ABSTRACT

We present a novel approach that improves the performance of reverberant speech separation. Our approach is based on an accurate geometric acoustic simulator (GAS) which generates realistic room impulse responses (RIRs) by modeling both specular and diffuse reflections. We also propose three training methods - pre-training, multi-stage training and curriculum learning that significantly improve separation quality in the presence of reverberation. We also demonstrate that mixing the synthetic RIRs with a small number of real RIRs during training enhances separation performance. We evaluate our approach on reverberant mixtures generated from real, recorded data (in several different room configurations) from the VOiCES dataset. Our novel approach (curriculum learning+pre-training+multi-stage training) results in a significant relative improvement over prior techniques based on image source method (ISM).

Index Terms— Speech Separation, Room Impulse Response, Geometric Acoustic Simulator, Pre-training, Curriculum Learning

1. INTRODUCTION AND RELATED WORK

Speech separation (also referred to as the cocktail party problem) has been well-studied for several decades. Humans are able to easily separate multiple streams of audio/speech because they use both spatial audio information as well as higher contextual cues (such as the content of what is being spoken). However, state-of-the-art algorithms or models still struggle to match human performance, especially in the presence of noise and reverberation. The earliest approaches to speech separation were based on signal processing techniques such as computational auditory scene analysis (CASA) [1], non-negative matrix factorization (NMF) [2] and independent component analysis (ICA) [3].

With recent advances in deep learning, supervised approaches to speech separation have become popular. In such approaches, CNN/LSTM models are trained on large datasets to learn the mapping between the speech mixture and individual components. Some well known deep learning methods for speech separation include deep clustering [4] and permutation invariant training (PIT) [5].

In real-world scenarios, speech signals are reflected from the walls and objects present in the room to create reverberation effects. Most well-studied algorithms and models for source separation do not adequately account for such reverberation effects. As a result, this can impact the real-world performance of speech separation systems. Recently, there have been several works in reverberant speech separation. In [6], the authors release the WHAMR! dataset which is a noisy reverberant augmentation of the wsj-mix [4] dataset. The authors present a multi-stage dereverberation, denoising and separation network, along with baseline speech separation results on the WHAMR! dataset. The Wavesplit architecture [7] demonstrates state-of-the-art results on the WHAMR! dataset. Auxiliary autoencoding training (A2T) [8] has also been shown to improve reverberant speech separation. DB-Net [9] is a single network that can be used for direction-of-arrival estimation, beam-forming and reverberant speech enhancement. In [10], the authors propose a multi-channel time domain speech extraction network that uses speaker embeddings to extract speech from a specific speaker, given a reverberant and noisy input mixture. In most existing work on reverberant speech separation, the models are trained and tested on synthetically generated datasets. As a result, their accuracy is governed by these datasets. Other techniques focus on improving reverberant speech separation performance by modifying the underlying model architecture.

In addition to generation of synthetic data, there is some work on using different learning methods to improve the training performance. In our approach, we make use of curriculum learning [11]. It corresponds to a training procedure, where the model is first trained on simpler data and the model is slowly exposed to more complex data as the training progresses. Curriculum learning has been shown to be helpful in many tasks such as automatic speech recognition (ASR) [12], far-field ASR [13], speech translation [14], audiovisual speech recognition [15] and audiovisual speech enhancement [16]. In [12], curriculum learning is used to make the speech recognition model more robust to ambient noise. This is performed by first training the model with speech samples at high signal-to-noise ratio (SNR) of 50 dB and gradually reducing...
the SNR to 0 dB as training progresses. In [13], the authors attempt to improve the performance of far-field ASR by applying a curriculum which increases the distance between the source and the listener, while the training progresses. The authors show that slowly progressing from training the model on near-field utterances to far-field utterances improves far-field ASR performance. For audio-visual ASR and speech enhancement, curriculum learning has typically been applied as a pre-training step to ensure that the model does not ignore the visual modality in favour of the audio modality. (as the audio modality is usually a richer source of information for such tasks). In such cases, the visual model is first pre-trained on tasks of slowly increasing difficulty before the combined audio-visual model is trained together for the specified task. To the best of our knowledge, such curriculum learning techniques have not been applied to the task of reverberant speech separation.

Pre-training is another well-known machine learning technique that has been shown to improve model robustness and uncertainty estimates [17]. In speech processing, pre-training techniques have been used for a variety of applications. Pre-training has been utilized to train low resource ASR systems using data from a high resource language [13]. Pre-training has also been used to improve the rate of convergence and the word-error-rate (WER) in the case of end-to-end training of automatic speech recognition (ASR) systems [19]. Unsupervised pre-training has also been shown to improve the accuracy of ASR systems [20]. Pre-training has also been shown to reduce label permutation instability while training speech separation models [21]. In this work, we show that a simple pre-training method causes a significant improvement in the performance of reverberant speech separation.

**Main Contributions:** We present new techniques to train a model using a mixture of synthetic and real data. We use more accurate methods to improve separation quality by focusing on the quality of synthetic RIR generation methods used during training. We also propose novel training procedures which seek to make better use of synthetic data to improve the real-world performance.

- We present a novel approach that augments training data by using synthetic RIRs generated by an geometric acoustic simulator that accounts for specular and diffuse reflections. In particular, higher order diffuse reflections can accurately model the reverberation effects. Our formulation improves reverberant speech separation performance as compared to the synthetic RIRs generated by an image source method (ISM) [22, 23]. We show that an accurate geometric acoustic simulator (GAS) shows an average relative improvement of 21% in SI-SDRi as compared to the traditional image source method.
- We present improved training techniques based on curriculum learning [11], multi-stage training and pre-training to improve the overall performance. We show that pre-training the model on non-reverberant speech separation data can significantly improve real-world separation performance. We show that training techniques such as pre-training and curriculum learning result in a relative improvement of 43% in SI-SDRi, when compared to the baseline.

In section 2 we present the details of the datasets used in our approach. Section 3 describes our approach to generate synthetic RIRs. Section 4 presents details about the model architecture and the model training parameters used in our experiments.

## 2. DATASETS

The LibriMix dataset [24] is an open-source speech separation dataset based on the LibriSpeech Corpus [25]. All experiments in this paper are run on the 100-hour split of Libri2Mix data (the two speaker mixture subset of the LibriMix dataset) at a sampling rate of 8000 hertz. The "min" criterion is used for mixing speech signals; that is, the duration of the mixed speech signal is set to be the minimum of the duration of the two speech signals being mixed. There are 13,000 data samples in the training split and 3,000 data samples each in the testing and validation splits. All experiments in this paper are done on the two speaker subset of LibriMix data (Libri2Mix).

The LibriMix dataset is a non-reverberant speech separation dataset. Reverberation is introduced on the fly during training by convolving the separated speech signals with a randomly chosen RIR (can be either real or synthetic) before mixing. We do not employ dynamic mixing [7] while generating speech mixtures.

Real RIRs are obtained from the BUTReverb RIR dataset [26]. We split the real RIRs into train (1171 RIRs), dev (251 RIRs) and test (251 RIRs) subsets. The same splits are used to generate all experimental results. Synthetic RIRs are generated as specified in section 3.

All the models were trained on the reverberant LibriMix dataset and then tested on recordings from the VOiCES dataset [27]. This was done to ensure that we have one common test set consisting of real reverberant mixtures on which the performance of different approaches can be compared. The VOiCES dataset consists of four different room configurations in which data has been recorded. For each room configuration, we generate 400 test mixtures by randomly mixing two recordings. The room configurations used to record VOiCES data is mentioned in Table 3.

## 3. RIR GENERATION AND TRAINING

Sections 3.1, 3.2, 3.3 and 3.4 describe the methods used to generate synthetic RIRs used in our experiments. Sections
Table 1: Room dimensions (in meters) used to generate synthetic RIRs using GAS and gpuRIR. These are the same room dimensions used to capture real RIR data in the BUTReverb dataset [26].

| Length | Width | Height |
|--------|-------|--------|
| 10.7   | 6.9   | 2.6    |
| 4.6    | 6.9   | 3.1    |
| 7.5    | 4.6   | 3.1    |
| 6.2    | 2.6   | 14.2   |
| 28.1   | 11.1  | 3.3    |
| 11.5   | 20.1  | 4.8    |
| 17.2   | 22.8  | 6.9    |
| 7.0    | 4.1   | 3.6    |
| 4.4    | 2.8   | 2.7    |

3.3. IR-GAN

IR-GAN [37] is a GAN based RIR generator that can generate realistic RIRs. IR-GAN has been shown to improve the performance of far-field speech recognition. IR-GAN learns acoustic features (e.g., reverberation time ($T_{60}$), direct to reverberation ratio (DRR) etc.) from real RIRs and can generate RIRs with different combination of acoustic features by considering different linear combinations of the noise vector used to generate RIRs. The performance of IR-GAN depends on the real-world RIRs used to train the network. We train IR-GAN on real RIRs from the BUTReverb dataset in order to generate synthetic RIRs for our speech separation experiments.

3.4. TS-RIRGAN

TS-RIRGAN [38] is a CycleGAN model that learns an unpaired data mapping from synthetic RIRs to real RIRs. TS-RIRGAN improves the quality of synthetic RIRs by compensating low frequency wave effects. We used pre-trained TS-RIRGAN [38] to improve the quality of synthetic RIRs generated using GAS. TS-RIRGAN model is trained using real RIRs from BUT ReverbDB dataset and synthetic RIRs from GAS. We translate the synthetic RIRs generated by GAS in section 3.2 to generate improved synthetic RIRs. No further post-processing of these RIRs is done prior to training the speech separation model.

[38] https://github.com/anton-jeran/TS-RIR
3.5. Pre-training

We initialize the model weights used for the reverberant training runs with the weights of the converged model trained on non-reverberant speech separation data (the unmodified Libri2Mix dataset). The pre-trained model achieved an SI-SDRi of 13.9 and SDRi of 14.31 on the unmodified Libri2Mix dataset. The intuition behind such a pre-training step was that the model has already learned to separate speech signals from mixtures and must now learn to account only for the reverberation caused by repeated reflections from the walls and nearby objects present in the room. This is a slightly simpler problem to learn as compared to separating speech signals and handling reverberant effects in a single step. When pre-training and curriculum learning (described in the next section) are applied together, the model training becomes a gradual process where the speech separation model learns to handle increasing amounts of reverberation.

3.6. Curriculum Learning

The synthetic and real RIRs are arranged in ascending order of $T_{60}$ values. At the start of the training, only those RIRs with low $T_{60}$ values are chosen to generate reverberant data on which the model is trained. As training progresses, the $T_{60}$ threshold is slowly increased over time and the model learns to separate mixtures with increasing reverberation in a gradual manner. We generate 40k synthetic RIRs of differing $T_{60}$ values using GAS. This is done by varying the sound absorption coefficient from 0 to 1 in steps of 0.01. For each value of absorption coefficient, we generate 400 RIRs. The room dimensions used to generate these RIRs are specified in Table 1. The histogram of $T_{60}$ values of the RIRs generated for curriculum learning is shown in Figure 2. The RIRs are sorted in ascending order of $T_{60}$ values. At the start of the training, the model is initialized with weights from the pre-trained model. This pre-trained model performs well on the task of reverb-free speech separation. When training begins, the 400 RIRs with the lowest $T_{60}$ values are chosen to generate the reverberant signals from which the reverberant mixtures are obtained for training. From the histogram in Figure 2 we see that the first 400 RIRs have $T_{60}$ of close to zero. Convolving speech signals with such RIRs produces mixtures with very low reverberation which the pre-trained model can easily learn to separate. After every 2nd epoch, we include the next set of 400 RIRs with slightly higher $T_{60}$ values in the set of available RIRs for training. Hence, at each stage the model slowly adjusts to increasing reverberation and training proceeds smoothly. Since we have 40k RIRs in total and we train for 200 epochs, at the end of training all the synthetic RIRs generated (including those with high $T_{60}$) will have been used for training the model.
3.7. Multi-stage training

We propose a training pipeline where RIRs generated from the methods described in Sections 3.2 - 3.4 are used to train the speech separation model in multiple stages. After pre-training on anechoic data, the model is first trained on reverberant data generated using RIRs from GAS. The model is then fine-tuned using RIRs generated from GAN based methods - IR-GAN and TS-RIRGAN. The intuition is that GAS can generate RIRs with a wide range of reverberation parameters ($T_{60}$ and DRR) which is used for the initial training. The GAN based methods have been shown to generate realistic RIRs and are used to fine-tune the model to improve performance on real reverberant data. We show that training the model in multiple stages leads to better performance when compared to a single training stage (where RIRs from different RIR generation methods are combined to generate the reverberant training data).

4. EXPERIMENTS

4.1. Model Architecture and Training Details

All experiments are run on the DPRNN-TasNet [39] model. The model has 8 DPRNN blocks with 512 units in the RNN cell state. The ADAM optimizer [40] is used with an initial learning rate of $10^{-3}$ and no weight decay. The learning rate is halved every time the validation loss plateaus. We use early stopping with a delay of 10 epochs to terminate the training. A batch size of 16 is used for all experiments. The model is trained for a maximum of 200 epochs. The asteroid framework [41] is used for all experiments in this paper.

Synthetic RIRs are generated as specified in Section 3. While the model is being trained, reverberant data is generated on the fly by convolving a randomly chosen real or synthetic RIR with the source signal. The reverberant mixture is then obtained by mixing the reverberant speech signals. For each of the RIR generation methods specified in Section 3, we combine real and synthetic RIRs and train the same DPRNN-TasNet model as specified above. The model is trained to generate the separated reverberant speech signals given a reverberant input mixture.

4.2. Results

We report the improvement in scale-invariant signal-to-distortion ratio (SI-SDRi) as the metric to compare the different training approaches. We use the mir_eval [42] library to generate this metric. The improvements are computed by obtaining the difference in metric values for the input mixture and the predicted separated signals. We report results separately for each of the room configurations present in the VQiCES dataset. The four room configurations are specified in Table 3.

In Table 2, we have reported the SI-SDRi values for the models trained on Libri2Mix and tested on two speaker mixtures created from the VOiCES dataset.

The non-reverb baseline - that is, the model trained on clean, non-reverberant data does extremely poorly on the reverberant speech separation task.

As expected, we see that RIR generation method that employs the image source method (gpuRIR) has lower SI-SDRi. This is reasonable because the image source method just models only specular reflections. Since GAS simulates both specular and diffuse reflections, it performs significantly better than gpuRIR when tested on real data. GAS has an average relative improvement of 21% in SI-SDRi compared to gpuRIR.

The results also show that fine-tuning the GAS model using RIRs generated from IR-GAN and TS-RIRGAN improves the average SI-SDRi from 4.49 dB to 5.04 dB. This is an average relative improvement of 12.24% over all room configurations.

The training names which include a "+" sign indicate that the RIRs generated from different training methods were used in a single training step. For example, "GAS + IR-GAN" indicates that half the training data was generated using RIRs from GAS and the other half was generated using RIRs from IR-GAN. The training names which include a "→" specifies a multi-stage training pipeline. For example, "GAS → IR-GAN" implies that the model was first trained on reverberant data generated from GAS RIRs and was then fine-tuned on data generated from IR-GAN RIRs. The results clearly show that a multi-stage training approach works much better as compared to single stage training where different RIR generation methods are used at once.

We obtain the best SI-SDRi value of $x$ (averaged over all rooms) when we employ a multi-stage training pipeline combining GAS and GAN based RIR generation methods along...
Table 2: Ablation results (SI-SDRi) that quantify the contribution of real RIR data, pre-training, multi-stage training and curriculum learning to improving model performance. Our overall approach based on (curriculum learning+pre-training+GAS) gives the best results.

| RIR Generation | Pre-training | Real RIRs used? | Curriculum learning | SI-SDRi Room 1 | SI-SDRi Room 2 | SI-SDRi Room 3 | SI-SDRi Room 4 |
|----------------|--------------|-----------------|---------------------|----------------|----------------|----------------|----------------|
| Non-reverb baseline | NA           | NA              | NA                  | -4.25          | -4.34          | -4.25          | -4.18          |
| gpuRIR (ISM) | ✔️           | ❌              | ❌                  | 2.27           | 2.13           | 1.48           | 2.19           |
| GAS            | ❌           | ✔️              | ❌                  | 4.35           | 3.71           | 1.96           | 3.61           |
| GAS            | ✔️           | ❌              | ✔️                 | 3.44           | 2.09           | 1.09           | 2.73           |
| GAS + IR-GAN  | ✔️           | ✔️              | ✔️                 | 4.47           | 3.00           | 1.77           | 3.31           |
| GAS + IR-GAN + TS-RIRGAN | ✔️ | ✔️             | ✔️                 | 5.53           | 4.04           | 2.28           | 4.28           |
| GAS → IR-GAN  | ✔️           | ✔️              | ❌                  | 5.85           | 4.62           | 2.51           | 4.27           |
| GAS → IR-GAN → TS-RIRGAN | ✔️ | ✔️             | ✔️                 | 5.51           | 5.15           | 2.51           | 4.8            |
| GAS → IR-GAN → TS-RIRGAN | ✔️ | ✔️             | ✔️                 | 5.06           | 4.78           | 2.25           | 4.34           |
| GAS + IR-GAN + TS-RIRGAN | ✔️ | ✔️             | ✔️                 | 5.85           | 5.52           | 3.27           | 5.06           |
| GAS + IR-GAN + TS-RIRGAN | ✔️ | ✔️             | ✔️                 | 5.4            | 4.55           | 2.43           | 4.5            |
| GAS + IR-GAN + TS-RIRGAN | ✔️ | ✔️             | ✔️                 | 5.93           | 5.55           | 3.41           | 5.23           |
| GAS → IR-GAN → TS-RIRGAN | ✔️ | ✔️             | ✔️                 | 5.96           | 5.27           | 2.98           | 5.16           |

Table 3: Room dimensions (in meters) used to capture VOiCES test data. Room 4 consists of two adjacent cuboidal rooms and both dimensions are specified.

| Room     | Length  | Width  | Height   |
|----------|---------|--------|----------|
| Room 1   | 3.7     | 2.7    | 2.7      |
| Room 2   | 5.7     | 4.01   | 2.77     |
| Room 3   | 7.62    | 7.62   | Not specified |
| Room 4   | 9.75+3.05 | 4.87+3.05 | Not specified |

4.3. Ablation Studies

In Table 2 we demonstrate the effects of three factors on the performance of reverberant speech separation. The three factors studied are - inclusion of real RIRs during training, applying curriculum learning and pre-training the model.

All results shown in Table 2 have been trained on the same model (DPRNN-TasNet). The dataset used for the ablation experiments is the reverberant LibriMix generated by convolving the original LibriMix dataset with synthetic RIRs generated from GAS/gpuRIR and real RIRs from BUTReverb data. We observe the following benefits from the results in Table 2:

- The inclusion of real RIRs in the training process is important. We see that the addition of even a small quantity of real RIR data in the training process significantly enhances the real-world performance of the reverberant speech separation system. When pre-training is not done, SI-SDRi shows a relative improvement of 34% with the inclusion of real RIRs during training. When pre-training is done, a slightly lower relative improvement of 7% of in SI-SDRi is observed. The relative improvements reported here are for training runs where RIRs from GAS are used.

- Curriculum learning improves the SI-SDRi by about 5% relative to the non-curriculum baseline (averaged over all rooms). However, we see that curriculum learning does not improve performance when multi-stage training is applied (the last two rows of Table 2 show this). Applying curriculum learning in the later stages of multi-stage training scenario does not show the expected improvement as the model has already been exposed to RIRs for both high and low RT60 values in the first training stage.

- Pre-training the model on the non-reverberant separation task improves SI-SDRi by about 37% relative to the non-pre-trained baseline (averaged over all rooms).

- Multi-stage training provides a relative improvement of 19.6% over single stage training (averaged over all such runs in the above table over all room configurations).

- Fine-tuning on GAN RIRs gives a relative improvement of 16.7% when compared to the GAS only training pipeline (averaged over all room configurations).

5. CONCLUSION AND FUTURE WORK

We have shown that a combination of pre-training, multi-stage training and training on a combination of RIRs generated from accurate acoustic simulators and GAN based RIR generation methods can significantly improve the performance of reverberant speech separation compared to the ISM
Our acoustic simulator generates RIRs based on specular and diffuse reflections, which considerably improve the accuracy. We hope to extend our approach to multi-channel and multi-speaker (>2 speakers) scenarios. These techniques based on curriculum learning and accurate synthetic data generation could also be useful for audio-visual speech separation.

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