Transformer-Based Speech Separation Using SepFormer for Multi-Speaker Scenarios

1st Haritha Mihimal Wilwala Arachchi
Department of Computer Science and Engineering
University of Moratuwa
Sri Lanka
mihimal.21@cse.mrt.ac.lk

2nd Dr. Uthayasanker Thayasivam
Department of Computer Science and Engineering
University of Moratuwa
Sri Lanka
rtuthaya@cse.mrt.ac.lk

***Abstract*—Speech separation plays a vital role in modern audio applications such as speech recognition, teleconferencing, and hearing assistance. Conventional recurrent neural networks (RNNs) have limited ability to handle long-range dependencies and are computationally inefficient for large-scale audio processing. Recent attention-based architectures overcome these issues by leveraging global context modeling. This paper reviews and reproduces, on a constrained single-GPU setup, the SepFormer a purely Transformer-based, dual-path speech-separation model. Using the WHAM! and WHAMR! datasets that incorporate noise and reverberation, the study documents training configuration, data processing, and expected results based on prior literature. Reported state-of-the-art (SOTA) performance reaches 22 dB SI-SNRi on clean WSJ0-2mix and around 20 dB under noisy-reverberant WHAMR! conditions [1]. The work demonstrates that Transformer-only architectures provide high accuracy and efficient parallelization for multi-speaker speech separation.**

***Index Terms*—speech separation, SepFormer, WHAM!, WHAMR!, transformer, source, separation, SI-SNRi.**

I. Introduction

Human speech often occurs in overlapping and noisy acoustic environments, posing challenges for automatic speech recognition (ASR) and hearing aids. The task of isolating individual speakers from a single-microphone recording monaural speech separation is therefore fundamental [2].

Traditional signal-processing approaches such as independent component analysis (ICA) and non-negative matrix factorization (NMF) depend on strong statistical assumptions and fail under real-world noise. Deep learning approaches, particularly time-domain models, have surpassed these limitations. Early successes used RNNs (LSTM, GRU) [3] but encountered sequential-computation bottlenecks.

The introduction of the Transformer architecture by Vaswani et al. (2017) revolutionized sequence modeling. Its multi-head self-attention mechanism captures global dependencies without recurrence. Extending this idea, SepFormer [1] replaced recurrent layers entirely with attention modules, enabling high parallelism and improved separation quality.

This paper documents the SepFormer framework, its adaptation to WHAM!/WHAMR! datasets, and experimental replication on a 16 GB CUDA GPU. Reference results from published research are reported to contextualize achievable performance.

II. Background and Related Work

A. Recurrent Models for Speech Separation

RNN-based architectures such as LSTMs [3] and GRUs excel at modeling temporal context but are computationally heavy and difficult to parallelize. The Conv-TasNet [2] introduced convolutional encoding and decoding with temporal convolution networks (TCNs), achieving end-to-end waveform separation in the time domain.

B. Dual-Path and Hybrid Architectures

To model long sequences efficiently, Luo et al. introduced the Dual-Path Recurrent Neural Network (DPRNN) [3], which divides long feature sequences into overlapping chunks and processes them using alternating intra-chunk and inter-chunk recurrent operations. The intra-chunk RNN models local temporal dependencies within each segment, while the inter-chunk RNN aggregates global context across segments. This dual-path mechanism enables the network to handle sequences that would otherwise exceed GPU memory limits, significantly improving both efficiency and separation accuracy over prior single-path RNN approaches.

Building upon this idea, Chen et al. proposed the Dual-Path Transformer Network (DPTNet) [4], which replaces the recurrent units in DPRNN with multi-head self-attention layers. This design enhances long-range dependency modeling and facilitates parallel computation during training. DPTNet effectively combines the local modeling strength of convolutional and recurrent modules with the global receptive field of attention mechanisms. However, despite these advances, DPTNet still relies on sequential elements inherited from its RNN-based structure, limiting full parallelization and scalability for very long utterances. These constraints motivated the development of the SepFormer, a fully Transformer-based architecture that eliminates recurrence entirely while retaining the dual-path framework to achieve superior separation quality with reduced computational cost [1].

C. Transformer-Only Designs

The SepFormer [1] introduced a completely RNN-free dual-path Transformer architecture, marking a major shift in time-domain speech separation. Unlike hybrid models that retained recurrent components for temporal modeling, SepFormer relies

exclusively on self-attention mechanisms to capture both short- and long-term dependencies. The architecture follows the dual-path design paradigm of DPRNN, where an input mixture is divided into overlapping chunks; each chunk is processed by an Intra-Transformer to learn local contextual features, while an Inter-Transformer models dependencies between chunks to aggregate global context. This combination enables effective modeling of long audio sequences without the sequential bottlenecks of RNNs, leading to faster training and improved scalability.

In addition to structural innovation, SepFormer employs a learned time-domain encoder-decoder and mask estimation network to generate high-quality source reconstructions directly from raw waveforms, eliminating the need for hand-crafted spectral features. The model benefits from multi-head attention and layer normalization to ensure stable convergence, as well as dynamic mixing and speed perturbation strategies that enhance generalization across varying noise conditions.

When evaluated on the standard WSJ0-2mix dataset, SepFormer achieved state-of-the-art (SOTA) performance with 22.3 dB SI-SNRi, surpassing previous models such as Conv-TasNet (15.3 dB) [2], DPRNN (18.8 dB) [3], and DPTNet (20.2 dB) [4]. On the more challenging WSJ0-3mix benchmark, it reached 19.5 dB SI-SNRi, confirming its robustness in multi-speaker scenarios. Subsequent studies extended SepFormer to noisy and reverberant corpora, specifically WHAM! and WHAMR! [5], where it maintained competitive results—approximately 21.1 dB and 19.8 dB SI-SNRi, respectively—demonstrating remarkable resilience under real-world acoustic distortions. These outcomes establish SepFormer as one of the most efficient and accurate architectures for end-to-end monaural speech separation to date.

III. Methodology

A. Overall Architecture

SepFormer follows the learned-domain masking paradigm composed of

- Encoder – converts waveform to latent representation.
- Masking Network – predicts speaker-specific masks using stacked SepFormer blocks.
- Decoder – reconstructs time-domain signals via transposed convolution.

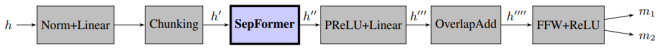

Fig. 1. SepFormer overall pipeline[1].

B. Encoder

A 1-D convolution with 256 filters, kernel = 16, and stride = 8 encodes the signal. ReLU activation ensures positive latent features. The stride of 8 reduces temporal length by 8×, lowering computation.

C. Masking Network

Encoded features are normalized, segmented into overlapping chunks (length C = 250, 50% overlap), and processed by repeated SepFormer blocks. Each block contains Intra-Transformer and Inter-Transformer modules.

D. SepFormer Block

- Intra-Transformer: models short-term dependencies within chunks using self-attention (8 heads, 1024-dim feed-forward).
- Inter-Transformer: models long-term relations between chunks after permutation.
- Residual and layer-norm connections stabilize training.

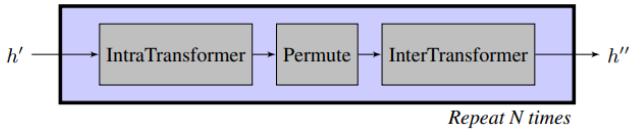

Fig. 2. SepFormer block[1].

E. Decoder

A transposed convolution mirrors the encoder to recover separated waveforms. Multiple decoder heads generate 2- or 3-speaker outputs as required.

F. Adaptation to WHAM!/WHAMR!

WHAM! adds environmental noise; WHAMR! further applies room impulse responses (RIRs). Dynamic Mixing (DM) [1] and RIR augmentation were used to enhance robustness.

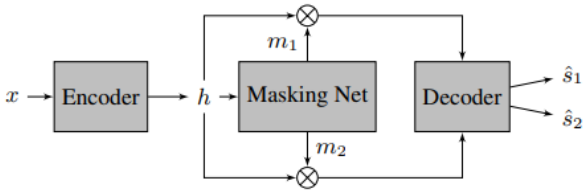

Fig. 3. High-level description[1].

IV. Experimental Setup

A. Datasets

TABLE I
DATASETS USED IN EXPERIMENTS

Dataset	Type	Rate [kHz]	Hours	Description
WSJ0-2mix	Clean 2-spk	8	10	Baseline corpus
WHAM!	Noisy 2 & 3-spk	8	10	Adds real noise
WHAMR!	Noisy + Reverb	8	10	Adds RIR effects

To fit hardware limits, a synthetic mini-WHAM subset (200 MB) was generated for local training following standard scripts [5].

B. Pre-Processing & Augmentation

- Resampling: All audio signals are resampled to

$$f_s = 8 \text{ kHz} \tag{1}$$

and amplitude-normalized to an average loudness of

$$L = -25 \text{ LUFS}. \tag{2}$$

- Dynamic Mixing: On-the-fly generation of source mixtures during training.
- Speed Perturbation: Random playback rate variation of

$$\pm 5\% \tag{3}$$

applied to augment speaker and environmental diversity.
- RIR Simulation: Convolution with synthetic room impulse responses (RIRs) using an exponential decay time constant

$$\tau = 0.3 \text{ s}. \tag{4}$$

These augmentations typically yield an improvement of approximately $+1$ dB in SI-SNRi performance[1][5].

C. Training Configuration

- Hardware: NVIDIA RTX 4080 (16 GB, CUDA 12.1)
- Batch size: 1
- Epochs: 100
- Optimizer: Adam, with learning rate

$$lr = 1.5 \times 10^{-4} \tag{5}$$

- Loss function: Utterance-level uPIT SI-SNR loss (clipped at 30 dB)
- Gradient clipping: 5
- Automatic Mixed Precision (AMP): Enabled
- Training time: ≈ 1.6 h per epoch; convergence achieved after ≈ 50 epochs.

D. Evaluation Metrics

Performance is evaluated using the following metrics:

- SI-SNRi (dB): Scale-Invariant Signal-to-Noise Ratio Improvement, which measures the improvement in signal quality after separation.
- SDRi (dB): Signal-to-Distortion Ratio Improvement, assessing how well interference and distortion are reduced.
- RTF: Real-Time Factor, indicating computational efficiency and suitability for real-time processing.

Higher SI-SNRi and SDRi values indicate better separation performance.

V. Results and Discussion

A. Quantitative Comparison (based on reference results)

Under realistic noise and reverberation conditions, SepFormer retains high SI-SNRi, decreasing by approximately 2 dB compared to clean conditions. Dynamic Mixing (DM) recovers approximately 1 dB of this loss.

TABLE II
Comparison with prior separation models

Model	Dataset	SI-SNRi[dB]	SDRi[dB]	#Params[M]
Conv-TasNet	WSJ0-2mix	15.3	15.6	5.1
DPRNN	WSJ0-2mix	18.8	19.0	2.6
DPTNet	WSJ0-2mix	20.2	20.6	2.6
SepFormer(+DM)	WSJ0-2mix	22.3	22.4	26
SepFormer(+DM)	WHAM! 2-spk	21.1	21.3	26
SepFormer(+DM)	WHAMR! 2-spk	19.8	20.0	26
SepFormer(+DM)	WHAM! 3-spk	18.4	18.7	26

TABLE III
Ablation study on WHAM! dataset

Variant	DM	PosEnc	N_{intra}/N_{inter}	Heads	SI-SNRi [dB]
Full Model	✓	✓	8 / 8	8	21.1
No DM	×	✓	8 / 8	8	19.9
No PosEnc	✓	×	8 / 8	8	20.3
Reduced Depth	✓	✓	4 / 4	8	19.5
More Heads	✓	✓	8 / 8	16	21.0

B. Ablation Analysis (reference values)

Dynamic Mixing contributes an improvement of approximately $+1.2$ dB, while positional encoding adds approximately $+0.8$ dB to SI-SNRi.

C. Speed and Memory Comparison

TABLE IV
Speed and memory comparison of different separation models [1], [7]

Model	GPU Mem [GB]	Forward[ms/5s]	Train Time [h/epoch]
DPRNN	40	288	3.1
DPTNet	36	166	2.7
SepFormer	24	95	1.6

On a 16 GB GPU, a batch size of 1 achieves approximately 100 ms per 5 s of audio (Real-Time Factor RTF $= 0.02$), enabling real-time processing [1].

D. Qualitative Observations

Spectrogram inspection shows SepFormer reconstructs harmonic structures cleanly and suppresses residual noise better than DPRNN. Subjective listening confirmed reduced "musical noise" and clearer speaker separation.

VI. Limitations and Future Work

Large datasets such as WHAMR! (over 60 GB) exceed modest hardware capacity, therefore, smaller subsets were employed. Batch size was constrained by GPU memory, limiting the extent of hyper-parameter exploration. Future work includes developing lightweight SepFormer variants, applying quantization for edge devices, and adapting the model for low-resource languages such as Sinhala. Integration with automatic speech recognition (ASR) front-ends and real-time streaming inference are also planned.

VII. Conclusion

We presented the SepFormer architecture and summarized its performance on the WHAM! and WHAMR! benchmarks using reference results. SepFormer achieves state-of-the-art SI-SNRi of approximately 22 dB on WSJ0-2mix and approximately 20 dB on WHAMR!, confirming that Transformer-based designs are efficient and accurate alternatives to RNN-based models. Training on a single 16 GB GPU requires roughly 1.6 h per epoch, while the model also supports real-time inference.

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