

Edge-Aware Image Manipulation via Diffusion Models with a Novel Structure-Preservation Loss

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Abstract

Recent advances in image editing leverage latent diffusion models (LDMs) for versatile, text-prompt-driven edits across diverse tasks. Yet, maintaining pixel-level edge structures—crucial for tasks such as photorealistic style transfer or image tone adjustment—remains as a challenge for latent-diffusion-based editing. To overcome this limitation, we propose a novel Structure Preservation Loss (SPL) that leverages local linear models to quantify structural differences between input and edited images. Our training-free approach integrates SPL directly into the diffusion model’s generative process to ensure structural fidelity. This core mechanism is complemented by a post-processing step to mitigate LDM decoding distortions, a masking strategy for precise edit localization, and a color preservation loss to preserve hues in unedited areas. Experiments confirm SPL enhances structural fidelity, delivering state-of-the-art performance in latent-diffusion-based image editing. Our code will be publicly released at <https://github.com/gongms00/SPL>.

1. Introduction

Image editing has seen remarkable progress, yet developing a universal image editing method that preserves *pixel-level edge structures* of the input image remains a long-standing challenge. By pixel-level edge structure, we mean the fine-grained spatial discontinuities in intensity that define object contours and texture details. Maintaining these structures is crucial for various tasks like relighting, tone adjustment, image harmonization, photorealistic style transfer, time-lapse generation, seasonal or weather changes, and background replacement. In these editing tasks, even minor structural distortions in the edited image, relative to the input, can compromise the intention of the edit.

Traditionally, pixel-level-edge-preserving image editing

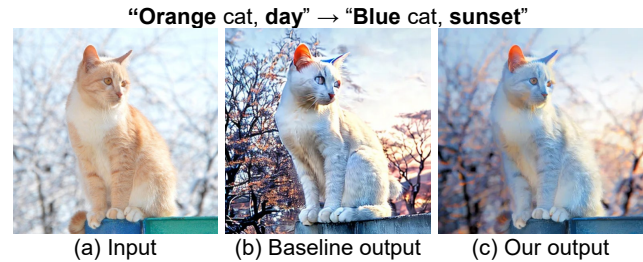


Figure 1. **Structure-preserving edit.** Our method achieves pixel-level structural fidelity without compromising the intended edit.

tasks have been approached individually using tailored methods [29, 30, 51, 56, 77]. While these methods achieve high structural fidelity, they face two significant drawbacks. First, none of these methods offer a unified framework that can handle multiple editing tasks, which results in task-specific pipelines with limited generalization. Second, lacking a generative prior, they struggle to introduce additional details or creative variations aligned with desired edits.

Recent image editing methods leverage robust generative priors such as large-scale text-to-image latent diffusion models (LDMs) [49, 53]. This has enabled general image editing through text-based instructions, allowing them to address multiple tasks within a single framework [4, 6, 20, 25, 40, 67]. While these LDM-based editing methods overcome the limitations of generalization and detail generation in traditional image editing methods, they often fall short of preserving the pixel-level structure of the input image even when strict preservation is needed. This challenge mainly stems from the absence of explicit guidance to maintain pixel-level edge structures. Moreover, LDM-based editing methods also suffer from structural distortions arising from the lossy RGB-to-latent mapping, exacerbating structure preservation difficulties.

To tackle these challenges, we propose *Structure Preservation Loss* (SPL), a novel loss function designed to enforce pixel-level edge structure fidelity between the input and edited output. The key idea behind the structure preservation loss is to leverage the notion of local linear models (LLMs) in image processing [18, 19, 33, 80] to capture and

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maintain structural relationships between images. We incorporate the structure preservation loss into the sampling process of diffusion models, achieving high structure fidelity to the input image without harming its editing capabilities as demonstrated in Fig. 1. Our approach is plug-and-play and does not require any additional training on the base LDM-based editing model. Furthermore, the modularity of our loss offers users fine-grained control to tailor structural constraints to their specific intent. We also introduce a post-processing step that refines the decoded output to correct structural distortions arising from the latent-to-RGB mapping, ensuring pixel-level edge structure preservation. Additionally, we propose a simple masking strategy that generates a high-resolution edit mask based on the edit text prompt to enable precise edit localization. Our method establishes a general framework for structure-preserving editing, unifying a class of tasks traditionally handled by separate, specialized methods. By integrating our loss, conventional LDM-based editors can now overcome their inherent limitation in preserving pixel-level structures, significantly expanding their applicability and making them more versatile, all-purpose editing tools.

Experiments conducted on various editing tasks confirm that our method successfully produces edited images that maintain the input image’s pixel-level edge structure while being faithful to the provided edit prompts.

To summarize, our main contributions are as follows:

- We introduce a novel structure preservation loss that maintains the pixel-level edge structure of the input image during image editing.
- We propose a training-free latent-diffusion-model-based image editing method that allows pixel-level edge structure preservation while leveraging latent-diffusion models’ generative image editing capabilities.
- We suggest a simple strategy to acquire a high-resolution edit mask from the diffusion model’s internal features to support local editing.
- We demonstrate state-of-the-art quality in pixel-level structure-preserving image editing through comprehensive experiments.

2. Related Work

Structure-Preserving Image Editing Prior to the emergence of diffusion models, structure-preserving image editing tasks were predominantly tackled using specialized, task-dependent methods. Techniques for image relighting leveraged physics-based priors [12, 28, 42, 44, 58, 66, 77], while tone adjustment relied on color transformations or look-up tables [7, 15, 17, 27, 31, 64, 70, 73]. Harmonization and background replacement employed image gradient or color statistics manipulation [9, 10, 23, 38, 47, 48, 52, 59, 61, 68], and style transfer utilized image statistics or deep feature matching [9, 13, 34, 36, 39, 48, 52, 57, 71].

While these task-specific methods often demonstrated high structural fidelity within their respective domains, they are inherently limited in scope and generalization due to their domain-specific assumptions.

Diffusion-Based Image Editing Large-scale text-to-image LDMs [49, 53] have enabled versatile image editing methods, offering text-driven edits with a single pre-trained model [2–4, 6, 11, 14, 20, 21, 24–26, 40, 41, 45, 62, 63, 67, 76]. These methods broadly fall into training-based and training-free approaches, both facing challenges in preserving fine-grained structural details from the input image.

Training-based approaches include methods that overfit to a single image [3, 25] or learn from editing datasets [4, 14, 26, 76]. However, overfitting to a single image incurs a significant computational overhead, limiting its scalability, while dataset-trained models are limited by dataset biases. Furthermore, the training objectives of training-based methods do not guarantee pixel-level fidelity.

Training-free methods leverage a pre-trained diffusion model without additional training or fine-tuning. Early approaches edit images by steering the generative process of diffusion models to match the edit prompt by modifying the intermediate noisy latent representations [2, 11, 40]. However, these techniques are often limited in editing performance and struggle to retain the original image’s structure. More recent training-free methods have improved on fidelity by manipulating the diffusion model’s denoising U-Net attention maps [6, 20, 45, 62, 67]. For example, Prompt-to-Prompt [20] reuses cross-attention maps generated during input image generation to maintain its global layout, while Plug-and-Play [62] injects self-attention to preserve local structure. Unifying these ideas, InfEdit [67] combines controls for both attention types. However, lacking an explicit pixel-level guidance, these methods only allow for coarse structure preservation.

Full-Reference Metrics for Structural Fidelity While full-reference metrics are often used as loss functions to preserve fidelity to a reference, they are ill-suited for structure-preserving editing tasks where appearance (e.g., color, brightness, contrast) is intentionally modified. These metrics typically fail to disentangle structural content from appearance attributes. For instance, pixel-wise losses like L1 and MSE penalize valid appearance changes, while perceptual metrics like LPIPS [75] do not explicitly enforce structural accuracy. SSIM [65] does account for structure yet remains sensitive to changes in brightness and contrast, as it evaluates luminance and contrast alongside structural correlation.

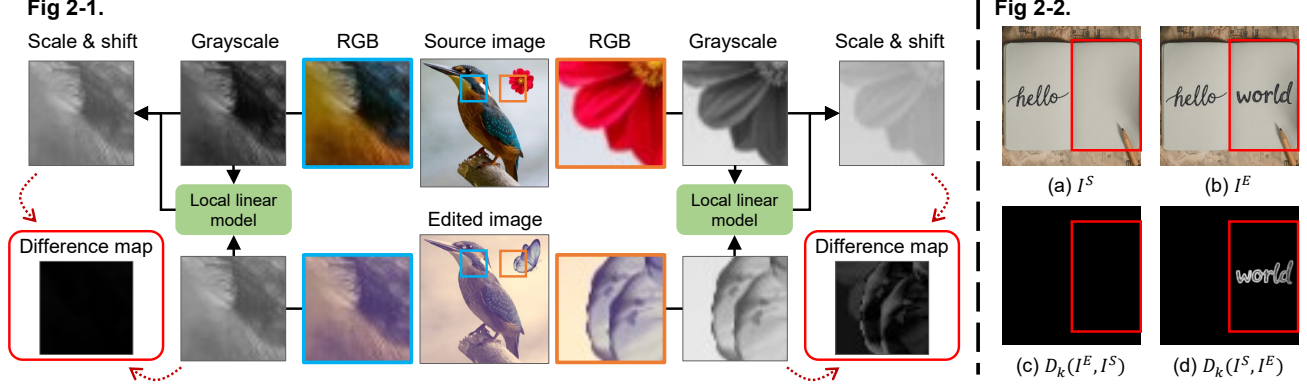


Figure 2. **Motivation of the structure preservation loss.** (Fig 2-1) An edited image may contain both structure-preserving (marked in blue) and structure-breaking regions (marked in orange). Our approach is motivated by the local linear model’s ability to analyze these regions on a local window-by-window basis. (Left) When structure is preserved, the model finds an accurate linear fit, resulting in low error. (Right) When structure is broken, the model fails to find a good fit, producing a high error that signals the distortion. (Fig 2-2) Unidirectional structural comparison fails to fully capture mutual differences, motivating the bidirectional design of our structure preservation loss.

3. Method

Our method performs LDM-based image editing while preserving the pixel-level edge structure of the input. To achieve this, we first introduce a novel structure preservation loss that explicitly quantifies structural discrepancies (Sec. 3.1). We then integrate SPL into the LDM’s denoising pipeline (Sec. 3.2). Additionally, to offer users precise control over which regions should remain unchanged, we also propose a text-driven edit mask generation scheme to be used in conjunction with the structure preservation loss (Sec. 3.3).

3.1. Structure Preservation Loss

Local Linear Model for Structure Preservation Our structure preservation loss is designed to quantify structural differences between a source image I^S and an edited output I^E . To achieve this, our loss is grounded in the local linear model, which is well-established for its structure awareness and has been applied to various tasks that require accurate structure preservation, e.g., alpha matting, edge-aware filtering, dehazing, joint upsampling, and super-resolution [18, 19, 33, 80]. The key assumption is that for structure to be preserved, the edited image I^E must be a local linear transformation of the source image I^S . We visualize this idea in Fig. 2-1.

We formalize this relationship mathematically within a local window ω_k as:

$$I_i^S = a_k I_i^E + b_k, \quad \forall i \in \omega_k, \quad (1)$$

where a_k and b_k are coefficients assumed to be constant within the window centered at pixel k . A key property of this model is that it preserves edges, since taking the gradient of Eq. (1) yields $\nabla I_i^S = a_k \nabla I_i^E$. The coefficients are

obtained by solving a least-squares problem, yielding the closed-form solution:

$$a_k = \frac{\frac{1}{|\omega_k|} \sum_{i \in \omega_k} I_i^E I_i^S - \mu_k^E \mu_k^S}{(\sigma_k^E)^2 + \rho}, \quad \text{and} \quad (2)$$

$$b_k = \mu_k^S - a_k \mu_k^E, \quad (3)$$

where μ_k^E and μ_k^S are the mean intensities of I^E and I^S in ω_k , respectively. σ_k^E is the standard deviation of I^E in ω_k , and $|\omega_k|$ is the number of pixels in the window. ρ is a small constant to avoid degenerate solutions. We provide a detailed derivation in the supplementary.

While previous works employ the local linear model as a filtering mechanism, our key contribution is to adapt it as a differentiable loss. This loss serves as an explicit structural guide for the diffusion model’s generative process, ensuring fidelity across a wide range of editing tasks.

Structure Preservation Loss Based on Eq. (1), we define the directional structure difference between I^E and I^S as:

$$D_k(I^E, I^S) = \frac{1}{|\omega_k|} \sum_{i \in \omega_k} (I_i^{E \rightarrow S} - I_i^S)^2, \quad (4)$$

where $I_i^{E \rightarrow S}$ represents a linearly transformed local patch of I^E , defined as $I_i^{E \rightarrow S} = a_k I_i^E + b_k$. Here, $D_k(I^E, I^S)$ quantifies the discrepancy between the transformed and original images. It is noteworthy that $D_k(I^E, I^S) \neq D_k(I^S, I^E)$, as the operation is not symmetric. Consequently, $D_k(I^E, I^S)$ alone may fail to fully capture the structural differences between two images. For example, consider a case where a region in I^S is structurally flat while the corresponding region in I^E contains structural details (see highlighted region in Fig. 2-2). In such a scenario, a

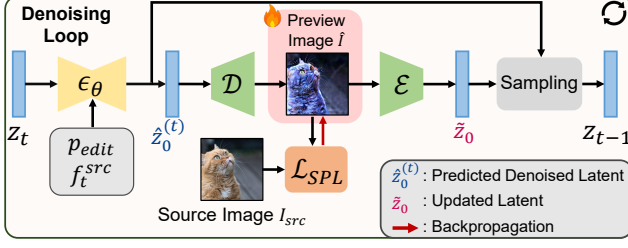


Figure 3. **Structure-preserving denoising loop.** At each denoising timestep t , we decode the predicted clean latent $\hat{z}_0^{(t)}$ to compute our structure preservation loss $\mathcal{L}_{SPL}$ in the image space. The resulting gradient is then used to update the latent, producing a corrected version $\tilde{z}$ that steers the generation trajectory to maintain structural fidelity for the subsequent denoising step.

trivial transformation ($a_k \approx 0, b_k \approx \mu_k^S$) can map I^E to I^S . This results in a deceptively low value for $D_k(I^E, I^S)$ despite the significant structural disparities, as shown in the corresponding error map (Fig. 2-2-c). To address this limitation, we introduce a reverse mapping $D_k(I^S, I^E)$ (Fig. 2-2-d). Finally, we combine the forward and reverse mappings to define the structure preservation loss:

$$\mathcal{L}_{SPL}(I^E, I^S) = \frac{1}{N} \sum_k (D_k(I^E, I^S) + D_k(I^S, I^E)), \quad (5)$$

where N is the total number of pixels in the image, and the summation is performed over all pixels k . By enforcing consistency across both forward ($E \rightarrow S$) and reverse ($S \rightarrow E$) transformations, this loss function robustly penalizes mismatches in underlying structures. For RGB images, we convert them to HSI color space, and use the I channel to compute $\mathcal{L}_{SPL}$ in our approach.

Color Preservation Loss In tasks like local color editing, we must ensure that changing an object’s color does not alter the hues of its surroundings. To address this, we introduce an optional color preservation loss, $\mathcal{L}_{CPL}$, that can be used alongside $\mathcal{L}_{SPL}$. We compute $\mathcal{L}_{CPL}$ as the mean squared error between the Cb and Cr channels of I^A and I^B in the YCbCr color space:

$$\mathcal{L}_{CPL}(I^E, I^S) = \frac{1}{N} \sum_k \|\text{CbCr}(I_k^E) - \text{CbCr}(I_k^S)\|_2^2, \quad (6)$$

We empirically found that using HSI for $\mathcal{L}_{SPL}$ and YCbCr for $\mathcal{L}_{CPL}$ yields higher-quality results. This is because they provide simple linear conversions from the RGB color space. This simplicity enables more efficient loss optimization. Furthermore, the I channel in the HSI color space, calculated as the average of the color channels with equal weights, ensures uniform updates across all RGB components when optimizing $\mathcal{L}_{SPL}$.

3.2. Structure-Preserving Editing with LDMs

In this section, we explain how our structure preservation loss enhances the denoising process of LDMs to achieve pixel-level structure-preserving image editing. We first outline conventional coarse-structure-preserving editing in LDMs and its limitations, then describe our approach, which integrates $\mathcal{L}_{SPL}$ through the denoising diffusion process and a post-processing step. We provide an overview in Fig. 3.

Review of Coarse-Structure-Preserving Image Editing in LDMs In LDMs, an encoder $\mathcal{E}$ maps images to latents, and a decoder $\mathcal{D}$ reconstructs images from these latents. The diffusion process of LDMs is defined in this latent space, enabling efficient image generation and manipulation [49, 53].

Coarse-structure-preserving image editing with LDMs, such as Prompt-to-Prompt [20] and InfEdit [67], typically involves three inputs: a source image I_{src} , its associated text prompt p_{src} , and a target edit prompt p_{edit} . The editing process begins with a latent code z_T sampled from pure Gaussian noise, i.e., $z_T \sim \mathcal{N}(0, I)$, where T is the maximum timestep. The reverse diffusion process then iteratively denoises this latent from $t = T$ to $t = 1$, guided by a noise prediction model ϵ_θ , parameterized by θ .

To achieve coarse-structure-preserving edits, ϵ_θ is conditioned on the target prompt p_{edit} and source features f_t^{src} (e.g., attention maps, estimated noise), extracted from the generation of the source image I_{src} using its prompt p_{src} [20, 67]. This conditioning preserves the coarse structure of the source image during the generation of the edited image. For a forward process defined as $z_t = \alpha_t z_0 + \sigma_t \epsilon$ with $\epsilon \sim \mathcal{N}(0, I)$, the predicted denoised latent $\hat{z}_0^{(t)}$ at each timestep t is computed as:

$$\hat{z}_0^{(t)} = \frac{1}{\alpha_t} (z_t - b_t \epsilon_\theta(z_t, t, p_{edit}, f_t^{src})). \quad (7)$$

From $\hat{z}_0^{(t)}$, the noisy latent for $t - 1$ is computed as:

$$z_{t-1} = \mathcal{S}(\hat{z}_0^{(t)}, z_t, t, \hat{\epsilon}_t), \quad (8)$$

where $\mathcal{S}$ denotes a sampling function and $\hat{\epsilon}_t$ is the estimated noise $\epsilon_\theta(z_t, t, p_{edit}, f_t^{src})$. The iterative denoising process then advances to timestep $t - 1$. While the attention conditioning strategy leveraging f_t^{src} in Eq. (7) preserves coarse image layouts, it does not retain fine-grained structural details of the input image, as will be shown in Sec. 4.

Editing with Structure Preservation Loss Our task of preserving pixel-level edge structure is fundamentally defined in the image space and thus requires a corresponding pixel-space guidance. Hence, we apply $\mathcal{L}_{SPL}$ to the

VAE-decoded image of the denoised latent $\hat{z}_0^{(t)}$ at intermediate timesteps, following prior works that have successfully guided latent denoising with pixel-space objectives [32, 37, 54, 79].

At each timestep t , we compute $\hat{z}_0^{(t)}$ using Eq. (7). Next, we update $\hat{z}_0^{(t)}$ by solving:

$$\hat{z} = \underset{\hat{z}}{\operatorname{argmin}} \mathcal{L}_{\text{SPL}}(I_{\text{src}}, \mathcal{D}(\hat{z})) + \lambda \mathcal{L}_{\text{CPL}}(I_{\text{src}}, \mathcal{D}(\hat{z})) \quad (9)$$

where $\hat{z}$ is initially set to $\hat{z}_0^{(t)}$, $\hat{z}$ is the updated latent, and λ is a weight for the optional color preservation loss, which we set to a small value. Finally, $\hat{z}$ is substituted into Eq. (8) in place of $\hat{z}_0^{(t)}$, and the denoising process continues to timestep $t - 1$. The updated latent $\hat{z}$ guides the subsequent denoising steps to not only retain the source image’s structural details, but also synthesize natural-looking image contents that align with the retained details.

To solve Eq. (9), we adopt the gradient descent method. However, direct application of gradient descent requires repeated, computationally expensive gradient calculations due to backpropagation through $\mathcal{D}$. To circumvent this problem, we introduce an auxiliary image $\hat{I}$, initialized as $\hat{I} = \mathcal{D}(\hat{z}_0^{(t)})$, and reformulate the optimization problem as:

$$\hat{I} = \underset{\hat{I}}{\operatorname{argmin}} \mathcal{L}_{\text{SPL}}(I_{\text{src}}, \hat{I}) + \lambda \mathcal{L}_{\text{CPL}}(I_{\text{src}}, \hat{I}). \quad (10)$$

After solving this, we compute $\hat{z} = \mathcal{E}(\hat{I})$ and substitute it into Eq. (8). Eq. (10) is efficiently solved using a gradient descent update:

$$\hat{I} \leftarrow \hat{I} - \eta \nabla_{\hat{I}} \left\{ \mathcal{L}_{\text{SPL}}(I_{\text{src}}, \hat{I}) + \lambda \mathcal{L}_{\text{CPL}}(I_{\text{src}}, \hat{I}) \right\}, \quad (11)$$

where η is the learning rate.

We apply this optimization selectively during the later stages of the denoising process (i.e., timesteps $t \leq t_{\text{SPL}}$). This approach allows for early denoising steps to maintain generative flexibility while later stages prioritize accurate preservation of structural details. Further analysis of this scheduling is provided in the supplementary.

Post-Processing Step While the diffusion process with the structure preservation loss improves structural consistency, the final decoding $\hat{I}_0 = \mathcal{D}(\hat{z}_0)$ may still lose fine details due to its inherent compression characteristics. To mitigate this, we introduce a post-processing step that refines $\hat{I}_0$ directly in the image space by solving Eq. (10). This step ensures pixel-level fidelity to the source image’s fine structures, compensating for the decoder’s limitations.

3.3. Cross-Attention Mask Upsampling for Structure-Preserving Localized Editing

For localized editing such as background replacement (Fig. 4), we apply structure and color preservation losses

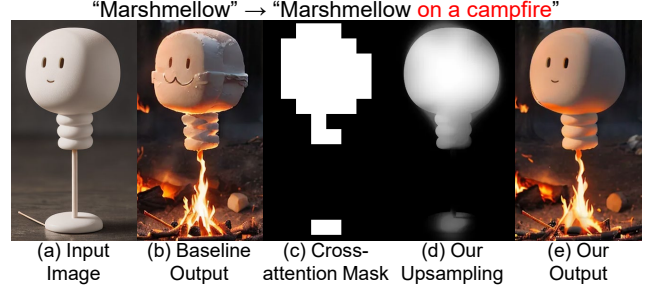


Figure 4. **Cross-attention mask upsampling.** For the background editing task, the baseline method unintentionally distorts the foreground (b). By upsampling the coarse attention map (c), our method generates a sharp, high-resolution mask (d). This enables targeted application of our structure loss, preserving the foreground’s fidelity in the final edit (e).

to specific regions defined by a binary mask. We derive an initial coarse mask by thresholding the low-resolution (16×16) cross-attention map corresponding to the edit prompt [20] (Fig. 4-c). However, naively upsampling this mask with bilinear interpolation produces blurry and misaligned boundaries. To overcome this, we introduce a simple yet effective iterative refinement algorithm. Starting with the coarse mask, we progressively upscale it by a factor of two. At each step, we use the input image, downsampled to the current mask’s resolution, as a guidance image for the guided filter [19]. This process sharpens and aligns the mask’s boundaries by transferring structural details from the guide image. The result is a high-resolution mask with sharp, structurally accurate boundaries (Fig. 4-d), enabling precise and artifact-free local editing (Fig. 4-e). We provide a pseudocode and further details in the supplementary.

4. Experiment

Implementation Details We integrate our method into InfEdit [67], a training-free, latent-diffusion-based framework for image editing. While InfEdit is our primary backbone, our approach is model-agnostic. We demonstrate its application to another backbone in the supplementary. For tasks requiring localized edits, we use the color preservation loss and the upscaled edit masks as detailed in Sec. 3.3. We report the hyperparameters in the supplementary.

4.1. Evaluation Details

Benchmark for Diffusion-Based Image Editing Models We primarily evaluate our method on a curated subset of PIE-Bench [24]. This curation is necessary because standard benchmarks, such as AnyEdit [72] or RealEdit [60], often do not strictly distinguish edits requiring pixel-level edge preservation, frequently mixing them within broader categories. Our curated benchmark provides a more controlled setting for a targeted evaluation. We categorize the



Figure 5. **Qualitative comparison of global editing tasks.** Our method (b) successfully applies the edit while preserving fine-grained structural details. Other methods (c-g) exhibit either low prompt fidelity or significant structural distortions

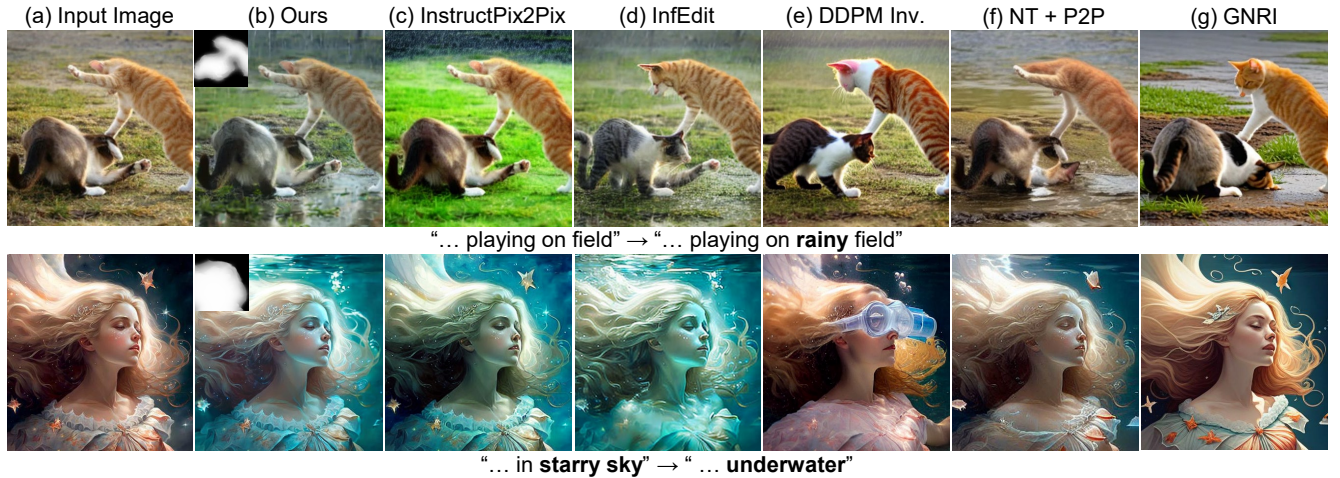


Figure 6. **Qualitative comparison of local editing tasks.** Our method can generate an edit mask from the text prompt (b, top-left) to enable precise local editing. Other methods (c-g) fail to preserve the structure of the content shared between the source and target prompts.

editing tasks based on the scope of structure preservation:

- 1) **Global editing:** Edits applied across the entire image, requiring structure preservation of the whole input image. Examples include relighting, photorealistic style transfer, tone adjustment, and time-lapse generation.
- 2) **Local editing:** Edits requiring structure preservation of specific regions. Examples include background replacement and weather changes, where only the structure of the foreground needs to be preserved.

For this adapted subset, we generate task-specific textual prompts using GPT-4o [43], followed by manual refinement, resulting in approximately 470 image-prompt pairs.

We also provide a supplementary evaluation on the standard AnyEdit [72] benchmark and show that the results confirm the findings from our main experiments. We conduct our evaluation on three categories from AnyEdit that align with our focus on structure-preserving edits: tone transfer, color alteration, and background change.

Method	Preservation					Prompt fidelity	
	SPL ($\times 10^2$) $\downarrow$	SSIM $\uparrow$	LPIPS $\downarrow$	FSIM $\uparrow$	GMSD $\downarrow$	CLIP S. $\uparrow$	CLIP D. $\uparrow$
Ours	0.107	0.854	0.212	0.927	0.062	0.272	0.163
InfEdit (Baseline) [67]	0.748	0.600	0.375	0.792	0.180	0.284	0.163
IP2P [4]	0.517	0.668	0.348	0.839	0.134	0.262	0.153
DDPMInv [21]	0.710	0.702	0.238	0.841	0.161	0.271	0.091
NT+P2P [20, 41]	0.545	0.736	0.214	0.881	0.126	0.256	0.135
GNRI [55]	0.972	0.635	0.286	0.801	0.184	0.247	0.066

Table 1. **Quantitative comparison of LDM-based image editing on PIE-Bench** Our method outperforms other models in LDM-based image editing, scoring the highest in preservation metrics. It also stays faithful to the edit prompt, as shown in the prompt fidelity scores.

Method	Preservation					Prompt fidelity	
	SPL $\downarrow$	SSIM $\uparrow$	LPIPS $\downarrow$	FSIM $\uparrow$	GMSD $\downarrow$	CLIP S. $\uparrow$	CLIP D. $\uparrow$
Ours	0.085	0.906	0.120	0.953	0.046	0.263	0.078
InfEdit (Baseline) [67]	0.865	0.648	0.280	0.813	0.176	0.277	0.103
IP2P [4]	0.576	0.683	0.307	0.840	0.140	0.261	0.118
DDPMInv [21]	0.838	0.711	0.217	0.838	0.168	0.276	0.077
NT+P2P [20, 41]	0.637	0.759	0.170	0.887	0.125	0.265	0.084
GNRI [55]	1.120	0.669	0.229	0.816	0.179	0.253	0.050

Table 2. **Quantitative comparison of LDM-based image editing on AnyEdit benchmark.** Consistent with our findings on PIE-Bench, our method demonstrates state-of-the-art performance in all preservation metrics while maintaining competitive prompt fidelity.

Evaluation Metric We assess our method based on two key criteria:

(1) **Preservation:** We measure how well the edited image preserves the original image’s features. Our evaluation relies on a suite of standard, independent metrics, including SSIM [65] for structural similarity, LPIPS [75] for perceptual similarity, FSIM [74] for feature similarity, and GMSD [69] for gradient similarity. We also report our structure preservation loss as it offers a direct measure for the fine-grained structural fidelity that current metrics do not exclusively capture.

(2) **Prompt fidelity:** We assess how well the edited image aligns with the edit text prompt. We employ CLIP [50] Score to measure the similarity between the target edit prompt and the edited image, and the CLIP Directional Similarity to quantify consistency between the textual prompt changes and corresponding image edits.

4.2. Comparison with SoTA Editing Methods

We compare our method against state-of-the-art latent diffusion-based editing methods, including InstructPix2Pix [4], InfEdit [67], DDPM Inversion [21], GNRI [55] and a combination of null-text inversion [41] and Prompt-to-Prompt [20]. InstructPix2Pix relies on supervised training from editing datasets, InfEdit uses unified attention control for text-guided edits, DDPM Inversion employs inversion-based editing, GNRI introduces a fast inversion technique for real-time editing. Prompt-to-Prompt shows a source image layout preserving editing, where the source image is inverted with null-text inversion.

Quantitative evaluations on both PIE-Bench (Tab. 1) and the AnyEdit benchmark (Tab. 2) indicate that our method significantly outperforms baselines in preservation. This improvement is largely attributed to our structure preservation loss, achieved without compromising prompt fidelity. Qualitative comparisons further illustrate these advantages. In global editing tasks (Fig. 5), InstructPix2Pix often generates either overly exaggerated or insufficient edits, DDPM Inversion and GNRI struggle with both structure preservation and prompt fidelity, and InfEdit preserves only coarse-level structure, compromising fine structural details. In contrast, our method accurately reflects edit prompts while precisely preserving pixel-level edge structures. For local editing tasks (Fig. 6), our proposed mask acquisition method effectively confines edits to regions specified by the prompt (e.g., weather or background), maintaining key elements that remain the same in both source and target prompts. Conversely, methods without region-specific editing inadvertently change the entire image, failing to respect localized changes described by the prompt.

In the supplementary, we also provide comparisons with task-specific structure-preserving methods, including photo-realistic style transfer, image harmonization, tone adjustment, seasonal change, and time-lapse editing, alongside qualitative results on the AnyEdit benchmark.

4.3. Analysis

Comparison with Other Structure-Similarity Losses

We illustrate the effectiveness of our structure preservation loss compared to other common structural similarity measures, e.g., SSIM, MSE, and the directional structure difference loss in Eq. (4). The editing task transforms the input image (Fig. 7-a) into a “futuristic night” style. Since MSE and SSIM penalize pixel-wise luminance and contrast differences, using them leads to results that fail to fully reflect the intended night-style contrast and brightness (Fig. 7-b, c). The directional structure difference loss does not effectively penalize structural artifacts when the source image can be approximated by the edit image with a local linear transform, causing visible distortions at object boundaries (Fig. 7-d). In contrast, our full structure preservation loss successfully maintains pixel-level edge fidelity while accurately following the target edit prompt (Fig. 7-e).

Component-wise Ablation

The ablation studies in Fig. 8 and Tab. 3 show the contribution of each component in the structure preservation loss. In Fig. 8, we edit the color of the cover text from red to yellow. The baseline undesirably alters elements like clothing and cover text (Fig. 8-b). Adding SPL first improves overall structural preservation (Fig. 8-c). Then, CPL with a mask excluding the book specifically restores the original clothing color (Fig. 8-d), and post-processing recovers fine details like the cover text

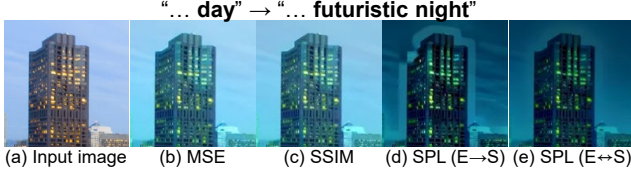


Figure 7. **Ablation study on different loss functions for optimization.** While other structural losses (b-d) penalizes valid appearance changes (e.g., brightness and contrast), our proposed loss (d) successfully disentangles structure from appearance, enabling a faithful edit while preserving structural fidelity.



Figure 8. **Qualitative component-wise ablation of our editing method.** Each component of our editing method progressively improves the quality of the baseline edit (b) to our final result (e). PP: Post-processing.

(Fig. 8-e). Quantitative results in Tab. 3 also falls in line with the qualitative result, where each component builds up better preservation without loss of prompt fidelity.

We also show the necessity of incorporating the structure preservation loss within the diffusion pipeline in Fig. 9. Note that applying our post-processing step to the edited result obtained without this intermediate guidance is equivalent to applying SPL directly to the edited image (Fig. 9-b). However, this approach cannot prevent LDM from generating structural changes that go beyond what the post-processing step can handle (Fig. 9-c).

Computational Cost We analyze the computational cost of our method in Tab. 4, with all experiments conducted on a single NVIDIA A6000 GPU. Our method is substantially faster than inversion-based approaches like DDPM Inversion [21] and the combination of null-text inversion [41] and Prompt-to-Prompt [20]. Compared to the baseline InfEdit [67], our approach adds a modest overhead of approximately 2 seconds. We argue this is a valuable trade-off, as this overhead enables the precise, pixel-level structural control that the baseline lacks.

5. Conclusion

We presented a novel structure preservation loss that penalizes the genuine structural differences between two images. Our method integrates this loss into a training-free LDM-based editing pipeline, achieving edits that preserve pixel-level structure. Our approach also includes a color preservation loss and a text-driven edit mask generation scheme for

Method	Preservation					Prompt fidelity	
	SPL ($\times 10^2$) ↓	SSIM↑	LPIPS↓	FSIM↑	GMSD↓	CLIP S.↑	CLIP D.↑
Baseline	0.594	0.653	0.312	0.834	0.151	0.281	0.172
+SPL	0.351	0.720	0.265	0.890	0.102	0.274	0.168
+CPL	0.351	0.720	0.252	0.892	0.102	0.272	0.161
+PP	0.107	0.853	0.209	0.927	0.063	0.272	0.163

Table 3. **Quantitative component-wise ablation of our editing method.** Adding each component progressively improves all preservation scores while maintaining strong prompt fidelity. PP: Post-processing.

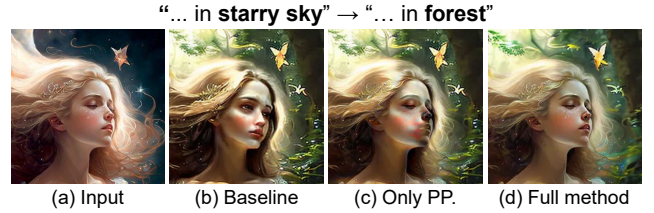


Figure 9. **Guidance vs. Post-Processing.** Applying our loss only as post-processing (c) fails to fix the baseline’s severe structural errors (b). In contrast, our iterative guidance (d) prevents these errors from forming in the first place. PP: Post-processing.

Method	Time(s)	Peak memory(GB)
GNRI [55]	0.39	13.99
InfEdit (Baseline) [67]	2.26	5.82
Ours without PP.	4.18	5.82
Ours with PP.	4.58	5.82
IP2P [4]	5.29	2.61
DDPMInv [21]	23.64	6.09
NT+P2P [20, 41]	130.99	14.9

Table 4. **Computational cost comparison.** Our method demonstrates competitive performance, being substantially faster than inversion-based methods like DDPMInv and NT+P2P, while adding a modest overhead to the fast InfEdit baseline for significantly improved structure preservation. PP: Post-processing.

precise local control. Together, these contributions enable a universal image editing method that preserves pixel-level edge structures of the input image, outperforming state-of-the-art baselines as demonstrated in our evaluations.

Limitations and Future Work Our method’s performance depends on the underlying diffusion model’s quality and speed. While our approach will benefit from future advancements in LDMs, its effectiveness may be limited when paired with older or lower-quality backbones. Additionally, the optimization-based application of our loss introduces a computational overhead. We provide an analysis of this overhead and our method’s failure cases, including the impact of imperfect masks and challenging edit scenarios, in Appendix A. Future work would explore integrating our loss directly into the pre-training of diffusion models to mitigate the computational overhead.

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