

UNIFYING SPEECH ENHANCEMENT AND SEPARATION WITH GRADIENT MODULATION FOR END-TO-END NOISE-ROBUST SPEECH SEPARATION

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ABSTRACT

Recent studies in neural network-based monaural speech separation (SS) have achieved a remarkable success thanks to increasing ability of long sequence modeling. However, they would degrade significantly when put under realistic noisy conditions, as the background noise could be mistaken for speaker’s speech and thus interfere with the separated sources. To alleviate this problem, we propose a novel network to unify speech enhancement and separation with gradient modulation to improve noise-robustness. Specifically, we first build a unified network by combining speech enhancement (SE) and separation modules, with multi-task learning for optimization, where SE is supervised by parallel clean mixture to reduce noise for downstream speech separation. Furthermore, in order to avoid suppressing valid speaker information when reducing noise, we propose a gradient modulation (GM) strategy to harmonize the SE and SS tasks from optimization view. Experimental results show that our approach achieves the state-of-the-art on large-scale Libri2Mix- and Libri3Mix-noisy datasets, with SI-SNRi results of 16.0 dB and 15.8 dB respectively. Our code is available at GitHub¹.

Index Terms— Unify speech enhancement and separation, gradient modulation, noise-robust speech separation, multi-task learning, end-to-end network

1. INTRODUCTION

Recent progress in neural network-based monaural speech separation (SS) has achieved a remarkable success in time-domain methods [1–5], thanks to the increasing long sequence modeling ability of dilated CNN, RNN and Transformer [6]. As a result, the time-domain methods outperform conventional time-frequency domain methods and achieve state-of-the-art on various benchmarks.

However, their performance would degrade significantly when put under the real-world noisy conditions. The reason could be that some background noise is mistaken for speaker’s speech and thus interferes with the separated sources [7], just like we humans also get confused under noisy mixture scenes. Current studies on end-to-end noise-robust speech separation are quite limited.

Speech enhancement (SE) [8] has been proved effective in reducing noise from the noisy speech to improve speech quality for many downstream tasks, *e.g.*, automatic speech recognition [9–14], with multi-task learning to make full use of the clean supervision information [15]. Nevertheless, such joint network could also bring another over-suppression problem [16, 17] where SE suppresses some important speech information together with the background noise, resulting in sub-optimal performance for downstream tasks. From the optimization view, there could exist conflicts between the gradients of SE task and downstream tasks, which would hinder the multi-task learning and degrade the downstream task performance.

In this paper, we propose a novel network to unify speech enhancement and separation with gradient modulation for end-to-end noise-robust speech separation. Specifically, we first build a unified network by combining speech enhancement and separation modules, where the front-end SE serves to reduce noise for back-end speech separation. Multi-task learning strategy is employed to make full use of the supervision information in parallel clean mixture, which is available in most benchmark datasets since they usually create noisy mixtures by simulation. Furthermore, in order to avoid suppressing valid speaker information when reducing noise, we propose a gradient modulation (GM) strategy to harmonize the SE and SS tasks from optimization view. Experimental results indicate that our proposed approach improves the noise-robustness of speech separation model and significantly outperforms the previous state-of-the-arts. To the best of our knowledge, this is the first exploration to unify speech enhancement and separation with harmonized multi-task learning.

2. PROPOSED METHOD

2.1. System Overview

In this work, we first build a unified network in Figure 1 with multi-task learning for optimization, where the SE module is supervised by parallel clean mixture to reduce noise for back-end speech separation. However, we observe that apart from noise, the SE module can also suppress some valid speaker information, *i.e.*, over-suppression problem [16], which may degrade the downstream SS performance. From the optimization view, there exists some conflicts between the gradients of SE and SS tasks, which would hinder the multi-task learning and finally lead to sub-optimal SS performance. To this end, we propose a gradient modulation strategy to harmonize the two task gradients and thus alleviate the over-suppression problem.

2.2. Unified Network

2.2.1. Architecture

Inspired by the popular mask-learning framework [1–4], we design a unified network that consists of an encoder, a speech enhancement (SE) network, a speech separation (SS) network and a decoder, as shown in Figure 1. The encoder first learns deep representations of the input mixtures. The SE network then learns a mask to filter out background noise, followed by SS network to predict multiple masks to separate different sources in the mixture. Finally, the decoder reconstructs the separated speech in the time domain.

Encoder. The encoder takes in the time-domain noisy mixture $x_n \in \mathbb{R}^T$ and learns a STFT-like representation $h_n \in \mathbb{R}^{F \times T'}$ using a convolutional layer. The same process is done for the parallel clean mixture $x_c \in \mathbb{R}^T$, generating a clean representation $h_c \in \mathbb{R}^{F \times T'}$ to supervise speech enhancement task:

$$\begin{aligned} h_n &= \text{ReLU}(\text{Conv1d}(x_n)), \\ h_c &= \text{ReLU}(\text{Conv1d}(x_c)), \end{aligned} \quad (1)$$

¹<https://github.com/YUCHEN005/Unified-Enhance-Separation>

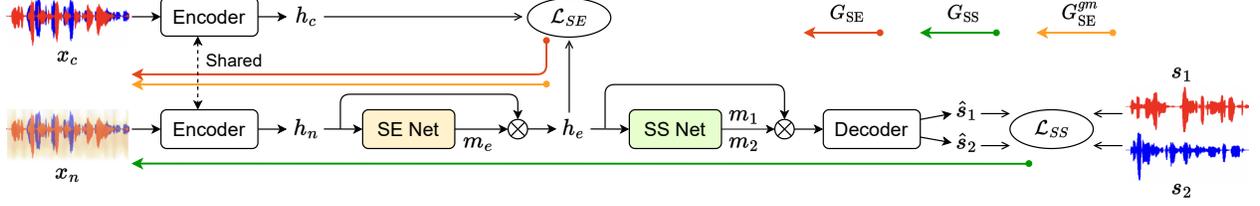


Fig. 1. The overall architecture of our proposed unified network, which consists of encoder, SE network, SS network and decoder. The x_n denotes noisy mixture, x_c denotes parallel clean mixture, s_1 and s_2 denote the target sources. The \mathbf{G} denotes gradient.

Speech Enhancement (SE) Network. The SE network takes in the noisy mixture representation h_n and learns a mask m_e to filter out background noise, resulting in enhanced mixture representation h_e :

$$\begin{aligned} m_e &= \text{SE-Net}(h_n), \\ h_e &= m_e \cdot h_n, \end{aligned} \quad (2)$$

where the SE network follows the same architecture as SS network described in Figure 3. In particular, SE network is a special case of the SS network where the number of separated sources is 1.

The generated h_e is employed to calculate speech enhancement loss by compared to the clean mixture representation h_c , and then it will be sent into the SS network for source separation.

Speech Separation (SS) Network. Figure 3 illustrates the architecture of SS network, which follows prior works like Dual-Path RNN [2] and SepFormer [3]. It takes in the enhanced mixture representation h_e and predicts a mask $m_k \in \{m_1, m_2, \dots, m_C\}$ for each of C sources in the mixture.

$$m_k = \text{SS-Net}(h_e), \quad (3)$$

As shown in Figure 3(a), the SS network first sends the input representation h_e into layer normalization and a linear layer with output dimension F . Then, it creates overlapping chunks of size K by chopping up h_e along the time axis with 50% overlap between neighbors, resulting in an output $h'_e \in \mathbb{R}^{F \times K \times S}$, where K is chunk length and S is the resulted number of chunks.

The representation h'_e then feeds the sequence modeling block as illustrated in Figure 3(b), where we employ Dual-Path RNN block [2] or SepFormer block [3] with dual-path structure to learn both local and global contexts for long sequence modeling.

After that, the output $h''_e \in \mathbb{R}^{F \times K \times S}$ is processed by parametric ReLU (PReLU) activation [18] and a linear layer. The output is denoted as $h'''_e \in \mathbb{R}^{(C \times F) \times K \times S}$, where C is the number of sources. Following this, the overlap-add scheme described in [2] is employed to obtain $h''''_e \in \mathbb{R}^{(C \times F) \times T'}$. This representation finally goes through two feed-forward layers and a ReLU [19] activation to generate source masks, which are divided along the channel dimension for each source $k \in \{1, 2, \dots, C\}$.

Decoder. The decoder takes in the element-wise multiplication of source mask m_k and enhanced mixture representation h_e , and reconstruct the separated speech in time-domain using a transposed convolution layer with same kernel size and stride as the encoder. The transformation is expressed as:

$$\hat{s}_k = \text{TransposeConv1d}(m_k * h_e), \quad (4)$$

where $\hat{s}_k \in \mathbb{R}^T$ is the separated speech for source k .

2.2.2. Multi-task Learning

We build two training objectives to optimize the unified network, *i.e.*, SE loss and SS loss. Firstly, the SE loss is calculated via mean square

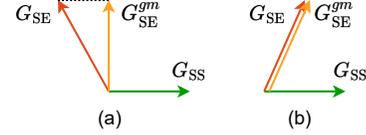


Fig. 2. Block diagrams of gradient modulation: (a) If \mathbf{G}_{SE} conflicts with \mathbf{G}_{SS} (*i.e.*, the angle between them is larger than 90°), we set the updated \mathbf{G}_{SE}^{gm} as the projection of \mathbf{G}_{SE} on the normal plane of \mathbf{G}_{SS} . (b) If \mathbf{G}_{SE} is aligned with \mathbf{G}_{SS} , we set \mathbf{G}_{SE}^{gm} equals to \mathbf{G}_{SE} .

error (MSE) between enhanced and clean mixture representations, in order to direct the SE network to produce better h_e for separation, making full use of the supervision information in clean mixture:

$$\mathcal{L}_{SE} = \frac{1}{FT'} \|h_e - h_c\|_2^2, \quad (5)$$

where $\|\cdot\|_2$ denotes L_2 norm, $h_e, h_c \in \mathbb{R}^{F \times T'}$, F denotes the embedding size and T' denotes the sequence length.

Secondly, the SS loss \mathcal{L}_{SS} is calculated using scale-invariant signal-to-noise ratio (SI-SNR) [20] via utterance-level permutation invariant loss [21], following prior works [1–3].

The entire system is optimized in an end-to-end manner via multi-task learning strategy, where the overall training objective is formed as: $\mathcal{L} = \lambda_{SE} \cdot \mathcal{L}_{SE} + \mathcal{L}_{SS}$, where λ_{SE} is a weighting parameter.

2.3. Gradient Modulation (GM)

From the back-propagation view, we denote the SE task gradient as $\mathbf{G}_{SE} = \nabla_v(\lambda_{SE} \cdot \mathcal{L}_{SE})$, and the SS task gradient as $\mathbf{G}_{SS} = \nabla_v \mathcal{L}_{SS}$, where v stands for model parameters. As shown in Figure 1, \mathbf{G}_{SE} goes back through SE network and encoder (red arrow), and \mathbf{G}_{SS} passes the entire system (green arrow). Therefore, the front-end SE network and encoder would be optimized by both gradients, so that the overall gradient can be expressed as follows:

$$\mathbf{G} = \mathbf{G}_{SE} + \mathbf{G}_{SS}, \quad (6)$$

However, we have observed some conflicts between the gradients \mathbf{G}_{SE} and \mathbf{G}_{SS} , *i.e.*, the angle between them is larger than 90° . It indicates that the SE gradient is hindering, instead of assisting in, the optimization of SS task, which is essentially the same as the over-suppression problem described in Section 2.1.

To this end, we propose a gradient modulation (GM) strategy to harmonize the two task gradients, as illustrated in Figure 2: (1) The angle between \mathbf{G}_{SE} and \mathbf{G}_{SS} is larger than 90° (Figure 2(a)), which means they are conflicting and thus the SE gradient will hinder the optimization of SS task. In this case, we project \mathbf{G}_{SE} to the normal plane of \mathbf{G}_{SS} to remove the conflict, which avoids increasing the SS loss. (2) Their angle is smaller than 90° (Figure 2(b)), which means there is no conflict between the two gradients, so that we safely set the updated SE gradient \mathbf{G}_{SE}^{gm} as \mathbf{G}_{SE} . Therefore, our gradient modulation strategy is mathematically formulated as:

$$\mathbf{G}_{SE}^{gm} = \begin{cases} \mathbf{G}_{SE} - \frac{\mathbf{G}_{SE} \cdot \mathbf{G}_{SS}}{\|\mathbf{G}_{SS}\|_2^2} \cdot \mathbf{G}_{SS}, & \text{if } \mathbf{G}_{SE} \cdot \mathbf{G}_{SS} < 0 \\ \mathbf{G}_{SE}, & \text{otherwise.} \end{cases} \quad (7)$$

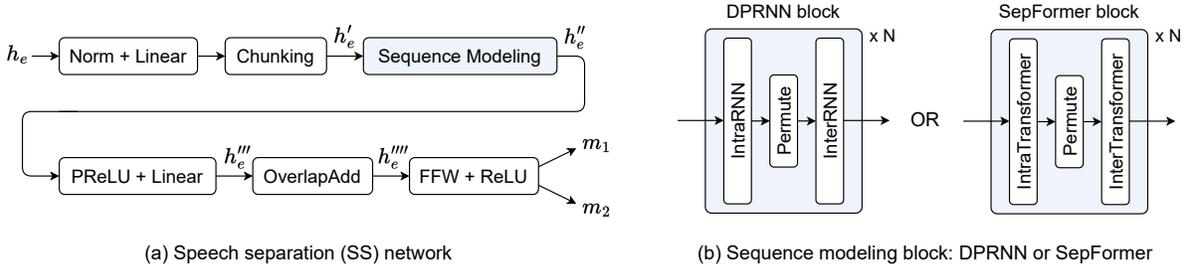


Fig. 3. Block diagrams of speech separation (SS) network: (a) overall architecture, (b) sequence modeling block.

In particular, this strategy is conducted on the gradients of each layer in SE network and encoder, which are flattened to 1-dimensional long vectors in advance and reshaped back after modulation.

As a result, the two task gradients would harmony with each other after modulation and promote the multi-task learning, where the auxiliary SE task could effectively reduce noise to benefit the target SS task while without suppressing valid speaker information. Finally, the overall gradient is formulated as follows:

$$\mathbf{G}^{gm} = \mathbf{G}_{SE}^{gm} + \mathbf{G}_{SS}, \quad (8)$$

3. EXPERIMENTS AND RESULTS

3.1. Datasets

We conduct experiments on the large-scale benchmark Libri2Mix and Libri3Mix [22] datasets² (noisy version) to evaluate our proposed approach, where all the waveforms are sampled at 8 kHz.

Libri2Mix is a popular benchmark for speech separation, which contains four partitions, *i.e.*, train-360 (212 h), train-100 (58 h), dev (11 h) and test (11 h), and in this work we only use the train-360 partition for training. The mixtures are created by randomly mixing utterances of two different speakers from LibriSpeech [23]. The noisy version is created by adding noise samples from WHAM! [24] dataset, which contains 82 hours of noise data recorded in coffee shops, restaurants and bars. The resulting SNRs are normally distributed with a mean of -2 dB and a standard deviation of 3.6 dB.

Libri3Mix follows the same structure as Libri2Mix, *i.e.*, train-360 (146 h), train-100 (40 h), dev (11 h) and test (11 h), where we only use the train-360 partition for training in this work. The mixtures are created with three different speakers from LibriSpeech, and the noisy version is created similar to that of Libri2Mix.

3.2. Experimental Setup

3.2.1. Network Configurations

Following prior works [3, 4], we employ 256 filters for the convolution layer in encoder, with kernel size of 16 and stride of 8, and decoder uses the same kernel size and stride as encoder.

The SE and SS networks in our system share the same architecture, which process chunks of size $K = 250$ with 50% overlap. In SE network, the sequence modeling block contains 2 DPRNN blocks [2] using BLSTM [25] with 256 units in each direction, or 2 SepFormer blocks [3] with 1 Transformer [6] layer in both IntraT and InterT. In SS network, the sequence modeling block contains 6 DPRNN blocks using BLSTM with 256 units in each direction, or 2 SepFormer blocks with 8 Transformer layers in IntraT and InterT, with the attention heads/feed-forward dimension set to 8/1024.

3.2.2. Training Details

We train 200 epochs for all models, where Adam algorithm [26] is used for optimization, with initial learning rate of $1.5e^{-4}$. After 85 epochs with DPRNN (5 epochs with SepFormer), the learning rate

Table 1. Comparison with the state-of-the-arts on Libri2Mix-noisy dataset. “DPRNN” or “SepFormer” in brackets denotes the backbone of sequence modeling block. * denotes self-reproduced results.

Method	SI-SNRi (dB)	SDRi (dB)	# Params
ConvTasNet [1]	12.0	12.4	5.1 M
Dual-Path RNN* [2]	14.2	14.7	14.6 M
SepFormer [3]	14.9	15.4	25.7 M
Wavesplit [5]	15.1	15.8	29.0 M
Ours (DPRNN)	15.4	16.0	19.7 M
Ours (SepFormer)	16.0	16.5	29.2 M

Table 2. Comparison with the state-of-the-arts on Libri3Mix-noisy dataset. * denotes self-reproduced results.

Method	SI-SNRi (dB)	SDRi (dB)	# Params
ConvTasNet [1]	10.4	10.9	5.1 M
Wavesplit [5]	13.1	13.8	29.0 M
Dual-Path RNN* [2]	14.0	14.4	14.7 M
SepFormer [3]	14.3	14.8	25.7 M
Ours (DPRNN)	15.4	15.9	19.7 M
Ours (SepFormer)	15.8	16.4	29.2 M

is halved if there is no improvement of validation performance for 5 consecutive epochs. The batch size is set to 1. Gradient clipping is used to limit the L_2 norm of gradients to 5. No dynamic mixing [5] strategy is used for data augmentation. The weighting parameter λ_{SE} is set to 0.1. All hyper-parameters are tuned on validation set.

3.3. Results

3.3.1. Comparison with the State-of-the-Arts

Table 1 compares our proposed approach with the best results of prior works on Libri2Mix-noisy dataset. Our best system achieves the state-of-the-art with a SI-SNR improvement (SI-SNRi) of 16.0 dB and a Signal-to-Distortion Ratio improvement (SDRi) of 16.5 dB. Our system with DPRNN and SepFormer backbones significantly outperform corresponding baselines (14.2 dB→15.4 dB, 14.9 dB→16.0 dB), while only cost a bit more model parameters.

Table 2 compares our approach with prior works on Libri3Mix-noisy dataset, where our best system achieves the state-of-the-art with SI-SNRi result of 15.8 dB and SDRi of 16.4 dB.

As a result, our approach shows superior performance under noisy conditions, for separation of both two and three speakers.

3.3.2. Effect of Unified Network

We study the effect of unified network using Libri2Mix-noisy dataset in Table 3. Compared to DPRNN baseline, our unified network with 2 DPRNN blocks in SE network and 4 blocks in SS network achieves better SI-SNRi result (14.2 dB→14.5 dB) while without extra model parameters, indicating that front-end SE can benefit the downstream SS task. Further increasing the DPRNN blocks in SS network brings

²<https://github.com/JorisCos/LibriMix>

Table 3. Effect of unified network and gradient modulation in our proposed approach with Libri2Mix-noisy dataset. “# DP / SF” denotes the number of DPRNN or SepFormer blocks. “# RNN / T” denotes the number of RNN or Transformer layers in each Intra-/Inter-RNN or Intra-/Inter-Transformer. “GM” denotes whether use gradient modulation. “# Params” denotes the total number of model parameters.

Method	SE Network		SS Network		λ_{SE}	GM	SI-SNRi (dB)	SDRi (dB)	# Params
	# DP / SF	# RNN / T	# DP / SF	# RNN / T					
Dual-Path RNN [2]	-	-	6	1	-	-	14.2	14.7	14.6 M
Ours (DPRNN)	2	1	4	1	0	×	14.5	15.0	14.9 M
	2	1	6	1	0	×	14.6	15.1	19.7 M
	2	1	6	1	0.1	×	14.8	15.4	19.7 M
	2	1	6	1	0.1	✓	15.4	16.0	19.7 M
SepFormer [3]	-	-	2	8	-	-	14.9	15.4	25.7 M
Ours (SepFormer)	2	1	2	7	0	×	15.2	15.7	26.0 M
	2	1	2	8	0	×	15.3	15.7	29.2 M
	2	1	2	8	0.1	×	15.5	16.0	29.2 M
	2	1	2	8	0.1	✓	16.0	16.5	29.2 M

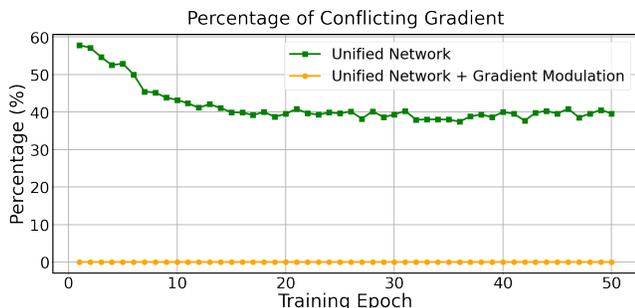


Fig. 4. Percentage% of conflicting gradient in all layers of SE network and encoder during training stage on Libri2Mix-noisy dataset. The percentage value of each epoch is obtained by averaging all the batches in it. We use SepFormer as backbone and present the first 50 epochs here (percentage value is stable in subsequent epochs).

more improvements (14.5 dB→14.6 dB). Based on this, adding SE loss for multi-task learning achieves higher SI-SNRi (14.6 dB→14.8 dB), which benefits from the supervision information in clean mixture. Similar improvements are observed on SepFormer backbone.

3.3.3. Effect of Gradient Modulation

To illustrate the effect of proposed gradient modulation strategy, we present the percentage of conflicting gradient in all layers of SE network and encoder in Figure 4. We observe that the unified network with multi-task learning suffers a lot from gradient conflict (around 40%). In comparison, our gradient modulation strategy completely removes the conflicts, and thus alleviates the over-suppression problem as analyzed in Figure 5 and Section 3.3.4. As a result, we can observe significant improvements of the final SI-SNRi performance, *i.e.*, 14.8 dB→15.4 dB, 15.5 dB→16.0 dB, as shown in Table 3.

3.3.4. Visualization of Mixture and Separated Speech

To further show the overall effect of our approach, we visualize the spectrums of noisy mixture and separated speech using a test sample from Libri2Mix-noisy dataset, as presented in Figure 5. We first observe a lot of noise in the noisy mixture (a), which makes it difficult to separate each target source. The SepFormer baseline separates the two sources from mixture as presented in (b) and (e), while we can still observe some noise in the separated speech (orange boxes). In comparison, our unified network not only separates the two sources well, but also reduces the background noise, as shown in (c) and (f). It indicates that speech enhancement with clean supervision information can effectively reduce noise for downstream speech separation.

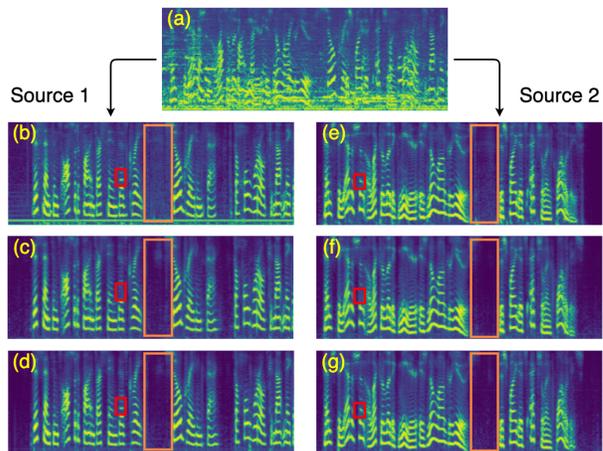


Fig. 5. Spectrums of mixture and separated speech: (a) noisy mixture; separated source 1 in (b) SepFormer baseline, (c) our unified network, (d) our unified network + GM; source 2 in (e) SepFormer baseline, (f) our unified network, (g) our unified network + GM.

However, we can also observe some loss of valid speaker information caused by SE, *i.e.*, over-suppression (red boxes). In comparison, our proposed gradient modulation strategy can alleviate this problem by harmonizing SE and SS tasks from optimization view, where some over-suppressed information is recovered as indicated by the red boxes in (d) and (g). As a result, our proposed approach can effectively improve the noise-robustness of speech separation while avoid suppressing valid speaker information at the same time.

4. CONCLUSION

In this paper, we propose a novel network to unify speech enhancement and separation with gradient modulation for end-to-end noise-robust speech separation. Specifically, we first build a unified network by combining speech enhancement and separation modules, with multi-task learning for optimization, where SE module is supervised by parallel clean mixture to reduce noise for downstream speech separation. Furthermore, in order to avoid suppressing valid speaker information when reducing the noise, we propose a gradient modulation strategy to harmonize the SE and SS tasks from optimization view. Experimental results demonstrate that our proposed approach improves the noise-robustness of speech separation model and achieves the state-of-the-art on large-scale benchmarks.

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