TF-ATTENTION-NET: AN END TO END NEURAL NETWORK FOR SINGING VOICE SEPARATION

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ABSTRACT

In terms of source separation task, most of deep neural networks have two main types: one is modeling in the spectrogram, and the other is in the waveform. Most of them use CNNs, LSTMs, but due to the high sampling rate of audio, whether it is LSTMs with a long-distance dependent or CNNs with sliding windows is difficult to extract long-term input context. In this case, we propose an end-to-end network: Time Frequency Attention Net (TF-Attention-Net), to study the ability of the attention mechanism in the source separation task. Later, we will introduce the Slice Attention, which can extract the acoustic features of time and frequency scales under different channels while the time complexity of which is less than Multi-head Attention. Also, attention mechanism can be efficiently parallelized while the LSTMs cannot because of their time dependence. Meanwhile, the receptive field of attention mechanism is larger than the CNNs, which means we can use shallower layers to extract deeper features. Experiments for singing voice separation indicate that our model yields a better performance compared with the SotA model: spectrogram-based U-Net and waveform-based Wave-U-Net, given the same data.

Index Terms— Music Information Retrieve, Source separation, Attention Mechanism, TF-Attention-Net

1. INTRODUCTION

In the general source separation problem, we are given several mixture signals that consists of different original source signals [1], which may include sound, drums, bass or guitar. Our task is to separate source signals in a given mixture, especially the vocal signal and accompaniment signal.

At present, most of the currently successful audio source separation technologies are two main types. One models in the spectrogram [2, 3, 4], the other models in the waveform [5, 6, 7]. They all use CNNs, LSTMs as feature extraction tools, but all of them have certain drawbacks. For CNNs, the receptive field has certain limitations [8], that is, deeper layers are needed to obtain a wider receptive field, and CNNs has the long-term dependency problems that cannot be solved due to the sliding window. In addition, because of the limitation of the structure, the LSTMs cannot perform parallel calculation, which makes the calculation efficiency low. Furthermore, it still can not solve the long-term dependency problem well [9].

Vaswani et al. proposed a new neural network model that is neither CNNs nor LSTMs but Transformer [10], which uses only the attention mechanism structure to obtained the SotA in the translation of English-French in WMT 2014. Transformer is a method that can automatically capture sequence distribution. Experiments show that Transformer is more suitable for processing sequences than LSTMs, because it can solve long-term dependence problems better than LSTMs. In addition, since Transformer has no time dependence for calculating, it does not has the problem that can not be computed in parallel. Furthermore, Transformer has a larger receptive field compared to CNNs with the same number of layers, so it might be useful if it is used for source separation.

In this paper, we discuss the feature extraction ability of the encoder of Transformer in the source separation task, and propose an end-to-end spectrum separation network, that is, TF-Attention-Net, which apply sliced attention to both the time and frequency axis of each channel. According to the experiment, our model has achieved the new state-of-the-art result.

Fig. 1. The flow chart of our training system, and the specific structure of TF-Attention-Net will be introduced later.

2. SINGING VOICE SEPARATION

Our network are designed on the spectrogram like [11, 12, 13], and the mono music mixture \( x \in \mathbb{R}^{1 \times T} \) can be expressed as a linear combination of \( c \) sources \( s \in \mathbb{R}^{1 \times T} \):

\[
x(t) = \sum_{i=0}^{c} s_i(t)
\]

Then we take the short Fourier transform (STFT) of each segment, so that each music segment \( S_i(t, f) \) can be mapped to a time-frequency bin \( X(t, f) \):

\[
X(t) = \sum_{i=0}^{c} S_i(t, f)
\]

We assume that the phase of the mix audio is the same as that of the original, so we only input the magnitude of the music segments \( |X_i(t, f)| \) into the model. The estimated source \( \hat{S} \) is calculated by
performing element-wise multiplication between the mask \( M_i \) and the mixture spectrogram \( |X(t,f)| \).
\[
\hat{S}_i(t,f) = |X(t,f)| \times M_i(t,f) + \varphi(X(t,f))
\] (3)
where \( M \) is Wiener-Filter Like Mask (WFM) \([14]\), which can be used to estimate the individual sources. The formula is as follows:
\[
M_i(t,f) = \frac{|S_i(t,f)|^2}{\sum_{i=0}^{c}|S_i(t,f)|^2} \quad \text{s.t.} \quad \sum_{i=0}^{c} M_i = 1
\] (4)
So the task can be denoted as minimizing the following objective function:
\[
\mathcal{L} = \arg \min_M \sum_{i=0}^{c} \left\| S_i(t,f) - \hat{S}_i(t,f) \right\|_2^2
\] (5)

3. PROPOSAL: TF-ATTENTION-NET

Inspired by the fact that BERT \([15]\) can deal with sequence problems very efficiently in machine translation task, we proposed the TF-Attention-Net model, which has only the encoder of the Transformer and reconstructs the mask of each source by focusing on the global features at time and frequency scales simultaneously.

The structure of the model is shown in the figure 2. First we embed it into the k-dimensional space through a embedding layer. For each time-frequency bin, we apply the temporal attention module and the frequency attention module to capture the characteristic dependency of the global feature \([16]\) (we will describe them in detail in Section 3.3). To further enhance the ability of the network to express, we design a Position-wise CNN (PWC) layer (we will discuss it in Section 3.4) to get vocal and accompaniment information at different resolution scales. Next, we will introduce the details of TF-Attention-Net.

![fig2.png](attachment:fig2.png)

**Fig. 2.** Model architecture of TF-Attention-Net.

3.1. Scaled Dot-Product Attention

The attention mechanism is a method of learning the distribution of its own weight by calculating the similarity of sequences. The commonly used methods of attention mechanism are dot product, concatenation, perceptron and etc. Here we use the first method. Specifically, it divides a sequence into three inputs, query \( Q \), key \( K \), and value \( V \), and then calculates the attention of the three elements. The formula is as follows:
\[
Attention(Q, K, V) = \text{softmax} \left( \frac{QK^T}{\sqrt{d_k}} \right) V
\] (6)
where \( 1/\sqrt{d_k} \) plays a regulating role, so that the inner product is not too large.

3.2. Sliced Attention

In the singing voice separation task, it is more advantageous to slice it in advance instead of directly scaling the audio signal to Scaled Dot-Product Attention. Because singing voice separation is not like machine translation, it does not require too long-term dependencies (we will talk about it in section 4), but require more useful sample values to be combined to predict the current sample value, so we proposed a new method called Sliced Attention rather than the Scaled Dot-Product Attention stacking like Multi-Head Attention, which slices the input metrics \( Q, K, V \) and it can be expressed as:
\[
\begin{cases}
Q = \{Q_{s_1}, Q_{s_2}, ..., Q_{s_i}\} \\
K = \{K_{s_1}, K_{s_2}, ..., K_{s_i}\} \\
V = \{V_{s_1}, V_{s_2}, ..., V_{s_i}\}
\end{cases}
\] (7)

Every three \( Q_{s_i}, K_{s_i}, V_{s_i} \) is combined as a group \( (Q_{s_i}, K_{s_i}, V_{s_i}) \). Each group does Scaled Dot-Product Attention, then all attention results are concatenated as the output, which can be expressed as:
\[
slice_i = Attention(Q_{s_i}, K_{s_i}, V_{s_i})
\] (8)
\[
\text{Sliced}(Q, K, V) = \text{Concat} (\text{slic}_{1}, \text{slic}_{2}, ..., \text{slic}_{i})
\] (9)

3.3. Sliced Time-frequency Attention

The general attention usually applies in the 2-dimensional sequence, but the number of the dimension of the spectrogram is three, i.e., [time, frequency, channel]. Because the dataset we use is mono audio signals and as authors in \([6]\) pointed out, mapping the number of channels to a higher-dimensional space will result in better separation, so we embed the channel of the spectrogram into the dimension \( d_k \), then do the temporal sliced attention and frequency sliced attention operations. The former is sliced by the time axis while the latter is sliced by the frequency axis. As shown in the figure 3, the block on the left operates in the time domain, while the right operates in the frequency domain. Finally, we stack the results of the two operations in the channel axis and use a CNN to compress it. The above illustration can be expressed by the following formula (\( W^O \in \mathbb{R}^{d_{2k} \times d_k} \) is the convolution operation):
\[
\text{Time} = \text{Sliced}(Q, K, V)
\] (10)
\[
\text{Freq} = \text{Sliced}(Q^T, K^T, V^T)^T
\] (11)
\[
\text{TF-Attention} = \text{Concat} (\text{Time}, \text{Freq}) \ast W^O
\] (12)

3.4. Position-Wise CNN

In addition to the slice attention sub-layers, each block also contains a Position-wise CNN (PWC), which includes three CNN and Batch Normalization, where the number of channels after three CNN is the same as before the convolution, and the output of the first two Batch
Normalizations is activated by the ReLU function. Meanwhile, the input of this layer is also connected with the residual after the third convolution, so the output of the PWC can be expressed as:

$$PWC(Z) = \max(0, \max(0, Z \ast W_1 + b_1) \ast W_2 + b_2) \ast W_3 + Z$$  \hspace{1cm} (13)

where $Z$ is the output of TF-Attention, $W_i \in \mathbb{R}^{d_k \times d_k}$, $b_i \in \mathbb{R}^{d_k}$ and $Z \ast W$ is convolution operation.

### 3.5. Layer Norm

We use residual connections in the two sub-layers above, and then perform layer normalization \cite{17}, so the output of each sublayer is:

$$LayerNorm(x + Sublayer(x))$$  \hspace{1cm} (14)

where $Sublayer(x)$ is a function implemented by the sublayer itself.

## 4. WHY SLICED ATTENTION

Unlike the machine translation task, the interdependence of each segment is not that stable, because it often has a sudden change in style, such as playing with drum at that moment, but suddenly change to bass or a human voice at the next moment. Under this circumstance, if we focus on the globalization of the field of view, it will increase the distribution of irrelevant samples, resulting in a lack of focus on the key points and can not locate the sampling points with strong correlation precisely. Conversely, the attention of small fragments is more likely to express the interdependence between sampling points and avoid the focus being too scattered, which increases the focus of the attention operation on useful sample values and reduces the interference of unwanted sample values.

The Temporal Slice Attention is segmented on the frequency axis, and each slice stores the complete time information. For each instrument, the frequency has a regular harmonic structure on a complete time segment, which means the weight of one of the instruments may be larger in a certain frequency band, which can make the focus of each slice different. For example, one of the slices will focus more on people while the other focus more on instrument.

Similarly, Frequency Slice Attention is segmented on the time axis, and each slice retains complete frequency information. At the same time, the scope of attention is narrowed down, so that the slices are more concerned with the features that are most likely to affect each other’s recent time period. There also has a advantage, that is, when the two music segments are very collinear but the time interval is big, it can be avoided that the two concerns fall on each other, which makes its correlation with the false-positive segments weaken but the true-positive segments strengthen. In fact, when they are far apart, the styles of the music may completely change, so we don’t have to give them attention so much.

## 5. EXPERIMENTS

### 5.1. Experimental setup

We use the MUSDB18 \cite{18} and CCMixer \cite{19} datasets. In order to compare with the SotA, the proportions of training set, validation set and test set we used are consistent with them, that is, we randomly select 75 tracks from the training set of MUSDB18 and take all the CCMixer dataset as the training set, and we use the remaining 25 tracks of MUSDB18 as the validation set to determine whether it is needed to early stop in case of overfitting. At the end of the training stage, we used all the test sets of MUSDB18, i.e., 50 songs, for evaluating the model. All the data are converted to mono and down-sampling to 8192 Hz.

TensorFlow framework \cite{20} are used to build our models and we train them with 1 NVIDIA Tesla M40 GPU. During the training process, we randomly extract the audio clips and fill them correspondingly based on the context of the audio clips in order to align the dimensions, because the length of each song is not the same. The window function of the STFT is set to the Hamming window, and the frame length and frame step are set to 1024 and 768, respectively. We use ADAM optimizer with a learning rate of 0.0001 and the decay rates $\beta_1 = 0.9$ and $\beta_2 = 0.999$. We set the batch size to 2 and set 2000 steps as one epoch. If the validation loss does not descend after 20 epoch, the early stop will be performed and the training stage will end.

We use signal-to-distortion ratio (SDR) \cite{21} as an evaluation metrics, which mainly divides the audio track into multiple non-overlapping audio segments. We also take the method proposed in \cite{6} to evaluate performances in order to make SDR metrics more precisely.

### 5.2. Results

As shown in table 1, when the number of slices increases from 1 to 2, the separation effect of our model increases, but when the number increases from 2 to 4 and 8, the effect drops gradually, which makes us suspect that attention weight distribution can be calculated accurately with an appropriate number of slices, but when slices too large, it will cause the segments to be too small, making the attention weight distribution inaccurate. Also, we found that when the channel was increased from 32 to 64, the separation effect improved. But when the channel was increased from 64 to 128, more abnormal segments have appeared, resulting in a lower mean of SDR. We guess this is because mono audio has a certain range of embedding, and
Table 1. Comparison SDR (in dB) of each model, and the best performances among comparison models are shown in bold.

| Model                | # Param | Epoch | Time    | Med. | MAD  | Mean  | SD  | Med. | MAD  | Mean  | SD  |
|----------------------|---------|-------|---------|------|------|-------|-----|------|------|-------|-----|
| 1S-64C-3Attention    | 15.86M  | 83    | 10.3 hours | 4.15 | 2.86 | 1.34 | 11.56 | 7.50 | 2.03 | 7.67 | 3.40 |
| **2S-64C-3Attention** | 15.86M  | 147   | 14.8 hours | 4.19 | 2.88 | **1.97** | 10.42 | **7.58** | 2.01 | **7.74** | 3.36 |
| 4S-64C-3Attention    | 15.86M  | 151   | 16.3 hours | **4.23** | 2.87 | 1.73 | 10.87 | 7.56 | 2.02 | 7.71 | 3.43 |
| 4S-64C-3Attention(Temporal) | 10.79M | 168   | 12 hours | 4.01 | 2.80 | 0.46 | 12.92 | 7.46 | 2.04 | 7.63 | 3.36 |
| 4S-64C-3Attention(Frequency) | 10.79M | 101   | 18.5 hours | 3.85 | 2.76 | 0.89 | 11.75 | 7.39 | 2.01 | 7.55 | 3.39 |
| 8S-64C-3Attention    | 15.86M  | 100   | 13 hours | 4.04 | 2.90 | 1.67 | 10.59 | 7.45 | 2.03 | 7.63 | 3.39 |
| 8S-64C-2Attention    | 10.58M  | 152   | 17 hours | 4.01 | 2.79 | 1.02 | 11.79 | 7.47 | 2.04 | 7.62 | 3.35 |
| 8S-64C-2Attention    | 10.58M  | 76    | 10.1 hours | 3.90 | 2.77 | 0.54 | 12.4  | 7.39 | 2.02 | 7.55 | 3.36 |
| 2S-128C-3Attention   | 63.23M  | 48    | 6.3 hours | 4.07 | 2.92 | 1.88 | 10.29 | 7.58 | 2.03 | 7.70 | 3.36 |
| 4S-32C-2Attention    | 2.67M   | 96    | 4.8 hours | 3.74 | 2.73 | 0.25 | 12.74 | 7.29 | 2.00 | 7.45 | 3.37 |
| 8S-32C-2Attention    | 2.67M   | 158   | 18.4 hours | 3.75 | 2.69 | 0.13 | 12.85 | 7.30 | 1.99 | 7.46 | 3.36 |
| 4S-32C-3Attention    | 3.99M   | 127   | 16.5 hours | 3.87 | 2.79 | 0.73 | 12.10 | 7.41 | 2.03 | 7.58 | 3.33 |
| U-Net                | 224.83M | 103   | 3.5 hours | 2.90 | 2.56 | -0.42 | 12.59 | 6.87 | 1.99 | 7.01 | 3.59 |
| Wave-U-Net           | 235.69M | 72    | 13.5 hours | 3.43 | 2.79 | -0.27 | 13.03 | 7.11 | 2.05 | 7.13 | 4.01 |

6. CONCLUSION

In this paper, we propose an end-to-end spectrum-based audio source separation network called TF-Attention-Net, which apply the attention mechanism to singing voice separation task. In the evaluation stage, we used a median-based metric that \[6\] proposed to solve the problem of evaluating abnormalities in quiet audio segments in SDR analysis. As the experiment results show, our model achieved competitive SDR performance although the parameters of which had twenty times less than the Sota’s, which verifies that our model is more advantageous for the treatment of abnormal segments.

For future work, in order not to ignore the difference of the phase between the mix audio and the separated audio, we intend to model directly in the waveform or use the Griffin-Lim algorithm \[23\]. In addition, we intend to search for a better loss function for source separation.

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