MCLC: Measurement-Consistent Langevin Corrector for Stabilizing Latent Diffusion Inverse Problem Solvers

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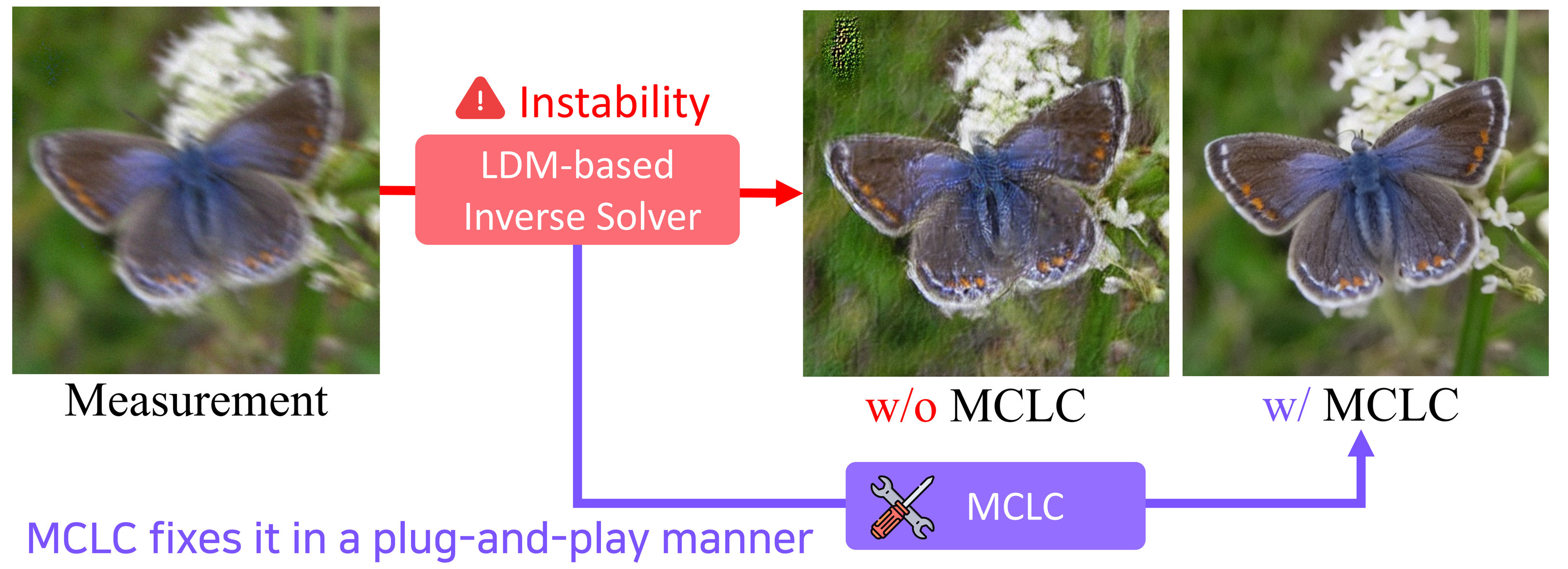
ICML International Conference On Machine Learning

TL;DR. MCLC stabilizes latent diffusion inverse solvers by reducing distributional gap in solver-induced dynamics without sacrificing measurement consistency

Overview

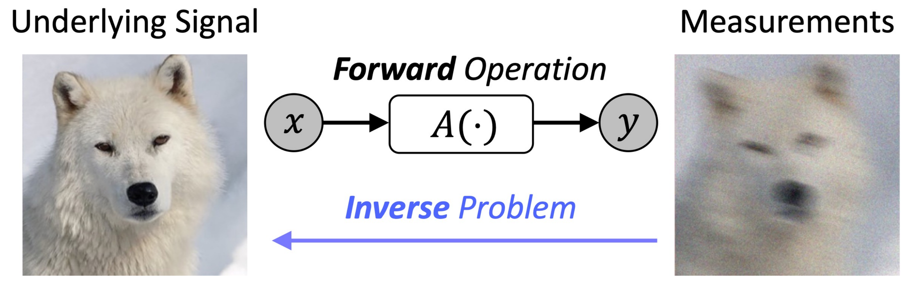
MCLC provides a plug-and-play solution to instability in LDM-based inverse problem solvers while preserving measurement fidelity.



Background

Inverse Problem

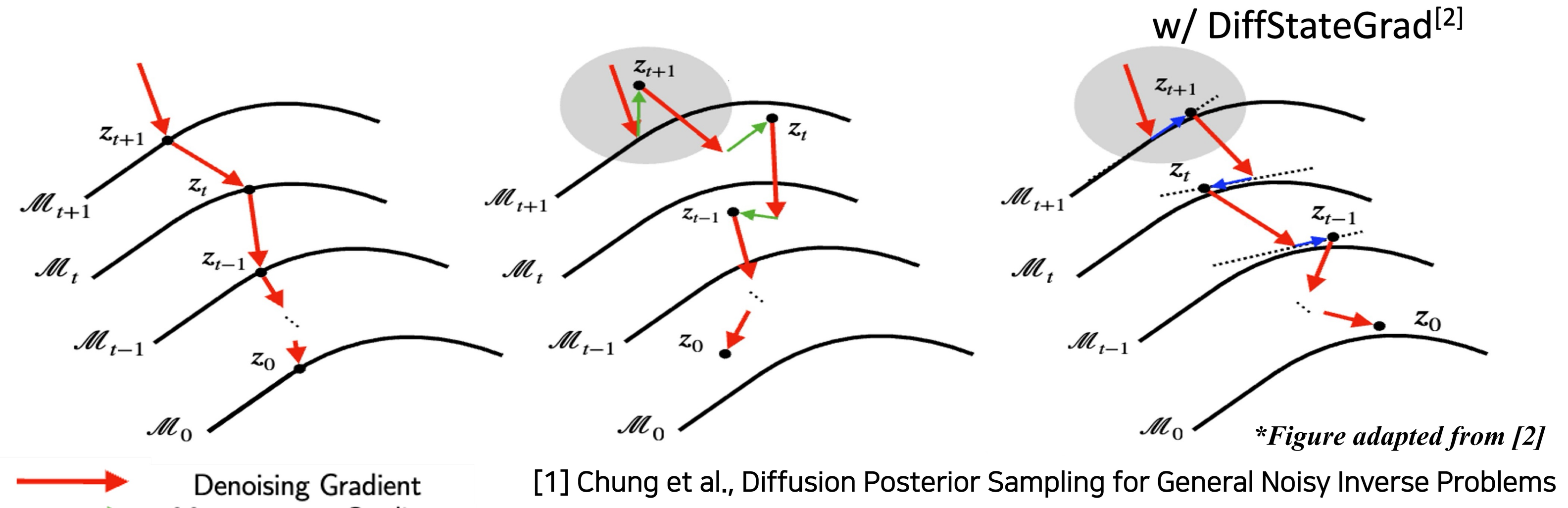
❖ Recover underlying signal x from noisy measurements $y = A(x) + n$.



Diffusion-based Inverse Solvers

❖ "Ill-posed" inverse problems require priors for plausible solution, and diffusion models provide powerful data-driven priors.

❖ Many diffusion-based inverse solvers are built on the geometric perspective based on linear manifold assumption.

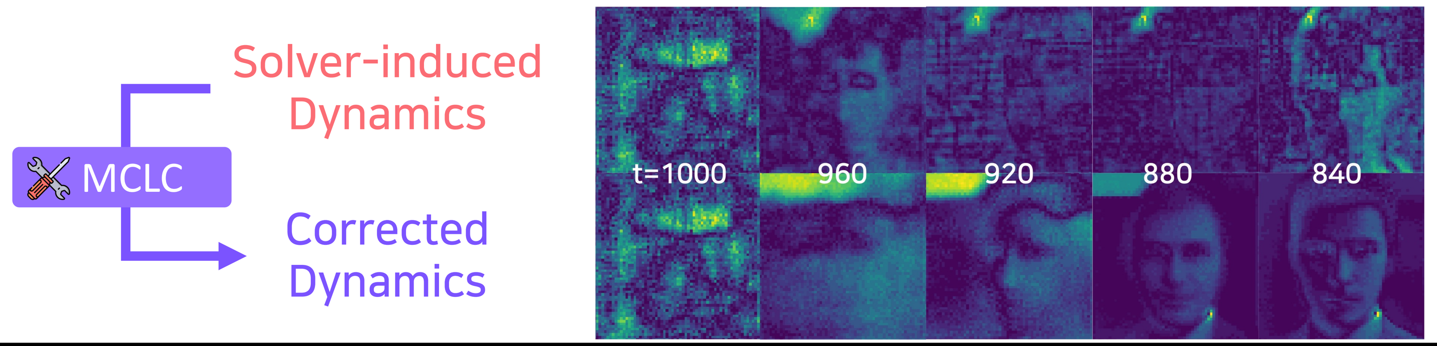


[1] Chung et al., Diffusion Posterior Sampling for General Noisy Inverse Problems
[2] Zirvi et al., Diffusion State-Guided Projected Gradient for Inverse Problems

Problem Definition

❖ LDM-based inverse solvers remain unstable, as the geometric assumption may not hold in latent space.

❖ The dynamics induced by LDM-based inverse solvers exhibit divergence from stable reverse dynamics.

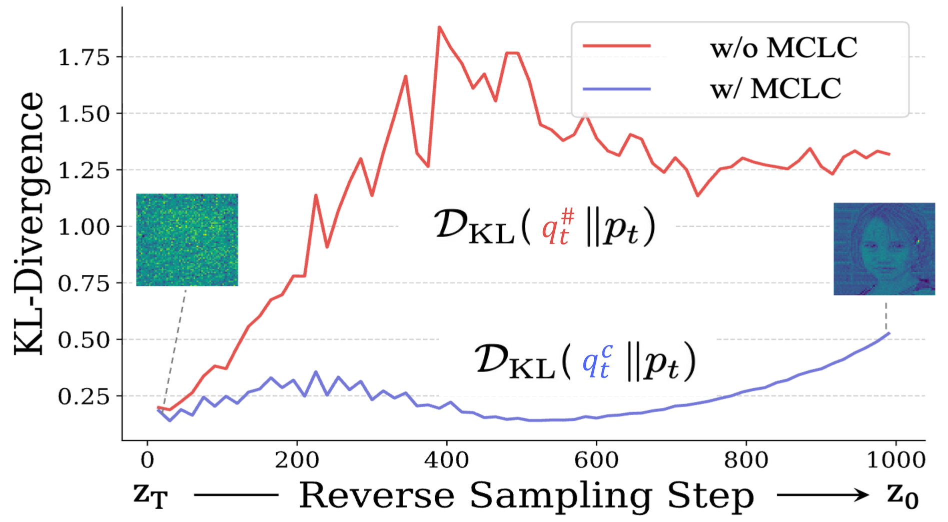


Key Idea

[Instability Characterization: Deviation from p_t]

We characterize this instability as a **distributional gap** (Kullback–Leibler divergence) between the solver-induced time-evolving distribution $q_t^\#$ and **the learned time-marginal distribution** p_t of the diffusion or flow model.

$$\mathcal{D}_{\mathrm{KL}}(q_t^\# \| p_t) \ \geq\ \gamma_t, \quad \text{for some } \gamma_t > 0$$



How to deal with it? How can we stabilize the solvers?

❖ Langevin dynamics is a principled way for reducing the KL divergence toward the target stationary distribution p_t.

❖ At a fixed timestep t, the post-update Langevin corrector evolution $\{Z_t^c\}_{c\geq 0} : dZ_t^c = \nabla \log p_t(Z_t^c)dc + \sqrt{2}dW_c$, initialized with $Z_t^0 \sim q_t^\#$, guarantees that KL divergence decrease monotonically along the corrector process:

$$\mathcal{D}_{\mathrm{KL}}(q_t^c \| p_t) \ \leq \mathcal{D}_{\mathrm{KL}}(q_t^\# \| p_t), \qquad \forall c\ \geq 0 \text{ and } Z_t^c \sim q_t^c.$$

Measurement-consistent Langevin correction

❖ The vanilla Langevin correction may disturb measurement consistency $r(z_t)$. Taylor expansion of $r(z_t + \Delta z_t)$, *i.e.*, after Langevin update, is as follows:

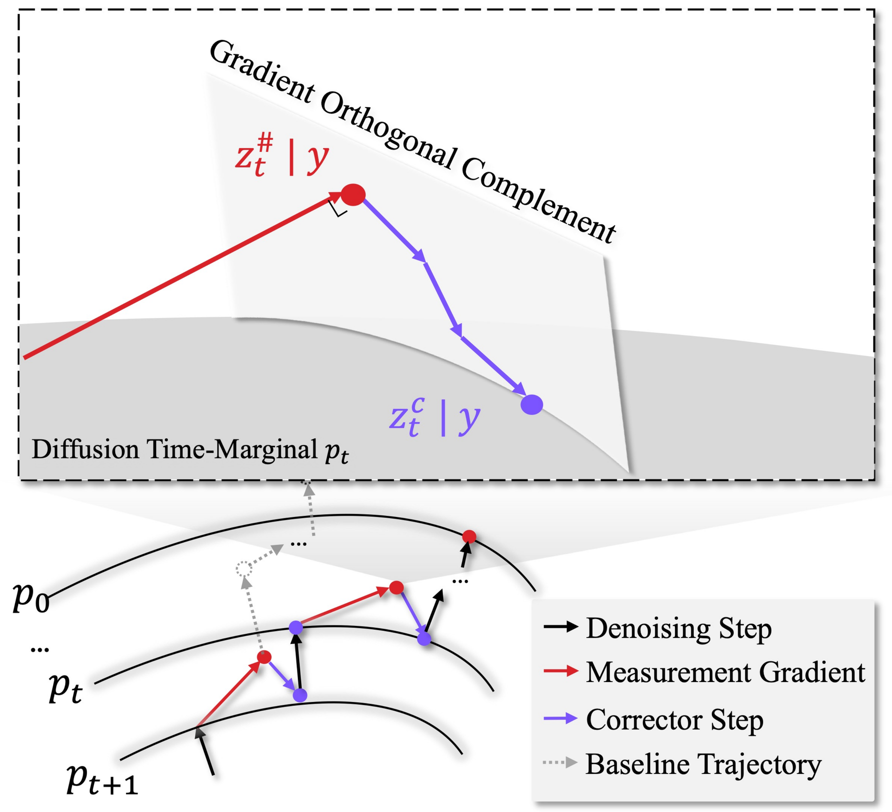
$$r(z_t + \Delta z_t) \ \approx r(z_t) + \underbrace{\nabla_{z_t} r(z_t)\, \Delta z_t}_{=0} + \underbrace{O(\|\Delta z_t\|^2)}_{\text{Higher-order terms} \leq Ck + O(k)}$$

* Δz_t is the discretized Langevin update

❖ MCLC restricts the Langevin update to orthogonal complement of measurement gradient, maintaining monotonic KL decrease and preserving measurement-consistency up to contolled bound under a sufficient step-size condition (Δz_t satisfies $\mathbb{E}[\|\Delta z_t\|^2] \leq k < 1$) :

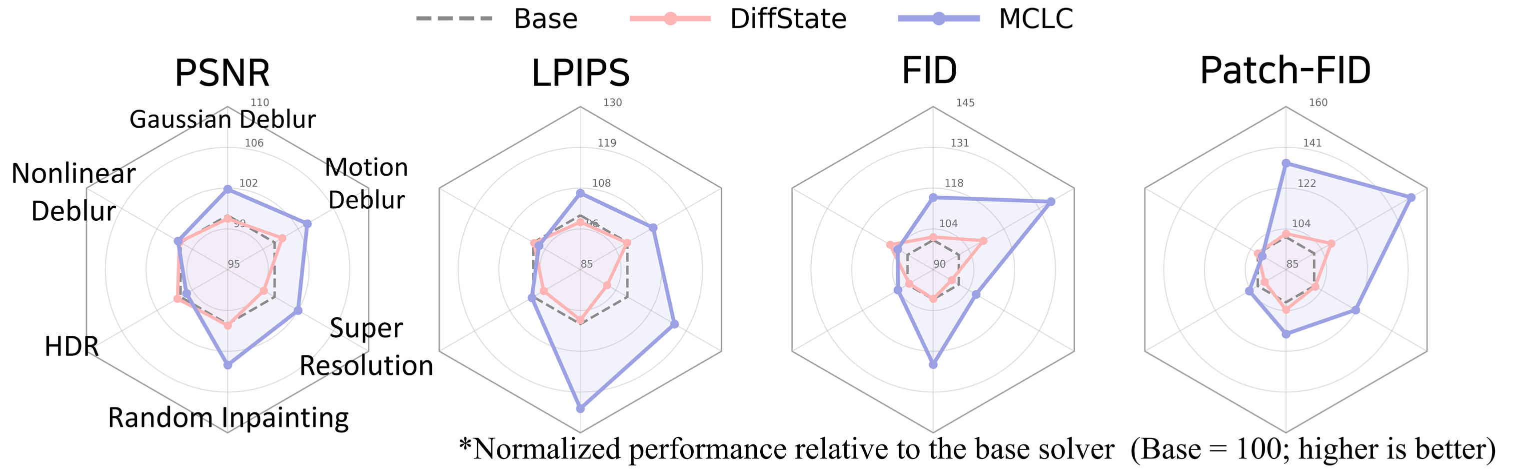
$$z_t^c \leftarrow z_t^\# + \underbrace{\eta_t P_{\perp g_t} \nabla \log p_t(z_t) + \sqrt{2\eta_t} P_{\perp g_t} \epsilon}_{\Delta z_t}, \quad \text{where } g_t := \frac{\nabla_{z_t} r(z_t)}{\|\nabla_{z_t} r(z_t)\|} \text{ and } P_{\perp g} = (I - gg^T).$$

[MCLC Algorithm Illustration]

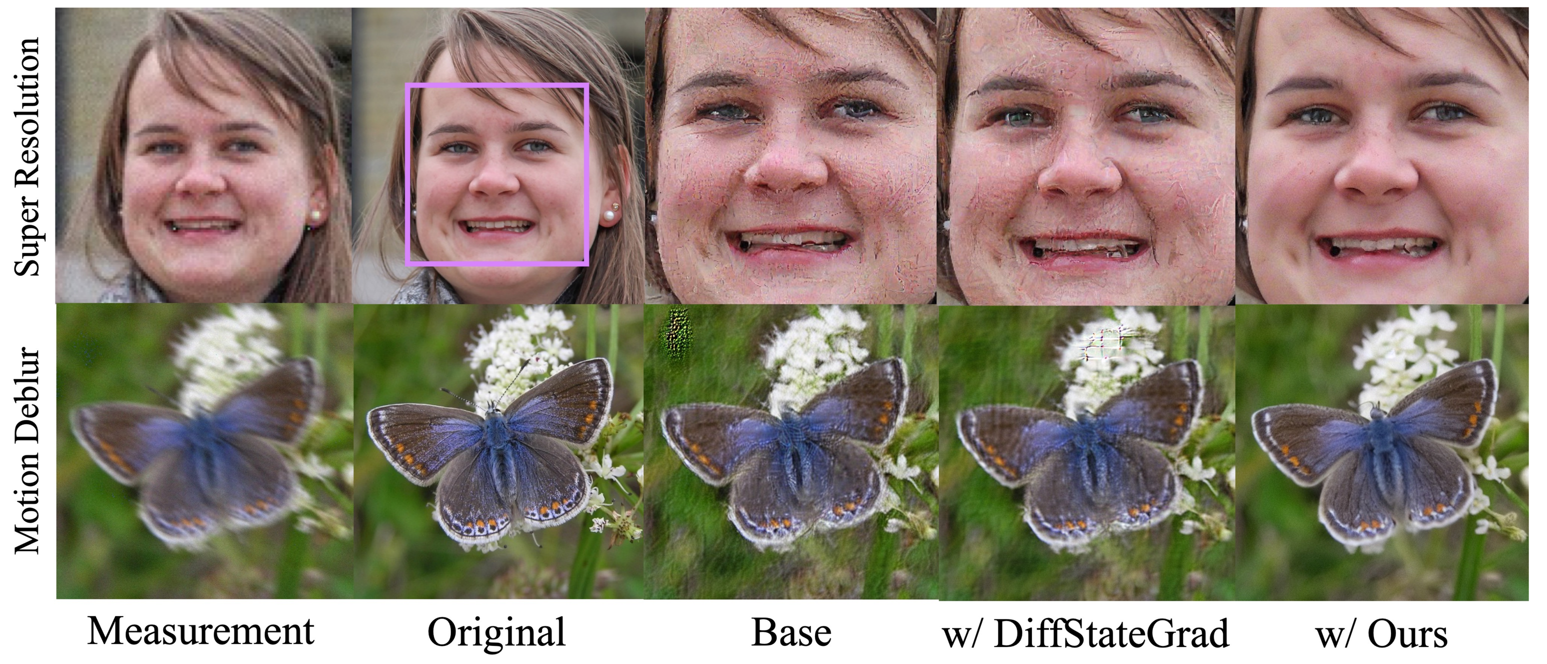


Experimental Results

Main Results (Quantitative/Qualitative)

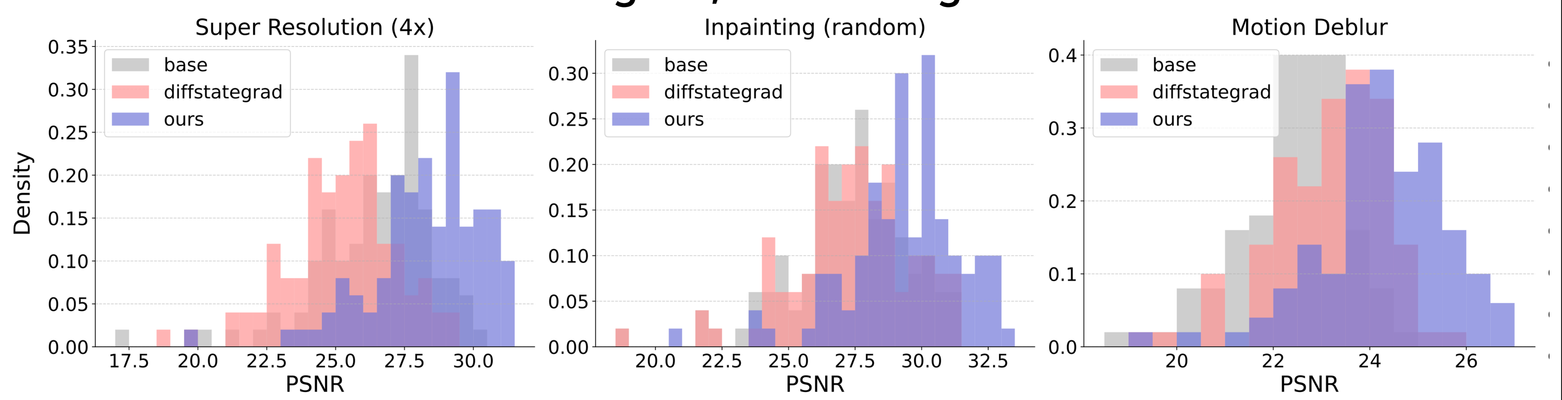


*Normalized performance relative to the base solver (Base = 100; higher is better)



PSNR Histograms

PSNR histograms across tasks demonstrate that MCLC shifts the PSNR distribution toward higher, increasing the success rate.



Step-size Condition Verification

The theoretically derived sufficient condition, $\mathbb{E}[\|\Delta z_t\|^2] \leq k < 1$, is satisfied in real runs at $\lambda \lesssim 0.005$ and remains robust to mild violations.

* λ is reparameterized MCLC step-size

λ	$E[\|\Delta z_t\|]$	y-PSNR (↑)	PSNR (↑)	LPIPS (↓)
0 (base)	0	35.34	25.04	0.421
0.005	0.89	35.28	25.14	0.405
0.05	8.93	35.18	**27.00**	**0.304**
0.15	26.17	34.73	26.27	0.389
0.5	89.97	27.48	16.57	0.742