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

- **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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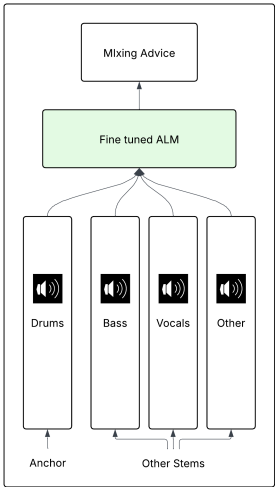

Related Work

Rule-Based & Deep Learning Approaches

Georgia Tech · College of Design
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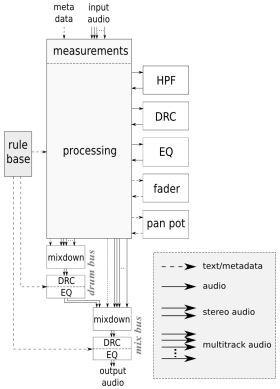
Rule-Based and Traditional Machine Learning Systems

- Knowledge-engineered autonomous mixing [1]
- A machine-learning approach for instrument-specific application of artificial reverberation. **placeholder-reverb**

Deep Learning Architectures

- Wave-U-Net autoencoders for automatic mixing **placeholder-waveunet**
- Differentiable mixing console with neural effects [2]



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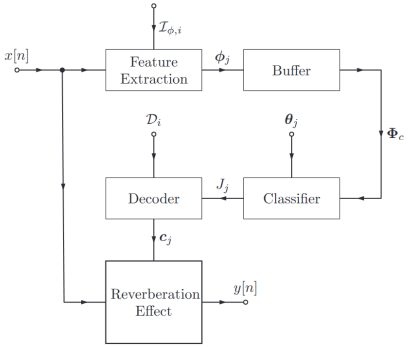

Fig. 1. Reverb application.

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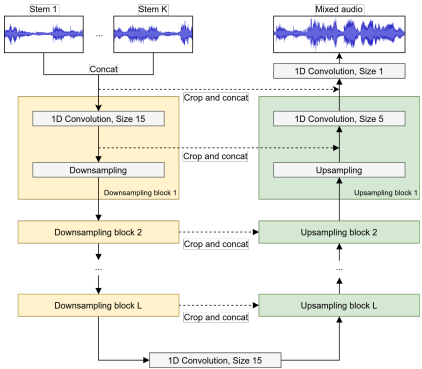

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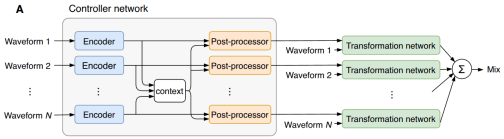

Related Work
Semantic Approaches

Language-Audio Integration

- Word-embedding approaches linking audio and language for effects/EQ recommendations **placeholder-semantic-mixing**, [3], [4]
- Text-driven interfaces mapping natural language to effect parameters and mix actions **Clemens˙Marasovic˙2025**, [5], [6]

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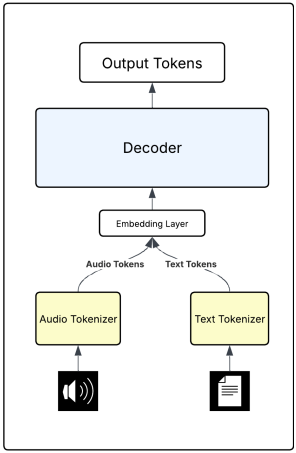
Multi-Modal LLMs

Architectural Approaches for Audio-Language Models

- 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 LLMs

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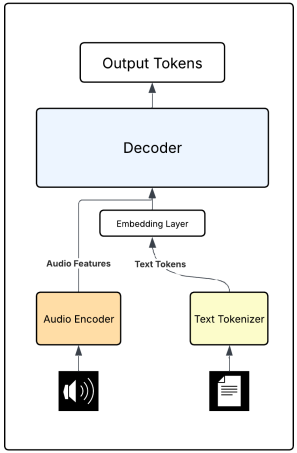

Cascade Approach

Multi-Modal LLMs

The Roles of LLMs in Audio Language Models

- **LLM as Backbone**: The LLM acts as the core processing engine, unifying audio and text into a single model [7], [8], [9].
- **LLM as Conditioner**: The LLM converts text instructions into embeddings to guide audio generation models **placeholder-musicgen**, **placeholder-tango**.
- **LLM as Agent**: The LLM acts as an intelligent controller, orchestrating multiple specialized AI tools to execute complex audio tasks **placeholder-audiogpt**, **placeholder-wavjourney**, **placeholder-musicagent**.

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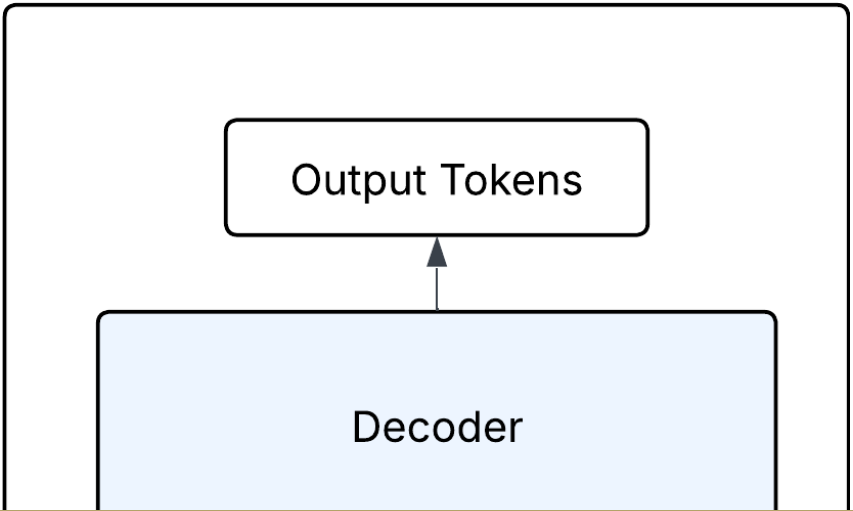
Proposed Method

- **Multimodal LLM Architecture**
  - Audio encoder for multitrack analysis
  - Text encoder for natural language instructions
  - Cross-modal attention mechanisms
- **Anchor-Conditioned Training**
  - Reference track conditioning
  - Relative level prediction
  - Context-aware mixing advice
- **Training Data**
  - Professional mixing examples
  - Synthetic multitrack datasets
  - Expert annotations and feedback

Proposed Method

Architecture Overview



Proposed Method

Key Components

Audio Processing

- Multitrack feature extraction
- Temporal context modeling
- Spectral analysis

Integration

- Cross-modal attention mechanisms
- Joint representation learning
- Contextual advice generation

Text Processing

- Natural language understanding
- Mixing terminology mapping
- Instruction parsing

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?
- **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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Evaluation
Human Evaluation

Study with Semi-Professional Audio Engineers

- **Participants**: Semi-professional audio engineers and producers
- **Evaluation Criteria**:
  - **Effectiveness**: How well does the advice address the mixing challenge?
  - **Actionability**: How clear and implementable is the advice?
  - **Adherence to Conventions**: How well does the advice follow established mixing practices?
- **Methodology**: Rating scales and qualitative feedback collection

Evaluation

Automated Evaluation

Complementary Metrics to Human Ratings

- **LLM-as-a-Judge**: Using language models to evaluate the quality and relevance of generated advice
- **Semantic Similarity**: Measuring similarity between generated advice and expert annotations
- **Gain Advice Accuracy**: Evaluating the direction and magnitude of gain recommendations
  - Direction accuracy: Does the model suggest increasing or decreasing levels correctly?
  - Magnitude accuracy: How close are the suggested gain changes to optimal values?

Evaluation

Evaluation Framework

Human Evaluation

- Real-world applicability
- Professional judgment
- Workflow integration

Automated Evaluation

- Scalable assessment
- Objective metrics
- Reproducible results

Combined Approach: Human evaluation provides ground truth for real-world effectiveness, while automated metrics enable systematic model comparison and iteration.

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