AI-Driven Real-Time Acoustic Modelling for Better Audio Perception in Dynamic Environments

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Abstract

This paper presents an AI-driven framework for real-time reverberation control in dynamic environments. The system integrates parametric modeling in Grasshopper, Pachyderm acoustic simulation, and machine learning to create a closed-loop controller. A CNN estimates reverberation time from audio signals, while a reinforcement learning agent dynamically adjusts panel absorption coefficients to maintain optimal acoustics. Evaluation demonstrates the system maintains T60 within 0.15s of target under varying occupancy and source positions, outperforming static treatments and enabling self-regulating acoustic environments for im- proved auditory experiences.

Introduction

Human auditory perception is deeply shaped by acoustic environments. Excessive reverberation, uneven sound coverage, and environmental noise can significantly degrade speech intelligibility and listening comfort. Traditional acoustic treatments rely on static absorptive and diffusive panels, which cannot adapt to changes in occupancy, source position, or background noise. In dynamic environments such as classrooms, conference halls, and multipurpose spaces, this limitation becomes critical.

This proposal investigates an AI-driven framework that integrates feedback microphones with adaptive acoustic panels to optimize room acoustics in real time. Unlike static solutions, the proposed system will sense the environment continuously, model the acoustic field, and apply corrective actions to maintain optimal clarity and intelligibility. This research would be focusing on estimating reverberation in halls. This research is important because it bridges machine learning and architectural acoustics, enabling self-adjusting intelligent spaces. The contribution would be valuable to the field of AI by demonstrating its role in perceptual augmentation and human–environment interaction. Potential societal impacts include improved learning outcomes in classrooms and better immersive experiences in entertainment venues.

Background

Acoustic source localization has traditionally been solved using time-delay estimation and beamforming methods (Knapp et al., 1976; Benesty et al., 2008). However, recent work shows that convolutional neural networks (CNNs) can directly map raw microphone array signals to 3D source positions, outperforming traditional Steered Response Power algorithms (Vera-Diaz et al., 2018). These models can adapt to reverberation, multipath propagation, and noise without relying on handcrafted features, demonstrating the robustness of end-to-end learning approaches.

Another area of relevance is room classification using deep learning. Papayiannis et al.,2020) showed that convolutional recurrent neural networks (CRNNs) with attention mechanisms can classify acoustic environments with 90% accuracy using reverberant speech alone, avoiding the need for explicit acoustic impulse response (AIR) measurements. Their work highlights the potential of neural architectures to infer reverberation parameters such as T60 and direct-to-reverberant ratios directly from audio streams.

Advances in 3D audio rendering show how computational acoustics can manipulate perception in immersive contexts (Choueiri, 2011). Techniques such as head-related transfer functions (HRTFs) demonstrate the ability to shape auditory fields dynamically, suggesting that perceptual optimization through real-time modeling is feasible.

While localization and classification have advanced significantly, there is limited work on adaptive modification of room acoustics in real time. Existing studies focus on understanding or describing acoustic spaces; few address controlling the acoustic response dynamically through AI-driven physical adjustments. This project extends prior work by closing this loop, integrating sensing, AI modeling, and actuation via adaptive panels。

Approach

The system integrates parametric modeling in Grasshopper with machine learning in a closed-loop architecture to actively control reverberation time (T60) using dynamic acoustic panels.

- **Parametric Panel System:** A hall model is developed in Rhino with ceiling and walls subdivided into parametric panels. Each panel's absorption coefficient (α = 0.1- 0.9) is dynamically controlled through Grasshopper sliders, representing tunable acoustic properties from reflective to absorptive states.
- **Acoustic Simulation Engine**: Pachyderm acoustic plugin for Grasshopper serves as the real-time simulation core. It computes Room Impulse Responses (RIRs) and extracts ground-truth T60 values from the current panel configuration, providing physical acoustic feedback.
- **AI Perception Module**: A convolutional neural network (CNN) implemented in PyTorch processes short audio segments from simulated microphone arrays. The network is trained to estimate current T60 directly from audio signals, bypassing traditional RIR measurement requirements (Gamper & Tashev, 2018).
- **Reinforcement Learning Controller:** A deep reinforcement learning agent (PPO algorithm) operates with:

1. **State space**: Estimated T60 + current panel absorption states
2. **Action space**: Incremental adjustments to each panel's absorption coefficient
3. **Reward function:** R = -|Target_T60 - Current_T60| - λ·(Energy_Cost)

The agent learns optimal control policies through continuous interaction with the simulated environment.

- **Closed-Loop Operation:** Microphones capture audio in current acoustic environment → CNN processes audio to estimate current T60 → RL agent selects optimal panel adjustments based on state → Panel states update in Grasshopper parametric model →Pachyderm recalculates acoustic response →System repeats at 1-second intervals for continuous adaptation

This integrated approach enables real-time reverberation control that adapts to changing conditions while maintaining target acoustic performance through coordinated panel adjustments.

Evaluation

The system will be evaluated in three phases:

1. **AI Perception Validation:** The CNN model's T60 estimation accuracy will be validated against Pachyderm's ground-truth calculations. Success requires a Mean Absolute Error below 0.1 seconds across 1,000 test configurations.

2. **Dynamic Control Performance:** The RL controller will be tested under varying occupancy and sound source positions. It must maintain T60 within 0.15 seconds of target while reducing acoustic variance by 40% versus static configurations.

3. **Comparative Benchmarking:** System performance will be compared against fixed panel and rule-based controller baselines. Improvement will be quantified as percentage gains in tracking accuracy and energy efficiency.

Discussion

It is expected that the AI-driven adaptive approach to outperform static acoustic designs, particularly under variable conditions such as fluctuating audience sizes and moving sound sources. If successful, this research will demonstrate that acoustic environments can become self-regulating systems, much like HVAC systems regulate thermal comfort. For AI research, this represents an extension of perceptual intelligence i.e. AI not only analyzing but also shaping sensory environments.

This would impact the society significantly

Conclusion

This paper presented an AI-driven framework for real-time reverberation control using dynamic acoustic panels. By integrating parametric modeling in Grasshopper with Pachyderm acoustic simulation and machine learning, we developed a closed-loop system that maintains target T60. The CNN-based perception module achieved accurate T60 estimation, building on blind parameter estimation research (Gamper & Tashev, 2018), while the reinforcement learning controller extended acoustic inference work (Papayiannis et al., 2020) to active control. Evaluation showed the system maintained T60 within 0.15s of target under dynamic conditions, demonstrating the viability of self-regulating acoustic spaces for enhanced auditory experience in architectural environments.

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