Denoising Auto-encoder with Recurrent Skip Connections and Residual Regression for Music Source Separation

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Abstract—Convolutional neural networks with skip connections have shown good performance in music source separation. In this work, we propose a denoising Auto-encoder with Recurrent skip Connections (ARC). We use 1D convolution along the temporal axis of the time-frequency feature map in all layers of the fully-convolutional network. The use of 1D convolution makes it possible to apply recurrent layers to the intermediate outputs of the convolution layers. In addition, we also propose an enhancement network and a residual regression method to further improve the separation result. The recurrent skip connections, the enhancement module, and the residual regression all improve the separation quality. The ARC model with residual regression achieves 5.74 signal-to-distortion ratio (SDR) in vocals with MUSDB in SiSEC 2018. We also evaluate the ARC model alone on the older dataset DSD100 (used in SiSEC 2016) and it achieves 5.91 SDR in vocals.

Index Terms—Music source separation, recurrent neural network, skip connections, residual regression

I. INTRODUCTION

Music source separation aims at separating music sources such as vocals, drums, strings, or accompaniment from the original song. It can facilitate tasks that require clean sound sources, such as music remixing and karaoke [1]. In this work, we introduce a new model that uses denoising auto-encoder with symmetric skip connections for music source separation. Symmetric skip connections have been used for biomedical image segmentation [2] and singing voice separation [3]. Our model is different in that it uses 1D convolutions instead of 2D convolutions. Using 1D convolutions has the benefit that we can use recurrent layers right after the convolution layers. Furthermore, an enhancement module and a residual regression method are introduced in addition to the separation module.

II. PROPOSED MODELS

In this section, we introduce the separation model, the enhancement model, and residual regression.

A. Separation model

The separation model is a fully-convolutional network (FCN) [4], [5]. All the convolution layers use 1D convolution. We call it the ARC model, for it is in principal a denoising auto-encoder with recurrent skip connections.

CNN with symmetric skip connections had been used for singing voice separation by Jansson et al. [3]. They used 2D convolutions in their convolutional neural networks (CNNs). The output tensor of a 2D convolution layer is of the shape (channels, frequency bins, temporal points). If we want to apply recurrent layers to this tensor, the dimension of frequency bins will pose some problems.

In our model, the convolution layers use 1D convolutions, namely doing convolutions along the temporal axis [6], [7]. The output tensor of an 1D convolution layer takes the shape (channels, temporal points). This allows us to directly apply recurrent layers to the convolution output tensors.

The proposed architecture is presented in Fig. 1. It contains...
Fig. 2: Diagram of the proposed enhancement model. Each tuple in the figure represents (output channels, filter size, stride) of the corresponding convolution layer.

The separation model is in charge of the task of music source separation. The small noises could be ignored in the training process because the losses introduced by other sources could be much larger than the losses introduced by the smaller artifacts. But, we human beings are very sensitive to those smaller artifacts, especially in vocals.

In order to reduce these small artifacts, we introduce an extra enhancement model as a post-processing module. The enhancement model is another denoising auto-encoder that takes the output of a separation model (i.e. the ARC) as its input, and estimates an enhanced version of the separation result. Each source has its own enhancement model, and the training target is that specific source spectrogram.

C. Residual regression

Residual regression is also used to improve the separation result. Unlike the enhancement model, the model with residual regression uses the separation model itself to further improve the separation result.

The process of residual regression is depicted in Fig. 3. The separation model in Fig. 3 is similar to the one introduced in Section II-A. The difference is that the separation model takes another input feature map (the left arrow below the separation model) that is the output from the previous iteration. In iteration $i$, the separation model takes both the output $i-1$ and the mixture feature map as the input. For the iteration 1, the output 0 is set to an all-zero tensor with the same shape as the mixture feature map. The total output of iteration $i$ is the output of the separation model plus the total output of iteration $i-1$. In this way, the separation model will only estimate the residual of the target sources. In the training process, the total loss is the average of the losses from all the iterations.

III. Evaluation

The evaluation is conducted by using the official dataset MUSDB (100 songs for training and 50 songs for testing) and the official packages¹ from SiSEC2018 [13]. The models are implemented with PyTorch.² We will report the evaluation result in terms of signal-to-distortion ratio (SDR) [14], as it is the most widely used metric in literature [13], [15], [16]

¹https://github.com/sigsep/sigsep-mus-eval and https://github.com/sigsep/sigsep-mus-2018-analysis
²https://pytorch.org/
TABLE I: Performance (in SDR) for MUSDB in SiSEC 2018

| SiSEC ID | Skip connections | Enhancement | Residual regression | vocals | drums | bass | other | accompaniment |
|----------|------------------|-------------|---------------------|--------|-------|------|-------|---------------|
| JY1      | 1 GRU layer      | No          | No                  | 5.57   | 4.60  | 3.18 | 3.45  | 11.81         |
| JY2      | 1 GRU layer      | Yes         | No                  | 5.69   | 4.76  | 3.58 | 3.70  | 11.90         |
| JY3      | 1 GRU layer      | No          | Yes (3 iterations)  | 5.74   | 4.66  | 3.67 | 3.40  | 12.08         |

A. Training process

The training dataset is MUSDB. It contains 100 songs, each of which has four sources: drums, bass, other, and vocals. We randomly choose 90 songs as the training set and 10 songs as the validation set. The validation set is used for early stopping. Each song is divided into 5-second sub-clips.

The short-time Fourier transform (STFT) is applied to the sub-clips for feature extraction. The native sampling rate 44,100 is used with a window size 2,048 and a hop size 1,024.

Uhlich et al. [15] showed that data augmentation is crucial to compensate for the scarcity of training data in music source separation. We conduct the online data augmentation to increase the number of training data as follows. Assume we have N 5-second sub-clips. First, we randomly choose one sub-clip from the N sub-clips for each source. Note that the sub-clip chosen for one source could be different from the sub-clip chosen for another source. The four sub-clips from the four sources are summed, leading to the mixture of one training instance. Then, we use the spectrogram of this mixture as the input and use the concatenated spectrograms of the four source sub-clips as the training target.

We use mean square error (MSE) as the loss function for updating the network. Assume that the mini-batch size is B, and there are S sources, T temporal points, and F frequency bins. Then, the loss function is \( \sum_{b=1}^{B} \sum_{s=1}^{S} \sum_{t=1}^{T} \sum_{f=1}^{F} (P_{b,s,t,f} - \log(1 + G_{b,s,t,f}))^2 / (BSTF) \), where \( P_{b,s,t,f} \) is the prediction and \( G_{b,s,t,f} \) is the target source spectrogram.

We use Adam [17] and a mini-batch of 10 instances to train the models. The initial learning rate is set to 0.001 for the convolution layers, and it is set to 0.0001 for the GRU layers. We found that using 0.001 learning rate often lead to gradient explosion for the GRU layers, while the training process was stable when we used 0.0001 for the GRU layers.

B. Testing process

In the testing phase, an entire song is processed at once. Because we adopt a FCN design, our model can deal with songs of arbitrary length. Multi-channel Wiener filter is used for post-processing [14], [15]. We use the phases of the mixture to convert the estimated source spectrograms into waveforms via the inverse STFT. We use the sum of the estimates of the four sources as the estimate of the accompaniment (‘accomp.’).

C. Result

In this subsection, we show the performance of our submissions to SiSEC2018. The result is shown in TABLE I. In the model with residual regression (JY3), we run three iterations. We can see from this table that JY2 (using enhancement model) and JY3 (using residual regression) improves over JY1 in almost all sources.

Fig. 4 display the SiSEC 2018 results of the models using supervised approaches without using additional training data, showing the best model of each author group. Statistically the result of JY3 in vocals is not significantly different from that of the other two leading models TAK1 [18], [19] and UHL2 [15], according to the official SiSEC2018 report [13].

D. Effect of different skip connections

We compare different skip connections in this subsection. The four compared architectures are shown in Fig. 5, and the result is shown in TABLE II. We can see that the models with skip connections outperform the one without skip connections, and the model with recurrent skip connections outperforms the one with convolution skip connections.

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3https://sigsep.github.io/datasets/musdb.html#tools

4This figure is generated with a modified version of the code provided by the organizers https://github.com/sigsep/sigsep-mus-2018-analysis. We specify “not using additional training data” here, because some submissions did use additional training data (not by data augmentation but by actually including more songs with clean sources for training).

5https://github.com/sigsep/sigsep-mus-2018/blob/master/submissions/TAK1/description.md

6https://github.com/sigsep/sigsep-mus-2018/blob/master/submissions/UHL2/description.md
TABLE II: Comparison of different skip connections (in SDR) for MUSDB in SiSEC 2018

| Skip connections | vocals | drums | bass | other | accomp. |
|------------------|--------|-------|------|-------|---------|
| None             | 4.41   | 4.48  | 3.43 | 2.91  | 10.74   |
| Direct (identity)| 5.05   | 4.65  | 3.41 | 3.02  | 11.25   |
| 1 Convolution layer | 5.03 | 4.78  | 3.37 | 2.80  | 11.39   |
| 1 GRU layer (JY1) | 5.57   | 4.60  | 3.18 | 3.45  | 11.81   |

E. Applying recurrent layers at different locations

The recurrent layers could be applied at different locations of the separation model. We tested several possibilities, and many of them improves over the non-recurrent versions. For example, another possible way of using recurrent layers is shown in Fig. 6b and its performance is shown in TABLE III. Among these variants, we found that applying the recurrent layers to the skip connections is the most effective one.

TABLE III: Recurrence at different layers (in SDR) for MUSDB in SiSEC 2018

| Where to use recurrent layers | vocals | drums | bass | other | accomp. |
|--------------------------------|--------|-------|------|-------|---------|
| Skip connections (JY1)         | 5.57   | 4.60  | 3.18 | 3.45  | 11.81   |
| After TConv4 output           | 5.36   | 4.38  | 3.53 | 3.66  | 11.91   |

F. Batch normalization VS Weight normalization

We have found that the separated audios subjectively sound less noisy using weight normalization [10] in convolution layers than the separated audios using batch normalization [11] after convolution layers. However, the objective evaluation with SDR suggests that their results are very close in vocals and the one with batch normalization is even better in the other sources, as shown in TABLE IV.
TABLE IV: Batch normalization VS Weight normalization (in SDR) for MUSDB in SiSEC 2018

| Normalization      | vocals | drums | bass | other | accomp. |
|--------------------|--------|-------|------|-------|---------|
| Weight norm (JY1)  | 5.57   | 4.60  | 3.18 | 3.45  | 11.81   |
| Batch norm         | 5.56   | 4.92  | 3.63 | 3.57  | 11.98   |

G. Qualitative Result

Fig. 7 shows the groundtruth spectrograms and the estimated spectrograms of two example songs from the MUSDB test set. The groundtruths and the estimates have similar patterns. We can see clear activations of the fundamental frequencies and their harmonics from the estimated spectrograms. On the other hand, we can observe that the estimated spectrograms are less sharp and noisier compared to the groundtruth spectrograms, which indicate rooms for improvement in the future work.

We also build a website (http://mss.ciaua.com) to demo the result of the proposed model JY3 for songs not in MUSDB.

H. Evaluating with DSD100 dataset

We also evaluate the proposed ARC net with DSD100 dataset that was used in SiSEC2016 [16]. We evaluate ARC with batch normalization as introduced in Section III-F with DSD100 by using the official toolkit. The enhancement and residual regression are not used in this evaluation. We use the 50/50 train/test split specified by SiSEC2016. The result is shown in TABLE V. The result of our model is only second to that of the MMDenseNet [18] and MMDenseLSTM [19] models proposed by Takahashi et al. The TAK1 method shown in Fig. 4 is an extended version of these models.

TABLE V: Evaluation on DSD100 (in SDR). We use ARC with batch normalization for our model here.

| Normalization      | vocals | drums | bass | other | accomp. |
|--------------------|--------|-------|------|-------|---------|
| DeepNMF [20]       | 2.75   | 2.11  | 1.88 | 2.64  | 8.90    |
| NUG [14]           | 4.55   | 3.89  | 2.72 | 3.18  | 10.29   |
| MaDTwinNet [21]    | 4.57   | —     | —    | —     | —       |
| BLSTM [15]         | 4.86   | 4.00  | 2.89 | 3.24  | 11.26   |
| SH-4stack [22]     | 5.16   | 4.11  | 1.77 | 2.36  | 12.14   |
| BLEND [15]         | 5.23   | 4.13  | 2.98 | 3.52  | 11.70   |
| MMDenseNet [18]    | 6.00   | 5.37  | 3.91 | 3.81  | 12.10   |
| MMDenseLSTM [19]   | 6.31   | 5.46  | 3.73 | 4.33  | 12.73   |
| Ours               | 5.91   | 4.11  | 2.54 | 3.53  | 11.31   |

IV. Conclusions

In this paper, we have presented our models for music source separation. We proposed to use 1D convolutions in convolution layers so that we can naturally apply recurrent layers to the convolution outputs. The experiments show that the recurrent skip connections largely improve the separation result. Moreover, the proposed enhancement model and residual regression can further improve the separation result.

For future work, we would be interested in applying the source separation models for other applications, such as singing style transfer [23], vocal melody extraction [24], [25], instrument recognition [26], and lyrics transcription [27].

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Fig. 7: Examples of spectrograms of the groundtruth sources and the estimated sources for two songs in the test set of MUSDB used by SiSEC 2018. The first row contains the groundtruth sources and the second row contains the estimated sources by the model with residual regression (JY3). The first column shows the original song, that is, the mixture.

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