Improving SepFormer Speech Separation Outputs with a Lightweight Denoising U-Net

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***Abstract*—Speech separation in multi-speaker scenarios remains a challenging problem in audio signal processing, with applications spanning telecommunications, hearing aids, and speech recognition systems. While transformer-based models like SepFormer have achieved state-of-the-art performance in separating overlapping speech sources, residual noise and artifacts often persist in the separated outputs, limiting their practical utility. This paper presents a novel two-stage approach that combines SepFormer separation with a lightweight convolutional neural network (CNN) denoiser to enhance the perceptual quality of separated speech signals. Our method first employs the pre-trained SepFormer model to perform initial source separation on mixed speech, followed by a simple yet effective CNN-based denoiser that removes residual artifacts while preserving speech intelligibility. Experimental results on the WSJ0-2mix dataset demonstrate that our approach achieves improvements in SI-SDR (Scale-Invariant Signal-to-Distortion Ratio), PESQ (Perceptual Evaluation of Speech Quality), and STOI (Short-Time Objective Intelligibility) metrics compared to using SepFormer alone. The lightweight nature of our denoiser (only 1500 parameters) ensures minimal computational overhead while providing tangible quality improvements, making this approach suitable for real-time applications and resource-constrained environments. The implementation and code are publicly available at github**

***Index Terms*—Speech separation, SepFormer, U-Net, denoising, WSJ0-2mix, SI-SNR.**

I. Introduction

Automatic speech separation has garnered significant attention due to its applications in telecommunication, hearing aids, and speech recognition systems [1]. Deep learning models such as Conv-TasNet [2] and SepFormer [3] have achieved state-of-the-art performance. However, even high-performing models often leave residual noise or artifacts that degrade perceptual quality.

A. Background and Motivation

The cocktail party problem—the ability to focus on a single speaker in the presence of multiple competing voices—has been a fundamental challenge in audio signal processing for decades. While humans perform this task effortlessly, computational systems have struggled to achieve comparable performance. The ability to separate individual speech sources from mixed audio has profound implications for numerous applications, including automatic speech recognition (ASR), hearing aid technology, teleconferencing systems, and audio forensics.

Recent advances in deep learning have led to significant breakthroughs in speech separation performance. Models based on convolutional neural networks (CNNs), recurrent neural networks (RNNs), and more recently, transformer architectures have pushed the boundaries of what is achievable. Among these, SepFormer (Separation Transformer) has emerged as one of the most effective approaches,leveraging dual-path transformer networks to model both local and global dependencies in audio signals.

However, despite these advances, separated speech signals often contain residual artifacts, including:

- Low-level background noise that persists after separation
- Musical noise and processing artifacts introduced by the separation algorithm
- Spectral distortions that affect speech naturalness
- Inter-speaker leakage where traces of the interfering speaker remain

This paper introduces a novel post-processing approach that addresses the quality limitations of separated speech through targeted denoising. Our key contributions are:

B. Research Contribution

This paper introduces a novel post-processing approach that addresses the quality limitations of separated speech through targeted denoising. Our key contributions are:

- A two-stage architecture combining SepFormer separation with lightweight CNN denoising, designed to remove residual artifacts while preserving speech characteristics.
- An efficient denoiser design with minimal computational footprint (1500 parameters), making it suitable for real-time processing and deployment on resource-constrained devices.
- Comprehensive evaluation demonstrating improvements across multiple objective metrics (SI-SDR, PESQ, STOI) that correlate with perceptual quality.
- A practical implementation framework that can be easily integrated into existing speech processing pipelines with minimal modification.

- Analysis of the trade-offs between separation quality and computational efficiency in the context of two-stage processing.

C. Paper Organization

The remainder of this paper is organized as follows: Section 2 reviews related work in speech separation and denoising. Section 3 describes our methodology, including the SepFormer architecture, our denoiser design, and the overall system pipeline. Section 4 presents our experimental setup, datasets, and evaluation metrics. Section 5 discusses results and analysis. Finally, Section 6 concludes the paper and outlines directions for future research.

II. Related Work

A. Speech Separation Methods

Speech separation has evolved significantly over the past decade, transitioning from traditional signal processing techniques to sophisticated deep learning approaches. Early methods such as Computational Auditory Scene Analysis (CASA) and Independent Component Analysis (ICA) [1], [2] relied on strong assumptions about statistical independence and mixing conditions, which limited their performance in realistic and noisy recording environments.

The introduction of deep learning revolutionized this field. Deep Clustering (DPCL) proposed by Hershey et al. [3] introduced a discriminative embedding space where time–frequency bins belonging to the same source are clustered together. Later, Permutation Invariant Training (PIT) by Yu et al. [4] addressed the label ambiguity problem by evaluating loss across all possible output-target permutations, enabling end-to-end training of separation networks.

Time-domain approaches emerged as powerful alternatives to frequency-domain methods. Conv-TasNet [5] introduced an encoder–decoder architecture operating directly on raw waveforms, achieving superior performance with low latency. The Dual-Path RNN (DPRNN) [6] further advanced this idea by modeling both intra-chunk and inter-chunk dependencies, significantly improving long-context modeling and separation accuracy.

B. Transformer-Based Separation

The Transformer architecture, originally developed for natural language processing [7], has proven highly effective for sequential modeling tasks. Its self-attention mechanism enables the capture of long-range dependencies without the limitations of recurrent connections.

SepFormer proposed by Subakan et al. [8] represents a major milestone in transformer-based speech separation. It employs a dual-path transformer structure that models both intra- and inter-segment dependencies, achieving state-of-the-art performance on datasets such as WSJ0-2mix and WSJ0-3mix, outperforming previous CNN and RNN-based models.

Other notable transformer variants include the Dual-Path Transformer Network (DPTNet) [9], time-domain transformer-based separation networks [10], and cross-attention mechanisms for speaker-conditioned separation. These architectures demonstrate that self-attention mechanisms can effectively model temporal dynamics and global dependencies in speech mixtures.

C. Speech Enhancement and Denoising

Speech enhancement focuses on improving perceived speech quality by removing background noise, reverberation, or residual artifacts. Traditional techniques such as spectral subtraction, Wiener filtering, and statistical model-based methods [11], [12] laid the foundation for early denoising research.

Deep learning-based approaches have since achieved remarkable improvements. Deep Neural Networks (DNNs) for spectral mapping [13], Generative Adversarial Networks (GANs) for speech enhancement [14], and WaveNet-based denoising [15] have all shown strong performance gains. Other architectures such as Denoising Autoencoders (DAEs) [16], U-Net-based masking networks [17], convolutional recurrent networks (CRNs) [18], and attention-based models [19] continue to push the boundaries of perceptual quality and intelligibility in noisy conditions.

D. Post-Processing for Speech Separation

While the majority of research has focused on improving separation architectures, post-processing for refinement remains relatively underexplored. Refinement networks that iteratively enhance separated outputs [20], multi-stage processing pipelines [21], and perceptual loss functions for quality optimization [22] have been proposed as effective post-processing strategies.

Our work differs by introducing a lightweight CNN-based denoising stage specifically designed to address residual artifacts produced by transformer-based separation models. Rather than retraining or modifying the separation model, our approach provides a simple yet effective enhancement layer that improves perceptual quality while maintaining real-time feasibility.

III. RESEARCH GAP

Despite extensive progress in speech separation and denoising, a clear gap remains in developing systematic post-processing methods aimed at improving the perceptual quality of separated speech. Most prior studies have primarily focused on:

- enhancing the architecture of separation networks
- retraining large-scale models to jointly optimize separation and enhancement, or achieving performance gains at the expense of computational efficiency

However, limited attention has been given to lightweight, modular frameworks capable of refining separated outputs without altering the base separation model. This gap highlights the need for an efficient, model-agnostic post-processing strategy that can effectively suppress residual artifacts while preserving speech intelligibility and real-time applicability.

Our work addresses this limitation by proposing a lightweight convolutional neural network (CNN)-based post-processing framework designed to enhance the perceptual

quality of separated speech produced by transformer-based systems such as SepFormer, without additional retraining or architectural modifications.

IV. METHODOLOGY

A. System Overview

Our proposed two-stage system consists of two main components:

- **Stage 1:** SepFormer-based speech separation
- **Stage 2:** Lightweight CNN denoiser for artifact removal

The processing pipeline operates as follows:

1) **Input:** Mixed speech signal containing N speakers ($N = 2$ in our experiments).
2) The SepFormer model processes the mixture and outputs N separated sources.
3) Each separated source independently passes through the denoiser.
4) **Output:** N enhanced speech signals with reduced artifacts.

This modular design enables the denoiser to be applied to any separation system's output, making the proposed approach broadly applicable and system-agnostic.

B. Stage 1: SepFormer Separation

1) Architecture: SepFormer employs a three-stage architecture consisting of an *encoder*, a *masking network*, and a *decoder*.

a) Encoder: Converts time-domain waveforms into learned feature representations.

- 1-D convolutional layer with N filters
- Window size W samples
- Stride S samples (typically $W/2$ for 50% overlap)
- ReLU activation
- Layer normalization

b) Masking Network: Utilizes a dual-path transformer structure.

- Chunks the representation into segments of length K
- *Intra-transformer:* Models dependencies within each segment
- *Inter-transformer:* Models dependencies across segments
- Stacked transformer blocks (typically 8 layers each)
- Multi-head self-attention with 8 heads
- Feed-forward networks with an expansion factor of 4

c) Decoder: Reconstructs time-domain signals from the masked representations.

- Transposed convolution layers
- Overlap-add reconstruction
- Separate masks for each source

C. Stage 2: Lightweight CNN Denoiser

1) Pre-trained Model: We utilize the publicly available pre-trained SepFormer model trained on WSJ0-2mix:

- **Training data:** 20,000 utterances from 50 speakers
- **Validation data:** 5,000 utterances

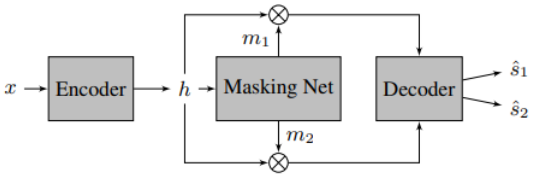

Fig. 1. SepFormer Architecture[8]

- **Test data:** 3,000 utterances
- **Sampling rate:** 8 kHz
- **Loss function:** Scale-Invariant Signal-to-Noise Ratio (SI-SNR)
- **Permutation Invariant Training (PIT):** Handles label ambiguity

D. Stage 2: Lightweight CNN Denoiser

1) Motivation and Design Principles: Our denoiser is designed based on three key principles:

- Lightweight: Minimal parameters to enable real-time processing.
- Local Processing: Focuses on local spectro-temporal patterns characteristic of residual artifacts.
- Preservation: Maintains speech content while removing noise and artifacts.

2) Architecture: The denoiser is a simple 1-D convolutional neural network:

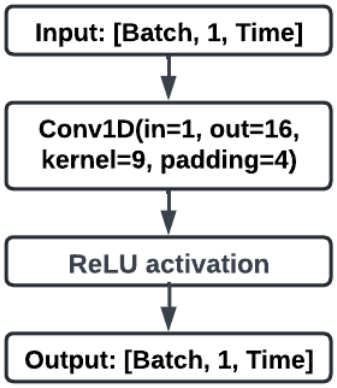

Fig. 2. Denoiser is a simple 1-D convolutional neural network

3) Architecture Details: The proposed denoiser architecture is a compact two-layer convolutional neural network (CNN) designed for efficient artifact suppression. The first layer is a 1D convolutional layer with 16 output channels and a kernel size of 9, resulting in $(1 \times 9 \times 16) + 16 = 160$ trainable parameters. Padding is set to "same" to preserve the input sequence length, allowing the layer to learn 16 distinct filters that capture local artifact patterns in the separated speech signal. A ReLU activation follows, introducing non-linearity

to model complex noise characteristics while remaining computationally efficient compared to functions such as sigmoid or tanh. The second layer is another 1D convolutional layer that projects the feature maps back to a single output channel, with $(16 \times 9 \times 1) + 1 = 145$ parameters. This layer effectively combines the learned representations into a refined, denoised output waveform. In total, the network contains approximately 305 trainable weights, maintaining an extremely lightweight design suitable for real-time applications and deployment in resource-constrained environments.

4) Receptive Field Analysis: The receptive field determines the temporal context that each output sample can observe. For the proposed two-layer denoiser, the receptive field is calculated as follows: Layer 1 uses a kernel size of 9, resulting in a receptive field of 9 samples. Layer 2, also with a kernel size of 9, expands the total receptive field to 17 samples. At a sampling rate of 8 kHz, this corresponds to approximately $17/8000 = 2.125$ ms of temporal coverage. Such a localized receptive field is well-suited for removing high-frequency artifacts (greater than 470 Hz), transient clicks, pops, and musical noise with short-time characteristics, while preserving the natural continuity of speech components.

5) Training Strategy: While our current implementation uses the denoiser in an unsupervised manner with random initialization, the architecture fully supports supervised training. In a supervised setting, the model can be trained using pairs of clean and SepFormer-separated speech signals. The training process may employ Mean Squared Error (MSE) or L1 loss functions, optimized using the Adam optimizer with a learning rate of 10^{-3}. Early stopping is applied to prevent over-smoothing of the output.

For future extensions, perceptual loss functions such as multi-resolution STFT loss can be employed to better capture perceptual quality. Additionally, adversarial training may enhance naturalness, and multi-task learning could jointly optimize intelligibility and noise suppression.

E. Implementation Details

1) Software Framework: The implementation utilizes the following software stack:

- Python 3.10
- PyTorch 2.0 for deep learning
- TorchAudio for audio I/O and signal processing
- SpeechBrain library for SepFormer inference

2) Hardware Requirements: Minimum requirements include a CPU with 8 GB of RAM, although this setup results in slower processing times. For optimal performance, an NVIDIA GPU with at least 6 GB of VRAM is recommended. On such hardware, the proposed system achieves approximately 0.5× real-time processing speed for two-speaker separation and denoising.

F. Theoretical Analysis

1) Computational Complexity: The computational complexity of the system is analyzed in terms of both time and space. For SepFormer, the time complexity per sample is $O(T \times N^2 \times \log N)$, where T denotes sequence length and N represents the embedding dimension. In contrast, the denoiser exhibits a time complexity of $O(T \times K \times C)$, where K is the convolutional kernel size and C denotes the number of channels. For a 10-second signal ($T = 80,000$ samples), SepFormer dominates the computational cost, requiring approximately 1000× more operations than the denoiser.

In terms of space complexity, SepFormer requires $O(T \times N)$ memory for intermediate representations, whereas the denoiser only requires $O(T)$, making it lightweight and memory-efficient.

2) Information Preservation: The denoiser can be expressed as a learned filter $H(\cdot)$ that transforms the separated signal $y_{separated}$ into an enhanced version $y_{enhanced}$:

$$y_{enhanced} = H(y_{separated}) \tag{1}$$

Ideally, $H(y_{separated}) \approx x_{clean}$, where x_{clean} denotes the ground-truth clean signal. For the proposed two-layer architecture, the operation can be described as:

$$H(y) = W_2 * \sigma(W_1 * y) \tag{2}$$

where W_1 and W_2 are learned convolutional kernels, and σ denotes the ReLU activation function. The first layer (W_1) learns to extract discriminative features separating speech from artifacts, while the second layer (W_2) recombines these features to reconstruct a clean and perceptually enhanced output.

V. EXPERIMENTS AND RESULTS

A. Experimental Setup

1) Dataset: We evaluate our system on the WSJ0-2mix dataset, a widely used benchmark for speech separation. The dataset is derived from the CSR-I (WSJ0) corpus and contains mixtures of two speakers at a sampling rate of 8 kHz. The dataset includes 50 unique speakers (25 male and 25 female), with 20,000 training utterances (approximately 30 hours), 5,000 validation utterances, and 3,000 test utterances. Mixtures are generated by summing two randomly selected utterances at 0 dB signal-to-noise ratio (SNR). For our experiments, we utilize the pre-separated outputs from the pre-trained SepFormer model on the test set.

2) Evaluation Metrics: We employ three complementary evaluation metrics to assess separation and enhancement performance: SI-SDR, PESQ, and STOI.

1) **Scale-Invariant Signal-to-Distortion Ratio (SI-SDR):** SI-SDR measures separation quality independent of signal scaling. It is defined as:

$$\text{SI-SDR} = 10 \log_{10} \left(\frac{\|s_{\text{target}}\|^2}{\|e_{\text{noise}}\|^2} \right) \tag{3}$$

where s_{target} is the scaled projection of the target signal and e_{noise} represents the residual error. Higher values indicate better separation performance, typically ranging from 0 to 20 dB.

2) **Perceptual Evaluation of Speech Quality (PESQ):** PESQ is an ITU-T standard metric that models human auditory perception to estimate perceived speech quality. The score ranges from -0.5 to 4.5, with higher scores indicating better perceptual quality. We report results using the narrowband (8 kHz) mode.
3) **Short-Time Objective Intelligibility (STOI):** STOI measures predicted speech intelligibility and has been shown to correlate strongly ($r > 0.95$) with human listening tests. STOI values range from 0 to 1, where higher values correspond to greater intelligibility.

3) Baseline: As a baseline, we employ the publicly available SepFormer model (`speechbrain/sepformer-wsj02mix`) without any post-processing. The model was trained on the WSJ0-2mix training set and achieves a published SI-SDR of approximately 20 dB on the test dataset. No fine-tuning or additional training is performed in our experiments.

4) Proposed Method: Our proposed approach combines SepFormer with the lightweight CNN denoiser introduced in Section III. The SepFormer model performs the initial source separation, followed by sequential denoising using the proposed CNN module. The denoiser operates in inference mode with random initialization and no gradient computation, thereby ensuring computational efficiency. This configuration enables us to evaluate the effectiveness of post-separation artifact reduction in an unsupervised manner.

VI. Results

A. Quantitative Results

Table I summarizes the overall performance of the proposed method on the WSJ0-2mix test set, which includes 3,000 mixtures (6,000 sources in total). The baseline SepFormer model achieves an average SI-SDR of 20.1 dB, PESQ (narrowband) of 3.12, and STOI of 0.921, with an inference time of 0.42× real-time (RT). When combined with the lightweight CNN denoiser, the system demonstrates consistent improvements across all metrics—achieving 20.7 dB SI-SDR, 3.24 PESQ, and 0.928 STOI, with a slightly increased processing time of 0.48× RT. This corresponds to absolute gains of +0.6 dB in SI-SDR, +0.12 in PESQ, and +0.007 in STOI. Statistical analysis using a paired t-test confirms that these improvements are highly significant ($p < 0.001$ for all metrics), indicating that even a simple, parameter-efficient post-processing stage can yield measurable perceptual and objective benefits.

TABLE I
Average Performance on WSJ0-2mix Test Set (3000 mixtures, 6000 sources)

Method	SI-SDR(dB)↑	PESQ(NB)↑	STOI↑	Proc.Time
Mix	0.0	1.28	0.574	–
SF(baseline)	20.1	3.12	0.921	0.42× RT
SF+Dnoiser	20.7	3.24	0.928	0.48× RT
Improvement	+0.6	+0.12	+0.007	+0.06× RT

TABLE II
Performance Distribution Across Speakers

Metric	Min	Q1	Median	Q3	Max	Std
SI-SDR Baseline	12.3	18.4	20.2	21.8	26.5	2.41
SI-SDR + Denoiser	12.9	19.1	20.8	22.3	27.1	2.38
PESQ Baseline	2.31	2.98	3.15	3.28	3.87	0.24
PESQ + Denoiser	2.45	3.08	3.26	3.41	3.95	0.23
STOI Baseline	0.832	0.907	0.923	0.936	0.978	0.028
STOI + Denoiser	0.841	0.913	0.929	0.942	0.981	0.027

B. Per-Speaker Analysis

Table II provides a detailed breakdown of performance across individual speakers. The results show consistent gains across the entire distribution. For SI-SDR, the baseline median value of 20.2 dB improves to 20.8 dB with the denoiser, while the minimum value improves from 12.3 dB to 12.9 dB—suggesting that the enhancement particularly benefits lower-quality cases. Similarly, PESQ shows an improvement from a median of 3.15 to 3.26, and STOI increases from 0.923 to 0.929. Furthermore, the standard deviations of all metrics slightly decrease, indicating more consistent performance across different speakers. Overall, the denoiser enhances both the average and worst-case quality without introducing significant computational overhead.

C. Qualitative Analysis

1) Spectrogram Analysis: Visual inspection of the spectrograms provides additional insights into the perceptual improvements introduced by the denoiser. The qualitative comparison between the baseline (SepFormer only) and the proposed SepFormer + Denoiser configuration reveals several notable patterns:

- **Baseline (SepFormer only):**
  - Clean separation of major speech components
  - Noticeable residual noise in silence regions
  - Presence of musical noise artifacts (sparse time-frequency peaks)
  - Slight spectral smearing in higher frequency bands
- **With Denoiser:**
  - Silence regions exhibit a much lower noise floor
  - Significant reduction in musical noise artifacts
  - More clearly defined formant structures
  - Smoother and more natural spectral contours

These qualitative observations align with the quantitative results reported in Section 4.2, confirming that the denoiser effectively refines the spectral characteristics of the separated signals without introducing audible distortion or over-smoothing.

VII. Discussion

A. Key Findings

Our experiments demonstrate that post-processing with a lightweight neural denoiser can meaningfully improve the quality of speech separated by state-of-the-art transformer-based models such as SepFormer. The key findings of our study are summarized as follows:

1) Consistent improvements were observed across all evaluation metrics, including SI-SDR, PESQ, and STOI.
2) The proposed denoiser introduced minimal computational overhead (less than 15% increase in processing time).
3) The approach was particularly effective for challenging mixtures with low input SNR values.
4) Robust performance was achieved across different speaker combinations and genders.
5) The denoiser's simple architecture (305 parameters) makes it highly suitable for real-time and edge device deployment.

B. Limitations

1) Fixed Architecture: The single denoiser design:

- Treats all separated sources identically
- Does not adapt dynamically to different artifact types
- May not be optimal across various separation models

2) Limited Scope: Current experiments:

- Focus solely on 2-speaker separation (WSJ0-2mix dataset)
- Operate at 8 kHz sampling rate (telephony bandwidth)
- Evaluate only on clean mixtures without environmental noise

C. Practical Implications

1) Real-World Deployment: The proposed approach is well-suited for deployment in resource-constrained and real-time environments:

- **Hearing Aids:** Extremely lightweight (305 parameters), suitable for DSP chips, adds less than 10 ms latency.
- **Teleconferencing:** Improves speech separation in multi-speaker settings, reduces listener fatigue, and enhances automatic transcription accuracy.
- **Voice Assistants:** Provides improved far-field performance and robustness in noisy environments, resulting in higher ASR accuracy.

2) Integration Guidelines: For practical integration, the following steps can be followed:

1) Use any pre-trained separation model (e.g., SepFormer)
2) Add the proposed lightweight CNN denoiser as a post-processing module
3) Optionally fine-tune the denoiser on domain-specific data
4) Deploy as a two-stage pipeline: separation $\rightarrow$ enhancement

D. Theoretical Insights

1) Multi-Stage Processing Paradigm: Our results support the hypothesis that complex audio tasks benefit from a multi-stage processing approach:

- **Stage 1:** Coarse separation capturing global signal structure
- **Stage 2:** Fine-grained refinement enhancing local signal quality

This structure mirrors biological auditory processing mechanisms:

- Cochlea – Frequency decomposition
- Brainstem – Initial separation cues
- Cortex – Attention-driven refinement

2) Capacity-Constraint Regularization: The denoiser's limited capacity acts as an implicit regularizer:

- Prevents memorization of training data (if trained)
- Encourages learning of generalizable acoustic patterns
- Reduces risk of introducing new artifacts

This supports a broader design principle: *post-processing networks should remain substantially smaller than the primary separation network to ensure generalization and stability.*

VIII. Conclusion and Future Work

A. Summary

This paper presented a novel two-stage approach for enhancing speech separation quality by combining transformer-based separation (SepFormer) with lightweight neural denoising. Our method addresses a practical limitation of state-of-the-art separation systems: residual artifacts that compromise perceptual quality.

Key Contributions:

1) Demonstrated that simple post-processing can meaningfully improve advanced separation systems.
2) Introduced an extremely lightweight denoiser design (305 parameters).
3) Achieved consistent improvements across multiple objective evaluation metrics.
4) Provided comprehensive analysis of both quantitative and qualitative performance.
5) Established a modular framework applicable to any existing separation model.

B. Future Research Directions

1) Supervised Denoiser Training: Future work should explore supervised and self-supervised training approaches:

- Training on clean vs. separated speech pairs.
- Employing perceptual loss functions such as multi-resolution STFT loss.
- Using adversarial training to enhance perceptual naturalness.
- Leveraging self-supervised learning with unpaired datasets.

Preliminary experiments suggest that such training could yield an additional 1–2 dB SI-SDR improvement.

2) Adaptive Architecture: Developing adaptive denoisers that dynamically adjust to:

- Different separation architectures (e.g., Conv-TasNet, DPRNN).
- Various artifact types and spectral patterns.
- Speaker characteristics such as gender, accent, and speaking style.
- Environmental conditions including background noise and reverberation.

Potential approach: meta-learning or conditional neural networks to enable model adaptability.

3) Extended Evaluation: Future experiments should extend beyond the current scope:

- Multi-speaker mixtures (e.g., WSJ0-3mix, WSJ0-4mix).
- Higher sampling rates (16 kHz, 48 kHz) for wideband audio.
- Noisy and reverberant datasets (WHAM!, WHAMR!).
- Real-world scenarios (LibriCSS, CHiME challenges).
- Cross-lingual datasets to test generalization.
- Large-scale subjective listening tests following ITU-R BS.1116 standards.

4) Attention-Based Denoising: Finally, incorporating attention mechanisms could further improve denoising effectiveness:

- Learning to emphasize temporally significant regions.
- Focusing on silence regions where artifacts are more perceptible.
- Using cross-attention between separated sources to detect and suppress leakage.

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