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Algorithmic Methods for Calibrating Material Absorption Within Geometric Acoustic Modeling

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ABSTRACT

In room acoustic modeling, digital geometric room models are commonly created to aid acousticians in auditioning different possible changes that could be made to a room. It is critically important to have the mathematical parameters and final auralization of the space match, so acousticians can know with confidence changes made in the simulation will translate to the room itself. Traditionally, acousticians have been required to laboriously adjust acoustic and scattering coefficients of planes in the room model in order to align various measured metrics like reverb time (T30) and speech clarity (C50) to predicted ones. This express paper presents an alternative procedure where a heuristic algorithm is used to automate the acoustic calibration process. In addition, this paper showcases how a statistical database that includes mean and standard deviation measurements for acoustic coefficients can be implemented to account for material density deviation.

1 Introduction

In room acoustic modeling, geometric acoustic (GA) room models are commonly used to aid acousticians. GA models do not account for the full acoustic wave equation but allow fast computational simulations of sound in large rooms and performance spaces within certain assumptions [1]. It is critically important to have the parameters of the room and simulation match to assure physical realism within the model, as such models can easily deviate from the measured sound field in a space. Traditionally, acousticians manually adjust absorption coefficients of planes in the model to align simulated parameters, such as reverberation time (T30) or speech clarity (C50), with values measured from the real room. One of the largest setbacks to this method of manual calibration is the time-consuming process of adjusting the absorption coefficients of planes in the model. The acoustician has to ensure absorption coefficients stay within a reasonable range while simultaneously deciding which planes to adjust, depending on their size and proximity to relevant source and receiver positions. Some background on calibration techniques is provided, as well as a new software-based approach to automate the heuristic modeling process, which can aid an acoustician in the calibration process.

2 Background

2.1 Calibration of GA Models

GA simulations, including the Image-Source Method [2] and Ray Tracing [3], model sound as a specular reflective wavefront whose wavelength is small compared to interacting materials [4]. Though these models are theoretically sound within their assumptions, models alone can lead to deviations from real-world acoustic environments [5].

As a result of these possible errors, many studies have focused on the need for empirical calibration for increased accuracy in GA models of real-world acoustic spaces [6-8]. Early work in this area stressed the calibration of global parameters (like T30) followed by more directional acoustical energy ratios (like C50), in an iterative loop to continue improving the simulation within realistic physical constraints. Since then, work by Postma, Dubouilh, and Katz [9, 10] has established a more rigorous 6-step heuristic process to account for specular vs. scattered reflections and minimize potential sources of error within a GA calibration. For large spaces with many surfaces, the iterative calibration requires many rounds to achieve acoustic parameters with 1-2 Just-Noticeable Differences (JNDs) of measured values [11, 12].

2.2 Existing Auto-Calibration Techniques

The time-consuming nature of such hand-calibration has motivated the search for software tools to automate this process. The most developed such tool uses a Genetic Algorithm machine learning approach to map a solution space to the complex interdimensional problem posed by large spaces with many different acoustic materials. This work, by Christiansen et al. [13] has been developed into a calibration tool within the popular GA software Odeon and has already been used in major acoustic simulation projects [14]. Other work by Pilch similarly maps the solution space and applies other optimization algorithms to improve computational runtime [15].

Though such machine learning approaches undoubtedly have much promise for future simulations, they suffer (as many ML applications do) from the "black-box" nature of their solution: if GA models ran the risk of acousticians just plugging in values and hoping for the best, attaching ML calibration to such models exacerbates this risk even further. If such a model were to violate physical realism (by overfitting to measured data or going beyond reasonable acoustic values for a specific surface) the acoustician would likely never notice, as the human element has been largely removed from the loop. Given this danger it is worth considering whether alternative software approaches to auto-calibration could include the human in calibration process while handling some of the "busy work" inherent in multiple iterations of the simulation.

3 Methods

3.1 Toolchain

The heuristic auto-calibration procedure is being implemented in Python 3.10.2 via the Pyroomacoustics library [17]. This package contains a computationally efficient C++ implementation of the Image-Source Method, which provides the speed necessary to efficiently generate and compare room impulse responses. The current implementation of the calibration runs in linear time complexity and is dependent on the distance between the measured and expected JND's. The Pyroomacoustics ISM model is being implemented using a maximum order of five first reflections at a sample rate of 8000Hz on an M1 Max MacBook Pro with 32 gigabytes of RAM. The implementation uses NumPy and Matplotlib respectively for numerical calculation and visualization of the 3D room model [20-21].

3.2 Procedure

In order to recursively calibrate the room's predicted metrics to measured ones, two composite JND parameters are created representing the Just-Noticeable Difference between measured and expected T30 and C50 values. The base cases for T30 and C50 measurements used in the algorithm's control flow are in alignment with perceptual benchmarks discussed by Christensen, Koutsouris and Rindel (5% for T30, 1 dB for C50) [13]. Initially, 2D wall positions are defined as a list of Cartesian coordinate pairs representing plane dimensions for the room which undergo a linear extrusion process similar to CAD software [16]. Source and receiver positions are defined in 3D space once the model has been extruded.

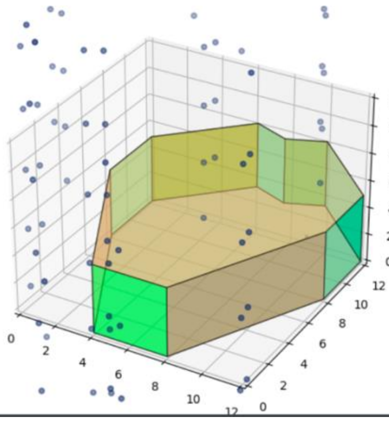

Fig. 1: Geometric model of an example room used for algorithm testing.

Once extrusion has been performed, initial multiband absorption coefficients are assigned per wall ID for every plane in the model. Unlike previous auto-calibration algorithms that have used percentages to limit their search spaces [13], this heuristic algorithm is proposed to be used in conjunction with an aggregated material database that includes mean and standard deviation measurements for each octave frequency band. Instead of the acoustician having to determine the bounds of the algorithm, a dataset with measured variance could be used, allowing for absorption coefficient deviation to be empirically derived as opposed to being estimated by the acoustician. Currently, a prototype database that includes variance for a single material is being implemented in the current algorithm.

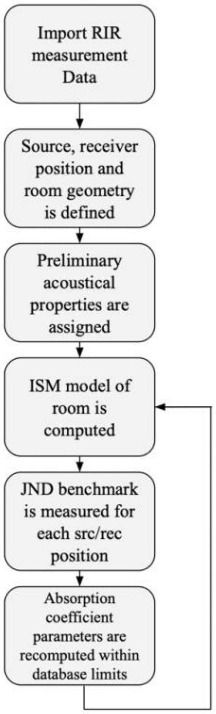

Fig. 2: Diagram showing the heuristic algorithm's control flow.

Since speech clarity and reverberation time are inversely correlated, global T30 calibration is computed first in the calibration procedure, and then C50 is optimized for a single source-receiver combination. Acoustic coefficients of all planes are either incremented or decremented until the JND target is reached. For C50, a plane prioritization algorithm is used which calculates the relative importance of planes in the model based on source/receiver distance and the area of the plane. This process is accomplished by calculating the perpendicular distances to each wall for every source/receiver and then setting them proportionally to the area of the current wall index.

For a given surface *n* the priority score relative to a position in the room is given by:

$$\boldsymbol{P_n} = \frac{s_n}{r_n} \tag{1}$$

where S_n is the surface area for surface *n* and r_n is its perpendicular distance to the source or receiver position being considered. As surfaces close to either the point or receiver tend to be important for local acoustic parameters like C50, two rankings are computed for each source-receiver combination: one ranking of near/large surfaces to the source, and another for near/large surfaces to the receiver.

4 Results

In order to test the control flow of the algorithm, test scenarios were generated that forced different calibration tasks (e.g. recursively edit T30 once C50 had been calibrated). For testing, a room with the geometry of **Fig. 1** was generated and acoustic coefficients were assigned based on the JCW Absorption Coefficient table [19], representing a room with a plasterboard ceiling, concrete floor, and plaster walls. Initially when calibrating, material variance was disabled.

Material	125	250	500	100	2000	4000
Walls	0.01	0.02	0.02	0.03	0.04	0.05
Floor	0.01	0.01	0.02	0.02	0.02	0.02
Ceiling	0.15	0.11	0.04	0.04	0.07	0.08

Fig. 3: Initial absorption coefficients of the room.

The robustness of the algorithm was tested with target T30 and C50 values of 0.18 and 0.6. It is important to note that these initial parameters do not reflect realistic amounts of material density deviation. During calibration, 81 total adjustments were executed until the JND thresholds were reached. The total calibration process was executed in just under 9.5 seconds.

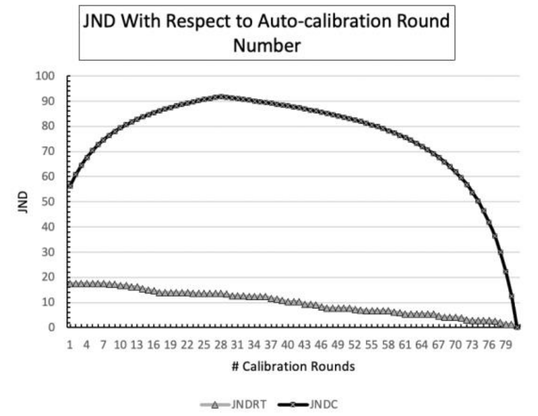

Fig. 4: JNDRT and JNDC50 values with respect to calibration round number

After calibration, the following absorption coefficients were recorded:

Material	125	250	500	100	2000	4000
Walls	0.27	0.28	0.28	0.29	0.4	0.31
Floor	0.81	0.81	0.82	0.82	0.82	0.82
Ceiling	0.95	0.91	0.84	0.84	0.87	0.88

Fig. 3: Absorption coefficients of the room after autocalibration.

It is clearly seen that the algorithm provides a satisfactory solution that aligns to perceptual JND metrics, however the material density deviation expressed in **Fig. 3** is unrealistic. Successful implementation of the programmatic concepts behind the material deviation management have been tested, however the values themselves are arbitrary. To fully test the extent to which this heuristic process can calibrate including material density, more research needs to be performed to reach non-arbitrary material deviation measurements that can be applied to the testing scenario.

5 Conclusions

Overall, this express paper presents a different methodology and procedure to calibrate GA models based on algorithmically simulating plane prioritization and global RT adjustment steps done by an acoustician. Its intended use is to replace the traditionally laborious process of manual acoustic calibration through aligning reverb time (T30) and speech clarity (C50). In addition, this paper describes how a statistical database that includes mean and standard deviation measurements for acoustic coefficients is implemented to act as lower and upper limits for material density deviation within the model.

5 Future Work

Significant work needs to be done to further parameterize the relationship between area, distance and other highly significant parameters that further help isolate the highly correlated T30 and C50 measurements. As expressed in other auto-calibration projects [13], it is crucially important to manage the range of coefficient possibilities that each material can deviate from during calibration in order to present realistic solutions. Although it is more time consuming, more scenario testing using real spaces is needed to test the limitations of the program. Included in more real-world testing is the development of the materials database which could be used during testing to ensure physically realistic solution generation. Furthermore, the example database structure can be developed to not only be used as a calibration reference for this algorithm, but for others, including the aforementioned genetic and other meta-heuristic algorithms [13, 15]. This would allow absorption coefficient deviation to be empirically derived as opposed to being estimated by the acoustician.

Algorithm optimization should also be done to improve the increment/decrement step. Currently a linear step algorithm is being used however a predictive algorithm or more advanced control flow algorithm like a PID algorithm would be more optimal for runtime [18].

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