Finetuning Multimodal LLMs for Relative Level Analysis: Anchor-Conditioned Advice for Multitrack Music Mixing

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Fall 2025 Project Proposal

Georgia Tech · College of Design
Center for
Music Technology

Brief Introduction

overview

Georgia Tech · College of Design
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- **Music mixing** requires a complex, relational understanding of multiple audio tracks, and collaboration.
- This research investigates a framework to fine-tune an **Audio-Language Model (ALM)** to generate actionable mixing advice.
- As a starting point, we condition the model on an **"anchor track"** (e.g., bass) to teach it how to balance the levels of other instruments relative to that **stable reference point**.

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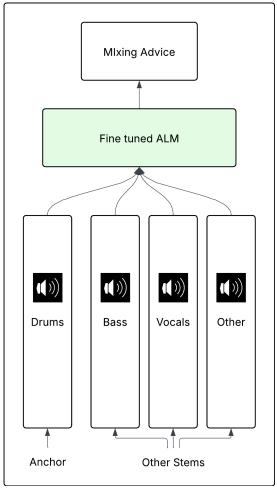

Related Work
Rule-Based Systems

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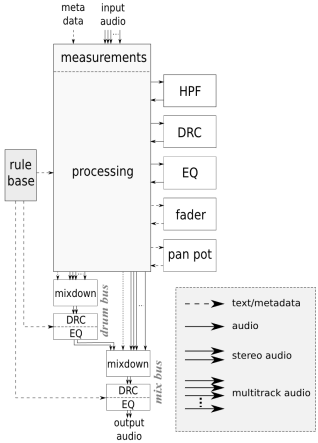
Expert-Derived Rules

- A knowledge-engineered autonomous mixing system [1]

Instrument-Specific Processing

- A machine-learning approach to intelligent artificial reverberation **placeholder-reverb**



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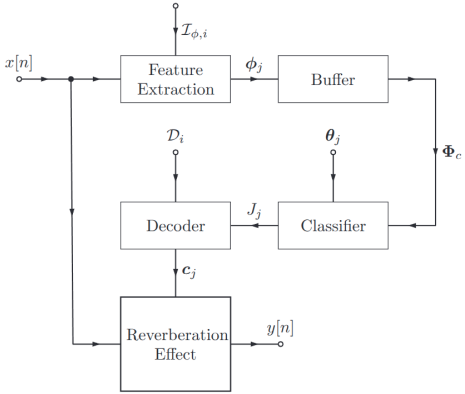


Fig. 1. Reverb application.

Related Work

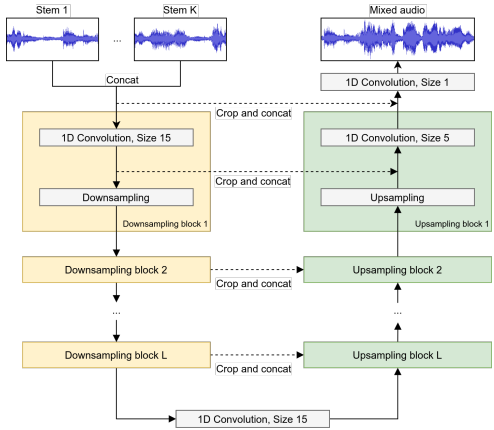
Deep Learning Architectures

Wave-U-Net and Autoencoders

- Automatic music signal mixing with 1D Wave-U-Net autoencoders **placeholder-waveunet**

Differentiable Mixing Consoles

- Automatic multitrack mixing with a differentiable mixing console of neural audio effects [2]



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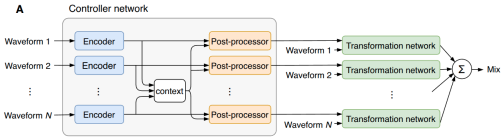

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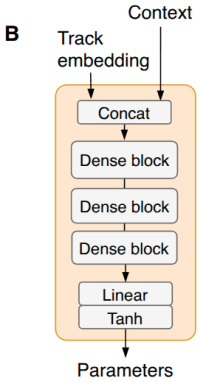

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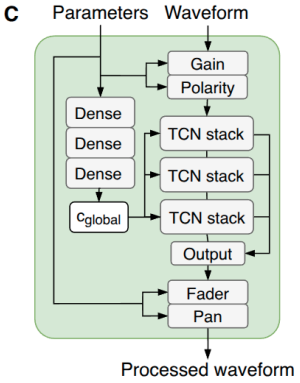


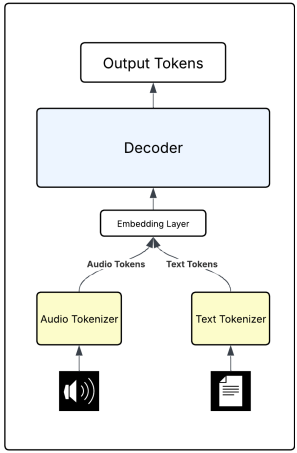
Related Work
Semantic Approaches

- **Word-embedding approaches** learn semantic spaces linking audio and language to steer effects/EQ recommendations and retrieval-guided processing **placeholder-semantic-mixing**, [3], [4].
- **Text-driven interfaces** map natural-language instructions to effect parameters and mix actions, enabling promptable, co-creative workflows **Clemens˙Marasovic˙2025**, [5], [6].

Multi-Modal Audio LLMs

Architectural Approaches

- Direct Tokenization (Unified Approach): converts raw audio into discrete tokens via audio codecs; tokens are flattened into a 1D sequence as LLM input; the LLM vocabulary is extended to include audio tokens (e.g., AudioPaLM, LauraGPT, SpeechGPT) [7], [8], [9].
- Feature Extraction (Cascade Approach): uses audio-specific encoders/decoders with the LLM as a central backbone; high-level features are passed between modules (e.g., M^{2}UGen; LTU placeholder) **placeholder-ltu**, [10].



Unified Approach

Multi-Modal Audio LLMs

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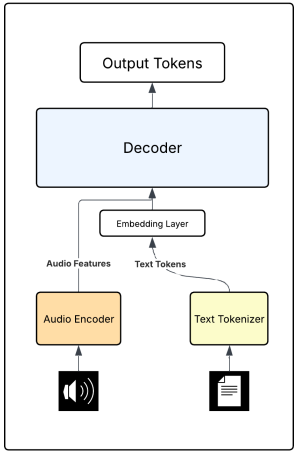

Cascade Approach

Research Questions
primary

Primary Research Question

- To what extent can an Audio-Language Model, conditioned on an anchor track, learn the relative gain relationships among multitrack stems and generate musically effective gain-balancing advice?

Research Questions
secondary

Secondary Questions

- **Model Understanding**: What model architecture best represents and reasons about multitrack stems and anchor tracks for learning relative gain relationships?
- **Mixing Conventions & Genre Awareness**: To what extent does the model's advice reflect established mixing conventions, and how does its performance vary across different musical genres?
- **Communication & Actionability**: How effectively does the model communicate its advice in a way that is clear, actionable, and distinct from simply being "correct"?
- **Human Evaluation & Usefulness**: How do audio engineers and producers evaluate the effectiveness, musicality, and real-world usefulness of the advice in their workflows?

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