Zero-Shot Reference-Based Image Editing Without Training or Guidance

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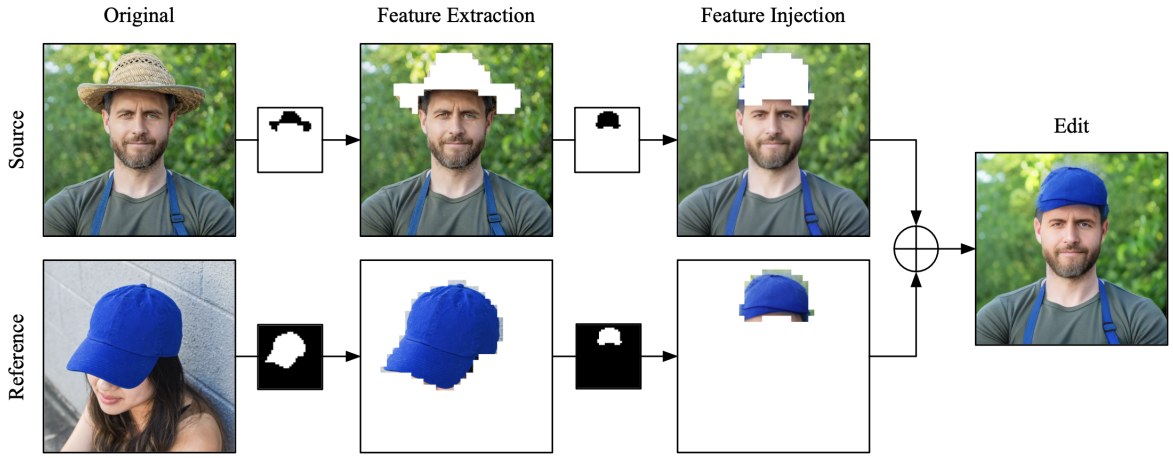


Figure 1. A visualization of our method. We extract desired information from the source and reference images and inject these information into the appropriate spatial regions of the edit image to generate the final output.

Abstract

Recent advancements in text-to-image diffusion models have significantly improved text-conditioned image generation and editing. However, expressing fine-grained modifications through text prompts alone remains inherently limited. To address this, reference-based editing methods have been explored, but they often require test-time fine-tuning, additional training, or expensive test-time computations (e.g., guidance), limiting their practicality and generalizability. We introduce a zero-shot, training-free and guidance-free reference-based image editing framework that allows for a wide range of precise edits by leveraging reference images. Our key innovation is the Hybrid Attention mechanism, which replaces standard self-attention in the diffusion U-Net with a novel masked cross-image attention approach. This mechanism enables controlled extraction and injection of spatial features from reference images into a target image during sampling. Additionally, we propose the use of automatic masks derived from the cross-attention maps of the diffusion UNet to define region selection, removing the need for manual input.

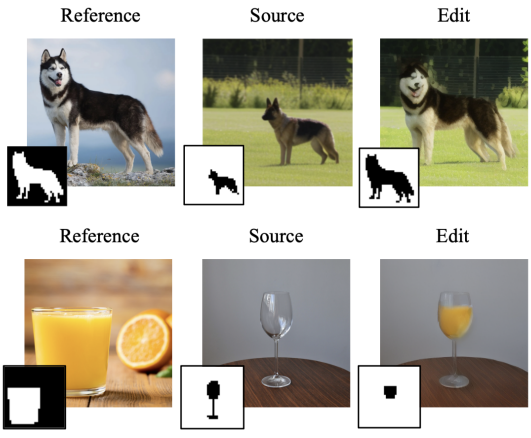


Figure 2. A preview of our results.

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1. Introduction

The rapid advancement of text-to-image (T2I) generative models has enabled high-quality image generation and editing from natural language prompts. However, while these models produce impressive results, prompt-driven generation remains fundamentally limited in capturing a user's exact intent. Expressing nuanced edits through text alone is challenging, as natural language descriptions often fail to specify the fine details and localized modifications required for precise image editing.

To address this limitation, many reference-based image editing methods have emerged. Instead of relying solely on text, reference images provide additional visual guidance, allowing for more controlled and targeted edits. However, existing methods typically fall into one of the following categories:

- **Test-time fine-tuning** methods adapt the diffusion U-Net [12, 21] or an auxiliary model [22] to a given image by optimizing its parameters during inference. This approach allows the model to tailor directly to the specific image. However, these methods are computationally expensive at test-time and hence impractical for real-time applications.
- **Pretraining-based** methods [2, 3, 6, 8, 13, 26–29] train base diffusion models on large-scale datasets with paired images for various editing tasks. By leveraging extensive training, these models learn how to perform specific edits, enabling faster inference without requiring optimization at test time. However, this approach is constrained by the availability of paired training data, limiting the model's ability to generalize beyond predefined tasks such as object insertion or style transfer.
- **Guidance-based** methods [5, 16, 18] optimize the latent embedding throughout the diffusion process using specialized score functions, enabling more precise control compared to text-only inputs. While these approaches do not require additional training, they impose a substantial computational cost during inference, increasing both runtime and GPU memory consumption due to the need for backpropagation through the diffusion model.

Existing methods that are both training-free and guidance-free are limited in scope, often supporting only basic edits like object insertion [7, 14, 25] or global style/structure/appearance transfer [1, 4, 11, 15], failing to provide a generalizable framework for more diverse, complex editing tasks.

To this end, we introduce a novel training-free, zero-shot, and guidance-free framework for reference-based image editing that extends beyond basic edits, supporting a wide range of localized, and high-fidelity modifications in a fully automatic manner. Furthermore, our framework provides deeper insights into the role of attention layers in diffusion models, shedding light on their semantic reasoning capabilities.

1.1. On-Device Image Editing

Beyond expressiveness, the practicality of image editing methods significantly depends on computational efficiency and their ability to run locally on user devices. With the rise of powerful yet compact neural architectures, state-of-the-art diffusion models such as Stable Diffusion 2.1 have been successfully adapted to run efficiently on personal computing devices, including laptops and smartphones [19]. This shift toward on-device editing brings critical privacy advantages, as sensitive user data—often present in personal photos or creative projects—no longer needs to be uploaded to external servers, mitigating concerns regarding data security and confidentiality.

Moreover, enabling efficient, local image editing directly empowers user creativity. Users gain the flexibility to experiment with complex and nuanced image modifications in real-time and on-the-go, opening up new possibilities for interactive and iterative creative workflows. This approach aligns particularly well with emerging mobile-first creative tools, allowing everyday users—not just professionals—to benefit from advanced, privacy-conscious editing capabilities wherever they are.

2. Preliminaries

2.1. DDIM Inversion

Denoising Diffusion Probabilistic Models (DDPM) [10, 23] are trained to optimize the objective:

$$\min_{\theta} \mathbb{E}_{z_0,\epsilon\sim\mathcal{N}(0,I),t\sim\text{Uniform}(1,T)} \left\|\epsilon - \epsilon_\theta(z_t, t, C)\right\|_2^2 .$$

Here, the diffusion model learns to predict the noise component ϵ given a noisy latent z_t, timestep t, and conditioning information C. During sampling, the noise is gradually removed by sequentially predicting it across T timesteps, transforming a noisy latent z_T to a clean latent z_0.

Denoising Diffusion Implicit Models (DDIM) [24] extend the diffusion framework by introducing a deterministic sampling process. Unlike the stochastic nature of DDPMs, DDIM ensures consistent transformations between noisy latents and clean latents. This makes it particularly useful for latent reconstruction and editing, as it preserves structural and semantic consistency throughout the sampling trajectory. Given an initial noisy latent z_T, the DDIM sampling process iteratively refines it into a clean latent z_0. This is achieved through a deterministic update rule:

$$z_t = \frac{1}{\sqrt{\alpha_{t+1}}} \left(z_{t+1} - \frac{1-\alpha_{t+1}}{\sqrt{1-\bar{\alpha}_{t+1}}} \cdot \epsilon_\theta(z_{t+1}, t+1) \right) .$$

DDIM inversion [17] maps a starting latent z_0 to a corresponding noisy latent z_T. The DDIM inversion follows a deterministic update rule:

$$z_{t+1} = \sqrt{\bar{\alpha}_{t+1}}\hat{z}_0 + \sqrt{1-\bar{\alpha}_{t+1}} \cdot \epsilon_\theta(z_t, t),$$

where the estimated clean latent $\hat{z}_0$ is given by:

$$\hat{z}_0 = \frac{z_t - \sqrt{1-\bar{\alpha}_t} \cdot \epsilon_\theta(z_t, t)}{\sqrt{\bar{\alpha}_t}}.$$

Through iterative application of the DDIM inversion update rule, an initial clean latent z_0 is transformed into progressively noisier latents z_t, with the final noisy latent z_T capturing the structural and semantic properties of the original latent while aligning with the learned diffusion process. This latent representation serves as the starting point for downstream tasks such as image reconstruction or image editing.

2.2. Diffusion U-Net Architecture

Many pretrained text-to-image (T2I) diffusion models are text-conditioned U-Nets, consisting of an encoder-decoder structure. These models employ a combination of convolutional layers, self-attention layers, and cross-attention layers. Self-attention helps capture both local and global dependencies, while cross-attention allows for effective conditioning on textual prompts.

2.2.1. Self-Attention

Self-attention plays a crucial role in conveying both short-range and long-range dependencies across the entire latent. It ensures a coherent image construction by enabling each spatial position to attend to every other spatial position. The self-attention mechanism is expressed as:

$$\mathbf{Q} := \mathbf{h}_{l,t}\mathbf{W}_l^Q, \quad \mathbf{K} := \mathbf{h}_{l,t}\mathbf{W}_l^K, \quad \mathbf{V} := \mathbf{h}_{l,t}\mathbf{W}_l^V$$

where $\mathbf{h}_{l,t} \in \mathbb{R}^{(hw)\times d}$ represents the diffusion features at time step t, and $\mathbf{W}_l^Q, \mathbf{W}_l^K, \mathbf{W}_l^V \in \mathbb{R}^{d\times d}$ are linear projections for query, key, and value matrices. The attention scores are computed as:

$$\mathbf{A} := \text{Softmax}\left(\frac{\mathbf{Q}\mathbf{K}^\top}{\sqrt{d}}\right)$$

where $\mathbf{A} \in \mathbb{R}^{(hw)\times(hw)}$ represents the attention map, encoding how each pixel in $\mathbf{Q}$ corresponds to each pixel in $\mathbf{K}$, with higher scores indicating higher similarity. Each pixel's self-attention output is then computed as:

$$\mathbf{h}_{l,t} \leftarrow \mathbf{A}\mathbf{V}$$

This operation ensures that each pixel aggregates information from other pixels, weighted by their relevance, resulting in spatially aware feature refinement.

2.2.2. Cross-Attention

In cross-attention layers, the query ($\mathbf{Q}$) is derived from the spatial latents, while the key ($\mathbf{K}$) and value ($\mathbf{V}$) originate from the encoded textual prompt. This mechanism enables effective conditioning of the generated latents on text. The cross-attention map [9] in this case reflects how each pixel attends to different textual tokens, guiding the diffusion model in aligning textual attributes with specific spatial regions. Notably, the cross-attention map allows us to identify the spatial regions associated with particular objects described in the prompt.

3. Method

Our approach begins with DDIM inversion applied to both the source and reference images, denoted as $z_{s,0}$ and $z_{r,0}$, respectively. During each inversion step, we store the queries (Q), keys (K), and values (V) from the self-attention and cross-attention layers. The final noised latent of the source image $z_{s,T}$ produced by the DDIM inversion is used as the starting latent for the edit path. $z_{s,T}$ serves as a strong initialization point for image editing by encapsulating essential structural information about the image thus facilitating accurate reconstruction. In the edit path, we replace the self-attention blocks with a novel Hybrid Attention mechanism. This mechanism allows for fine-grained extraction and injection of information in the edit path via the stored queries (Q), keys (K), and values (V) of the self-attention layers. At the end of the edit path, we arrive at our edited latent $z_{e,0}$ This process is outlined in Figure 3.

3.1. Hybrid Attention

As illustrated in Figure 1, our approach follows a two-step process: (1) extracting relevant information from the source and reference images, and (2) injecting these information into the appropriate spatial regions of the edit image to generate the final output.

To achieve information extraction, we apply a masked cross-image attention (MaskAttn) mechanism. Specifically, we use the query ($\mathbf{Q}_e$) from the edit image while utilizing the key ($\mathbf{K}_s, \mathbf{K}_r$) and value ($\mathbf{V}_s, \mathbf{V}_r$) representations from the source and reference images, respectively. The extraction process is guided by a binary extraction mask M_s or M_r, which defines the spatial regions to be extracted from each image. :

$$O_s = \text{MaskAttn}(\mathbf{Q}_e, \mathbf{K}_s, \mathbf{V}_s; M_s)$$

$$O_r = \text{MaskAttn}(\mathbf{Q}_e, \mathbf{K}_r, \mathbf{V}_r; M_r)$$

$$\text{MaskedAttn}(\mathbf{Q}, \mathbf{K}, \mathbf{V}; M) = \text{Softmax}\left(\frac{\mathbf{Q}\mathbf{K}^\top}{\sqrt{d}} + M\right)\mathbf{V}$$

where M assigns large negative values (e.g., $-\infty$) to positions to be excluded. Once the relevant information has

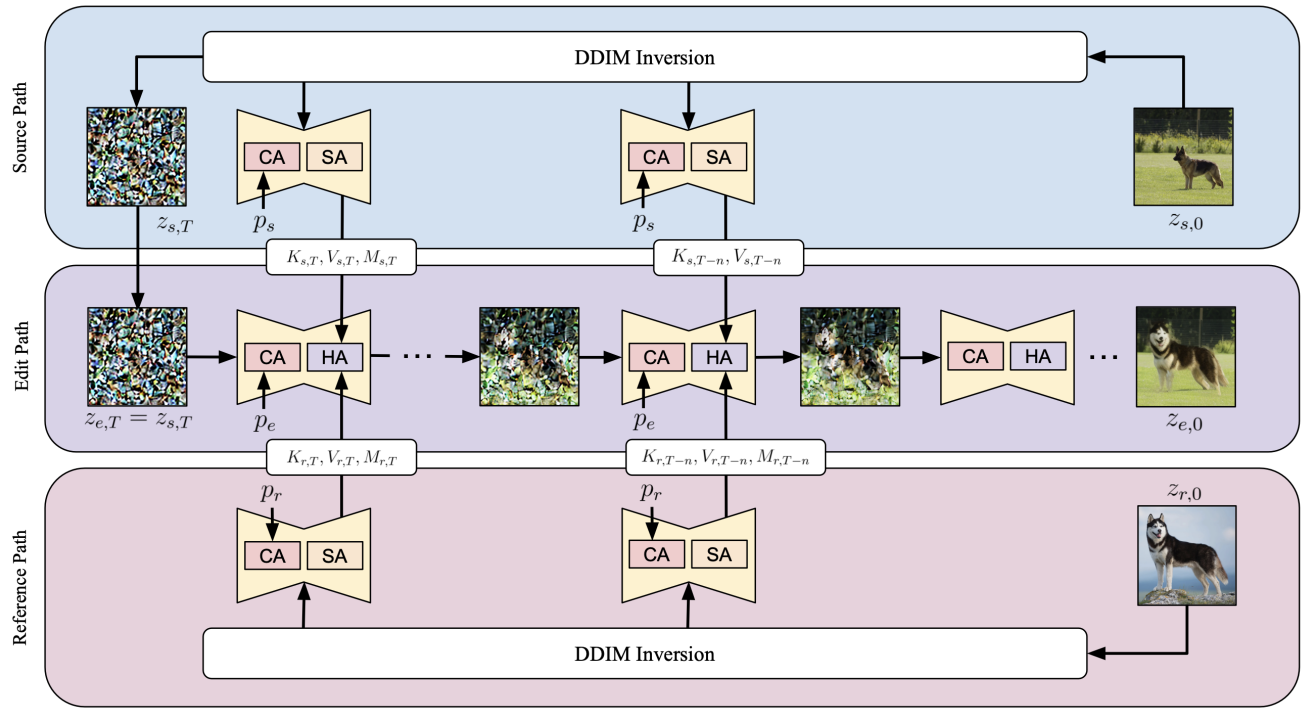


Figure 3. An overview of the architecture. We perform DDIM inversion on the source $z_{s,0}$ and reference $z_{r,0}$ images. During each inversion step, we store the queries (Q), keys (K), and values (V) from the self-attention and cross-attention layers. The final noised latent of the source image $z_{s,T}$ produced by the DDIM inversion is used as the starting latent for the edit path. In the edit path, we replace the self-attention blocks with the Hybrid Attention mechanism to extract and inject desired information via the stored queries (Q), keys (K), and values (V) of the self-attention layers. At the end of the edit path, we arrive at our edited latent $z_{e,0}$

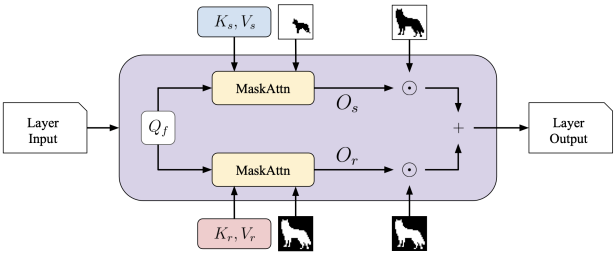


Figure 4. Hybrid Attention block.

been extracted, we proceed to information injection, ensuring that the extracted features are transferred to the desired regions of the edit image. This is controlled by a binary injection mask M_e, which specifies where the injected information should be placed. The final Hybrid Attention output is computed as follows:

$$\text{HybridAttn} = O_s \odot (1 - M_e) + O_r \odot M_e$$

3.2. Automatic Masks

Masks play a crucial role in our pipeline by defining the regions for information extraction and injection. While users have the option to manually specify the source extraction, reference extraction and injection masks, automating this process is often preferable. To generate masks automatically, we utilize cross-attention maps extracted from the U-Net's cross-attention layers during the DDIM inversion process. These maps act as heatmaps, highlighting the relevance of each textual token to different regions of the image. By applying a thresholding operation to these attention maps, we obtain binary masks for objects of interest, which can then be used as the extraction or injection masks.

4. Experiment

We applied our method to the Stable Diffusion 2.1 [20] model using publicly available pretrained weights. All editing experiments were conducted on real images, covering a variety of subjects including human portraits, animals and objects.

4.1. Types of Edits

Our method enables a variety of fine-grained edits, including reference-based object replacement, reference-based object insertion, object removal as well as prompt-based edits. The extraction and injection masks can either

be manually provided by the user or taken from the cross-attention maps. Figure 5 depicts some of our results.

4.2. Optimizations

4.2.1. Layer Configuration for Hybrid Attention

We explored different configurations of layers for integrating our proposed Hybrid Attention mechanism in place of self-attention within the edit path. The Stable Diffusion 2.1 model consists of three main resolution blocks, each capturing different levels of abstraction.

- Deeper layers in the network encode global structure and high-level semantics. Modifying these layers can introduce unintended global changes, disrupting the overall composition of the image.
- Shallower (higher) layers focus on fine-grained textures and localized details, making them more suitable for precise edits while preserving the broader structure.

By strategically selecting which layers to modify, we ensure that edits remain localized and do not disrupt the structural integrity of the original image.

4.2.2. Post-Processing for Mask Refinement

Cross-attention maps, particularly during early diffusion steps, can be noisy, making direct binary thresholding ineffective. To address this, we apply a Gaussian filter to reduce noise, followed by a normalization step to rescale attention values to a consistent range. Next, we apply thresholding, where pixels exceeding a selected threshold are retained as part of the mask. To further refine the mask and improve smoothness, we perform morphological operations, including dilation to expand regions and erosion to remove small artifacts. This results in cleaner, more robust masks suitable for use in Hybrid Attention.

4.3. Quantitative Results

We evaluate our pipeline on a set of image pairs constructed similarly to the COCO EE dataset introduced in the Paint by Example paper [26]. Each pair consists of a source image, a reference image, a mask specifying the target region, and an associated editing prompt to support controlled experiments in exemplar-based image editing.

Different types of edits present distinct challenges, making it difficult to generalize a single configuration across tasks. We found that swapping higher-down and higher-up layers with our Hybrid Attention mechanism provides the most reliable results across the tested range of tasks.

Our experiments focus on object insertion and replacement actions. These tasks stress both the precision of spatial control and the ability to preserve background fidelity. We compare two versions of our method, one using manual masks, and another relying on automatically generated masks derived from cross-attention maps.



Figure 7. Visualization of our editing metrics and comparisons. (**Left**) The edited result (top) and reference image (bottom), used for computing the CLIP image-to-image (I2I) similarity. (**Middle**) The edited result (top) and source image (bottom), highlighting the regions where we measure the L2 difference. (**Right**) The original image (top) and final edited image (bottom), employed for computing CLIP alignment with the edit prompt.

Metric	Automatic Masks	Manual Masks
Copy Region CLIP-I2I	0.767	0.847
Background L2 Distance	0.058	0.052
CLIP-I2P Improvement (%)	+10.8%	+17.9%

Table 1. Quantitative results comparing Hybrid Attention with and without manual masks. Manual masks offer slightly improved region alignment and background preservation, preventing corruption and improving the overall edit quality. In contrast, the automated mask pipeline achieves competitive results without demanding user input.

In addition to the qualitative results presented earlier, we measure three quantitative metrics across our test set to assess the editing performance:

- **Copy Region CLIP-I2I Score:** We extract the edited region from the final image and compare it against the corresponding region in the reference image using a CLIP-based cosine similarity. A higher score indicates better semantic preservation, though a perfect score of 1 is not expected since the content is adapted (e.g., shape or texture) to fit the new context.
- **Background L2 Distance:** We compute the pixel-wise L2 distance between the unedited (background) regions of the source image and the final edited image. Lower values indicate that the background is better preserved.
- **CLIP-I2P Improvement (%):** We measure the CLIP similarity between (i) the source image and the edit prompt, and (ii) the final edited image and the same prompt. The percentage change quantifies how much closer the final image aligns to the edit prompt relative to the original.



Figure 5. Our results prove our method to work across a wide range of editing domains, including reference-based object replacement, reference-based object insertion, object removal and prompt-based edits. For some of the prompt-based edits, we utilized an adaptive (A) cross-attention map as the insertion mask.

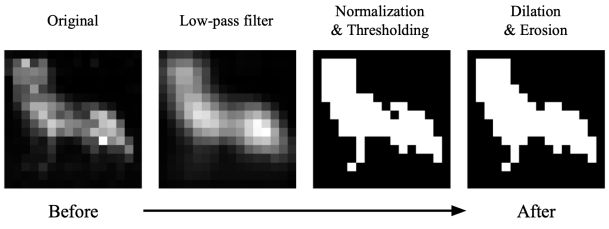


Figure 6. Automated thresholding for masks derived from cross-attention maps.

Table 1 shows an example of the average results over our evaluation set. The CLIP-I2I score indicates that, on average, the edited region closely resembles the reference content without being a mere copy-paste. The low background L2 distance confirms that the unedited portion of the source image remains largely unchanged. Finally, the CLIP-I2P improvement demonstrates that our edits make the image more aligned with the specified edit prompt.

5. Conclusion

We introduce a zero-shot, training-free, and guidance-free framework for precise, reference-based image editing. Our novel Hybrid Attention mechanism enables fine-grained, localized control by leveraging masked cross-image attention, allowing seamless extraction and injection of visual features from reference images without compromising computational efficiency. Moreover, our automatic mask generation approach, derived from the diffusion U-Net's cross-attention maps, eliminates the need for manual intervention, significantly enhancing usability and practicality. Through extensive experimentation, we demon-

strate strong semantic alignment with both reference images and textual prompts while preserving background fidelity. Beyond its practical utility, our method provides valuable insights into the semantic reasoning processes within diffusion U-Nets, highlighting how different attention layers contribute to spatial understanding and feature abstraction. Our work illustrates how pretrained models can be further exploited for advanced image editing, unlocking new potential for real-time, privacy-focused applications and interactive creative workflows.

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