Abstract

The materials of surfaces in a room play an important role in shaping the auditory experience within them. Different materials absorb energy at different levels. The level of absorption also varies across frequencies. This paper investigates how cues from a measured impulse response in the room can be exploited by machines to detect the materials present. With this motivation, this paper proposes a method for estimating the probability of presence of 10 material categories, based on their frequency-dependent absorption characteristics. The method is based on a CNN-RNN, trained as a multi-task classifier. The network is trained using prior knowledge about the absorption characteristics of materials from the literature. In the experiments shown, the network is tested on over 5,000 impulse responses and 167 materials. The F1 score of the detections was 98%, with an even precision and recall. The method finds direct applications in architectural acoustics and in creating more parsimonious models for acoustic reflections.

Keywords Room acoustics · reverberation · deep learning · material detection · sound absorption.

1 Introduction

In [1], the question was asked “Can one hear the shape of a room?”. The question led to a discussion on the task of geometry estimation and subsequent interest in the field [2]. It was shown that the Acoustic Impulse Response (AIR) encodes information that enables the inference of the shape of the room. In this paper, we ask a similar question, which is: Can one hear the materials in a room?. The materials of surfaces in a room play an essential part in shaping the auditory experience within them. As sound interacts with surfaces, energy is absorbed and the level of absorption depends on the material of the surface [3]. The level of absorption does not only depend on the material but also on the frequency of the sound. The aim of this work is to be able to detect the presence of materials in an acoustic environment from a single AIR, based on these frequency-dependent absorptions. This is in contrast to other methods that require the extraction of samples of materials from the environment, such as ISO-354 and ISO-10534. Detecting the present materials finds direct applications in modeling for architectural acoustics and also paves the way for more parsimonious material-aware representations of reflections in AIRs [4].

Related work was motivated by the need to recreate the acoustics of a room. Knowledge of how sound is absorbed in an enclosure improves computer models of it. The models enable a study of the room’s acoustics through simulations.
and help to find ways to improve its acoustics by altering its architecture. In [5], a method based on Genetic Algorithms (GAs) was proposed for the simple case of uniform and frequency-independent absorptions across all surfaces. GAs were also used in [6] for the more generalizable task of estimating frequency-dependent absorptions by different surfaces in a room. To do so, measured values of acoustic parameters were matched to simulated ones by adjusting the absorption levels. GAs are an attractive choice for this problem as the search space for solutions is large and direct minimization of a loss function using a gradient based optimizer is likely to lead to a number of issues. However, the performance of any method that relies only on audio information to identify materials is limited by the inherent ambiguities in the problem. These ambiguities are due to the fact that many materials can share similar sound-absorption characteristics. One way to address this is to leverage information from other modalities. This was done in [7] by using camera images to first detect materials in the room. A Convolutional Neural Network (CNN) detector was first trained and used to initialize a model for the estimation of frequency-dependent absorptions. The estimates were later optimized to match measured AIRs.

Computer-vision methods for solving the problem have adopted state-of-the-art machine learning. This paper aims to bring state-of-the-art machine learning in material-detection from audio only and to address the ambiguities in the process. A method is proposed that estimates the probability of presence of materials in a room. The method accounts for ambiguities by grouping materials in categories based on the level of sound energy they absorb at different frequencies. Furthermore, instead of attempting to calculate numerical values for the coefficients of each of the unknown number of surfaces in the room, the task is treated as a detection task over the finite number categories. The detector model is a Convolutional Recurrent Neural Network (CRNN), which is trained as a multi-task classifier. The training data is created using a priori knowledge about the sound absorption properties of various materials. This knowledge is used to create simulated acoustic environments composed of surfaces with specific materials. AIRs generated from these simulations are presented to the network during training. The network uses information from the reflections encoded in the AIRs to learn how to detect the materials present.

This rest of this paper is organized as follows: Section 2 introduces the notation used to model the interaction of sound with material surfaces and presents the proposed method. The network’s training method, the way that training data is generated and experiments are given in Section 3. A discussion and conclusion are given in Section 4.

2 Method

2.1 Signal Model

Considering the case of a perfectly smooth surface, incident sound of frequency $f$ is reflected specularly, resulting in reduced energy and different phase [3]. The complex factor that represents this process is

$$R(f) = |R(f)| \exp(i\chi),$$

with $\chi$ representing the phase difference between the reflected and incident sound. The energy of the incident sound absorbed at the surface is described by the absorption coefficient

$$\alpha(f) = 1 - |R(f)|^2.$$

This coefficient is dependent on the frequency of the incident sound.

Assuming $\Theta_{\text{tot}}$ material categories, a category $\theta$ is described by the mean of the absorption coefficients of the materials it describes. The coefficients are typically given in 8 1-octave bands for frequencies between 125 Hz and 8 kHz [8]. This gives 8 energy absorption coefficients for each material and material category. Packing these 8 values together forms column vector $a_\theta$. Values for $\Theta_{\text{tot}}$ categories form the matrix of absorption coefficients $A_{\text{tot}} = [a_1, a_2, \ldots, a_{\text{tot}}]^T$, with $0 < a < 1 \forall a \in a \forall \text{a} \in A_{\text{tot}}$.

The detector model proposed in this paper estimates the probability of presence of materials belonging to each category. The matrix of frequency-dependent absorption coefficients of the materials present in an environment is $A$. Using the presence probabilities, the method described in this paper constructs an estimate $\hat{A}$ of this matrix by choosing the appropriate rows of the matrix of known absorptions $A_{\text{tot}}$. The selected rows will correspond to the categories that are detected as present. Therefore, the aim of the detector is to perform the function $d$, described as

$$\hat{A} = d(h, A_{\text{tot}}).$$

Treating this estimation task as a detection task offers a twofold advantage. It simplifies the problem, as the filter coefficients can be drawn from pre-designed material-filterbanks. It also allows for the use of state-of-the-art detector Deep Neural Networks (DNNs) from the literature.
2.2 Material-category detector CRNN

A CRNN model is used as the detector mechanism for the presence of materials in the room. CRNNs have shown great success in the field of Sound Event Detection (SED), as illustrated in the recent DCASE 2019 challenge [9, 10]. In [4], the architecture was also successful in processing AIRs to categorise individual rooms. Their success in SED and in classifying reverberant environments motivates their consideration for the detection of materials in this paper.

As in SED, a CRNN is trained to estimate the probability of occurrence of an event of a certain category. Here, an event is considered to be an acoustic reflection. The way that sound energy is absorbed upon reflection defines the type of event. The CRNN is trained as a multi-task classifier, similarly to the task of polyphonic SED [11]. This means that after processing a single AIR $h$, the DNN returns the posterior probability that absorption of each of the $\Theta_{tot}$ categories occurred. Expressing this in the notation introduced in the previous Section, the network therefore estimates the probabilities

$$p(a_{\theta} \in A|h) \forall \theta \in \{1, \ldots, \Theta_{tot}\}.$$  \hspace{1cm} (4)

To detect whether a material category $\theta$ is present in the environment, a threshold $\zeta_{\theta} = 0.5$ is applied to the posterior.

The diagram in Figure 1 shows the network used as the detector. Its inputs are formed using the Finite Impulse Response (FIR) taps of AIRs. The FIR taps are segmented into frames of duration 3 ms and a 1.5 ms overlap. This provides fine temporal resolution in order to analyze recordings at the reflection level and still a large enough number of samples to maintain significant spectral resolution. The log-power in the discrete frequency domain is presented for each frame at the input, similar to [12].

2.3 Absorption-coefficient data and material clustering

To train the network, a dataset is needed that is labeled with ground truth information about the materials present in the room. Abortion coefficient tables are available in the literature as acousticians use them as a reference for auralisation experiments and in the design of auditoria. The software package Odeon[1] is a modeling software that combines such information with acoustic models to create auralisations. Given the popularity of the software and the fact that a number of manufacturers release their data in a compatible format with it, the data that is available on the software’s

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[1] Software homepage: [https://odeon.dk/](https://odeon.dk/)
Table 1: Partitioning of AIRs into sets for the training and evaluation of the CRNN detector. AIRs are simulated in shoe-box rooms, using known material frequency dependent absorptions.

| Material Category θ | 0  | 1  | 2  | 3  | 4  | 5  | 6  | 7  | 8  | 9  |
|---------------------|----|----|----|----|----|----|----|----|----|----|
| Materials (out of 143) | 20 | 13 | 12 | 15 | 10 | 3  | 44 | 11 | 19 | 16 |
| Positive Test Samples | 3,080 | 1,738 | 1,573 | 1,564 | 1,910 | 507 | 4,696 | 2,011 | 2,495 | 2,497 |

| Baseline SVMs IIR (200,200) Coef. | Precision | 0.77 | 0.42 | 0.38 | 0.38 | 0.64 | 0.24 | 0.93 | 0.63 | 0.65 | 0.63 |
|----------------------------------|-----------|------|------|------|------|------|------|------|------|------|------|
|                                  | Recall    | 0.54 | 0.52 | 0.67 | 0.53 | 0.72 | 0.65 | 0.67 | 0.69 | 0.69 | 0.74 |
|                                  | F1 Score  | 0.64 | 0.46 | 0.48 | 0.44 | 0.68 | 0.35 | 0.78 | 0.66 | 0.67 | 0.68 |

| Proposed CRNN FIR Taps | Precision | 0.98 | 0.95 | 0.97 | 0.97 | 0.98 | 0.98 | 1.00 | 0.99 | 0.99 | 0.97 |
|------------------------|-----------|------|------|------|------|------|------|------|------|------|------|
|                        | Recall    | 0.99 | 0.98 | 0.96 | 0.98 | 0.99 | 0.98 | 1.00 | 0.96 | 0.98 | 0.98 |
|                        | F1 Score  | **0.98** | 0.97 | **0.96** | **0.97** | **0.98** | **0.98** | **1.00** | **0.97** | **0.98** | **0.98** |

Table 2: CRNN material-category detector test performance on 5,288 test AIRs compared to the SVM-IIR baseline. Positive samples for each material category indicate the number of test AIRs that contained at least one surface that falls into the specific category.

As mentioned previously, the proposed method will detect materials in categories. Each category will represent a subset of the 143 materials. k-means \(^{[13]}\) is used for creating categories of materials as clusters. The Davies-Bouldin criterion \(^{[14]}\) and the Variance Ratio Criterion (VRC) \(^{[15]}\) are used to deduce the number of categories. The absorption coefficients of 143 materials in the 8 1-octave bands are clustered by the k-means algorithm for a range of number of clusters between 2–80. The different formulations of the two criteria lead to their optimal values being at opposite extremes. However, the choice of 10 clusters gives a trade-off between the two. Therefore, the 143 materials are grouped into \(\Theta_{\text{tot}} = 10\) categories.

### 3 Experiments

Simulated AIRs are used as the training examples for the detector network of Figure 1. The training AIRs are generated by simulating 141 three-dimensional shoe-box rooms with walls of known frequency-dependent absorptions, using \(^{[16]}\). The size of the simulated rooms is random-uniformly chosen between \([2.5, 2.5, 2.5]\) and \([7.0, 7.0, 2.6]\) m. For each one of the 6 walls of the room, the frequency-dependent absorptions are chosen from one of the 143 materials in the list described in Section 2.1. Each room is populated with 10 sources and 5 receivers at random locations. Collecting the AIR between each source and receiver pair results in 70,500 AIRs. Each one serves as an in individual training example. The sampling rate used is 16 kHz. The 70,500 generated AIRs are split into 3 sets, the training, test and validation set. Each room contributed AIRs to only one set. The data partitioning is shown in Table 1. Stratified partitioning is used which preserves the positive sample ratios.

The detector model is trained using the Adam \(^{[17]}\) optimizer with a cross-entropy loss. The batch size is set to 128 AIRs of duration 200 ms, which are split into frames of 3 ms with 1.5 ms overlap. Overfitting is prevented by early stopping which stops the training of the model 10 epochs after the training loss stopped improving or 15 epochs after the validation loss stopped improving. The final model is selected at the epoch with the minimum validation loss. Since the ratios of positive samples are not even across each of the 10 material categories, the contribution to the cross-entropy loss of each AIR is weighted as proposed in \(^{[18]}\).

As a baseline, a set of SVMs are trained to perform the same task. This compares the use of the proposed end-to-end CRNN for the detection with a feature-based classifier. For this baseline, one SVM is trained per material category to make the binary decision of material presence or not. Training the 10 SVMs using the AIR FIR taps is impractical due to their high dimensionality. To address this, an alternative AIR representation is considered. IIR models offer a parsimonious representation of AIRs \(^{[19]}\) that can capture information regarding resonances and frequency-regions.

\(^{2}\)The list is freely and publicly available in an electronic format at the time of writing this paper here: https://odeon.dk/sites/all/themes/odeon/images/Materials/Material.Li8
of sound absorption in a room. Given their relevance to the task and their low-dimensionality, the coefficients of IIR models of AIRs are then used as the feature-vector inputs to the SVMs. The number of coefficients in the numerator and denominator are 200 each. This choice gave a trade-off between accuracy and training times. Further increasing the number of coefficients did not significantly improve the results but significantly increased training times. The FIR taps of AIRs were used to derive the IIR coefficients using Prony’s method [20]. When training the SVMs, the samples were weighted to counter imbalances and make the comparison fair.

The detection performance of the model and the baseline is measured using the harmonic mean of precision and recall, the $F_1$ score.

The result of evaluating the CRNN based on the above measures is given in Table 2. The $F_1$ score for the network’s predictions is 96% for the worst performing category and 100% for the best. In terms of individual material types, unsurprisingly the best results are obtained for $\theta = 6$, which is the biggest cluster, containing 63.9% of the training examples. The baseline SVM detector models show worst performance across all categories despite taking proportional training times to the CRNN model. Despite the class weighting being applied to both the baseline and the CRNN, the baseline detectors for minority categories show significantly lower $F_1$ scores. The low precision of the SVMs for those categories indicate a high-number of false positives, which make this baseline a far less attractive option when compared to the proposed CRNN.

4 Discussion and conclusion

This paper proposed a novel method for estimating the probability of presence of material categories in a room, based on their sound absorption characteristics. The method takes as input the FIR filter taps of one AIR. It does not assume visual access to the room, which is the case for previously proposed methods [7]. The detection is performed by a CRNN that is trained as a multi-task classifier. In the experiments presented in this paper, the material detector network was tested on more than 5,000 simulated AIRs and 143 materials. The $F_1$ score for the network’s predictions in the tests was 96% for the worst performing category and 100% for the best. The model was compared to a set of SVM detectors, which relied on the IIR representation of AIRs. Comparing this with the proposed CRNN that was inspired by SED, shows that the $F_1$ for the proposed model is on average 40.3% higher. Therefore, allowing a DNN to process short frames of the AIRs and treat reflections as indicators for acoustic events outperforms methods that rely on aggregate representations of the spectrum of the AIR.

The detected material categories allow for the estimation of the frequency-dependent absorption coefficients of the surfaces in an acoustic environment. This is done by simply processing a single AIR measured in the room. This is in contrast to other methods that require the extraction of samples of materials from the environment, such as ISO-354 and ISO-10534. This estimation allows for the reconstruction of the acoustics of a given room [7]. Furthermore, using the estimates, the parametric modeling of AIRs becomes more accurate and improves the estimation of the Times-of-Arrival (ToAs) of acoustic reflections [4]. This leads to a cascade of other applications, such as room geometry estimation [2].

References

[1] I. Dokmanic, Y. Lu, and M. Vetterli, “Can one hear the shape of a room: The 2-D polygonal case,” pp. 321–324, May 2011.

[2] A. H. Moore, M. Brookes, and P. A. Naylor, “Room geometry estimation from a single channel acoustic impulse response,” (Marrakech, Morocco), pp. 1–5, Sept. 2013.

[3] H. Kuttruff, Room Acoustics, Fifth Edition. 2009.

[4] C. Papayiannis, Models for learning reverberant environments. PhD thesis, Imperial College London, 2018.

[5] D. Arteaga, D. Garcia-Garzón, T. Mateos, and J. Usher, “Scene Inference from Audio,” (Rome, Italy), May 2013.

[6] C. L. Christensen, G. Koutsouris, and J. H. Rindel, “Estimating absorption of materials to match room model against existing room using a genetic algorithm,” in Proc. of Forum Acusticum, (Krakow, Poland), pp. 7–12, 2014.

[7] C. Schissler, C. Loftin, and D. Manocha, “Acoustic Classification and Optimization for Multi-Modal Rendering of Real-World Scenes,” IEEE Trans. on Visualization and Computer Graphics, vol. 24, pp. 1246–1259, Mar. 2018.
[8] M. Ermann, *Architectural Acoustics Illustrated*. 2015.

[9] S. Kapka and M. Lewandowski, “Sound source detection, localization and classification using consecutive ensemble of cnns models,” tech. rep., DCASE2019 Challenge, June 2019.

[10] L. Mazzon, M. Yasuda, Y. Koizumi, and N. Harada, “Sound event localization and detection using foa domain spatial augmentation,” tech. rep., DCASE2019 Challenge, June 2019.

[11] F. Vesperini, L. Gabrielli, E. Principi, and S. Squartini, “Polyphonic sound event detection by using capsule neural networks,” *IEEE Journal of Selected Topics in Signal Processing*, vol. 13, pp. 310–322, May 2019.

[12] L. Mazzon, M. Yasuda, Y. Koizumi, and N. Harada, “Sound event localization and detection using foa domain spatial augmentation,” tech. rep., DCASE2019 Challenge, June 2019.

[13] C. Papayannis, J. Amoh, V. Rozgic, S. Sundaram, and C. Wang, “Detecting Media Sound Presence in Acoustic Scenes,” (Hyderabad, India), pp. 1363–1367, Sept. 2018.

[14] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. MIT press, 2016.

[15] D. L. Davies and D. W. Bouldin, “A Cluster Separation Measure,” vol. PAMI-1, pp. 224–227, Apr. 1979.

[16] T. Caliński and J. Harabasz, “A dendrite method for cluster analysis,” *CISTM*, vol. 3, no. 1, pp. 1–27, 1974.

[17] A. Wabnitz, N. Epain, C. Jin, and A. van Schaik, “Room acoustics simulation for multichannel microphone arrays,” in *Proceedings of the Intl. Symp. on Room Acoustics*, 2010.

[18] D. P. Kingma and J. Ba, “Adam: A Method for Stochastic Optimization,” vol. abs/1412.6980, 2014.

[19] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, “Scikit-learn: Machine Learning in Python,” *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.

[20] M. Karjalainen, P. A. A. Esquef, P. Antsalo, A. Mäkivirta, and V. Välimäki, “Frequency-Zooming ARMA Modeling of Resonant and Reverberant Systems,” vol. 50, pp. 1012–1029, Dec. 2002.

[21] T. W. Parks and C. S. Burrus, *Digital Filter Design*. Wiley, 1987.