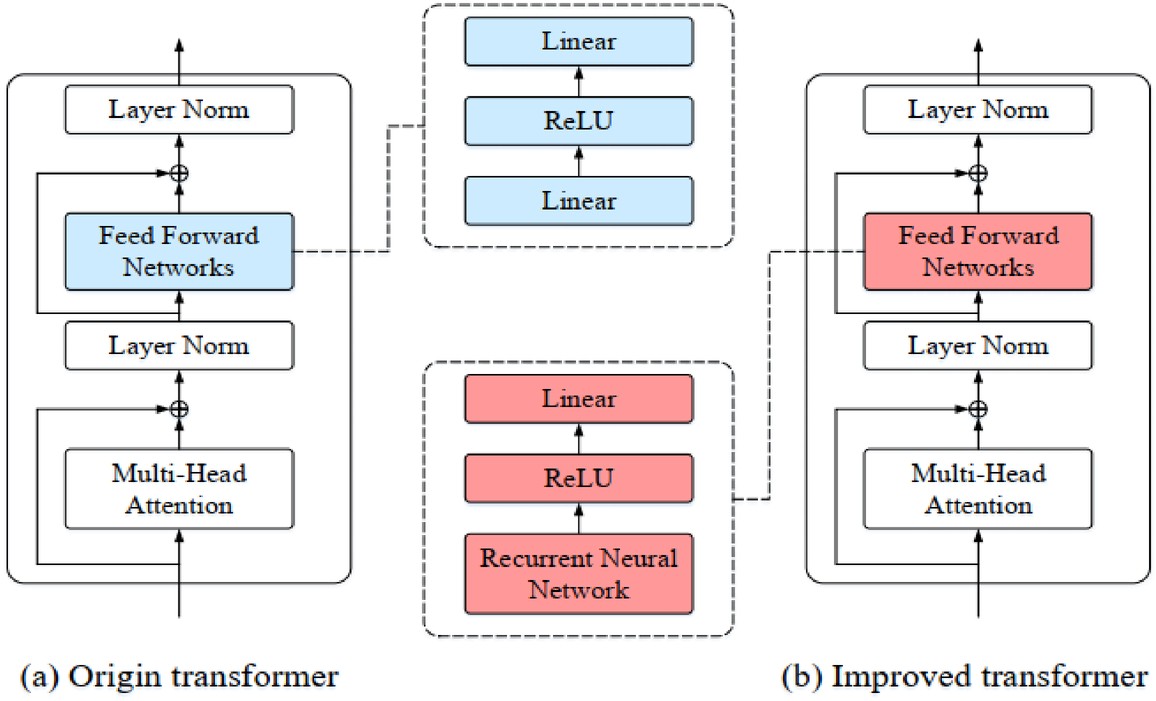

Fig 3: The diagram of dual-path transformer for speech separation

[8] J. Chen, Q. Mao, and D. Liu, "Dual-path transformer network: Direct context-aware modeling for end-to-end monaural speech separation," arXiv preprint arXiv:2007.13975, 2020.

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Proposed Method

Dual-branch Attention-In-Attention Transformer for single-channel SE

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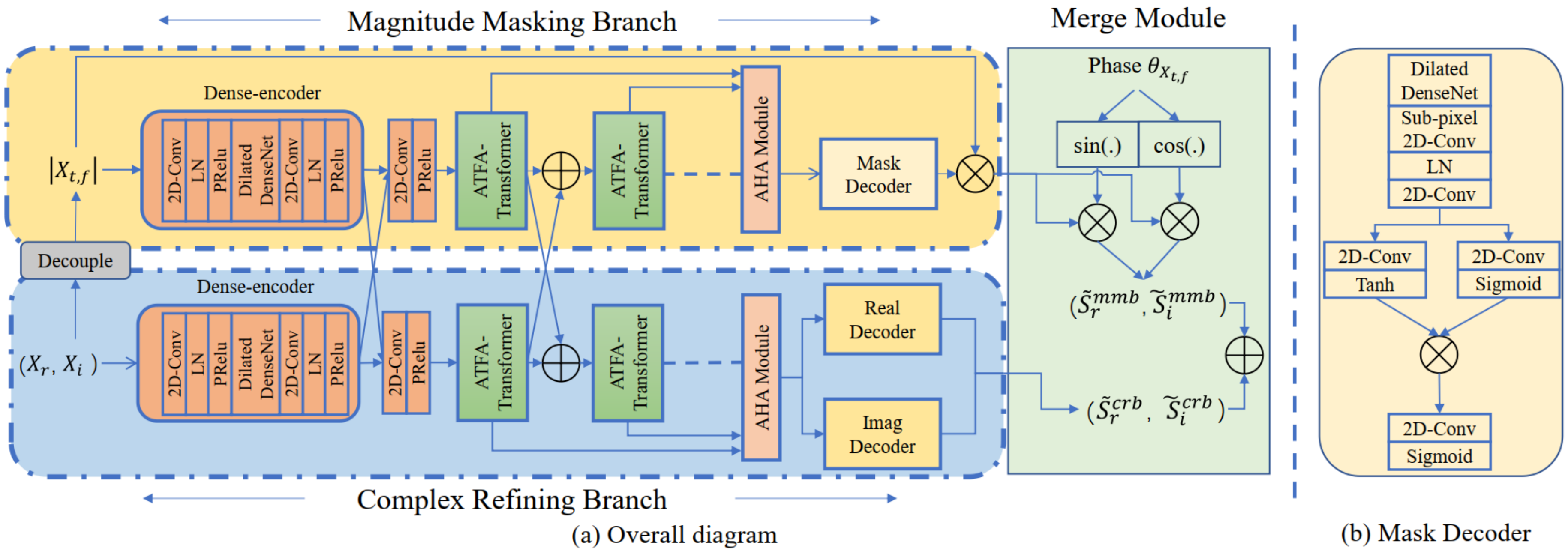

Fig 4： Proposed dual-branch system flowchart

- Two core branches are elaborately designed in parallel:
  - A magnitude masking branch (MMB): filtering out most of the noise in the magnitude domain.
  - A complex refining branch (CRB): compensate for the lost spectral details and implicitly recover phase in the complex domain

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Proposed Method

- MMB path estimates the magnitude mask to coarsely recover the magnitude of the target speech, and the coarsely estimated spectral magnitude is coupled with the noisy phase.

- CRB path receives noisy real and imaginary (RI) components as the input and focuses on the residual fine-grained spectral structures which is lost in MMB.

- Finally, we sum the coarse-denoised complex spectrum in MMB and the fine-grained complex spectral details in CPB together to reconstruct the clean complex spectrum

- The training procedure can be expressed as:

$$\left|\tilde{S}^{mmb}\right| = \left|X_{t,f}\right| \otimes M^{mmb} \tag{1}$$

$$\tilde{S}_r^{mmb} = \left|\tilde{S}^{mmb}\right| \otimes \cos(\theta_X) \tag{2}$$

$$\tilde{S}_i^{mmb} = \left|\tilde{S}^{mmb}\right| \otimes \sin(\theta_X) \tag{3}$$

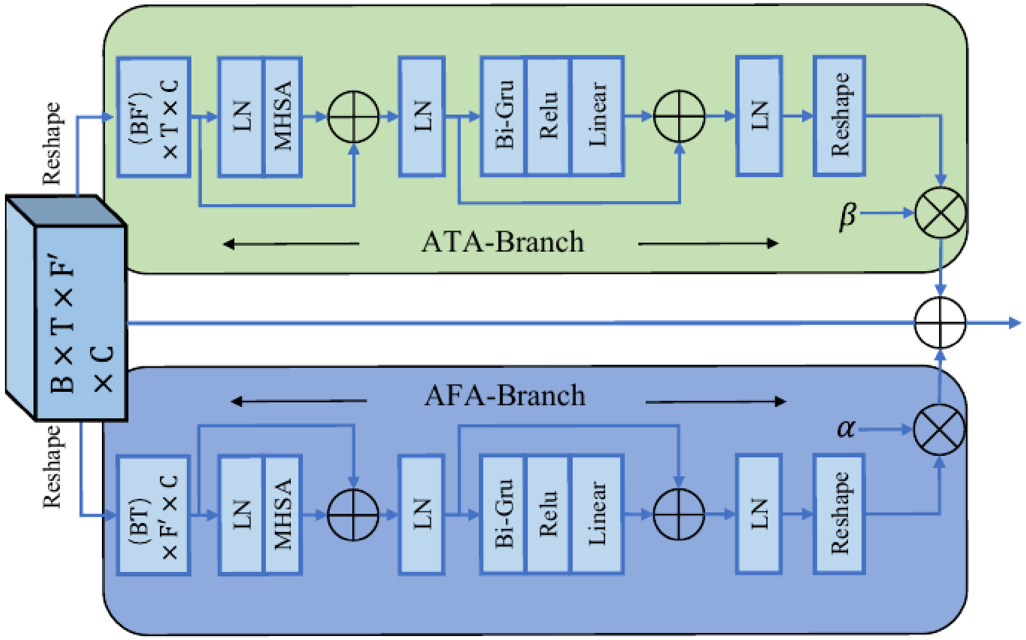
$$\tilde{S}_r = \tilde{S}_r^{mmb} + \tilde{S}_r^{crb} \tag{4}$$

$$\tilde{S}_i = \tilde{S}_i^{mmb} + \tilde{S}_i^{crb} \tag{5}$$

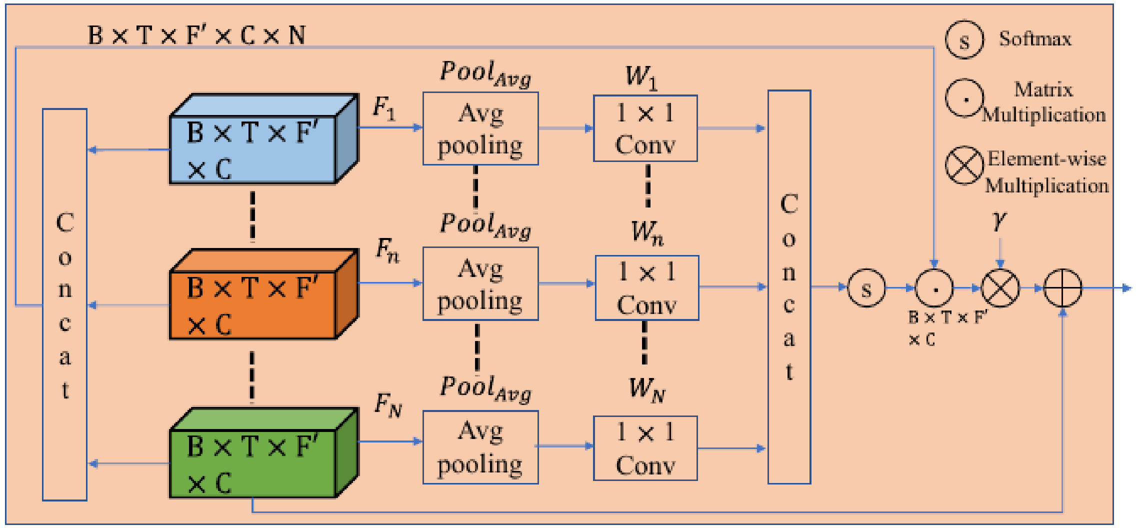
Proposed Method

Attention-in-attention transformer:

consists of four adaptive time-frequency attention transformer-based (ATFA-T) blocks and an adaptive hierarchical attention (AHA) module.



(a)



(b)

Fig 5: The diagram of ATFA-T blocks

Fig 6: The diagram of AHA module

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Proposed Method

- The loss function of the proposed dual-branch model:

$$L^{Mag} = \left\| \sqrt{\left|\tilde{S}_r\right|^2 + \left|\tilde{S}_i\right|^2} - \sqrt{\left|S_r\right|^2 + \left|S_i\right|^2} \right\|_F^2 \tag{6}$$

$$L^{RI} = \left\| \tilde{S}_r - S_r \right\|_F^2 + \left\| \tilde{S}_i - S_i \right\|_F^2 \tag{7}$$

$$L_{FULL} = L^{Mag} + L^{RI} \tag{8}$$

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Experiments and Analysis

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Dataset

- Corpus: Voice Bank [9], which includes 28 speakers for training and 2 unseen speakers for testing.

- Training set

  - ✓ 11572 utterances from 28 speakers (14 male and 14 female)

  - ✓ ten environmental noise from DEMAND database [10], mixed at 0, 5,10, 15 dB.

- Test set ：

  - ✓ 824 utterances from 2 unseen speakers

  - ✓ SNRs and Noises: five unseen environmental mixed at 2.5, 7.5, 12.5, 17.5 dB.

[9] C. Veaux, J. Yamagishi, and S. King, “The voice bank corpus: Design, collection and data analysis of a large regional accent speech database,” in Proc. O-COCOSDA/CASLRE. IEEE, 2013, pp. 1–4.
[10] J. Thiemann, N. Ito, and E. Vincent, “The diverse environments multichannel acoustic noise database: A database of multichannel environmental noise recordings,” Acoustical Society of America Journal, vol. 133, no. 5, pp. 3591, 2013.

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Experiments and Analysis

Experimental setup:

- Sampling rate: 16kHz

- STFT Window size: 320 samples (20ms), Overlap: 160 samples (10ms), 161-dimensional STFT spectrum

- Power compression [11]: compression coefficient η is set to 0.5 towards magnitude. Input feature:

$$Cat\left(|X|^{0.5}\cos\left(\theta_X\right), |X|^{0.5}\sin\left(\theta_X\right)\right)$$

- β_1=0.9， β_2=0.999 in Adam[12] with with the learning rate of 5e-4.

- 80 epochs for training, and the batch size is set to 4.

[11] A. Li, C. Zheng, R. Peng, and X. Li, "On the importance of power compression and phase estimation in monaural speech dereverberation," JASA Express Letters, vol. 1, no. 1, pp. 014802, 2021
[12] D. Kingma and J. Ba, "Adam: A method for stochastic optimization," arXiv preprint arXiv:1412.6980, 2014.

Experiments and Analysis

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- Baselines:

  Magnitude domain baselines:

  - MMSE-GAN, MetriGAN, CRGAN, RDL-Net, MetriGAN+

  Time domain baselines:

  - SEGAN, SERGAN, MHSA-SPK, TSTNN, Demucs, SE-Conformer

  Complex domain baselines:

  - DCCRN, TGSA

  Decoupling-style baselines:

  - GAG-NET, PHASEN

- Evaluation metrics:
  - PESQ, STOI, segmental signal-to-noise ratio (SSNR)
  - The MOS prediction of speech distortion (CSIG), background noise (CBAK) and overall effect (COVL).[13]

[13] Y. Hu and P. C. Loizou, “Evaluation of objective quality measures for speech enhancement,” IEEE/ACM Trans. Audio. Speech, Lang. Process., vol. 16, no. 1, pp. 229–238, 2007.

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Experimental Results

Table 1: Comparison with other state-of-the-art methods including time and T-F domain methods.

Methods	Year	Feature type	Param.	PESQ	STOI(%)	CSIG	CBAK	COVL	SSNR
Noisy	–	–	–	1.97	92.1	3.35	2.44	2.63	1.68
SOTA time and T-F Domain approaches									
SEGAN [24]	2017	Waveform	43.2 M	2.16	92.5	3.48	2.94	2.80	7.73
MMSEGAN [25]	2018	Gammatone	–	2.53	93.0	3.80	3.12	3.14	–
MetricGAN [26]	2019	Magnitude	1.86 M	2.86	–	3.99	3.18	3.42	–
CRGAN [27]	2020	Magnitude	–	2.92	94.0	4.16	3.24	3.54	–
DCCRN [8]	2020	RI components	3.7 M	2.68	93.7	3.88	3.18	3.27	8.62
RDL-Net [28]	2020	Magnitude	3.91 M	3.02	93.8	4.38	3.43	3.72	–
PHASEN [29]	2020	Magnitude+Phase	–	2.99	–	4.21	3.55	3.62	10.18
MHSA-SPK [30]	2020	Waveform	–	2.99	–	4.15	3.42	3.53	–
T-GSA [31]	2020	RI components	–	3.06	93.7	4.18	3.59	3.62	10.78
TSTNN [10]	2021	Waveform	0.92 M	2.96	95.0	4.17	3.53	3.49	9.70
DEMUCS [11]	2021	Waveform	128 M	3.07	95.0	4.31	3.40	3.63	–
GaGNet [13]	2021	Magnitude+RI	5.94 M	2.94	94.7	4.26	3.45	3.59	9.24
MetricGAN+ [32]	2021	Magnitude	–	3.15	–	4.14	3.16	3.64	–
SE-Conformer [33]	2021	Waveform	–	3.13	95.0	4.45	3.55	3.82	–
Proposed approaches									
MMB-AIAT	2021	Magnitude	0.90 M	3.11	94.9	4.45	3.60	3.79	9.74
CRB-AIAT	2021	RI components	1.17 M	3.15	94.7	4.48	3.54	3.81	8.81
DB-AIAT	2021	Magnitude+RI	2.81 M	**3.31**	**95.6**	**4.61**	**3.75**	**3.96**	**10.79**

- when only either single-path is adopted, MMB-AIAT and CRB-AIAT achieves competitive performance compared with advanced single-branch baselines.

- By simultaneously adopting two branches in parallel, DB-AIAT consistently surpasses existing SOTA time and T-F domain methods in terms of most metrics.

Experimental Results

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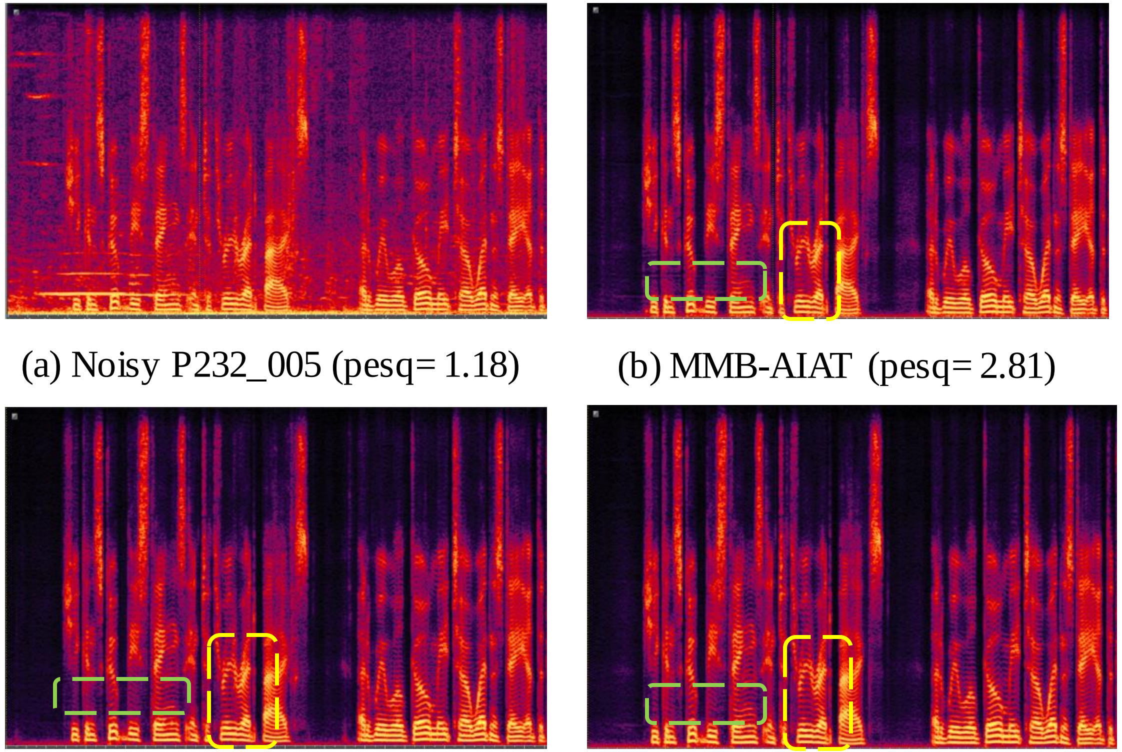
Table 2： Ablation study on dual-branch strategy and attention-in-attention transformer structure.

Models	ATAB /AFAB	AHA	PESQ	STOI(%)	CSIG	CBAK	COVL
Unprocessed	–	–	1.97	92.1	3.35	2.44	2.63
Single-Branch approaches							
MMB-ATFAT	✓/✓	✗	3.05	94.6	4.37	3.53	3.71
MMB-AIAT	✓/✓	✓	3.11	94.9	4.45	3.60	3.79
CRB-ATFAT	✓/✓	✗	3.07	94.5	4.40	3.52	3.72
CRB-AIAT	✓/✓	✓	3.15	94.7	4.48	3.54	3.81
Dual-Branch approaches							
DB-ATAT	✓/✗	✗	2.82	94.2	4.17	3.29	3.47
DB-AFAT	✗/✓	✗	2.93	94.4	4.28	3.31	3.63
DB-ATFAT	✓/✓	✗	3.18	95.0	4.50	3.68	3.86
DB-AIAT	✓/✓	✓	3.31	95.6	4.61	3.75	3.96



(a) Noisy P232_005 (pesq= 1.18)

(b) MMB-AIAT (pesq= 2.81)

(c) CRB-AIAT (pesq= 2.85)

(d) DB-AIAT (pesq= 3.19)

Fig 7： Visualization of the spectrograms.

- The proposed attention-in-attention transformer significantlt improve speech quality.
- Merging two branches can collaboratively facilitate the spectrum recovery from the complementary perspective.

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01 Introduction

02 Related works

03 Proposed Method

04 Experiments and Analysis

05 Conclusion

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Conclusion

- We propose a dual-branch transformer-based method to collaboratively recover the clean complex spectrum from the complementary perspective.
- A magnitude masking branch (MMB) is designed to coarsely estimate the magnitude spectrum of clean speech, and the residual spectral details are derived in parallel by a complex refining branch (CRB).
- We propose an attention-in-attention transformer (AIAT) to capture long-range temporal-frequency dependencies and aggregate global hierarchical contextual information
- Experimental results show that DB-AIAT yields state-of-the-art performance (3.31 PESQ, 95.6% STOI and 10.79dB SSNR) over previous advanced systems with a relatively small model size (2.81M).