A study on more realistic room simulation for far-field keyword spotting

Eric Bezzam¹, Robin Scheibler², Cyril Cadoux³, Thibault Gisselbrecht⁴

¹Sonos Inc., Paris, France
²Tokyo Metropolitan University, Japan
³École Polytechnique Fédérale de Lausanne, Switzerland

Abstract

We investigate the impact of more realistic room simulation for training far-field keyword spotting systems without fine-tuning on in-domain data. To this end, we study the impact of incorporating the following factors in the room impulse response (RIR) generation: air absorption, surface- and frequency-dependent coefficients of real materials, and stochastic ray tracing. Through an ablation study, a wake word task is used to measure the impact of these factors in comparison with a ground-truth set of measured RIRs. On a hold-out set of re-recordings under clean and noisy far-field conditions, we demonstrate up to 35% relative improvement over the commonly-used (single absorption coefficient) image source method. Source code is made available in the Pyroomacoustics package, allowing others to incorporate these techniques in their work.

Index Terms: room simulation, image source method, stochastic ray tracing, multi-condition training, keyword spotting

1. Introduction

Deep-learning approaches are the state-of-the-art when it comes to keyword spotting (KWS) and automatic speech recognition (ASR) [1]. Their recent success can be attributed to the availability of large datasets, improved computing resources, and a cocktail of deep-learning heuristics that have been tried-and-tested by an active research community. Each data point and its reproducibility contribute to a better understanding of the best practices for speech recognition training.

Given an appropriate dataset, deep neural networks (DNN) are able to learn internal representations that are relatively stable with respect to variables independent of the desired output. For example in KWS and ASR tasks, the speaker’s pronunciation should not impact the understanding of what the speaker is saying. Robustness to speaker pronunciation, e.g. gender and accents, is typically handled by collecting a sufficiently varied dataset, such as Librispeech for ASR [2], Google’s speech commands for KWS [3] and the “Hey Snips” dataset for wake word (WW) detection [4]. Additional variations, e.g. speed and pitch, can be simulated to further augment the original dataset and expose the model to more variety during training [5,6].

With the recent proliferation of smart speaker devices, there has been a growing interest and need for robust, far-field recognition, namely speech in the presence of reverberation and various types of noise. As collecting and labelling such in-domain data for training can be difficult and time-consuming, multi-condition training (MCT), i.e. simulating various acoustic environments, offers an attractive alternative [7,8,9]. Far-field settings are simulated by convolving clean anechoic recordings with room impulse responses (RIR), which can be either simulated or measured. In [8,9], the authors augmented their dataset through MCT with room impulse responses (RIR) generated with the image source method (ISM) [10]. Both [8] and [9] showed gains on a hold-out set of real recordings. The authors of [11] investigated a room simulation technique that uses stochastic ray tracing (SRT), in order to incorporate factors not taken into account by ISM, i.e. diffuse reflections and late reverberation. Their results demonstrate an improved performance on KWS and ASR tasks when using SRT instead of ISM.

The use of measured RIRs for MCT is ideal as simulation cannot capture the complexity of real rooms. However, the collection of a sufficiently-varied dataset with multiple positions per room is a tedious task and needs to be repeated for different microphone geometries. There have been numerous studies on the differences between using simulated and measured RIRs, with several attempts to close the performance gap: point-source noises [8], directional sources [12], and artificially mimicking low-frequency wave effects [13].

SpecAugment [14] is another data augmentation technique that has shown promising results for ASR. Within the context of far-field recognition, its effect is unclear, with worse results shown in [15] when using it on top of MCT. As our focus is on far-field recognition and the use of MCT to generalize to these conditions, we do not use SpecAugment in our study.

While only SRT is used in [11], we propose to employ a hybrid approach by complementing ISM with SRT [16]. Moreover, we incorporate air absorption and surface- and frequency-dependent absorption coefficients of real materials in an attempt to bring simulation closer to reality.

The goal of this paper is two-fold:
- Study the impact of incorporating the above factors into ISM with an ablation study on a WW detection task.
- Demonstrate and make available such techniques through the Pyroomacoustics package [17].

The paper is organized as such: Section 2 presents ISM and SRT; Section 3 describes how the proposed additional factors are incorporated; Section 4 and 5 detail our experimental setup and results; and Section 6 contains concluding remarks.

2. Modeling room impulse responses

For $I$ sources, we can model far-field speech as:

$$x[n] = \sum_{i=1}^{I} g_i \cdot (p_i[n] \ast h_i[n]),$$

where $\{ p_i[n] \}_{i=1}^{I}$ are the $I$ source signals (target and noise), each convolved with an RIR $\{ h_i[n] \}_{i=1}^{I}$ from the $i$-th source to the microphone and scaled with a constant $\{ g_i \}_{i=1}^{I}$.

1. [github.com/LCAV/pyroomacoustics]
2. Room impulse response generation code for this paper: [github.com/ebzzam/room-simulation]
2.1. Image source method

The ISM technique is a popular approach for generating RIRs, mainly due to its simplicity [8, 9, 10]. It models reflections off walls as virtual sources outside of the room, but at a distance corresponding to the length of the reflection path within the room. With ISM, we can write the RIR for the i-th source as:

$$h_i[n] = \sum_{s \in V(m, s)} \frac{R(m, s)}{\pi \|m - s\|} \delta_{1,P}(n - F_s \|m - s\| / c),$$  
(2)

where $m$ is the position of the microphone, $s$ is the position of the i-th source, $V(m, s)$ is the set of visible image sources for the reflections between $m$ and $s$, and $\delta_{1,P}$ is a windowed sinc function [17]. $F_s$ is the sample rate, $c$ is the speed of sound, and $R(m, s)$ is the accumulated reflection coefficient between $m$ and $s$:

$$R(m, s) = \prod_{w \in W(m, s)} \sqrt{1 - \alpha_w^2},$$  
(3)

where $W(m, s)$ is the list of surfaces in the reflection path between $m$ and $s$, and $\alpha_w$ is the absorption coefficient of surface $w$.

A reflection order $d$, i.e. how many wall reflections to simulate, is selected to build $V(m, s)$. The simulation complexity is exponential with regards to the reflection order: $O(N^d)$ where $N$ is the number of reflective surfaces. For cuboid-shaped (i.e. shoebox) rooms, the complexity reduces to $O(d^3)$.

2.2. Stochastic ray tracing

Up to a desired order $d$, the ISM technique is able to perfectly model specular reflections, i.e. reflections that have the same outgoing angle as the incident angle to a surface. This modeling is accurate only as long as the wavelength of the sound is small relative to the size of the reflector. When this is not the case, we have diffuse reflections that scatter in all directions [18]. Figure 1 illustrates this separation into specular and scattered energy.

Furthermore, the reflection order $d$ limits the ability of ISM to capture the late reverberation of a room. Increasing the ISM order can capture more reflections in order to better model the late reverberation, but diffuse reflections are still not taken into account. With SRT, we can model these diffuse reflections and the late reverberation [11][19]. From each point source, a large number of rays are emitted and traced until the energy of each ray falls below a certain threshold. Each microphone is modeled as a receiver volume, with specular rays that intersect with it contributing to the resulting RIR. The received rays are logged with an amplitude and timestamp in order to produce an energy histogram.

Unlike ISM, each reflection may emit scattered sound energy back to the receiver. In this work, we employ the diffuse rain technique [16], in which a secondary ray is emitted at each reflection point in the direction of the receiver. The energy of this secondary ray can be written as:

$$E_{en} = E_{in}(1 - \alpha) \cdot s \cdot P_{hit},$$  
(4)

where $E_{en}$ is the ray’s incoming energy, $\alpha$ and $s$ are the surface’s absorption and scattering coefficients respectively, and $P_{hit}$ is the probability that the scattered energy reaches the receiver [16]. Meanwhile, the specular ray’s energy is given by: $E_{es} = (1 - \alpha) \cdot (1 - s)$.

In order to produce the RIR, the envelope of the resulting energy histogram is used to shape the envelope of a randomly generated sequence of Dirac deltas [16].

3. Proposed simulation for training

In Section 3.1 we describe the hybrid room simulation technique; and in Section 3.2, we discuss how to incorporate air absorption and surface- and frequency-dependent coefficients.

3.1. Hybrid approach

Due to its stochastic nature, we are not guaranteed to receive all specular reflections with SRT. A hybrid approach can capture these reflections up to a desired order $d$:

1. Apply ISM of order $d$ for specular reflections: $h_i^{ISM}[n]$.
2. Apply SRT for diffuse reflections and late reverberation: $h_i^{SRT}[n]$.
3. Add the two simulations for the hybrid RIR:

$$h_i[n] = h_i^{ISM}[n] + h_i^{SRT}[n].$$  
(5)

When performing SRT, specular reflections which are at or below $d$ should be neglected, as to avoid counting the same reflections twice. Moreover, the energy levels between ISM and SRT must be balanced at the start of simulation [16].

3.2. Additional factors

Air absorption is incorporated by introducing a $e^{-\gamma r}$ factor to the RIRs, where $r$ is the total distance travelled and $\gamma$ is an air attenuation coefficient. This coefficient depends on temperature, humidity, and frequency [13].

Current approaches to room simulation for speech recognition employ a single absorption coefficient for the entire room [8][9]. In reality, absorption properties depend on the material of the surface and on the frequency. This dependence can be taken into account by performing ISM and SRT with unique absorption coefficients for each surface (Equation 5) and on separate octave bands. An appropriately designed filter bank $\{\phi_f[n]\}_{f=1}$ is used to combine the frequency-dependent RIRs at the end of simulation:

$$h_i[n] = \sum_{f=1}^F \phi_f[n] \ast (h_i^{ISM,f}[n] + h_i^{SRT,f}[n]).$$  
(6)

4. Experimental setup

A WW task was chosen for our ablation study as the smaller model size allows for quicker iterations and more trainings in order to perform a more in-depth analysis. Moreover, a binary task allows the use of DET (Detection Error Tradeoff) curves to
analyze the performance over a wide range of operating points instead of a fixed point.

Three types of datasets are used in our study:

1. WW data (positive and negative utterances from the same speakers): “Hey Snips” dataset [3].
2. Measured RIRs: BUT Speech@FIT Reverb Database (ReverbDB) [19].
3. Noise datasets: MUSAN [20] for non-speech sounds and Librispeech [2] for interfering speech.

We use ReverbDB as the oracle RIRs that we wish to emulate via simulation. The dataset contains essential metadata in order to study the impact of the factors we wish to investigate. In Table 1, the train / dev / test set distribution (before augmentation) are detailed.

In Section 4.2 we explain how ReverbDB is used to simulate RIRs with the different simulation factors; and in Section 4.4 we explain how the original train, dev, and test sets are augmented for our study.

4.1. RIR simulation

For each room simulation variation, we emulate the RIRs from the ReverbDB dataset using the provided metadata. The split in Table 1 corresponds to 1032 RIRs for the train set and 280 RIRs for the dev set. For all simulations, the same room dimensions, microphone positions, and speaker positions are used, as specified in the ReverbDB metadata.

1. Baseline: a single absorption coefficient is used for all frequencies and all walls of a shoebox room as in [8, 9]. Using Eyring’s equation as in [9], this coefficient is computed from the measured RT60 provided in the ReverbDB metadata for each microphone-speaker pair.
2. AIR: the measured temperature for each room in ReverbDB is used to set the appropriate frequency-dependent air absorption coefficients as specified in [9].
3. MAT: using the floor, ceiling, and wall materials for each room in ReverbDB, we identify the corresponding frequency-dependent coefficients in [11]. These values are used instead of the single absorption coefficient.
4. MAT AIR: Finally, we use both AIR and MAT.

All four of the above variations are applied for ISM, SRT, and the hybrid approach (HYB) for our ablation study. An ISM order of 17 is used, and for the ray tracing approaches we use the percentage of furniture covering in the ReverbDB metadata as the scattering coefficient. All of the simulation variations are generated using Pyroomacoustics. As a direct comparison to [11], we also perform Baseline with their simulator.\(^3\)

\(^3\)Time for the sound to decay by 60dB.

\(^4\)speed of sound = 331.4 + 0.6 × temperature

\(^5\)https://github.com/RoyJames/pygsound

4.2. Augmented dataset description

The original train and dev sets are augmented as such, with the WW data (positive and negative utterances) as the target speaker:

1. A room is sampled at random, from which we sample a microphone, one speaker for the target speaker, and (75% of the time) 1 or 2 speaker(s) to serve as point-source noise(s) as in [3].
2. Pitch and speed variations are applied to the target speaker as in [3].
3. Using Equation[1] the target and sampled noise sources are simulated in the corresponding room with an SNR sampled as in [9].

Each sample in the original train set is augmented 16 times with different samplings in order to produce the dataset that is used for training the WW detector. This 16x augmentation is performed for all 13 room simulation variations described in Section 4.1 and the ReverbDB dataset, resulting in a total of 14 types of room simulation.

For evaluating the different room simulation approaches, we use re-recordings in order to observe how the simulation approaches generalize to real far-field scenarios. The original test set in Table 1 is re-recorded in five conditions within a typical office setting: clean, 5dB non-speech, 5dB speech, 2dB non-speech, and 2dB speech. The target speaker is placed 3m away. For the noisy conditions, a single speaker is placed 2m away at a 45° angle with respect to the target.

4.3. Model architecture and training

Our WW model is inspired by WaveNet [22]. As the focus of this paper is on room simulation techniques, we refer the interested reader to [4] for more information on our model architecture and training hyper-parameters.

For each simulation approach, 10 models are trained with different seeds in order to prevent random effects due to initialization or sampling from affecting the analysis of our results (by averaging the performance over the 10 models).

5. Results and analysis

The top half of Table 2 shows the average relative change in false rejection rate for each simulation approach with respect to using ISM.

Table 2: (Top half) average relative change in false rejection rate with respect to using measured RIRs (ReverbDB), for three false alarms per day. Higher is better, with values closer to 0 indicating that the simulation technique is on par with using measured RIRs. (Bottom half) average relative change with respect to using ISM.

| Model    | Baseline | AIR   | MAT   | MAT AIR |
|----------|----------|-------|-------|---------|
| ISM      | -55.1%   | -16.7%| 0.78% | -14.8%  |
| SRT [11] | -32.2%   | -     | -     | -       |
| SRT      | -18.0%   | -14.6%| -52.2%| -25.1%  |
| HYB      | -10.4%   | -5.02%| -40.3%| -34.9%  |
| ISM      | -       | 24.3% | 35.3% | 25.3%   |
| SRT [11] | 15.2%    | -     | -     | -       |
| SRT      | 24.1%    | 27.1% | 3.92% | 20.0%   |
| HYB      | 28.8%    | 33.0% | 10.5% | 13.9%   |

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3. Using Equation 1, the target and sampled noise sources are simulated in the corresponding room with an SNR sampled as in [9].

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4. Time for the sound to decay by 60dB.

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5. Speed of sound = 331.4 + 0.6 × temperature

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6. https://github.com/RoyJames/pygsound
to using measured RIRs (ReverbDB). This value is computed by averaging over the relative changes for the five re-recorded far-field conditions. Figure 2 shows the DET curves for a select few simulation techniques.

A significant gap can be observed between ISM and ReverbDB (55.1% drop in average relative performance). This gap can be seen for each condition in Figure 2. From the Baseline column in Table 2, we observe that the proposed HYB approach outperforms currently used techniques (ISM [8][9] and SRT [11]). As presented in [11], we observe an improvement of SRT over ISM. The further increase in performance from SRT to HYB seems to indicate the need for early specular reflections, which are not guaranteed with SRT alone. The difference between our implementation of SRT and [11] may arise from different simulation parameters and internal implementations.

From Table 2, we see that AIR benefits all baseline techniques; perhaps the induced energy decay results in more realistic RIRs. On the other hand, the impact of MAT is not clear. For ISM, we observe a significant improvement, effectively closing the gap with ReverbDB. For the ray tracing techniques, we see a large degradation in performance with respect to the baseline approaches. A potential reason for this is the scattering coefficient used in simulation. As there is no metadata on the scattering properties of the rooms in the ReverbDB, we use the furniture coverage as a scattering coefficient for all surfaces and frequencies. This modeling choice does not impact ISM simulation as scattering is not taken into account. Furthermore, the MAT AIR column seems to indicate we do not get additive gains from incorporating both proposed factors. The effect of MAT highlights a fundamental issue that arises when trying to match simulation to real-world RIRs, namely the appropriate choice of simulation parameters and their distribution.

Despite the unclear results on incorporating MAT, there is a clear indication that adding ray tracing and AIR is beneficial. Moreover, all proposed simulation factors display an improvement over ISM (bottom half of Table 2).

5.1. Profiling RIR simulators

In Figure 3 we compare the computational time between our implementation of SRT in Pyroomacoustics with that of pygsound, namely the simulator used in [11]. For an increasing number of emitted rays in Figure 3a, we observe that Pyroomacoustics is roughly an order of magnitude faster than pygsound. For an increasing specular depth in Figure 3b, we see an exponential growth in pygsound. This seems to suggest that pygsound does not take into account the symmetry of shoebox-shaped rooms.

6. Conclusions and future work

In this paper, we investigated the impact of more realistic room simulations on far-field wake word (WW) training without fine tuning on in-domain, recorded data. To this end, we quantified the gap between an oracle set of measured RIRs (ReverbDB) and the commonly used ISM approach for room simulation. Through an ablation study, we studied the effect of incorporating additional simulation factors, i.e. stochastic ray tracing for diffuse and late reverberation, air attenuation (AIR), and surface- and frequency-dependent absorption coefficients (MAT).

On a hold-out set of re-recordings under clean and noisy far-field conditions, we observe a 28.8% average relative improvement to ISM when complementing it with ray tracing (HYB). Moreover, we find that incorporating AIR benefits all simulation techniques (a further improvement to 33.0% when used with HYB). The impact of MAT is unclear. With ISM, we found the gap between simulated and measured RIRs to be effectively closed. With ray tracing techniques, we found a degradation in performance, which may be due to improper modeling of scattering properties.

As future work, we would like to investigate the impact of such factors on other far-field speech recognition tasks, e.g. command detection and ASR. Finally, the source code for gen-
erating the RIRs is made available in the Pyroomacoustics package. We hope this will aid other researchers and engineers in incorporating such techniques in their work.

7. References

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