

OminiControl: Minimal and Universal Control for Diffusion Transformer

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<https://github.com/Yuanshi9815/OminiControl>

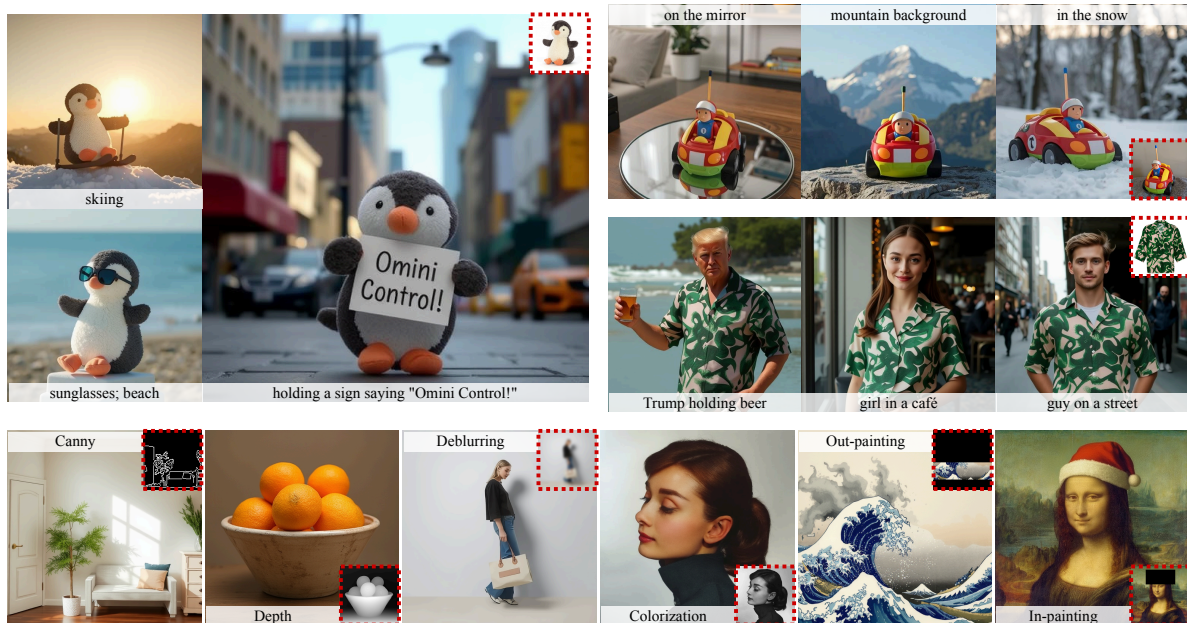


Figure 1. Results of our OminiControl on both subject-driven generation (top) and spatially-aligned tasks (bottom). The small images in red boxes show the input conditions.

Abstract

We present *OminiControl*, a novel approach that rethinks how image conditions are integrated into Diffusion Transformer (DiT) architectures. Current image conditioning methods either introduce substantial parameter overhead or handle only specific control tasks effectively, limiting their practical versatility. *OminiControl* addresses these limitations through three key innovations: (1) a minimal architectural design that leverages the DiT’s own VAE encoder and transformer blocks, requiring just 0.1% additional parameters; (2) a unified sequence processing strategy that combines condition tokens with image tokens for flexible token interactions; and (3) a dynamic position encoding mechanism that adapts to both spatially-aligned and non-aligned control tasks. Our extensive experiments show that this streamlined approach not only matches but sur-

passes the performance of specialized methods across multiple conditioning tasks. To overcome data limitations in subject-driven generation, we also introduce *Subjects200K*, a large-scale dataset of identity-consistent image pairs synthesized using DiT models themselves. This work demonstrates that effective image control can be achieved without architectural complexity, opening new possibilities for efficient and versatile image generation systems.

1. Introduction

The ability to generate high-quality images with precise user control remains a central challenge in computer vision. While diffusion models [17, 44] have significantly advanced image generation, surpassing traditional GAN-based approaches [11] in both quality and diversity, fine-grained control remains problematic. Text-conditioned models [9, 24, 41, 44] serve as the primary controllable generation paradigm, yet fundamentally lack the capacity to

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specify exact spatial details and visual attributes that users often need. To address this limitation, some works have explored image-based control methods [2, 14, 15, 18, 26–30, 37, 42, 46, 50, 52, 54, 56, 57, 60, 61, 63], enabling users to specify their intentions through reference images, offering more precise guidance than text alone [44].

However, current image control methods face several key challenges: First, existing methods require substantial architectural modifications with dedicated control modules [38, 60, 61]. Second, these approaches show clear task bias – they typically work well for either spatially aligned controls (e.g., edge-guided or depth-guided generation [2, 15, 29, 30, 37, 42, 52, 61, 63]) or spatially unaligned ones (e.g., style transfer or subject-driven generation [18, 27, 28, 50, 60][14, 33]), but rarely both. Third, current approaches are built primarily for UNet architectures [45]. These approaches yield suboptimal results when applied to newer Diffusion Transformer (DiT) models [40] due to fundamental architectural differences, despite the latter’s superior generation capabilities [4, 9, 24].

These challenges, particularly within the emerging paradigm of Diffusion Transformer models, motivate us to rethink the fundamental approach to image control. We propose **OminiControl**, an **omni**-capable yet **minimal** framework that achieves effective and flexible **control**.

For minimal architecture, OminiControl employs a parameter reuse strategy that leverages DiT’s existing components—particularly its VAE encoder and transformer blocks—which already possess the necessary capabilities to process visual control signals. By reusing these components with minimal fine-tuning, our approach dramatically reduces parameter overhead while maintaining control effectiveness, requiring only 0.1% additional parameters compared to the base model.

To achieve omni-capability across diverse tasks, OminiControl introduces a unified sequence processing approach that fundamentally differs from previous methods’ rigid feature addition. By directly concatenating condition tokens with noisy image tokens in a unified sequence, we allow the multi-modal attention mechanism to discover appropriate relationships between tokens—whether spatial or semantic—without imposing artificial constraints. This flexibility is crucial for handling both spatially-aligned tasks like edge-guided generation and non-aligned tasks like subject-driven generation within a single framework.

Building on this unified approach, OminiControl incorporates a dynamic positioning strategy that adaptively assigns position indices based on the task type, enabling true omni-capability without task-specific architectural modifications. Furthermore, for practical flexibility, we introduce an attention bias mechanism that allows users to dynamically adjust the influence of image conditions at inference time, providing crucial control over the generation process.

The effectiveness of our architecture depends on high-quality training data, particularly for subject-driven generation. Recognizing that state-of-the-art DiT models can generate remarkably consistent image pairs of the same subject, we develop an automated data synthesis pipeline that creates Subjects200K—a dataset of over 200,000 diverse, identity-consistent images that provides the rich training signals needed to fully realize OminiControl’s potential.

In summary, we highlight our contributions as follows:

- We propose OminiControl, a minimal and universal control framework for DiT models that requires only 0.1% additional parameters while effectively handling both spatially-aligned and non-aligned tasks, demonstrating that extensive architectural modifications are unnecessary for effective image conditioning.
- We identify two key technical innovations that enable omni-capability: (1) unified sequence processing that outperforms traditional feature addition, and (2) adaptive position encoding that strategically assigns position indices based on task requirements.
- We design a flexible attention bias mechanism that allows precise adjustment of conditioning strength at inference time, enhancing practical control within the multi-modal framework without compromising performance.
- We develop and release Subjects200K, a large-scale dataset containing over 200,000 identity-consistent images to advance future research.

2. Related works

2.1. Diffusion models

Diffusion models have emerged as a powerful framework for image generation[17, 44], demonstrating success across diverse tasks including text-to-image synthesis [4, 44, 49], image-to-image translation [48], and image editing [1, 35]. Recent advances have led to significant improvements in both quality and efficiency, notably through the introduction of latent diffusion models [44]. To further enhance generative capabilities, large-scale transformer architectures have been integrated into these frameworks, leading to advanced models like DiT[4, 5, 24, 40]. Building on these architectural innovations, FLUX[24] incorporates transformer-based design with flow matching objectives [31], achieving state-of-the-art generation performance.

2.2. Controllable generation

Controllable generation has been extensively studied in the context of diffusion models. Text-to-image models[41, 44] have established a foundation for conditional generation, while various approaches have been developed to incorporate additional control signals such as image. Notable methods include ControlNet [61], enabling spatially aligned control in diffusion models, and T2I-Adapter [37], which

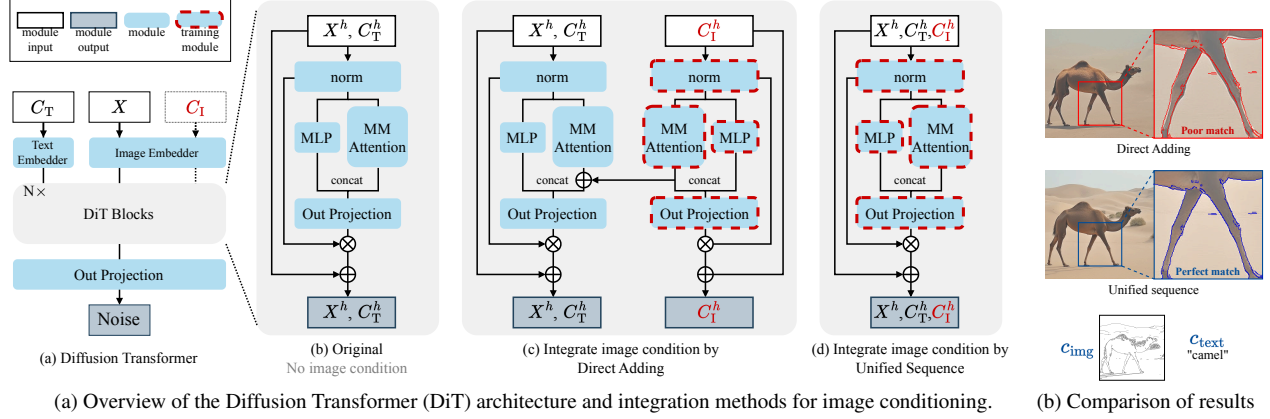


Figure 2. Exploration of different methods for integrating image conditions.

improves efficiency with lightweight adapters. UniControl [42] uses Mixture-of-Experts (MoE) to unify different spatial conditions, further reducing model size. However, these methods rely on spatially adding condition features to the denoising network’s hidden states, inherently limiting their effectiveness for spatially non-aligned tasks like subject-driven generation. IP-Adapter [60] addresses this by introducing cross-attention through an additional encoder, and SSR-Encoder [62] further enhances identity preservation in image-conditioned tasks. Despite these advances [10, 14, 18, 23, 27, 32, 33, 38, 47], a unified solution for both spatially aligned and non-aligned tasks remains elusive.

3. Methods

3.1. Preliminary

The Diffusion Transformer (DiT) model [40], employed in architectures like FLUX.1 [24], Stable Diffusion 3 [44], and PixArt [4], uses transformer as denoising network to refine noisy image tokens iteratively.

A DiT model processes two types of tokens: noisy image tokens $X \in \mathbb{R}^{N \times d}$ and text condition tokens $C_T \in \mathbb{R}^{M \times d}$, where d is the embedding dimension, N and M are the number of image and text tokens respectively (Figure 2a). Throughout the network, these tokens maintain consistent shapes as they pass through multiple transformer blocks.

In FLUX.1, each DiT block consists of layer normalization followed by Multi-Modal Attention (MMA) [39], which incorporates Rotary Position Embedding (RoPE) [51] to encode spatial information. For image tokens X , RoPE applies rotation matrices based on the token’s position (i, j) in the 2D grid:

$$X_{i,j} \rightarrow X_{i,j} \cdot R(i, j), \quad (1)$$

where $R(i, j)$ is the rotation matrix at position (i, j) . Text

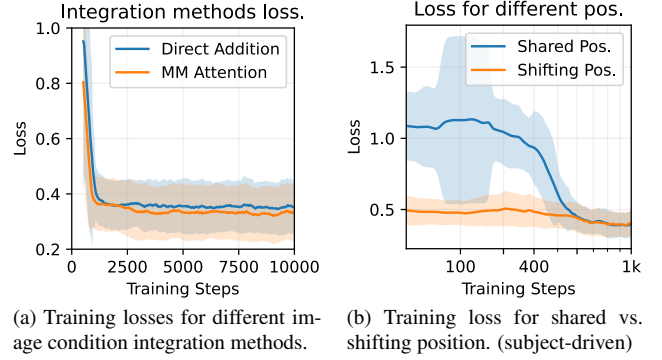


Figure 3. Training loss comparisons.

tokens C_T undergo the same transformation with their positions set to $(0, 0)$.

The multi-modal attention mechanism then projects the position-encoded tokens into query Q , key K , and value V representations. It enables the computation of attention between all tokens:

$$\text{MMA}([X; C_T]) = \text{softmax} \left(\frac{QK^\top}{\sqrt{d}} \right) V, \quad (2)$$

where $[X; C_T]$ denotes the concatenation of image and text tokens. This formulation enables bidirectional attention.

3.2. OminiControl

Building upon the DiT architecture, with FLUX.1 [24] as our base model, we aim to develop a **minimal**, **omni**-capable and **controllable** generation framework that accepts flexible control signals. This vision leads to our OminiControl, which we describe in this section.

3.2.1. Minimal architecture

To minimize the extra architectural and parameter overhead, OminiControl adopts a *parameter reuse strategy*.

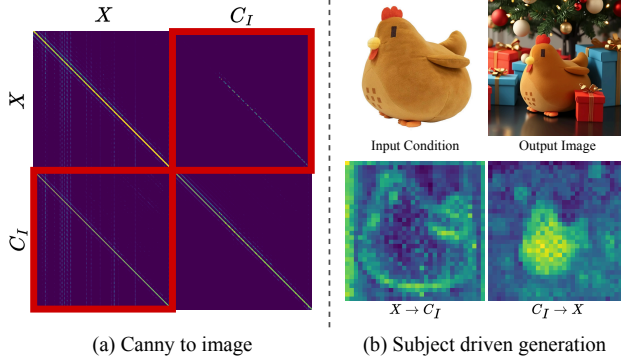


Figure 4. (a) Attention maps for the Canny-to-image task (with setting from Figure 2b), showing interactions between noisy image tokens X and condition tokens C_I ; strong diagonal patterns indicate effective spatial alignment. (b) Attention maps for the subject-driven generation task (Prompt: *This item is placed on a table with Christmas decorations around it.*), depicting $X \rightarrow C_i$ and $C_i \rightarrow X$ interactions that focus accurately on the subject. All maps are averaged over every transformer layer and all denoising timesteps.

As its name implies, we reuses the VAE [22, 44] encoder from the base DiT model encode the condition image. These images are projected into the same latent space as the noisy input tokens, ensuring compatibility without introducing new modules. Following this, OminiControl processes both noisy image tokens and condition tokens jointly through the original DiT blocks. To adapt the shared DiT blocks for handling condition tokens, only lightweight LoRA fine-tuning [8] is applied, avoiding costly full-parameter updates.

This approach contrasts with previous methods that rely on separate feature extractors like CLIP [43, 60] or additional control modules [62], significantly reducing architectural complexity. Meanwhile, LoRA fine-tuning ensures parameter efficiency compared to duplicating the entire network as done in ControlNet [61].

3.2.2. Omni-capable token interaction

To achieve effective control across diverse tasks, OminiControl needs to enable flexible interactions between condition tokens and image tokens. We address this challenge through two key mechanisms: unified sequence processing and position-aware token interaction.

Unified sequence processing. Building upon the shared latent space, we now think how to integrate condition tokens into the model for flexible control across.

Previous methods [37, 61] incorporate condition images through direct feature adding:

$$h_X \leftarrow h_X + h_{C_I}, \quad (3)$$

where the condition features h_{C_I} are spatially aligned and added to the noisy image features h_X .

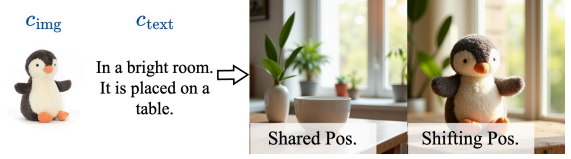


Figure 5. The results from models with shared and shifted position indices. Both models are fully trained with 15k iterations.

We first implement this direct adding approach as illustrated in Figure 2a. While the bare effectiveness is shown in Figure 2b, this approach faces two limitations: (1) it lacks flexibility for non-aligned scenarios where spatial correspondence doesn't exist, and (2) the rigid addition operation constrains potential interactions between condition and image tokens.

We then explored the unified sequence processing to integrate condition tokens into the model. Specifically, this approach directly concatenates condition tokens with noisy image tokens $[X; C_I; C_I]$ for multi-modal attention processing. This formulation enables flexible token interactions through DiT's multi-modal attention mechanism, allowing direct relationships to emerge between any pair of tokens without imposing rigid spatial constraints.

As shown in Figure 4, this approach effectively handles both spatially aligned and non-aligned tasks, with attention maps revealing clear cross-token relationships and interaction patterns. Empirically, this unified sequence approach consistently achieves lower training loss compared to direct feature adding (Figure 3a), demonstrating its superior conditioning capability across diverse generation scenarios.

Position-aware token interaction. While the unified sequence approach allows flexible token interactions, encoding position information for the newly appended conditional tokens is not straightforward.

FLUX.1 adopts the RoPE mechanism to encode spatial information for both image and text tokens. Specifically, for a 512×512 input image, the VAE encoder produces a 32×32 grid of latent tokens, with each token assigned a position index (i, j) where $i, j \in [0, 31]$.

We first assign the same position indices to condition tokens as noisy image tokens, it works well for spatially aligned tasks like edge-guided generation. However, for non-aligned tasks like subject-driven generation, this shared position indexing can lead to suboptimal performance due to spatial overlap between condition and noisy image tokens. But if we shift the position indices of condition tokens by a fixed offset Δ (e.g., $(0, 32)$), ensuring no spatial overlap with noisy image tokens, the training convergence accelerates significantly and final performance improves. (see Figure 3b and Figure 5).

This observation suggests that for spatially aligned tasks,

a shared position indexing facilitates direct spatial correspondence between condition and image tokens, while for non-aligned tasks, shared position indexing can constrain the model’s ability to establish semantic relationships. Hence, we propose a dynamic positioning strategy based on the control task:

$$(i, j)_{C_1} = \begin{cases} (i, j)_X & \text{for aligned tasks} \\ (i, j) + \Delta & \text{for non-aligned tasks} \end{cases} \quad (4)$$

which makes OminiControl truly omni-capable by adapting to both spatially aligned and non-aligned control tasks.

3.2.3. Control with flexibility

Although our unified sequence processing and position-aware token interaction mechanisms effectively enable joint attention between conditions and images, they also present a new challenge. Unlike previous methods [60, 61] that could simply scale condition features (e.g., $h_X \leftarrow h_X + \alpha \cdot h_{C_1}$ where α controls strength), the joint attention approach of OminiControl does not inherently support adjustable conditioning strength, which is crucial for practical applications where users need to balance text and image influences.

To address this limitation, we design a flexible control mechanism by introducing a bias term into the multi-modal attention computation. Specifically, for a given strength factor γ , we modify the attention operation in Equation 2 to:

$$\text{MMA}([X; C_T; C_I]) = \text{softmax} \left(\frac{QK^\top}{\sqrt{d}} + B(\gamma) \right) V, \quad (5)$$

where $B(\gamma)$ is a bias matrix modulating the attention between concatenated tokens $[X; C_T; C_I]$. Given $C_T \in \mathbb{R}^{M \times d}$ and $X, C_I \in \mathbb{R}^{N \times d}$, the bias matrix has the structure:

$$B(\gamma) = \begin{bmatrix} \mathbf{0}_{M \times M} & \mathbf{0}_{M \times N} & \log(\gamma) \mathbf{1}_{N \times N} \\ \mathbf{0}_{N \times M} & \mathbf{0}_{N \times N} & \mathbf{0}_{N \times N} \\ \log(\gamma) \mathbf{1}_{N \times N} & \mathbf{0}_{M \times N} & \mathbf{0}_{N \times N} \end{bmatrix}. \quad (6)$$

This formulation preserves the original attention patterns within each token type while scaling attention weights between X and C_I by $\log(\gamma)$. At test time, setting $\gamma = 0$ removes the condition’s influence, while $\gamma > 1$ enhances it, which makes OminiControl more flexible.

3.2.4. Comparison with concurrent works

Several recent works also explore controllable image generation with DiT models. Some approaches [12, 24, 34] employ channel concatenation to integrate condition tokens, which offers less flexibility than our unified sequence processing. Others [3, 6] focus exclusively on specific tasks such as style transfer or subject-driven generation, limiting their flexibility and generality. In contrast, our approach combines dynamic positioning with a flexible control mechanism to provide a more comprehensive and adaptable control framework compared to existing methods.



Figure 6. Examples from our Subjects200K dataset. Each pair of images shows the same object in varying contexts.

3.3. Subjects200K datasets

A critical challenge in developing universal control frameworks lies in obtaining high-quality training data for subject-driven generation. While OminiControl’s architecture enables flexible control, effective training requires data that maintains subject consistency while incorporating natural variations in pose, lighting, and context.

Existing solutions often rely on identical image pairs [60] or limited-scale datasets [23, 47], which present several limitations. Using identical pairs can lead to overfitting in our framework, causing the model to simply reproduce the input. Meanwhile, existing datasets with natural variations often lack either the scale or diversity needed for robust training.

To address this data challenge, we leverage a key observation: state-of-the-art DiT models like FLUX.1 [25] can generate identity-consistent image pairs when provided with appropriate prompts [19, 20]. Building on this, we develop an pipeline to create Subjects200K, a large-scale dataset specifically designed for subject-driven generation¹:

- **Prompt Generation.** We use GPT-4o to generate over 30,000 diverse subject descriptions. Each description represents the same subject in multiple scenes.
- **Paired-image synthesis.** We then reorganized the collected descriptions into structured prompts. Each prompt describes the same subject in two different scenes. The template of such prompt is shown in the Figure A3 of supplementary material. These prompts are then fed into FLUX to generate image pairs. Each pair is designed to maintain subject consistency while varying in context.
- **Quality Assessment.** Finally, we use GPT-4o to evaluate the generated pairs. Misaligned pairs are removed to ensure identity consistency and high image quality.

The resulting dataset (Figure 6) contains over 200,000 high-quality images spanning diverse categories. Each subject appears in multiple contexts, providing rich training signals for learning robust subject-driven control. To facilitate future research, we release both the dataset and our complete generation pipeline².

¹Detailed prompt design and synthesization pipeline are provided in the Section A of supplementary material.

²Dataset: <https://github.com/Yuanshi9815/Subjects200K>

4. Experiment

4.1. Setup

Tasks and base model. We evaluate our method on two categories of conditional generation tasks: spatially aligned tasks (including Canny-to-image, depth-to-image, masked-based inpainting, and colorization) and subject-driven generation. We build our method upon FLUX.1 [24], a latent rectified flow transformer model for image generation. By default, we use FLUX.1-dev to generate images for spatially aligned tasks. In subject-driven generation tasks, we switch to FLUX.1-schnell as we observed it tend to produce better visual quality.

Implement details. Our method utilizes LoRA [8] for fine-tuning the base model with a default rank of 4. To preserve the model’s original capabilities and achieve flexibility, the LoRA scale is set to 0 by default when processing non-condition tokens.

Training. Our model is trained with a batch size of 1 and gradient accumulation over 8 steps (effective batch size of 8). We employ the Prodigy optimizer [36] with safeguard warmup and bias correction enabled, setting the weight decay to 0.01. For spatially aligned tasks, we use text-to-image-2M[13] dataset with the last 300,000 images. For subject-driven generation, we utilize our proposed Subjects200K dataset. The experiments are conducted on 2 NVIDIA H100 GPUs (80GB each). For spatially aligned tasks, models are trained for 50,000 iterations, while subject-driven generation models are trained for 15,000 iterations.

Baselines. For spatially aligned tasks, we compare our method with both the original ControlNet [61] and T2I-Adapter [37] on Stable Diffusion 1.5, as well as ControlNetPro [25], the FLUX.1 implementation of ControlNet. For subject-driven generation, we compare with IP-Adapter [60], evaluating its implementations FLUX.1 [58]. Additionally, we also with the official FLUX.1 Tools [24] implementation.

Evaluation of spatially aligned tasks. We evaluate our model on both spatially aligned tasks and subject-driven generation. For spatially aligned tasks, we assess two aspects: generation quality and controllability. Generation quality is measured using FID [16], SSIM, CLIP-IQA[53], MAN-IQA [59], MUSIQ [21], and PSNR[7] for visual fidelity, along with CLIP Text and CLIP Image scores [43] for consistency. For controllability, we compute F1 Score between extracted and input edge maps in edge-conditioned generation, and MSE between extracted and original condition maps for other tasks (using Depth Anything for depth, color channel separation for colorization, etc.). We use 5,000 images from COCO 2017 validation set, and resize them to 512×512, then generate task-specific conditions and associated captions as prompts with a fixed seed of 42.

Methods	Base model	Parameters	Ratio
ControlNet	SD1.5 / 860M	361M	~42%
T2I-Adapter		77M	~9.0%
IP-Adapter		449M	~52.2%
ControlNet	FLUX.1 / 12B	3.3B	~27.5%
IP-Adapter		918M	~7.6%
FLUX.1 Tools		612M	~5.1%
Ours	FLUX.1 / 12B	14.5M / 48.7M w/ Encoder	~0.1% / ~0.4% w/ Encoder

Table 1. Additional parameters introduced by different image conditioning methods. For IP-Adapter, the parameter count includes the CLIP Image encoder. For our method, we also report results when using the original VAE encoder from FLUX.1.

Evaluation of subject-driven generation. For subject-driven generation, we propose a five-criteria framework evaluating both preservation of subject characteristics (identity preservation, material quality, color fidelity, natural appearance) and accuracy of requested modifications, with all assessments conducted through GPT-4o’s vision capabilities to ensure systematic evaluation³. We test on 750 text-condition pairs (30 subjects × 25 prompts) from DreamBooth[47] dataset with 5 different seeds, using one selected image per subject as the condition.

4.2. Main result

Spatially aligned tasks As shown in Table 2, we comprehensively evaluate our method against existing approaches on five spatially aligned tasks. Our method achieves the highest F1-Score of 0.38 on depth-to-image generation, significantly outperforming both SD1.5-based methods ControlNet [61] and T2I-Adapter [37], as well as FLUX.1-based ControlNetPro [25]. In terms of general quality metrics, our approach demonstrates consistent superiority across most tasks, showing notably better performance in SSIM [55], CLIP-IQA[53], MAN-IQA [59], MUSIQ [21] and PSNR[7] scores. For challenging tasks like deblurring and colorization, our method achieves substantial improvements: the MSE is reduced by 77% and 93% respectively compared to ControlNetPro, while the FID scores [16] improve from 30.38 to 11.49 for deblurring. The CLIP-Text and CLIP-Image metrics [43] indicate that our method maintains high consistency across all tasks, suggesting effective preservation of semantic alignment and image alignment while achieving better control and visual quality. As shown in Figure 7, our method produces sharper details and more faithful color reproduction in colorization tasks, while maintaining better structural fidelity in edge-guided generation and deblurring scenarios.

Subject driven generation Figure 8 presents a comprehensive comparison against existing baselines. Our method demonstrates superior performance, particularly in identity

³Details are shown in the Section B.2 of the supplementary material.

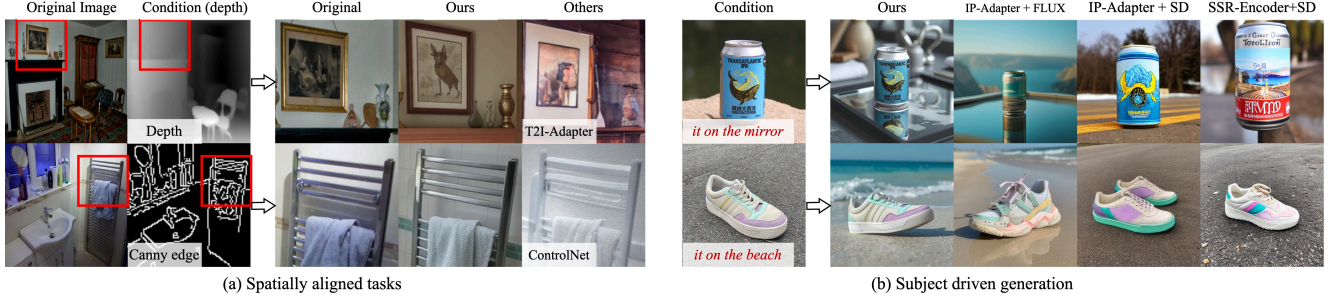


Figure 7. Qualitative comparison. Left: Spatially aligned tasks. Right: Subject-driven generation with beverage can and shoes. Our method demonstrates superior controllability and quality across all tasks. (More results are provided in supplementary material.)

Task	Methods / Setting	Base Model	Controllability		Image Quality					Alignment	
			F1↑ / MSE↓	FID↓	SSIM ↑	CLIP-IQA↑	MAN-IQA↑	MUSIQ↑	PSNR ↑	CLIP Text↑	CLIP Image↑
Canny	ControlNet	SD1.5	0.35	18.74	<u>0.36</u>	0.65	0.45	67.81	<u>10.27</u>	0.305	<u>0.752</u>
	T2I Adapter		0.22	<u>20.06</u>	0.35	0.57	0.39	67.89	9.53	0.305	0.748
	ControlNet Pro	FLUX.1	0.21	98.69	0.25	0.48	0.37	56.91	9.22	0.192	0.537
	Flux Tools		0.20	22.13	0.32	<u>0.66</u>	<u>0.60</u>	75.47	9.69	0.308	0.701
	Ours		0.50	24.20	0.45	0.66	0.62	<u>74.87</u>	11.34	<u>0.305</u>	0.785
Depth	ControlNet	SD1.5	923	23.03	<u>0.34</u>	0.64	0.47	70.73	10.63	0.308	0.726
	T2I Adapter		1560	24.72	0.28	0.61	0.39	69.99	9.50	0.309	0.721
	ControlNet Pro	FLUX.1	2958	62.20	0.26	0.55	0.39	66.85	9.38	0.212	0.547
	Flux Tools		767	24.56	0.32	0.68	0.59	75.30	10.15	0.308	0.715
	Ours		537	31.04	0.39	0.68	0.60	74.04	<u>10.53</u>	0.305	0.749
Mask	ControlNet	SD1.5	7588	13.14	0.68	<u>0.58</u>	0.42	67.22	<u>18.96</u>	0.300	0.848
	Flux Tools	FLUX.1	6610	11.40	0.73	0.56	0.45	68.92	18.37	0.305	0.874
	Ours		6351	10.20	0.78	0.59	0.49	70.78	19.59	0.305	0.892
Colorization	ControlNet Pro	FLUX.1	994	30.38	0.75	0.40	0.31	54.38	16.23	0.279	0.781
	Ours		73	10.37	0.92	0.56	0.48	69.40	21.56	0.305	0.884
Deblur	ControlNet Pro	FLUX.1	338	16.27	0.64	0.55	0.43	70.95	20.53	0.294	0.853
	Ours		62	18.89	0.58	0.59	0.54	70.98	21.82	0.301	0.856

Table 2. Quantitative comparison with baseline methods on five spatially aligned tasks. We evaluate methods based on Controllability (F1-Score for Canny, MSE for others), Image Quality (SSIM, FID, CLIP-IQA, MAN-IQA, MUSIQ, PSNR), and Alignment (CLIP Text and CLIP Image). For F1-Score (used in Canny to Image task), higher is better; for MSE, lower is better. Best results are shown in **bold**. The second-best results are highlighted with underlines.

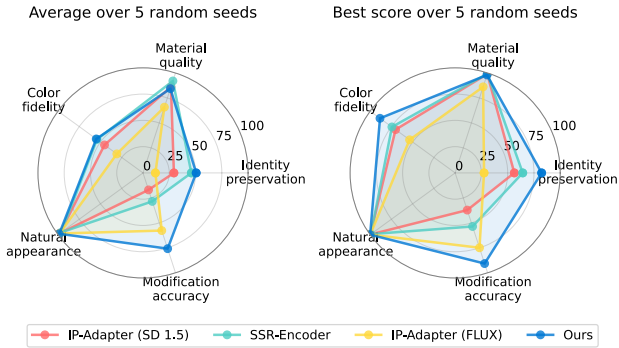


Figure 8. Radar charts visualization comparing our method (blue) with baselines across five evaluation metrics.

preservation and modification accuracy. Averaging over random seeds, we achieve 75.8% modification accuracy compared to IP-Adapter (FLUX)’s 57.7%, while maintaining 50.6% identity preservation against IP-Adapter (SD 1.5)’s 29.4%. The advantage amplifies in best-seed scenarios, achieving 90.7% modification accuracy and 82.3%

identity preservation - surpassing the strongest baselines by 15.8 and 18.0 percentage points, demonstrating effective subject-fidelity editing. These quantitative results are further corroborated by user studies presented in supplementary material B.2.

Parameter efficiency As shown in Table 1, our approach achieves remarkable parameter efficiency compared to existing methods. For the 12B parameter FLUX.1 model, our method requires only 14.5M extra parameters (0.1%), which is significantly lower than ControlNet (27.5%) and IP-Adapter (7.6%). Even when utilizing the original VAE encoder from FLUX.1, our method still maintains high efficiency with just 0.4% additional parameters, demonstrating the effectiveness of our parameter-efficient design.

Condition strength factor We evaluate our condition strength control mechanism (Section 3.2.3) through qualitative experiments. Figure 9 shows that strength factor γ effectively controls the generation process for both spatially aligned tasks like depth-to-image generation and non-aligned tasks like subject-driven generation.

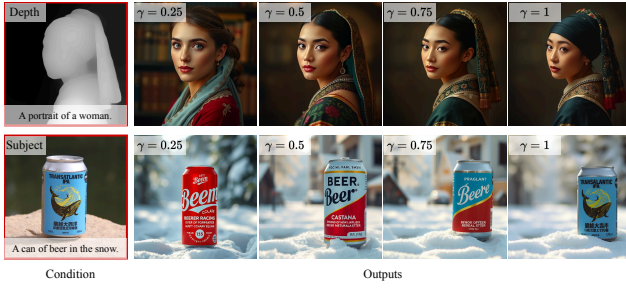


Figure 9. Demonstration of the condition strength control.

Study	Setting	FID ↓	SSIM ↑	F1 Score ↑	CLIP Score ↑
LoRA Rank	1	21.09	0.412	0.385	0.765
	2	21.28	0.411	0.377	0.751
	4	20.63	0.407	0.380	0.761
	8	21.40	0.404	0.3881	0.761
	16	19.71	0.425	0.407	0.764
Condition Blocks	Early	25.66	0.369	0.23	0.72
	Full	20.63	0.407	0.38	0.76

Table 3. Ablation studies on (1) LoRA rank for the *Canny-to-image* task and (2) condition signal integration approaches. Results show that LoRA rank of 16 and full-depth integration achieve the best performance. Rows with blue background indicate our default settings (LoRA rank=4, Full condition integration). Best results are in **bold**.

4.3. Ablation Studies

To better understand the key factors that influence our model’s control capabilities, we conducted comprehensive ablation studies examining parameter efficiency, architectural decisions, and component contributions.

Impact of LoRA rank. We conducted extensive experiments with different LoRA ranks (1, 2, 4, 8, and 16) for the Canny-to-image task. As shown in Table 3, our experiments show that increasing the LoRA rank generally improves model performance, with rank 16 achieving the best results across multiple aspects. However, even with smaller ranks (e.g., rank 1), the model demonstrates competitive performance, especially in text-image alignment, showing the efficiency of our approach even with limited parameters.

Conditioning depth. FLUX.1’s transformer architecture features two distinct types of blocks: early blocks that employ separate normalization modules for different modalities tokens (text and image) and later blocks that share unified normalization across all tokens. As shown in Table 3, experiments reveal that restricting condition signal integration to only these early blocks results in insufficient controllability. This suggests that allowing the condition signals to influence the entire transformer stack is crucial for generate better results. Notably, this finding indicates that the preview approaches[25, 37, 58, 60, 61] of injecting condition signals primarily in early blocks, which were effective in UNet-based architectures, may not fully translate to DiT-based models like FLUX.1.

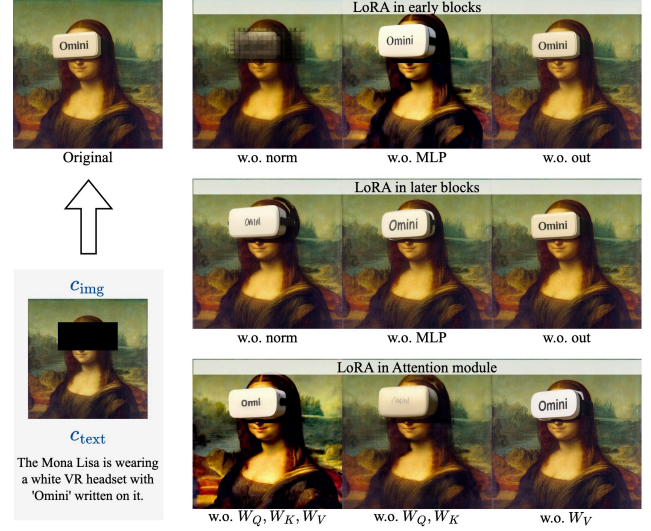


Figure 10. Ablation study of critical modules for conditional generation. Given the censored Mona Lisa image and text prompt (bottom left), we test removing LoRA from different components.

Critical module analysis. To identify essential components for effective control, we conducted fine-grained ablation studies as shown in Figure 10. Results demonstrate that normalization layers and attention projections—particularly query (W_Q) and key (W_K)—are critical for maintaining control quality. Removing LoRA from these components significantly degrades conditional rendering, while value projections (W_V) have less impact. These insights reveal that control signals might propagate through normalization pathways and attention routing mechanisms rather than feature transformation processes.

Additional experiments and analyses, including further model validations, detailed ablation studies, and inference efficiency comparisons, are provided in the Section B of the supplementary material.

5. Conclusion

OminiControl offers parameter-efficient image-conditional control for DiT across diverse tasks using a unified token approach, requiring only 0.1% additional parameters. The Subjects200K dataset — featuring over 200,000 high-quality, subject-consistent images—further supports advancements in subject-driven generation, with experimental results confirming OminiControl’s effectiveness in both spatially-aligned and non-aligned tasks.

However, the unified sequence approach increases the total number of tokens processed through the network, potentially limiting computational efficiency during inference. Addressing this token efficiency challenge while maintaining our method’s control capabilities represents an important direction for future research in parameter-efficient conditional generation.

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