Deep Attention Gated Dilated Temporal Convolutional Networks with Intra-Parallel Convolutional Modules for End-to-End Monaural Speech Separation

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Abstract

Monaural speech separation techniques are far from satisfactory and are a challenging task due to interference from multiple sources. Recently the deep dilated temporal convolutional networks (TCN) has proven to be very effective in sequence modeling. This work explores how to extend TCN to result a new, state-of-the-art monaural speech separation method. First, a new gating mechanism is introduced and added to generate a gated TCN. The gated activation controls the flow of information. Further in order to combine multiple training models to reduce the performance variance and improve the effect of speech separation, we propose to use the principle of ensemble learning in the gated TCN architecture by replacing the convolutional modules corresponding to each dilated factor with multiple identical branches of the convolutional components. For the sake of objectivity, we propose to train the network by directly optimizing in a permutation invariant training (PIT) style of the utterance level signal-to-distortion ratio (SDR). Our experiments with the public WSJ0-2mix data corpus resulted in an 18.2 dB improvement in SDR, indicating that our proposed network can improve the performance of speaker separation tasks.

Index Terms: speech separation, cocktail party problem, temporal convolutional neural network, gating mechanism, parallel convolutional networks

1. Introduction

Multi-talker monaural speech separation has a wide range of applications. For example, in a home environment or conference environment where many people talk, the human auditory system can easily track and follow the speech of the target speaker from the mixed speech of multiple speakers. In this case, it is necessary to separate the clean speech signal of the target speaker from the mixed speech. There are two difficulties with this task. The first problem is that since we don't have any prior information about the user, a really useful system must be independent of the speaker. 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) [1, 2, 3], non-negative matrix factorization (NMF) [4, 5] and probability model [6], do not solve these two difficulties well.

Recently, a large number of techniques based on deep learning have been proposed for this task. These methods can be briefly divided into three categories. The first type is based on deep clustering (DPCL) [7, 8], which maps the time-frequency (TF) points of the spectrogram to the embedding vectors, and then clusters these embedding vectors into corresponding classes corresponding to different speakers, and finally these clusters are used as masks to inversely transform the spectrogram to the separated clean voices; the second is permutation invariant training (PIT) [9, 10], which minimizes the lowest error output in all possible permutations of N mixed resource allocations to resolve label permutation issues; the third category is end-to-end speech separation in the time domain [11, 12, 13, 14], which is a natural way to overcome the obstacles of the upper bound source-to-distortion ratio improvement (SDRi) in short-time Fourier transform (STFT) mask estimation based methods and real-time processing requirements in actual use.

This paper is based on the end-to-end approach [11, 12, 13, 14], which has achieved better results than DPCL-based or PIT-based methods. Since most DPCL and PIT based methods use STFT as the front end, specifically, the mixed speech signal is first transformed from a one-dimensional signal in the time domain to a two-dimensional spectral signal in the TF domain, and then the mixed spectrum is separated by deep clustering or mask estimation to generate a corresponding spectrum to different sources of speech. The method ultimately recovers the cleaned source speech signal through the inverse STFT on each spectrum. This framework has several limitations. First, it is not clear whether the STFT is optimal (even if it is assumed that the parameters it depends on are optimal, such as the size and overlap of audio frames, window types, etc.) for the transformation of the signal for speech separation. Second, most STFT-based methods generally assume that the phase of the separated signal is equal to the mixed phase, which is usually incorrect and imposes a significant upper limit on the separation performance by using an ideal mask. As a method for overcoming the above problems, several speech separation models have recently been proposed, which run directly on the time domain speech signal [11, 12, 13, 14]. Recurrent neural networks (RNN), including long short-term memory (LSTM), are the preferred method for simulating time-dependent sequences. However, one of their main drawbacks is the exploding and vanishing gradient problem and the difficulty of parallel training and separation. In addition, recent literature also shows that the feedforward convolution model is empirically superior to the recurrence models, and can be parallelized, making it easier to train with a more stable gradient [15]. Inspired by these preliminary results, we present FurcaPorta and FurcaPa [1]. FurcaPorta adds a novel gating mechanism to TCN,

where in each dilated convolutional module corresponding to each dilated factor, two gates are introduced, one gate controls information inflow, and one gate controls information processing and outflow. In addition, we propose to replace two convolutional related modules in each dilated convolutional module by two intra-parallel convolutional modules, which can reduce the variance of this model. The intra-parallel convolutional modules replicate weight matrices and take the average from the feature maps produced by those layers. This convenient technique can effectively improve separation performance.

The rest of this paper is organized as follows: Section 2 introduces monaural speech separation with TCN. Section 3 details our proposed FurcaPorta, FurcaPa and the separation algorithm. The experiment settings and results are displayed in Section 4. We conclude this paper in Section 5.

2. Speech separation with TCN

The goal of monaural speech separation is to estimate the individual target signals from a linearly mixed single-microphone signal, where the target signals overlap in the TF domain. Let $x_i(t), i = 1, .., S$ 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. [12] introduce TCN [16, 15] to do this task. TCN is proposed as an alternative to RNN in various tasks [16, 15]. Each layer in the TCN contains a 1-D convolution block with an increased dilation factor. The dilation factor is increased exponentially to ensure a suitable large time context window to take advantage of the long-range dependence of the speech signal, as shown in Figure 1. Dilated convolution in WaveNet has been a huge success for audio generation [17]. Dilated convolutions with different dilation factors have different receptive fields. Stacked dilated convolution provides a very large receptive fields for the network, with only a few layers, because the dilation range grows exponentially. This allows the network to capture the temporal dependence of various resolutions with input sequences. TCN introduces a temporal hierarchy: the upper layer can access longer input subsequences and learn representations on a larger time scale. Local information from lower layers is propagated through the hierarchy through residuals and skip connections.

There are two important elements in the original TCN [15] as shown in Figure 1, one is the dilated convolutions, and the other is residual connections. Dilated convolutions follow the work of [17], it is defined as

$$(x *_d k)(p) = \sum_{s+dt=p} x(s)k(t),$$

where x is the 1-D input signal, k is the filter(a.k.a. kernel), and d is the dilation factor. Therefore, dilation is equivalent to
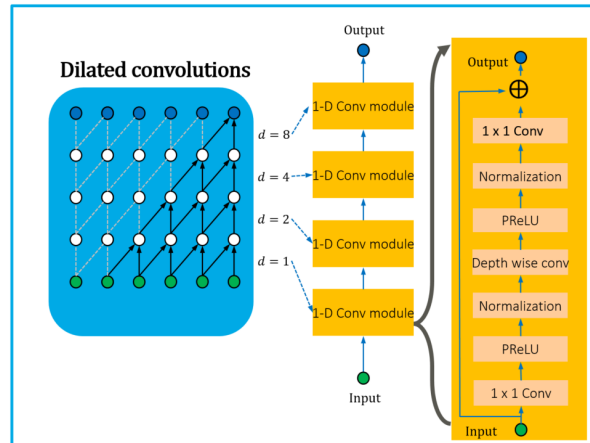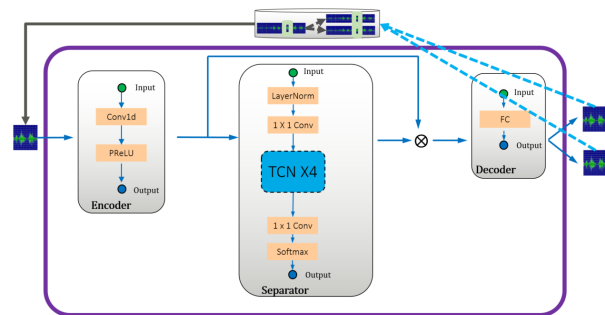

Figure 1: *The structure of TCN.*

Figure 2: *The pipeline of TCN based speech separation in [12].*

introducing a fixed step size between every two adjacent filter taps. The general way to increase the receptive field of the TCN is to increase the dilation factor d. In this work we increase d exponentially with the depth of the network and $d = 2$ as shown in Figure 1, and this TCN has four layers of 1-D Conv modules with dilation factors of $1, 2, 4, 8$ respectively. As shown in Figure 1, each 1-D Conv module is a residual block [18], which contains one layer of dilated convolution (Depth wise conv [19]), two layers of 1×1 convolutions (1×1 Conv), two non-linearity activation layers (parametric rectified linear unit, PReLU [20]), and two normalization layers (Normalization). For normalization, we applied global normalization [12] to the convolutional filters.

Luo et al. proposed a TCN based speech separation method [12], which consists of three processing stages, as shown in Figure 2: encoder (Conv1d is followed by a PReLU), separator (consisted in the order by a LayerNorm, a 1×1conv, 4 TCN layers, 1×1conv, and a softmax operation) and decoder (a 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 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.
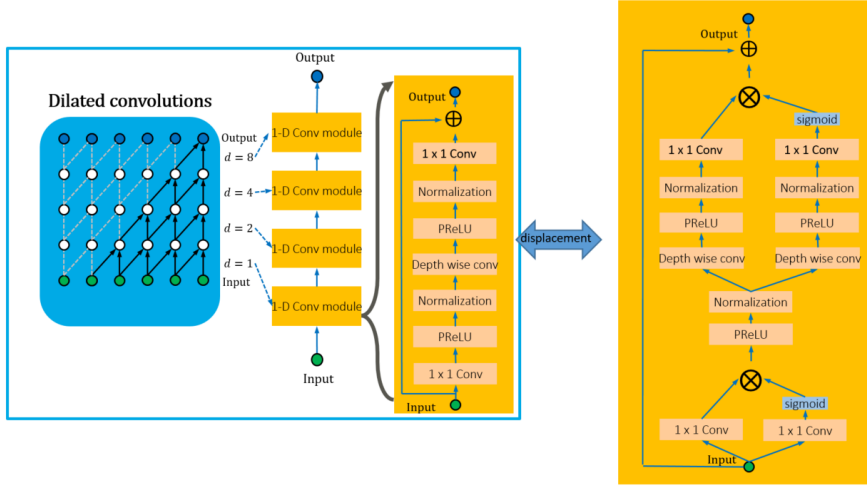
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[1]"Furca" is the Latin ''fork", which we used to mean that mixed speech is divided into two streams by our network, just like water. "Porta" is the Latin "gate". "Pa" is an abbreviation for Parallel.

Figure 3: *The structure of gated TCN.*

3. End-to-end Speech separation with FurcaPorta and FurcaPa

The main work of this paper is to make several improvements to the TCN (Figure 1) and TCN based framework (Figure 2) for speech separation. First, we introduced a novel gating mechanism in this TCN, as shown in Figure 3. Nonlinear gated activation had been used in prior work on sequence modeling [17, 21], it can control the flow of information and may help the network to model more complex interactions. Two gates are added to each 1-D convolutional module in the plain TCN, one gate is corresponding to the first 1×1 convolutional layer in the 1-D convolutional module and this gate is used to control the inflow information. The other gate is corresponding to all the layers from the depth-wise convolutional layer to the output 1×1 convolutional layer and this gate is used to control the processing and outflow of information. This gated TCN based speech separation pipeline is called FurcaPorta in this work.

3.1. FurcaPa: Gated TCN with intra-parallel convolutional components

The performance of a single predictive model can always be improved by ensemble, that is to combines a set of independently trained networks. The most commonly used method is to do the average of the model, which can at least help to reduce the variance of the performance. As shown in Figure 4, in the different layers of each 1-D convolutional module of gated TCN in FurcaPorta, two identical **pa**rallel branches are added. This structure is called FurcaPa. The total output of each intra-parallel convolutional components is obtained by averaging the outputs of all the different branches. In each single dilated 1-D convolutional module layer, two intra-parallel convolutional components are introduced, the first one is near the input layer and covers the Conv1d, PReLU, and Normalization layers; the other one is near the output and it covers the rest all layers, including the Depthwise conv, PReLu, Normalization and 1×1 Conv layers. The reason why we do this ensemble in two places is to reduce the sub-variances of each block.

3.2. Perceptual metric: Utterance-level SDR objective

Since the loss function of many STFT-based methods is not directly applicable to waveform-based end-to-end speech separation, perceptual metric based loss function is tried in this work. The perception of speech is greatly affected by distortion [22, 23]. Generally in order to evaluate the performance of speech separation, the BSS_Eval metrics signal-to-distortion ratio (SDR), signal-to-Interference ratio (SIR), signal-to-artifact ratio (SAR) [24, 25], and short-time objective intelligibility (STOI) [26] have been often employed. In this work we directly use SDR, which is most commonly used metrics to evaluate the performance of source separation, as the training objective. SDR measures the amount of distortion introduced by the output signal and define it as the ratio between the energy of the clean signal and the energy of the distortion.

SDR captures the overall separation quality of the algorithm. There is a subtle problem here. We first concatenate the outputs of FurcaPorta or FurcaPa into a complete utterance and then compare with the input full utterance to calculate the SDR in the utterance level instead of calculating the 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 SDR can be given as [24, 25]

$$
\begin{aligned}
\tilde{x} &= \frac{\langle x, s\rangle}{\langle x, x\rangle}x, \\
e &= \tilde{x} - s, \\
\mathrm{SDR} &= 10 * \log_{10}\frac{\langle \tilde{x}, \tilde{x}\rangle}{\langle e, e\rangle}.
\end{aligned}
$$

Then our target is to maximize SDR or minimize the negative SDR as loss function respect to the s.

In order to solve tracing and permutation problem, the PIT training criteria [9, 10] was employed in this work. We calculate the SDRs for all the permutations, pick the maximum one, and use the negative as the loss. In this work, it is called the uSDR loss.
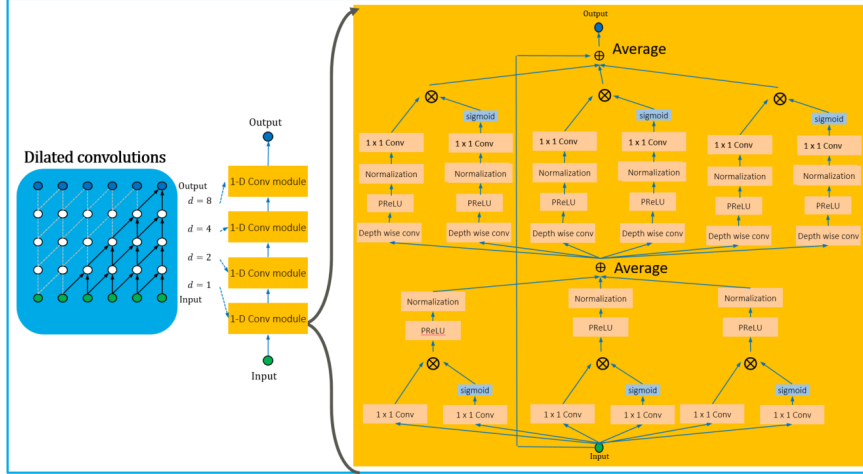
Figure 4: *The structure of gated TCN with intra-parallel convolutional modules. This structure is the key block of FurcaPa, which employs the same pipeline as in Figure 2 by replacing the original TCN with this novel structure of gated TCN.*

4. Experiments

4.1. Dataset and neural network

We evaluated our system on two-speaker speech separation problem using WSJ0-2mix dataset [7, 8], which contains 30 hours of training and 10 hours of validation data. The mixtures are generated by randomly selecting 49 male and 51 female speakers and utterances in Wall Street Journal (WSJ0) training set si_tr_s, and mixing them at various signal-to-noise ratios (SNR) uniformly between 0 dB and 5 dB. 5 hours of evaluation set is generated in the same way, using utterances from 16 unseen speakers from si_dt_05 and si_et_05 in the WSJ0 dataset.

4.2. Results

We evaluate the systems with the SDR improvement (SDRi) [24, 25] metrics used in [8, 27, 28, 29, 9]. The original SDR, that is the average SDR of mixed speech $y(t)$ for the original target speech $x_1(t)$ and $x_2(t)$ is 0.15.

$$M_s = \frac{|X_s(t, f)|}{\sum_{s=1}^{S} |X_s(t, f)|} \quad (1)$$

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 $x_s(t)$.

In this experiment, as baselines, we reimplemented several classical approaches, such as DPCL [7], TasNet [11] and Conv-TasNet [12]. Table 1 lists the SDRis 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 an average increase of nearly 2dB SDRi is obtained. FurcaPorta and FurcaPa has achieved the most significant performance improvement compared with baseline systems, and it break through the upper bound of STFT based methods a lot (nearly 5dB).

5. Conclusion

In this paper we investigated the effectiveness of deep dilated temporal convolutional networks modeling for multi-talker monaural speech separation. Benefits from the strength of end-to-end processing, the novel gating mancinism and

Table 1: *SDRi (dB) in a comparative study of different separation methods on the WSJ0-2mix dataset. * indicates our reimplementation of the corresponding method.*

Method	SDRi
DPCL [7]	5.9
uPIT-BLSTM [10]	10.0
cuPIT-Grid-RD [28]	10.2
DANet [29]	10.5
ADANet [27]	10.5
DPCL*	10.7
DPCL++ [8]	10.8
CBLDNN-GAT [30]	11.0
TasNet [11]	11.2
TasNet*	11.8
Chimera++ [31]	12.0
FurcaX [32]	12.5
IRM	12.7
FurcaNet [14]	13.3
Conv-TasNet [12]	15.0
Conv-TasNet*	15.8
FurcaPorta	17.3
FurcaPa	18.2

intra-parallel convolutional components reducing variance, FurcaPorta and FurcaPa leads to 9% and 14% relative improvement, and we achieve the new state-of-the-art on the public WSJ0-2mix data corpus. For further work, although SDR is widely used and can be useful, but it has some weaknesses [33]. In the future, maybe we can use SNR to evaluation our models. It would be interesting to see how consistent the SDR and SNR are.

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7. References

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