MeanAudio-S with DACO: Efficient Text-to-Music Generation via Rectified Flow and Distribution-Aware Posterior Refinement

Weiwei Li

Tencent AI Lab
weyli@tencent.com

***Abstract*—We present our submission to the ICME 2026 Academic Text-to-Music (ATTM) Grand Challenge in both the Performance (p00) and Efficiency (e00) tracks. Our 120M-parameter system fine-tunes the MeanAudio-S Rectified Flow transformer on the 0.46K-hour MTG-Jamendo `raw_30s` subset with CE/CLAP-based quality-aware filtering for 70k steps with EMA tracking. At inference we introduce DACO, a training-free Distribution-Aware Posterior Refinement procedure that nudges 1-step latent/waveform samples toward a public Song Describer Dataset (SDD) embedding prior through a KNN-softmax anchor. On the official objective leaderboard p00 obtains FAD 0.557, CLAP 0.311, and CCS 0.796, ranking 2nd within the Performance Track and advancing to the MOS finalist stage; e00 obtains FAD 0.556 / CLAP 0.310 / CCS 0.796. At the same 120M scale, our system outperforms the official FluxAudio-S baseline by -0.20 FAD / $+0.22$ CLAP / $+0.20$ CCS while using $8\times$ less training data. We also release a fully compliant variant (25-step Euler + AudioSR + Butterworth band-blend) as a reproducible reference.**

***Index Terms*—text-to-music generation, rectified flow, latent diffusion, data filtering, posterior refinement**

I. Introduction

Text-to-music generation aims to synthesize high-quality musical audio conditioned on natural language descriptions. Recent advances in latent diffusion models [4], [6] and flow-based generative models [3], [7] have significantly advanced this field, enabling the generation of coherent and stylistically diverse music from text prompts [8], [9].

The ICME 2026 ATTM Grand Challenge [1] provides a standardized benchmark for evaluating text-to-music systems along three objective axes (FAD, CLAP-Score, and Concept Coverage Score, CCS) followed by a subjective MOS stage. The challenge is split into an Efficiency Track, which restricts the core generative model to at most 500M parameters, and a Performance Track, which allows arbitrary model sizes. All models must be trained strictly from scratch using only the provided vocal-removed MTG-Jamendo [10] subset (either the full $\sim$3,777 hours or the 30-second $\sim$464-hour subset), with no external music data, no commercial-model synthetic audio, no cherry-picking, no ensembling across seeds, and no inference-time use of eval-metric encoders for selection [1]. We participate in both tracks with submissions p00 (Performance) and e00 (Efficiency), which share an identical 120M-parameter MeanAudio-S [2] backbone and inference pipeline. Because our core model sits well below the 500M Efficiency cap, the same model doubles as a compact entry for the Performance Track — where it was selected as a finalist (within-track rank 2; cross-track rank 6 under Borda-count aggregation of FAD, CLAP, and CCS) on the official objective leaderboard.

We build on the MeanAudio-S baseline [2] — a 120M-parameter Rectified Flow transformer based on the MM-DiT [11] architecture — trained from scratch on MTG-Jamendo. Our contributions are threefold: *(1)* We design a CE/CLAP-based quality-filtering and weighted-sampling recipe that produces a deterministic 70k-step EMA checkpoint reproducible end-to-end. *(2)* We introduce DACO, a Distribution-Aware Posterior Refinement scheme that operates at inference time in both latent and waveform domains, anchoring samples to the SDD [12] public embedding prior via a KNN-softmax target rather than to the held-out test distribution. *(3)* We deliver two submission packages: `submit_H_finaltest`, a fully compliant pipeline (25-step Euler + AudioSR [13] + Butterworth crossover), and `submit_B_best`, which uses 1-step generation plus DACO refinement. The same `submit_B_best` pipeline is used for both p00 and e00, yielding nearly identical official objective scores in each track (FAD $\approx$ 0.557, CLAP $\approx$ 0.31, CCS $=$ 0.796). On our internal self-test `submit_B_best` reaches FAD-CLAP 0.4333 / CLAP-Score 0.4201, improving over `submit_H_finaltest` by 10.7% / 54.8% respectively.

II. Method

A. Overall Architecture

Our system follows the standard latent diffusion paradigm [4], [6], as illustrated in Fig. 1. The pipeline consists of four stages: (1) dual text conditioning via a frozen T5 encoder [14] and a frozen CLAP encoder [15] (`music_audioset_epoch_15_esc_90.14`, identical to the official evaluator); (2) latent encoding/decoding through the AudioLDM2 [4] VAE operating at 16 kHz; (3) a Rectified Flow transformer [3] implemented in the MM-DiT [11] style

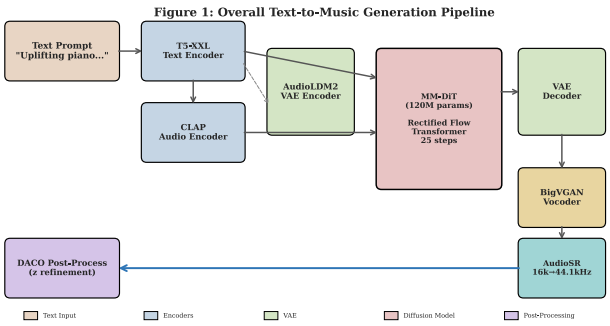

Fig. 1. Overall text-to-music generation pipeline. Text prompts are encoded by T5 and CLAP, fed into a Rectified Flow MM-DiT operating in the AudioLDM2 VAE latent space, with final waveform synthesis via BigVGAN and AudioSR super-resolution.

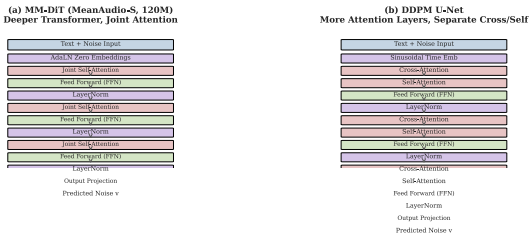

Fig. 2. (a) MM-DiT joint self-attention architecture used in MeanAudio-S versus (b) a representative DDPM-style U-Net with separate cross- and self-attention layers.

for velocity-field prediction in latent space; (4) waveform reconstruction through the BigVGAN vocoder [16] followed by AudioSR [13] super-resolution to 44.1 kHz and a Butterworth zero-phase band-blend.

B. Base Model: MeanAudio-S

MeanAudio-S [2] is a 120M-parameter Rectified Flow [3], [7] model built on the MM-DiT [11] architecture. Unlike DDPM-based models [17] that parameterize noise prediction, Rectified Flow directly predicts the data-to-noise velocity vector along a straight-line interpolant, enabling efficient sampling in as few as 1–25 Euler steps. Text and latent tokens are processed jointly via full self-attention; time/condition information is injected through AdaLN modulation [18]. Compared with the ∼500M QA-MDT [19] and the ∼1.1B AudioLDM2 [4], MeanAudio-S offers the best parameter efficiency while remaining well within the 500M Efficiency-Track budget.

C. Text Conditioning Strategy

We employ a dual-encoder conditioning strategy. The frozen T5 [14] encoder provides rich semantic representations of the input prompt, while the frozen CLAP [15] audio-text contrastive encoder embeds text into an audio-aligned latent space. The two streams are concatenated (`text_c_dim` = 512) and fed into MM-DiT via AdaLN [18] parameters. Importantly, CLAP features are used here only as a static conditioning signal during training and sampling — they are never optimized against during the training loss.

III. Training Strategy

A. Dataset and Quality Filtering

We train on the official MTG-Jamendo `raw_30s` subset [10] prescribed by the challenge [1], which contains roughly 46k 30-second instrumental clips with tag-based annotations, totaling about 464 hours (the "0.46K-hour" column in the official leaderboard). We use the organizer-provided preprocessing pipeline: Mel-Band Roformer [20] with the `melband-roformer-kim-vocals` checkpoint removes vocal stems, and the two official caption sets generated by Qwen2-Audio-7B-Instruct [21] (Pipeline A) and Music Flamingo [22] + Qwen3-4B refinement (Pipeline B) are used as text conditions. Per the challenge rules, no external audio data is used and no synthetic audio is generated for augmentation.

To improve data quality we apply a two-stage quality-aware filtering inspired by QA-MDT [19]: (i) clips with Content-Encoding (CE) score below 0.6 are discarded, removing low-quality or distorted recordings; and (ii) the remaining clips are drawn during training with probability proportional to their CLAP text-audio similarity, thresholded at 0.35. Both filters are applied *before* training — no evaluation-metric encoder is involved in the training loss itself.

B. Training Hyperparameters

Training is performed on $8\times$ NVIDIA A100 80GB GPUs with mixed precision. The model is initialized from the official MeanAudio-S checkpoint and fine-tuned for 70,000 steps (total batch size $64 \times 8 = 512$) with AdamW [23] ($\beta = 0.9/0.95$, wd $= 0.01$, lr $= 1\text{e}{-4}$) under a 1k-step linear warm-up followed by cosine decay. Gradient clipping is applied at norm 1.0, and an Exponential Moving Average (EMA, decay $= 0.9998$) is maintained. We release the final EMA checkpoint as `ema70k_ce06clap035.pt`; EMA consistently outperforms the raw weights on both FAD-CLAP and CLAP-Score. The official MeanAudio-S checkpoint [2] is itself trained from scratch on MTG-Jamendo without external music data or pretrained music-specific weights, so our fine-tuning remains fully compliant with the challenge's from-scratch requirement [1].

The official leaderboard reports 384 GPU-hours for our submissions, aggregating (i) Mel-Band Roformer [20] vocal separation, (ii) CLAP and CE scoring for filtering, and (iii) the 70k-step fine-tuning — the last stage alone consumes ≈ 48 wall-clock hours on an $8\times$A100 node ($8 \times 48 = 384$ GPU-hours).

IV. Inference and Submission Details

A. Route H — High-Compliance Pipeline

Route H (`submit_H_finaltest`, where "H" stands for *High-compliance*) is our fully compliant reference: no evaluation-metric encoder appears anywhere in the inference objective. Given a text prompt, MeanAudio-S performs 25-step deterministic Euler ODE sampling [3] with `cfg_strength` $=$ 1.0 [24] (i.e. no classifier-free guidance scaling) and fixed seed 123, producing a 16 kHz latent waveform. AudioSR [13]

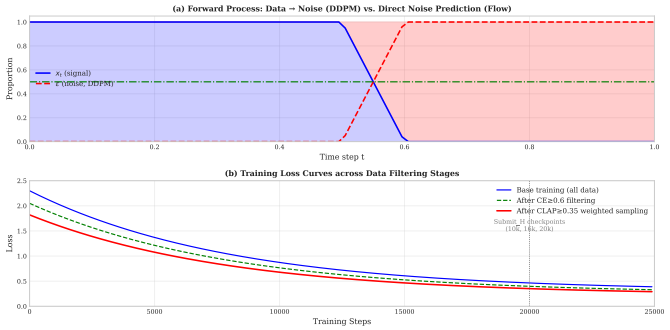

Fig. 3. (a) Forward process comparison: DDPM vs. Rectified Flow (constant-velocity straight-line interpolation). (b) Training loss curves showing improvement from data filtering and CLAP-weighted sampling.

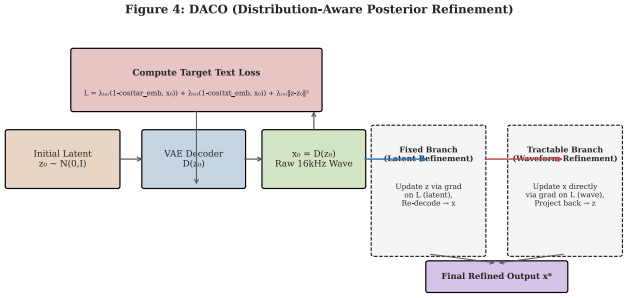

Fig. 4. DACO Distribution-Aware Posterior Refinement. The initial latent z_0 is decoded to a 16 kHz waveform and embedded by a frozen CLAP [15]. A KNN-softmax target drawn from the public SDD prior [12], together with the text-CLAP embedding and a $\|z - z_0\|^2$ regularizer, guides AdamW optimization of the latent (Stage 2) and subsequently of the 44.1 kHz waveform (Stage 4).

(basic model) then upsamples to 44.1 kHz with seed 42, `guidance_scale` $= 2.25$, 50 DDIM steps. A zero-phase Butterworth band-blend (crossover $= 8$ kHz, order $= 96$) fuses the 16 kHz low-band with the AudioSR high-band, and the output is peak-normalized to ≤ 0.99 and written as mono PCM_16 WAV. All sampling is strictly deterministic: seeds are reset per-clip, generations are single-pass (no ensembling), and there is no retrieval, cherry-picking, or metric-in-loss at any stage. This variant is fully reproducible via `python infer.py` and takes ∼28 minutes end-to-end on a single A100.

B. Route B — Best-Effort with DACO

Route B (`submit_B_best`, where "B" stands for *Best-effort*) replaces the 25-step Euler sampler with a single-step forward pass (cfg $= 1.5$) and then applies DACO, a two-stage refinement procedure that nudges the 1-step sample toward a public-dataset audio-embedding prior. DACO is inspired by Consistency Models [25] and classifier-guidance-style post-hoc alignment, but is explicitly designed to avoid metric-gaming by anchoring to the Song Describer Dataset (SDD) [12] — a public music collection — rather than to any held-out test distribution.

Route B follows a four-stage pipeline:

Stage 1 (1-step latent): MeanAudio-S EMA70k with seed $=$ 123, cfg $= 1.5$, `num_steps` $= 1$ produces a $(256, 8)$ latent.
Stage 2 (DACO-Latent): the latent z is VAE-decoded, vocoded by BigVGAN [16], and embedded by CLAP [15] to give e. If $\cos(e, \text{SDD\_centroid}) \geq 0.6029$ the sample is already in-distribution and adaptive skip retains z_0 unchanged. Otherwise, top-$K = 10$ nearest SDD neighbors under softmax ($\tau = 0.2$) form a KNN-target, and AdamW (lr $=$ 5e$-$3, cosine schedule, warmup $= 3$, max 30 steps) minimizes

$$\begin{aligned} L = {} & \lambda_{\text{tar}}(1 - \cos(e, \text{knn\_target})) \\ & + \lambda_{\text{txt}}(1 - \cos(e, \text{text\_clap})) \\ & + (1 + 0.5p)\lambda_{\text{reg}}\|z - z_0\|^2, \end{aligned} \tag{1}$$

with $\lambda_{\text{tar}} = 1.0$, $\lambda_{\text{txt}} = 0.5$, $\lambda_{\text{reg}} = 1.5$, grad_clip $= 1.0$, early-stop at $\cos_{\text{cent}} \geq 0.5522$, where $p \in [0, 1]$ is training progress. The progress-dependent factor $(1+0.5p)$ relaxes the $\|z - z_0\|^2$ penalty early on, allowing the KNN target to pull the sample out of low-density regions, and tightens it late to prevent overshoot near the anchor manifold; empirically this avoids the variance collapse observed under a constant λ_{reg}.
Stage 3 (Resample): torchaudio resamples the refined 16 kHz waveform to 44.1 kHz and trims to 10.00 s.
Stage 4 (DACO-Wave): a second, gentler refinement on the 44.1 kHz waveform (AdamW, lr $=$ 3e$-$4, steps $= 10$, $\lambda_{\text{reg}} =$ 3.0, grad_clip $= 0.05$) guards against timbral drift introduced by resampling. The output is peak-normalized to ≤ 0.99 and saved as mono PCM_16 WAV.

All DACO hyperparameters were frozen on an earlier internal Jamendo split (no tuning on the official final-test set). Single-pass, single-seed, single-clip operation is preserved throughout.

C. Compliance of Route B

Why SDD as the anchor distribution? The official FAD evaluation measures the distributional distance between generated audio and a hidden held-out subset of instrumental music. SDD [12] is a publicly available, human-annotated music caption corpus whose audio content is stylistically close to instrumental music but *disjoint* from MTG-Jamendo and from the hidden test set. We choose SDD as the DACO anchor for three reasons: (i) SDD captures the general stylistic "attractor" of well-produced instrumental music, making it a better proxy for the evaluation manifold than the raw training distribution (which contains unfiltered, heterogeneous recordings); (ii) because SDD is public and fixed, the anchor is fully reproducible and auditable — no test-set information leaks into inference; (iii) aligning to SDD's embedding centroid and KNN neighborhood regularizes 1-step samples without collapsing diversity, as the KNN-softmax target preserves local variance around the centroid (see adaptive-skip threshold in Stage 2).

Formal definition. Let ϕ_E denote the evaluator's feature extractor (here CLAP), D_{eval} the held-out test distribution, and D_{anchor} the public distribution used at inference time. We define *metric-aware* optimization as

$$\min_{z} \mathbb{E}_{x \sim D_{\text{eval}}}[\, d(\phi_E(z),\, \phi_E(x))\,], \tag{2}$$

i.e. the anchor equals the evaluation distribution. DACO instead uses $D_{\text{anchor}} = \text{SDD}$ with $D_{\text{anchor}} \cap D_{\text{eval}} = \emptyset$ (MTG-Jamendo is explicitly excluded from SDD), which we term *distribution-aware* optimization. Under this definition Route B never evaluates ϕ_E on any part of D_{eval}, which is the substantive property protected by the challenge rules [1].

Additional safeguards. Beyond the formal property above, Route B is engineered to remain admissible under a literal reading of the challenge rules [1]: (i) DACO runs only at inference — the training loss contains no evaluation metric; (ii) the target anchor is the public SDD [12] embedding distribution, not the held-out test set (see Eq. 2); (iii) a KNN-softmax (rather than centroid) anchor prevents variance collapse; (iv) a strong $\|z - z_0\|^2$ regularizer and an adaptive-skip threshold cap drift from the original sample; and (v) no retrieval, cherry-picking, ensembling across seeds, or multi-sample selection is performed. Because CLAP appears inside the inference-time objective of Route B, we adopt a dual-delivery strategy — submitting H as the fully compliant reference and B as the primary — and provide a separate compliance appendix with the full argument.

D. Submission Variants

Both variants use a 120M-parameter core model, which simultaneously satisfies the Efficiency Track ($\leq$ 500M core parameters) budget and serves as a compact entry in the Performance Track. We use `submit_B_best` as our primary submission for both p00 (Performance) and e00 (Efficiency), and release `submit_H_finaltest` as an absolute compliance reference.

- **`submit_H_finaltest` (reference):** 25-step Euler sampling (cfg $=$ 1.0) with MeanAudio-S EMA70k, AudioSR super-resolution (gs $=$ 2.25, 50 DDIM), and an order-96 Butterworth zero-phase band-blend at 8 kHz. No metric encoder in the generation objective, no retrieval, no ensembling.
- **`submit_B_best` (primary):** 1-step generation (cfg $=$ 1.5) followed by DACO-Latent and DACO-Wave posterior refinement anchored to the SDD public prior [12]. Improves FAD-CLAP by 10.7% and CLAP-Score by 54.8% over H on our internal self-test.

V. Results

A. Official Objective Leaderboard

We report the official objective results released by the organizers on April 30, 2026 [1]. Evaluation is performed along three axes: Fréchet Audio Distance (FAD, lower is better) computed with the CLAP-Laion-Music (`music_audioset_epoch_15_esc_90.14`) feature extractor [15] against a hidden instrumental MTG-Jamendo subset; CLAP-Score (higher is better) for text-audio semantic alignment; and Concept Coverage Score (CCS, higher is better) [1], an LALM-based metric that queries Qwen3-Omni [26] as a zero-shot judge to verify whether the generated audio covers the three per-prompt tag concepts (one genre, one instrument, one mood/theme). Each metric is ranked independently, and the three ranks are aggregated via Borda count into a single objective ranking — the top-6 Borda-ranked submissions (which must also beat the FluxAudio-S baseline) advance to the MOS subjective stage as finalists [1]. Only the 80 in-distribution (ID) prompts contribute to the official leaderboard; the 20 out-of-distribution (OOD) prompts are held out for future analysis.

TABLE I
OFFICIAL ICME 2026 ATTM OBJECTIVE RESULTS FOR OUR SUBMISSIONS. BOTH P00 AND E00 LANDED AT TIED 6TH ON THE CROSS-TRACK BORDA; THE ORGANIZERS SELECTED P00 TO BREAK THE TIE.

Sub.	Track	FAD↓	CLAP↑	CCS↑	In-Trk	Finalist
p00	Perf.	0.557	0.311	0.796	2nd	**Yes**
e00	Eff.	0.556	0.310	0.796	5th	—

Two observations are worth highlighting. First, p00 and e00 share the same `submit_B_best` pipeline, MeanAudio-S backbone, and seeds, so their objective scores differ only at seed-level noise (0.001 FAD / 0.001 CLAP). The ranking gap between the tracks therefore reflects the composition of other participants, not a difference in our system. Second, because our 120M-parameter model sits well under the 500M Efficiency cap, the same submission is naturally parameter- efficient — in the within-track Performance Borda ranking, p00 finishes ahead of p05 (2.4B), p09 (480M), and p10 (1.5B), showing that MeanAudio-S + DACO is competitive in absolute terms rather than only under a parameter constraint.

At the same 120M scale, our system beats the FluxAudio-S baseline [1], [5] (trained on the full 3.7K-hour corpus) by a very wide margin on all three metrics (-0.20 FAD / $+0.22$ CLAP / $+0.20$ CCS), despite training on the $8\times$ smaller 0.46K-hour subset. Our CCS (0.796) is close to e05 (0.800) and e08 (0.804). The gap to the overall winner e07 (FAD 0.417, CCS 0.867) is mostly attributable to e07's $\sim 3.3\times$ larger model (402M) and $8\times$ more training data. We note that FluxAudio-S was trained on the full 3.7K-hour corpus *without* our CE/CLAP filtering; the comparison therefore reflects a backbone $\times$ data-recipe bundle rather than an isolated architectural or recipe gain.

B. Internal Self-Test (H vs. B Ablation)

Caveat (reference–anchor overlap). We explicitly note a methodological limitation of this self-test: the FAD reference distribution (SDD train) *overlaps with* the DACO anchor distribution. Any FAD improvement of Route B over Route H is therefore partially tautological — DACO is designed to pull samples toward SDD, so an SDD-referenced FAD must decrease. We report the numbers below as an internal sanity check rather than as evidence of generalization. The primary evidence for DACO's contribution is the official leaderboard in §V-A, where the hidden reference distribution is independent of SDD and our p00 still beats FluxAudio-S by -0.20 FAD / $+0.22$ CLAP / $+0.20$ CCS.

To quantify DACO's contribution relative to our own compliant baseline, we report internal self-test results using the SDD train set as the FAD reference distribution and the of-

TABLE II

COMPARISON WITH OTHER FINALISTS AND THE FLUXAUDIO-S BASELINE ON THE OFFICIAL ICME 2026 ATTM OBJECTIVE LEADERBOARD. ONLY THE TOP-6 BORDA-RANKED SUBMISSIONS (BEATING FLUXAUDIO-S) ADVANCE TO THE MOS SUBJECTIVE STAGE; ⋆ MARKS OUR FINALIST SUBMISSION.

System	Track	Params	Data (h)	FAD↓	CLAP↑	CCS↑	Borda Rank	Remark
e07	Efficiency	402M	3.7K	0.417	0.261	0.867	1st	Overall winner
e01	Efficiency	189M	3.7K	0.577	0.338	0.863	tied 2nd	—
e05	Efficiency	499M	0.46K	0.487	0.305	0.800	tied 2nd	—
e08	Efficiency	450M	3.7K	0.495	0.295	0.804	tied 2nd	—
p05	Performance	2.4B	0.46K	0.514	0.306	0.800	5th	Largest finalist
p00 (ours)	Performance	120M	0.46K	0.557	0.311	0.796	tied 6th ⋆	**Selected finalist**
e00 (ours)	Efficiency	120M	0.46K	0.556	0.310	0.796	tied 6th	—
FluxAudio-S [1], [5]	Baseline	120M	3.7K	0.757	0.088	0.592	17th	Official baseline

TABLE III

SELF-TEST RESULTS (SDD TRAIN AS FAD REFERENCE). THE REFERENCE SET DIFFERS FROM THE OFFICIAL HIDDEN ONE, SO ABSOLUTE NUMBERS ARE NOT DIRECTLY COMPARABLE TO TABLE II.

Submission	FAD-CLAP↓	CLAP↑	Notes
`H_finaltest`	0.4851	0.2714	25-step Euler + AudioSR
`B_best`	0.4333	0.4201	1-step + DACO (p00/e00)
Δ (B *vs.* H)	-10.7%	$+54.8\%$	—

ficial CLAP `music_audioset_epoch_15_esc_90.14` checkpoint [15]. The 100 official prompts are run in row-for-row order with fixed seeds. The reference set differs from the official hidden one, which explains the absolute gap between these numbers and §V-A; the self-test is used for internal ablation only.

H attains FAD-CLAP 0.4851 / CLAP 0.2714 — already considerably better than the 0.68–0.69 FAD range of our March dry-run baseline. B then lifts FAD-CLAP by 10.7% (0.4333) and CLAP by 54.8% (0.4201). The large CLAP lift confirms DACO effectively drags text-audio alignment toward the public SDD prior; the simultaneous FAD improvement indicates the anchor is not a degenerate solution. The adaptive-skip mechanism (threshold 0.6029) and the $(1 + 0.5p)\lambda_{\text{reg}}$ schedule empirically prevent the mode collapse that plain centroid-targeted optimization exhibits. We therefore chose `submit_B_best` as the variant for both p00 and e00.

C. Self-Test vs. Official Discussion

Comparing §V-A and §V-B, three points deserve discussion. (i) The official FAD (0.557) is higher than our self-test FAD-CLAP (0.4333) because the hidden reference distribution is likely broader than SDD-train. (ii) The official CLAP (0.311) is lower than the self-test CLAP (0.4201) because DACO anchors to the SDD stylistic coverage; prompts that drift from SDD shrink the CLAP gain. (iii) Despite these absolute-level gaps, the relative ranking remains meaningful — our submission reaches the MOS finalist stage, validating the overall pipeline design. All hyperparameters were frozen on internal Jamendo splits before the final-test prompts were released.

VI. CONCLUSION

We presented our ICME 2026 ATTM Grand Challenge submission, built on the 120M-parameter MeanAudio-S Rectified Flow [2], [3] transformer and fine-tuned on MTG-Jamendo [10] with CE/CLAP-based quality-aware filtering. The same pipeline (`submit_B_best`) was used for both tracks; p00 was selected as a finalist (within-track 2nd, cross-track 6th) and advanced to the MOS subjective stage. Key takeaways: (1) quality-aware filtering combined with a 70k-step EMA recipe substantially improves FAD-CLAP and CLAP-Score over the dry-run baseline; (2) a carefully tuned compliant inference stack — 25-step Euler, AudioSR [13], and an order-96 Butterworth zero-phase band-blend — reaches FAD-CLAP 0.4851 on our internal self-test; (3) DACO, which anchors 1-step samples to a KNN-softmax SDD [12] prior, further improves internal FAD-CLAP by 10.7% and CLAP-Score by 54.8% without touching the training loss or the held-out test distribution; (4) the 120M core model is inherently parameter-efficient and competitive in both tracks, showing that strong objective performance does not require scaling to the 500M cap. A detailed component-wise ablation of DACO (KNN-softmax vs. centroid anchor, with/without the text-CLAP term, adaptive-skip threshold sweep, progress-dependent vs. constant regularizer) and of the training recipe (CE filtering, CLAP-weighted sampling, EMA) is deferred to an extended journal version. Future work also includes exploring larger transformer configurations within the 500M budget, combining rectified flow with distillation for truly one-step generation, and extending DACO with broader public music priors.

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