CONTINUOUS SPEECH SEPARATION WITH CONFORMER

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ABSTRACT

Continuous speech separation plays a vital role in complicated speech related tasks such as conversation transcription. The separation model extracts a single speaker signal from a mixed speech. In this paper, we use transformer and conformer in lieu of recurrent neural networks in the separation system, as we believe capturing global information with the self-attention based method is crucial for the speech separation. Evaluating on the LibriCSS dataset, the conformer separation model achieves state of the art results, with a relative 23.5 \% word error rate (WER) reduction from bi-directional LSTM (BLSTM) in the utterance-wise evaluation and a 15.4 \% WER reduction in the continuous evaluation.

1. INTRODUCTION

Thanks to the advance in deep learning, a drastic improvement on accuracy and robustness has been brought to modern automatic speech recognition (ASR) system in the past decade [1, 2, 3, 4, 5, 6, 7, 8]. However, when applied to more complicated scenarios such as conversation transcription [9, 10], ASR systems often suffer from the performance limitation, due to the overlapped speech and the quick speaker turns, that break the “single active speaker” assumption used in most ASR training. Additionally, the overlapped speech brings the “permutation problem” [11], further increasing the difficulty in conversation recognition.

Speech separation is usually applied as a remedy for this problem, where the mixed speech is first processed by a specially trained separation network, before being fed into the recognition. Started from Deep Clustering (DC) [11, 12] and Permutation Invariant Training (PIT) [13, 14], a series of separation models have been shown effective in handling overlapped speech. In [15, 16], the author proposed the time domain separation methods that lead to major improvements in separation audio quality. In [17, 18, 19], the additional speaker identification module is introduced to enhance the separation performance for both perceptual and recognition.

Inspired by the recent advance of transducer-based end-to-end modeling in ASR which progresses from recurrent neural network transducer [4, 30] to transformer transducer [31] and then conformer transducer [32], in this work, we incorporate the transformer and its variation conformer in the framework of continuous speech separation [21], where the separation network continuously routes the input mixed speech stream into two unmixed channels, each containing separated single speaker segments. Then a speech recognition system that is trained with single speaker utterances is applied on each channel to generate the transcription. The proposed system is evaluated with the LibriCSS dataset [29], a real recorded speech corpus containing different overlap ratio setups. We show that, the proposed network significantly outperforms the baseline systems with recurrent network architecture, achieving the new state of the art performance on this data set. If we use an end-to-end Transformer ASR model to evaluate separation systems on LibriCSS 40\% overlap recordings, the conformer based separation system reduces the WER by a relatively 23.5\% and 15.4\% for the utterance-wise evaluation and continuous evaluation respectively.

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And in [20, 21], the multi-channel extension separation has been shown to be effective. In [10, 22], the authors propose to apply the speech separation in a continuous processing manner and integrate it in a conversation transcription system that results in significant word error rate (WER) reduction on the task of real recorded meetings.

The network architecture has been rigorously explored for better separation capability [16, 23, 24]. Among which, the transformer [24] based approach achieved a promising result. The Transformer was firstly introduced in [25] for machine translation, and extended to speech processing in [26, 27]. In [24], a transformer based speech separation architecture is proposed and achieves the state of the art separation quality on WSJ0-2mix dataset. In [28], the authors incorporate the transformer with the end to end multi-speaker recognition network, and reports a better recognition accuracy. However, both works were evaluated on artificially simulated data set that only considers the overlapped speech and assumes the utterance boundary is provided, which significantly differs from the real world conversation as suggested in [29].

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2. APPROACH

2.1. Problem Formulation

The goal of continuous speech separation is to estimate the individual target signals from a continuous mixed signal, where the target signals may have overlaps in time frequency domain. It is formulated as

\[ y(t) = \sum_{s=1}^{S} x_s(t) \]  

(1)

where \( t \) is the time index, \( x_s(t) \) denotes the \( s \)-th individual signals and \( y(t) \) is the mixed signal. The corresponding short-time Fourier transformation (STFT) is represented as \( Y(t, f) \) and \( X(t, f) \) respectively.

Suppose that we have \( C \) input channels, then the input is written as

\[ Y(t, f) = Y^1(t, f) \oplus \text{IPD}(2) \ldots \oplus \text{IPD}(C) \]  

(2)

where \( \oplus \) means the concatenation operation, \( Y^1(t, f) \) refers to the STFT features of the first channel, \( \text{IPD}(i) \) refers to the inter-channel phase difference between the \( i \)-th channel and the first channel, i.e. \( \text{IPD}(i) = \cos(\theta^i(t, f) - \theta^1(t, f)) \), and \( \theta^i(t, f) \) is the phase of \( Y^i(t, f) \). If \( C = 1 \), it becomes the single channel speech separation task [11, 12, 13, 14].

Following [33, 34], we estimate a group of masks \( M_s(t, f) \) with a deep learning model \( f(\cdot) \) instead of directly computing the STFT of the \( s \)-th individual signal \( X_s(t, f) \). The masks are constrained by \( M_s(t, f) = 0 \) and \( \sum_{s=1}^{C} M_s(t, f) = 1 \). Then, \( X_s(t, f) \) is obtained by \( M_s(t, f) \odot Y^1(t, f) \) where \( \odot \) is the elementwise-product.

In this paper, we employ Conformer structure [32] as \( f(\cdot) \) to estimate the masks for continuous speech separation.

2.2. Model Structure

Conformer [32] is the state-of-the-art speech recognition encoder architecture, which inserts a convolution layer into a Transformer block to increase the ability of local information modeling of the traditional Transformer model [25].

The architecture of the Conformer is shown in Fig. 1 where each block consists of a self-attention module, a convolution module, and a macron-feedforward module. A chunk of \( Y(t, f) \) is the input of the first conformer block. Supposing that the input of the \( i \)-th block is \( z \), the computation process is formulated as

\[ \hat{z} = z + \frac{1}{2} \text{FFN}(z) \]  

(3)

\[ z' = \text{selfattention}(\hat{z}) + \hat{z} \]  

(4)

\[ z'' = \text{conv}(z') + z' \]  

(5)

\[ \text{output} = \text{layernorm}(z'' + \frac{1}{2} \text{FFN}(z'')) \]  

(6)

where FFN(\cdot), selfattention(\cdot), conv(\cdot), and layernorm(\cdot) denote feed forward network, self-attention module, convolution module, and layer normalization respectively. In the self-attention module, \( \hat{z} \) is linearly converted to \( Q_kK_kV_k \) with three different parameter matrices. Then, we apply a multi-head self-attention mechanism

\[ \text{Multihead}(Q, K, V) = [H_1 \ldots H_{\text{dhead}}]W_{\text{head}} \]  

(7)

where \( H_i = \text{softmax}(\frac{Q_i(K_i + \text{pos})^\top}{\sqrt{d_k}})V_i \)  

(8)

where \( d_k \) is the dimension of the feature vector, \( d_{\text{head}} \) is the number of attention heads. \( \text{pos} = \{rel_{m,n}\} \in \mathbb{R}^{M \times M \times d_k} \) is the relative position embedding [35], where \( M \) is the maximum chunk length. \( rel_{m,n} \in \mathbb{R}^{d_k} \) is a vector representing the offset of \( m \) and \( n \). \( m \) denotes the \( m \)-th vector in \( Q_i \) and \( n \) denotes the \( n \)-th vector in \( K_i \). The Convolution starts with a pointwise convolution and a gated linear unit (GLU). A 1-D depthwise convolution layer with a Batchnorm [36] and a Swish activation are followed.

After obtaining the conformer output, we further convert it to a mask matrix

\[ M_s(t, f) = \text{sigmoid}(\text{FFN}_s(\text{output})) \]  

(9)
training sample, we add simulated isotropic noise with between reference and masked speech signals. PIT is employed to minimize the Euclidean distance beamforming process. The permutation invariant training of adjacent windows, we average their mask matrices for the forming in our experiment. Regarding the overlap region, we rewrite as attention module. Following Transformer-XL, the Equation is rewritten as
\[
\text{softmax}(\frac{Q_i(K_i \oslash K_{cache,i} + \text{pos})^T}{\sqrt{d_k}})(V_i \oslash V_{cache,i})
\]
where Q is obtained by the current chunk, while K and V is the concatenation of previous key/value and current key/value, and the dimension of K_{cache,i} depends on how many history chunks are considered.

We use either spectral masking or mask-based adaptive minimum variance distortionless response (MVDR) beamforming in our experiment. Regarding the overlap region of adjacent windows, we average their mask matrices for the beamforming process. The permutation invariant training (PIT) is employed to minimize the Euclidean distance between reference and masked speech signals.

3. EXPERIMENT

3.1. Datasets

The training dataset consists 219 hours of artificially reverberated and mixed speech signals, which are randomly sampled from WSJ1. Four different mixture types are included in the training data, as in [21]. To generate each training mixture, we randomly pick two speakers from the WSJ1 dataset, convolving each with 7 channel room impulse response (RIR) simulated using image method, and then rescale and combine them with an source energy ratio of −5 to 5 dB. For each training sample, we add simulated isotropic noise with 0 dB signal to noise ratio. The total overlap ration in the training data is around 50%.

It should be noted that we don’t apply the original training set from LibriCSS, as we would like to see the potential impact from the data set mismatch. We observe that the model trained on simulation from WSJ1 resulted in similar performance as ones using Librispeech as source data.

We evaluate the models on the LibriCSS dataset, which consists of 10 hours recordings in a meeting room as the test data. We test our model performance under a one-channel setting and a seven-channel setting. We conducted both the utterance-wise evaluation and continuous input evaluation.

3.2. Implementation Details

We use BLSTM and Transformers as our baseline speech separation models. The BLSTM model has three BLSTM layers with 1024 input dimension and 512 hidden dimension and 21.80M params. There are three masks, two for speakers and one for noise. We use three sigmoid projection layers to estimate each mask. The BLSTM model is trained with the Adam optimizer for 100 epochs. The learning rate is initialized to 1e-3, and decays by half if the validation loss stops decreasing for 2 epochs.

Transformer-base and Transformer-large models with 21.90M and 58.33M parameters are two baselines. The Transformer-base model consists of 16 Transformer encoder layers with 4 attention heads, 256 attention dimension and 2048 FFN dimension. The Transformer-large model consists of 18 Transformer encoder layers with 8 attention heads, 512 attention dimension and 2048 FFN dimension.

Similar with the Transformers baseline models, we experiment with Conformer-base and Conformer-large models with 22.07M and 58.72M params respectively. Conformer-base model consists of 16 Conformer encoder layers with 4 attention heads, 256 attention dimension and 1024 FFN dimension. Conformer-large model consists of 18 Conformer encoder layers with 8 attention heads, 512 attention dimension and 2048 FFN dimension.

We use two speech recognition (SR) models to evaluate the speech separation accuracy. One is the SR model used in LibriCSS, which is a hybrid SR model with a BiLSTM based acoustic model and a 4-gram language model. The other one is one of the best open source end-to-end transformer based SR models which achieves 2.08/4.95 on the Librispeech test-clean and test-other dataset.

Following [29], we generate the separated speech signals with spectral masking and mask-based adaptive minimum variance distortionless response (MVDR) beamforming for the single-channel and seven-channel speech separation, respectively. For a fair comparison, we follow the LibriCSS...
setting in chunk-processing (Section 2.3), where $N_h$, $N_c$, $N_f$ is set to 1.2s, 0.8s, 0.4s respectively.

3.3. Results for the utterance wise evaluation

Table 1 shows the WER of the utterance wise evaluation under the seven-channel setting and single-channel setting. We can achieve state-of-the-art results with Conformer models. Compared to BLSTM, Conformer-base obtains about a relative 15.4% gain on the large-overlap settings (overlap ratio 40%) with a hybrid ASR model, and achieves a 23.5% gain with an E2E Transformer model, demonstrating the superiority of the self-attention mechanism. Conformer-base models are better than the Transformer-base models in almost all the settings, which is attributed to the better local modeling capability of the Conformer. Besides, larger models show better performance in the large-overlap setting. Conformer-large is better than Conformer-base 8% in the 40%-overlap separation task with Transformer SR system.

It is obvious that the result degrades significantly if only one channel is used, indicating the importance of multi-channel microphone. The model comparison result is consistent with the seven-channel setting, except in the non-overlap scenario. For 0S and 0L, all models show similar performance if seven channels are used, while self-attention models are better if only one channel is used. It could be argued that seven-channel signals contain rich information so simpler networks can do the task well, while seven-channel signal is quite limited which requires a more advanced structure.

3.4. Results for the continuous input evaluation

Table 2 is the continuous speech separation evaluation. In contrast to the utterance-wise evaluation, all models become worse in the continuous setting, indicating the scenario is much more difficult for speech separation. Conformer models and Transformer models are consistently better than BLSTM, but the gap becomes smaller in the large overlap test-sets. Conformer-base only outperforms BLSTM relatively 4% and 15% in the evaluation of two SR systems. A possible explanation is that self-attention based methods are good at using global information, and the input length in utterance-wise evaluation is much longer than the chunk size in continuous evaluation.

Another interesting phenomenon is 0S result is much worse than 0L in the continuous evaluation, while their performance are comparable in the utterance-wise evaluation. An explanation is that a longer silence makes the task easier, so 0L enjoy better performance. It shows the quick turn poses a challenge for speech separation system. We can observe a clear improvement of self-attention models on the 0S, indicating self-attention model is not only effective on speech with overlap, but also effective on quick turn conversations.

To utilize more historical information, we conduct a continuous separation experiment with the Conformer, as described in Section 2.3. However, we don’t observe significant improvement, especially in the large-overlap settings. We summarize two possible reasons for the negative result. 1) The unexpected noises are introduced if longer history is considered. More speakers’ voice will be seen if the chunk size is large in the continuous evaluation. 2) We don’t consider the overlap regions of the adjacent windows in training, so the gap between testing and training can also lead to sub-optimal performance.

| System                  | 0S    | 0L    | 10%  | 20%  | 30%  | 40%  |
|-------------------------|-------|-------|------|------|------|------|
| No separation [29]      | 11.8/5.5 | 11.7/5.2 | 18.8/11.4 | 27.2/18.8 | 35.6/27.7 | 43.3/36.6 |
| **Seven-channel Evaluation** |       |       |      |      |      |      |
| BLSTM                   | 7.0/3.1 | 7.5/3.3 | 10.8/4.3 | 13.4/5.6 | 16.5/7.5 | 18.8/8.9 |
| Transformer-base        | 8.3/3.4 | 8.4/3.4 | 11.4/4.1 | 12.5/4.8 | 14.7/6.4 | 16.9/7.2 |
| Transformer-large       | 7.5/3.1 | 7.7/3.4 | 10.1/3.7 | 12.3/4.8 | 14.1/5.9 | 16.0/6.3 |
| Conformer-base          | 7.3/3.1 | 7.3/3.3 | 9.6/3.9 | 11.9/4.8 | 13.9/6.0 | 15.9/6.8 |
| Conformer-large         | 7.2/3.1 | 7.5/3.3 | 9.6/3.7 | 11.3/4.8 | 13.7/5.6 | 15.1/6.2 |
| **Single-channel Evaluation** |       |       |      |      |      |      |
| BLSTM                   | 15.8/6.4 | 14.2/5.8 | 18.9/9.6 | 25.4/15.3 | 31.6/20.5 | 35.5/25.2 |
| Transformer-base        | 13.2/5.5 | 12.3/5.2 | 16.5/8.3 | 21.8/12.1 | 26.2/15.6 | 30.6/19.3 |
| Transformer-large       | 13.0/5.3 | 12.4/5.1 | 15.5/7.4 | 20.1/11.1 | 24.6/13.5 | 27.9/17.0 |
| Conformer-base          | 13.8/5.6 | 12.5/5.4 | 16.7/8.2 | 21.6/11.8 | 26.1/15.5 | 30.1/18.9 |
| Conformer-large         | 12.9/5.4 | 12.2/5.0 | 15.1/7.5 | 20.1/10.7 | 24.3/13.8 | 27.6/17.1 |

Table 1. Utterance-wise evaluation in seven-channel and single-channel setting. Two numbers in a cell denote %WER of the hybrid SR model used in LibriCSS [29] and end-to-end transformer based SR model [41]. 0S: 0% overlap with short inter-utterance silence. 0L: 0% overlap with a long inter-utterance silence.
### Table 2. Continuous speech separation evaluation in seven-channel and single-channel setting.

| System               | Overlap ratio in % |
|----------------------|--------------------|
|                      | 0S     | 0L     | 10     | 20     | 30     | 40     |
| No separation [29]   |        |        |        |        |        |        |
| BLSTM                | 11.4/6.0 | 8.4/4.1 | 13.1/7.0 | 14.9/7.9 | 18.7/11.5 | 20.5/12.3 |
| Transformer-base     | 12.0/5.6 | 9.1/4.4 | 13.4/6.2 | 14.4/6.8 | 18.5/9.7 | 19.9/10.3 |
| Transformer-large    | **10.9/5.4** | **8.8/4.0** | **12.6/6.0** | **13.6/6.7** | **17.2/9.3** | **18.9/10.2** |
| Conformer-base       | 11.1/5.6 | 8.7/4.0 | 12.8/6.1 | 13.8/6.7 | 17.6/9.4 | 19.6/10.4 |
| Conformer-large      | 11.0/5.2 | 8.7/4.0 | 12.6/5.8 | 13.5/6.8 | 17.6/9.0 | 19.6/10.0 |
| Conformer$_{sf}$-base | 11.4/5.4 | 8.7/4.1 | 12.6/5.8 | 13.7/6.7 | 17.5/9.4 | 19.8/10.6 |
| Conformer$_{sf}$-large | 11.0/5.2 | 8.8/4.1 | 12.9/5.8 | 13.7/6.7 | 17.5/9.4 | 19.8/10.6 |
| BLSTM                | 11.4/6.0 | 8.4/4.1 | 13.1/7.0 | 14.9/7.9 | 18.7/11.5 | 20.5/12.3 |
| Transformer-base     | 12.0/5.6 | 9.1/4.4 | 13.4/6.2 | 14.4/6.8 | 18.5/9.7 | 19.9/10.3 |
| Transformer-large    | **10.9/5.4** | **8.8/4.0** | **12.6/6.0** | **13.6/6.7** | **17.2/9.3** | **18.9/10.2** |
| Conformer-base       | 11.1/5.6 | 8.7/4.0 | 12.8/6.1 | 13.8/6.7 | 17.6/9.4 | 19.6/10.4 |
| Conformer-large      | 11.0/5.2 | 8.7/4.0 | 12.6/5.8 | 13.5/6.8 | 17.6/9.0 | 19.6/10.0 |
| Conformer$_{sf}$-base | 11.4/5.4 | 8.7/4.1 | 12.6/5.8 | 13.7/6.7 | 17.5/9.4 | 19.8/10.6 |
| Conformer$_{sf}$-large | 11.0/5.2 | 8.8/4.1 | 12.9/5.8 | 13.7/6.7 | 17.5/9.4 | 19.8/10.6 |

### 3.5. Discussion and Analysis

We use the same chunk size and look-ahead frames with BLSTM [29], but it is interesting to discuss the hyper-parameter impact for Conformer. We test the performance of the Conformer-large model in different settings of chunk size while fixing the SR model as BLSTM and keeping the seven-channel input.

Table 3 illustrates the impact of size $N_h$, $N_c$, and $N_f$. 1) A counter-intuitive result is that a small $N_h$ may provide a better performance. It indicates that adjacent frames provide enough information, and longer history may introduce noise in testing. 2) Regarding $N_c$, the performance of 0.8s chunk size shows the best performance. A larger or smaller chunk size both hurt the final performance. 3) The trend of chunk size of $N_f$ is similar to the trend of $N_c$. A proper look-ahead window plays a vital role in continuous speech separation.

### Table 3. Conformer-large performance with different $N_h - N_c - N_f$ for continuous speech separation in seven-channel setting.

| System               | Overlap ratio in % |
|----------------------|--------------------|
|                      | 0S     | 0L     | 10     | 20     | 30     | 40     |
| No separation [29]   |        |        |        |        |        |        |
| BLSTM                | 11.4/6.0 | 8.4/4.1 | 13.1/7.0 | 14.9/7.9 | 18.7/11.5 | 20.5/12.3 |
| Transformer-base     | 12.0/5.6 | 9.1/4.4 | 13.4/6.2 | 14.4/6.8 | 18.5/9.7 | 19.9/10.3 |
| Transformer-large    | **10.9/5.4** | **8.8/4.0** | **12.6/6.0** | **13.6/6.7** | **17.2/9.3** | **18.9/10.2** |
| Conformer-base       | 11.1/5.6 | 8.7/4.0 | 12.8/6.1 | 13.8/6.7 | 17.6/9.4 | 19.6/10.4 |
| Conformer-large      | 11.0/5.2 | 8.7/4.0 | 12.6/5.8 | 13.5/6.8 | 17.6/9.0 | 19.6/10.0 |
| Conformer$_{sf}$-base | 11.4/5.4 | 8.7/4.1 | 12.6/5.8 | 13.7/6.7 | 17.5/9.4 | 19.8/10.6 |
| Conformer$_{sf}$-large | 11.0/5.2 | 8.8/4.1 | 12.9/5.8 | 13.7/6.7 | 17.5/9.4 | 19.8/10.6 |

### 4. CONCLUSION

In this work, we propose to incorporate the transformer and conformer in the framework of continuous speech separation. The experiment result shows that the self-attention based methods significantly outperform conventional RNN based methods in both utterance-wise evaluation and continuous evaluation, reaching the state of the art. This indicates the power and great potential of self-attention based methods in speech separation. However, we find a large chunk size may introduce noise, resulting in performance regression. In the future, we will study how to filter out noise and use the long history information better. Besides, how to joint optimize SR system and separation system is another promising direction.
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