On Using Transformers for Speech-Separation

Cem Subakan\textsuperscript{1,2}, Mirco Ravanelli\textsuperscript{1}, Samuele Cornell\textsuperscript{3}, François Grondin\textsuperscript{2}, Mirko Bronzi\textsuperscript{1}
\textsuperscript{1}Mila-Quebec AI Institute,
\textsuperscript{2}Université de Sherbrooke,
\textsuperscript{3}Università Politecnica delle Marche.

Abstract—Transformers have enabled major improvements in deep learning. They often outperform recurrent and convolutional models in many tasks while taking advantage of parallel processing. Recently, we have proposed SepFormer, which uses self-attention and obtains state-of-the-art results on WSJ0-2/3 Mix datasets for speech separation. In this paper, we extend our previous work by providing results on more datasets including LibriMix, and WHAM!, WHAMR! which include noisy and noisy-reverberant conditions. Moreover we provide denoising, and denoising+dereverberation results in the context of speech enhancement, respectively on WHAM! and WHAMR! datasets. We also investigate incorporating recently proposed efficient self-attention mechanisms inside the SepFormer model, and show that by using efficient self-attention mechanisms it is possible to reduce the memory requirements significantly while performing better than the popular convtasnet model on WSJ0-2Mix dataset.

Index Terms—speech separation, source separation, transformer, attention, deep learning.

I. INTRODUCTION

TRANSFORMERS are playing a pivotal role in modern deep learning [1]. They contributed to a paradigm shift in sequence learning and made it possible to achieve unprecedented performance in many Natural Language Processing (NLP) tasks, such as language modeling, machine translation, and many other applications [2], [3]. Transformers are becoming increasingly dominant in speech processing as well. For instance, they have been recently adopted for speech recognition, speaker verification, speech enhancement, and more recently for speech separation [4]–[6]. Transformers enable more accurate modeling of longer term dependencies which render them suitable for audio processing, especially for speech separation, where long-term modeling has been shown to impact performance significantly [7], [8]. Motivated by this reason, we proposed SepFormer [6], a transformer-based model which obtains state-of-the-art results on speech separation.

In this paper, building on top of this first work, we study to what extent transformers architectures are a viable choice for speech separation and speech enhancement applications. In particular, in our previous work [6] we focused on the standard WSJ0-2/3 Mix benchmark datasets. Here, we expand the study performed in our previous work [6], by providing additional experiments and insights on more realistic and challenging datasets such as Libri2/3-Mix [9], which include longer mixtures, WHAM! [10] and WHAMR! [11], featuring noisy and noisy & reverberant conditions respectively. Moreover, on WHAM! and on WHAMR! datasets we also provide results for speech enhancement. The training recipes for these experiments are all available in the Speechbrain [12] toolkit.

Another contribution of this paper is investigating different types of self-attention for speech separation. Even though transformers consist only of feed-forward layers and therefore are able to leverage parallel processing capabilities of GPUs, the main building block of transformers, the attention mechanism, comes with a $O(N^2)$ computation cost that presents itself as a major memory bottleneck. That is, for a sequence of length $N$, we need to compare $N^2$ elements, leading to a computational bottleneck that emerges more clearly when processing long signals. In addition, the large number of parameters usually required by Transformers further aggravate this memory problem.

Mitigating the memory bottleneck of Transformers has been the object of intense research in the last years [13]–[16]. To address this issue, these methods assume that attending to a subset of elements is sufficient in most applications and propose more constrained, memory efficient self-attention mechanisms. For instance, Sparse Transformer [13] employs local and dilated sliding windows over a fixed number of elements to learn short and long-term dependencies. LongFormer [14] augments the Sparse Transformer by adding global attention heads. Linformers [15], approximate the full sparse attention with low-rank matrix multiplication, while Reformers [16] clusters the elements to attend through an efficient locality-sensitive hashing function.

In this paper, we explore the use of three popular efficient self-attention mechanisms with and without the dual-path processing pipeline [7]. Namely, we compare the regular self-attention [1] with Longformer [14], Linformer [15], and Reformer [16] attention. We observe that using the full attention mechanism, as used in our previously proposed Sepformer [6], provides the best performance overall. However, Reformer and Longformer attention mechanisms, present favourable trade-offs in terms of performance versus memory requirements. Namely, we observe that using reformer without the dual-path pipeline results in 16.7 dB SI-SNR improvement. We compare the efficiency of this model with the popular convtasnet model, and observe that the proposed model is slightly more efficient while yielding better performance.

The paper is organized as follows. First, in Section II we introduce the building blocks of transformers and also describe about the three different efficient attention mechanisms (Longformer, Linformer and Reformer) we explore in this work. Next, in Section IV we describe the SepFormer model in detail with special focus on the dual-path processing pipeline.
In this paper, we utilize the encoder part of the Transformer architecture, which is depicted in Fig. 1. The encoder turns an input sequence $X = \{x_1, \ldots, x_T\} \in \mathbb{R}^{F \times T}$ into an output sequence $Y = \{y_0, \ldots, y_T\} \in \mathbb{R}^{F \times T}$ using a pipeline of computations that involve positional embedding, multi-head self-attention, normalization, feed-forward layers, and residual connections.

A. Multi-head self-attention

The multi-head self-attention mechanism allows the Transformer to model dependencies across all the elements of the sequence. The first step is to calculate the Query, Key, and Value matrices from the input sequence $X$ of length $T$. This operation is performed by multiplying the input vector by weight matrices: $Q = W_QX$, $K = W_KX$, $V = W_VX$, where $W_Q, W_K, W_V \in \mathbb{R}^{F \times F}$. The attention layer consists of the following operations:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V,$$  \hspace{1cm} (1)

where $d_k$ represents the latent dimensionality of the $Q$ and $K$ matrices. We observe that the attention weights derive from a scaled dot-product between queries and keys. Closer query and key vectors will have higher dot products. The softmax function ensures that the attention weights range between 0 and 1. The attention mechanism produces $T$ weights for each input element (i.e., $T^2$ attention weights). All in all, the softmax part of the attention layer computes relative importance weights, and then we multiply this attention map with the input value sequence $V$.

In practice a multi-head-attention mechanism is employed consisting of several parallel attention layers. More in detail, the multi-head-attention is computed as follows:

$$\text{MultiHeadAttention}(Q, K, V) = \text{Concat}(\text{head}_1, \ldots, \text{head}_h)W^O,$$ \hspace{1cm} (2)

where $\text{head}_i = \text{Attention}(Q, K, V_i)$,

where $h$ is the number of parallel attention heads and $W^O \in \mathbb{R}^{hF \times d_{\text{model}}}$ is the matrix that combines the parallel attention heads, and $d_{\text{model}}$ denotes the latent dimensionality of this combined model.

B. Feedforward Layers

The feed-forward component of the transformer architecture simply consists of a two-layer perceptron. The exact definition of which is as follows,

$$FFN(x) = \text{ReLU}(xW_1 + b_1)W_2 + b_2,$$ \hspace{1cm} (3)

where $x$ is the input. In the context of sequences, this feed-forward transformation is applied to each time point separately. $W_1$ and $W_2$ are learnable matrices, and $b_1$ and $b_2$ are learnable bias vectors.

C. Positional encoding

As the self-attention layer and feed-forward layers do not contain any notion of ordering, the transformer makes use of
a positional encoding scheme used to inject sequence ordering information. The positional encoding is defined as follows \(1\),

\[
P E_{t, 2i} = \sin(t/10000^{2i/d_{	ext{max}}}) \\
P E_{t, 2i+1} = \cos(t/10000^{2i/d_{	ext{max}}})
\]

This encoding therefore relies on sinusoids of different frequencies in each latent dimension to encode positional information.

D. Reducing the memory bottleneck

1) Longformer: Longformer \(14\), aims to reduce the quadratic complexity by replacing the full self-attention structure with a combination of local and global attention. Specifically, Longformer relies on a local attention mechanism that captures dependencies only from nearby elements, and a global attention mechanism that globally captures dependencies from all the elements. To keep the computational requirements manageable, the global attention is only performed for few special elements in the sequence.

2) Linformer: Linformer \(15\), avoids the quadratic complexity by reducing the size of the time dimension of the matrices \(K, V \in \mathbb{R}^{C \times F}\). This is done by projecting the time dimension \(C\) to a smaller dimensionality \(k\). This is done by using projection matrices \(P, F \in k \times C\). The multi-head attention equation therefore becomes the following:

\[
\text{LFSelfAttention}(Q, K, V) = \text{softmax} \left( \frac{Q(PK)^\top}{\sqrt{d_k}} \right) (FV),
\]

which effectively limits the complexity of the matrix product between the softmax output and the \(V\) matrix.

3) Reformer: Reformer \(16\) uses locality sensitive hashing (LSH) to reduce the complexity of the self attention. In fact, LSH is used to find the vector pairs \((q, k), q \in Q, k \in K\) that are closer. The intuition is that those pairs, being closer, will have a bigger dot product and will contribute the most to the attention matrix. Because of this, the authors limit the attention computation to the close pairs \((q, k)\), while ignoring the others (saving time and memory). In addition to this, the Reformer, inspired by \(20\), implements reversible Transformer layers that avoid the linear memory complexity scaling with respect to the amount of layers.

IV. Separation Transformer (SepFormer)

In this section we explain the components of the neural network that constitute the SepFormer. We first of all define the masking-based source separation framework on which SepFormer is based.

In the mask-based end-to-end source separation pipeline, popularized by \(21\), \(22\), an input mixture \(x \in \mathbb{R}^T\) is given as the input to the architecture. A learnable encoder obtains a representation \(h \in \mathbb{R}^{F \times T'}\). Afterwards a masking network estimates the masks \(m_1, m_2 \in \mathbb{R}^{F \times T'}\). The separated time domain signals for source 1 and source 2 are obtained with passing the \(h \ast m_1\), and \(h \ast m_2\) through the decoder, where \(\ast\) denotes element-wise multiplication. Next, we explain each block separately.

A. Encoder

The encoder takes in the time-domain mixture-signal \(x \in \mathbb{R}^T\) as input. It learns an Short-Time Fourier Transform (STFT) like representation \(h \in \mathbb{R}^{F \times T'}\) using a single convolutional layer:

\[
h = \text{ReLU} (\text{conv1d}(x)).
\]

As we will describe in Section \(V.C\) the stride factor of this convolution impacts significantly the performance, speed, and memory of the model.

B. Decoder

The decoder simply uses a transposed convolutional layer, with the same stride and kernel size of the encoder. The input to the decoder is the element-wise multiplication between the mask \(m_k\) relative to the \(k\)-th source, and the output of the encoder \(h\). The transformation of the decoder can therefore be expressed as follows:

\[
\hat{s}_k = \text{conv1d-transpose}(m_k \ast h),
\]

where \(\hat{s}_k \in \mathbb{R}^T\) denotes the separated source \(k\).

C. Masking Network

Figure 2 (top) shows the detailed architecture of the masking network (Masking Net). The masking network is fed by the encoded representations \(h \in \mathbb{R}^{F \times T'}\) and estimates a mask \(\{m_1, \ldots, m_{N_s}\}\) for each of the \(N_s\) speakers in the mixture.

As in \(22\), the encoded input \(h\) is normalized with layer normalization \(23\) and processed by a linear layer (with dimensionality \(F\)). Following the dual-path framework introduced in \(7\), we create overlapping chunks of size \(C\) by chopping up \(h\) on the time axis with an overlap factor of 50%. We denote the output of the chunking operation with \(h' \in \mathbb{R}^{F \times C \times N_c}\), where \(C\) is the length of each chunk, and \(N_c\) is the resulting number of chunks.

The representation \(h'\) feeds the SepFormer separator block, which is the main component of the masking network. This block, which will be described in detail in Sec. \(IV\) employs a pipeline composed of two transformers able to learn short and long-term dependencies.

The output of the SepFormer \(h'' \in \mathbb{R}^{F \times C \times N_c}\) is processed by PReLU activations followed by a linear layer. We denote
the output of this module \( h'' \in \mathbb{R}^{(F \times N_s) \times C \times N_c} \), where \( N_s \) is the number of speakers. Afterwards we apply the overlap-add scheme described in \([7]\) and obtain \( h''' \in \mathbb{R}^{F \times N_s \times T'} \). We pass this representation through two feed-forward layers and a ReLU activation at the end to obtain a mask \( m_k \) for each one of the speakers.

D. Dual-Path Processing Pipeline and SepFormer

The dual-path processing pipeline \([7]\) (shown in Fig. 3) enables a combination of short and long term modeling, while making long sequence processing feasible with a self-attention block. In the context of the masking based end-to-end source separation shown in Fig. 2 the latent representation \( h \in \mathbb{R}^{F \times T''} \) is divided into overlapping chunks.

A transformer encoder is applied on each chunk separately. We call this block IntraTransformer (IntraT) and denote it with \( f_{\text{intra}}(.) \). This block effectively operates as a block diagonal attention structure, modeling the interaction between all elements in each chunk separately so that the attention memory requirements are bounded. Another transformer encoder is applied to model the inter-chunk interactions, i.e. between each chunk element. We call this block InterTransformer (InterT) and denote with \( f_{\text{inter}}(.) \). Because this block attends to all elements that occupy the same position in each chunk, it effectively operates as a strided attention structure. Mathematically, the overall transformation can be summarized as follows:

\[
h'' = f_{\text{inter}}(f_{\text{intra}}(h')). \tag{9}
\]

In the standard SepFormer model defined in \([6]\), \( f_{\text{inter}} \) and \( f_{\text{intra}} \) are chosen to be full self-attention blocks. In Section IV-E we describe the full self-attention block employed in SepFormer in detail.

E. Full Self-Attention Transformer Encoder

The architecture for the full self-attention transformer encoder layers follows the original Transformer architecture \([1]\). Figure 4 (Bottom) shows the architecture of the employed full-attention transformer encoder layers used both for IntraTransformer and InterTransformer blocks.

We use the variable \( z \) to denote the input to the Transformer. First of all, sinusoidal positional encoding \( e \) is added to the input \( z \), such that,

\[
z' = z + e. \tag{10}
\]

Positional encoding injects information on the order of the various elements composing the sequence, thus improving the separation performance. We follow the positional encoding definition in \([1]\).

We then apply multiple Transformer layers. Inside each Transformer layer \( g(.) \), we first apply layer normalization, followed by multi-head attention (MHA):

\[
z'' = \text{MultiHeadAttention}(\text{LayerNorm}(z')). \tag{11}
\]

As proposed in \([1]\), each attention head computes the scaled dot-product attention between all the elements of the sequence.

The Transformer finally employs a feed-forward network (FFW), which is applied to each position independently:

\[
z''' = \text{FeedForward}(\text{LayerNorm}(z'' + z')) + z'' + z'. \tag{12}
\]

The overall transformer block is therefore defined as follows:

\[
f(z) = g^K(z + e) + z, \tag{13}
\]

where \( g^K(.) \) denotes \( K \) layers of transformer layer \( g(.) \). We use \( K = N_{\text{inter}} \) layers for the IntraT, and \( K = N_{\text{inter}} \) layers for the InterT. As shown in Figure 4 (Bottom) and Eq. (13), we add residual connections across the transformer layers, and across the transformer architecture to improve gradient backpropagation.

V. EXPERIMENTS

A. Datasets

In our experiments, we use the popular WSJ0-2mix and WSJ0-3mix datasets \([24]\), where mixtures of two speakers and three speakers are created by randomly mixing utterances in the WSJ0 corpus. The relative levels for the sources are sampled uniformly between 0 dB to 5 dB. Respectively, 30, 10, 5 hours of speech is used for training, validation, and test.

The training and test sets are created with different sets of speakers. We use the 8kHz version of the dataset, with the ‘min’ version where the added waveforms are clipped to the shorter signal’s length. These datasets have become the de facto standard benchmark for source separation algorithms.

In addition to the WSJ0-2/3 Mix, in this paper we also provide experimental data on WHAM! \([10]\), and WHAMR! datasets \([11]\) which are essentially derived from WSJ0-2Mix dataset by adding environmental noise and environmental noise plus reverberation respectively. We also provide experimental results on the LibriMix dataset \([9]\), which contains longer and more challenging mixtures than the WSJ0-Mix dataset.

B. Architecture and Training Details of SepFormer

The encoder of the SepFormer is based on 256 convolutional filters with a kernel size of 16 samples and a stride factor of 8 samples. The decoder uses the same kernel size and the stride factors of the encoder.

In our best models, the SepFormer masking network processes chunks of size \( C = 250 \) with a 50 % overlap between them and employs 8 layers of transformers in both IntraTransformer and InterTransformer. The dual-path processing pipeline is repeated \( N = 2 \) times. We used 8 parallel attention heads, and 1024-dimensional positional feed-forward networks within each Transformer layer. The model has a total of 25.7 million parameters.

We explored the use of dynamic mixing (DM) data augmentation \([25]\) which consists in on-the-fly creation of new mixtures from single speaker sources. In this work we expanded this powerful technique by applying also speed perturbation on the sources before mixing them. The speed randomly changes between 95 % slow-down and 105 % speed-up.

We used the Adam algorithm \([26]\) as optimizer, with a learning rate of \( 1.5e^{-4} \). After epoch 65 (after epoch 85 with
DM), the learning rate is annealed by halving it if we do not observe any improvement of the validation performance for 3 successive epochs (5 epoch for DM). Gradient clipping is employed to limit the $l^2$-norm of the gradients to 5. During training, we used a batch size of 1, and used the scale-invariant signal-to-noise Ratio (SI-SNR) \cite{VaF20} via utterance-level permutation invariant loss \cite{VaF20}, with clipping at 30 dB \cite{VaF20}. We used automatic mixed-precision to speed up training. The system is trained for a maximum of 200 epochs. Each epoch takes approximately 1.5 hours on a single NVIDIA V100 GPU with 32 GB of memory with automatic mixed precision.

### C. Results on WSJ0-2/3 Mix datasets

WSJ0-2/3 Mix datasets are commonly used as benchmarking datasets in the source-separation literature. In Table \ref{tab:results} we compare the performance achieved by the proposed SepFormer with the best results reported in the literature on the WSJ0-2mix dataset. The SepFormer achieves an SI-SNR improvement (SI-SNRi) of 22.3 dB and a Signal-to-Distortion Ratio (SDR) improvement of 22.4 dB on the test-set with dynamic mixing. When using dynamic mixing, the proposed architecture achieves state-of-the-art performance. The SepFormer outperforms previous systems without using dynamic mixing except Wavesplit, which however achieves such impressive performance by leveraging speaker identity as additional information.

We also study the effect of various hyperparameters and data augmentations strategies on the performance of the SepFormer using the WSJ0-2mix dataset. The results are summarized in Table \ref{tab:hyperparams}. The reported performance in this table is calculated on the validation set.
We observe that the number of InterT and IntraT blocks has an important impact on the performance. The best results are achieved with 8 layers for both blocks replicated two times. We also would like to point out that a respectable performance of 19.2 dB is obtained even when we use a single layer transformer for the InterTransformer. This suggests that the IntraTransformer, and thus local processing, has a greater influence on the performance. It also emerges that positional encoding is helpful (e.g. see lines 3 and 5 of Table I). A similar outcome has been observed in [36] for speech enhancement. As for the number of attention heads, we observe a slight performance difference between 8 and 16 heads. Finally, it can be observed that dynamic mixing helps the performance significantly.

Table III showcases the best performing models on the WSJ0-3mix dataset. SepFormer obtains the state-of-the-art performance with an SI-SNRi of 19.5 dB and an SDRi of 19.7 dB. We used here the best architecture as found for the WSJ0-2mix dataset in Table II. The only difference is that SepFormer is faster than DPRNN and DPTNeT. Figure 5 (middle&right) compares the average computation time (in ms) and the total memory allocation (in GB) during inference when single precision is used. We analyze the speed of our best model for both WSJ0-2Mix and WSJ0-3Mix datasets. We compare our models against DP-RNN, DPTNeT, and Wavesplit. All the models are stored in the same NVIDIA RTX8000-48GB GPU and we performed this analysis using the PyTorch profiler [37].

From this analysis, it emerges that the SepFormer is not only faster but also less memory demanding than DPTNet, DPRNN, and Wavesplit. We observed the same behavior using the CPU for inference. Such a level of computational efficiency is achieved even though the proposed SepFormer employs more parameters than the other RNN-based methods (see Table I). This is not only due to the superior parallelization capabilities of the proposed model, but also because the best performance is achieved with a stride factor of 8 samples, against a stride of 1 for DPRNN and DPTNeT. Increasing the stride of the encoder results in downsampling the input sequence, and therefore the model processes less data. In [7], the authors showed that the DPRNN performance degrades when increasing the stride factor. The SepFormer, instead, reaches competitive results even with a relatively large stride, leading to the aforementioned speed and memory advantages.

D. Speed and Memory Comparison

We now compare the training and inference speed of our model with DPRNN [7] and DPTNet [8]. Figure 5 (left) shows the training curves of the aforementioned models on the WSJ0-2mix dataset. We plot the performance achieved on the validation set in the first 48 hours of training versus the wall-clock time. For a fair comparison, we used the same machine with the same GPU (a single NVIDIA V100-32GB) for all the models. Moreover, all the systems are trained with a batch size of 1 and employ automatic mixed precision. We observe that the SepFormer is faster than DPRNN and DPTNeT. Figure 5 (left), highlights that SepFormer reaches above 17dB levels only after a full day of training, whereas the DPRNN model requires two days of training to achieve the same level of performance.

We observe the number of InterT and IntraT blocks has an important impact on the performance. The best results are achieved with 8 layers for both blocks replicated two times. We also would like to point out that a respectable performance of 19.2 dB is obtained even when we use a single layer transformer for the InterTransformer. This suggests that the IntraTransformer, and thus local processing, has a greater influence on the performance. It also emerges that positional encoding is helpful (e.g. see lines 3 and 5 of Table I). A similar outcome has been observed in [36] for speech enhancement. As for the number of attention heads, we observe a slight performance difference between 8 and 16 heads. Finally, it can be observed that dynamic mixing helps the performance significantly.

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Table I: Best results on the WSJ0-2-mix dataset (test-set). DM stands for dynamic mixing.

| Model       | SI-SNRi | SDRi | # Param | Stride |
|-------------|---------|------|---------|--------|
| Tasnet [21] | 10.8    | 11.1 | n.a.    | 20     |
| SignPredictionNet [29] | 15.3    | 15.6 | 55.2M   | 8      |
| ConvTasnet [22] | 15.3    | 15.6 | 5.1M    | 10     |
| Two-Step CTN [30] | 16.1    | n.a. | 8.6M    | 10     |
| MGST [19]   | 17.0    | 17.3 | n.a.    | n.a.   |
| DeepCAS [31] | 17.7    | 18.0 | 12.8M   | 1      |
| FurcaNeXt [32] | n.a.    | 18.4 | 51.4M   | n.a.   |
| DualPathRNN [7] | 18.8    | 19.0 | 2.6M    | 1      |
| sudo rm -rf [33] | 18.9    | n.a. | 2.6M    | 10     |
| VSUNOS [34] | 20.1    | 20.4 | 7.5M    | 2      |
| DPTNet** [25] | 20.2    | 20.6 | 2.6M    | 1      |
| Wavesplit** [25] | 21.0    | 21.2 | 29M     | 1      |
| SepFormer   | 20.4    | 20.5 | 26M     | 8      |
| SepFormer + DM | 22.3    | 22.4 | 26M     | 8      |

Table II: Ablation of the SepFormer on WSJ0-2-Mix (validation set).

| SI-SNRi | N | Ninter | Ninter | # Heads | DFF | PosEnc | DM |
|---------|---|--------|--------|---------|-----|--------|----|
| 22.3    | 2 | 8      | 8      | 8       | 1024| Yes    | Yes|
| 20.3    | 2 | 8      | 8      | 8       | 1024| Yes    | Yes|
| 20.4    | 2 | 4      | 4      | 16      | 2048| Yes    | No |
| 20.2    | 2 | 4      | 4      | 8       | 2048| Yes    | No |
| 19.9    | 2 | 4      | 4      | 8       | 2048| Yes    | No |
| 19.8    | 2 | 4      | 4      | 8       | 2048| Yes    | No |
| 19.4    | 2 | 4      | 4      | 8       | 2048| No     | No |
| 19.2    | 2 | 4      | 4      | 8       | 2048| Yes    | No |
| 19.1    | 2 | 3      | 3      | 8       | 2048| Yes    | No |
| 19.0    | 2 | 3      | 3      | 8       | 2048| No     | No |

Table III: Best results on the WSJ0-3-mix dataset.

| Model       | SI-SNRi | SDRi | # Param |
|-------------|---------|------|---------|
| ConvTasnet  | 12.7    | 13.1 | 5.1M    |
| DualPathRNN | 14.7    | n.a  | 2.6M    |
| VSUNOS [34] | 16.9    | n.a  | 7.5M    |
| Wavesplit   | 17.3    | 17.6 | 29M     |
| Wavesplit + DM | 17.8    | 18.1 | 29M     |
| SepFormer   | 17.6    | 17.9 | 26M     |
| SepFormer + DM | 19.5    | 19.7 | 26M     |
TABLE IV
BEST RESULTS ON THE WHAM DATASET.

| Model                  | SI-SNRi | SDRi |
|------------------------|---------|------|
| ConvTasnet             | 12.7    | -    |
| Learnable fbank        | 12.9    | -    |
| MGST [19]              | 13.1    | -    |
| Wavesplit + DM [25]    | 16.0    | 16.5 |
| Sepformer + SpeedA.    | 16.3    | 16.7 |
| Sepformer + DM         | 16.4    | 16.7 |

TABLE V
BEST RESULTS ON THE WHAMR DATASET.

| Model                  | SI-SNRi | SDRi |
|------------------------|---------|------|
| ConvTasnet             | 8.3     | -    |
| BiLSTM Tasnet          | 9.2     | -    |
| Wavesplit + DM [25]    | 13.2    | 12.2 |
| Sepformer + SpeedA.    | 13.7    | 12.7 |
| Sepformer + DM         | 14.0    | 13.0 |

E. Results on WHAM! and WHAMR! datasets

WHAM! [10] and WHAMR! [11] datasets are respectively versions of the WSJ0-2Mix dataset with environmental noise and environmental noise and reverberation. We use the same model configuration as the WSJ0-2Mix dataset both for WHAM! and WHAMR!. For both datasets, we train the model so that it does source-separation and speech enhancement at the same time. In the WHAM! dataset, the model learns to de-noise while also separating, and in WHAMR! dataset, the model learns to de-noise and de-reverberate in addition to separating. In WHAMR! when using speed augment and or dynamic mixing, we also randomly choose a room-impulse response from the training set of the WHAMR! dataset when creating new mixtures.

In Tables IV [10] and WHAMR! datasets compared to the other methods in the literature. We observe that on both WHAM! and WHAMR! datasets SepFormer outperforms the previously proposed methods even without the use of DM, which further improves the performance.

F. Results on Libri-2/3Mix datasets

LibriMix [9] is proposed as an alternative to WSJ0-2/3Mix with more diverse and longer utterances. In Table VI, we provide results from the Libri-2/3Mix datasets with SepFormer, both for clean any noisy versions, using the same model configuration as found on WSJ0-2mix in Table I. Similar to the WHAM! dataset, for Libri-2/3 Mix datasets the network is trained to separate and denoise at the same time. We train the models on the train-360 set, both with and without dynamic mixing. In addition providing the performance of the models that were trained on LibriMix, we also provide the performance of the model that was pre-trained on the WSJ0-Mix dataset. One common criticism of the WSJ0-Mix is that the models trained on it do not generalize well to other tasks. Here, we showcase that SepFormer is able to obtain respectable performance on Libri 2/3 Mix clean versions even when trained on WSJ0-2/3Mix, surpassing the performance of a Convtasnet model trained on LibriMix as shown in row Sepformer PT of Table VI. We also show the case where we fine-tune a pretrained SepFormer model on LibriMix in the row SepFormer + DM of Table VI. We also show the case where we fine-tune a pretrained SepFormer model on LibriMix in the row SepFormer + DM PT+FT of Table VI.

G. Speech Enhancement

We trained the SepFormer for speech enhancement on the WHAM! and WHAMR! datasets for noisy an noisy-reverberant mixtures with one speaker. The obtained enhancement performances in terms of SI-SNR, SDR, and PESQ [38] are presented in Table VII and Table VIII respectively.

Note that in WHAM! dataset the model is trained to denoise and on the WHAMR! dataset the model is trained to both dereverberate and denoise at the same time. The SepFormer models are trained to maximize the output SI-SNR between the estimated and the ground truth signals in the time domain.

In addition to training SepFormer, we also trained a Bidirectional LSTM, CNNTransformer, CFDN models from Speechbrain [12], which are trained to minimize the Euclidean distance of the estimated magnitude spectrogram and the
spectrogram of the clean signals. We observe that SepFormer is able to outperform these methods with a large margin in terms of SI-SNR, SDR and PESQ.

**TABLE VII**

**SPEECH ENHANCEMENT RESULTS ON WHAM! DATASET (DENOISING)**

| Model            | SI-SNR | SDR  | PESQ |
|------------------|--------|------|------|
| 2DFCN            | 7.90   | 8.70 | 2.36 |
| 2DFCN-BLSTM      | 7.09   | 7.89 | 2.32 |
| BLSTM            | 5.15   | 6.2  | 2.11 |
| CNNTransformer   | 8.3    | 8.9  | 2.52 |
| SepFormer        | 14.35  | 13.04| 3.07 |

**TABLE VIII**

**SPEECH ENHANCEMENT RESULTS ON WHAMR! DATASET (DENOISING + DEREVERBERATION)**

| Model            | SI-SNR | SDR  | PESQ |
|------------------|--------|------|------|
| 2DFCN            | 6.84   | 7.75 | 2.18 |
| 2DFCN-BLSTM      | 5.87   | 6.82 | 2.15 |
| BLSTM            | 5.58   | 6.49 | 2.11 |
| CNNTransformer   | 7.38   | 8.21 | 2.27 |
| SepFormer        | 10.58  | 12.29| 2.84 |

**H. Ablations on the type of Self-Attention**

In Table IX we compare the WSJ0-2Mix test set performance of four different architectural choices for Full (regular), LongFormer, Linformer and Reformer self-attention previously described in Section III-D. We train all models using only speed augment (no dynamic mixing), using 4 second long training segments. The architectural choices in this ablation experiment given in Table IX are summarized as follows:

- (second column, C=250v1) in the IntraTransformer, and InterTransformer blocks, we use the same type of attention mechanism, indicated on the first column. The chunk size for the IntraTransformer is set to $C = 250$.
- (third column, $C=250v2$) in the IntraTransformer we use the self attention mechanism indicated on the first column, and in the InterTransformer we use the full attention mechanism. The chunk size for the IntraTransformer is set to $C = 250$.
- (fourth column, $C=1000$) in the IntraTransformer we use the self-attention mechanism indicated on the first column, and in the InterTransformer we use the full attention mechanism. The chunk size for the IntraTransformer is set to $C = 1000$.
- (fifth column, No Chunking) we do not apply chunking, and therefore only the InterTransformer block is applied. We have observed out-of-memory (O.O.M.) behavior on the test-set for the full self-attention due to long sequences, and therefore we denote O.O.M. for the corresponding entry.

We observe from Table IX that the architectural choices adopted in the original SepFormer paper lead to the best overall performance in terms of SI-SNR and SDR improvement. We also show the memory usage and forward pass time (in CPU using Pytorch profiler [37]) for some of the relevant models in Figure 6 as well as SpeechBrain implementation of convtasnet [22], for inputs of varying lengths between 1 second and 8 seconds. The chunking/dual-path mechanism in the SepFormer architecture provides a significant reduction in memory demand compared to the architecture where no chunking is applied. We also see from Figure 6 that using the Longformer or Reformer blocks on the whole sequence without applying chunking is an efficient alternative which also yields close performance as can be seen from Table IX. Furthermore from Figure 6 we observe that compared to convtasnet, Reformer without chunking results in almost equivalent memory usage, and faster forward pass time, while yielding slightly better performance, namely 16.7 dB SI-SNRi on the test set of WSJ0-2Mix, compared to 15.3 dB SI-SNRi obtained with convtasnet [22].

We also observe that the full attention is more efficient than using reformer inside the dual-path pipeline in terms of forward pass time and memory usage, and full-attention is not significantly more expensive than longformer in terms of memory. Another observation is the fact that Linformer does not yield competitive performance. We suspect that this stems from the fact that Linformer has a reduced modeling capacity since it projects the time dimension inside the attention mechanism to a lower dimensionality.
VI. CONCLUSION

In this paper, we have explored the application of Transformers for speech separation and speech enhancement, expanding upon our previous work where we introduced SepFormer, an attention-only masking network that is able to achieve state-of-the-art performance on WSJ0-2/3 Mix speech separation datasets. Here, we expanded this work performing additional experiments for speech separation on LibriMix, WHAM!, WHAMR! datasets and speech enhancement on noisy WHAM! and WHAMR! datasets which respectively capture noisy and noisy-reverberant conditions.

As another major contribution we investigate the use of more efficient self-attention mechanisms such as Longformer, Linformer and Reformer. Our results suggest that Longformer and especially Reformer self-attention are suitable for speech separation applications and obtain an highly favourable trade-off between performance and computational requirements. Namely, we observe that using Reformer self-attention without applying chunking results in being computationally more efficient than the popular convtasnet model, and consequently yielding 1.4 dB better performance than convtasnet in terms of SI-SNR improvement on the test of WSJ0-2Mix dataset.

Finally we would like to indicate that the the code for the training recipes for SepFormer on the WSJ0-2/3Mix, Libri2/3Mix, WHAM! and WHAMR! datasets are all available on Speechbrain toolkit [12], as well as the pretrained models.

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