Single-channel speech separation is required for multi-speaker speech recognition. Recent deep learning-based approaches focused on time-domain audio separation net (TasNet) because it has superior performance and lower latency compared to the conventional time-frequency-based (T-F-based) approaches. Most of these works rely on the masking-based method that estimates a linear mapping function (mask) for each speaker. However, the other commonly used method, the mapping-based method that is less sensitive to SNR variations, is inadequately studied in the time domain. We explore the potential of the mapping-based method by introducing attention augmented DPRNN (AttnAugDPRNN) which directly approximates the clean sources from the mixture for speech separation. Permutation Invariant Training (PIT) has been a paradigm to solve the label ambiguity problem for speech separation but usually leads to suboptimal performance. To solve this problem, we propose an efficient training strategy called Hierarchical Constraint Training (HCT) to regularize the training, which could effectively improve the model performance. When using PIT, our results showed that mapping-based AttnAugDPRNN outperformed masking-based AttnAugDPRNN when the training corpus is large. Mapping-based AttnAugDPRNN with HCT significantly improved the SI-SDR by 10.1% compared to the masking-based AttnAugDPRNN without HCT.

Index Terms— mapping-based speech separation, time domain, hierarchical constraint training

1. INTRODUCTION

Deep learning-based audio separation [2] techniques are needed in practical applications of automatic speech recognition (ASR). In real-world communication, the speech usually is mixed with other signals, such as ambient sounds, reverberation, or other people speech, and these mixed signals may decrease the quality of the speech and dramatically reduce the performance of ASR. Speech separation aims to approximate the clean source for each speaker, which is necessary for a complete ASR system.

Source and speech separation from a mixture waveform has been studied for many years. Most speech separation models are based on two domains: 1) Time-frequency (T-F) based models, 2) Time-domain based models. The T-F-based method uses T-F bins that are calculated by Short Time Fourier Transform (STFT), separates these features for each speaker, and applies the inverse STFT to reconstruct the clean sources. Time-domain-based models replace the STFT and iSTFT with the trainable front-end. Recent studies showed that Time-domain based method has a better performance and lower latency compared to T-F based method.

We focused on the time-domain speech separation methods. The time-domain speech separation was first proposed in [3], where it used 1-D convolution and 1-D transposed convolution to replace the STFT and iSTFT in T-F based method. It showed a better performance than the previous T-F-based method and significantly reduced the latency. ConvTasNet [4] was the first model that outperformed the ideal T-F magnitude masking using a fully dilated convolutional separation module. Dual-Path RNN [5] aimed to solve the long sequence modeling challenge and greatly improve the performance. The latter works [6-9] used the same idea as [5] but incorporated the attention mechanism [10] to further improve the performance. These works are all based on the masking-based method in the time domain, which aims to find a mask (weighted function) that could linearly apply to the representation of mixture waves to reconstruct the original clean sources. The other commonly used method is mapping-based [11, 12] and aims to approximate the clean sources directly from the mixture. Recent studies [13, 14] compared the masking and mapping-based methods using T-F-based method. It [13] reported that the masking-based method is more sensitive to SNR for a speaker-dependent dataset. Therefore, mapping-based is more useful in the scenarios where a wide range of SNR is expected. To our knowledge, there was only one preliminary attempt to use the mapping-based method in time-domain speech separation [15]. However, the experiment results showed that the mapping-based only slightly outperformed the masking-based method using TCN [4] in the wsj0-2mix dataset [16]. Here we propose attention augmented DPRNN (AttnAugDPRNN) using the mapping-based method in time-domain speech separation. We used a more challenging dataset LibriMix [1] as it covers a wider range of distinct speakers and vocabulary.

Permutation invariant training (PIT) [17, 18] has been a standard solution to solve the label permutation problem during training of speech separation. Although the PIT provides reasonable performance, it often leads to suboptimal training. Many studies concentrate on regularizing the PIT. In [19], authors proposed several flexible label assignment strategies to avoid the label assignment switches for the same audio in different training epochs. In [20], the authors used speech enhancement as a pre-training stage to stabilize the label switches. However, the above training strategies required either extra training steps or training data, and still used the PIT in an end-to-end manner (abbreviated as E2E PIT). We propose a regularized training strategy—hierarchical constraint training (HCT)—to regularize the PIT, which forces our model to gradually separate the mixed audio.

Our results show that with the E2E PIT, masking-based time-domain speech separation outperformed the mapping-based method by 2.3% in SI-SDR when the number of the training sets is relatively small. However, with larger training data, the mapping-based method achieved 2.4% performance improvement compared to the masking-based method. Additionally, the mapping-based method
consistently outperformed the masking-based method when we applied HCT, where the mapping-based method using HCT improved the SI-SDR by 10.1% compared to the masking-based method using E2E PIT.

Our paper contributes:
1. A mapping-based speech separation method in the time-domain using the attention-augmented DPRNN. This method outperformed the masking-based method under a large training corpus setting.
2. An efficient training strategy, HCT, which improves the performance for time-domain separation without additional training costs or datasets. The mapping-based method with HCT achieved the best performance.

The paper is organized as follows: Section 2 introduces the masking and mapping-based time-domain speech separation approaches and introduces the baseline model for our experiment. Section 3 introduces the HCT. Section 4 describes the experiment setup and the experiment results are discussed in Section 5. Finally, we conclude in Section 6.

2. SEPARATION APPROACHES AND MODEL

TasNet shares a common two-part architecture: (1) a convolutional encoder and decoder that replace the roles of STFT and iSTFT respectively, and (2) a separation module that acts as its name suggests. The separation module plays a different role in the masking and mapping-based methods.

2.1. Masking-based approach

The assumption for the masking-based method is that the mixed waveform is linearly added by the clean sources so that:

$$X = \sum_{i=1}^{c} s_i + n, \quad s_i \in \mathbb{R}^T,$$

where $X$ is the mixture of the waveforms, $s_i$ is the clean source for speaker $i$, $c$ is the total number of speakers and $n$ is the background noise. The separation module in this approach aims to estimate a weighted function that could apply to the mixture so that:

$$\tilde{s}_i = M_i \odot X(t),$$

where $\tilde{s}_i$ is the reconstructed source, $M_i$ is the estimated mask for the source $i$ that is generated from the separation module, $\odot$ denotes the element-wise multiplication. Figure 1 (top) depicts the overall framework for the masking-based method. This method is effective in utilizing cleaning utterances of a target speaker [13].

2.2. Mapping-based approach

In the mapping-based approach, the separation module aims to approximate the target source directly from the mixture:

$$\{\tilde{s}_1; \ldots; \tilde{s}_c\} = \text{Separation}(X),$$

The overall framework for this method is shown in Figure 1 (bottom). The mapping-based method is less sensitive to SNR variations of training data [13], which is more similar to the real world.

2.3. Attention augmented DPRNN

Many variations based on Dual-Path RNN [5], including [6-9], are proposed to perform the separation function. These works use the dual-path processing as described in [5], which segments the long audio into several short segments, then applies the intra and inter


3. HIERARCHICAL CONSTRAINT TRAINING

Permutation invariant training (PIT) has long been used in speech separation tasks to allow the deep neural network to handle the label ambiguity problem between estimated sources and clean sources. The PIT finds the minimum pair-wise loss from $N!$ possible combinations, where $N$ is the number of target sources. In previous speech separation works, the PIT with a time-domain loss was used to update the entire model jointly, that is, the model was trained in an end-to-end manner. However, the model trained using E2E PIT tends to be suboptimal. To better standardize the training of speech separation, we propose a variant of E2E PIT called hierarchical constraint training (HCT). Our initial intention for HCT was to force the separation, we propose a variant of E2E PIT called hierarchical constraint training (HCT). Our initial intention for HCT was to force the separation module to gradually improve the consistency of training of the entire model, we set half of the early-break indices as the number of basic blocks used in the model, which tends to be suboptimal. To better standardize the training of speech separation, we propose a variant of E2E PIT called hierarchical constraint training (HCT). Our initial intention for HCT was to force the separation module to gradually improve the performance relative to the previous layer. Many regularization techniques require auxiliary loss or extra output from the model, while usually increasing the computational load during training. To avoid the additional computational load, we used the HCT with the early breaking method, as described next.

Consider a TasNet with $B$ repeats of basic blocks in the separation module. During the forward pass of training, the HCT selects an early-break layer index in the range from 1 to $B$. For example, if the layer index is $i$, the forward pass will only go through the first $i$ layers in the separation module and skip the remaining $B - i$ layers. After that, the next module will directly use the intermediate output from $i_{th}$ layer for either mask generation for the masking-based method or source estimation for the mapping-based method. Such training methodology could both force each layer towards steadily separating the mixed wave, and reduce the training time since some of the layers are left out during training. To maintain the consistency of training of the entire model, we set half of the early-break indices as the number of basic blocks used in the model, which is same as in E2E PIT, and the remaining early-break indices are generated randomly. We also applied weight for the final loss based on the early-break index $i$. The loss for HCT is as follows:

$$\text{Loss}_{\text{HCT}} = \lambda^B \cdot \text{Loss}_{\text{PIT}}$$

where $\lambda$ is the decay scalar. The loss will recover the original PIT loss when $i = B$.

4. EXPERIMENT SETUP

4.1. Dataset description

Previous works trained and evaluated on the wsj0-2mix dataset [16]. To evaluate our model and training strategy in a more general setting, we used the open-source LibriMix dataset [1] which was created from the Librispeech dataset [23]. The LibriMix used train-100, train-360, dev-clean and test-clean subsets in the Librispeech with disjoint speakers. We used the Libri2Mix clean subset with a sample rate of 8k which consists of two-speaker mixtures. Train-100 (58 hours) and train-360 (212 hours) are used independently to measure the impact of the data scale on the performance of the model. Clean speech mixtures are generated by mixing pairs of utterances from different speakers, uniformly sampled between -33 and -25 loudness units relative to full scale (LUFS). Each clean utterance is only used once during the generation of the LibriMix dataset. These characteristics together result in the LibriMix dataset being a more challenging dataset for speech separation. We used the dataset with 8 kHz sample rate.

4.2. Model configuration and training details

We implemented the model based on the asteroid toolkit [24]. Although smaller window size and stride for convolutional encoder and decoder will have a better performance, we used a window size of 16 and stride of 8 for faster training and inference. For the baseline experiments, we used the model configuration described in the original papers for DPRNN and DPTNet. For dual-path settings, we set a chunk size of 100 and hop length of 50. ReLU is used as an activation function for encoder and separation module output for the masking-based method to guarantee the non-negativity for both encoder output and mask. We omitted these activation functions in the mapping-based method because non-negativity is not needed. For reproducibility and fair comparison, we fixed the seed for all random processes. We set 200 for training epochs and set the batch size as 24 in all experiments. $\lambda$ is set to 0.95 for HCT. Adam [25] was used as an optimizer with an initial learning rate of 1e-3. The gradient is clipped with a maximum $L_2$ norm of 5. We reduced the learning rate if the validation loss could not improve in 5 consecutive epochs. The audios were segmented to 3 seconds during training and validation. No other regularization techniques were applied.

We used SI-SDR (Scale-invariant signal-to-distortion) [26] as a training objective in all the experiments. To fully justify the effectiveness of our proposed model and training strategy, we compared the improvement of signal fidelity including SI-SDR improvement (SI-SDRI) and SDR [27] improvement (SDRI).

5. RESULTS AND ANALYSIS

We conducted a series of experiments. First, we compared our modified model with several baseline models using a masking-based approach. Second, we compared the performance between masking and mapping-based method using our proposed model. Note that we used E2E PIT in the first two experiments. Third, we compared the performance when using HCT against the original E2E PIT.

5.1. Performance comparison for baseline models

Table 1: Performance on Libri2Mix 100 and 360 subsets. SI-SDR and SDR (dB) are reported

| Model              | train-100 | train-360 |
|--------------------|-----------|-----------|
| ConvTasNet [1]     | 13.0/13.4 | 14.7/15.1 |
| DPRNN              | 14.57/14.99 | 15.46/15.83 |
| DPTNet             | 14.90/15.37 | 15.35/15.75 |
| AttnAugDPRNN-mapping | 15.17/15.57 | 15.91/16.27 |
| AttnAugDPRNN-masking | 14.82/15.03 | 16.30/16.66 |
We first compared our modified model with baseline models. As observed from Table 1, all the dual-path-based models achieved better performance than ConvTasNet. DPTNet achieved better performance than DPRNN in a smaller training set (train-100) but behaved the opposite in a larger training set (train-360). Our proposed AttnAugDPRNN masking consistently achieved best results in both train-100 and train-360 compared to other models. We used this AttnAugDPRNN in the following experiments.

5.2. Performance comparison between masking and mapping-based approaches

We compared masking- and mapping-based approaches using AttnAugDPRNN. The results in Table 1 show that the masking-based approach was more effective when the amount of training data was limited. On the other hand, the mapping-based method performed better if the training data was sufficient.

We also compared the model performance in a more realistic and conversation-like scenario. We evaluated the model performance based on SparseLibri2Mix, the results are based on the model trained on the train-360 set (Table 2). The SI-SDRi decreased as the overlap ratio increased. Interestingly, we can observe that the masking-based method outperformed than mapping-based method when the overlap ratio is 0%, while it performed worse for the remaining overlap ratios. This might be caused by the choice of non-linear activation function of the encoder output, while the masking-based method used a ReLU activation function to zero out the negative outputs. An auxiliary autoencoder loss [28] might be a remedy to fix this problem.

5.3. Performance comparison and analysis of E2E PIT and HCT

We introduced in Section 4 an efficient training strategy called HCT to regularize the training of middle layers of the separation module for speech separation task. The validation loss over training epochs is shown in Figure 3. The HCT training accelerated the convergence speed and improved the overall performance in validation set. Table 3 shows the separation performance using E2E PIT and HCT for different training sets. As seen, our proposed HCT improved both masking and mapping-based methods by a significant margin (1.18 dB and 1.23 dB respectively in SI-SDRi). In addition, mapping-based approach with HCT contradicted the results from Section 5.2. Namely, HCT helped the mapping-based approach to achieve a better performance than the masking-based method even on a small training set (train-100). To better understand how HCT helped to improve the performance, we compared the separation performance of the middle layers in the separation module (Table 4). For E2E PIT, the separation performance from each output layer was not regularized. The role of middle layers in E2E PIT seems unclear, because the mixed speech was not separated or poorly separated in these layers. However, unexplainably the performance sharply improved in the last layer. We believe that the lack of regularization of middle layers in the separation module using E2E PIT causes the model to be suboptimal. Unlike this, the performance for both approaches with HCT steadily improved for successive layers and it achieved overall better performance compared to E2E PIT.

6. CONCLUSION

We studied the potential of mapping-based methods in time-domain speech separation. Our proposed AttnAugDPRNN achieved better performance than baseline models in both masking and mapping-based methods. Our results showed that using E2E PIT, the mapping-based method achieved better performance with a larger training corpus but performed worse on a smaller training corpus. We proposed an efficient training strategy called hierarchical constraint training (HCT) to regularize the training of speech separation tasks. Our HCT significantly improved the performance for both masking and mapping-based method on both small and large training corpuses without extra computational consumption. The mapping-based method with HCT achieved 10.1% better performance compared to the masking-based model using PIT.

| Overlap ratio | masking | mapping |
|---------------|---------|---------|
| 0%            | 37.11/37.68 | 32.54/33.19 |
| 20%           | 21.66/22.06 | 21.76/22.18 |
| 40%           | 18.97/19.36 | 19.18/19.59 |
| 60%           | 17.75/18.12 | 17.87/18.27 |
| 80%           | 17.03/17.41 | 17.35/17.75 |
| 100%          | 16.67/17.04 | 16.80/17.19 |

Table 2: Performance for SparseLibri2Mix; SI-SDRi and SDRi (dB) are reported.

| Layer index | Masking with PIT | Masking with HCT | Mapping with PIT | Mapping with HCT |
|-------------|------------------|------------------|-----------------|-----------------|
| 1           | -5.82            | 8.78             | -3.59           | 8.33            |
| 2           | -5.21            | 11.85            | -3.09           | 11.32           |
| 3           | -5.30            | 13.74            | -3.48           | 13.56           |
| 4           | -5.42            | 14.99            | -1.57           | 14.91           |
| 5           | -4.93            | 16.14            | -1.34           | 16.10           |
| 6 (last)    | 15.91            | 17.09            | 16.29           | 17.52           |

Table 3: The separation performance masking and mapping-based approach; SI-SDRi and SDRi (dB) are reported.

| Layer index | Masking with PIT | Masking with HCT | Mapping with PIT | Mapping with HCT |
|-------------|------------------|------------------|-----------------|-----------------|
| 1           | -5.82            | 8.78             | -3.59           | 8.33            |
| 2           | -5.21            | 11.85            | -3.09           | 11.32           |
| 3           | -5.30            | 13.74            | -3.48           | 13.56           |
| 4           | -5.42            | 14.99            | -1.57           | 14.91           |
| 5           | -4.93            | 16.14            | -1.34           | 16.10           |
| 6 (last)    | 15.91            | 17.09            | 16.29           | 17.52           |

Figure 3: The loss curve for the validation set.
6. REFERENCES

[1] Cosentino, J., et al., Librimix: An open-source dataset for generalizable speech separation. arXiv preprint arXiv:2005.11262, 2020.

[2] Huang, P.-S., et al. Deep learning for monaural speech separation, in 2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). 2014. IEEE.

[3] Luo, Y. and N. Mesgarani. Tasnet: time-domain audio separation network for real-time, single-channel speech separation, in 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). 2018. IEEE.

[4] Luo, Y., N.J.I.A.t.o.a. Mesgarani, speech, and l. processing, Conv-tasnet. Surpassing ideal time–frequency magnitude modeling for speech separation. 2019. 27(8): p. 1256-1266.

[5] Luo, Y., Z. Chen, and T. Yoshioka. Dual-path rnn: efficient long sequence modeling for time-domain single-channel speech separation. in ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). 2020. IEEE.

[6] Chen, J., Q. Mao, and D. Liu. Dual-path transformer network: Direct context-aware modeling for end-to-end monaural speech separation. arXiv preprint arXiv:2007.13975, 2020.

[7] Lam, M.W., et al. Sandglasset: A Light Multi-Granularity Self-Attentive Network for Time-Domain Speech Separation. in ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). 2021. IEEE.

[8] Subakan, C., et al. Attention is all you need in speech separation. in ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). 2021. IEEE.

[9] Zhang, Z., B. He, and Z. Zhang. TransMask: A Compact and Fast Speech Separation Model Based on Transformer. in ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). 2021. IEEE.

[10] Vaswani, A., et al. Attention is all you need. in Advances in neural information processing systems. 2017.

[11] Xu, Y., et al., A regression approach to speech enhancement based on deep neural networks. IEEE/ACM Transactions on Audio, Speech, and Language Processing, 2014. 23(1): p. 7-19.

[12] Xu, Y., et al., An experimental study on speech enhancement based on deep neural networks. IEEE Signal processing letters, 2013. 21(1): p. 65-68.

[13] Zhang, X.-L. and D. Wang, A deep ensemble learning method for monaural speech separation. IEEE/ACM transactions on audio, speech, and language processing, 2016. 24(5): p. 967-977.

[14] Nossier, S.A., et al. Mapping and Masking Targets Comparison using Different Deep Learning based Speech Enhancement Architectures. in 2020 International Joint Conference on Neural Networks (IJCNN). 2020. IEEE.

[15] Wu, X., et al. Time-Domain Mapping with Convolution Networks for End-to-End Monaural Speech Separation. in 2020 IEEE 5th International Conference on Signal and Image Processing (ICSIP). 2020. IEEE.

[16] Hershey, J.R., et al. Deep clustering: Discriminative embeddings for segmentation and separation. in 2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). 2016. IEEE.

[17] Yu, D., et al. Permutation invariant training of deep models for speaker-independent multi-talker speech separation. in 2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). 2017. IEEE.

[18] Kolbæk, M., et al. Multitalker speech separation with utterance-level permutation invariant training of deep recurrent neural networks. IEEE/ACM Transactions on Audio, Speech, and Language Processing, 2017. 25(10): p. 1901-1913.

[19] Yang, G.-P., et al. Interrupted and cascaded permutation invariant training for speech separation. in ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). 2020. IEEE.

[20] Huang, S.-F., et al., Stabilizing Label Assignment for Speech Separation by Self-Supervised Pre-Training}. Proc. Interspeech 2021, 2021: p. 3056-3060.

[21] Nair, V. and G.E. Hinton. Rectified linear units improve restricted boltzmann machines. in Icml. 2010.

[22] Hochreiter, S. and J. Schmidhuber, Long short-term memory. Neural computation, 1997. 9(8): p. 1735-1780.

[23] Panayotov, V., et al. Librispeech: an asr corpus based on public domain audio books, in 2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). 2015. IEEE.

[24] Pariente, M., et al., Asteroid: the pytorch-based audio source separation toolkit for researchers. arXiv preprint arXiv:2005.04132, 2020.

[25] Kingma, D.P. and J. Ba, Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980, 2014.

[26] Le Roux, J., et al. SDR–half-baked or well done? in ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). 2019. IEEE.

[27] Vincent, E., R. Gribonval, and C. Févotte, Performance measurement in blind audio source separation. IEEE transactions on audio, speech, and language processing, 2006. 14(4): p. 1462-1469.

[28] Luo, Y. and N. Mesgarani, Separating varying numbers of sources with auxiliary autoencoding loss. arXiv preprint arXiv:2003.12326, 2020.