Guided Training: A Simple Method for Single-channel Speaker Separation

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Abstract—Deep learning has shown a great potential for speech separation, especially for speech and non-speech separation. However, it encounters permutation problem for multi-speaker separation where both target and interference are speech. Permutation Invariant training (PIT) was proposed to solve this problem by permuting the order of the multiple speakers. Another way is to use an anchor speech, a short speech of the target speaker, to model the speaker identity. In this paper, we propose a simple strategy to train a long short-term memory (LSTM) model to solve the permutation problem in speaker separation. Specifically, we insert a short speech of target speaker at the beginning of a mixture as guide information. So, the first appearing speaker is defined as the target. Due to the powerful capability on sequence modeling, LSTM can use its memory cells to track and separate target speech from interfering speech. Experimental results show that the proposed training strategy is effective for speaker separation.

Index Terms: speaker separation, long short-term memory, guided training.

I. INTRODUCTION

Speech signal for processing and analyzing is usually degraded by interference sources. Separating the target speech from the other interference sources is often referred to as speech separation, which is a challenging but meaningful work.

Over the past decades, several speech separation approaches have been proposed [1] [2]. Speech separation in literature can be broadly decomposed into two categories, multi-channel separation and single-channel separation, depending on the number of the sensors (microphones) applied in the signal recording. Since the multi-channel recording contains more than one sensor, the spatial information for each source can be employed for speech separation, e.g. beamforming technology [1]. The effect of multi-channel based methods is directly related to the number of sensors. To achieve a good performance, these methods always need a large number of sensors. However, single channel recording is the most common scenario in the real world. It is also more challenging for target speaker separation. In this paper, we mainly focus on single channel recording.

Recently, deep neural network (DNN) is introduced to solve the signal processing problems and has achieved substantial improvements over the traditional methods [3]. In [4], Delfarah et al. proposed a RNN-based method for speaker-dependent separation in reverberant environments. More impressively, Deep Clustering (DC) [5], Deep Attractor Networks (DANs) [6] and PIT [7] have made speaker-independent separation possible. In particular, DC and DANs combine a neural network and a K-means clustering algorithm cleverly to obtain source separation masks. PIT casts speech separation as a multi-class segregation problem where the supervision is provided as a set instead of an ordered list. DC, DANs and PIT deal with the speech separation as an one-pass problem that separate all sources at once. In addition, they all assume that the correct number of speakers in the test stage is known in advance.

The mixture signal of a target speech with background speech can be separated into individual source signals by the above algorithms. However, these algorithms cannot identify which output signal corresponds to the target speech. This problem is regarded as the permutation problem [8], and some work has been proposed to solve it by imposing constraints about speaker gender [9] or signal intensity [10]. In [11], King et al. proposed EncDec that utilizes an encoder projecting an anchor speech to a fixed-size embedding. The output of the last frame is used as identity of the target speaker, and fed into the decoder to predict the target speech. The encoder and the decoder are jointly trained to improve performance.

Recently, LSTM [12] shows powerful sequence modeling capabilities on many fields [13]. In this paper, we make full use of LSTM’s capability, and propose a simple training strategy for single-channel target speaker separation. In the method, the first appearing speaker is defined as the target. To ensure that the speech does not appear at the same time, we insert a short duration speech of target speaker at the beginning of a mixture as guide information. Due to LSTM’s powerful capability on sequence modeling, the target speaker can be tracked and separated.

The rest of the paper is organized as follows. We will describe our proposed algorithm in Section 2 and Section 3. The experimental setup and evaluation results are presented in Section 4. We conclude this paper in Section 5.

II. ALGORITHM DESCRIPTION

A. Problem formulation

The purpose of the method is to extract the first appearing speaker in a linearly mixed signal which can be written as,

\[ y = s_t + s_i, \]  

(1)

where \( y \) is the mixture, \( s_t \) and \( s_i \) indicate the first speaker and interference speaker signal, respectively. As shown in Fig. [1], the red part in \( s_t \) is the guided speech, such as wake-up voice
in a smart speaker, which is used to guide the separation model and track the $s_t$ from $y$.

The key to speaker tracking is how to use the guide speech segment. RNN seems to be the most suitable neural network model since it makes use of the context information by connecting hidden nodes to the counterparts in the previous step of the sequence. However, gradient vanishing and exploding issues make a vanilla RNN hard to optimize. By introducing a memory cell and employing gate mechanism to control the information flow, LSTM has shown powerful ability to model long range dependencies in the sequential data. Consequently, to capture the long history of the guided speech, LSTM is used to track first speaker directly.

![Image](69x404 to 75x437)

![Image](69x483 to 75x516)

![Image](82x534 to 86x558)

![Image](112x370 to 114x394)

![Image](112x449 to 114x473)

![Image](184x450 to 187x473)

![Image](184x529 to 187x552)

![Image](209x370 to 212x393)

![Image](209x449 to 212x473)

![Image](209x528 to 212x552)

![Image](233x370 to 236x394)

![Image](233x449 to 236x473)

![Image](233x528 to 236x552)

![Image](304x107)

![Image](304x95)

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![Image](304x-191)

![Image](304x-179)

![Image](304x-60)

![Image](304x-131)

![Image](304x437)

![Image](304x568)

Finally, after obtaining the estimation of $\hat{M}$, the timedomain signal is resynthesized by using the phase of mixed speech and ISTFT (inverse STFT), as follows,

$$\hat{s}_t = \text{ISTFT}(\hat{M} \circ Y),$$

the operator $\circ$ denotes the Hadamard product (element-wise product).

### III. NETWORK ARCHITECTURE

#### A. LSTM block

The LSTM block used in this study is defined by the following equations,

$$i_t = \text{sigmoid}(W_{i\Park t}x_t + W_{i\Park h}h_{t-1} + b_i)$$

$$f_t = \text{sigmoid}(W_{f\Park t}x_t + W_{f\Park h}h_{t-1} + b_f)$$

$$g_t = \tanh(W_{g\Park t}x_t + W_{g\Park h}h_{t-1} + b_g)$$

$$o_t = \text{sigmoid}(W_{o\Park t}x_t + W_{o\Park h}h_{t-1} + b_o)$$

$$c_t = f_t \circ c_{t-1} + i_t \circ g_t$$

$$h_t = o_t \circ \tanh(c_t),$$

where $i_t, f_t, g_t, o_t$ are the input, forget, cell and output gates at time step $t$, respectively. $h_t$ is the hidden state. $c_t$ is the memory cell state. $x_t$ is the input of the first layer or the hidden state of the previous layer. $W$ and $b$ denote the weights and biases in the linear transformations, respectively. The subscript $t$ indexes the time step. The initial values are $c_0 = 0$ and $h_0 = 0$.

LSTM introduces the concept of a “memory cell” with input, output, cell and forget gates, which are also basically recurrent units that have outputs in the range between 0 and 1, and modify the scalars or vectors stored in the cells using the multiplication operation. In the proposed method, the “memory cell” can store target speaker information for tracing and separating target speaker.

![Image](152x370 to 154x394)

![Image](154x449 to 154x473)

![Image](154x528 to 154x552)
**B. System diagram**

The system diagram of the proposed algorithm used in this paper is illustrated in Fig. 2, where the feature of the mixture $Y$ is the input, and the PSM is the target. We use three unidirectional LSTM layers followed by one fully-connected layer in the proposed structure. The output layer uses rectified linear units (ReLUs) \([15]\) as the activity function to predict the PSM of the first speaker. The number of memory cells in each LSTM is 512. The number of nodes in the fully-connected layer is 1024. The cost function is mean square error (MSE). Weights of the networks are randomly initialized. The ADAM optimizer \([16]\) is utilized for back propagation. We also use the dropout \([17]\) in LSTM layers to avoid overfitting. The dropout rate is 0.2.

**IV. EXPERIMENTS**

**A. Dataset**

The proposed system is evaluated by using the WSJ0-2mix dataset. In WSJ0-2mix, each sentence contains two speakers. The WSJ0-2mix dataset introduced in \([5]\) is derived from the WSJ0 corpus \([18]\). The 30h training set and the 10h validation set contain two-speaker mixtures generated by randomly selecting from 49 male and 51 female speakers from set \(s\). The Signal-to-Noise Ratios (SNRs) are uniformly chosen between 0 dB and 5 dB. The 5h test set is generated similarly by using utterances from 16 speakers from set \(s_{et} 05\). Which don’t appear in the training and validation sets. The test set includes 1603 F&M sentences, 867 M&M sentences, and 530 F&F sentences.

For each mixture, we randomly choose an anchor utterance from the target speaker (different from the utterance in the mixture), and insert the anchor speech to the beginning of the mixture as guide information. The length of the anchor speech is 1 second on average.

Fig. 2. System diagram of the proposed algorithm.

**B. Metrics and parameters**

The performance is evaluated with two objective metrics: perceptual evaluation of speech quality (PESQ) \([19]\) and Signal-to-Distortion Ratio (SDR) \([20]\). The PESQ measures the speech quality by computing the disturbance between clean and processed speech. The range of PESQ score is from -0.5 to 4.5. SDR is also a metric widely used to evaluate speech enhancement performance. For both of the PESQ and SDR metrics, the higher number indicates the better performance.

**C. Baseline model setting**

We compare the proposed method with EncDec \([11]\). For EncDec, two fully-connected layers with 1024 ReLUs for each one are used in decoder. The encoder uses three unidirectional LSTM layers, the number of memory cells in each LSTM is 512.

**D. Evaluation results**

Table I and Table II show the average scores of SDR and PESQ on the test set, respectively. It can be seen that the proposed method outperforms EncDec. Compared with the mixture, the PESQ score and the SDR of the separated speech
improve by 0.30 and 5.38 dB, respectively, indicating the effectiveness of proposed method to perform target speaker separation.

The EncDec extracts the embedding feature using the guided speech in encoder. Then, the fixed embedding serves as an additional input to the decoder. One problem is that, the output of the last frame in encoder does not represent the speaker well [21]. By taking advantage of LSTM’s powerful sequence modeling ability, the proposed method can track the target speaker better, and the guide information stored in memory cells is time-varying according to the mixture.

It should be mentioned that as the speech of female and male has strong distinguishability [9], compared with F&F (PESQ increased by 0.18, SDR increased by 3.07) and M&M (PESQ increased by 0.07, SDR increased by 3.10), F&M (PESQ increased by 0.45, SDR increased by 7.35) has better separation performance.

### TABLE III
RESULTS UNDER DIFFERENT TIME PARTS.

| Method      | Criterion | SDR part I | SDR part II | PESQ part I | PESQ part II |
|-------------|-----------|------------|-------------|-------------|-------------|
| unprocessed |           | 2.82       | 2.80        | 2.10        | 2.18        |
| proposed    |           | 8.17       | 8.19        | 4.43        | 4.48        |
| ∆           |           | +5.35      | +5.39       | +2.33       | +2.30       |

The performance change during long-term tracking is also explored. Table [III] shows SDR and PESQ results under different time parts, where part I and part II indicate the first and the second half segments of the test speech, respectively. Compared with unprocessed speech, in part I, SDR and PESQ increased by 5.35 dB and 0.33, respectively; in part II, SDR and PESQ increased by 5.39 dB and 0.30, respectively. We can find that the performance on part II is similar to that of the part I, which means that long-term tracking has no effect on performance.

### TABLE IV
PESQ SCORE FOR DIFFERENT LENGTH OF GUIDE SPEECH.

|                  | F&M | F&F | M&M | Average |
|------------------|-----|-----|-----|---------|
| 0.4 s            | 2.53| 2.26| 2.28| 2.41    |
| 0.6 s            | 2.67| 2.30| 2.32| 2.48    |
| 0.8 s            | 2.60| 2.29| 2.33| 2.47    |
| 1.0 s            | 2.60| 2.31| 2.32| 2.47    |
| 1.2 s            | 2.61| 2.30| 2.32| 2.47    |
| 1.4 s            | 2.60| 2.32| 2.33| 2.48    |
| 1.6 s            | 2.61| 2.32| 2.34| 2.48    |
| 1.8 s            | 2.61| 2.31| 2.33| 2.48    |

We also explore the effect of guide speech length on the results. Table [IV] lists the average PESQ and SDR score for different guide speech length on test set. It can be found that the performance becomes better as guide speech duration increases. The reason is that, for a longer guide speech, the model can obtain a better target speaker identity with LSTM memory cells. We also find that the effect will stabilize as the guide speech length reaches approximate 1.4s.

![Fig. 3](image) Spectrograms of extracted speech using different methods. The first graph is the spectrogram of the mixture signal. The second graph is the spectrogram of the target speech. The third graph is the spectrogram of the separated target speech using EncDec method. The fourth graph is the spectrogram of the separated target speech using the proposed method.

### V. CONCLUSION
In this paper, a simple training strategy for target speaker separation is proposed. By leveraging the capacity of recurrent connections to model the long-term dependencies in speech, the first appearing speaker can be tracked well. According to the experiments results, the proposed method achieves better performance than other baseline methods. In the future, we will explore the robustness problem in the presence of noise and reverberation.

### VI. ACKNOWLEDGEMENT
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