A Demand-Driven Perspective on Generative Audio AI

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We asked real users of audio gen AI.
We defined the task, challenges, and proposed solutions.

To foster deployable research on audio gen AI,

- Insights for **industry-side demands** from a survey with individuals in the movie sound production
- Summary of related **challenges** and a **proposal** on potential solutions

are presented in this poster.

Link for Full Paper

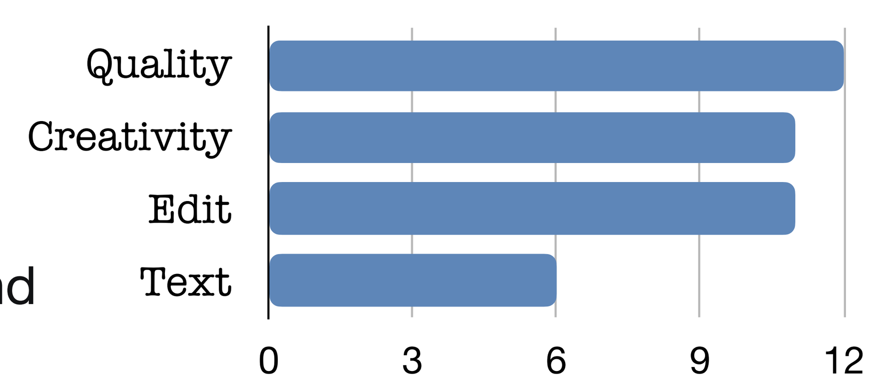
Motivations

- While essential, creating foley effects lacks reproducibility, scalability, and reusability, and the advent of audio gen AI offers a promising solution to these problems.
- We want to encourage more industry-oriented research and bridge the gap between industry and the research community.

Insights from the survey

- **What are the challenges faced in foley recording?**
  - The biggest challenge is **time synchronization** with the corresponding visual contents.
  - **Consistency in tone** with other sources or synchronous recordings is also a big challenge.
- **What is the (expected) limitation(s) of the current text-conditioned audio generation as a product?**
  - Before the questionnaire, we presented a demo page for AudioLDM, a state-of-the-art system for audio gen AI.
  - Most of the concerns are about the **sound quality**.
  - Other concerns include **controllability for detail** and a **lack of creativity or art**.

Figure 1. Bar chart for Question 2. ***Edit*** indicates 'detailed audio editing.' And ***Text*** refers to 'audio-text alignment.'



- **How would you like to condition the audio generation?**
  - First: **Video**, as they are in movie sound production.
  - Second: **Reference audio**, an example of audio excerpts to offer desired tone or mood.

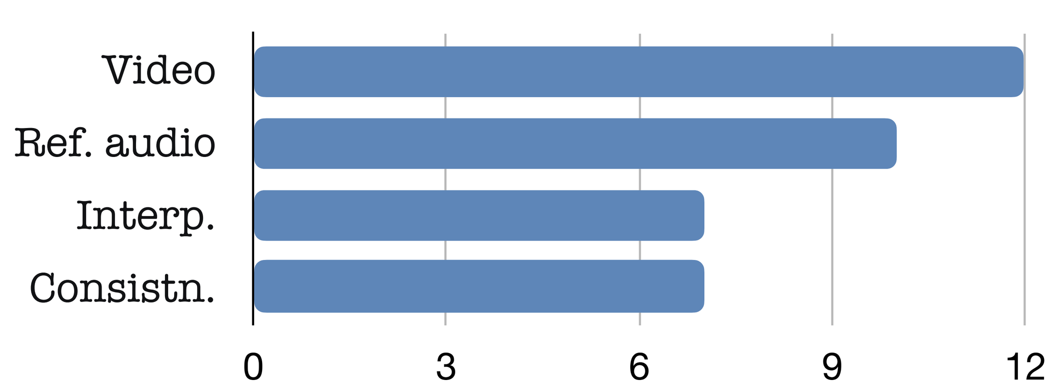


Figure 2. Bar chart for Question 3. ***Interp.*** Refers to 'interpolation,' and ***Consistn.*** is to 'consistency with other sources.'

Challenges and Solutions

- **Dataset improvement for audio quality**
  - Data scarcity deteriorates the model training and resulting audio quality.
    - There are **fewer datasets** compared to image datasets.
    - Most of the datasets suffer from **noise and interference** signals.
    - Audio datasets are often **weak-labeled**. Their labels often lack temporal information about the event.
  - Proposed ***quality-aware training (QAT)*** provides a remedy for these problems.
    - The model is trained with an additional label for dataset quality and can control cleanness in the inference phase.

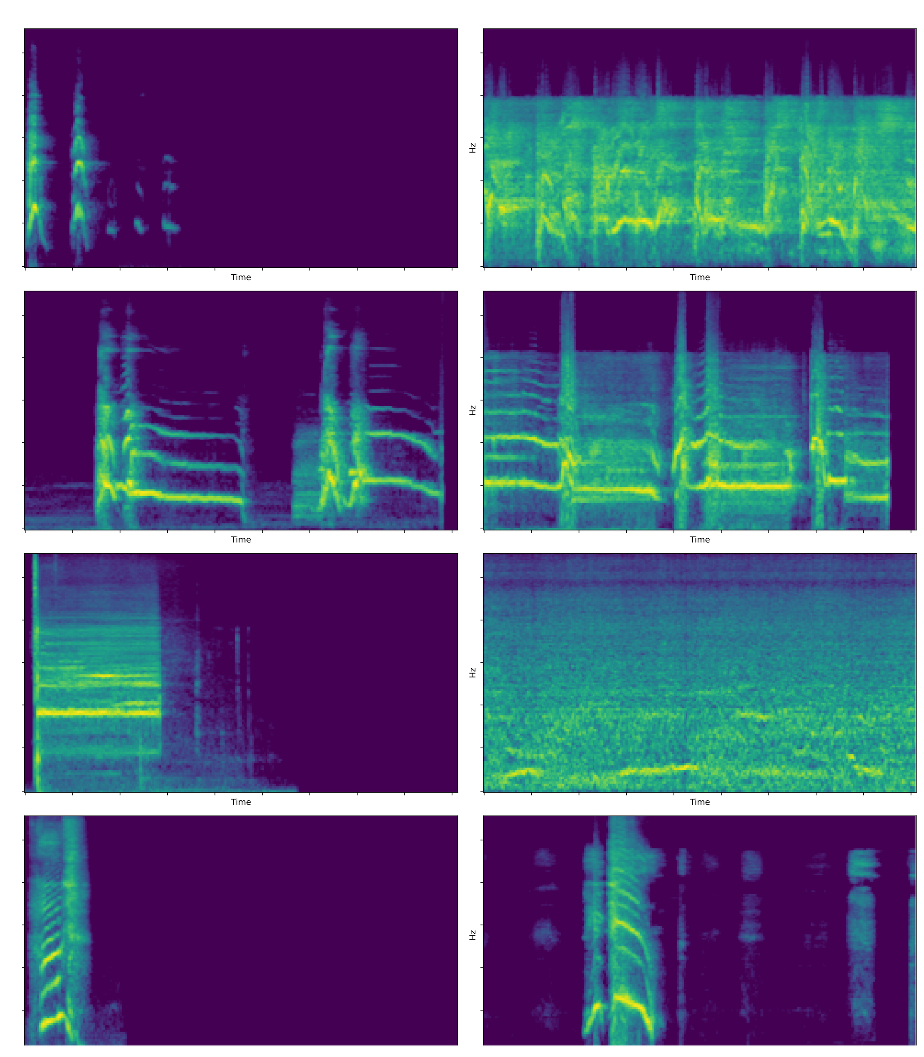


Figure 3. Spectrograms of generated audio samples. (*left*) samples with 'clean' embedding, and (*right*) samples with 'noisy' embedding.

- **Methodological improvement for audio quality**
  - Controllability is another major concern in our survey, and it is crucial to deliver sound engineers' intent
  - Classifier-free guidance is a widely adopted solution across diffusion-based and transformer-based models.
  - Research for various exemplar-based audio generation is required. We plan to explore this direction as our future direction.