**Individualized Conditioning and Negative Distances for Speaker Separation**

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**Abstract**—Speaker separation aims to extract multiple voices from a mixed signal. In this paper, we propose two speaker-aware designs to improve the existing speaker separation solutions. The first model is a speaker conditioning network that integrates speech samples to generate individualized speaker conditions, which then provide informed guidance for a separation module to produce well-separated outputs.

The second design aims to reduce non-target voices in the separated speech. To this end, we propose negative distances to penalize the appearance of any non-target voice in the channel outputs, and positive distances to drive the separated voices closer to the clean targets. We explore two different setups, weighted-sum and triplet-like, to integrate these two distances to form a combined auxiliary loss for the separation networks. Experiments conducted on LibriMix demonstrate the effectiveness of our proposed models.

**Index Terms**—Speaker separation, conditioning, negative distances, speech representation, wav2vec, Conv-TasNet.

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**I. INTRODUCTION**

Speech separation, also known as the cocktail party problem, aims to separate a target speech from its background interference [1]. It often serves as a preprocessing step in real-world speech processing systems, including ASR, speaker recognition, hearing prostheses, and mobile telecommunications. **Speaker separation** (SS) is a sub-problem of speech separation, where the main goal is to extract multiple voices from a mixed signal.

Following the mechanism of the human auditory system, traditional speaker separation solutions commonly rely on certain heuristic grouping rules, such as periodicity and pitch trajectories, to separate mixed signals [2]–[4]. Two-dimensional ideal time-frequency (T-F) masks are often generated based on these rules and applied to mixed signals to extract individual sources. Due to the hand-crafted nature, these grouping rules, however, often have limited generalization capability in handling diverse real-world signals [5].

Similar to many other AI-related areas, deep neural networks (DNNs) have recently emerged as a dominant paradigm to solve the SS problems. Early DNNs were mostly frequency-domain models [6]–[10], aiming to approximate ideal T-F masks and rely on them to restore individual sources through short-time Fourier transform (STFT). As the modified T-F representations may not be converted back to the time domain, these methods commonly suffer from the so-called invalid STFT problem [11].

Waveform-based DNN models have grown in popularity in recent years, partly because they can avoid the invalid STFT problem [11]–[15]. Pioneered by TasNet [11] and Conv-TasNet [13], early waveform solutions tackle the separation task with three stages: encoding, separating, and decoding. However, speaker information is often not explicitly integrated into the network training and/or inference procedures.

Speaker-aware SS models [16]–[21] provide a remedy in this regard. This group of solutions can be roughly divided into **speaker-conditioned** methods [16]–[18] and **auxiliary-loss** based methods [19]–[21]. The former rely on a speaker module to infer speaker information, which is then taken as conditions by a separation module to generate separated output waveforms. The existing speaker-conditioned solutions, however, are either not in the time-domain [16]–[18] or do not explicitly integrate speech information into the speaker conditioning process [18].

Auxiliary-loss based methods [19]–[21] achieve speaker awareness through composite loss functions. In addition to a main loss, an auxiliary loss (or losses) is used to incorporate speakers’ information into the network training procedure. Such auxiliary losses are commonly formulated to ensure a match between network outputs and the target speakers. However, to the best of our knowledge, no solution has attempted to explicitly suppress voices from other non-target speakers. As a result, residual voices of non-target speakers are often noticeable in the network outputs.

In this paper, we propose two waveform speaker separation models to address the aforementioned limitations. The first model is a **speaker conditioning** network that integrates individual speech samples in the speaker module to produce tailored speaker conditions. The integration is based on speaker embeddings computed through a pretrained speaker recognition network. The second solution aims to completely suppress non-target speaker voices in the separated speech. We propose an **auxiliary loss** with two terms: the first drives the separated voices close to target clean voices, while the second term penalizes the appearance of any non-target voice in the

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II. BACKGROUND

We start with this section to provide some background knowledge concerning our proposed speaker-aware SS models, which includes conditioning in machine learning, triplet loss, and speech representations generated through self-supervised learning.

A. Conditioning and FiLM

In everyday life, it is often helpful to process one source of information in the context of another. For example, video and audio in a movie can be better understood in the context of each other. This context-based processing is called conditioning in machine learning, where computations through a model are conditioned or modulated by information extracted from auxiliary inputs. For speaker-conditioned speaker separation, conditioning in a network can be done through its separation module, which would take speaker information as the context to produce the output voices.

Feature-wise Linear modulation (FiLM) [22] is a popular feature conditioning method that was shown to enhance the performance of neural network solutions for a variety of tasks, including visual reasoning and speech separation [16], [18]. FiLM learns to adaptively influence the output of a neural network by applying an affine transformation to the network’s intermediate features, based on some input. As shown in Fig. 1, FiLM conditioning architecture consists of a FiLM generator and one or more FiLM layers. The generator takes a conditioning representation as input and generates FiLM vector parameters, which are later used in the FiLM layers to modulate the input with an affine transformation, i.e., a combination of conditional biasing and conditional scaling.

B. Triplet Loss

In machine learning, we often consider triplet samples [23], each consisting of an anchor input, a matching input with the same label (called a positive sample), and a non-matching input with a different label (called a negative sample). The triplet loss, initially introduced in metric learning [24], is a loss function based on relative comparisons, i.e., an anchor $x^a$ is compared to one positive sample $x^p$ and one negative sample $x^n$.

Shown in Fig. 2, a triplet loss learns embeddings to minimize the distance between an anchor input and the positive samples, and at the same time maximize the distance from the anchor to the negative inputs. More specifically, for one triplet, we want:

$$\left\| f(x^a) - f(x^p) \right\|_2^2 + \alpha < \left\| f(x^a) - f(x^n) \right\|_2^2,$$

where $f(\cdot)$ is the embedding function and $\alpha$ is defined as the minimum margin between positive and negative pairs.

C. Speech Representations via Self-supervised Learning

In self-supervised learning (SSL), models are trained to predict one part of the data from other parts [25]. SSL models for speech data and tasks commonly aim to output speech representations in the form of compact vectors that capture high-level semantic information from raw speech data [26]–[30]. In our work, we utilize the speech feature representations generated from Wav2vec [27], an SSL network, to pass high-level meaningful features to our networks.

Wav2vec is trained on LibriSpeech corpus using the contrastive predictive coding (CPC) loss [30] to pretrain speech representations for ASR tasks. Experiment results showed that wav2vec can significantly improve the performance over the chosen baseline solutions. Wav2vec consists of two parts, an encoder and a context network. The former is a seven-layer convolutional network, and its functionality is to extract latent features from the inputs. The context network combines multiple outputs from the encoder into a contextualized tensor, which then could be used for downstream tasks.

III. METHOD

Let $X$ be a waveform produced by mixing $C$ sources $x_1, x_2, ..., x_C$, i.e.,

$$X = \sum_{i=1}^{C} x_i$$

A waveform monaural speaker separation model aims to directly separate the mixed signal $X$ into $C$ estimations $\hat{x}_1, \hat{x}_2, ..., \hat{x}_C$. 

Fig. 1: Feature-wise Linear Modulation (FiLM) architecture.
A. Baseline Model

Conv-TasNet \cite{13}, a variation of TasNet \cite{11} is adopted as the baseline model in this work. Conv-TasNet has been shown to generate remarkable results for many speech tasks including speech separation. Inspired by the T-F domain masking-based speech separation solutions, Conv-TasNet follows an encoder-separator-decoder architecture. The encoder converts a waveform mixture into a feature map by a linear transformation that emulates STFT. The separator is a network which learns the masks for each source in the mixed inputs. After the learned masks are applied to the encoder output, the results are fed into the decoder, which also carries out a linear transformation. The decoder emulates the inverse STFT (iSTFT) operation to compute the final separated outputs.

B. Proposed Speaker-conditioned Model

The architecture of our proposed speaker-conditioned pipeline is shown in Fig. 3. It consists of two major modules, a speaker module (red box), followed by a separation module. The speaker module infers the speaker information in the input audio samples, which is then sent as conditions to the separation module to generate outputs.

In the speaker module, a basic model is first used to infer intermediate separated sources from input mixture waveforms. These separated sources, illustrated as Wav1 and Wav2 in Fig. 3, are then fed into a pretrained speaker identification (SI) network to generate respective speaker embeddings of the separated sources (Embed 1 and Embed 2 in Fig. 3). Speaker embeddings generated this way contain not only the collective information about the speaker, but also individualized details of each speech sample. As a result, rich and better customized speech information is integrated.

In this work, Conv-TasNet and RawNet2 \cite{31} (a pretrained waveform speaker verification model) are used as the basic model and SI model, respectively. Note the choices are not unique – for example, speaker separation models such as Dual-path methods \cite{32}–\cite{34} could also be used as the basic model.

In the separation module of our proposed pipeline, the input mixture signal is modulated by FiLM parameters generated through the speaker embeddings, prior to being mapped into final separated results. The implementation of our separation module is the same as that in Wavesplit \cite{18}, which has 40 dilated causal convolution layers. Among these 40 layers, every 10 layers are put into a group. The dilation rate of the first layer of each group is set to 1, and the subsequent dilations increase sequentially. A similar layer setup has also been used in Conv-TasNet.

It is worthy to note that our proposed speaker-conditioned pipeline can be further refined by extending it into a recurrent model: final separated outputs of the separation module can be taken as intermediate separated sources to the SI model to generate refined speaker embeddings, which are then inserted as conditions into the separation module for the next iteration.

C. Proposed Auxiliary-loss based Models

Fig. 4 shows the architecture of our proposed auxiliary-loss based solutions, where we take two-speaker separation as an example to illustrate our design. Mixtures are fed into a basic model, which is Conv-TasNet \cite{13} in this work. The basic model is trained with the SI-SNR loss to produce separated sources $\xi_1$ and $\xi_2$. In this work, we use speech representations generated through wav2vec \cite{27}, a pretrained self-supervised learning model, as speaker embeddings in our proposed framework.

Most existing auxiliary-loss based solutions are designed to ensure separated voices sound like target speakers, which can be achieved by minimizing the dissimilarities (or distances) between speaker embeddings of predicted sources and clean (ground-truth) target sources. We call these distances attraction or positive distances, which can be written as:

$$d^i_{pos} = \sum_{m} \frac{1}{1-||\phi_m(\xi_i) - \phi_m(\tilde{x}_i)||^2}$$

where $\phi_m(x_i)$ represents the $m^{th}$ vector in the representation of $x_i$. These solutions, however, have no mechanism to suppress sounds of non-target speakers. As a result, residual sounds of non-target speakers can be easily perceived in the separated voices. To address this issue, we propose to a new repulsion term to reduce the output from non-target speakers. More specifically, this term reduces non-target voices by maximizing repulsion or negative distances, which are defined as the distances between speaker embeddings of the predicted source and the ground-truth non-target sources:

$$d^i_{neg} = \sum_{j \neq i} \frac{1}{||\phi_m(x_i) - \phi_m(x_j)||^2}$$

Two different integration schemes There could be many different ways to integrate our proposed negative distances $d_{neg}$ with the positive distances $d_{pos}$. In this work, we explore two setups for this task. Both of them form an auxiliary loss function for the network, which we call perceptual loss.

In the first setup, we define collective distances over the entire training set, $D_{pos}$ and $D_{neg}$, as:

$$D_{pos} = \frac{1}{N} \sum_i d^i_{pos}, \quad D_{neg} = \frac{1}{N} \sum_i d^i_{neg}$$

where $N$ is the number of training examples. We then define the perceptual loss as a weighted summation of $D_{pos}$ and $D_{neg}$:

$$L_{perc} = \lambda_1 D_{pos} + \lambda_2 D_{neg}$$

where $\lambda_1$ and $\lambda_2$ are weighting coefficients, which can be set manually or empirically in experiments.

In the second setup, we emulate a triplet loss to enforce a minimal margin $\alpha$ between the positive distance $d^i_{pos}$ and negative distance $d^i_{neg}$ for each data sample:
Thus, the perceptual loss can be defined as:

$$L_{\text{perc}} = \frac{1}{N} \sum_i \max(0, \text{dist}_{\text{pos}}^{(i)} - \text{dist}_{\text{neg}}^{(i)} + \alpha),$$

where $N$ is the number of training examples.

The overall loss in both setups is designed as a weighted summation of the basic loss $L_{\text{basic}}$ (from Conv-TasNet) and the respective perceptual loss:

$$L = \lambda_b L_{\text{basic}} + \lambda_p L_{\text{perc}},$$

where $L_{\text{perc}}$ is either $L_{\text{perc}}^1$ from Eqn. 6 or $L_{\text{perc}}^2$ from Eqn. 8. $\lambda_b$ and $\lambda_p$ are weighting coefficients to decide the contributions, which can be set manually or empirically in experiments. We name the model using $L_{\text{perc}}^1$ as $P_{\text{weighted-sum}}$ and that using $L_{\text{perc}}^2$ as $P_{\text{triplet-like}}$.

IV. EXPERIMENTS AND RESULTS

In this section, we conduct experiments to evaluate the effectiveness of our proposed models. First, we introduce the dataset used in the experiments, followed by the training strategy and evaluation metrics for the competing models. Then, we report the results of the three proposed speaker-aware solutions and compare them with the baseline model. Finally, we conduct an ablation study on $P_{\text{weighted-sum}}$, one of the proposed perceptual-loss based solutions, to analyze the effects of the contributing terms.
A. Data and Training

LibriMix [35] is an open-source dataset for single-channel speech separation. The utterances in the mixtures of LibriMix are taken from LibriSpeech [36]. All our models are trained for 200 epochs. During training, the mixtures in the train-100 of clean Libri2Mix (min mode, 16 kHz) are divided into 3-second segments as the training set. The optimizer is Adam [37] with the learning rate 0.001 and early stopping patience 30. We apply the utterance-level permutation invariant training (uPIT) [8] with the label assignments evaluated by SI-SNR values to train the Conv-TasNet in our proposed models.

Objective performance for speech separation can be evaluated by metrics concerning signal fidelity (e.g., SNR and SI-SNR) and output perceptual quality (e.g., PESQ [38] and STOI [39]). In this work, we choose SI-SNR and STOI as the objective metrics to evaluate our models.

B. Results and Analysis

As we mentioned in the Method section, Conv-TasNet is taken as the basic model for our proposed models. In our perceptual-loss based model $P_{\text{weighted-sum}}$, the weights of the combined loss ($\lambda_1$ and $\lambda_2$) are empirically set to 1.0 and 1.0, and the weights of the positive and negative terms ($\lambda_3$ and $\lambda_4$) in Eqn. [5] are set to 100 and 0.001. In the triplet-loss based model $P_{\text{triplet-like}}$, the weights of the combined loss ($\lambda_1$ and $\lambda_2$) are set to 1 and 300, and the margin $\alpha$ is set to 0.0035.

Table I shows the results from the competing models on the LibriMix dataset. The first line is the results from Conv-TasNet. The second and third lines show the results from our perceptual-loss models using weighted-sum and triplet-like, respectively. The fourth line is for our proposed model using speaker-conditioning. It is evident that all the three proposed models outperform the baseline models in terms of the evaluation metrics, especially in the SI-SNR where the performance gains are more prominent. Among the three proposed models, the conditioning-based solution achieves the best performance. The performance of the two auxiliary-loss based solutions is comparable, while $P_{\text{weighted-sum}}$, the model with the weighted-sum perceptual loss, performs slightly better.

The demonstrated advantage of the conditioning-based solution over the auxiliary-loss solutions may be attributed to the nature of the conditioning operation in overhauling the internal structure of the networks, where auxiliary-loss based solutions work mostly to provide an external guidance. In other words, the former may have enhanced the baseline network more fundamentally. Nonetheless, these two proposed strategies both demonstrate the ability to improve the baseline model, achieving our design goals.

The primary innovation in our proposed auxiliary-loss models lies in the design and integration of $D_{\text{neg}}$, which aims to suppress sounds of non-target speakers in the outputs. To investigate the effect of this term, as well as the relationship with the positive distances $D_{\text{pos}}$, we conduct an ablation study upon the proposed $P_{\text{weighted-sum}}$ model. To this end, we implemented two additional models, which have the same architecture as $P_{\text{weighted-sum}}$ but have only one part of the proposed auxiliary loss. More specifically, the first model has a loss function combining the basic loss (same as in Conv-TasNet) and $D_{\text{pos}}$. The second model goes with the combination of basic loss and $D_{\text{neg}}$. The baseline Conv-TasNet has only the basic loss, and $P_{\text{weighted-sum}}$ can be regarded as a model with basic loss + $D_{\text{pos}} + D_{\text{neg}}$.

The results are shown in Table II. While the model with the $D_{\text{pos}}$ distance outperforms the baseline model, performance of the former falls short of $P_{\text{weighted-sum}}$, the model with combined three losses. In contrast, performance of “Basic loss + $D_{\text{neg}}$” model is very close (but inferior) to our combined model. These results indicate that the proposed negative distance $D_{\text{neg}}$ plays a significant role in the combined models, and is rather effective in reducing the residual sounds of non-target speakers.

V. CONCLUSION

In this paper, we propose two speaker-aware approaches to improve the existing speaker separation solutions. The first strategy is to integrate the information of speech samples to provide individualized conditions for the separation module. Such individualization is achieved through the combination of a basic model (Conv-TasNet) and a pretrained SI network (RawNet2).

The second model falls in the auxiliary-loss based category. We design negative distances to reduce the residual sounds from non-target speakers and positive distances to strengthen target outputs. Two different integration setups are design to combine the proposed distances. Experiments show the effectiveness of our proposed solutions. Exploring more pretrained speech representation models, as well as studying their guiding capabilities, is our ongoing effort.

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