Unsupervised Source Separation via
Self-Supervised Training

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Abstract—We introduce two novel unsupervised (blind) source separation methods, which involve self-supervised training from single-channel two-source speech mixtures without any access to the ground truth source signals. Our first method employs permutation invariant training (PIT) to separate artificially-generated mixtures of the original mixtures back into the original mixtures, which we named mixture permutation invariant training (MixPIT). We found this challenging objective to be a valid proxy task for learning to separate the underlying sources. We improve upon this first method by creating mixtures of source estimates and employing PIT to separate these new mixtures in a cyclic fashion. We named this second method cyclic mixture permutation invariant training (MixCycle), where cyclic refers to the fact that we use the same model to produce artificial mixtures and to learn from them continuously. We show that MixPIT outperforms a common baseline (MixIT) on our small dataset (SC09Mix), and they have comparable performance on a standard dataset (LibriMix). Strikingly, we also show that MixCycle surpasses the performance of supervised PIT by being data-efficient, thanks to its inherent data augmentation mechanism. To the best of our knowledge, no other purely unsupervised method is able to match or exceed the performance of supervised training.

Index Terms—Blind source separation, Deep learning, Self-supervised learning, Unsupervised learning

I. INTRODUCTION

SUPERVISED speech separation has been very successful using the power of deep learning methods. Recent state-of-the-art methods [1], [2], [3] have achieved separation results with almost no perceptible distortion. However, supervised speech separation requires a large dataset of mixture recordings and the corresponding ground truth source recordings, which is challenging and impractical to acquire in the same acoustic environment [4]. Therefore, current methods are usually trained on synthetic mixtures that are generated by mixing clean single-speaker recordings which may not reflect real-life mixture recordings and still require a large dataset of clean recordings. In order to avoid this data collection problem, unsupervised, semi-supervised or weakly-supervised [5], [6] methods can be employed. Recently, unsupervised and semi-supervised mixture invariant training (MixIT) [7], [8] has been proposed which generalizes permutation invariant training (PIT) [9], [10] by using mixtures as references and mixture of mixtures as input. However, MixIT estimates a greater number of sources than the number of underlying sources in the test stage which causes the over-separation problem where parts of the source signals get spread out between the outputs.

In [8], applying sparsity, covariance and classification losses to MixIT is proposed to lessen the over-separation issue. In [11], an unsupervised MixIT model is used to decompose a naturalistic sound scene into a collection of simpler channels which are improved with several contrastive learning objectives. Teacher-student MixIT [12] addresses the over-separation issue of MixIT. First, a teacher model using MixIT is trained. Second, a student model is trained using the outputs of the teacher model that contain the most energy. RemixIT [13] is a self-supervised training method for speech enhancement. In this method, a teacher model for separation is trained on an out-of-domain dataset in a supervised fashion. Then, a student model is trained using artificial mixtures generated from in-domain clean and noise signal estimates of the teacher model. Finally, the parameters of the teacher model are updated periodically with a moving average based on the student model. This study is possibly the most similar to our work in the way that it utilizes the estimates of the model itself to learn a better model iteratively but the first difference is that our methods are designed for source separation rather than speech enhancement. Second, our methods are purely unsupervised and do not require supervised out-of-domain pre-training. Third, our methods use short-time Fourier transform (STFT) rather than a learned representation which we defer tackling to future work. Note that none of these methods are able to match or exceed the performance of supervised training.

A. Contributions

In this work, we explore training source separation models without having access to the ground truth source signals that constitute single-channel two-source speech mixtures. Our main contributions are summarized as follows:

1) We present two novel purely unsupervised source separation methods that are based on self-supervised training. Our first method, MixPIT, utilizes artificially-generated mixtures of the original mixtures as in MixIT while avoiding the over-separation problem. Our second method, MixCycle, improves upon MixPIT and is trained in a cyclic fashion using the artificial mixtures created by mixing its own source estimates.

2) In the experiments, we observe that MixCycle exceeds the performance of supervised training on two different datasets which also demonstrates a remarkable potential
in data-limited domains due to its data efficiency. To the best of our knowledge, no prior method is able to match or exceed the performance of supervised training.

II. BACKGROUND

A. Permutation Invariant Training (PIT)

PIT [9, 10] treats speech separation as a multi-class segregation problem where the targets are provided as a set instead of an ordered list. We define a supervised training dataset \( X_s = \{ (x_{i,j}, s_i, s_j) \}_{i,j} \) where \( x_{i,j} = s_i + s_j \) is a mixture signal of the time-domain source signals \( s_i, s_j \in \mathbb{R}^L \) with length \( L \). The model \( \hat{S} = f_\theta(x_{i,j}) \) outputs the source estimates \( \hat{s}_i, \hat{s}_j \) in the rows of \( \hat{S} \). The details of our base model \( f_\theta \) are given in Fig. 1. The loss function for utterance-level PIT [10] is

\[
L_{\text{PIT}}(\cdot) = \min_P \left[ L(s_i, [PS]_1) + L(s_j, [PS]_2) \right]
\]

where \( P \) is a \( 2 \times 2 \) permutation matrix, \( [\cdot]_r \) selects the \( r \)-th row of a matrix and \( L \) is a time-domain loss function calculated between reference sources and their estimates. The model is illustrated in Fig. 2a.

We use the negative thresholded signal-to-noise ratio (SNR) [7] as our time-domain loss function:

\[
L(s, \hat{s}) = -10 \log_{10} \frac{\|s\|^2}{\|s - \hat{s}\|^2 + \tau \|s\|^2}
\]

where \( \tau = 10^{-\text{SNR}_{\text{max}}/10} \) is a threshold that clamps the loss at \( \text{SNR}_{\text{max}} \). In this study, we use \( \text{SNR}_{\text{max}} = 30 \) dB as in [7].

B. Mixture Invariant Training (MixIT)

MixIT [7, 8] is a generalization of PIT that allows training unsupervised separation models by utilizing mixtures of mixtures. We define an unsupervised training dataset \( X_u = \{ (x_{i+j}, x_{k+l}) \}_{i+j, k+l} \). The input to the model is formed by summing two mixtures \( x_{i+j} \) and \( x_{k+l} \). The model \( \hat{S} = f_\theta(x_{i,j} + x_{k+l}) \) outputs the source estimates \( \hat{s}_i, \hat{s}_j, \hat{s}_k, \hat{s}_l \). The loss function for MixIT is calculated between reference mixtures and their estimates as

\[
L_{\text{MixIT}}(\cdot) = \min_A \left[ L(x_{i+j}, [A\hat{S}]_1) + L(x_{k+l}, [A\hat{S}]_2) \right]
\]

where \( A \) is a \( 2 \times 4 \) binary mixing matrix. The model is illustrated in Fig. 2b.

In the test stage, a single mixture is supplied to the model \( f_\theta(x_{i,j}) \).

III. PROPOSED METHODS

A. Mixture Permutation Invariant Training (MixPIT)

The main limitation of MixIT is the over-separation problem which stems from having more model outputs than the number of sources in the test stage. Here we investigate the opposite case where we have four sources (i.e. a mixture of mixtures) to separate but only have two model outputs. We use the model \( f_\theta(x_{i,j} + x_{k+l}) \) to obtain the mixture estimates \( \hat{x}_{i,j}, \hat{x}_{k+l} \) as illustrated in Fig. 2c.

Recall that each mixture contains two sources, and we have four sources in total; therefore, a mixture estimate \( x_{i+j} \) should consist of one of the \( C(4, 2) = 6 \) source combinations. Using the PIT loss \( L_{\text{PIT}} \) in (1), we achieve permutation invariance among the outputs which reduces the overall source combinations to three. Specifically, the model should decide between these three output pairs: \( (\hat{x}_{i,j}, \hat{x}_{k+l}), (\hat{x}_{i+l}, \hat{x}_{k+j}) \) and \( (\hat{x}_{i+k}, \hat{x}_{j+l}) \). However, if we acknowledge that the sources \( s_i, s_j, s_k, s_l \) are statistically independent, we will see that there is no way for the model to learn to output the correct pairing of the sources. Nevertheless, there is still \( 1/3 \) probability to get a match and we discovered that it is sufficient for the model to obtain a learning signal despite the high level of noise. As discussed in [16], human hearing suggests that general principles of source separation exist and can be learned from large datasets with a method such as PIT. Considering that PIT has to learn the discriminative features of the sources to be able to separate them, we think that MixPIT learns only the most prominent discriminative patterns between the sources and ignores the rest as noise.

Ultimately, the model is trained with a harder proxy task of separating mixtures of mixtures which also covers our main objective of separating single mixtures. In the test stage, we supply the model with a single mixture as input \( f_\theta(x_{i,j}) \) to obtain the source estimates \( \hat{s}_i \) and \( \hat{s}_j \).

B. Cyclic Mixture Permutation Invariant Training (MixCycle)

Here we propose a new method that improves the performance of the proposed MixPIT method by gradually converting the problem from separating mixtures of mixtures, which is a challenging task, into separating single mixtures, which is the easier original task.

First, we use a teacher model \( f_\theta \) to estimate four sources from the two input mixtures

\[
(\hat{s}_i, \hat{s}_j) = f_\theta(x_{i,j}), \quad (\hat{s}_k, \hat{s}_l) = f_\theta(x_{k+l})
\]

where \( \theta' = \theta^{(\tau - 1)} \) are the parameters at the previous training step \( \tau - 1 \). Second, we use these estimated sources to generate unique mixtures such that each constituent source estimate originates from a different mixture such as the ones shown below:

\[
x_{j+k} = \hat{s}_j + \hat{s}_k, \quad \hat{x}_{i+l} = \hat{s}_i + \hat{s}_j.
\]
This mixing strategy acts as a data augmentation mechanism by increasing the effective size of the available dataset, similar to dynamic mixing [17]. Finally, we train a student model \( f_\theta \) on these artificial mixtures with PIT using the following arrangement:

\[
\hat{s}_i = f_\theta(\tilde{x}_{i+j}), \quad \hat{s}_j = f_\theta(\tilde{x}_{j+k})
\]

where \( \theta = \theta^{(\tau)} \) are the parameters at the current training step \( \tau \). The model is illustrated in Fig. 2 and the algorithm is given in Fig. 3.

We designed the model \( f_\theta \) such that it produces informative initial source estimates and helps prevent the source estimates from diverging throughout the training process. We accomplish this by employing time-frequency masking and ensuring that the masks add up to one as given in Fig. 1. Therefore, we have mixture consistency [15] as \( \hat{s}_i + \hat{s}_j = x_{i+j} \).

Let us define the initial source estimates \( \tilde{s}_j^{(0)} \) and \( \tilde{s}_k^{(0)} \) of the teacher model \( f_{\theta'} \) in (4) when the parameters \( \theta' = \theta^{(0)} \) are randomly initialized at the first training step \( \tau = 1 \):

\[
\begin{align*}
\tilde{s}_j^{(0)} &= \text{iSTFT} \left( X_{i+j}, M_j^{(0)} + M_j^{(0)} \right) \quad (7) \\
\tilde{s}_k^{(0)} &= \text{iSTFT} \left( X_{k+i}, M_k^{(0)} + M_k^{(0)} \right) \quad (8)
\end{align*}
\]

where \( X_{i+j}, X_{k+i} \) and \( M_{i+j}, M_{k+i} \) are the magnitude and phase spectrograms of the mixture signals \( x_{i+j}, x_{k+i} \), respectively. \( M_j^{(0)}, M_j^{(0)}, M_k^{(0)}, M_k^{(0)} \in (0, 1)^{F \times T} \) with \( F \) frequency bins and \( T \) time frames denote the mask outputs of the untrained model, which contain only noise. If we consider the initial input mixture \( \hat{x}_{i+j}^{(0)} = \tilde{s}_j^{(0)} + \tilde{s}_k^{(0)} \) of the student model \( f_{\theta} \) in (3) using (7) and (8), we can see that this is similar to the proposed MixPIT method because we have a mixture of noisy mixtures \( \hat{x}_{i+j}^{(0)} \) as input and try to separate it into single noisy mixtures \( \tilde{s}_j^{(0)} \) and \( \tilde{s}_k^{(0)} \). In contrast to MixPIT, the input mixture \( \hat{x}_{i+j}^{(0)} \) is not static and refined at each training step \( \tau \) such that the constituent teacher source estimates \( \tilde{s}_j \), \( \tilde{s}_k \), which start as noisy copies of the original mixtures, are transformed into accurate estimates of the corresponding sources \( s_j, s_k \) as we optimize the parameters \( \theta \).

In practice, the initial source estimates are very noisy due to the random initialization. To reduce the noise and stabilize the training process, we initialize the model by training it with the proposed MixPIT method for the first \( I \) epochs.

### IV. Experiments

#### A. Datasets

We evaluate the performance of the proposed methods on two datasets: SC09Mix and LibriMix [19]. We built SC09Mix by mixing two one-second-long utterances from the Speech Commands Dataset [20]. The utterances were selected by cycling through the subset that contains the utterances of the numbers from zero to nine in random order. Each source signal is downsampled to 8 kHz and normalized to zero mean and unit variance before mixing. The training set contains 15,000 utterances (~4.2 hours in total). Each of the validation and test sets contains 5,000 utterances (~1.4 hours in total).
is a standard speech separation dataset. We used the clean version of the train-360 split of the Libri2Mix (two-speaker) dataset with its min mode and an 8 kHz sampling rate. The training set contains 50,800 utterances (212 hours in total). Each of the validation and test sets contains 3,000 utterances (11 hours in total).

B. Network Architecture

We make use of the popular supervised source separation architecture, Conv-TasNet. As given in [19], the best-performing configuration uses \( X = 8 \) dilated convolutions in each repeated block. It also uses a window size of 16 and a hop size of 8 for its learned representation. On the other hand, we use STFT/\( \hat{\text{STFT}} \) with a window size of 512, a hop size of 128, and a Hann window. To compensate for our shorter representation, we used \( X = 4 \) which keeps the receptive field of the stacked dilated convolutions similar between the representations.

C. Training Details

We randomly sampled three-second-long segments from the utterances while training on Libri2Mix. We used the Adam optimization algorithm with its default parameters [21] and a batch size of 128. We applied gradient clipping with a maximum \( L_2 \)-norm of 5. We calculated a validation score at every epoch and stopped the training if it does not improve for 50 consecutive epochs. We used the models with the best validation score for testing. We initialized the MixCycle models with MixPIT for \( I = 50 \) epochs.

We used PyTorch with an NVIDIA GTX 1080 Ti GPU to develop and evaluate our methods. We provide audio samples\(^1\) to demonstrate our results. We will publish the source code\(^1\) to help reproduce all of our experiments.

D. Results

We evaluate the methods using scale-invariant SNR improvement (SI-SNRi) [22] which is calculated between the reference sources \( s \), source estimates \( \hat{s} \) and the mixtures \( x \) as:

\[
\text{SI-SNR}(s, \hat{s}) = 10 \log_{10} \frac{\|os\|^2}{\|os - \hat{s}\|^2}
\]

\[
\text{SI-SNRi}(x, s, \hat{s}) = \text{SI-SNR}(s, \hat{s}) - \text{SI-SNR}(s, x)
\]

where \( \alpha = s^T\hat{s}/\|s\|^2 \). We find the best match between the sources and the model outputs to calculate the SI-SNRi.

Table I compares the performance of the models on two datasets. The top section of the table lists the ideal ratio mask (IRM) [15] and the supervised methods: Conv-TasNet [19] and PIT, which can be considered as an empirical upper bound on the performance of the unsupervised methods. The bottom section of the table lists the unsupervised methods.

We can see that MixPIT performed significantly better than MixIT on SC09Mix in addition to a comparable performance on Libri2Mix. This suggests that MixIT requires large and complex datasets like Libri2Mix while MixPIT works reasonably well on smaller and simpler datasets like SC09Mix.

MixCycle improved upon MixPIT as expected and achieved the best performance among the unsupervised methods. Strikingly, its score is also better than a supervised method, PIT. This is due to the inherent data augmentation mechanism of MixCycle, which creates a regularization effect, thus making our method data-efficient. We see that the regularization effect is more pronounced for SC09Mix compared to Libri2Mix because SC09Mix is a small dataset and benefits more from it. This demonstrates that MixCycle can be employed in data-limited domains. The progress of validation scores through the training processes is given in Fig. 4.

V. CONCLUSION

We introduced two purely unsupervised source separation methods: MixPIT and MixCycle. MixPIT avoids the over-separation issue of MixIT, and MixCycle picks up where MixPIT left off to close the performance gap between supervised and unsupervised training. Employing a learned representation instead of STFT/\( \hat{\text{STFT}} \) will potentially improve the performance further and may eliminate the need for supervised datasets. MixPIT can be trained end-to-end with a learned representation, but MixCycle requires the model to copy the input mixture to the outputs without any training. To fulfill this requirement, a two-step learning approach [23] could prove useful. We also defer evaluating our methods on the noisy version of Libri2Mix and real-life mixtures\(^4\) to future work.

ACKNOWLEDGMENT

We would like to thank Ali Taylan Cemgil and Cem Subakan for their insightful comments.

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\(^1\) https://github.com/ertug/MixCycle

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TABLE I

| Model          | Supervised? | SC09Mix | Libri2Mix |
|----------------|-------------|---------|-----------|
| Conv-TasNet [19] | Yes         | –       | 14.7      |
| IRM            | Oracle      | 18.4    | 13.9      |
| PIT            | Yes         | 13.0    | 11.2      |
| MixIT          | No          | 5.3     | 7.5       |
| MixPIT (proposed) | No        | 10.4    | 7.1       |
| MixCycle (proposed) | No      | 15.9    | 11.3      |

Fig. 4. Validation scores of different models on Libri2Mix in terms of SI-SNRi over training epochs. PIT converged faster while MixCycle converged to a slightly higher score. MixIT and MixPIT converged at a comparable rate. Note the jump of MixCycle at the 51st epoch where the initialization with MixPIT ended. Also note that we only show the first 300 epochs for brevity.
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