Do Joint Language-Audio Embeddings Encode Perceptual Timbre Semantics?

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Overview

- Joint language–audio models are widely used for retrieval, captioning, and text-guided audio generation.
- Unclear whether these models encode **perceptual timbre semantics** (e.g., bright, rough).
- We evaluate three embedding models using both **human-rated instrument timbre** and **DSP-controlled timbre manipulations.**

Background

- Timbre descriptors (bright, dark, warm) are central in music production, effects control, and sound design
- Joint language-audio embeddings map audio and text into a shared space.
- Excel at identifying sound sources/events
- Their representation of **subtle perceptual sound qualities**, especially timbre, has not been systematically studied.

Research Questions

- **Do joint language–audio embeddings reflect human-perceived timbre semantics?**
- How well do different models align with:
  - **Human timbre ratings** across diverse instruments?
  - **Controlled timbre changes** produced by EQ and reverb?
- Which model provides the most perceptually grounded timbre representation?

Experiment 1: Instrumental Timbre Semantics

Dataset: Jiang et al.'s **CCMusic-Database-Instrument-Timbre** datase (**37** Chinese, **24** Western instruments, **16** descriptors rated by trained listeners).

instrument_name	slim	bright	dim	sharp	thick	thin
violin	5.2	5.3	3.4	4.1	4.1	3.7
viola	3.5	4.4	4.4	3.4	6.2	2.9

human-rated data sample from CCMusic, each descriptor is rated out of a scale of 9(maximum)

Data: **61** Audio clips of different instruments
16 human-rated timbre descriptors.

Audio Encoder →Audio Embeddings (N x D)

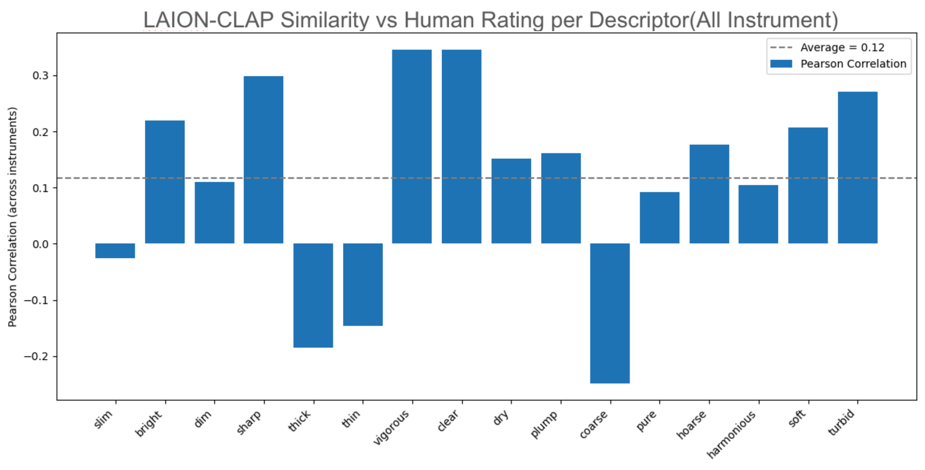
Text Encoder → Text Embeddings (16 x D)

Cosine Similarity Computation
Instrument i, audio embedding a_i,
Descriptor d, text embedding t_d
$s_i = \text{cosine similarity}(a_i, t_d),\ \ s_i = [s_{i,d}]_{d \in D}$

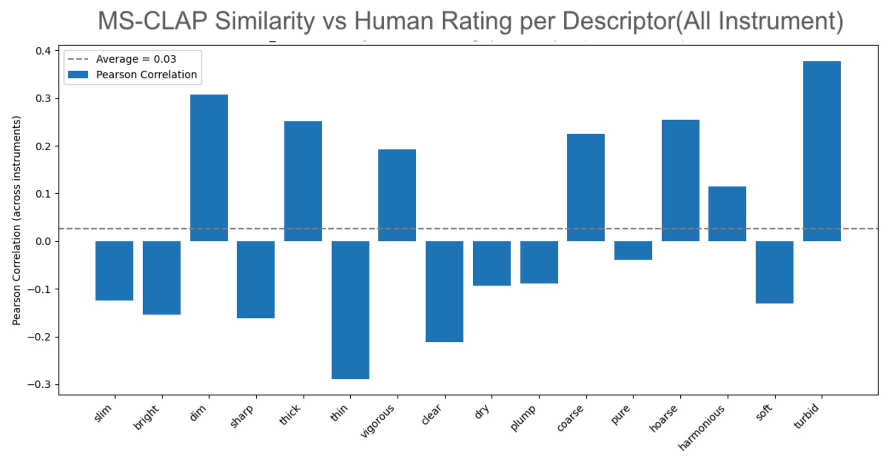
Correlation Computation
calculated similarities: $s_{i,d}$ human-rated scores: $h_{i,d}$
Per Descriptor: $r_d^{\text{Pearson}} = \text{corr}_{\text{Pearson}}(h_{i,d}, s_{i,d})$
Per Instrument: $r_i^{\text{Pearson}} = \text{corr}_{\text{Pearson}}(h_i, s_i)$

Results

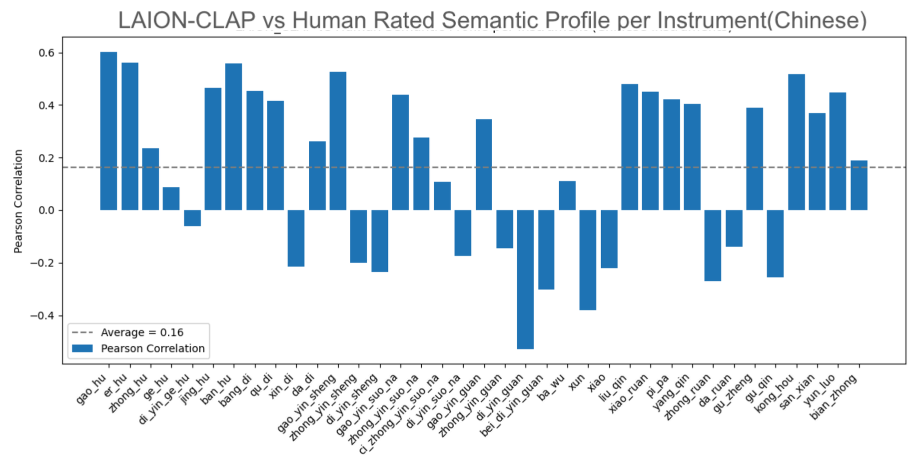
LAION-CLAP Similarity vs Human Rating per Descriptor(All Instrument)



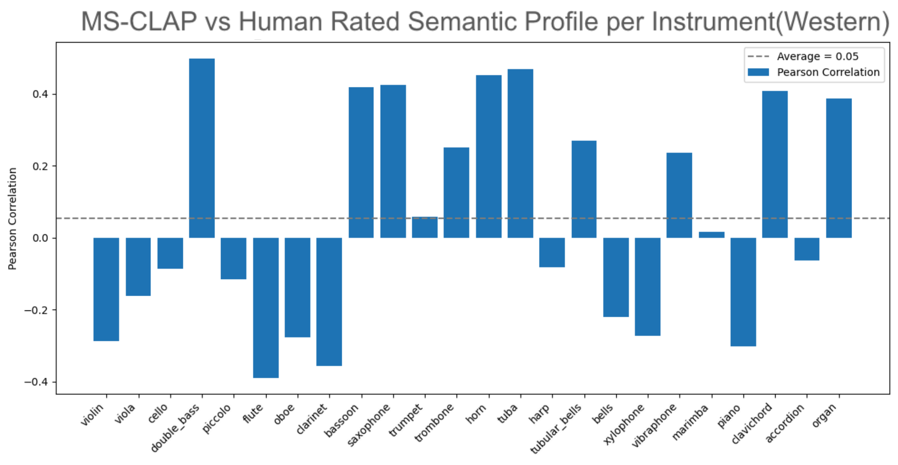
MS-CLAP Similarity vs Human Rating per Descriptor(All Instrument)



LAION-CLAP vs Human Rated Semantic Profile per Instrument(Chinese)



MS-CLAP vs Human Rated Semantic Profile per Instrument(Western)



Model	Descriptor Level (#Positive /16)	Chinese Instrument (# Positive /37)	Western Instrument (# Positive /24)
Laion-CLAP	12	24	10
MS-CLAP	7	24	12
MUQ-MULAN	7	16	10

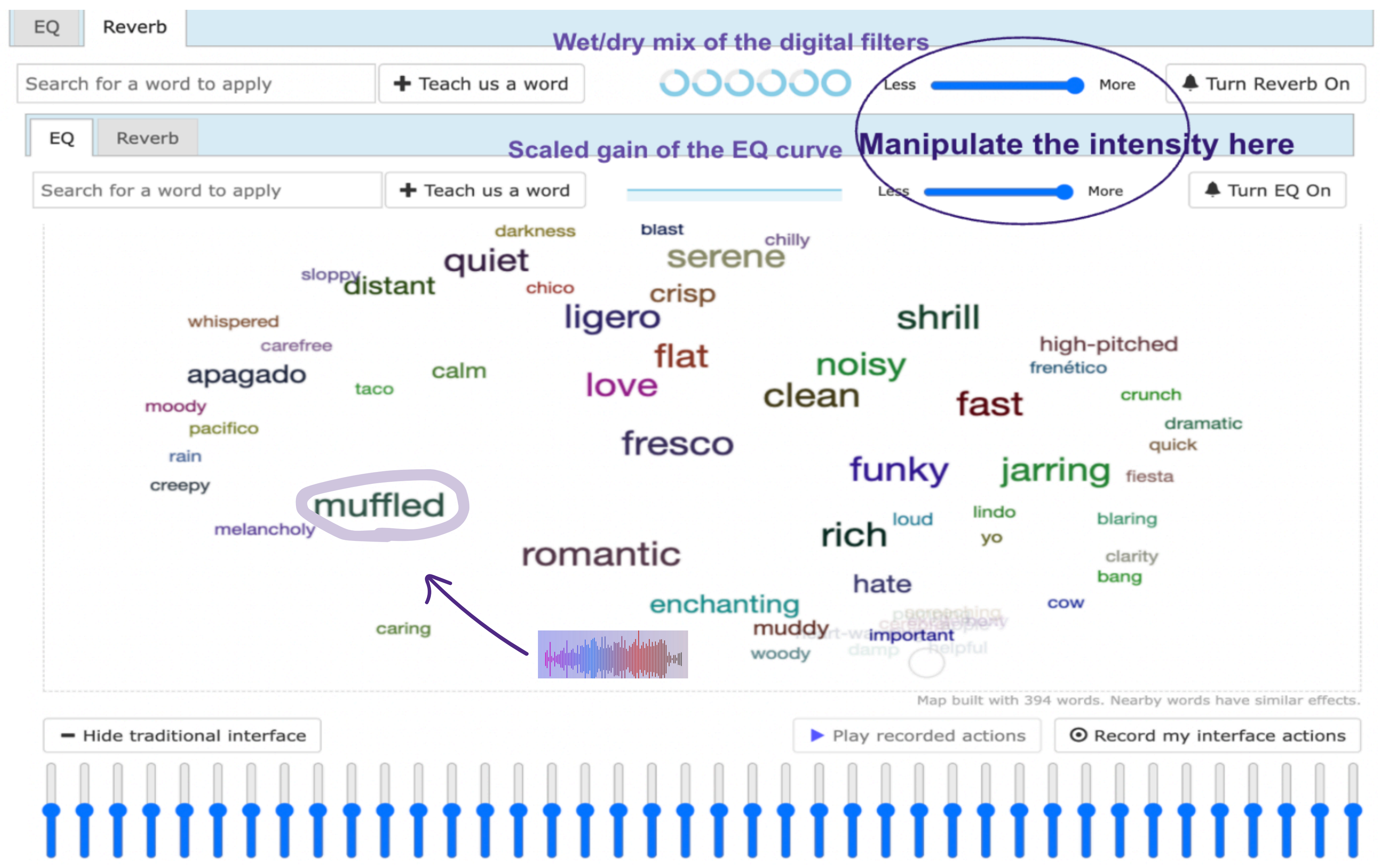
Conclusion

- Across both instrumental timbre and audio-effect manipulations, all three embedding spaces show **limited alignment** with human timbre perception.
- **LAION-CLAP is relatively stronger,** but significant gaps remain.
- MS-CLAP and MuQ-MuLan show weak or inconsistent alignment.

Experiment 2: Audio Effect Timbre Semantics

Dataset: Top 20 EQ and Top 20 Reverb descriptors and their corresponding parameters from **Audealize**.

For each descriptor: Original reference + audio EQ or reverb at three intensity levels (0.3, 0.6, 1.0) → **7 audio files per descriptor**



text embeddings for descriptor d, audio embedding (original + manipulated)
Compute similarity change:

$$\Delta(a) = Sim(\text{audio}_{\text{manip}}(d, a), \text{text(d)}) - Sim(\text{audio}_{\text{orig}}), \text{text(d)})$$

Δ↑ monotonic: strong semantic alignment
Δ flat: inconsistent encoding
Δ↓ monotonic: opposite perceptual meaning

Results

LAION-CLAP = Best performance, 14 / 20 monotonic ↑ trend for EQ and **12/20** monotonic ↑ for reverb
MS-CLAP: No prominent trend of alignment for both EQ and reverb
MUQ-MULAN: 8/20 monotonic ↑ trend for EQ, no prominent trend of alignment for reverb

Descriptor	MS-CLAP	LAION-CLAP	MuQ-MuLan
bass	-	-	↓
big	-	-	↓
church	-	↑	↓
clear	↓	↓	↓
deep	↓	↑	↓
distant	↓	↑	↓
distorted	↑	-	↓
echo	↓	↑	↑
hall	-	↑	↓
haunting	↑	↑	↑
hollow	↓	↑	-
loud	-	-	↓
low	-	↑	-
muffled	↓	-	↑
sad	↑	-	-
soft	↓	↑	↓
spacious	-	↑	↓
strong	-	↑	↓
tinny	↓	↑	↓
warm	↓	↓	↓

Reverb

Descriptor	MS-CLAP	LAION-CLAP	MuQ-MuLan
bright	-	↑	-
calm	↓	↑	↓
clear	-	↑	-
cold	↓	-	↓
cool	-	↓	↓
crisp	↓	↑	-
dark	-	↑	↑
gentle	-	↓	↓
hard	↓	↑	↑
harsh	-	-	↓
heavy	↓	↑	↑
loud	-	↑	↑
mellow	-	↑	↑
peaceful	↓	-	↑
sharp	↓	↑	↓
smooth	-	↑	↑
soft	-	↑	↓
soothing	↓	↑	↓
tinny	-	↑	↓
warm	↓	↓	↑

EQ

Reference

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