IR-GAN: ROOM IMPULSE RESPONSE GENERATOR FOR SPEECH AUGMENTATION

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ABSTRACT
We present a Generative Adversarial Network (GAN) based room impulse response generator for generating realistic synthetic room impulse responses. Our proposed generator can create synthetic room impulse responses by parametrically controlling the acoustic features captured in real-world room impulse responses. Our GAN-based room impulse response generator (IR-GAN) is capable of improving far-field automatic speech recognition in environments not known during training. We create far-field speech training set by augmenting our synthesized room impulse responses with clean LibriSpeech dataset [1]. We evaluate the quality of our room impulse responses on the real-world LibriSpeech test set created using real impulse responses from BUT ReverbDB [2] and AIR [3] datasets. Furthermore, we combine our synthetic data with synthetic impulse responses generated using acoustic simulators, and this combination can reduce the word error rate by up to 14.3% in far-field speech recognition benchmarks.

Index Terms— acoustic simulation, room impulse response, generative adversarial network, speech recognition

1. INTRODUCTION
Reverberation is a part of the speech signal which characterizes the acoustic environment that is used to capture the speech signal. Reverberation can be characterized by the transfer function known as the room impulse response (RIR). A room impulse response represents the relationship between the dry sound and the reflection of the sound signal from the boundaries of the room [4].

RIRs are frequently used in many practical applications such as far-field speech recognition [5 2], speech enhancement [6], sound rendering [7], audio forensics [8], etc. One challenge for these applications is that existing recorded or real-world RIR datasets are collected in specialized environments and this can be a limiting factor for speech recognition. In our paper, we address this issue by augmenting RIRs using a Generative Adversarial Network (GAN).

Many prior techniques for generating synthetic RIRs are based on acoustic simulators [9 10]. These simulators use room geometry, sound absorption and sound reflection coefficients as input and generate RIRs by simulating occlusion, specular and diffuse reflection. In practice, such synthetic RIR generators can model some sound propagation phenomena in regularly shaped or mostly empty rooms. On the other hand, simulating the sound reverberation effects in complex scenarios like stairways are more difficult [5]. As a result, we need other synthetic RIR generator methods that can model the sound effects in complex environments.

Main Contributions: We present a novel GAN-based RIR generator (IR-GAN) that is trained on real-world RIRs. IR-GAN can parametrically control different acoustic features learned from real RIRs and generate synthetic RIRs that can imitate new or different environments. Moreover, we propose a constrained RIRs generation approach that can eliminate synthesizing RIRs with noisy artifacts to a greater extent.

Our IR-GAN uses WaveGAN [11] architecture to synthesize new RIRs by learning from recorded RIRs. IR-GAN maps all acoustic features in recorded RIRs to a high-dimensional space and generates RIRs by controlling various acoustic parameters. As a result, we can train on real-world RIRs corresponding to complex locations like stairways and can augment speech signals for such locations. Figure 1 highlights the spectrogram of a recorded RIR from BUT ReverbDB dataset [2] and the spectrogram of a generated RIR using our approach. Our GAN-based synthetic RIR generation approach is complementary to prior synthetic RIR generators based on acoustic simulators. We evaluate the performance by conducting far-field automatic speech recognition (ASR) tests and show that combining RIRs synthesized from IR-GAN, and state-of-the-art geometric acoustic simulator reduce the word error rate by up to 14.3%.
We convolve clean speech from LibriSpeech dataset with real RIRs in BUT ReverberDB and AIR datasets to create real-world far-field speech. Our code is publicized for follow-up research.

2. RELATED WORKS

Physically-based acoustic simulators have been used to generate synthetic RIRs for far-field speech research. Geometric acoustic simulators [12, 10] are most widely used to model both specular and diffuse sound reflections. In many scenarios, the target room environment (i.e., exact geometric shape and material parameters) is unknown or too complex for these simulators. As a result, their ability to generate RIRs for all kinds of scenarios can be limited.

GANs have made steady progress over the years in image generation [13], image inpainting [14] and domain adaptation [15]. The success of GAN in computer vision motivated researchers to use it in other fields. Recently GANs have been becoming popular in audio generations. GANs have shown progress from music generation [16] to any short audio clip generation [11]. In this work, we aim to use GANs for RIR generation as complementary to the prior works.

3. OUR APPROACH: IR-GAN

3.1. Room Impulse Response Statistics

Room impulse response acoustic parameters are used to characterize the acoustic environment [17] and control RIR generation using GAN. Reverberation time ($T_{60}$), direct-to-reverberant ratio (DRR), early-decay-time (EDT) and early-to-late index (CTE) are four acoustic parameters that can be estimated from RIRs. We use these acoustic parameters to constrain IR-GAN-based RIR augmentation. Reverberation time measures the amount of time taken to delay the sound pressure by 60 decibels (dB). The $T_{60}$ value depends on room size and the characteristics of the material (e.g., floor, walls, furniture, etc.). DRR is calculated by dividing the sound pressure level of a direct sound source by the sound pressure level of the sound arriving after one or more surface reflections [18]. DRR is measured in dB. Time taken for sound pressure to decay by 10 dB is multiplied by a factor of 6 to get early-decay-time. EDT depends on the type and location of the sound source. CTE measures the proportion of the total sound energy received in the first 50 ms to the energy received during the rest of the period [4].

3.2. Room Impulse Response Representation

The representation of the input data and the data generated by the neural network is important for synthesizing high-quality RIRs. Therefore, lossy representations of RIRs like Mel-frequency cepstral coefficients (MFCCs) are less favourable. Audio samples are a lossless representation that can be easily converted to an audio signal. As different datasets store RIRs with different sampling rate. We re-sample all the RIRs to 16 kHz. We pass audio samples as a 32-bit floating-point vector of length 16384 to the GAN. The vector length is sufficient to represent RIRs because most of the RIRs are less than one second in duration. We can represent slightly more than one second with 16384 samples with a sampling rate of 16 kHz.

3.3. GAN

GAN is a generative model that learns a mapping from a low-dimensional vector space to a high-dimensional space where the data is represented. We adapt the WaveGAN architecture proposed in [11] to generate high-quality RIRs. WaveGAN is a one-dimensional version of DCGAN [19] where two-dimensional filters are replaced by one-dimensional filters.

GANs trained using the value function proposed in the original GAN paper [20] are often unstable, and mode collapse can occur when the generator architecture is varied. Therefore, we use a stable cost function introduced in WGAN [21]. In this cost function, we minimize the Wasserstein-1 distance between data distribution $p_{data}(x)$ and model distribution (Equation 1). Model distribution is implicit in the second part of the equation because $G(z)$ represents the mapping from a latent vector $z$ with distribution $p_z(z)$ to the data space. In WGAN, the discriminator network $D_{WGAN}$ gives a score based on the realness of the given image instead of predicting the probability that $x$ comes from the real distribution. In Equation 1 $E$ represents expectation.

$$V_{WGAN}(D_{WGAN}, G) = E_{x \sim p_{data}(x)}[\log D_{WGAN}(x)] - E_{z \sim p_z(0)}[\log D_{WGAN}(G(z))]. \tag{1}$$

3.4. Constrained RIR Generation

In our approach, we train a GAN to learn the mapping from the 100-dimensional latent vector $z$ drawn from a Gaussian distribution to the RIR in data space. As the number of real-world RIR datasets is limited, we propose a constrained generation of RIRs from the generator network. There is an infinite possibility to generate a 100-dimensional vector where each dimension can take any floating-point number between -1 and 1. Since we train GAN with a limited number of RIRs in real RIR datasets (BUT ReverberDB contains less than 2000 RIRs), there is a chance that some of the mappings will lead to noisy RIR generation. Figure 2 shows one such noisy mapping. To prevent such mappings, we calculate the key acoustic parameters of the training samples ($T_{60}$, DRR, CTE, and EDT) and put them in a histogram. Later, we generate RIRs by constraining them to follow a similar distribution of
key acoustic parameters as the training samples. In this way, we can avoid noisy mapping to a greater extent.

Fig. 2: Spectrogram of noiseless (Left) and noisy (Right) RIRs. In the noisy spectrogram, we can see many horizontal artifacts around 600ms.

4. VECTOR ARITHMETIC ON RIR

The key challenge of training neural networks to estimate DRR and $T_{60}$ from an RIR is that available recorded RIR datasets are small and imbalanced [17]. We can overcome this issue by parametrically controlling RIR augmentation and generating samples covering a wide range of variations.

Because the low-dimensional latent vectors $z$ encode all the acoustic features, we can parametrically control all the acoustic features by performing simple vector arithmetic on the latent vectors.

To illustrate, we parametrically control DRR by simple vector arithmetic. We randomly selected vector $\vec{V}_1$ which maps to an RIR with low DRR of -16 dB and vector $\vec{V}_2$ which maps to an RIR with high DRR of 0.56 dB. We then perform simple vector arithmetic to find nine intermediate vectors $\vec{V}_i^\prime$ in the linear path between $\vec{V}_1$ and $\vec{V}_2$ using the following formula:

$$\vec{V}_i^\prime = \frac{(10 - n)}{10} \vec{V}_1 + \frac{n}{10} \vec{V}_2.$$  \hspace{1cm} (2)

The intermediate vectors generate RIRs with DRR between -16 dB to 0.56 dB. Figure 3 shows RIRs generated from $\vec{V}_1$ and $\vec{V}_2$, and two intermediate latent vectors $\vec{V}_3^\prime$ and $\vec{V}_6^\prime$. When the DRR increases, the direct signal becomes stronger than the reverberation. We can see in Figure 3 that the direct response becomes stronger than the reverberation when we move from $\vec{V}_1$ to $\vec{V}_2$. The calculated DRR using a method based on ISO 3382-1:2009 for RIRs generated from $\vec{V}_1^\prime$ and $\vec{V}_2^\prime$ are -12 dB and -6 dB respectively. We consider DRR because it is easier to visualize. Similar to DRR, we can parametrically control different acoustic parameters using the latent vectors, and we can generate desired RIRs.

5. EXPERIMENTS AND RESULTS

We evaluate the effectiveness of our proposed approach by conducting a far-field automatic speech recognition (ASR) experiment, similar to the one described in [5]. In our experiment, we focus on two things. First, we compare the performance of the proposed IR-GAN with the state-of-the-art synthetic RIR generator [10]. Second, we evaluate the robustness of the IR-GAN when we train the GAN on one dataset [2] and test the GAN on another dataset [3] from different environments.

5.1. Data Preparation and Training

As proposed in [5], we generate far-field speech from clean LibriSpeech by convolving it with RIRs and adding environmental noise. Since we mainly focus on the quality of the synthesized RIRs, we use the same environmental noise from the BUT ReverbDB [2] for training and test set generation.

We use real RIRs from the BUT ReverbDB dataset [2] and the AIR [3] dataset to conduct our experiments. BUT ReverbDB consists of 1891 RIRs and 9114 environmental noises covering nine different rooms. To make fair comparisons, we use the 1209 BUT ReverbDB RIRs picked in [5]. The AIR dataset consists of 344 real RIRs from 6 different rooms. From these, we select 68 RIRs from the 4 rooms (studio booth, office room, lecture room and meeting room) mentioned in [3]. We split 1209 real-world RIRs from the BUT ReverbDB dataset into training, development and test sets by the same amount used in the previous benchmark. To test the robustness of our proposed approach, we use 68 RIRs from the AIR dataset [3]. Table 1 shows the detailed composition of the augmented datasets. The augmentation process does not change the overall duration of the original LibriSpeech dataset.

We use a modified Kaldi toolkit\(^\text{2}\) to conduct our experiment. All the training and testing is done on a 32 Intel(R) Xeon(R) Silver 4208 CPUs @ 2.10GHz and 2 GeForce RTX 2080 Ti GPUs. For a fair comparison, we generate all the results from the same environment. It takes around four days to prepare the dataset and conduct each experiment on the Kaldi toolkit.

\(^{2}\)https://github.com/RoyJames/kaldi.
In this paper, we present an IR-GAN to generate realistic RIRs. Our proposed approach outperforms the state-of-the-art geometric acoustic simulator (GAS) by up to 8.95% in far-field ASR tests. We train our GAN with 967 real RIRs from the BUT ReverbDB and AIR datasets, respectively. *BUT* and *AIR* represents the BUT ReverbDB and AIR dataset from which real RIRs are taken.

### Table 1: Detailed information about the augmented dataset.

In this table train.*, dev.* and test.* represent training, development and test sets, respectively. *.real, *.GAS and *.GAN represent real RIR, RIR synthesized using state-of-the-art Geometric Acoustic Simulator (GAS) [10], and the RIR generated using proposed IR-GAN, respectively. *GAN+GAS indicates an equal mixture of GAS and GAN synthesized RIRs. *BUT* and *AIR* represents the BUT ReverbDB and AIR dataset.

| Dataset | #IRs | LibriSpeech Dataset |
|---------|------|---------------------|
| train-real | 773 | train-clean-100,360 |
| dev-real | 194 | dev-clean |
| test-BUT-real | 242 | test-clean |
| test-AIR-real | 68 | test-clean |
| train-GAS / train-GAN | 773 | train-clean-100,360 |
| dev-GAS / dev-GAN | 194 | dev-clean |
| train-GAN+GAS / train-GAN | 1546 | train-clean-100,360 |
| dev-GAN+GAS / dev-GAN | 388 | dev-clean |

### Table 2: Far-field automatic speech recognition results obtained from the far-field LibriSpeech test set.

Word error rate (WER) is reported for the tri-gram phone (tglarge, med, small) and four-gram phone (fglarge) language models, and online decoding using tgsmall. Best results in each comparison are marked in **bold**.

| Training Data | Test Word Error Rate (WER) [%] |
|---------------|-------------------------------|
|               | fglarge | tglarge | tgmed | tgsml | online |
| train-real-BUT | 12.40 | 13.19 | 15.62 | 16.92 | 16.88 |
| train-GAS-BUT [10] | 16.53 | 17.26 | 20.24 | 21.91 | 21.83 |
| train-GAN-BUT | 15.05 | 15.86 | 18.85 | 20.57 | 20.50 |
| train-2*GAN-BUT | 14.86 | 15.69 | 18.50 | 20.25 | 20.17 |
| train-GAN+GAS-BUT | 14.16 | 14.99 | 17.56 | 19.21 | 19.21 |
| train-clean-AIR | 26.79 | 27.40 | 29.64 | 30.88 | 31.15 |
| train-GAN-AIR | 7.71 | 8.03 | 9.88 | 11.11 | 11.08 |

### 5.2. Synthetic RIR generation

For a fair comparison, we use the same synthetic RIR generated using the state-of-the-art geometric acoustic simulator [10] in the previous benchmark. The geometric acoustic simulator synthesizes RIR using the meta-info provided in BUT ReverbDB. The meta-info includes room dimensions and, loudspeaker and microphone locations. Therefore, the synthesized RIRs for the training and development sets mimic real RIR training and development sets to some extent.

We train our GAN with 967 real RIRs from the BUT ReverbDB dataset. They are composed of real-world RIRs allocated for training and development. We generate synthesized RIRs by the constrained RIR generation process in § 5.4.

### 5.3. Results

Table 2 presents the ASR test word error rate (WER) for far-field speech generated using BUT ReverbDB [2] and AIR [3]. WER is calculated for four different language models (fglarge, tglarge, tgmed, and tgsml) in Kaldi as well as for online decoding using a tgsml model.

WER is a metric used to measure the robustness of the trained model. A lower WER indicates that the trained model shows superior accuracy in test conditions. Robustness depends on the model architecture and the input data used to train the model. In our experiments, we keep the model constant while we train with different datasets. Different datasets are created by convolving the same LibriSpeech speech corpus with different RIRs. Therefore, the robustness of the model is only affected by the RIRs being used. The lowest test WER is reported when we train and test on the real RIRs.

In Table 2 we can see that the proposed IR-GAN gives lower WER than the state-of-the-art geometric acoustic simulator (GAS). Lower WER indicates that the RIRs synthesized using GAS are more realistic synthetic RIRs computed using physically-based acoustic simulator. When we look at the WER for the fglarge model, we can see that our IR-GAN gives an 8.95% lower error rate than the GAS.

Hybrid Combination: Because the IR-GAN and GAS try to mimic real RIRs using two different approaches, we evaluate the WER when trained using a combination of synthetic RIRs generated using IR-GAN and GAS. We observe that there is a further drop up to 5% in WER when compared to doubling the synthetic RIRs from IR-GAN. The drop in WER indicates that we can boost the robustness of ASR systems by combining RIRs generated from GAS and GAS.

In practical scenarios, the IR-GAN does not have the luxury of learning from the environment far-field speech needs to be recognized. Therefore, we augment RIRs using GAS trained with recorded BUT ReverbDB [2]. Then we train far-field speech generated using the augmented RIRs and test it on the far-field speech from the AIR dataset [3]. We can observe around a 19% absolute reduction in error when compared to training an ASR system with clean speech.

### 6. DISCUSSION AND FUTURE WORK

In this paper, we present an IR-GAN to generate realistic RIRs. Our proposed approach outperforms the state-of-the art geometric acoustic simulator (GAS) by up to 8.95% in far-field ASR tests. When we combine our RIRs with RIRs generated using GAS, we can see a total reduction in word error rate by up to 14.3% in far-field ASR tests. This reduction in word error rate indicates that synthetic data generated using IR-GAN and GAS can be combined to boost the performance of far-field ASR systems. We have tested our approach only on indoor scenes and extending to outdoor scenes is a good topic for future work.
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