SONICMASTER: TOWARDS CONTROLLABLE ALL-IN-ONE MUSIC RESTORATION AND MASTERING

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ABSTRACT

Music recordings often suffer from audio quality issues such as excessive reverberation, distortion, clipping, tonal imbalances, and a narrowed stereo image, especially when created in non-professional settings without specialized equipment or expertise. These problems are typically corrected using separate specialized tools and manual adjustments. In this paper, we introduce *SonicMaster*, the first unified generative model for music restoration and mastering that addresses a broad spectrum of audio artifacts with text-based control. *SonicMaster* is conditioned on natural language instructions to apply targeted enhancements, or can operate in an automatic mode for general restoration. To train this model, we construct the *SonicMaster* dataset, a large dataset of paired degraded and high-quality tracks by simulating common degradation types with nineteen degradation functions belonging to five enhancements groups: equalization, dynamics, reverb, amplitude, and stereo. Our approach leverages a flow-matching generative training paradigm to learn an audio transformation that maps degraded inputs to their cleaned, mastered versions guided by text prompts. Objective audio quality metrics demonstrate that *SonicMaster* significantly improves sound quality across all artifact categories. Furthermore, subjective listening tests confirm that listeners prefer *SonicMaster*'s enhanced outputs over other baselines. The model and demo samples are available through `https://msonic793.github.io/SonicMaster/`.

1 INTRODUCTION

Music recordings produced in amateur settings often suffer from a variety of quality issues that distinguish them from professionally mastered recordings (Wilson & Fazenda, 2016; Mourgela et al., 2024; Deruty & Tardieu, 2014). For instance, an enthusiast recording vocals in a garage may introduce excessive reverberation, making the voice sound distant and "echoey." Similarly, using inexpensive microphones or misconfigured interfaces can lead to distortion and clipping when loud peaks exceed the recording range, resulting in harsh crackles or flattened dynamics (Zang et al., 2025). Tonal imbalances are also common: a home recording might sound overly "muddy" or "tinny" if certain frequency bands dominate or vanish due to poor room acoustics or improper microphone placement. Even the stereo image can be narrowed or skewed, reducing the sense of space in the mix. In practice, engineers address these problems with specialized tools: e.g., dereverberation plugins to remove room echo, declipping algorithms to reconstruct saturated peaks, equalizers to rebalance frequencies, and stereo enhancers to widen the image. Mastering a flawed track has become a labor-intensive process requiring expert skill and multiple stages of manual adjustment.

The need for an automated all-in-one solution is evident. Creators with limited resources often lack the expertise to apply the right combination of restoration tools, and a piecemeal approach may fail to fully recover a track's fidelity. This motivates *SonicMaster*, a unified approach to music restoration and mastering that can correct a broad spectrum of audio degradations within a single model. We introduce a single flow-based generative framework (Liu et al., 2022; Esser et al., 2024) that simultaneously performs dereverberation, equalization, declipping, dynamic-range expansion, and stereo enhancement. The backbone is trained on a curated corpus of polyphonic music rendered through a combinatorial grid of simulated degradations, enabling the network to learn the joint statistics and cross-couplings of common artifacts rather than treating them in isolation. This joint

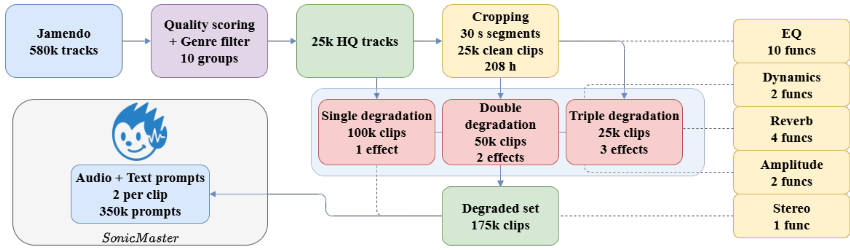

Figure 1: *SonicMaster* dataset creation pipeline and overview.

training eliminates the need for error-prone cascades of task-specific modules and reduces inference to a single forward pass.

Crucially, *SonicMaster* incorporates multimodal conditioning through natural language instructions that capture production objectives. A prompt such as `reduce the hollow room sound` attenuates late reflections without suppressing desirable early reverberation, whereas `increase the brightness` selectively enhances the treble frequencies while preserving spectral balance elsewhere.In the absence of a prompt, *SonicMaster* switches to an automatic mode that applies perceptually balanced mastering. Existing speech restoration models (e.g. VoiceFixer by Liu et al. (2021)) also address artifacts sequentially, ignoring their mutual influence. By unifying restoration and mastering tasks under a single, prompt-driven generative model, *SonicMaster* delivers professional-grade improvements while affording fine-grained creative control. Recent advances such as Mustango (Text-guided music generation) by Melechovsky et al. (2024), FlowSep by Yuan et al. (2025) (text-guided source separation), TangoFlux by Hung et al. (2024) (reward-optimized text-to-audio diffusion), and instruction-guided models like AUDIT (Wang et al., 2023) or AudioLDM/AudioLDM2 (Liu et al., 2023; 2024) illustrate powerful generative methods, but they target orthogonal tasks—generation, separation, or localized editing—rather than unified restoration. In contrast, *SonicMaster* uniquely addresses comprehensive multi-artifact music restoration and mastering through a single controllable rectified-flow architecture, bridging dereverberation, declipping, tonal rebalancing, dynamics, and stereo enhancement under prompt guidance.

In the absence of text-conditioned music-restoration data, we build a new large-scale corpus for controllable restoration. From $\approx 580\ k$ Jamendo recordings, we retain $\approx 25\ k$ high-quality 30-s segments, balanced across 10 genre groups by production quality score. Each clean clip is corrupted with one to three of 19 common effects drawn from five categories—EQ, dynamics, reverb, amplitude, and stereo—producing paired degraded versions. Every degraded sample is accompanied by a natural-language prompt describing the artifact or required fix, and all random effect parameters are stored as metadata. This genre-diverse collection of tens of thousands of prompt–audio pairs underpins *SonicMaster* training and offers a rigorous benchmark for controllable music-restoration research. Our main contributions are as follows:

- We introduce *SonicMaster*, the first *flow-matching* model to simultaneously address 19 common degradations, including reverb, EQ imbalance, clipping, dynamic range errors, and stereo artifacts in a *single* generative framework, eliminating sequential processing and cascading error.
- Our *SonicMaster* enables precise user control through natural language conditioning, allowing targeted corrections (e.g., `reduce hollow room sound` for dereverberation) while maintaining autonomous operation when prompts are unavailable, bridging automated and user-directed restoration paradigms.
- We construct and release [1] the first text-conditioned music-restoration corpus: 25k high-fidelity Jamendo segments spanning 10 genres, each paired with 7 degraded versions, detailed metadata, and a natural-language instruction describing the required fix, resulting in 175k audio pairs.

2 Related Work

Restoring and mastering audio spans speech and music enhancement, audio inpainting, and source separation—areas that have mostly been handled separately Záviška et al. (2020). Diffusion-based

[1] Public link suppressed due to anonymous submission

generative models and text-guided audio editing Hou et al. (2025); Jiang et al. (2025); Zhang et al. (2024); Manor & Michaeli (2024); Han et al. now let us tackle these problems together. We review these advances, their uses, and the gaps that *SonicMaster* aims to fill. Early audio restoration efforts typically focused on single domains or isolated tasks, addressing issues like noise, clipping, or reverb in separation. Speech enhancement Yousif & Mahmmod (2025) and music enhancement evolved largely independently, and tasks such as audio inpainting or source separation were treated with specialized methods Lemercier et al. (2025).

Audio Inpainting, Mixing and Declipping: Early signal-model and interpolation methods could patch only very short gaps (< 10 ms), leaving longer dropouts unresolved. Deep generative models now bridge that gap: diffusion-based systems convincingly regenerate missing music sections and clipped peaks Moliner & Välimäki (2023). The authors in Wang et al. (2023); Liu et al. (2023) extend this with instruction-guided diffusion for audio inpainting, while VoiceFixer Liu et al. (2021) jointly denoises, dereverbs, and declipse speech, though it is restricted to voice and does not offer user control. In music, Imort et al. (2022) removed heavy guitar distortion (including clipping) with neural networks, surpassing sparse-optimization baselines in quality and speed. Lee et al. (2024) introduce a pruning approach to recover sparse audio effect chains from mixed recordings, essentially reverse-engineering mixing graphs from input/output pairs. Alongside works like Bhandari et al. (2025) on iterative corruption refinement, Steinmetz et al. (2021) on differentiable mixing consoles and Martínez-Ramírez et al. (2022) on out-of-domain mixing generalization, and diffusion restorers such as MaskSR Li et al. (2024), these highlight emerging methods that bridge audio restoration with controllable, interpretable effect modeling. Moreover, Rice et al. (2023) introduce a compositional architecture for multi-effect audio removal using effect-specific removal modules.

Equalization and Tonal Restoration: Research on learning-based equalization is still emerging. Mockenhaupt et al. (2024) recently introduced CNN-based approach to automatically equalize instrument stems by predicting parametric EQ settings, showing improvements over earlier heuristic methods. Notably, the VoiceFixer (Liu et al., 2021) addressed bandwidth extension, essentially restoring high-frequency content as part of its speech restoration, which can be seen as a form of equalization correction. Similarly, diffusion-based restorers like MaskSR Li et al. (2024) treat low-frequency muffling as a distortion to fix, using discrete token prediction to restore a balanced spectrum. In Text2FX Chu et al. (2025), CLAP Elizalde et al. (2023) is used in inference mode to steer the parameters of EQ and reverb audio effects.

3 Method

3.1 Dataset

In the absence of text-conditioned music restoration datasets, we generate *SonicMaster* dataset by pairing high-quality audio with systematically applied degradations and corresponding natural language instructions. Our source comprises songs from Roy et al. (2025) and additional content from Jamendo[2] under Creative Commons licence using the official Jamendo API. In total, we have sourced 580k recordings. We ensure balanced genre representation by defining 10 groups, where each group consists of multiple semantically related genre tags, e.g., Hip-Hop genre group containing the following tags: "rap", "hiphop", "trap", "alternativehiphop", "gangstarap". Complete taxonomies are provided in the Appendix. Track selection employs Audiobox Aesthetics toolbox (Tjandra et al., 2025) for automated production quality assessment. We select $2,500$ songs per genre groups using adaptive production quality thresholds ranging from 6.5 to 8 to balance comprehensive sub-genre representation with sufficient production quality. We extract random 30s excerpts from each track, positioned between 15% and 85% of its total duration. The complete pipeline is illustrated in Figure 1. We train *SonicMaster* by applying 19 distinct degradations to the audio and pairing each with a matching natural language editing instruction. The degradations span five classes: (i) EQ, (ii) Dynamics, (iii) Reverb, (iv) Amplitude, and (v) Stereo.

Equalization (EQ): Spectral degradations cover 10 effects targeting perceptual audio characteristics: Brightness, Darkness, Airiness, Boominess, Muddiness, Warmth, Vocals, Clarity, Microphone, and X-band. Brightness, Darkness, Airiness, Boominess, and Warmth are emulated with low- or

[2] `https://www.jamendo.com/`

high-shelf EQ; Clarity with a Butterworth low-pass filter; Vocals and Muddiness with Chebyshev-II band-pass filters. Microphone applies one of 20 Poliphone transfer functions (Salvi et al., 2025), while X-band uses an 8–12-band, logarithmically spaced peaking EQ with 6 dB gain per band.

Dynamics: Temporal envelope modification via two functions: Compression (feedforward dynamic range compression) and Punch (transient shaping). Both exhibit lossy, non-invertible characteristics, rendering exact restoration mathematically ill-posed and requiring learned approximations.

Reverb: The Reverb category contains four distinct approaches: three of them utilise the Pyroomacoustics library (Scheibler et al., 2018), which simulates acoustic environments with the image source method. We simulate three types of rooms: Small, Big, and Mixed. For our fourth Reverb function, we utilize 12 selected room impulse responses from the openAIR library dataset (Howard & Angus, n.d.), which give us audio with more real-life properties. The resulting impulse responses from all the functions are convoluted with the clean signals.

Amplitude: Two complementary degradations target signal amplitude: Clipping/Volume. Clipping introduces hard nonlinear distortion by constraining peak amplitudes to predefined thresholds; Volume reduction attenuates signals to near-inaudible levels, degrading the signal-to-quantization-noise ratio and simulating poor recording practices.

Stereo: A function to de-stereo the audio recording – tracks undergo stereo content analysis via left-right channel difference standard deviation (threshold: 0.08); qualifying recordings are converted to monophonic by channel summation, simulating poor mixing or playback equipment limitations.

Each ground truth yields 7 corrupted variants: 4 with a single, 2 with double, and 1 with triple degradation. In multi-degradation, we sample at most one effect from each of the 5 categories, so an EQ choice, for instance, blocks further EQ picks. To avoid duplicates in the single-degradation set, high-probability effects with narrow parameter ranges: Stereo, Clipping, and Punch, are used only once (in the 4 versions per original, e.g., there cannot be two single-degraded versions with Stereo degradation, as they would be identical). Each degradation is linked to a one-sentence instruction from 8–10 possible options (all written by a music expert); these sentences are concatenated into the full prompt, and we store two prompt variants per clip for robustness. We also record every applied effect and its parameters (gain, absorption), supporting tasks such as parameter prediction. For Compression and Reverb, there is a 15% chance of injecting "hidden clipping" with no corresponding instruction to emulate real life cases of constructive interference in a reverberant room, or overcompensated gain setting of a compressor. When neither hidden clipping nor an Amplitude effect is present, the audio is peak-normalised to a random level between $0.8 - 1.0$. Further details can be found in Appendix.

3.2 *SonicMaster* ARCHITECTURE

SonicMaster employs a hybrid architecture combining Multimodal Diffusion Transformer (MM-DiT)(Esser et al., 2024) blocks with subsequent Diffusion Transformers (DiT) layers (Peebles & Xie, 2023). As outlined in Figure 2, stereo waveforms (44.1 kHz) (x_t) undergo VAE ecoding (Evans et al., 2024) into compact spectro-temporal latent representations. Restoration, therefore, occurs entirely in this learned space, allowing large receptive fields without sample-level overhead. The MM-DiT processes degraded latent representations alongside the text embeddings from a frozen FLAN-T5 encoder (Chung et al., 2024). The resulting conditioned representations pass through subsequent DiT layers to predict flow velocity v_t, steering the latent toward its clean target $\hat{x}_t$. Prompts like "reduce reverb" biases this prediction trajectory to suppress decay tails, while the downstream DiT layers refine musical coherence. A pooled-audio branch, active in 25% of training cases, concatenates a temporally averaged 5–15s clean cue with the pooled prompt embedding and injects it at every MM-DiT/DiT layer, enabling seamless chaining of 30s segments for long-form generation while degrading gracefully when no reference is supplied.

Audio and text encoding: We adopt the Stable Audio Open VAE (Evans et al., 2024) to encode–decode stereo signals sampled at 44.1 kHz, yielding a compact latent representation while retaining high-fidelity reconstruction. Text instructions are embedded with FLAN-T5 Large (Chung et al., 2024); the resulting tensor $c_{\text{text}} \in \mathbb{R}^{B \times S_{\text{text}} \times D_{\text{text}}}$ (with $D_{\text{text}} = 1024$) is used as a conditioning signal.

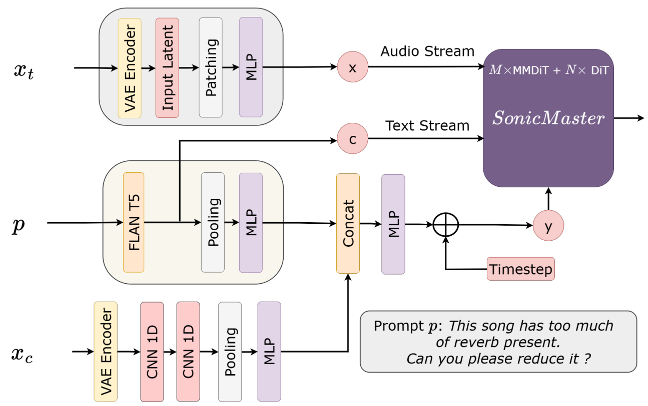

Figure 2: Overall architecture of *SonicMaster*.

Rectified Flow Training: *SonicMaster* employs rectified flow (Liu et al., 2022; Esser et al., 2024), to predict flow velocity from degraded to clean audio in latent space, unlike other models that map noise to output distributions (Fei et al., 2024; Hung et al., 2024).

We assign timestep $t = 1$ to the latent representation of the degraded audio x_1, and $t = 0$ to the latent representation of the clean audio target x_0. During training, we feed the model with samples x_t, which are linear interpolations between degraded input x_1 and clean target x_0:

$$x_t = tx_1 + (1-t)x_0 \tag{1}$$

where timestep t is drawn from a skewed distribution $p(t) = 0.5U(t)+t, \quad t \in [0,1]$ with increasing probability for higher t, where U represents a uniform distribution. This skewed distribution gives emphasis to more degraded inputs given the interpolation of training data in Eq. 1. The model is trained to predict the flow velocity v_t from the current x_t to the target clean audio x_0: $v_t = -\frac{dx_t}{dt} = x_0 - x_1$. The model f_θ with parameters θ estimates the velocity $\hat{v}_t$, $f_\theta(x_t, t, c_{text}) = \hat{v}_t$, where c_{text} is the text condition from the FLAN-T5 model, which is passed to the dual-stream MM-DiT blocks as one of the streams. The c_{text} condition is also passed through a pooled projection and used to control the scale and shift factors of the adaptive layer-norm layers in both MM-DiT and DiT blocks. The training loss is then given as:

$$L(\theta) = \mathbb{E}_{t,x_1,x_0}||\hat{v}_t - v_t||_2^2 = \mathbb{E}_{t,x_1,x_0}||f_\theta(x_t, t, c_{text}) - v_t||_2^2 \tag{2}$$

Inference transforms degraded audio input x_1 to clean audio output x_0 by integrating the predicted velocity $\hat{v}_t$ using the forward Euler method: $x_{t-h} = x_t + h\hat{v}_t$, where $h \in [0,1]$ is the step computed as the inverse of the total timesteps dedicated for integration.

Inference: During inference, *SonicMaster* takes in an audio input and a text instruction given by the user to perform the desired restoration/mastering operation. Inference is possible without text input in the so-called auto-correction mode. To process full-length songs, *SonicMaster* operates on chunks of 30s and then connects the segments together. After the first segment is inferred, the last 10s of this output are used to condition the next segment inference through the audio pooling branch. The overlapping regions of the resulting segments are then linearly interpolated over the overlapping 10s to connect the segments together.

4 Experimental Setup and Baselines

4.1 Baselines and training setup

We train *SonicMaster* using 5 NVIDIA L40S GPUs for 40 epochs with a total batch size of 80. We adopt classifier-free guidance (Ho & Salimans, 2022) by (i) dropping the text prompt in 10% of samples and (ii) replacing it in another 10% with one of four generic phrases ("Make it sound better!", "Master this track for me, please!", "Improve this!", "Can you improve the sound of this song?"). In 25% of cases, the model is additionally conditioned—via the pooling branch—on the first 10 s of clean audio. Unless stated otherwise, all experiments follow these conditioning settings while comparing multiple *SonicMaster* variants and baselines.

We compare against recent approaches, alongside ablation studies for different *SonicMaster* configurations:: (i) **Degraded input**—the original corrupted audio; (ii) **Reconstructed input**—the same audio passed through the VAE encoder–decoder; (iii) **Text2FX-EQ**, an EQ baseline using Text2FX (Chu et al., 2025) with 600 iterations and a 0.01 learning rate to correct EQ degradations via our prompts; (iv) **WPE** dereverberation, the Weighted Prediction Error algorithm (Nakatani et al., 2010) with a prediction order of 30; (v) **HPSS** dereverberation, harmonic–percussive source separation (`librosa.decompose.hpss`) with 6 dB and 12 dB harmonic attenuation; (vi) `Mel2Mel + DiffWave` (Kandpal et al., 2022) framework that treats mel-spectrogram enhancement as an image-to-image translation followed by diffusion vocoding for music restoration. and (vii) three *SonicMaster* variants—*SonicMaster*$_{Small}$ (2 MM-DiT + 6 DiT), *SonicMaster*$_{Medium}$ (4 MM-DiT + 12 DiT *or* 6 MM-DiT + 6 DiT), and *SonicMaster*$_{Large}$ (6 MM-DiT + 18 DiT).

Given that Text2FX[3] is not a restoration model, we further deploy its directional variant as a meaningful text-guided audio manipulation baseline. SonicMaster operates in a text-conditioned enhancement paradigm, where the model must follow natural-language instructions (e.g., "reduce muddiness", "increase clarity"). Text2FX-directional is specifically designed for instruction-following tasks: it steers the audio embedding in the same semantic direction defined by a target prompt and its contrast prompt.

Model	Clarity	Boom	Airy	Bright	Dark	Muddy	Warm	Vocals	Mic.	X-band
Snippet Evaluation (Short Segments)										
Degraded Input	0.0238	0.3601	0.0049	0.0143	0.0893	0.4560	0.4345	0.2525	0.2393	0.1782
Reconstructed Input	0.0243	0.3717	0.0051	0.0151	0.0728	0.4749	0.4456	0.2525	0.2379	0.1854
Mel2Mel + Diffwave Kandpal et al. (2022)	0.0278	0.3561	0.0049	0.0135	0.0855	0.4705	0.4436	0.2560	0.2604	0.1885
Text2FX$_{cos}$ Chu et al. (2025)	0.0219	0.3809	0.0055	0.0276	0.2112	0.3651	0.4955	0.2199	0.4441	0.3419
Text2FX$_{dir}$ Chu et al. (2025)	0.0421	0.3977	0.0206	0.0143	0.3021	0.2602	0.5461	0.2517	0.6120	0.5038
***SonicMaster* (Ours)**	**0.0114**	**0.0834**	**0.0019**	**0.0059**	**0.0058**	**0.0388**	**0.0617**	**0.0576**	**0.0088**	**0.0358**
Full Song Evaluation (Long-Form)										
Ablation – No Text Condition	0.0130	0.1432	0.0032	0.0101	0.0086	0.0448	0.0841	0.0668	0.0154	0.0424
Ablation – Shuffled Prompts	0.0187	0.2075	0.0077	0.0132	0.0362	0.0981	0.1648	0.1043	0.0424	0.0998
Full Song Evaluation (Long-Form)										
Degraded Input	0.0290	0.3231	0.0048	0.0124	0.0983	0.4606	0.4810	0.2274	0.2403	0.1737
***SonicMaster* (Ours)**	**0.0102**	**0.0639**	**0.0021**	**0.0060**	**0.0065**	**0.0329**	**0.0510**	**0.0517**	**0.0070**	**0.0289**

Table 1: EQ Objective Evaluation (Average Absolute Error). **Bold** = best performance (lowest error). *SonicMaster* outperforms baselines in all categories in snippet and full-song scenarios.

Evaluation is conducted along two orthogonal axes. (i) Global perceptual fidelity is quantified with FAD on CLAP embeddings (Elizalde et al., 2023), Kullback–Leibler divergence (KL), structural similarity (SSIM) on 128-bin mel-spectrograms, and the Production Quality (PQ) score from the Audiobox Aesthetics toolbox (Tjandra et al., 2025). (ii) Degradation-specific restoration efficacy is measured by average absolute error reduction: for every degraded clip in a 7000 clip test set, we compute the relevant (based on the degradation deployed) artefact-aware metric against its clean counterpart from a 1000 sample reference set, then recompute the metric after *SonicMaster* processing; the relative decrease indicates how closely each model variant approaches the ground-truth.

For X-band EQ and microphone-TF degradations, we compute the spectral balance over nine frequency bands and report their cosine distance. All other EQ effects are scored by the energy ratio between the affected band and the full spectrum. Compression is measured as the standard deviation of frame-level RMS (2048-sample frames, 1024 hop); punch as the mean onset-envelope value (`librosa.onset.onset_strength`). Because RT60 estimates are unreliable on dense mixes, reverb is assessed via the Euclidean distance of modulation spectra. Clipping uses spectral flatness; volume, the global RMS; and stereo width, the RMS ratio of the mid and side signals, $\mathrm{RMS}\left[\frac{L-R}{2}\right]/\mathrm{RMS}\left[\frac{L+R}{2}\right]$. We report the average absolute error value (GT vs inferred sample) of all the metrics except where mentioned differently (X-band, microphone-TF, and reverb). Details of each metric are described in Appendix A.5.

[3]Appendix A.3 has details of the Text2FX-directional, both loss formulation and EQ prompt construction.

Model	Reverb				Dynamics		Amplitude		Stereo
	Small	Big	Mix	Real	Comp.	Punch	Clip	Vol.	
Snippet Evaluation (Short Segments)									
Degraded Input	0.4457	0.4243	0.5045	0.4639	0.0496	0.1200	5.122	0.1813	0.4183
Reconstructed Input	0.4686	0.4507	0.5433	0.4908	0.0494	0.0590	3.871	0.1810	0.4181
HPSS 6 dB	0.4419	0.4240	0.4970	0.4537	-	-	-	-	-
HPSS 12 dB	0.4971	0.4739	0.5333	0.4814	-	-	-	-	-
WPE Nakatani et al. (2010)	0.4849	0.4732	0.5207	0.4854	-	-	-	-	-
Mel2Mel + Diffwave Kandpal et al. (2022)	0.4404	0.4387	0.4361	0.4368	-	-	-	-	-
***SonicMaster* (Ours)**	**0.3663**	**0.3726**	**0.3935**	**0.3109**	**0.0193**	**0.0871**	**1.506**	**0.0468**	**0.1058**
Ablation Studies									
Ablation – No Text Condition	0.3732	0.3805	0.4012	0.3264	0.0157	0.0730	2.812	0.0465	0.1416
Ablation – Shuffled Prompts	0.4161	0.4236	0.4538	0.3903	0.0225	0.0895	2.874	0.0895	0.3213
Full Song Evaluation (Long-Form)									
Degraded Input	0.3667	0.3654	0.4706	0.3852	0.0598	0.1103	6.363	0.1829	0.4133
***SonicMaster* (Ours)**	**0.3954**	**0.4511**	**0.4191**	**0.4066**	**0.0258**	**0.1101**	**3.734**	**0.0424**	**0.0850**

Table 2: Objective Scores: Reverb, Dynamics, Amplitude, and Stereo. Clip scores are multiplied by 1000. **Bold** indicates best performance (lowest error).

Model	Single Deg.				Double+Triple Deg.				All			
	FAD↓	KL↓	SSIM↑	PQ↑	FAD↓	KL↓	SSIM↑	PQ↑	FAD↓	KL↓	SSIM↑	PQ↑
Snippet Evaluation (Short Segments)												
GT Mastered Ref.	-	-	-	7.886	-	-	-	7.886	-	-	-	7.886
Degraded Input	0.061	3.859	**0.838**	7.321	0.184	6.827	**0.696**	6.632	0.106	5.131	**0.777**	7.026
Reconstructed Input	0.139	3.990	0.574	7.172	0.290	6.984	0.507	6.501	0.196	5.273	0.546	6.885
Mel2Mel + Diffwave Kandpal et al. (2022)	0.522	14.938	0.447	6.158	0.474	15.185	0.416	5.953	0.491	15.044	0.433	6.070
***SonicMaster* (Ours)**	**0.069**	**0.696**	0.624	**7.743**	**0.082**	**1.145**	0.589	**7.654**	**0.073**	**0.888**	0.609	**7.705**
Ablation Studies												
Ablation – No Text Condition	0.069	0.917	0.621	7.772	0.088	1.484	0.586	7.643	0.074	1.160	0.606	7.716
Ablation – Shuffled Prompts	0.081	2.014	0.598	7.610	0.131	3.249	0.558	7.283	0.098	2.543	0.581	7.470
Full Song Evaluation (Long-Form)												
GT Mastered Ref.	-	-	-	7.885	-	-	-	7.885	-	-	-	7.885
Degraded Input	**0.087**	2.937	**0.834**	7.325	0.223	5.679	**0.682**	6.606	0.142	4.308	**0.758**	6.965
Reconstructed Input	0.165	3.049	0.584	7.204	0.335	5.644	0.510	6.509	0.234	4.339	0.547	6.859
***SonicMaster* (Ours)**	0.095	**0.754**	0.380	**7.627**	**0.121**	**1.251**	0.368	**7.477**	**0.101**	**1.002**	0.374	**7.552**

Table 3: Objective Scores: FAD (↓), KL (↓), SSIM (↑), and PQ (↑). KL values are multiplied by 1000 for readability. **Bold** indicates best performance (excluding ground truth reference).

We presented listeners with 43 audio sample pairs – degraded inputs and *SonicMaster* outputs – to rate, consisting of 2 pairs for each degradation function ($2 \times 19 = 38$ single degraded samples), 3 pairs of double and 2 pairs of triple degraded samples. Using a 7-point Likert Scale, listeners were to rate: 1) The extent of improvement from the input to *SonicMaster* output represented by the text prompt (Text relevance), 2) audio quality of input (Quality1), 3) audio quality of the inferred *SonicMaster* sample (Quality2), 4) consistency and fluency of the inferred sample (Consistency), and 5) preference between the two samples, where 1 represents full preference of the ground truth degraded input, and 7 represents the *SonicMaster* inferred sample (Preference). The study was attended by 12 listeners (7 music experts and 5 Music Information Retrieval researchers).

Furthermore, to benchmark against existing methods, we conducted an additional study with 20 participants comparing *SonicMaster* against Text2FX (Chu et al., 2025), Text2FX-directional, and Mel2Mel + Diffwave (Kandpal et al., 2022) on 20 randomly selected samples from our test set. The evaluation included 10 samples with X-band EQ degradation and 10 with reverberation artifacts. Note that Text2FX and Text2FX-directional are limited to EQ effects as their reverb effect is only additive, thus excluded. Since the baseline methods' evaluation sets are not publicly available, we performed this comparison exclusively on our curated test data.

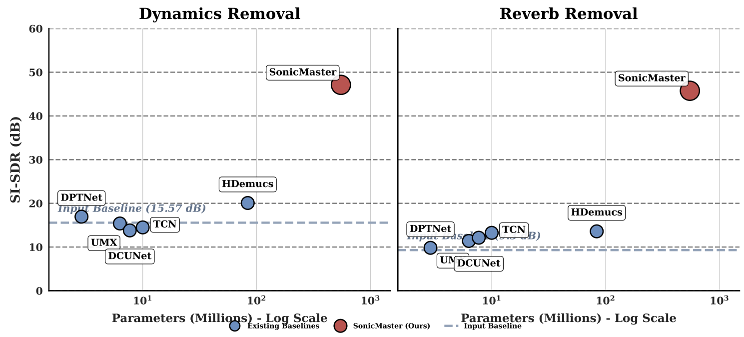

Figure 3: Comparison of SI-SDR scores (↑) for Dynamics and Reverb removal.

5 Results

5.1 Objective Evaluation

Degradation-Specific Performance: Tables 1 and 2 demonstrates *SonicMaster*'s superiority over baselines of Text2FX in EQ, and WPE/HPSS in Reverb. *SonicMaster* improves in all categories when compared to the degraded and reconstructed inputs. Furthermore, the reconstructed input metrics are overall slightly worse (with exceptions) than those of the ground truth degraded inputs.

Perceptual Quality Assessment: Table 3 reveals *SonicMaster* outperforms the degraded inputs in both PQ and KL. FAD is marginally higher than that of the degraded audio, yet markedly lower than the reconstructed baseline. Furthermore, *SonicMaster* achieves a significant increase in PQ, almost reaching the level of ground truth mastered reference. In SSIM, *SonicMaster* exhibits lower scores than degraded inputs but achieves superior performance compared to the reconstruction baseline.

Method	CE ↑	CU ↑	PC ↑	PQ ↑
Original	$6.94_{\pm 0.48}$	$7.29_{\pm 0.43}$	$3.45_{\pm 0.36}$	$6.70_{\pm 0.50}$
LTAS-EQ	$6.77_{\pm 0.54}$	$7.04_{\pm 0.57}$	$3.75_{\pm 0.45}$	$6.49_{\pm 0.57}$
BEHM-GAN	$6.82_{\pm 0.43}$	$7.19_{\pm 0.44}$	$3.47_{\pm 0.35}$	$6.63_{\pm 0.56}$
BABE	$\mathbf{6.96}_{\pm 0.37}$	$\mathbf{7.32}_{\pm 0.37}$	$3.32_{\pm 0.29}$	$6.79_{\pm 0.36}$
BABE-2	$6.79_{\pm 0.34}$	$7.16_{\pm 0.29}$	$3.46_{\pm 0.28}$	$\mathbf{7.05}_{\pm 0.27}$
SonicMaster (ours)	$6.87_{\pm 0.55}$	$7.25_{\pm 0.50}$	$\mathbf{3.86}_{\pm 0.39}$	$6.93_{\pm 0.52}$

Table 4: Comparison of mean across metrics CE, CU, PC, and PQ.

Comparison with removal models: While models such as DPTNet Chen et al. (2020), UMX Stöter et al. (2019), DCUNet Choi et al. (2018), TCN Rethage et al. (2018); Steinmetz & Reiss (2021), and HDemucs Défossez (2021) focus on effect removal with minimal alteration Rice et al. (2023) (best baseline: 20.08 dB for Dynamics, 13.59 dB for Reverb), *SonicMaster* performs text-guided mastering that applies intentional tonal and dynamic shaping. All baselines are trained following the RemFX protocol Rice et al. (2023) using effect-specific supervision with L1 + multi-resolution STFT losses, and evaluated on the official test split containing clean vs. effected pairs for each degradation type. We test *SonicMaster* on the same test set, focusing on the two degradation: Dynamics and Reverb used (Rice et al., 2023). This broader objective enables *SonicMaster* to reconstruct a more coherent musical structure as shown in Fig. 3, achieving substantially higher SI-SDR scores of 47.11 dB (Dynamics) and 45.76 dB (Reverb).

5.2 Ablation Studies

Text Prompt Dependency: Inference without text prompts maintains comparable FAD, SSIM, and PQ but shows degraded KL divergence (0.917 vs. 0.696). Critical drops occur in Clip restoration (2.812 vs. 1.506) and Stereo processing (0.1416 vs. 0.1058), with elevated EQ errors. To further

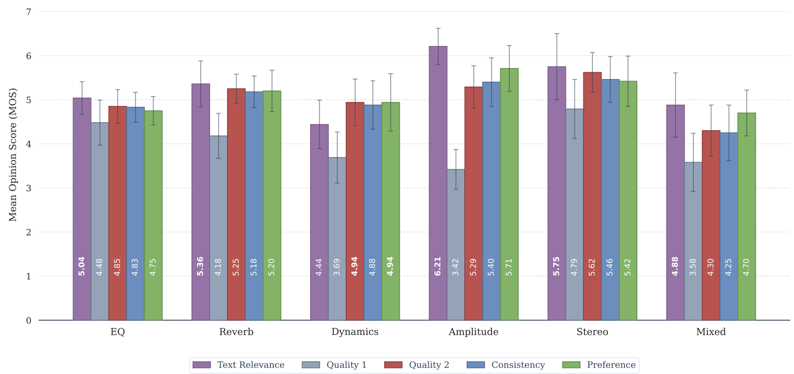

Figure 4: Listening study - *SonicMaster*'s performance on specific degradations – MOS 95% CI

assess the text controllability, we shuffled the prompts inside the test set and ran inference. Results (Tables 1, 2, 3 show worse performance than when no prompt was given (KL 2.014, Clip 2.874), but still show large improvement over the degraded input. This confirms text conditioning enables targeted restoration rather than generic improvements.

Architecture Scaling Analysis: We observe interesting scaling dynamics. *SonicMaster*$_{Small}$ performs comparably with *SonicMaster*$_{Large}$ in all metrics, but slightly worse in Reverb, Clip, and Stereo. *SonicMaster*$_{Medium}$ (4MM-DiT/12DiT) performs slightly better than the *SonicMaster*$_{Small}$, but still lacks behind *SonicMaster*$_{Large}$ in Clip. *SonicMaster*$_{Medium}$ (6MM-DiT/6DiT) performs the worst out of all variants across all metrics. See Appendix A.7.

Audio Conditioning Duration: We evaluated *SonicMaster*$_{Large}$ with different conditioning lengths (5s, 10s, 15s), finding comparable performance across configurations. The 10-second setting balances computational efficiency with temporal overlap for long-form processing. See Appendix A.7.

Conditioning Strategy Analysis: The no-conditioning variant achieves optimal Boom correction (0.0658 absolute error) but poor Clip restoration (2.055 vs. standard variants), highlighting multimodal guidance importance for challenging tasks. More details in Appendix A.7.

Long-Form Audio Evaluation: Full-song evaluations confirm *SonicMaster*'s effectiveness, with substantial improvements in EQ-related metrics (Table 1) and most degradation functions (Table 2). Reverberation metrics show mixed results, likely due to increased complexity of spatial processing in extended musical contexts where room acoustics interact with diverse instrumental timbres and dynamic variations. SSIM and FAD decrease compared to degraded inputs, except for FAD in multi-degradation samples, indicating *SonicMaster*'s ability to handle compound degradations.

5.3 Piano Recordings Evaluation

To test *SonicMaster* generalization, we evaluate historical solo piano pieces[4] using established baselines: LTAS-EQ, BEHM-GAN (Moliner & Välimäki, 2023) model for bandwidth extension, and BABE/BABE-2 diffusion-based generative equalizers (Moliner et al., 2024; Moliner & Välimäki, 2023). BABE-2 represents a state-of-the-art specialized method for old recordings, it uses a diffusion prior to restore lost high frequencies and remove coloration, and has shown impressive improvements in archival music (Moliner et al., 2024). Despite lacking domain-specific training, *SonicMaster* came surprisingly close to these specialized baselines (Table 4. In objective evaluations, SonicMaster restored samples achieved a PQ of 6.93, nearly matching the 7.05 obtained by BABE-2.

5.4 Subjective Evaluation

Figure 4 shows results of the first listening study. Text relevance ratings are highest in the Amplitude (6.21), Stereo (5.75), and Reverb (5.36) categories, indicating effective declipping, volume increase,

[4]http://research.spa.aalto.fi/publications/papers/dafx-babe2/

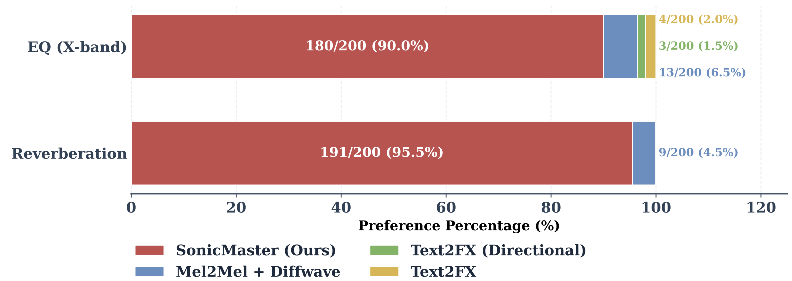

Figure 5: Comparative Listening Study Results ($N = 20$ participants $\times$ 10 samples per category).

expansion of the stereo image, and dereverberation. These three categories also show the highest consistency and preference ratings. The Dynamics and Amplitude categories show the biggest improvement in quality. EQ shows the fourth-best text relevance, but the worst preference ratings. This likely reflects the nature of some EQ effects being more stylistic or difficult to notice (e.g., airiness, boominess). Overall, *SonicMaster* samples are rated higher in quality compared to inputs and preferred across the board. A paired t-test on Quality1 and Quality2 ratings shows statistically significant differences ($p < 0.05$ for Stereo, $p < 0.01$ for the rest) in all categories except EQ.

The comparative evaluation against existing baselines demonstrates *SonicMaster*'s superior performance across both reverb and EQ degradation categories (Figure 5). For reverb artifacts, participants overwhelmingly preferred *SonicMaster* over Mel2Mel + Diffwave (Kandpal et al., 2022), selecting our method in 191 out of 200 total comparisons (10 samples $\times$ 20 participants), with Mel2Mel + Diffwave chosen only twice. In the EQ category, *SonicMaster* achieved similarly strong results with 180 out of 200 preferences, while Mel2Mel + Diffwave received 13 votes, Text2FX (Chu et al., 2025) garnered 4 votes and Text2FX-directional generated 3. These results show *SonicMaster*'s effectiveness in addressing both spatial acoustic degradations and spectral imbalances.

6 Discussion

Experiments confirm that *SonicMaster*'s generative approach is effective when trained on a large corpus with a suitable objective. The historical piano experiment demonstrated *SonicMaster*'s strong generalization: even on out-of-domain, severely degraded audio, it produced enhancements close to the best specialized solution, BABE-2. This highlights the potential of general-purpose audio restoration AI. However, a key limitation is that the lossy latent representation can introduce artifacts, such as robotic vocals or muted instruments, especially in certain genres. The observed decrease in *SonicMaster*'s performance on full songs in SSIM and Reverb metrics could be related to the way neighbouring segments are connected together. Improving on this aspect could increase the objective performance further. Evaluating reverberation in dense music is challenging, and how *SonicMaster* removes it in latent space is not explicitly observable, making metric selection difficult. A deeper study of this issue would benefit the community.

7 Conclusion

We introduced *SonicMaster*, the first unified text-guided generative model for music restoration and mastering, capable of handling 19 diverse degradations within a single framework. Our contributions further include the creation of a paired degraded–clean dataset with textual annotations, the introduction of a flow-matching paradigm for directly learning restoration mappings, and the integration of natural language conditioning for precise and flexible control. Evaluations show that *SonicMaster* consistently improves the audio quality, outperforming baselines in terms of objective metrics and listener studies. It also achieved strong zero-shot performance on old piano recordings, highlighting its versatility suggesting a path toward a generalist restoration framework–one capable of addressing diverse challenges through prompt guidance while approaching the quality of specialist methods.

REPRODUCIBILITY STATEMENT

We shall publicly release the implementation of model training, inference, evaluation, as well as dataset upon acceptance. We also mention the hyperparameters in the appendix.

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A APPENDIX

A.1 THE USE OF LARGE LANGUAGE MODELS

We employed a Large Language Model to assist with reducing wordy paragraphs to help the paper fit in the page limit.

A.2 GENRE TAGS

We grouped genre tags into genre groups, as depicted in Table 5. Each row links a coarse "Group" label—such as Rock, Electronic, or Jazz/Blues—to the fine-grained "Genre tags" that appear in the metadata. These tags enumerate substyles (e.g., `progressiverock`, `deephouse`, `acidjazz`), which allows us to aggregate diverse representations inside each of the genre groups.

Table 5: Genre groupings by metadata tags used in our dataset.

Group	**Genre tags**
Rock	rock, alternativerock, poprock, classicrock, hardrock, progressiverock, stoner, psychedelicrock, garage, indierock
Pop	pop, electropop, dancepop, dance, alternativepop, adultcontemporary, indiepop
Electronic	electronic, house, techno, trance, edm, electrohouse, deephouse, progressivehouse, electroswing, synthwave, electronica
Hip-Hop	rap, hiphop, trap, alternativehiphop, gangstarap
Folk	folk, singersongwriter, americana, country, bluegrass, folklore
Metal	metal, deathmetal, blackmetal, thrashmetal, heavymetal, numetal, metalcore, hardcore, alternativemetal, doommetal
World	world, latin, reggaeton, afrobeat, african, indian, oriental, celtic, salsa, flamenco, jpop, middleeastern, asian, reggae
Jazz/Blues	jazz, blues, funk, acidjazz, jazzfusion, smoothjazz, jazzfunk, soul, swing, rnb, alternativernb
Chill	ambient, downtempo, chillout, chillhop, lofi, newage, darkambient, triphop, chillwave, idm, dreampop
Classical	classical, filmscore, neoclassical, symphonic, opera, baroque, medieval, avantgarde, production, choral

A.3 TEXT2FX-DIRECTIONAL BASELINE FOR THE EQ TASK

For the equalization (EQ) experiments, we include the Text2FX-Directional method Chu et al. (2025) as a text-guided audio transformation baseline. Although Text2FX is not a restoration model, SonicMaster is instruction-conditioned; therefore, a text-conditioned FX optimizer offers a meaningful point of comparison for evaluating how well different systems follow natural-language EQ instructions.

A.3.1 DIRECTIONAL LOSS FORMULATION

Text2FX-Directional uses CLAP audio/text embeddings to align the *change in audio embedding* with the *semantic direction* defined by a target prompt and a contrast prompt. Let f_a and f_t denote the CLAP audio and text encoders, and let $g(x;\theta)$ be a differentiable 6-band parametric EQ (dasp-pytorch). Given degraded audio x_{deg} and prompts t_1 (contrast) and t_2 (target), we define:

$$\begin{aligned} A_1 &= f_a(x_{\text{deg}}), \\ A_2(\theta) &= f_a\big(g(x_{\text{deg}};\theta)\big), \\ T_1 &= f_t(t_1), \\ T_2 &= f_t(t_2). \end{aligned}$$

The method encourages the audio embedding to move from A_1 to A_2 in the same direction as the text embedding moves from T_1 to T_2. Let

$$d_a(\theta) = \frac{A_2(\theta) - A_1}{\|A_2(\theta) - A_1\|_2}, \qquad d_t = \frac{T_2 - T_1}{\|T_2 - T_1\|_2}.$$

The directional loss is then:

$$\mathcal{L}_{\text{dir}}(\theta) = 1 - \cos\big(d_a(\theta), d_t\big).$$

We follow the optimization settings of Chu et al. (2025): 600 Adam iterations (learning rate 1×10^{-2}), standard-normal parameter initialization, and a random circular time shift at each step to avoid fixation on audio content.

A.3.2 Prompt and Contrast-Prompt Construction

Our EQ dataset contains natural-language instructions rather than the short adjectives used in Chu et al. (2025). To maintain the $T_1 \rightarrow T_2$ structure required by the directional loss, we construct a semantically opposite *contrast prompt* for each instruction using GPT with a constrained template ("write the opposite EQ action") and manual verification.

Examples used in our EQ evaluation include:

- **Clarity / Treble Boost:**
  - Target prompt (T_2): "Increase the clarity of this song by emphasizing treble frequencies."
  - Contrast prompt (T_1): "Decrease the clarity of this song by softening or reducing the treble frequencies and making it sound more dull and muffled."
- **Boominess / Low-End Enhancement:**
  - Target prompt (T_2): "Add weight and depth to the bottom end."
  - Contrast prompt (T_1): "Do the opposite of the following instruction: Add weight and depth to the bottom end."
- **Mic / Narrow-Band Coloration:**
  - Target prompt (T_2): "Balance the EQ, please."
  - Contrast prompt (T_1): "Do the opposite of the following instruction: Balance the EQ, please."

These pairs ensure that Text2FX-Directional receives properly opposed EQ semantics while matching the full-sentence instruction style of our enhancement dataset.

A.3.3 Purpose of This Baseline

Text2FX-Directional does not use the clean reference audio during optimization; thus it is *not* evaluated as a restoration model. Instead, we include it as a text-conditioned equalization baseline that evaluates: *How well can a CLAP-guided, single-instance EQ optimizer follow the same natural-language instructions given to SonicMaster?* This provides a fair, instruction-aligned comparison for EQ-specific transformations under identical textual guidance.

A.4 Degradation functions

To create the SonicMaster dataset, we used a set of 19 degradation functions. The details of their implementation and parameter range are described in Table 6. Each of the groups, and subsequently each of the functions inside the groups, have their own probabilities/weights to be picked in our data creation pipeline. These are documented in Table 7.

Peak normalisation of tracks: In case of no intentional clipping, "hidden clipping", or a low volume degradation being used, all degraded versions of the SonicMaster dataset are normalised to a peak amplitude y_{peak} drawn from a uniform distribution $y_{peak} \sim U(0.8, 1.0)$, track is then normalised as:

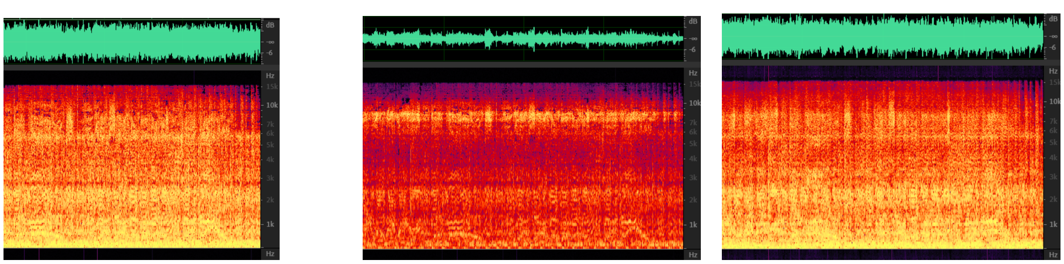
$$x_{norm} = \frac{x}{max(abs(x))} \times y_{peak}$$

Table 6: Detailed description of degradation functions used to create our dataset.

Degradation group	**Degradation type**	**Description**	**Prompt example (inverse)**
EQ	X-band EQ	Apply 8 to 12 band parametric EQ with -6 to $+6$ range for each band.	Correct the unnatural frequency emphasis.
	Microphone transfer function	Convolve the audio with one of 20 phone microphone transfer functions.	Reduce the coloration added by the microphone.
	Brightness	Reduce brightness using a high-shelf filter at 6 kHz by 6–15 dB.	Give the mix more shine and sparkle.
	Darkness	Increase perceived brightness with a high-shelf filter at 6 kHz by 6–15 dB.	Make the tone fuller and less sharp.
	Airiness	Reduce airiness via a high-shelf filter at 10 kHz by 10–20 dB.	Add more air and openness to the sound.
	Boominess	Reduce boominess with a low-shelf filter at 120 Hz by 10–20 dB.	Give the audio more roar and low-end power.
	Clarity	Degrade clarity using a Butterworth low-pass filter (order 3–5) with cutoff at 2 kHz.	Increase the clarity of this song by emphasizing treble frequencies.
	Muddiness	Increase muddiness with a 2nd-order Chebyshev Type II bandpass (200–500 Hz) by 6–15 dB.	Make the mix sound less boxy and congested.
	Warmth	Reduce warmth with a low-shelf filter at 400 Hz by 6–20 dB.	Make the sound warmer and more inviting.
	Vocals	Attenuate vocal-range frequencies using a 2nd-order Chebyshev Type II bandpass (350–3500 Hz) by 6–20 dB.	Make the vocals stand out more.
Dynamics	Compression	Apply a feedforward compressor with attack 3–80 ms, release 80–250 ms, threshold -45 to -38 dB, ratio 6–45, and make-up gain 16–25 dB.	Let the audio breathe more and improve the dynamics.
	Punch	Apply a feedforward transient shaper with attack 3 ms, release 150 ms, adaptive threshold, and reduction of 8–15 dB.	Add more impact and dynamic punch to the sound.
Reverb	Small room	Convolve with Pyroomacoustics simulated IR: room size $(7–15, 8–18, 4–14)$ m, absorption coefficient 0.05–0.30.	Clean this off any echoes!
	Big room	Convolve with Pyroomacoustics IR: room size $(4–8, 4–7, 2.5–3.5)$ m, 1–2 absorptive walls, frequency-dependent absorption.	Can you remove the excess reverb in this audio, please?
	Mixed material room	Convolve with Pyroomacoustics IR: room size $(3–7, 3–9, 2.5–4)$ m, absorption coefficient 0.05–0.30.	Remove excess reverb and make it sound cleaner.
	Real RIR	Apply one of twelve real impulse responses from the openAIR library.	Please, reduce the strong echo in this song.
Amplitude	Clipping	Modify the audio level to a maximum amplitude of {2,3,5} and apply clipping.	Reduce the clipping and reconstruct the lost audio, please.
	Volume	Adjust the audio gain to a maximum amplitude of {0.001, 0.003, 0.01, 0.05}.	Enhance the loudness without distorting the signal.
Stereo	Stereo	Combine the left and right channels to erase the spatial image.	Add depth and separation between left and right.

Group (weight)	Option	Probability / Weight
EQ (0.4)	xband	7.0
	mic	5.0
	bright	3.0
	dark	3.0
	airy	2.0
	boom	2.0
	clarity	3.0
	mud	3.0
	warm	3.0
	vocal	4.0
Dynamics (0.125)	comp	2.5
	punch	1.0
Reverb (0.225)	small	0.15
	big	0.15
	mix	0.30
	real	0.40
Amplitude (0.125)	clip	3.0
	volume	1.0
Stereo (0.125)	stereo	1.0

Table 7: Degradation groups with assigned probabilities and option weights.



(a) Original (clean). (b) Degraded input. (c) Restored output.

Figure 6: Original vs. degraded (via convolution with a phone microphone transfer function) and *SonicMaster*-restored spectrograms; restoration suppresses the microphone's coloration.

A.5 EVALUATION METRICS DETAILS

To evaluate SonicMaster's ability to deal with each of the 19 proposed degradations, we use a set of evaluation metrics as follows in this section. For all the metrics, except for X-band EQ, microphone transfer function, and all reverb options, we report absolute errors, i.e., the absolute value of difference of ground truth (GT) and inferred sample metric values:

$$AbsError_{metric} = \left|metric_{ground\_truth} - metric_{inferred}\right|.$$

EQ: The effect of all the EQ options, except for "xband" and "mic" is evaluated through absolute error of spectral energy ratio of two signals – the ground truth reference and the inferred signals. Spectral energy ratio ($Spectral\_ER$) is computed as:

$$Spectral\_ER = \frac{E_{band}}{E_{total}},$$

where E_{total} is the total energy of the signal, and E_{band} is the signal's energy in a spectral band given by the following boundaries B:

$$B = \begin{cases} (20, 150), & \text{if "boom"} \\ (20, 400), & \text{if "warm"} \\ (200, 500), & \text{if "mud"} \\ (350, 3500), & \text{if "vocal"} \\ (4000, f_s/2), & \text{if "clarity"} \\ (6000, f_s/2), & \text{if "bright"} \\ (6000, f_s/2), & \text{if "dark"} \\ (10000, f_s/2), & \text{if "airy"} \end{cases}$$

where f_s stands for sampling rate.

The remaining two EQ functions of "xband" and "mic" are evaluated through a cosine distance of spectral balance of the ground truth reference and inferred signal. Spectral balance (SB) is calculated as a normalised energy profile in 9 pre-defined frequency bands:

$$SB = \frac{[E_1, E_2, E_3, E_4, E_5, E_6, E_7, E_8, E_9]}{sum[E_1, E_2, E_3, E_4, E_5, E_6, E_7, E_8, E_9]}.$$

The bands are given as:

$$B_{balance} = \begin{cases} (20, 60), & \text{if index} = 1 \\ (60, 250), & \text{if index} = 2 \\ (250, 500), & \text{if index} = 3 \\ (500, 2000), & \text{if index} = 4 \\ (2000, 4000), & \text{if index} = 5 \\ (4000, 6000), & \text{if index} = 6 \\ (6000, 10000), & \text{if index} = 7 \\ (10000, 16000), & \text{if index} = 8 \\ (16000, 20000), & \text{if index} = 9 \end{cases}$$

The reported cosine distance is then gained as:

$$cosine\_distance = 1 - cos(SB_{ground\_truth}, SB_{inferred}).$$

Amplitude: Clipping correction is evaluated through spectral flatness using the LIBROSA.FEATURE.SPECTRAL_FLATNESS library function, which takes in a power spectrogram gained through STFT with n_fft=2048 and hop length = 512. The final metric for clipping is the absolute error of spectral flatness (GT vs inferred sample).

Volume is evaluated as the absolute error of the Root-Mean-Square (RMS) value.

Dynamics: Compression is evaluated as the standard deviation of the dynamic range (STD_DR), given as:

$$STD\_DR = std(RMS(\mathcal{F}_{H,L})),$$

where $\mathcal{F}_{H,L}$ represents a set of waveform frames with length 2048 and hop length 1024 each. The final metric is the absolute error from the GT.

The "punch" is measured through transient strength by taking the mean value of the transient envelope gained from the LIBROSA.ONEST.ONSET STRENGTH library function with default parameters.

Reverb: We evaluate the effect of dereverberation using modulation spectrum distance (MSD).

First, we get a set of temporal envelopes E_x from input signal x:

$$E_x^{(k)}(m) = \left|\mathrm{STFT}\{x\}(k,m)\right|,$$

where k indexes frequency bins and m indexes time frames. Modulation spectrum $S_x^{(k)}(b)$ is then calculated using demeaned temporal envelopes:

$$S_x^{(k)}(b) = \left|\mathrm{FFT}_m\left(E_x^{(k)}(m) - \frac{1}{M}\sum_{m'=0}^{M-1} E_x^{(k)}(m')\right)\right|_b, \qquad b = 0, \ldots, B-1.$$

where b represents modulation bins.

Modulation spectra from all frequency bands are then stacked into a single vector:

$$\mathbf{s}_x = \mathrm{vec}\Big(S_x^{(k)}(b)\Big),$$

and ℓ_2 normalized:

$$\hat{\mathbf{s}}_x = \frac{\mathbf{s}_x}{\|\mathbf{s}_x\|_2 + \varepsilon}.$$

The MSD between two signals, in our case the GT reference x_{GT} and relevant inferred sample x_{infer}, is given as Euclidean distance:

$$MSD(x_{GT}, x_{infer}) = \left\|\hat{\mathbf{s}}_{x_{GT}} - \hat{\mathbf{s}}_{x_{infer}}\right\|_2.$$

In code, this is realized with following parameters as:

```
import numpy as np
from scipy.spatial.distance import euclidean
from scipy.signal import stft

def modulation_spectrum_distance(x1, x2, fs=44100,
    n_fft=1024, hop_length=512, n_mod_bins=20):

    def get_modulation_spectrum(x):
        f, t, Zxx = stft(x, fs=fs, nperseg=n_fft, noverlap=n_fft - hop_length)
        mag = np.abs(Zxx)

        mod_spec = []
```

```
        for band in mag:
            envelope = band - np.mean(band)
            spectrum = np.abs(np.fft.fft(envelope))[:n_mod_bins]
            mod_spec.append(spectrum)

        mod_spec = np.array(mod_spec)
        mod_spec /= np.linalg.norm(mod_spec) + 1e-10
        return mod_spec.flatten()

    mod1 = get_modulation_spectrum(x1)
    mod2 = get_modulation_spectrum(x2)

    return euclidean(mod1, mod2)
```

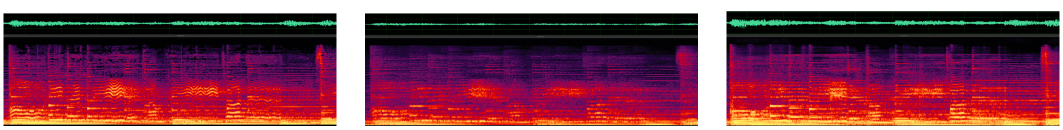
Stereo: We measure the level of stereoness using stereo energy ratio ($Stereo\_ER$), computed as:

$$Stereo\_ER = \frac{RMS(\frac{L-R}{2})}{RMS(\frac{L+R}{2}) + 10^{-10}} \tag{3}$$

We report the absolute error of this metric.

A.6 Spectrogram examples

We visualize time–frequency structure in spectrograms to provide qualitative evidence of restoration behavior. Each figure shows the clean reference, the degraded input (e.g., reverberation-induced smearing or clipping distortion), and the output of SonicMaster. Figures 6, 7, 8, 9, 10, and 11 compare clean, degraded, and restored spectrograms across selected scenarios (reverb, clipping, microphone transfer function, and clarity EQ).

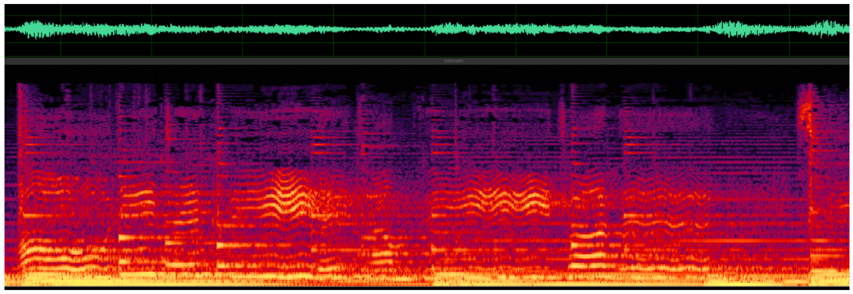


(a) Ground truth audio. (b) Degraded by reverb (smearing). (c) After SonicMaster: reverb removed.

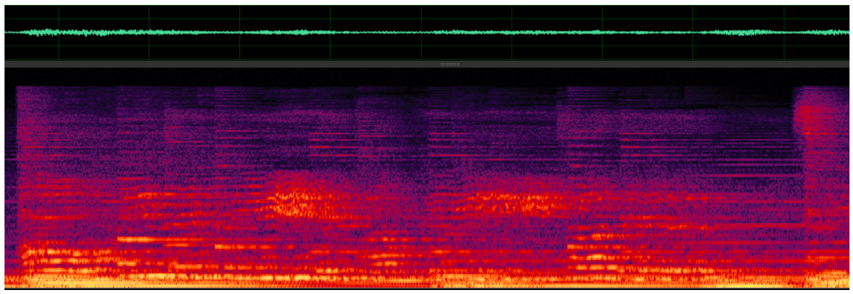
Figure 7: Comparison of spectrograms: (a) ground truth, (b) degraded with reverb, and (c) the output of SonicMaster where smearing is removed. Prompt: "Please, reduce the strong echo in this song."

Model (MMDiT/DiT)	**Clarity**	**Boom**	**Airy**	**Bright**	**Dark**	**Muddy**	**Warm**	**Vocals**	**Microphone**	**X-band**
					Snippet degraded input					
SonicMaster$_{Large}$ (6/18)	0.0114	0.0834	**0.0019**	0.0059	**0.0058**	**0.0388**	**0.0617**	0.0576	0.0088	**0.0358**
-w Euler 1 Step	**0.0100**	0.1146	0.0019	0.0059	0.0061	0.0425	0.0668	**0.0498**	0.0141	0.0384
-w Euler 100 Steps	0.0136	0.1540	0.0033	0.0100	0.0091	0.0540	0.0915	0.0749	0.0162	0.0444
-w Runge-Kutta 10 Steps	0.0120	**0.0810**	0.0019	**0.0058**	0.0058	0.0402	0.0630	0.0590	**0.0083**	0.0374
SonicMaster$_{Small}$ (2/6)	**0.0100**	0.0819	0.0020	0.0064	0.0060	0.0477	**0.0590**	0.0630	0.0122	0.0408
SonicMaster$_{Medium}$ (4/12)	0.0105	**0.0698**	0.0021	0.0067	0.0061	0.0400	0.0592	0.0602	0.0091	0.0383
SonicMaster$_{Medium}$ (6/6)	0.0225	0.2766	0.0020	0.0067	**0.0056**	0.1718	0.1737	0.2417	0.0462	0.0762
SonicMaster$_{Large}$ (6/18)	0.0114	0.0834	**0.0019**	**0.0059**	0.0058	**0.0388**	0.0617	**0.0576**	**0.0088**	**0.0358**
SonicMaster$_{Large}$ (6/18)	0.0114	0.0834	**0.0019**	**0.0059**	0.0058	0.0388	0.0617	0.0576	0.0088	0.0358
-w 5s Audio Cond.	0.0111	0.0716	0.0021	0.0061	0.0058	0.0386	0.0605	0.0628	0.0124	0.0387
-w 15s Audio Cond.	0.0117	0.0750	0.0020	0.0064	0.0063	**0.0320**	**0.0552**	**0.0525**	**0.0079**	0.0398
-w/o Audio Cond. (basic)	**0.0099**	**0.0658**	0.0021	0.0064	**0.0056**	0.0352	0.0595	0.0746	0.0097	0.0434
-w Cond. During Infer	0.0115	0.0840	0.0019	0.0060	0.0058	0.0389	0.0610	0.0572	0.0088	**0.0355**

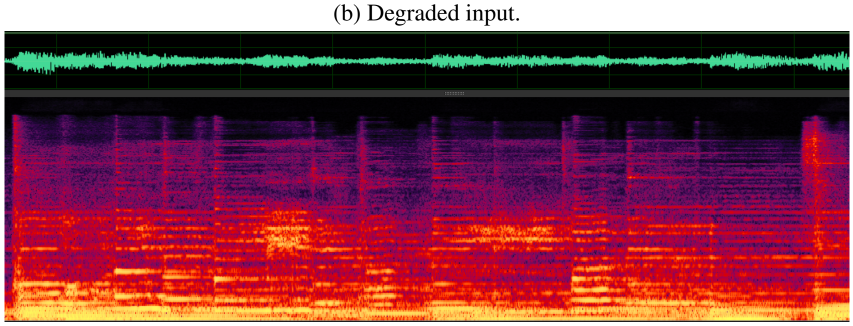
Table 8: EQ Objective evaluation (average absolute error) – the lower, the better.



(a) Original (clean).



(b) Degraded input.



(c) Restored output.

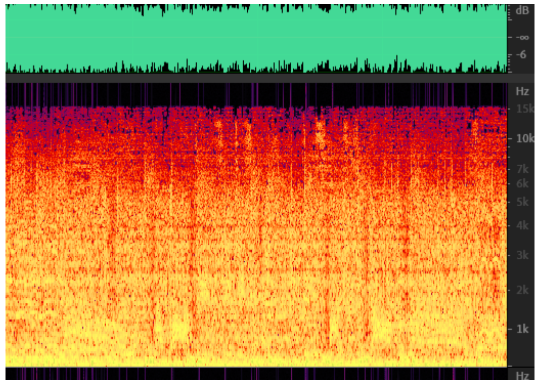
Figure 8: Effect of reverberation (example from the main text in larger size): top panel shows the original audio sample, middle panel shows audio convolved with a Pyroomacoustics simulated impulse response, and bottom panel shows the dereverberated result with echoes cleaned.

A.7 Ablation on ODE solvers, model size, and conditioning

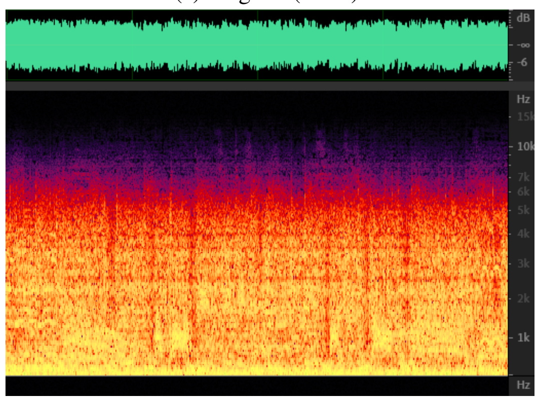
We evaluated Euler solvers with 1, 10 (baseline), and 100 steps, plus a 10-step 4th order Runge–Kutta (Dormand & Prince, 1980) solver. Tables 8, 9, and 10 outline the results and highlight the trade-off across degradation categories. Euler-1 matches the baseline overall but is weaker on Boom, Microphone, Clip, all Reverb subtasks, and shows higher KL. Euler-100 boosts Reverb and Punch yet lowers every EQ score versus the 1-/10-step runs. Runge–Kutta-10 equals Euler-10 on most metrics and tops Clip, but its inference is significantly slower.

We further performed a scaling analysis of the *SonicMaster* model. The results in Tables 8, 9, 10, show that *SonicMaster*$_{Small}$ performs comparably with *SonicMaster*$_{Large}$ in all metrics, but slightly worse in Reverb, Clip, and Stereo. The medium variant, *SonicMaster*$_{Medium}$ (4MM-DiT/12DiT), performs slightly better than the small model *SonicMaster*$_{Small}$ overall. It also performs comparably to the large model *SonicMaster*$_{Large}$, outperforming it in Boom, or Compression, but still lacking behind in Clip. *SonicMaster*$_{Medium}$ (6MM-DiT/6DiT) performs the worst out of all variants across all metrics, suggesting a non-optimal ratio of MM-DiT to DiT blocks.

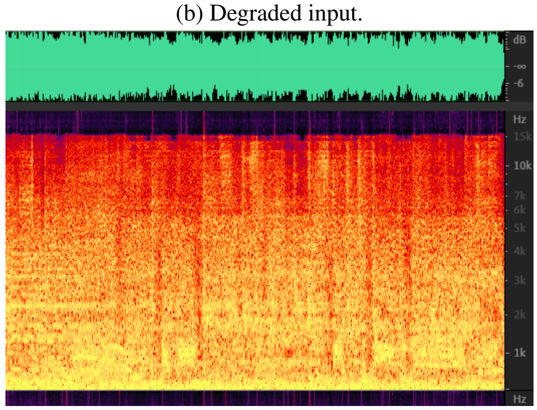
Regarding the audio condition and its duration, we evaluated *SonicMaster*$_{Large}$ with three different conditioning lengths (5s, 10s, 15s). The performance across configurations was found to be comparable (Tables 8, 9, 10). For our default model version, we chose the 10-second setting as it balances



(a) Original (clean).



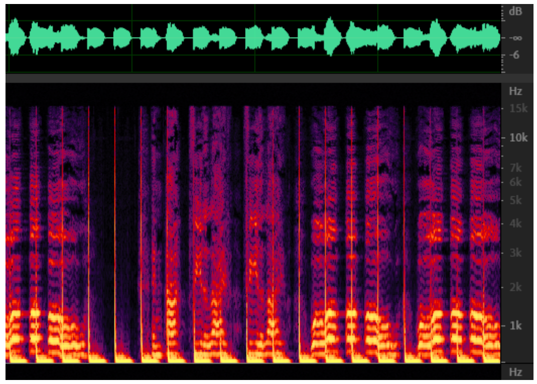
(b) Degraded input.



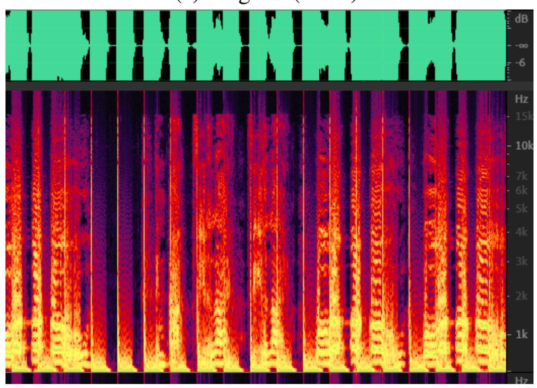
(c) Restored output.

Figure 9: Effect of clarity degradation and restoration on spectrograms. The treble frequencies are supressed in the degraded input sample, and then restored with SonicMaster. Prompt: "Make the audio clearer and more intelligible."

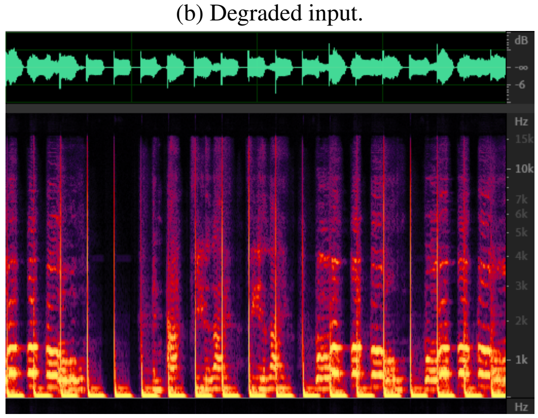
computational efficiency with temporal overlap for long-form processing. The variant that uses audio condition through the pooling layers during inference scored comparably to the default setup, however, we can observe improvement in Clip and Volume (Table 9). The model trained without audio conditioning performs similarly across the board, scoring the best in Boom (0.0658, Table 8), but shows a clear drop in Clip performance (2.055 vs 1.506, see Table 9), which highlights the importance of this condition for this reconstruction task.



(a) Original (clean).



(b) Degraded input.

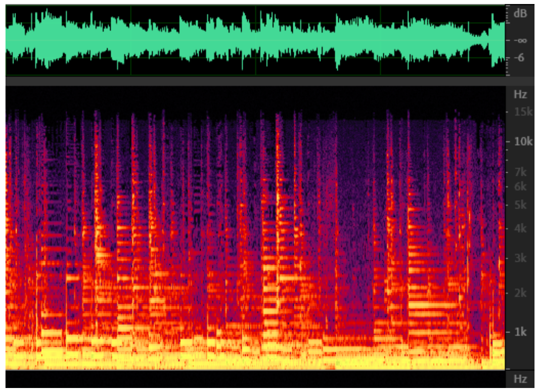


(c) Restored output.

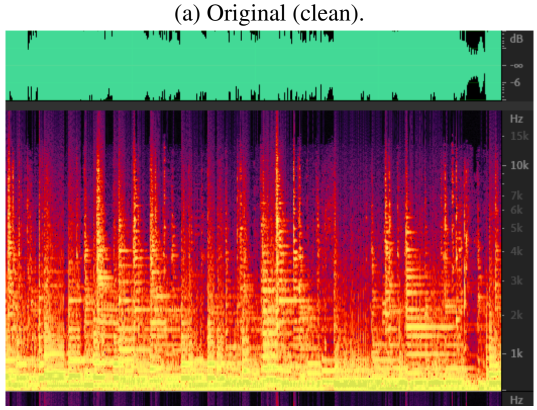
Figure 10: Effect of clipping degradation and related restoration. Drum hits clip in the degraded audio, showing as wideband spectral peaks, but are restored in the SonicMaster's output without distortion. Prompt: "Clean up the harshness in the signal."

A.8 Prompts for each degradation type

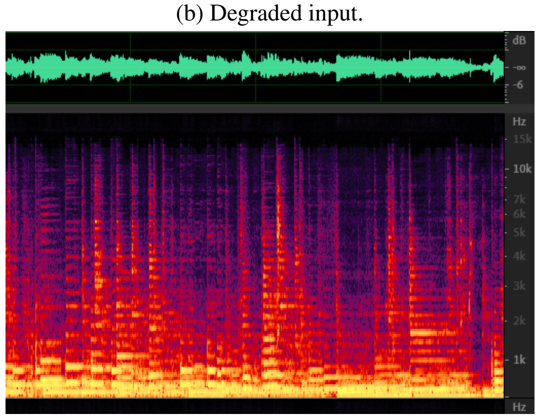
Prompt instructions for each degradation type are grouped by audio attribute in Table 11; for example, entries for Xband, microphone coloration, clarity, brightness, darkness, airiness, boominess, warmth, muddiness, vocals, compression, punch, reverb, volume, clipping, and stereo give natural-language commands that steer the restoration model. These instructions act as conditioning signals—e.g., "remove excess reverb and make it sound cleaner," "raise the level of the vocals," or "make this sound brighter"—so that the generative restoration trajectory emphasizes or suppresses specific signal characteristics.



(a) Original (clean).



(b) Degraded input.



(c) Restored output.

Figure 11: Another example of the effect of clipping and its restoration. The degraded input shows signs of distortion with visible increase in wideband spectral content at the parts of waveform clipping. This distortion is suppressed by SonicMaster. Prompt: "Clean up the noisiness in the audio."

Model (MMDiT/DiT)	**Reverb**				**Dynamics**		**Amplitude**		**Stereo**
	Small	**Big**	**Mix**	**Real**	**Compressor**	**Punch**	**Clip**	**Volume**	
Snippet degraded input									
SonicMaster$_{Large}$ (6/18)	0.3663	0.3726	0.3935	0.3109	0.0193	0.0871	1.506	0.0468	**0.1058**
-w Euler 1 step	0.4215	0.4378	0.4599	0.3459	**0.0124**	0.0906	2.171	**0.0461**	0.1261
-w Euler 100 Steps	0.3716	0.3754	0.3997	0.3255	0.0158	**0.0672**	2.753	0.0491	0.1497
-w Runge-Kutta 10 Steps	**0.3647**	**0.3684**	**0.3921**	**0.3087**	0.0210	0.0858	**1.422**	0.0481	0.1059
SonicMaster$_{Small}$ (2/6)	0.3812	0.3826	0.4050	0.3277	0.0172	0.0859	2.363	0.0457	0.1536
SonicMaster$_{Medium}$ (4/12)	0.3683	**0.3700**	**0.3934**	0.3138	**0.0147**	0.0891	2.455	**0.0409**	**0.1028**
SonicMaster$_{Medium}$ (6/6)	0.3952	0.3916	0.4422	0.4255	0.0366	**0.0833**	2.905	0.1228	0.4180
SonicMaster$_{Large}$ (6/18)	**0.3663**	0.3726	0.3935	**0.3109**	0.0193	0.0871	**1.506**	0.0468	0.1058
SonicMaster$_{Large}$ (6/18)	0.3663	0.3726	0.3935	0.3109	0.0193	0.0871	1.506	0.0468	0.1058
-w 5s Audio Cond.	0.3717	**0.3658**	0.3919	0.3079	0.0164	0.0893	1.779	0.0430	**0.0918**
-w 15s Audio Cond.	0.3676	0.3682	0.3901	0.3093	0.0172	0.0895	1.633	0.0485	0.1008
-w/o Audio Cond. During Training	**0.3620**	0.3682	**0.3888**	**0.3067**	**0.0146**	**0.0850**	2.055	0.0455	0.1015
-w Cond. During inference	0.3664	0.3724	0.3934	0.3112	0.0172	0.0870	**1.455**	**0.0412**	0.1060

Table 9: Objective evaluation: Reverb, Dynamics, Amplitude, and Stereo. Clip values are multiplied by 1000.

Model	**Single deg.**				**Double+triple deg.**				**All**			
	FAD ↓	**KL** ↓	**SSIM** ↑	**PQ** ↑	**FAD** ↓	**KL** ↓	**SSIM** ↑	**PQ** ↑	**FAD** ↓	**KL** ↓	**SSIM** ↑	**PQ** ↑
Snippet degraded input												
SonicMaster$_{Large}$ (6/18)	**0.069**	**0.696**	**0.624**	7.743	**0.082**	**1.145**	**0.589**	**7.654**	**0.073**	**0.888**	**0.609**	**7.705**
-w Euler 1 step	0.076	0.922	0.615	7.684	0.117	1.789	0.567	7.520	0.090	1.294	0.594	7.614
-w Euler 100 Steps	0.069	0.920	0.620	**7.764**	0.087	1.521	0.585	7.621	0.076	1.178	0.605	7.703
-w Runge-Kutta 10 Steps	0.070	0.701	0.624	7.740	0.084	1.171	0.588	7.642	0.074	0.902	0.608	7.698
SonicMaster$_{Small}$ (2/6)	0.071	0.726	0.623	7.716	0.088	1.215	0.586	7.609	0.077	0.935	0.607	7.670
SonicMaster$_{Medium}$ (4/12)	0.070	0.709	0.624	7.740	0.084	1.187	0.589	7.649	0.075	0.914	0.609	7.701
SonicMaster$_{Medium}$ (6/6)	0.086	1.893	0.603	7.571	0.154	3.241	0.555	7.231	0.110	2.470	0.583	7.426
SonicMaster$_{Large}$ (6/18)	**0.069**	**0.696**	**0.624**	**7.743**	**0.082**	**1.145**	**0.589**	**7.654**	**0.073**	**0.888**	**0.609**	**7.705**
SonicMaster$_{Large}$ (6/18)	**0.069**	0.696	0.624	**7.743**	**0.082**	1.145	0.589	**7.654**	**0.073**	0.888	0.609	**7.705**
-w 5s Audio Cond.	0.070	0.703	0.624	7.733	0.083	1.175	0.588	7.637	0.075	0.905	0.609	7.692
-w 15s Audio Cond.	0.069	0.694	0.623	7.742	0.083	1.161	0.588	7.650	0.073	0.894	0.608	7.702
-w/o Audio Cond. During Training	0.069	**0.691**	0.625	7.741	0.082	1.146	**0.590**	7.645	0.073	0.886	**0.610**	7.700
-w Cond. During Inference	0.069	0.693	**0.625**	7.742	0.082	**1.141**	0.589	7.653	0.073	**0.885**	0.609	7.704

Table 10: Objective evaluation: FAD, KL, SSIM, and PQ. For readability, KL values were multiplied by 1000.

Table 11: User instructions grouped by audio attribute.

Attribute	Example Instructions
Xband	Can you please correct the equalization?; Improve the balance in the audio by fixing the chaotic equalizer, please.; Make this sound balanced, please.; Balance the EQ, please.; Balance the tonal spectrum of the audio.; Correct the unnatural frequency emphasis.; Make the EQ curve smoother and more natural.; Even out the EQ.; Adjust the tonal balance for a more pleasing sound.
Microphone	This audio was recorded with a phone, can you fix that, please?; Please make this sound better than a phone recording.; Balance the EQ, please.; Improve the balance in this song.; Make the audio sound like it was recorded with a higher-quality microphone.; Reduce the coloration added by the microphone.; Make the tone more neutral and balanced.; Improve the naturalness of the recording.; Remove the harshness or boxiness from the mic coloration.
Clarity	Increase the clarity!; Can you please make this song sound more clear?; Increase the clarity of this song by emphasizing treble frequencies.; Make the audio clearer and more intelligible.; Sharpen the overall sound.; Bring more focus and definition to the details.; Make the mix sound less cloudy.; Tighten the articulation in the sound.
Brightness	Can you please make this sound brighter?; Increase the brightness!; Make this audio sound brighter by emphasizing the high frequencies.; Add some brightness to the high end.; Make the sound more vivid and lively.; Give the mix more shine and sparkle.; Lift the treble for a more open tone.; Enhance the presence of the upper frequencies.
Darkness	Make this sound darker!; Can you reduce the brightness, please?; Make the audio darker by suppressing the higher frequencies.; Bring in more low-mid richness to make the sound darker.; Make the tone fuller and less sharp.; Smooth out the highs with deeper low-end support.; Round out the sound with more body.; Soften the harshness with a warmer tone.
Airiness	Make this sound more fresh and airy by emphasizing the high end frequencies.; Make this feel more airy, please.; Increase the perceived airiness, please.; Give this a light sense of spaciousness by amplifying the higher frequencies.; Add more air and openness to the sound.; Make the audio feel more spacious and extended.; Enhance the sense of space in the highs.; Lift the top end for a more open character.; Give the mix a breathier, more open feel.
Boominess	Make it boom!; Make this song sound more boomy by amplifying the low end bass frequencies.; Increase the boominess, please!; Give me more bass!; Can you make this more bassy, please?; Give the audio more roar and low-end power.; Make the bass more impactful and solid.; Add weight and depth to the bottom end.; Reinforce the low frequencies for more energy.; Boost the bass presence.
Warmth	Can you make this song sound warmer, please?; Increase the warmth, please.; Emphasize the bass and low-mid frequencies to give this a more warm feel.; Make the sound warmer and more inviting.; Add some low-mid warmth to the mix.; Soften the tone with a bit more body.; Give the audio a warm analog feel.; Enhance the warmth for a fuller sound.
Muddiness	Can you make this song sound less muddy, please?; Decrease the muddiness!; Reduce the level of muddiness in this audio by lowering the low-mid frequencies.; Clean up the muddiness in the low-mids.; Make the mix sound less boxy and congested.; Improve definition by reducing mud.; Clear up the low-mid buildup.; Make the audio tighter and less murky.
Vocals	Raise the level of the vocals, please.; Can you amplify the vocals, please?; Emphasize the vocals by raising the level of the mid frequencies specific for vocals.; Bring the vocals forward in the mix.; Make the voice clearer and more present.; Increase the vocal presence by enhancing the midrange.; Make the vocals stand out more.; Strengthen the vocal clarity and focus.
Compression	Increase the dynamic range.; Decompress the audio, please.; Remove the compression, please.; Can you fix the strong compression effect in this audio by expanding the dynamic range?; Restore the dynamics of the audio.; Make the sound less squashed and more open.; Reduce the over-compression for a more natural feel.; Bring back the contrast in volume.; Let the audio breathe more and improve the dynamics.
Punch	Give this song a punch!; Make the transients sharper, please.; Increase the punchiness of the song by emphasizing the transients.; Make the audio more punchy and energetic.; Bring back the snap and attack of transients.; Add more impact and dynamic punch to the sound.; Make drums and hits sound more aggressive and tight.; Increase the percussive clarity and definition.
Reverb	Can you remove the excess reverb in this audio, please?; Please, dereverb this audio.; Remove the echo!; Please, reduce the strong echo in this song.; Remove the church effect, please.; Clean this off any echoes!; This song has too much reverb present, can you reduce it?; Make the audio sound more dry and direct.; Reduce the roominess or echo.; Remove excess reverb and make it sound cleaner.; Bring the sound closer and more focused.; Tighten the spatial feel of the audio.
Volume	The volume is low, make this louder please!; Can you make this sound louder, please?; Increase the amplitude.; Normalize the audio volume.; Make the audio louder and more powerful.; Increase the overall level.; Boost the volume without distorting the signal.
Clipping	This audio is clipping, can you please remove it?; Remove the loud hissing in this song?; Remove the clipping.; Reduce the clipping and reconstruct lost audio.; Clean up noisiness.; Make the audio smoother and less distorted.; Reduce the gritty or crushed character.; Fix digital distortion.
Stereo	Make it sound spacious!; Can you make this audio stereo, please?; Alter left/right channels to give spatial feel.; Widen the stereo image.; Add depth and separation between left and right.; Enhance the stereo field for immersive sound.