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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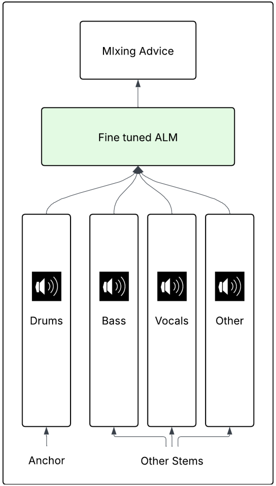
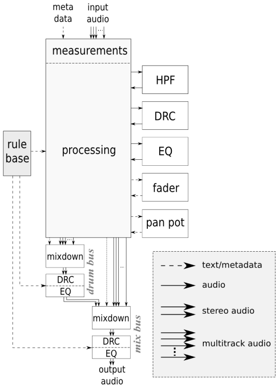


Automatic Mixing Review

Rule-Based & Deep Learning Approaches

Rule-Based and Traditional Machine Learning Systems

- Knowledge-engineered autonomous mixing [1]
- A machine-learning approach for instrument-specific application of artificial reverberation. [2]



Deep Learning Architectures

- Wave-U-Net autoencoders for automatic mixing [3]
- Differentiable mixing console with neural effects [4]

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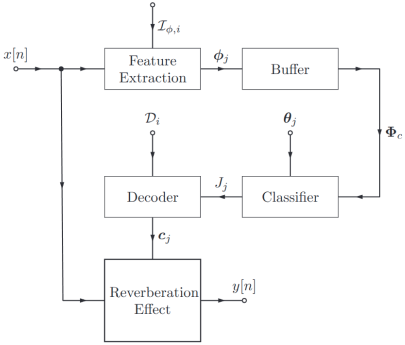

Fig. 1. Reverb application.

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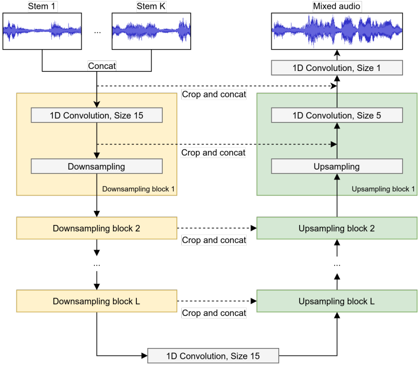

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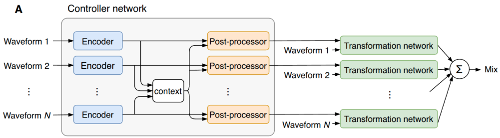

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Semantic Approaches

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Language-Audio Integration

- Word-embedding approaches linking audio and language for effects/EQ recommendations [5], [6], [7]
- Text-driven interfaces mapping natural language to effect parameters and mix actions [8], [9], [10]

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Architectural Approaches for Audio-Language Models

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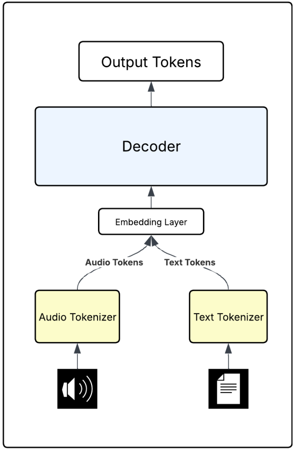
- **Direct Tokenization (Unified Approach)**: converts raw audio into discrete tokens via audio codecs; tokens are flattened into a 1D sequence as LLM input; the LLM vocabulary is extended to include audio tokens [11], [12], [13].
- **Feature Extraction (Cascade Approach)**: uses audio-specific encoders/decoders with the LLM as a central backbone; high-level features are passed between modules (e.g., M^2UGen) [14], [15].



Unified Approach

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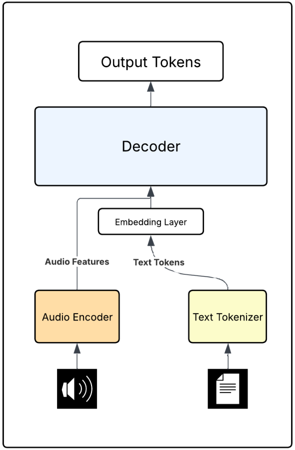

Cascade Approach

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The Roles of LLMs in Audio Language Models

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- **LLM as Backbone**: The LLM acts as the core processing engine, unifying audio and text into a single model [11], [12], [13].
- **LLM as Conditioner**: The LLM converts text instructions into embeddings to guide audio generation models [16].
- **LLM as Agent**: The LLM acts as an intelligent controller, orchestrating multiple specialized AI tools to execute complex audio tasks [17], [18], [19].

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Research Questions

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- 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**?

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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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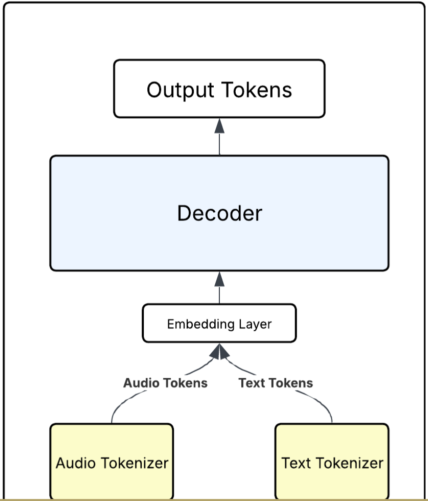
Proposed Method
Overview

- **Base Model**: A pretrained Audio LLM like Qwen-Audio [20] as the base model.
- **Dataset**: A multitrack dataset like MUSDB18 [21] for synthesizing the prompt-response pairs.
- **Input**: Anchor track and the rest of the tracks.
- **Output**: A structured response containing advice for the user to balance the levels of the tracks.
- **Architecture**: Cascade approach, with the LLM as the backbone.
- **Training strategy**: LoRA [22] or QLoRA [23] to fine-tune the model.



Proposed Method
Dataset Synthesis

- **Per-Sample Prompt**: We will have 4 categories of per-sample prompts:
  - **Audio-only prompts**: Response will default to giving advice.
  - **Incorrect description prompts**: Response will correct the description in addition to the advice.
  - **Advice-seeking prompts**: Response will be only advice.
  - **Correct description prompts**: Response will confirm the description in addition to the advice.
- **Audio**:
  - Chunk the song into 10-second segments.
  - Inject an error of $\pm n$ dB on the non-anchor track.
- **Response Formulation**: We will programmitically create structured responses.
  - We will first pick a template based on the prompt, containing both description and solution placeholders.
  - We populate the placeholders with the description and solution.

Evaluation Framework

Human Evaluation

- **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 Framework

Automated Evaluation

- **LLM-as-a-Judge**: Use LLMs to rate advice quality and relevance
- **Semantic Similarity**: Compare advice to expert annotations
- **Gain Advice Accuracy**:
  - Direction accuracy: Increase vs. decrease correctness
  - Magnitude accuracy: Proximity of suggested dB changes to optimal

- picture here

Limitations

- **Focus on Gain Only**: The model's scope is limited to gain-balancing advice; it does not address other effects like EQ, compression, or spatial effects.
- **Advisory, Not Prescriptive**: Evaluation focuses on the usefulness of the textual advice, not the numeric accuracy of specific gain predictions.
- **Dataset Dependency**: The project relies on the MUSDB18 dataset for valid "ground truth" for professional mixes.

Timeline

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Tasks Leading to Nov. 28th Submission

- ~~Dataset preprocessing and JSONL format conversion.~~
- ~~Initial codebase and data loading pipeline setup.~~
- ~~Partial fine-tuning experiments and architecture testing.~~
- Finalize and execute all remaining experiments.
- Submit and obtain IRB approval for human studies.
- Conduct the human evaluation study with audio professionals.
- Complete the final paper, web interface, and Hugging Face deployment.

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