

DBMSolver: A Training-free Diffusion Bridge Sampler for High-Quality Image-to-Image Translation

Sankarshana Venugopal · Mohammad Mostafavi · Jonghyun Choi

The Bottlenecks & The Insights

The Problem:

The Premise: Diffusion Bridge Models (DBMs) enable direct Image-to-Image (I2I) translation using arbitrary image priors. The Method **The Bottleneck:** Current DBM samplers (e.g., Hybrid Heun) are prohibitively slow, requiring 100+ Network Function Evaluations (NFEs) to generate coherent outputs.

Why Do N2I Solvers Fail Here?

Sampler Type	Prior Distribution	Valid for I2I?
Standard N2I DDIM, DPMSolver	$x_T \sim \mathcal{N}(\mathbf{0}, \sigma_T^2 \mathbf{I})$	❌ Fails (Artifacts)
DBMSolver (Ours)	Arbitrary prior, $p_T(x)$	✅ Yes

The Core Insight

By rigorously analyzing the underlying reverse-time Diffusion Bridge equations, we uncovered an overlooked semi-linear structure.

The Bridge Probability Flow ODE can be rewritten as:

$$\frac{dx_t}{dt} = \underbrace{L(t)x_t}_{\text{Linear Term}} + \underbrace{N(D_\theta(x_t), t, x_T)}_{\text{Non-linear Term}}$$

Using Exponential Integrators (EI), we analytically derive exact, closed-form solutions for the linear terms, eliminating a major source of approximation error.



DBMSolver in just 6 NFEs — sharp eye contours, hairlines, and mask edges.

The DBMSolver Algorithm

The Method:

Phase 1: Initial Stochastic Update

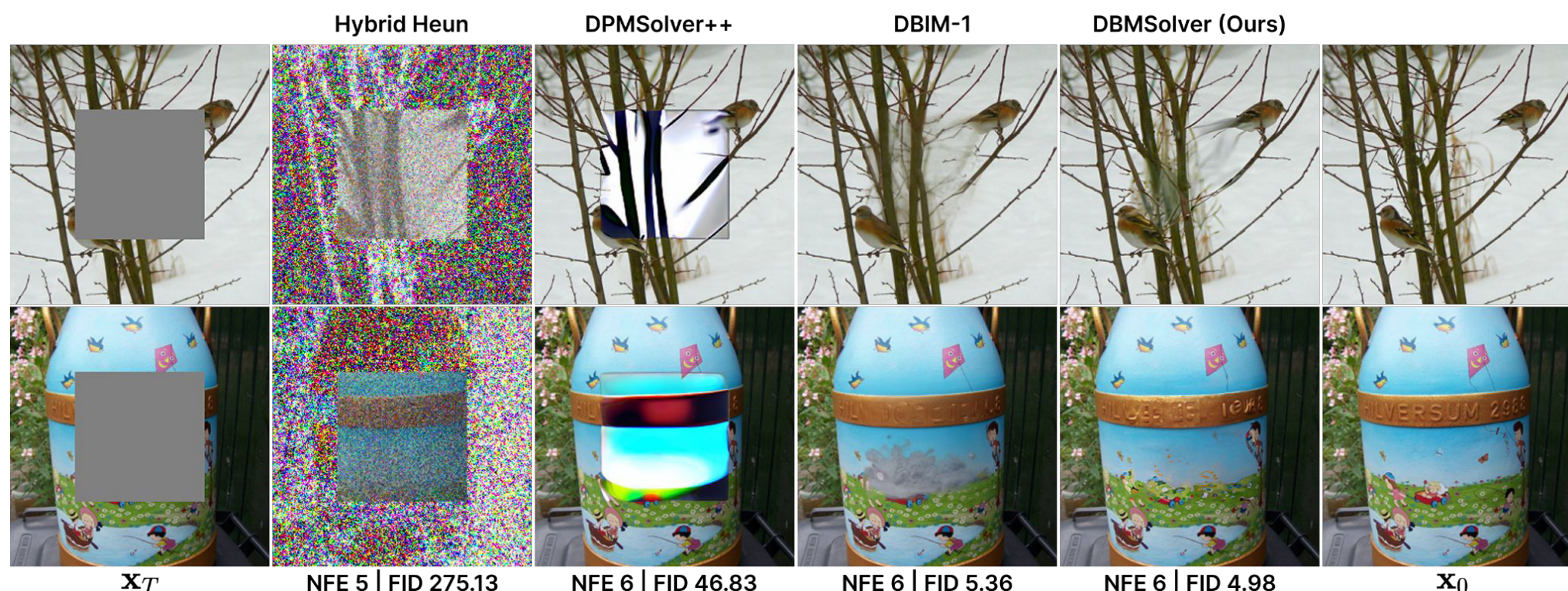
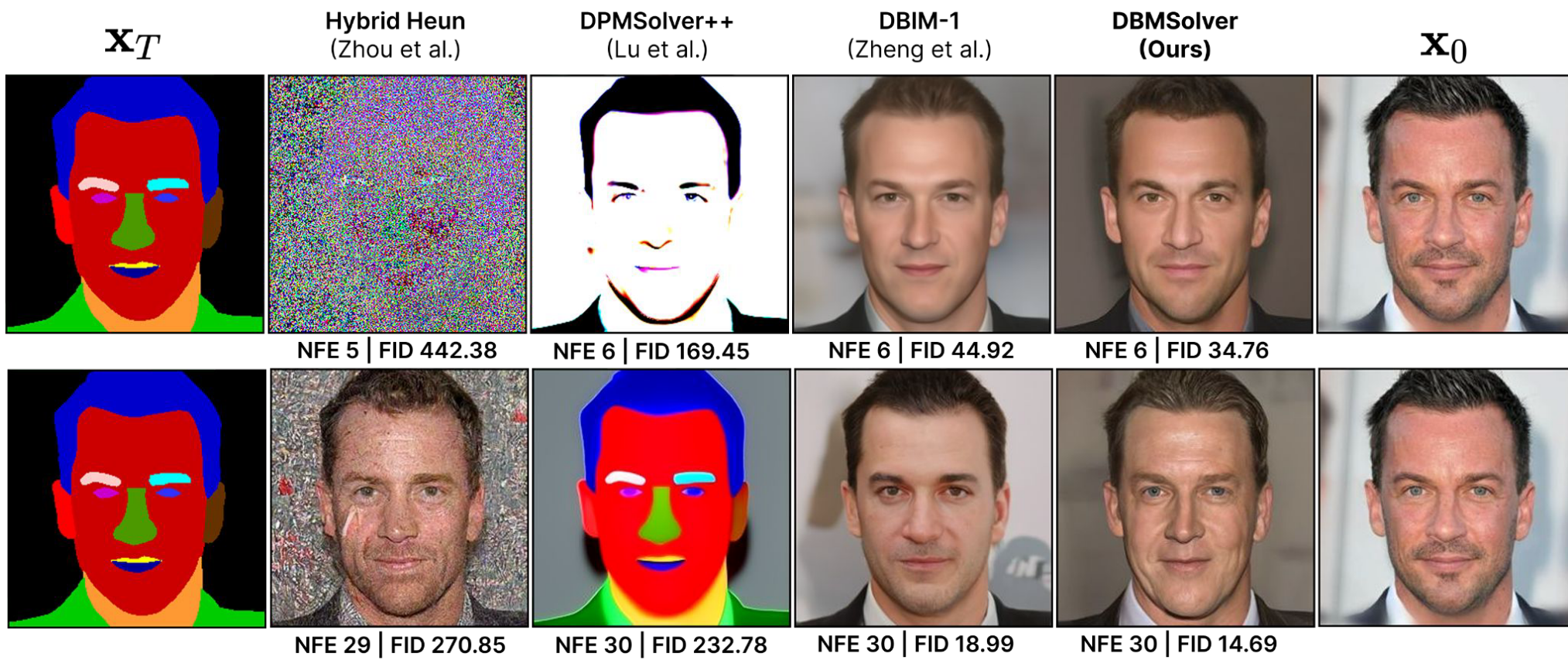
- Executes for the very first micro-step ($s = T$ to $t = T - \epsilon$).
- Uses a 1st-order SDE solution (Euler-Maruyama) to prevent coefficient divergence.

Phase 2: Deterministic Refinement

- Executes for all subsequent steps ($t < s \leq T - \epsilon$).
- Uses our exact, 2nd-order ODE solution to rapidly denoise the sample.
- Concludes with a final Euler update to yield the translated image $\tilde{x}_0$.

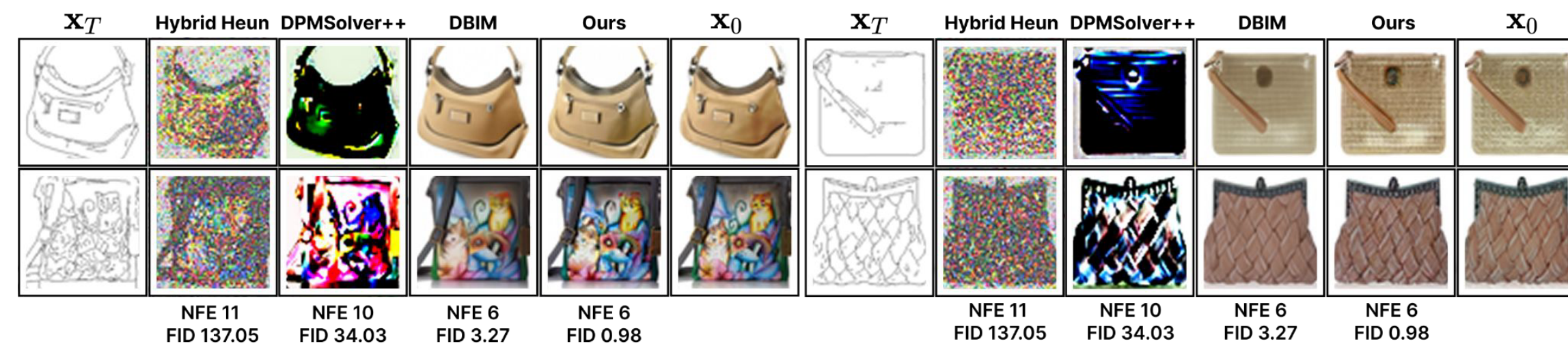
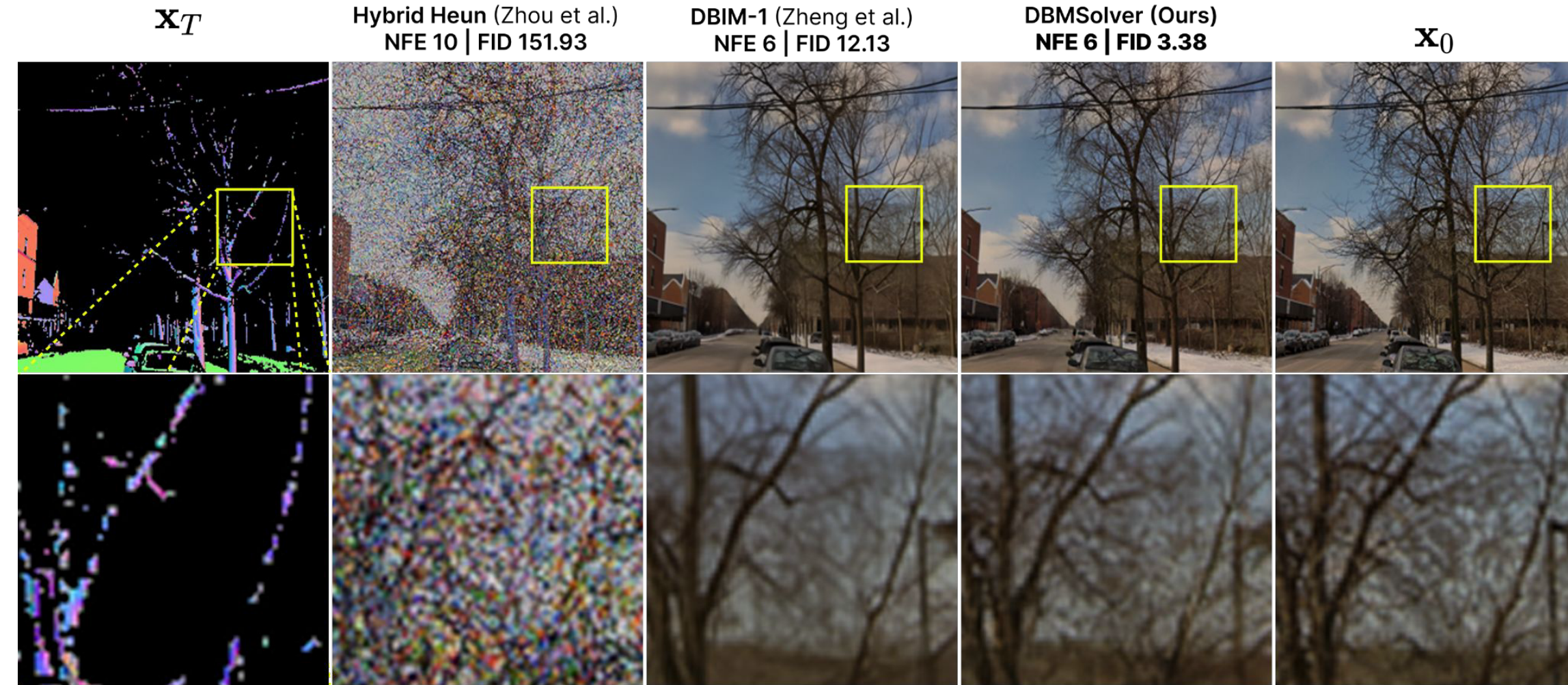
Order Selection: Why Stop at k = 2?

While 3rd-order ($k = 3$) solutions for the Bridge ODE exist, they require non-elementary antiderivatives. Solving these requires numerical approximations (like linear multistep methods used in DBIM-2/3), which paradoxically increases error bounds. Our 2nd-order solution remains analytically tractable, exact, and achieves superior FID scores.



State-of-the-Art Results

Unmatched Quality at 6 NFEs:



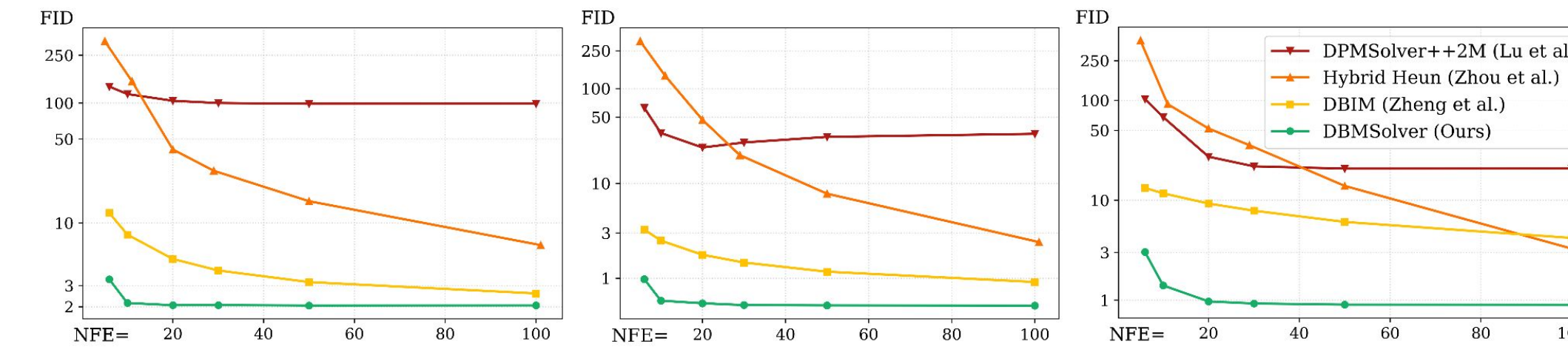
Visual Takeaways:

- DBMSolver flawlessly preserves delicate edge structures
 - e.g., tree branches, twigs, and handbag textures at just 6 NFEs.
- Baseline methods exhibit noticeable blurring and loss of detail at identical steps.

METHOD	NFE ↓	FID ↓	LPIPS ↓	MSE ↓
<i>DIODE (256x256) — surface-normals → image</i>				
Hybrid Heun	119	4.43	0.244	0.084
DBIM-1	20	4.99	0.201	0.017
DBIM-2	20	4.40	0.200	0.017
DBIM-3	20	4.23	0.201	0.017
ODES3	28	2.29	0.203	0.018
DBMSolver	6	3.38	0.196	0.015
DBMSolver	20	2.06	0.198	0.018
<i>Face2Comics (256x256) — stylization</i>				
BBDM	200	23.20	—	—
Hybrid Heun	119	2.36	—	—
DBIM-3	20	8.61	—	—
DBMSolver	6	3.04	—	—
DBMSolver	20	0.96	—	—

Training-Free Advantage & Conclusion

Efficiency Trends:



Metric Takeaways:

- DBMSolver curve drops faster and stabilizes earlier than all baselines.
- DIODE (256x256): 3.38 FID at 6 NFEs (vs. HH requiring 119 NFEs for 4.43 FID).

The "Training-Free" Value Proposition:

Recent distillation methods achieve fast sampling but require massive computational overhead to retrain the model. DBMSolver is a pure mathematical upgrade.

Method	NFE	DIODE FID	Training-Free?
CDBM	2	3.66	❌ (Requires retraining)
IBMD	1	4.07	❌ (Requires retraining)
DBMSolver	6	3.38	✅ (Drop-in Replacement)

Conclusion:

Recent distillation methods achieve fast sampling but require massive computational overhead to retrain the model. DBMSolver is a pure mathematical upgrade.

References & Contact:

- Zhou et al., "Denoising Diffusion Bridge Models," ICLR 2024.
- Zheng et al., "Diffusion Bridge Implicit Models," ICLR 2025.

Email: sankarshana.v@gmail.com

Code: github.com/snumprlab/dbmsolver