Toward the pre-cocktail party problem with TasTas+

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Abstract

Deep neural network with dual-path bi-directional long short-term memory (BiLSTM) block has been proved to be very effective in sequence modeling, especially in speech separation, e.g. DPRNN-TasNet \cite{12}, TasTas \cite{21}. In this paper, we propose two improvements of TasTas \cite{21} for end-to-end approach to monaural speech separation in pre-cocktail party problems, which consists of 1) generate new training data through the original training batch in real time, and 2) train each module in TasTas separately. The new approach is called TasTas+, which takes the mixed utterance of five speakers and map it to five separated utterances, where each utterance contains only one speaker’s voice. For the objective, we train the network by directly optimizing the utterance level scale-invariant signal-to-distortion ratio (SI-SDR) in a permutation invariant training (PIT) style. Our experiments on the public WSJ0-5mix data corpus results in 11.14dB SDR improvement, which shows our proposed networks can lead to performance improvement on the speaker separation task. We have open-sourced our re-implementation of the DPRNN-TasNet in https://github.com/ShiZiqiang/dual-path-RNNs-DPRNNs-based-speech-separation, and our TasTas+ is realized based on this implementation of DPRNN-TasNet, it is believed that the results in this paper can be reproduced with ease.

1 Introduction and Problem Statement

Multi-talker monaural speech separation has a vast range of applications. For example, a home environment or a conference environment in which many people talk, the human auditory system can easily track and follow a target speaker’s voice from the multi-talker’s mixed voice. In this case, a clean speech signal of the target speaker needs to be separated from the mixed speech to complete the subsequent recognition work. Thus it is a problem that must be solved in order to achieve satisfactory performance in speech or speaker recognition tasks. There are two difficulties in this problem, the first is that since we don’t have any prior information of the user, a practical system must be speaker-independent. The second difficulty is that there is no way to use the beamforming algorithm for a single microphone signal. Many traditional methods, such as computational auditory scene analysis (CASA) \cite{27,17,5}, Non-negative matrix factorization (NMF) \cite{23,8}, and probabilistic models \cite{26}, do not solve these two difficulties well.

Recently, a large number of techniques based on deep learning are proposed for this task. These methods can be briefly grouped into two categories: time-frequency (TF) domain methods (non-end-to-end) and time-domain methods (end-to-end). The first category is to use short-time Fourier transform (STFT) to decompose the time-domain mixture into the time-frequency domain to display and to separate therein. Usually, deep neural networks (DNN) is introduced for estimating the ideal binary or ratio masks (IBM or IRM), or phase-sensitive masks (PSM), and the source separation is transformed into a magnitude domain TF unit-level classification or regression problem, and mixed phases are usually retained for resynthesis. Notable work includes deep clustering (DPCL) \cite{4,6}, permutation invariant training (PIT) \cite{30}, and combinations of DPCL and PIT, such as Deep CASA \cite{10} and Wang et al. \cite{28}. The second category is end-to-end speech separation in time-domain \cite{13,11,24,20,19,32,12,31,15}, which is a natural way to overcome the obstacles of the upper bound source-to-distortion ratio improvement (SDRi) in STFT mask estimation based methods and real-time processing requirements in actual use.
This paper is based on the end-to-end method [13, 14, 24, 20, 19, 32, 12, 31, 15], which has achieved better results than DPCL based or PIT based approaches. Since most DPCL and PIT based methods use STFT as front-end. Specifically, the mixed speech signal is first transformed from a one-dimensional signal in the time domain to a two-dimensional spectrum signal in TF domain, and then the mixed spectrum is separated to result in spectrums corresponding to different source speeches by a deep clustering or mask estimation method, and finally, the cleaned source speech signal can be restored by an inverse STFT on each spectrum. This framework has several limitations. Firstly, it is unclear whether the STFT is optimal (even assume the parameters it depends on are optimal, such as size and overlap of audio frames, window type, and so on) transformation of the signal for speech separation [18]. Secondly, most STFT based methods often assumed that the phase of the separated signal to be equal to the mixture phase, which is generally incorrect and imposes an obvious upper bound on separation performance by using the ideal masks. As an approach to overcome the above problems, several speech separation models were recently proposed that operate directly on time-domain speech signals [13, 14, 24, 20, 19, 32, 12, 31, 15, 21]. These methods have shown good performance in two or speaker separation, but when we use one of the state-of-the-art methods, TasTas [21], in the separation of 5 different speakers, which is a bit like a separation problem in a pre-cocktail party problem, we find that there is no naive way to train TasTas successfully at all. The SI-SDR loss does not decrease at all. In this paper, we try to improve the training method of TasTas for 5-speaker separation in a pre-cocktail party problem.

Inspired by these first results, we propose TasTas+, which generalize the training of TasTas [21] in two ways. The first is to generate new training data through the original training batch in real time. In each batch, the original clean separated speech is remixed with other random dB to generate new training data and is used for training at the same time. The second is to train each module in TasTas separately. That means we first train the ID-Net to extract speaker features, then train the TasNet in the first stage, and finally train the TasNet in the second stage to refine the separation results from the first stage.

The remainder of this paper is organized as follows: section 2 briefly introduces end-to-end monaural speech separation based on deep neural networks with dual-path BiLSTM blocks (DPRNN-TasNet), and TasTas+ is built on the basis of DPRNN-TasNet. Section 3 describe our proposed TasTas+ and the separation algorithm in detail. The experimental setup and results are presented in Section 4. We conclude this paper in Section 5.

2 Speech separation with dual-path BiLSTM blocks (DPRNN-TasNet)

In this section, we review the formal definition of the monaural speech separation task in a pre-cocktail party problem and the original dual-path BiLSTM based separation architecture [12].

The goal of monaural speech separation in a pre-cocktail party problem is to estimate the individual target signals from a linearly mixed single-microphone signal of at least 5 speakers, in which the target signals overlap in the TF domain. Let \( x_i(t), i = 1, \ldots, S \) denote the \( S \) target speech signals and \( y(t) \) denotes the mixed speech respectively. If we assume the target signals are linearly mixed, which can be represented as:

\[
y(t) = \sum_{i=1}^{S} x_i(t),
\]

then monaural speech separation aims at estimating individual target signals from given mixed speech \( y(t) \). In this work it is assumed that the number of target signals is known.

In order to deal with this ill-posed problem, Luo et al. [14, 12] introduce adaptive front-end methods to achieve high speech separation performance on WSJ0-2mix dataset [4, 6]. Such methods contain three processing stages, here the state-of-the-art architecture [12] is used as an illustration. As shown in Figure 1, the architecture consists of an encoder 1-D convolution (Conv1D in the Figure 1 for abbreviation and the following description is in the same way and will not be repeated again) is followed by a parametric ReLU (PReLU), a separator (consisted in the order by a layer normalization (LayerNorm), a 1\( \times \)1 convolution, and a softmax operation) and a decoder of a fully connected (FC) layer. First, the encoder module is used to convert short segments of the mixed waveform into their corresponding representations. Then, the representation is used to estimate the multiplication
Figure 1: The pipeline of dual-path BiLSTM based speech separation in [12], which is called DPRNN-TasNet.

function (mask) of each source and each encoder output for each time step. The source waveform is then reconstructed by transforming the masked encoder features using a linear decoder module. This framework is called DPRNN-TasNet in [12].

The key factors for the best performance of DPRNN-TasNet on WSJ0-2mix dataset [4, 6] are the local and global data chunk formulation and the dual-path BiLSTM module [12]. Luo et al. [12] first splits the output of the encoder into chunks with or without overlaps and concatenates them to form a 3-D tensor, as shown in Figure 2(a). The dual-path BiLSTM modules will map these 3-D tensors to 3-D tensor masks, as shown in Figure 2(b). The output 3-D tensor masks and the original 3-D tensor are converted back to a sequential output by a 'Merge' operation as shown in Figure 2(c).

Some architectures similar to dual-path BiLSTM have been proposed as alternatives to the recurrent neural network (RNN) in various tasks [33, 9]. Dual-path BiLSTM can organize any type of RNN layer and model long sequence inputs in a very simple way. The intuition is to divide the input sequence into shorter blocks and interleave two BiLSTMs, intra-BiLSTM and an inter-BiLSTM, for local and global modeling, respectively. In a dual-path BiLSTM, the intra-BiLSTM first processes the local block independently, and then the inter-BiLSTM summarizes the information from all the blocks to perform sound level processing. As shown in Figure 2(b), the input of intra-BiLSTM is a segment composed of several consecutive frames in time, and an utterance is divided into several such segments. These segments are passed through a BiLSTM, a fully connected projection, and a group normalization (GroupNorm in Figure 2(b)) [29] operation respectively. A residue connection is added to the output of the group normalization to result in the final output of the intra-BiLSTM with the same shape as the input. The output of intra-BiLSTM will be used as the input of inter-BiLSTM, but a permutation will be performed on this input to let inter-BiLSTM capture global dependency. That is to say, adjacent frames in the input of the inter-BiLSTM are far apart and spread across the global actual time dimension of the input mixed utterance.

Although DPRNN-TasNet has achieved a very good signal to distortion ration improvement (SDRi) [3, 25] on WSJ0-2mix for two speakers, but we do need to extend DPRNN-TasNet to better structures and apply them to more complex problems. For example, Shi et al. [21] generalized DPRNN-TasNet to a new state-of-the-art TasTas structure, which will be introduced and generalized to tackle the separation task in a
In this section, we introduce TasTas and improve the training method towards the speech separation in the pre-cocktail party problem, especially the scene with 5 speakers.

As shown in Figure 3, TasTas [21] introduce a speaker identity-aware multi-stage iterative network is proposed to do monaural speech separation. In each stage, there is a complete separate pipeline mentioned earlier, such as any DPRNN-TasNet. The output of each stage pipeline is 5 separate utterances, and these 5 utterances will be sent to the next stage sub-network along with the original mixed utterance to continue through the exact same pipeline, such as DPRNN-TasNet, except that the input dimension becomes 6 times. As the insight pointed by Shi et al. [21] that 3 or more stages did not improve the performance anymore, thus only two stages are used in our implementation for the speech separation in pre-cocktail party problem.

At the same time, motivated by [15], an identity network (ID-Net) is introduced in TasTas to make further polish of separated utterances from the separation pipeline. As shown in Figure 4(a), the ID-Net here is obtained by connecting a differentiable STFT module* and a VGG11 network [22]. The ID-Net itself needs to be trained separately through the training data of WSJ0-5mix, which indeed has speaker

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**Figure 2:** Key components in the pipeline of DPRNN-TasNet

3 Speech separation in pre-cocktail party problem with TasTas+

In this section, we introduce TasTas and improve the training method towards the speech separation in the pre-cocktail party problem, especially the scene with 5 people in the next section.

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* STFT module

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identity information. Each utterance of training data is divided into 0.5 seconds, sent to ID-Net, and output one-hot speaker identity, as shown in Figure 4(a). After training the ID-Net, it is fixed and only the output of the penultimate layer of ID-Net is used as the speaker’s identity feature vector. Make the separated utterances correspond to the original utterances one by one (after the permutation has been optimized by the separation pipeline with PIT training), and feed them into the ID-Net to extract the speaker identity feature vector. The speaker identity-related loss (hereinafter referred to as ID-loss) are calculated as the mean square distances between the speaker identity feature vectors. At the same time, the SI-SDR related loss is added together for training.

TasTas does seem to have achieved good performance in the separation of two people’s voice [21], but when we use this method for 5 people’s voice separation, the network cannot be trained at all using naive training methods. In order to apply TasTas to the speech separation in the pre-cocktail party problem, we propose TasTas+, which has two improvements over TasTas.

The first improvement of TasTas is the introduction of online data augmentation [31]. During training, there are mixed voices and separate clean voices in each batch. We will remix these separate clean voices at different random dB ratios to generate more training data in real-time. The process is very simple, and is basically the same as the generation process of WSJ0-5mix. That is to say, first scaling the original clean separated voice, then multiplying each voice by a different dB coefficient, and then doing a unified scaling, and finally doing a simple summation.

The second improvement is a multi-step training method of TasTas. The original training algorithm of TasTas is naive, which is direct training. When TasTas is used for 5 people’s voice separation, this training algorithm fails. After trial and error, it is found that if we train different modules of TasTas separately in steps, it can be trained successfully. The multi-step training is shown in Algorithm 1. We first train ID-Net, and then ID-Net will be fixed in the subsequent process. Then we train the first stage of DPRNN-TasNet of TasTas, and after the training is completed, this first stage module is also fixed. Finally, we train the second stage refinement DPRNN-TasNet of TasTas, until it converges.

3.1 Utterance-Level Scale-Invariant SDR Objective Loss

In this work, we directly use the scale-invariant signal-to-distortion ratio (SI-SDR) [3, 25, 16]. SI-SDR captures the overall separation quality of the algorithm. There is a subtle problem here. We first concatenate

*https://github.com/pseeth/torch-stft/tree/master/torch_stft
The structure and training method of ID-Net.

Algorithm 1 Multi-step training in TasTas+

1: Train ID-Net until it converges, and then ID-Net will be fixed in the subsequent process.
2: Train the first stage of DPRNN-TasNet of TasTas until it converges, and this DPRNN-TasNet will be fixed in the subsequent process.
3: Train the second stage refinement DPRNN-TasNet of TasTas until it converges.

The usage of ID-Net.

Figure 4: The structure and usage of ID-Net.

Algorithm 1

1. Train ID-Net until it converges, and then ID-Net will be fixed in the subsequent process.
2. Train the first stage of DPRNN-TasNet of TasTas until it converges, and this DPRNN-TasNet will be fixed in the subsequent process.
3. Train the second stage refinement DPRNN-TasNet of TasTas until it converges.

the outputs of TasTas+ into a complete utterance and then compare with the input full utterance to calculate the SI-SDR in the utterance level instead of calculating the SI-SDR for one frame at a time. These two methods are very different in ways and performance. If we denote the output of the network by \( s \), which should ideally be equal to the target source \( x \), then SI-SDR can be given as

\[
\text{SI-SDR} = 10 \log_{10} \frac{\langle \tilde{x}, \tilde{x} \rangle}{\langle e, e \rangle}.
\]

Then our target is to maximize SI-SDR or minimize the negative SI-SDR as loss function respect to the \( s \).

To solve the tracing and permutation problem, the PIT training criteria [30] is employed in this work. We calculate the SI-SDRs for all the permutations, pick the maximum one, and take the negative as the loss. It is called the SI-SDR loss in this work. The SI-SDR losses of the separated speech outputs at all stages with ground truth will be calculated, and then be averaged as the final loss.

3.2 Training

During training Adam [27] serves as the optimizer to minimize the SDR loss with an initial learning rate of 0.001 and scale down by 0.98 every two epochs. When the training loss increased on the development set,
then restart training from the current best checkpoint with the halved initial learning rate. In other words, the learning rates of restart training are 0.001, 0.0005, 0.00025, etc. respectively. Due to the limitation of GPU memory, the batch size is set to 1 or 2 according to the size of the GPU.

There are three phases in training TasTas+. First, train the ID-Net with the paired original utterances and speaker identity information, and after the training is sufficient, the ID-Net will be fixed. Then we train the first stage DPRNN-TasNet of TasTas+ considering both ID-loss and SI-SDR loss. Finally, we train the second stage refinement DPRNN-TasNet of TasTas+ both ID-loss and SI-SDR loss to complete the training.

4 Experiments

4.1 Dataset and Neural Network

We evaluated our system on the 5-speaker speech separation problem using the WSJ0-5mix dataset [15], which is a benchmark dataset for 5-speaker mono speech separation in recent years, thus most of those methods are compared on this dataset. WSJ0-5mix contains about 24 hours of training and about 6.3 hours of validation data. The mixtures are generated by randomly selecting 49 male and 51 female speakers and utterances in the Wall Street Journal (WSJ0) training set $s_{tr,s}$, and mixing them at various signal-to-noise ratios (SNR) uniformly between 0 dB and 5 dB (the SNRs for different pairs of mixed utterances are fixed by the scripts provided by [15] for fair comparisons). About 4 hours of evaluation set is generated in the same way, using utterances from 16 unseen speakers from $s_{dt,05}$ and $s_{et,05}$ in the WSJ0 dataset.

We evaluate the systems with the SDRi [3, 25] metric used in [6, 11, 2, 10, 28]. Table 1 lists the results obtained by TasTas+ and almost all the results in the past two years, where IRM means the ideal ratio mask applied to the STFT $Y(t, f)$ of $y(t)$ to obtain the separated speech, which is evaluated to show the upper bounds of STFT based methods, where $X_s(t, f)$ is the STFT of $x_s(t)$.

4.2 Results and Discussions

In this experiment, TasTas+ is compared with several classical approaches, such as DPRNN-TasNet [12] and Nachmani’s [15]. Use notation TasTas+($x_1, x_2, \ldots, x_n$) to denote our proposed system with speaker identity-aware dual-path BiLSTM, and $x_1$ dual-path BiLSTM blocks in the first stage, $x_2$ blocks in the second stage, etc.. Thus DPRNN-TasNet is just TasTas+(6,0).

Table 1 lists the results obtained by our methods and almost all the results in the past two years, where IRM means the ideal ratio mask. Compared with these baselines, TasTas+ obtained an absolute advantage, once again surpassing the performance of stage-of-the-art. TasTas has achieved the most significant performance improvement compared with baseline systems, and it breaks through the upper bound of STFT based methods (more than 1.5dB).

For the ablation study, Table 1 shows that TasTas+(8, 9) is about 1.5dB better than TasTas+(6, 6) in SDRi, and TasTas+(6, 6) is 1.4dB better than TasTas+(6) in SDRi. That means the iterative multi-phase decontaminated scheme are effective in boost the performance.

Table 1: SDRi(dB) in a comparative study of different state-of-the-art separation methods on the WSJ0-5mix dataset.

| Method                  | SDRi |
|-------------------------|------|
| IRM                     | 9.6  |
| DPRNN-TasNet [12, 15]   | 8.4  |
| Nachmani’s [15]         | 10.6 |
| TasTas+(6, 0) (ours)    | 8.26 |
| TasTas+(6, 6) (ours)    | 9.65 |
| TasTas+(8, 9) (ours)    | 11.14|
5 Conclusion

In this paper, we investigated the effectiveness of TasTas [21] for 5-talker monaural speech separation in the pre-cocktail party problem. We propose TasTas+ do to speech separation. Benefits from the strength of end-to-end processing, dual-path BiLSTM, speaker identity consistency loss, the multi-stage elaborated iterative scheme, online voice augmentation, and multi-step training the best performance of TasTas+ achieves the new state-of-the-art of 11.14dB SDRi on the public WSJ0-5mix data corpus.

6 Acknowledgements

We would like to thank Dr. Nachmani at Tel-Aviv University & Facebook AI Research valuable discussions on the training of ID-Net.

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