arXiv:2507.02792v4 [cs.CV] 24 Nov 2025

RichControl: Structure- and Appearance-Rich Training-Free Spatial Control for Text-to-Image Generation

Liheng Zhang* Lexi Pang* Hang Ye Xiaoxuan Ma Yizhou Wang
Peking University
{zhangliheng, panglexi}@stu.pku.edu.cn, {yehang, maxiaoxuan, yizhou.wang}@pku.edu.cn

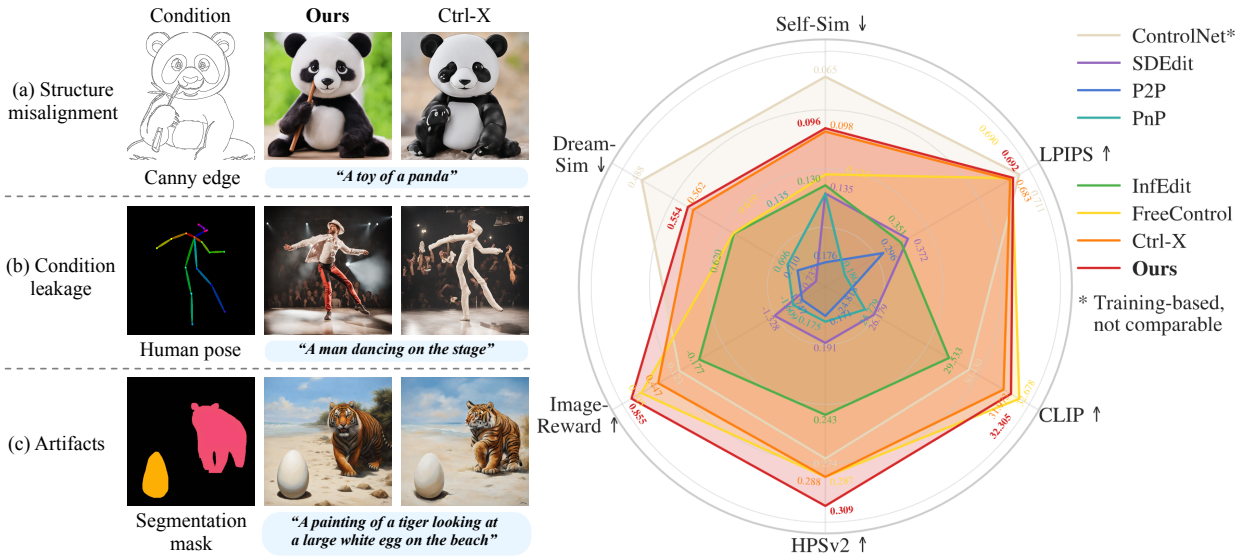


Figure 1. **Structure- and appearance-rich training-free spatial control for text-to-image generation.** We propose a training-free framework that enables high-quality spatial control for pretrained text-to-image diffusion models under arbitrary spatial conditions. (***Left***) By introducing strong and intuitive structure and appearance control, our method effectively addresses key limitations of prior work such as Ctrl-X [47], including structure misalignment, condition leakage, and artifacts, and (***Right***) achieves SOTA performance among all training-free methods; in the radar chart, greater distance from the center indicates superior results. Project page: https://zhang-liheng.github.io/richcontrol/.

Abstract

Text-to-image (T2I) diffusion models have shown remarkable success in generating high-quality images from text prompts. Recent efforts extend these models to incorporate conditional images (e.g., canny edge) for fine-grained spatial control. Among them, feature injection methods have emerged as a training-free alternative to traditional fine-tuning-based approaches. However, they often suffer from structural misalignment, condition leakage, and visual artifacts, especially when the condition image diverges significantly from natural RGB distributions. Through an empirical analysis of existing methods, we identify a key limitation: the sampling schedule of condition features, previously unexplored, fails to account for the evolving interplay between structure preservation and domain alignment throughout diffusion steps. Inspired by this observation, we propose a flexible training-free framework that decouples the sampling schedule of condition features from the denoising process, and systematically investigate the spectrum of feature injection schedules for a higher-quality structure guidance in the feature space. Specifically, we find that condition features sampled from a single timestep are sufficient, yielding a simple yet efficient schedule that balances structure alignment and appearance quality. We further enhance the sampling process by introducing a restart refinement schedule, and improve the visual quality with an appearance-rich prompting strategy. Together, these designs enable training-free generation that is both structure-rich and appearance-rich. Extensive ex-

* Equal contribution

periments show that our approach achieves state-of-the-art results across diverse zero-shot conditioning scenarios.

1. Introduction

With the success of text-to-image (T2I) diffusion models [61, 64, 70], recent research has explored integrating conditional images, *e.g.*, depth maps for spatial control. Early approaches, such as ControlNet [102], rely on fine-tuning or auxiliary networks trained on paired data, which constrains their flexibility and scalability. More recent studies have shown that the rich structural information encoded within diffusion features can be exploited to guide image generation without retraining, thereby enabling zero-shot control. They either introduce additional guidance terms to minimize the feature distance between the condition and target during denoising [6, 18, 52], or inject features extracted from the condition image at each timestep into the target image [28, 47, 80]. Among them, feature injection-based methods such as Ctrl-X [47] have shown promising performance across diverse conditioning scenarios.

However, these methods still encounter several failures, including structural misalignment, condition leakage, and visual artifacts (Fig. 1). These issues become more pronounced when the condition image deviates significantly from natural RGB distributions, *e.g.*, in pose or depth maps (Fig. 5). This suggests that a key challenge lies in the domain gap between condition and natural image features in pretrained T2I diffusion models. We hypothesize that the injected condition features often lie outside the distribution of natural image features, which hinders the synthesis of high-fidelity results. This motivates us to analyze the temporal dynamics of diffusion features, observing a trade-off between structural fidelity and domain alignment (see Figs. 2 and 3). These findings expose a fundamental limitation in existing training-free methods [28, 47, 80], which rely on condition features extracted at the *same* timestep during denoising. This schedule fails to accommodate the evolving trade-off across timesteps: early features leads to loss of structural detail, while late features result in domain mismatch and condition leakage (Fig. 3).

To address this, we generalize the sampling process of condition features and explore the design space of the feature injection schedule. The result shows that the optimal timestep is neither the same one as the target output image nor the latest one with the clearest features. Through a comprehensive investigation, we identify a family of candidate schedules that share an identical last timestep, among which a constant schedule yields consistently strong results. Building on these insights, we propose a more flexible feature injection framework that decouples the injection timestep from the denoising process. To further enhance control precision and visual fidelity, we apply a restart refinement schedule that iteratively mitigates visual artifacts introduced by injected features, and incorporate prompt augmentation to ensure semantic alignment with the condition image. Together, these designs enable structure- and appearance-richer control of pretrained diffusion models [61]. Fig. 4 provides an overview of our framework, which consists of three key components: (i) *Structure-Rich Injection (SRI)* injects condition features based on a principled sampling schedule; (ii) *Restart Refinement (RR)* performs iterative forward–backward denoising; (iii) *Appearance-Rich Prompting (ARP)* aligns the semantics of the appearance prompt with the condition image.

Extensive experiments validate the effectiveness of our approach across diverse types of condition images, demonstrating improved structural consistency, visual fidelity, and semantic alignment compared to state-of-the-art training-free methods. Furthermore, the idea of our framework can be readily incorporated into other training-free methods, such as FreeControl [52], where it yields notable improvements, highlighting its versatility. In summary, our contributions are threefold: (i) We reveal the inherent limitation of existing training-free methods in sampling schedules, and identify a spectrum of alternatives through a principled analysis of the design space. (ii) Building on this insight, we propose a novel framework that enables structure- and appearance-rich controllable T2I generation. (iii) Our proposed method demonstrates state-of-the-art performance in comparison to previous training-based and training-free baselines, delivering superior structure preservation, text-image alignment, and visual fidelity.

2. Related Work

2.1. T2I Diffusion Models

Text-to-image (T2I) diffusion models [31, 63, 64, 70] typically leverage U-Net [65] or transformer-based backbones [19, 41, 58] and integrate textual information via cross-attention or classifier-free guidance [29, 54, 64]. Latent diffusion models like Stable Diffusion [64] introduce compressed latent spaces to reduce computational cost. In addition to architectural innovations, some work focuses on improving sampling efficiency [36, 48, 49, 72, 73, 98, 109]. Restart Sampling [98] proposes alternating between adding noise and denoising to balance discretization error and contraction. Our work explores sampling strategies in the context of conditional text-to-image generation.

2.2. Training-based Controllable Diffusion Models

It is difficult to convey human preferences through text descriptions alone. Training-based controllable diffusion models mitigate this problem by training auxiliary modules or fine-tuning the model to incorporate additional input signals to guide the generation process. According to task charac-

teristics, these methods can be broadly classified into three categories: **(i) Image editing** [7, 12, 24, 26, 27, 37, 42, 71, 83, 88, 90, 92, 94] takes an input image and applies targeted modifications while preserving other regions of the image; **(ii) Image-to-image translation** [34, 55, 56, 69, 79] learns mappings between images of different domains; **(iii) Conditional text-to-image (T2I) generation** methods synthesize images that satisfy both a text prompt and a control condition. Among these approaches, some works condition the generation on layout cues (*e.g.*, bounding boxes) [46, 84, 100] or reference images of specific subjects [3, 12, 23, 42, 44, 60, 67, 68, 75, 76, 88, 90, 92, 104, 107]. Another line of work [4, 12, 27, 42, 45, 53, 75, 76, 88, 90, 92, 94, 101, 102, 104, 107, 108] enables fine-grained structural control by leveraging condition images of different modalities (*e.g.*, canny edges, OpenPose keypoints [9]). Despite their impressive performance, these methods all require retraining or fine-tuning on datasets tailored to the control signal, which limits their generalization to new model checkpoints and novel control conditions.

2.3. Training-free Controllable Diffusion Models

On the other hand, training-free controllable diffusion models operate at inference time to achieve condition control without additional training on task-specific paired data. Similar to Sec. 2.2, we categorize them into 3 groups: **(i) Image editing** [5, 8, 14, 15, 18, 21, 32, 35, 57, 77, 78, 82, 87, 96, 97, 99, 105, 111]; **(ii) Image-to-image translation** [74], with some works [2, 13, 25, 33, 40, 47] further conditioning the transformation on an additional appearance image; **(iii) Conditional text-to-image (T2I) generation**, which generates images consistent with both textual prompts and input control signals. These signals range from coarse layout constraint such as bounding boxes [11, 43, 86, 91, 93], semantic references like subject images [16, 20, 59, 66, 85, 106], to condition images that provide fine-grained control [6, 28, 39, 47, 51, 52, 80]. These approaches enable flexible control over pre-trained diffusion models and can generalize to novel control modalities without the cost of additional data collection or retraining. As a **training-free conditional T2I method** conditioned on **condition images**, our approach extends this line of work by improving both control fidelity and generation quality across diverse visual conditions.

3. Revisiting Sampling Schedules of Condition Features

Background. Given a text prompt $\mathcal{P}$ and a condition image $\mathbf{I}^{\text{struct}}$ of arbitrary modality, our goal is to generate an output image $\mathbf{I}$ that semantically aligns with the prompt $\mathcal{P}$ while preserving the structure of $\mathbf{I}^{\text{struct}}$. To align the structure of the generated image with that of the condition $\mathbf{I}^{\text{struct}}$, recent training-free approaches such as Ctrl-X [47] leverage the diffusion features of a noisy latent $\mathbf{x}_t^{\text{struct}}$ of the condition image. Specifically, they obtain a clean latent of the $\mathbf{x}_0^{\text{struct}}$ by encoding $\mathbf{I}^{\text{struct}}$ using a Variational Auto-Encoder, and then get its noisy version $\mathbf{x}_t^{\text{struct}}$ through DDIM inversion [72] or the diffusion forward process. Intermediate features are subsequently extracted from designated layers of the model backbone, and condition features are injected into those of $\mathbf{I}$ at each timestep. We denote these condition features as $\mathbf{f}_{l,t}^{\text{struct}}$, where l refers to the layer index and t denotes the timestep.

Limitations of Existing Methods. While enabling zero-shot spatial control with diverse condition modalities, these methods often suffer from structural misalignment and condition leakage. For instance, Ctrl-X [47] fails to preserve the structure of the panda (Fig. 1). Empirically, we observe that these failures are further exacerbated when the condition image deviates substantially from natural RGB images, as in the case of pose or depth maps shown in Fig. 5. This suggests that a key challenge lies in the domain gap between the condition and natural image distributions in the feature space of pretrained diffusion models. We hypothesize that the injected features $\mathbf{f}_{l,t}^{\text{struct}}$ fall outside the distribution of natural image features, thereby reducing their effectiveness in preserving the structure of the condition image $\mathbf{I}^{\text{struct}}$ during generation.

Empirical Analysis. To validate this hypothesis, we quantitatively analyze features from 100 pairs of condition images across five common modalities (see Sec. C). As shown by the orange curve in Fig. 2, self-similarity distance decreases as noise is reduced, reflecting a progressive gain of fine-grained spatial cues. However, this improved structural fidelity comes at the cost of reduced domain alignment: the green curve in Fig. 2 shows that the KL divergence increases at lower timesteps, indicating a widening domain gap between natural and condition features.

We further conduct principal component analysis and visualize the diffusion features in Fig. 3. There exists a visible discrepancy between the features of the condition image and its natural counterpart, which is more pronounced at smaller timesteps. Another notable pattern is that the primary structural information intended to be preserved emerges in the middle stage, while modality-specific details become more prominent in the late stage. These observations highlight the limitations of previous methods: as the sampling schedule progresses, the early features convey only coarse structural cues, whereas late features introduce out-of-distribution details in the output image, leading to structure misalignment and condition leakage.

Our Insight. Motivated by these observations, we generalize the sampling schedule of condition features, decoupling it from the denoising process, and explore the function space of feature injection schedules. In this framework, the structure latent from which the injected feature is extracted lies at

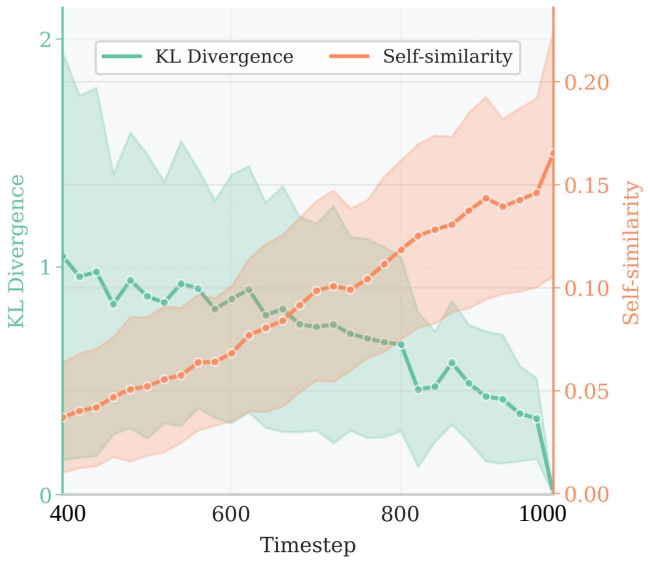


Figure 2. **The evolving curves of KL divergence and L2 distance of self-similarity matrices across diffusion timesteps**. The denoising process starts from timestep 1000 (right).

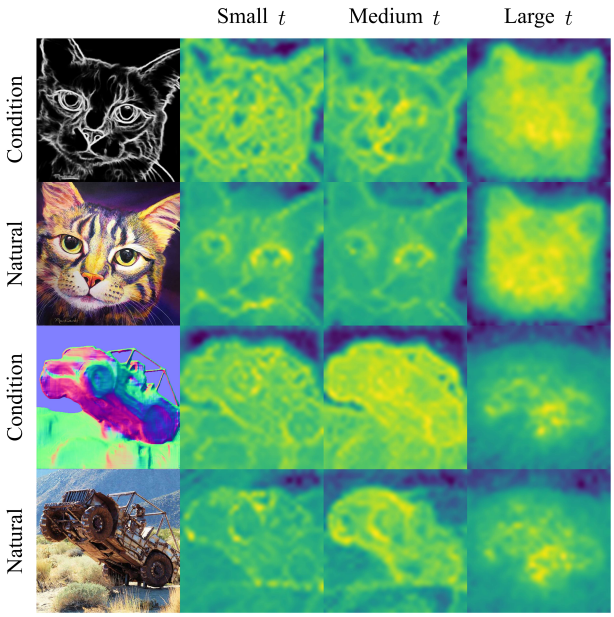


Figure 3. **Visualizing diffusion features extracted from the condition and natural images at different timesteps**. We display the first principal component computed for each time step across all images.

timestep $g(t)$, with $g(t) = t$ covering the case in previous approaches as a special instance. We systematically explore different forms of $g(t)$ and evaluate their impact on structure alignment and visual quality (see Sec. 5.3 for details).

After a principled investigation, we conclude that (i) the optimal condition timestep is neither the output timestep nor the smallest (clearest) one, but lies in the middle stage; and (ii) schedules with their last timestep anchored around medium timesteps consistently deliver the optimal balance between structural fidelity and visual quality, largely independent of their functional form.

4. Method

Building on the insights in Sec. 3, we introduce a training-free controllable T2I generation framework that enables flexible, structure- and appearance-richer control.

Our approach comprises three key components, as illustrated in Fig. 4: (i) **Structure-Rich Injection (SRI)** injects condition features based on a principled sampling schedule, with a better balance of structure preservation and domain alignment (Sec. 4.1); (ii) **Restart Refinement (RR)** schedule performs iterative refinement to suppress visual artifacts and improve overall image fidelity (Sec. 4.2). (iii) **Appearance-Rich Prompting (ARP)** enriches the original prompt $\mathcal{P}$ with detailed descriptions informed by $\mathbf{I}^{\text{struct}}$, facilitating appearance guidance (Sec. 4.3). Together, these modules enable structure- and appearance-aware generation across diverse conditions, all in a zero-shot, training-free manner. We now describe each component in detail.

4.1. Structure-Rich Injection

The structure-rich injection strategy adopts a sampling schedule where the extracted condition features are both semantically compatible and structurally informative. Specifically, we begin by encoding the structure condition image $\mathbf{I}^{\text{struct}}$ using the model backbone to obtain the condition features and attention maps, as illustrated in Fig. 4. Prior work [28, 47, 52, 80] typically extracts condition features $\mathbf{f}^{\text{struct}}_{l,t}$ and attention maps $\mathbf{A}^{\text{struct}}_{l,t}$ at the same timestep t as the denoising step used for generating the output image $\mathbf{I}$ (the bottom branch of the U-Net in Fig. 4), where l denotes the specific U-Net layer to be injected.

According to the empirical analysis in Sec. 3, however, we select features from a separate schedule $g(t)$, where $g(\cdot)$ is a general function of the current timestep t. The extracted features $\mathbf{f}^{\text{struct}}_{l,g(t)}$ and attention maps $\mathbf{A}^{\text{struct}}_{l,g(t)}$ are then used to replace their counterparts $\mathbf{f}_{l,t}$ and $\mathbf{A}_{l,t}$ in the generation backbone at timestep t:

$$\mathbf{f}_{l,t} \leftarrow \mathbf{f}^{\text{struct}}_{l,g(t)} \quad \text{and} \quad \mathbf{A}_{l,t} \leftarrow \mathbf{A}^{\text{struct}}_{l,g(t)}. \tag{1}$$

Note that we only apply our structure-rich injection for timesteps $t \geq \tau$, where τ denotes the structure control schedule.

Single-Step Sampling and Caching. Empirical findings in Sec. 3 demonstrate that medium-timestep schedules consistently yield the optimal balance between structure preservation and visual quality, largely independent of function forms,

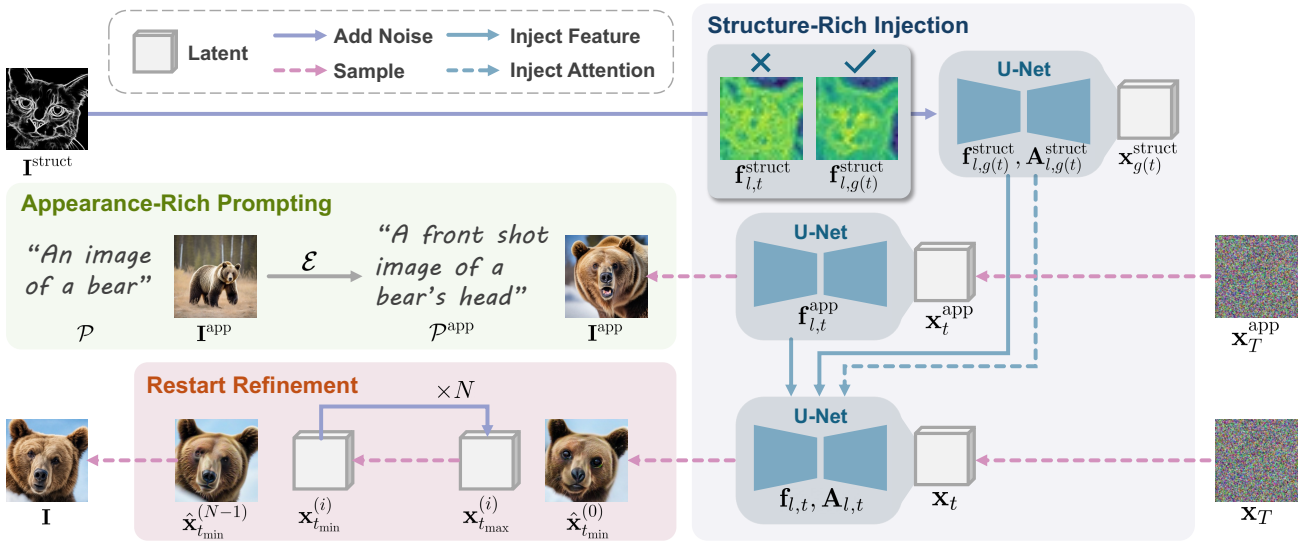


Figure 4. **Method overview.** Our framework consists of three key components. (i) The Structure-Rich Injection (SRI) module injects structure-rich features $\mathbf{f}^{\text{struct}}_{l,g(t)}$ and attentions $\mathbf{A}^{\text{struct}}_{l,g(t)}$ of the condition image into the output image feature space to enable spatial control (Sec. 4.1). (ii) The Restart Refinement (RR) module refines the image $\mathbf{I}$ by iteratively adding noise and denoising the output, leading to more realistic visual details such as the eyes of the bear (Sec. 4.2). (iii) The Appearance-Rich Prompting (ARP) module enriches the prompt $\mathcal{P}$ based on the semantics of the condition image $\mathbf{I}^{\text{struct}}$, producing an appearance-rich prompt $\mathcal{P}^{\text{app}}$ and thereby providing a semantically-aligned appearance image $\mathbf{I}^{\text{app}}$ (Sec. 4.3).

and even a constant-timestep schedule achieves competitive results. Guided by this observation, we adopt a constant schedule $g(t) = 600$ for all subsequent experiments. An additional benefit of a constant schedule is computational efficiency. Since the features of the condition image need to be computed only once, they can then be cached and reused throughout the denoising process. Please refer to Sec. F.1 for detailed results.

4.2. Restart Refinement

Despite a carefully designed injection schedule, structure-rich features can still introduce out-of-distribution artifacts and condition leakage during denoising. To address this, we adopt a restart refinement schedule inspired by diffusion-based sampling methods [98]. After several rounds of structure and appearance control, we inject noise at an intermediate timestep t_{min}, effectively restarting the denoising process by transitioning the latent to t_{max} step. A DDIM backward step [72] is then applied. This forward–backward cycle is repeated N times within $[t_{\text{min}}, t_{\text{max}}]$. In the i^{th} iteration ($i \in \{0, \dots, N-1\}$), the restart proceeds as follows:

$$\begin{aligned} \text{(Forward)}\ \mathbf{x}^{(i+1)}_{t_{\text{max}}} &= \mathbf{x}^{(i)}_{t_{\text{min}}} + \epsilon_{t_{\text{min}} \to t_{\text{max}}}, \\ \text{(Backward)}\ \mathbf{x}^{(i+1)}_{t_{\text{min}}} &= h_{\text{DDIM}}(\mathbf{x}^{(i+1)}_{t_{\text{max}}}, t_{\text{max}} \to t_{\text{min}}), \end{aligned} \tag{2}$$

where the initial $\mathbf{x}^{(0)}_{t_{\text{min}}}$ is obtained by simulating the DDIM step until t_{min}: $\mathbf{x}^{(0)}_{t_{\text{min}}} = h_{\text{DDIM}}(\mathbf{x}_T, T \to t_{\text{min}})$, and the noise $\epsilon_{t_{\text{min}} \to t_{\text{max}}}$ is sampled from the perturbation kernel from t_{min} to t_{max}. Through this schedule, our approach achieves better visual fidelity, as demonstrated in the ablation study in Fig. 8.

4.3. Appearance-Rich Prompting

To enhance the realism of the generated image, prior work [47, 52] generates an auxiliary appearance image $\mathbf{I}^{\text{app}}$ and perform appearance transfer (the middle branch of the U-Net in Fig. 4; see Sec. D for technical details). However, brief and ambiguous user prompts sometimes hinder the establishment of semantic correspondence between the appearance image $\mathbf{I}^{\text{app}}$ and the output image $\mathbf{I}$ in existing appearance transfer methods, leading to artifacts. For example, as illustrated in Fig. 4, the condition image is a frontal view of a cat's head, while the text prompt specifies "a bear", resulting in an appearance image $\mathbf{I}^{\text{app}}$ that depicts a full-body bear.

To tackle this issue, we propose Appearance-Rich Prompting (ARP), a strategy that leverages multimodal large language models [1] to systematically align the semantics of $\mathcal{P}$ with those of the conditions $\mathbf{I}^{\text{struct}}$. Illustrative examples are provided in the ablation study in Fig. 8. Please refer to Sec. D for details of the prompt engineering pipeline $\mathcal{E}$.

5. Experiments

5.1. Setup

Dataset. We base our evaluation on datasets from prior work [47, 52]. However, many of the condition types in prior datasets are underrepresented, resulting in an imbal-

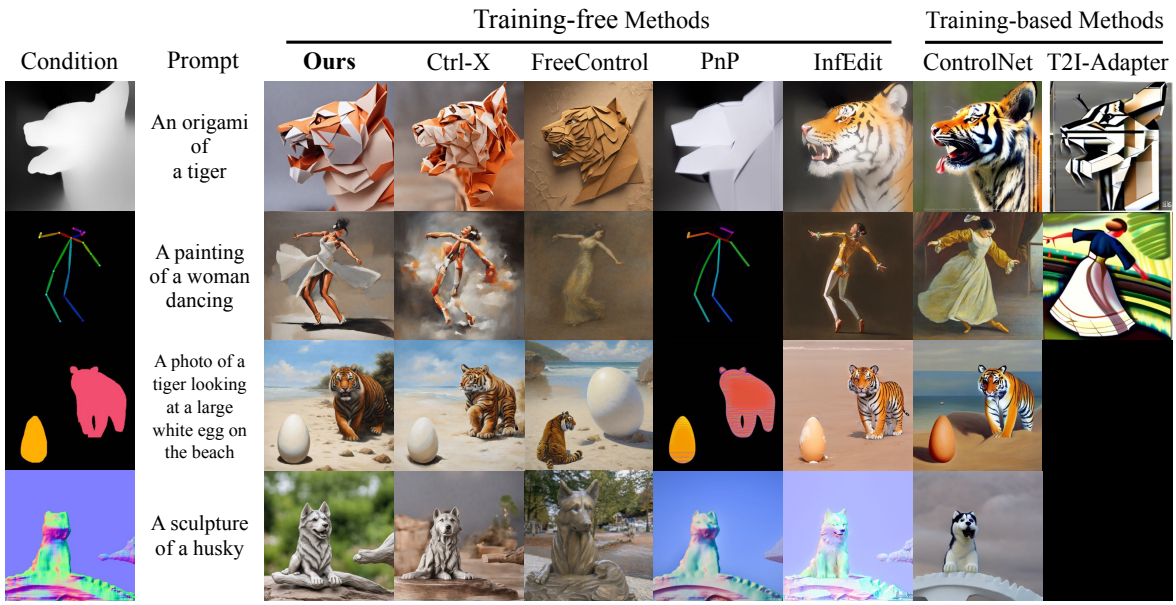


Figure 5. **Qualitative comparison with existing methods**. Our method effectively addresses common failure modes observed in previous methods: structure misalignment, condition leakage, and visual artifacts, generating high-quality images that adhere closely to the prompts with strong spatial alignment.

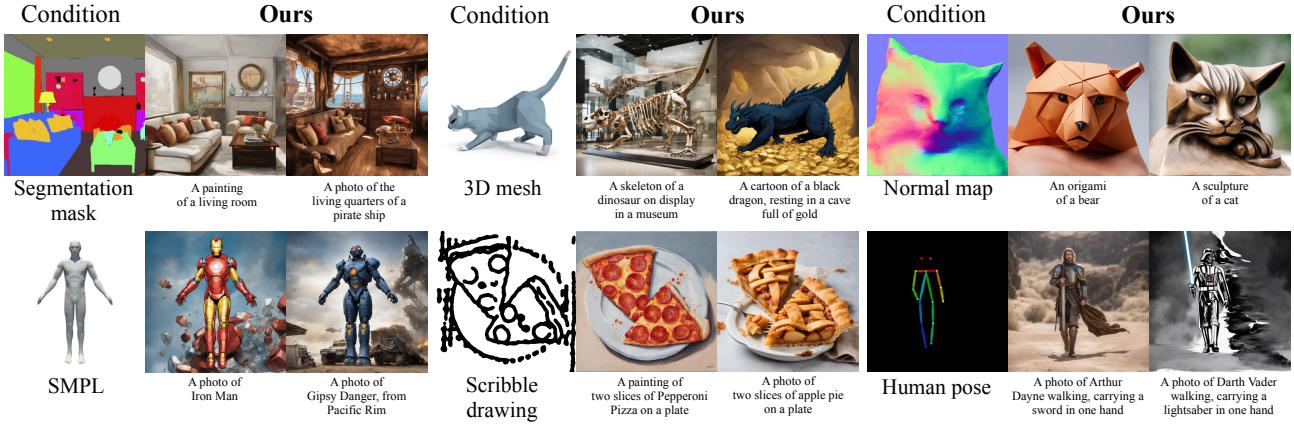


Figure 6. **Qualitative results for more control conditions**. Our method can handle a variety of challenging condition images and prompts, including those infeasible for training-based approaches.

anced distribution. To enable more consistent evaluation, we collect seven commonly used structural conditions: canny edges, depth maps, normal maps, human poses, segmentation masks, HED edges, and scribble drawings, and construct a more balanced dataset with over 20 image-text pairs for each condition type.

Baselines. We evaluate our method against 6 existing training-free baselines: Ctrl-X [47], FreeControl [52], PnP [80], P2P [28], SDEdit [51], and InfEdit [97], as well as 2 training-based baselines: ControlNet [102] and T2I-Adapter [53]. Experiment results on four condition types supported by T2I-Adapter-SDXL (canny, depth, normal, and pose) are provided in Sec. F.3.

Evaluation Metrics. Following prior work [47, 52], we employ three widely-adopted metrics for comparison. (i) CLIP score [62] measures text-image alignment via cosine similarity between the CLIP embeddings of the generated image and text prompt. (ii) DINO self-similarity score (Self-sim) [10, 79] quantifies structural alignment in the DINO-ViT feature space. (iii) Condition LPIPS score (LPIPS) [103] measures perceptual deviation between the generated image and the condition image.

In addition to traditional metrics, we further adopt three reward model metrics that more accurately reflect human preferences. (i) DreamSim [22] evaluates the perceptual similarity of two images by capturing both mid-level similarities

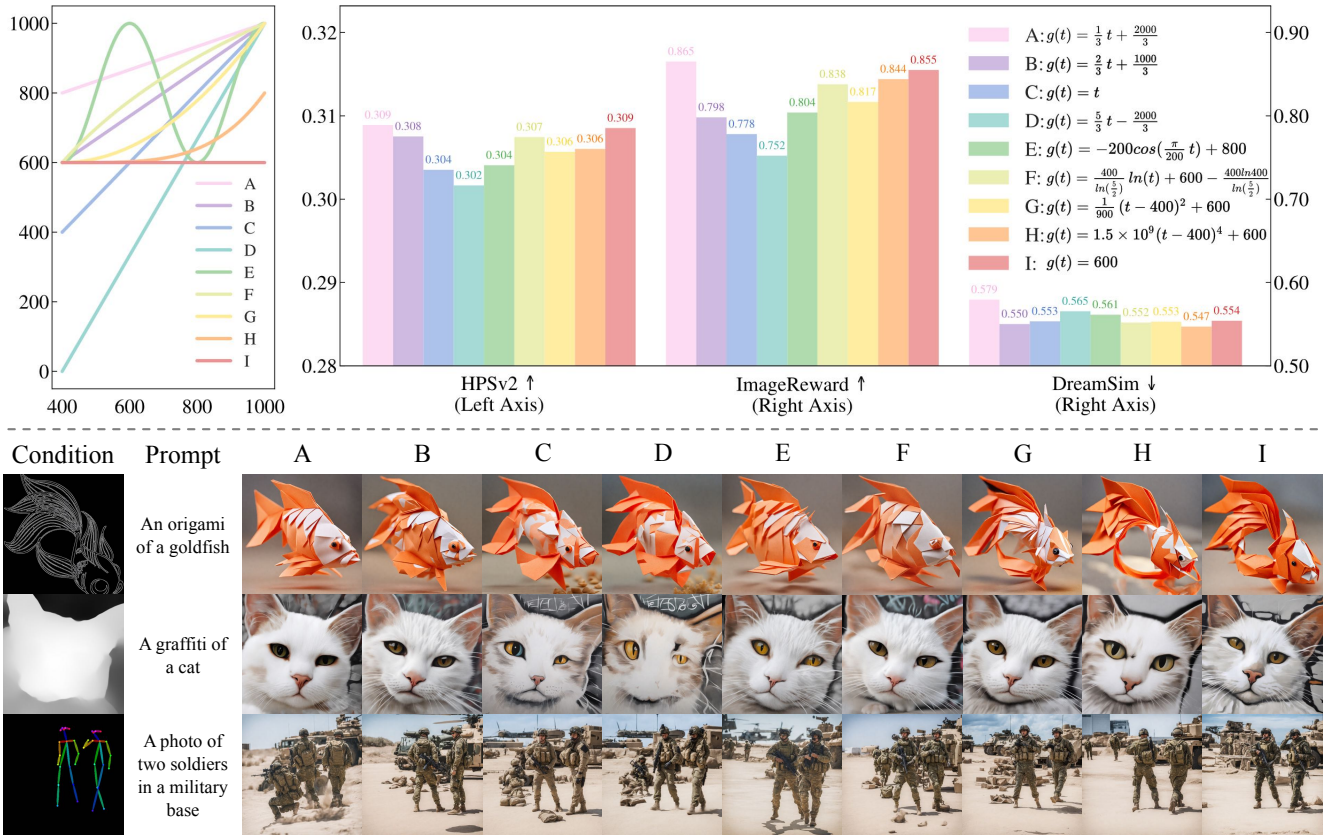


Figure 7. **Ablation of different injection schedules of SRI**. We report quantitative (***Top***) and qualitative (***Bottom***) results for different injection schedules.

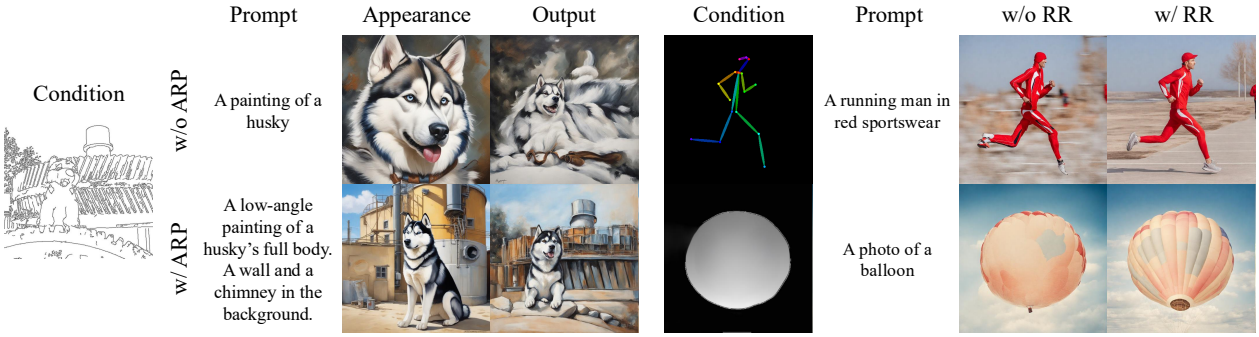


Figure 8. **Ablation of ARP and RR**. (***Left***) ARP mitigates incorrect appearance transfers and reduces artifacts. (***Right***) RR significantly reduces condition leakage and appearance artifacts while maintaining structural alignment. See Fig. 14 and Fig. 15 in the appendix for more cases.

(image layout, object pose, semantic content) and low-level attributes (color, texture). (ii) ImageReward [95] measures image quality and text-image alignment based on a reward model trained with human feedback. (iii) HPSv2 [89] serves as a reliable indicator of overall generation quality aligned with human judgments.

5.2. Comparison with State-of-the-Art (SOTA)

Figs. 1 and 5 present quantitative and qualitative comparisons between our method and existing baselines, respectively. While training-based approaches like ControlNet [102] and T2I-Adapter [53] exhibit lower Self-sim scores, they often fail to adhere to the text prompts (*e.g.*, *origami*, *white egg*, *sculpture* in Fig. 5), leading to impaired text-image alignment. In contrast, our method achieves ro-

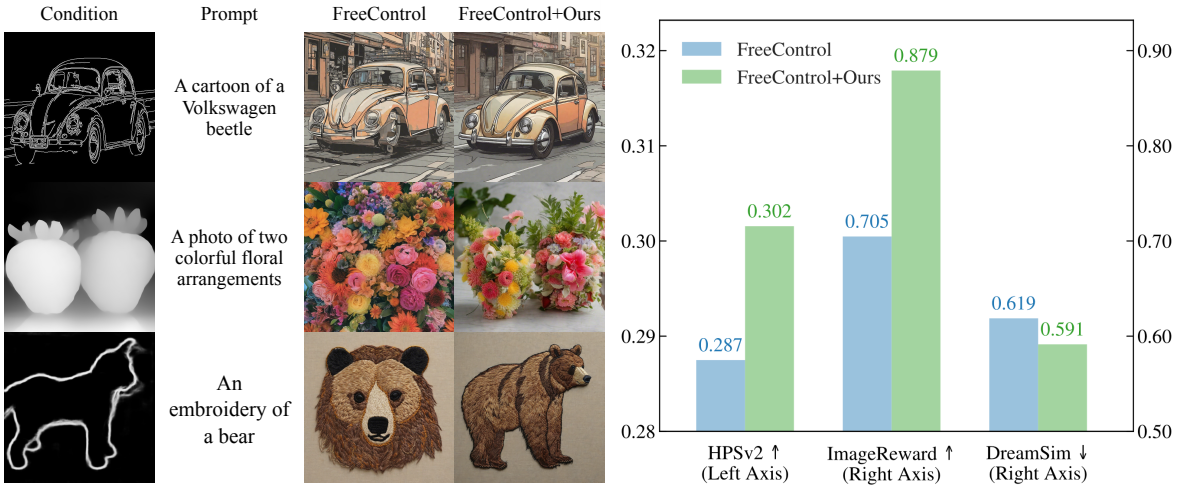


Figure 9. **Integrating our method as a plug-in into FreeControl [52].** Our method consistently improves FreeControl on both quantitative and qualitative evaluations, achieving stronger structure fidelity and perceptual quality.

bust structural alignment while maintaining superior text-image consistency.

On the other hand, training-free baselines exhibit several limitations. SDEdit [51], PnP [80], and P2P [28] are prone to condition leakage, producing outputs that closely resemble the condition image. FreeControl [52] and InfEdit [97] yield unstable results, often generating images with inferior text-image alignment and artifacts (rows 1-4). Ctrl-X [47] performs reliably in many cases but still suffers structural misalignment (row 4), condition leakage (row 2), and artifacts (rows 1 and 3) as shown in Fig. 5. In contrast, our method consistently outperforms these baselines in structural preservation, text-image alignment, and visual quality, excelling in difficult scenarios such as abstract conditions (*e.g.*, pose), multi-object scenes, and challenging prompts (*e.g.*, *origami*). Quantitative evaluations further confirm our advantage. As shown in Fig. 1, our method surpasses training-free baselines across nearly all metrics. Please refer to Figs. 16 and 17 and Tab. 2 in the appendix for additional results.

Similar to prior studies [22, 50, 89, 95], we find that reward models exhibit stronger alignment with human preferences than traditional metrics. Accordingly, in the subsequent experiments, we primarily report results based on three reward-model metrics.

5.3. Ablation Study

Structure-Rich Injection. In this section, we explore different forms of injection schedules $g(t)$ and evaluate their impact on structure alignment and visual fidelity. The results are shown in Fig. 7. Our ablation on linear schedules (Fig. 7 A–D) reveals a clear trade-off: schedules biased toward larger timesteps (A) weaken structural alignment and increase DreamSim scores, whereas those biased toward smaller timesteps (C–D) degrade both visual quality (lower HPSv2 and ImageReward scores) and structural fidelity due to excessive modality-specific cues. In contrast, the medium-timestep schedules (B) strike a favorable balance, yielding stronger structure preservation without sacrificing visual realism.

Beyond linear functions, we further examine a family of schedules (E–I) that share the same final timestep but differ in monotonicity, convexity, and initialization. Interestingly, all of them deliver consistently strong performance, suggesting robustness to functional variations. Empirically, we find that convex functions slightly outperform concave ones, and even a constant-timestep schedule achieves competitive results.

	Dream-Sim ↓	Image-Reward ↑	HPSv2 ↑
w/o ARP	0.558	0.799	0.308
w/o RR	0.544	0.518	0.286
Ours	0.554	0.855	0.309

Table 1. **Quantitative ablation of ARP and RR.**

Appearance-Rich Prompting. Fig. 8 demonstrates that the ARP module effectively adapts the prompt to capture key visual attributes of the condition image. As shown in Tab. 1, removing the ARP module decreases performance across all three metrics, verifying its effectiveness in enhancing structural preservation and visual fidelity.

Restart Refinement. As shown in Fig. 8, the RR schedule mitigates both condition leakage and artifacts, leading to improved generation quality while maintaining strong structural alignment. Tab. 1 suggests that RR improves visual fidelity but partly compromises structural alignment, which is consistent with its intended design: it relaxes overly rigid structural constraints in order to mitigate condition leakage

(see Fig. 1) and improve perceptual quality.

5.4. Improvement over Prior Methods

Our pipeline can serve as a plug-in to enhance other conditional T2I approaches. As an example, we applied our method to FreeControl [52], another recent conditional T2I model. As shown in Fig. 9, our approach consistently improves FreeControl across three evaluation metrics. Qualitative comparisons in Fig. 9 further highlight that FreeControl with our method yields outputs with both stronger structural preservation and higher perceptual quality.

6. Conclusion

We propose a training-free framework for conditional text-to-image (T2I) generation. By leveraging the features of pre-trained diffusion models in a principled manner, our method balances structural fidelity and appearance quality while automatically enhancing image realism and prompt relevance. Our investigation facilitates the understanding of the feature space of T2I diffusion models and achieves a strong, general, and robust solution for injection-based pipelines.

References

[1] Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023. 5, 16, 17

[2] Yuval Alaluf, Daniel Garibi, Or Patashnik, Hadar Averbuch-Elor, and Daniel Cohen-Or. Cross-image attention for zero-shot appearance transfer. In *ACM SIGGRAPH Conference on Computer Graphics and Interactive Techniques (SIGGRAPH)*, 2024. 3, 14

[3] Omri Avrahami, Kfir Aberman, Ohad Fried, Daniel Cohen-Or, and Dani Lischinski. Break-a-scene: Extracting multiple concepts from a single image. In *ACM SIGGRAPH Asia Conference on Computer Graphics and Interactive Techniques (SIGGRAPH Asia)*, 2023. 3

[4] Omri Avrahami, Thomas Hayes, Oran Gafni, Sonal Gupta, Yaniv Taigman, Devi Parikh, Dani Lischinski, Ohad Fried, and Xi Yin. Spatext: Spatio-textual representation for controllable image generation. In *Proceedings of Conference on Computer Vision and Pattern Recognition (CVPR)*, 2023. 3

[5] Omri Avrahami, Or Patashnik, Ohad Fried, Egor Nemchinov, Kfir Aberman, Dani Lischinski, and Daniel Cohen-Or. Stable flow: Vital layers for training-free image editing. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 7877–7888, 2025. 3

[6] Arpit Bansal, Hong-Min Chu, Avi Schwarzschild, Soumyadip Sengupta, Micah Goldblum, Jonas Geiping, and Tom Goldstein. Universal guidance for diffusion models. In *Proceedings of International Conference on Learning Representations (ICLR)*, 2023. 2, 3, 14

[7] Tim Brooks, Aleksander Holynski, and Alexei A Efros. Instructpix2pix: Learning to follow image editing instructions. In *Proceedings of Conference on Computer Vision and Pattern Recognition (CVPR)*, 2023. 3

[8] Mingdeng Cao, Xintao Wang, Zhongang Qi, Ying Shan, Xiaohu Qie, and Yinqiang Zheng. Masactrl: Tuning-free mutual self-attention control for consistent image synthesis and editing. In *Proceedings of International Conference on Computer Vision (ICCV)*, 2023. 3

[9] Z. Cao, G. Hidalgo Martinez, T. Simon, S. Wei, and Y. A. Sheikh. Openpose: Realtime multi-person 2d pose estimation using part affinity fields. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2019. 3

[10] Mathilde Caron, Hugo Touvron, Ishan Misra, Hervé Jégou, Julien Mairal, Piotr Bojanowski, and Armand Joulin. Emerging properties in self-supervised vision transformers. In *Proceedings of International Conference on Computer Vision (ICCV)*, 2021. 6, 15

[11] Minghao Chen, Iro Laina, and Andrea Vedaldi. Training-free layout control with cross-attention guidance. In *Proceedings of Winter Conference on Applications of Computer Vision (WACV)*, 2024. 3

[12] Xi Chen, Zhifei Zhang, He Zhang, Yuqian Zhou, Soo Ye Kim, Qing Liu, Yijun Li, Jianming Zhang, Nanxuan Zhao, Yilin Wang, Hui Ding, Zhe Lin, and Hengshuang Zhao. Unireal: Universal image generation and editing via learning real-world dynamics. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 12501–12511, 2025. 3

[13] Jiwoo Chung, Sangeek Hyun, and Jae-Pil Heo. Style injection in diffusion: A training-free approach for adapting large-scale diffusion models for style transfer. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 8795–8805, 2024. 3

[14] Guillaume Couairon, Jakob Verbeek, Holger Schwenk, and Matthieu Cord. Diffedit: Diffusion-based semantic image editing with mask guidance. In *Proceedings of International Conference on Learning Representations (ICLR)*, 2023. 3

[15] Yusuf Dalva, Kavana Venkatesh, and Pinar Yanardag. Fluxspace: Disentangled semantic editing in rectified flow transformers, 2024. 3

[16] Ganggui Ding, Canyu Zhao, Wen Wang, Zhen Yang, Zide Liu, Hao Chen, and Chunhua Shen. Freecustom: Tuning-free customized image generation for multi-concept composition. In *Proceedings of Conference on Computer Vision and Pattern Recognition (CVPR)*, 2024. 3

[17] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, and Neil Houlsby. An image is worth 16x16 words: Transformers for image recognition at scale. In *Proceedings of International Conference on Learning Representations (ICLR)*, 2021. 15

[18] Dave Epstein, Allan Jabri, Ben Poole, Alexei A. Efros, and Aleksander Holynski. Diffusion self-guidance for controllable image generation. In *Proceedings of Advances in Neural Information Processing Systems (NeurIPS)*, 2023. 2, 3, 14

[19] Patrick Esser, Sumith Kulal, Andreas Blattmann, Rahim Entezari, Jonas Müller, Harry Saini, Yam Levi, Dominik Lorenz, Axel Sauer, Frederic Boesel, Dustin Podell, Tim Dockhorn, Zion English, and Robin Rombach. Scaling rectified flow transformers for high-resolution image synthesis. In *Proceedings of International Conference on Machine Learning (ICML)*, 2024. 2

[20] Haoran Feng, Zehuan Huang, Lin Li, Hairong Lv, and Lu Sheng. Personalize anything for free with diffusion transformer. *arXiv preprint arXiv:2503.12590*, 2025. 3

[21] Kunyu Feng, Yue Ma, Bingyuan Wang, Chenyang Qi, Haozhe Chen, Qifeng Chen, and Zeyu Wang. Dit4edit: Diffusion transformer for image editing. *Proceedings of the AAAI Conference on Artificial Intelligence*, 39(3):2969–2977, 2025. 3

[22] Stephanie Fu, Netanel Tamir, Shobhita Sundaram, Lucy Chai, Richard Zhang, Tali Dekel, and Phillip Isola. Dreamsim: Learning new dimensions of human visual similarity using synthetic data. In *Proceedings of Advances in Neural Information Processing Systems (NeurIPS)*, 2023. 6, 8, 18

[23] Rinon Gal, Yuval Alaluf, Yuval Atzmon, Or Patashnik, Amit H Bermano, Gal Chechik, and Daniel Cohen-Or. An image is worth one word: Personalizing text-to-image generation using textual inversion. In *Proceedings of International Conference on Learning Representations (ICLR)*, 2023. 3

[24] Zigang Geng, Binxin Yang, Tiankai Hang, Chen Li, Shuyang Gu, Ting Zhang, Jianmin Bao, Zheng Zhang, Houqiang Li, Han Hu, Dong Chen, and Baining Guo. Instructdiffusion: A generalist modeling interface for vision tasks. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 12709–12720, 2024. 3

[25] Sooyeon Go, Kyungmook Choi, Minjung Shin, and Youngjung Uh. Eye-for-an-eye: Appearance transfer with semantic correspondence in diffusion models, 2024. 3

[26] Vidit Goel, Elia Peruzzo, Yifan Jiang, Dejia Xu, Xingqian Xu, Nicu Sebe, Trevor Darrell, Zhangyang Wang, and Humphrey Shi. Pair diffusion: A comprehensive multimodal object-level image editor. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 8609–8618, 2024. 3

[27] Zhen Han, Zeyinzi Jiang, Yulin Pan, Jingfeng Zhang, Chaojie Mao, Chenwei Xie, Yu Liu, and Jingren Zhou. Ace: All-round creator and editor following instructions via diffusion transformer, 2024. 3

[28] Amir Hertz, Ron Mokady, Jay Tenenbaum, Kfir Aberman, Yael Pritch, and Daniel Cohen-Or. Prompt-to-prompt image editing with cross attention control. In *Proceedings of International Conference on Learning Representations (ICLR)*, 2023. 2, 3, 4, 6, 8, 14, 18

[29] Jonathan Ho and Tim Salimans. Classifier-free diffusion guidance. In *NeurIPS 2021 Workshop on Deep Generative Models and Downstream Applications*, 2021. 2, 14

[30] Jonathan Ho, Ajay Jain, and Pieter Abbeel. Denoising diffusion probabilistic models. In *Proceedings of Advances in Neural Information Processing Systems (NeurIPS)*, 2020. 14

[31] Jonathan Ho, Chitwan Saharia, William Chan, David J Fleet, Mohammad Norouzi, and Tim Salimans. Cascaded diffusion models for high fidelity image generation. *Journal of Machine Learning Research (JMLR)*, 2022. 2

[32] Taihang Hu, Linxuan Li, Kai Wang, Yaxing Wang, Jian Yang, and Ming-Ming Cheng. Anchor token matching: Implicit structure locking for training-free ar image editing. In *Proceedings of International Conference on Computer Vision (ICCV)*, 2025. 3

[33] Bo Huang, Wenlun Xu, Qizhuo Han, Haodong Jing, and Ying Li. Attenst: A training-free attention-driven style transfer framework with pre-trained diffusion models, 2025. 3

[34] Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, and Alexei A Efros. Image-to-image translation with conditional adversarial networks. In *Proceedings of Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017. 3

[35] Yueru Jia, Aosong Cheng, Yuhui Yuan, Chuke Wang, Ji Li, Huizhu Jia, and Shanghang Zhang. Designedit: Unify spatial-aware image editing via training-free inpainting with a multi-layered latent diffusion framework. *Proceedings of the AAAI Conference on Artificial Intelligence*, 39(4): 3958–3966, 2025. 3

[36] Tero Karras, Miika Aittala, Timo Aila, and Samuli Laine. Elucidating the design space of diffusion-based generative models. In *Proceedings of Advances in Neural Information Processing Systems (NeurIPS)*, 2022. 2

[37] Gwanghyun Kim, Taesung Kwon, and Jong Chul Ye. Diffusionclip: Text-guided diffusion models for robust image manipulation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2426–2435, 2022. 3

[38] Yunji Kim, Jiyoung Lee, Jin-Hwa Kim, Jung-Woo Ha, and Jun-Yan Zhu. Dense text-to-image generation with attention modulation. In *Proceedings of International Conference on Computer Vision (ICCV)*, pages 7701–7711, 2023. 14

[39] Yunji Kim, Jiyoung Lee, Jin-Hwa Kim, Jung-Woo Ha, and Jun-Yan Zhu. Dense text-to-image generation with attention modulation. In *Proceedings of Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 7701–7711, 2023. 3

[40] Gihyun Kwon and Jong Chul Ye. Diffusion-based image translation using disentangled style and content representation. In *Proceedings of International Conference on Learning Representations (ICLR)*, 2023. 3

[41] Black Forest Labs. Flux. `https://github.com/black-forest-labs/flux`, 2024. 2

[42] Duong H. Le, Tuan Pham, Sangho Lee, Christopher Clark, Aniruddha Kembhavi, Stephan Mandt, Ranjay Krishna, and Jiasen Lu. One diffusion to generate them all. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2671–2682, 2025. 3

[43] Bonan Li, Yinhan Hu, Songhua Liu, and Xinchao Wang. Control and realism: Best of both worlds in layout-to-image without training. In *Proceedings of International Conference on Machine Learning (ICML)*, 2025. 3

[44] Dongxu Li, Junnan Li, and Steven Hoi. Blip-diffusion: Pre-trained subject representation for controllable text-to-image generation and editing. In *Proceedings of Advances in Neural Information Processing Systems (NeurIPS)*, 2023. 3

[45] Ming Li, Taojiannan Yang, Huafeng Kuang, Jie Wu, Zhaoning Wang, Xuefeng Xiao, and Chen Chen. Controlnet++: Improving conditional controls with efficient consistency feedback. In *Proceedings of European Conference on Computer Vision (ECCV)*, 2024. 3

[46] Yuheng Li, Haotian Liu, Qingyang Wu, Fangzhou Mu, Jianwei Yang, Jianfeng Gao, Chunyuan Li, and Yong Jae Lee. Gligen: Open-set grounded text-to-image generation. In *Proceedings of Conference on Computer Vision and Pattern Recognition (CVPR)*, 2023. 3

[47] Kuan Heng Lin, Sicheng Mo, Ben Klingher, Fangzhou Mu, and Bolei Zhou. Ctrl-x: Controlling structure and appearance for text-to-image generation without guidance. In *Proceedings of Advances in Neural Information Processing Systems (NeurIPS)*, 2024. 1, 2, 3, 4, 5, 6, 8, 16, 17, 18

[48] Xingchao Liu, Chengyue Gong, and Qiang Liu. Flow straight and fast: Learning to generate and transfer data with rectified flow, 2023. 2

[49] Cheng Lu, Yuhao Zhou, Fan Bao, Jianfei Chen, Chongxuan LI, and Jun Zhu. Dpm-solver: A fast ode solver for diffusion probabilistic model sampling in around 10 steps. In *Proceedings of Advances in Neural Information Processing Systems (NeurIPS)*, 2022. 2

[50] Yuhang Ma, Yunhao Shui, Xiaoshi Wu, Keqiang Sun, and Hongsheng Li. Hpsv3: Towards wide-spectrum human preference score. In *Proceedings of International Conference on Computer Vision (ICCV)*, 2025. 8

[51] Chenlin Meng, Yutong He, Yang Song, Jiaming Song, Jiajun Wu, Jun-Yan Zhu, and Stefano Ermon. Sdedit: Guided image synthesis and editing with stochastic differential equations. In *Proceedings of International Conference on Learning Representations (ICLR)*, 2022. 3, 6, 8, 18

[52] Sicheng Mo, Fangzhou Mu, Kuan Heng Lin, Yanli Liu, Bochen Guan, Yin Li, and Bolei Zhou. Freecontrol: Training-free spatial control of any text-to-image diffusion model with any condition. In *Proceedings of Conference on Computer Vision and Pattern Recognition (CVPR)*, 2024. 2, 3, 4, 5, 6, 8, 9, 14, 17, 18

[53] Chong Mou, Xintao Wang, Liangbin Xie, Jian Zhang, Zhongang Qi, Ying Shan, and Xiaohu Qie. T2i-adapter: Learning adapters to dig out more controllable ability for text-to-image diffusion models. In *Proceedings of AAAI Conference on Artificial Intelligence (AAAI)*, 2024. 3, 6, 7, 18

[54] Alex Nichol, Prafulla Dhariwal, Aditya Ramesh, Pranav Shyam, Pamela Mishkin, Bob McGrew, Ilya Sutskever, and Mark Chen. Glide: Towards photorealistic image generation and editing with text-guided diffusion models. In *Proceedings of International Conference on Machine Learning (ICML)*, 2022. 2

[55] Ziheng Ouyang, Zhen Li, and Qibin Hou. K-lora: Unlocking training-free fusion of any subject and style loras. In *Proceedings of Conference on Computer Vision and Pattern Recognition (CVPR)*, 2025. 3

[56] Taesung Park, Ming-Yu Liu, Ting-Chun Wang, and Jun-Yan Zhu. Semantic image synthesis with spatially-adaptive normalization. In *Proceedings of Conference on Computer Vision and Pattern Recognition (CVPR)*, 2019. 3

[57] Gaurav Parmar, Krishna Kumar Singh, Richard Zhang, Yijun Li, Jingwan Lu, and Jun-Yan Zhu. Zero-shot image-to-image translation. In *ACM SIGGRAPH Conference on Computer Graphics and Interactive Techniques (SIGGRAPH)*, 2023. 3

[58] William Peebles and Saining Xie. Scalable diffusion models with transformers. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 4195–4205, 2023. 2

[59] Kien T. Pham, Jingye Chen, and Qifeng Chen. Tale: Training-free cross-domain image composition via adaptive latent manipulation and energy-guided optimization. In *Proceedings of the 32nd ACM International Conference on Multimedia*, page 3160–3169, New York, NY, USA, 2024. Association for Computing Machinery. 3

[60] Ryan Po, Guandao Yang, Kfir Aberman, and Gordon Wetzstein. Orthogonal adaptation for modular customization of diffusion models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 7964–7973, 2024. 3

[61] Dustin Podell, Zion English, Kyle Lacey, Andreas Blattmann, Tim Dockhorn, Jonas Müller, Joe Penna, and Robin Rombach. SDXL: Improving latent diffusion models for high-resolution image synthesis. In *Proceedings of International Conference on Learning Representations (ICLR)*, 2024. 2, 14, 17

[62] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In *Proceedings of International Conference on Machine Learning (ICML)*, 2021. 6

[63] Aditya Ramesh, Prafulla Dhariwal, Alex Nichol, Casey Chu, and Mark Chen. Hierarchical text-conditional image generation with clip latents. *arXiv preprint arXiv:2204.06125*, 1 (2):3, 2022. 2

[64] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models. In *Proceedings of Conference on Computer Vision and Pattern Recognition (CVPR)*, 2022. 2, 14

[65] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015*, pages 234–241, Cham, 2015. Springer International Publishing. 2

[66] L Rout, Y Chen, N Ruiz, A Kumar, C Caramanis, S Shakkottai, and W Chu. Rb-modulation: Training-free stylization using reference-based modulation. In *Proceedings of International Conference on Learning Representations (ICLR)*, 2025. 3

[67] Nataniel Ruiz, Yuanzhen Li, Varun Jampani, Yael Pritch, Michael Rubinstein, and Kfir Aberman. Dreambooth: Fine tuning text-to-image diffusion models for subject-driven generation. In *Proceedings of Conference on Computer Vision and Pattern Recognition (CVPR)*, 2023. 3

[68] Nataniel Ruiz, Yuanzhen Li, Varun Jampani, Wei Wei, Tingbo Hou, Yael Pritch, Neal Wadhwa, Michael Rubinstein,

and Kfir Aberman. Hyperdreambooth: Hypernetworks for fast personalization of text-to-image models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 6527–6536, 2024. 3

[69] Chitwan Saharia, William Chan, Huiwen Chang, Chris Lee, Jonathan Ho, Tim Salimans, David Fleet, and Mohammad Norouzi. Palette: Image-to-image diffusion models. In *ACM SIGGRAPH Conference on Computer Graphics and Interactive Techniques (SIGGRAPH)*, 2022. 3

[70] Chitwan Saharia, William Chan, Saurabh Saxena, Lala Li, Jay Whang, Emily L Denton, Kamyar Ghasemipour, Raphael Gontijo Lopes, Burcu Karagol Ayan, Tim Salimans, et al. Photorealistic text-to-image diffusion models with deep language understanding. In *Proceedings of Advances in Neural Information Processing Systems (NeurIPS)*, 2022. 2

[71] Shelly Sheynin, Adam Polyak, Uriel Singer, Yuval Kirstain, Amit Zohar, Oron Ashual, Devi Parikh, and Yaniv Taigman. Emu edit: Precise image editing via recognition and generation tasks. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 8871–8879, 2024. 3

[72] Jiaming Song, Chenlin Meng, and Stefano Ermon. Denoising diffusion implicit models. In *Proceedings of International Conference on Learning Representations (ICLR)*, 2021. 2, 3, 5, 17

[73] Yang Song, Prafulla Dhariwal, Mark Chen, and Ilya Sutskever. Consistency models. In *Proceedings of International Conference on Machine Learning (ICML)*, 2023. 2

[74] Xuan Su, Jiaming Song, Chenlin Meng, and Stefano Ermon. Dual diffusion implicit bridges for image-to-image translation. In *Proceedings of International Conference on Learning Representations (ICLR)*, 2023. 3

[75] Zhenxiong Tan, Songhua Liu, Xingyi Yang, Qiaochu Xue, and Xinchao Wang. Ominicontrol: Minimal and universal control for diffusion transformer. In *Proceedings of International Conference on Computer Vision (ICCV)*, 2025. 3

[76] Zhenxiong Tan, Qiaochu Xue, Xingyi Yang, Songhua Liu, and Xinchao Wang. Ominicontrol2: Efficient conditioning for diffusion transformers. *arXiv preprint arXiv:2503.08280*, 2025. 3

[77] Yoad Tewel, Rinon Gal, Dvir Samuel, Yuval Atzmon, Lior Wolf, and Gal Chechik. Add-it: Training-free object insertion in images with pretrained diffusion models. In *Proceedings of International Conference on Learning Representations (ICLR)*, 2025. 3

[78] Vadim Titov, Madina Khalmatova, Alexandra Ivanova, Dmitry Vetrov, and Aibek Alanov. Guide-and-rescale: Self-guidance mechanism for effective tuning-free real image editing. In *Proceedings of European Conference on Computer Vision (ECCV)*, 2024. 3

[79] Narek Tumanyan, Omer Bar-Tal, Shai Bagon, and Tali Dekel. Splicing ViT features for semantic appearance transfer. In *Proceedings of Conference on Computer Vision and Pattern Recognition (CVPR)*, 2022. 3, 6, 15, 18

[80] Narek Tumanyan, Michal Geyer, Shai Bagon, and Tali Dekel. Plug-and-play diffusion features for text-driven image-to-image translation. In *Proceedings of Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 1921–1930, 2023. 2, 3, 4, 6, 8, 14, 18

[81] Patrick von Platen, Suraj Patil, Anton Lozhkov, Pedro Cuenca, Nathan Lambert, Kashif Rasul, Mishig Davaadorj, Dhruv Nair, Sayak Paul, William Berman, Yiyi Xu, Steven Liu, and Thomas Wolf. Diffusers: State-of-the-art diffusion models. https://github.com/huggingface/diffusers, 2022. 17

[82] Jiangshan Wang, Junfu Pu, Zhongang Qi, Jiayi Guo, Yue Ma, Nisha Huang, Yuxin Chen, Xiu Li, and Ying Shan. Taming rectified flow for inversion and editing. In *Proceedings of International Conference on Machine Learning (ICML)*, 2025. 3

[83] Su Wang, Chitwan Saharia, Ceslee Montgomery, Jordi Pont-Tuset, Shai Noy, Stefano Pellegrini, Yasumasa Onoe, Sarah Laszlo, David J. Fleet, Radu Soricut, Jason Baldridge, Mohammad Norouzi, Peter Anderson, and William Chan. Imagen editor and editbench: Advancing and evaluating text-guided image inpainting. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 18359–18369, 2023. 3

[84] Xudong Wang, Trevor Darrell, Sai Saketh Rambhatla, Rohit Girdhar, and Ishan Misra. Instancediffusion: Instance-level control for image generation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 6232–6242, 2024. 3

[85] Zhen Wang, Yilei JIANG, Dong Zheng, Jun Xiao, and Long Chen. Event-customized image generation. In *Proceedings of International Conference on Machine Learning (ICML)*, 2025. 3

[86] Zixuan Wang, Duo Peng, Feng Chen, Yuwei Yang, and Yinjie Lei. Training-free dense-aligned diffusion guidance for modular conditional image synthesis. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 13135–13145, 2025. 3

[87] Tianyi Wei, Yifan Zhou, Dongdong Chen, and Xingang Pan. Freeflux: Understanding and exploiting layer-specific roles in rope-based mmdit for versatile image editing. *Proceedings of International Conference on Computer Vision (ICCV)*, 2025. 3

[88] Chenyuan Wu, Pengfei Zheng, Ruiran Yan, Shitao Xiao, Xin Luo, Yueze Wang, Wanli Li, Xiyan Jiang, Yexin Liu, Junjie Zhou, Ze Liu, Ziyi Xia, Chaofan Li, Haoge Deng, Jiahao Wang, Kun Luo, Bo Zhang, Defu Lian, Xinlong Wang, Zhongyuan Wang, Tiejun Huang, and Zheng Liu. Omnigen2: Exploration to advanced multimodal generation, 2025. 3

[89] Xiaoshi Wu, Yiming Hao, Keqiang Sun, Yixiong Chen, Feng Zhu, Rui Zhao, and Hongsheng Li. Human preference score v2: A solid benchmark for evaluating human preferences of text-to-image synthesis. *arXiv preprint arXiv:2306.09341*, 2023. 7, 8, 18

[90] Bin Xia, Yuechen Zhang, Jingyao Li, Chengyao Wang, Yitong Wang, Xinglong Wu, Bei Yu, and Jiaya Jia. Dreamomni: Unified image generation and editing. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 28533–28543, 2025. 3

[91] Jiayu Xiao, Henglei Lv, Liang Li, Shuhui Wang, and Qingming Huang. R&b: Region and boundary aware zero-shot grounded text-to-image generation. In *Proceedings of International Conference on Learning Representations (ICLR)*, 2024. 3

[92] Shitao Xiao, Yueze Wang, Junjie Zhou, Huaying Yuan, Xingrun Xing, Ruiran Yan, Chaofan Li, Shuting Wang, Tiejun Huang, and Zheng Liu. Omnigen: Unified image generation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 13294–13304, 2025. 3

[93] Jinheng Xie, Yuexiang Li, Yawen Huang, Haozhe Liu, Wentian Zhang, Yefeng Zheng, and Mike Zheng Shou. Boxdiff: Text-to-image synthesis with training-free box-constrained diffusion. In *Proceedings of International Conference on Computer Vision (ICCV)*, 2023. 3

[94] Ming Xie, Chenjie Cao, Yunuo Cai, Xiangyang Xue, Yu-Gang Jiang, and Yanwei Fu. Anyrefill: A unified, data-efficient framework for left-prompt-guided vision tasks, 2025. 3

[95] Jiazheng Xu, Xiao Liu, Yuchen Wu, Yuxuan Tong, Qinkai Li, Ming Ding, Jie Tang, and Yuxiao Dong. Imagereward: Learning and evaluating human preferences for text-to-image generation. In *Proceedings of Advances in Neural Information Processing Systems (NeurIPS)*, 2023. 7, 8, 18

[96] Pengcheng Xu, Boyuan Jiang, Xiaobin Hu, Donghao Luo, Qingdong He, Jiangning Zhang, Chengjie Wang, Yunsheng Wu, Charles Ling, and Boyu Wang. Unveil inversion and invariance in flow transformer for versatile image editing. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 28479–28489, 2025. 3

[97] Sihan Xu, Yidong Huang, Jiayi Pan, Ziqiao Ma, and Joyce Chai. Inversion-free image editing with natural language. In *Proceedings of Conference on Computer Vision and Pattern Recognition (CVPR)*, 2024. 3, 6, 8, 14, 18

[98] Yilun Xu, Mingyang Deng, Xiang Cheng, Yonglong Tian, Ziming Liu, and Tommi Jaakkola. Restart sampling for improving generative processes. In *Proceedings of Advances in Neural Information Processing Systems (NeurIPS)*, 2023. 2, 5

[99] Yu Xu, Fan Tang, Juan Cao, Yuxin Zhang, Xiaoyu Kong, Jintao Li, Oliver Deussen, and Tong-Yee Lee. Headrouter: A training-free image editing framework for mm-dits by adaptively routing attention heads, 2024. 3

[100] Zhengyuan Yang, Jianfeng Wang, Zhe Gan, Linjie Li, Kevin Lin, Chenfei Wu, Nan Duan, Zicheng Liu, Ce Liu, Michael Zeng, and Lijuan Wang. Reco: Region-controlled text-to-image generation. In *Proceedings of Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 14246–14255, 2023. 3

[101] Hu Ye, Jun Zhang, Sibo Liu, Xiao Han, and Wei Yang. Ip-adapter: Text compatible image prompt adapter for text-to-image diffusion models. *arXiv preprint arxiv:2308.06721*, 2023. 3

[102] Lvmin Zhang, Anyi Rao, and Maneesh Agrawala. Adding conditional control to text-to-image diffusion models. In *Proceedings of International Conference on Computer Vision (ICCV)*, 2023. 2, 3, 6, 7, 14, 18

[103] Richard Zhang, Phillip Isola, Alexei A Efros, Eli Shechtman, and Oliver Wang. The unreasonable effectiveness of deep features as a perceptual metric. In *Proceedings of Conference on Computer Vision and Pattern Recognition (CVPR)*, 2018. 6

[104] Yuxuan Zhang, Yiren Song, Jiaming Liu, Rui Wang, Jinpeng Yu, Hao Tang, Huaxia Li, Xu Tang, Yao Hu, Han Pan, and Zhongliang Jing. Ssr-encoder: Encoding selective subject representation for subject-driven generation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 8069–8078, 2024. 3

[105] Yue Zhang, Chao Wang, Feifei Fang, Yunzhi Zhuge, Hehe Fan, Xiaojun Chang, Cheng Deng, and Yi Yang. Samcontrol: Controlling pose and object for image editing with soft attention mask. *ACM Trans. Multimedia Comput. Commun. Appl.*, 2024. 3

[106] Yanbing Zhang, Zhe Wang, Qin Zhou, and Mengping Yang. Freecus: Free lunch subject-driven customization in diffusion transformers. *Proceedings of International Conference on Computer Vision (ICCV)*, 2025. 3

[107] Yuxuan Zhang, Yirui Yuan, Yiren Song, Haofan Wang, and Jiaming Liu. Easycontrol: Adding efficient and flexible control for diffusion transformer. In *Proceedings of International Conference on Computer Vision (ICCV)*, 2025. 3

[108] Shihao Zhao, Dongdong Chen, Yen-Chun Chen, Jianmin Bao, Shaozhe Hao, Lu Yuan, and Kwan-Yee K Wong. Unicontrolnet: All-in-one control to text-to-image diffusion models. In *Proceedings of Advances in Neural Information Processing Systems (NeurIPS)*, 2023. 3

[109] Wenliang Zhao, Lujia Bai, Yongming Rao, Jie Zhou, and Jiwen Lu. Unipc: A unified predictor-corrector framework for fast sampling of diffusion models. In *Proceedings of Advances in Neural Information Processing Systems (NeurIPS)*, 2023. 2

[110] Bolei Zhou, Hang Zhao, Xavier Puig, Sanja Fidler, Adela Barriuso, and Antonio Torralba. Scene parsing through ade20k dataset. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017. 17

[111] Tianrui Zhu, Shiyi Zhang, Jiawei Shao, and Yansong Tang. Kv-edit: Training-free image editing for precise background preservation. In *Proceedings of International Conference on Computer Vision (ICCV)*, 2025. 3

Appendix

We first provide LLM usage statement in Sec. A. We provide preliminaries in Sec. B. In Sec. C, we further analyze the domain gap and structure preservation of diffusion features. Then we elaborate on the implementation details of our proposed method in Sec. D and the experimental setups in Sec. E. We show additional experimental results in Sec. F and discuss the limitations of our method in Sec. G.

A. The Use of Large Language Models (LLMs)

We used large language models (LLMs) to assist in refining the paper's writing and producing the appearance prompt in the ARP module. We used LLMs to enable ARP in the experiments. LLMs played no significant role in the research ideation of this paper.

B. Preliminaries

Diffusion Models. Diffusion models are a family of probabilistic generative models characterized by two processes.

The *forward process* iteratively adds Gaussian noise to a clean image $\mathbf{x}_0$ to obtain $\mathbf{x}_t$ for time step $t \sim [1, T]$, which can be reparameterized in terms of a noise schedule α_t where

$$\mathbf{x}_t = \sqrt{\alpha_t}\mathbf{x}_0 + \sqrt{1-\alpha_t}\epsilon, \tag{3}$$

for $\epsilon \sim \mathcal{N}(0, \mathbb{I})$.

The *backward process* generates images by iteratively denoising an initial Gaussian noise $\mathbf{x}_T \sim \mathcal{N}(0, \mathbb{I})$, also known as diffusion sampling [30]. This process uses a parameterized denoising network ϵ_θ conditioned on a text prompt $\mathcal{P}$, where at time step t we obtain a cleaner $\mathbf{x}_{t-1}$ as

$$\mathbf{x}_{t-1} = \sqrt{\alpha_{t-1}}\hat{\mathbf{x}}_t + \sqrt{1-\alpha_{t-1}}\epsilon_\theta(\mathbf{x}_t \mid t, \mathcal{P}), \tag{4}$$

$$\hat{\mathbf{x}}_t = \frac{\mathbf{x}_t - \sqrt{1-\alpha_t}\epsilon_\theta(\mathbf{x}_t \mid t, \mathcal{P})}{\sqrt{\alpha_t}}. \tag{5}$$

Intuitively, $\hat{\mathbf{x}}_t$ approximates the initial clean image, which is subsequently perturbed with an appropriate amount of noise to produce the input for the following timestep.

Guidance. The iterative inference of diffusion enables people to guide the sampling process on auxiliary information. *Guidance* modifies Eq. (4) to compose additional score functions that point toward richer and specifically conditioned distributions [6, 18], expressed as

$$\hat{\epsilon}_\theta(\mathbf{x}_t \mid t, \mathcal{P}) = \epsilon(\mathbf{x}_t \mid t, \mathcal{P}) - s\,\mathbf{g}(\mathbf{x}_t \mid t, y), \tag{6}$$

where $\mathbf{g}$ is an energy function and s is the guidance strength. In practice, $\mathbf{g}$ can range from classifier-free guidance (where $\mathbf{g} = \epsilon$ and $y = \emptyset$, *i.e.* the empty prompt) to improve image quality and prompt adherence for T2I diffusion [29, 64], to arbitrary gradients computed from auxiliary models or diffusion features common to guidance-based controllable generation [6, 18, 52]. Thus, guidance provides the customizability on the type and variety of conditioning for controllable generation, as it merely requires a differentiable loss with respect to $\mathbf{x}_t$. However, the need for backpropagation during inference often leads to increased memory consumption and slower inference speed. Moreover, guidance-based methods often fail to capture fine structural details in controllable generation tasks.

Diffusion U-Net architecture. Many pretrained T2I diffusion models are text-conditioned U-Nets, which contain an encoder and a decoder that downsample and then upsample the input $\mathbf{x}_t$ to predict ϵ, with long skip connections between matching encoder and decoder resolutions [30, 61, 64]. Each encoder/decoder block contains convolution layers, self-attention layers, and cross-attention layers: The first two control both structure and appearance, and the last injects textual information. Thus, many training-free controllable generation methods utilize these layers, through direct manipulation [2, 28, 38, 80, 97] or for computing guidance losses [18, 52], with self-attention most commonly used. Let $\mathbf{f}_{l,t} \in \mathbb{R}^{HW \times c}$ be the diffusion feature with height H, width W, and channel size c at time step t right before attention layer l. Then, the self-attention operation is

$$\begin{aligned} \mathbf{Q} = \mathbf{f}_{l,t}\mathbf{W}_l^Q, \quad \mathbf{K} = \mathbf{f}_{l,t}\mathbf{W}_l^K, \quad \mathbf{V} = \mathbf{f}_{l,t}\mathbf{W}_l^V, \\ \mathbf{f}_{l,t} \leftarrow \mathbf{A}\mathbf{V}, \quad \mathbf{A} = \mathrm{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^\top}{\sqrt{d}}\right), \end{aligned} \tag{7}$$

where $\mathbf{W}_l^Q, \mathbf{W}_l^K, \mathbf{W}_l^V \in \mathbb{R}^{c \times d}$ are linear transformations which produce the query $\mathbf{Q}$, key $\mathbf{K}$, and value $\mathbf{V}$, respectively, and d is the dimensionality of the attention space. The $\mathrm{softmax}$ operation is applied across the second (HW)-dimension (typically, $c = d$ in diffusion models). Intuitively, the attention map $\mathbf{A} \in \mathbb{R}^{(HW)\times(HW)}$ encodes how each pixel in $\mathbf{Q}$ corresponds to each in $\mathbf{K}$, which then rearranges and weighs $\mathbf{V}$. The rich structural information embedded in U-Net features lays the foundation for extensive training-free controllable generation approaches, and, together with the common issues of training-free methods, motivates us to study the temporal dynamics of diffusion features.

C. Additional Analyses

C.1. KL Divergence

To analyze the domain gap between natural images and condition images, we collect 20 natural images from the *ImageNet-T2IR* dataset from [80]. Then we use the ControlNet processor [102] to convert these natural images into 5 conditions (canny edge, depth map, normal map, HED edge, and scribble drawing), resulting in 100 natural-condition image pairs.

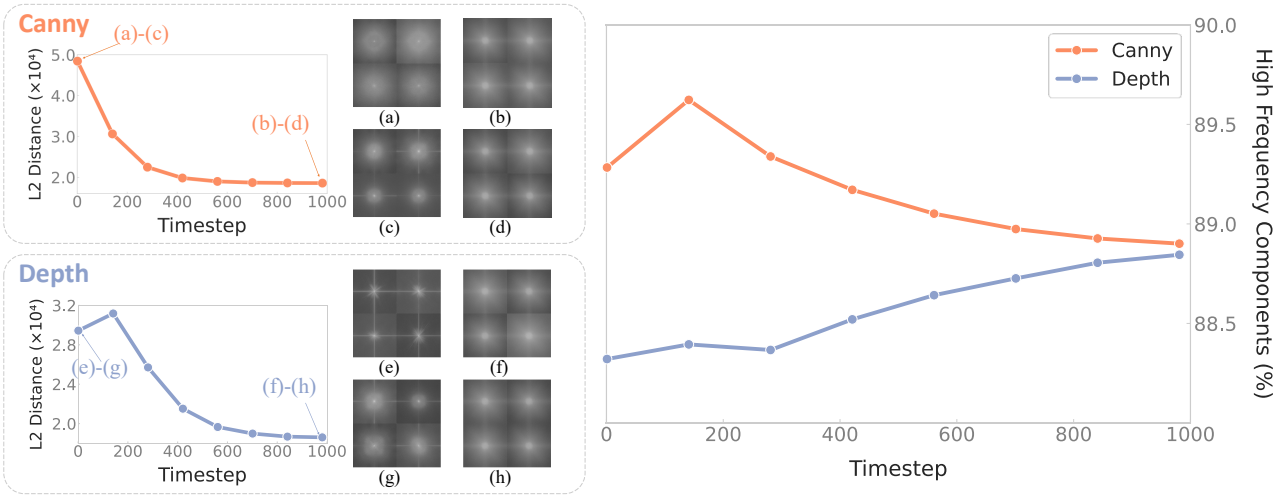


Figure 10. **Fourier analysis of noisy latents under canny edge and depth map conditions**. (***Left***) Average L2 distance between natural and condition image DFT spectra over timesteps. Subfigures (a)–(d) and (e)–(h) show the DFT spectra of four randomly selected images for both conditions at different timesteps. In each group, (a/e) and (b/f) correspond to condition latents at t_{low} and t_{high}, while (c/g) and (d/h) correspond to natural latents at t_{low} and t_{high}, respectively. (***Right***) Average high-frequency component ratio over timesteps.

To quantify the distributional difference, we extract diffusion features at a fixed timestep for each image, flatten them into feature maps (size $(HW) \times F$), and concatenate all features from each domain. We then apply PCA to the combined feature set and retain only the first principal component. Each image is thus projected into a 1-dimensional vector of HW values along this dominant component.

We estimate a probability distribution over these projections for each domain using Gaussian KDE. Specifically, we sample 1000 evenly spaced points between the minimum and maximum values observed in the two distributions. We then compute the KL divergence between the estimated densities of condition and natural images:

$$\mathrm{KL}(P\|Q) = \sum_{i=1}^{1000} p(x_i) \log \frac{p(x_i)}{q(x_i)}, \tag{8}$$

where $p(x)$ and $q(x)$ denote the normalized KDE densities of condition and natural images, respectively. We repeat this computation across timesteps to observe how the domain gap evolves during the diffusion process.

C.2. Self-Similarity

Following [79], we adopt the DINO self-similarity distance [10] to quantify structural similarity between images. In Vision Transformer (ViT) [17], an image is first divided into a sequence of non-overlapping patches, which are then linearly embedded and processed as tokens. In each Transformer layer, the tokens are projected into queries, keys, and values as follows:

$$\mathbf{Q}_l = \mathbf{T}_{l-1}\mathbf{W}_l^Q,\ \mathbf{K}_l = \mathbf{T}_{l-1}\mathbf{W}_l^K,\ \mathbf{V}_l = \mathbf{T}_{l-1}\mathbf{W}_l^V, \tag{9}$$

where $\mathbf{T}_l(\mathbf{I})$ denotes the output tokens for layer l for image $\mathbf{I}$, and $\mathbf{W}_l^Q$, $\mathbf{W}_l^K$, and $\mathbf{W}_l^V$ are the corresponding query, key, and value weight matrices, respectively.

To capture an image's internal structure, we compute its DINO self-similarity matrix at the final Transformer layer L:

$$S_L(\mathbf{I})_{ij} = \cos_\mathrm{sim}\left(k_L(\mathbf{I})_i, k_L(\mathbf{I})_j\right), \tag{10}$$

where $\mathbf{K}_L(\mathbf{I}) = [k_L(\mathbf{I})_{cls}, k_L(\mathbf{I})_1, \ldots, k_L(\mathbf{I})_n]$ are the key embeddings from the last layer for image $\mathbf{I}$ (n denotes the number of patch tokens), and $\cos_\mathrm{sim}$ denotes cosine similarity.

As shown in [79], this self-similarity-based descriptor can effectively capture the structure of an image while ignoring appearance details. Given two images $\mathbf{I}_1$ and $\mathbf{I}_2$, their structural distance is computed as the ℓ_2 distance between their self-similarity matrices:

$$\mathcal{L}^{\text{struct}} = \|S_L(\mathbf{I}_1) - S_L(\mathbf{I}_2)\|_2, \tag{11}$$

where $S_L(\mathbf{I})$ is defined in Eq. (10).

C.3. Discrete Fourier Transformation (DFT)

As an alternative to quantifying the domain gap between natural and condition images, we employ the Discrete Fourier Transformation (DFT) to analyze differences in their frequency components. Specifically, we begin by extracting diffusion feature maps for natural and condition images at a fixed timestep, following the method described in Sec. C.1. Since DFT typically operates on spatial images rather than high-dimensional feature tensors, we use the diffusion decoder to transform these feature maps back into RGB images. We then apply DFT to the decoded images to obtain their

frequency spectra and compute the L2 distance between the spectra of natural and condition image pairs.

This process is repeated across all diffusion timesteps, and the resulting distances are averaged over the same 100 natural-condition image pairs as described in Sec. C.1. As shown in Fig. 11, the average L2 distance between the frequency spectra decreases progressively as the diffusion timestep increases. This trend indicates that the diffusion process gradually reduces the frequency-domain gap between natural and condition images—consistent with our findings in Sec. 3.

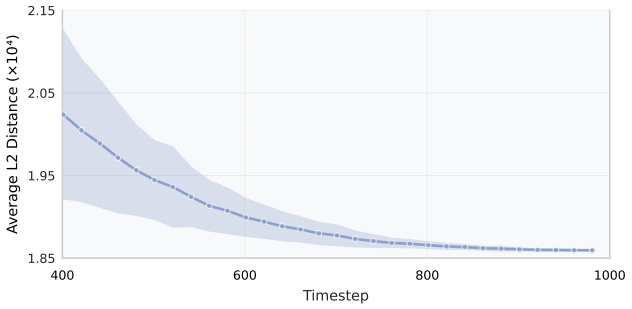


Figure 11. **Average L2 distance between natural and condition image DFT spectra over diffusion timesteps.** Results are averaged over all five conditions.

To further investigate how frequency components evolve through the diffusion process, we conduct a detailed analysis on two representative conditions: canny edge and depth map. Intuitively, canny edges, characterized by sharp edges and detailed contours, are expected to exhibit a higher proportion of high-frequency components in their DFT spectrum. In contrast, depth maps tend to be dominated by smooth gradients, suggesting a stronger presence of low-frequency components.

As illustrated in Fig. 10, the average L2 distance between the DFT spectra of natural and condition latents decreases over time for both conditions, consistent with the trend shown in Fig. 11. We also visualize DFT spectra of both image types at two representative timesteps of the denoising trajectory, denoted as t_{low} and t_{high}. In practice, we set $t_{\text{low}} = 1$ and $t_{\text{high}} = 981$. Since SDXL inference performs 50 denoising steps, steps 1 and 981 correspond to the lowest and highest noise levels in the denoising process. At t_{low}, canny edge spectra exhibit dispersed high-activation regions, indicative of prominent high-frequency composition. In contrast, depth map spectra show energy concentrated near the center, reflecting low-frequency dominance. Both differ markedly from the corresponding spectra of natural images. At t_{high}, due to accumulated noise, the DFT spectra for all images become visually similar.

This pattern is further confirmed by the right panel of Fig. 10, which plots the ratio of high-frequency components—defined as the proportion of DFT energy outside a centered circle with a radius equal to one-sixth of the image size—over timesteps. Initially, canny features are dominated by high-frequency content, while depth exhibits more low-frequency patterns. These differences gradually converge, reflecting a narrowing frequency-domain gap between different conditions.

D. Method Details

D.1. Spatially-Aware Appearance Transfer

We build our method on top of the spatially-aware appearance transfer mechanism proposed in Ctrl-X [47]. Specifically, given diffusion features $\mathbf{f}_{l,t}^{\text{out}}$ and $\mathbf{f}_{l,t}^{\text{app}}$ from the output and appearance branches respectively, Ctrl-X [47] computes a cross-image attention map as follows:

$$\mathbf{A} = \text{softmax}\left(\frac{\mathbf{Q}^{\text{out}}\mathbf{K}^{\text{app}\top}}{\sqrt{d}}\right), \quad \mathbf{Q}^{\text{out}} = \text{norm}(\mathbf{f}_{l,t}^{\text{out}})\mathbf{W}_l^Q, \quad \mathbf{K}^{\text{app}} = \text{norm}(\mathbf{f}_{l,t}^{\text{app}})\mathbf{W}_l^K, \tag{12}$$

where $\text{norm}(\cdot)$ is applied across the spatial dimension (HW) and removes global statistics across spatial dimensions to isolate structural correspondence.

Subsequently, attention-weighted statistics are computed from the appearance features:

$$\mathbf{M} = \mathbf{A}\mathbf{f}_{l,t}^{\text{app}}, \quad \mathbf{S} = \sqrt{\mathbf{A}(\mathbf{f}_{l,t}^{\text{app}} \odot \mathbf{f}_{l,t}^{\text{app}}) - (\mathbf{M} \odot \mathbf{M})}, \tag{13}$$

which are then used to modulate the output features:

$$\mathbf{f}_{l,t}^{\text{out}} \leftarrow \mathbf{S} \odot \mathbf{f}_{l,t}^{\text{out}} + \mathbf{M}. \tag{14}$$

D.2. Appearance-Rich Prompting

Directly using the original prompt for appearance transfer may lead to artifacts in the generated image, since such prompts tend to be brief and lacking in semantic correspondence with the condition image (see Sec. 4.3 for details). To overcome this limitation, we propose a pipeline that enriches the original text prompt $\mathcal{P}$ with semantic information extracted from the structure condition image $\mathbf{I}^{\text{struct}}$, yielding a more appearance-rich prompt $\mathcal{P}^{\text{app}}$ for generating the final appearance image $\mathbf{I}^{\text{app}}$. As illustrated in Fig. 12, we first utilize GPT-4o [1] to extract key semantic entities from the condition image to produce dictionary $\langle d1 \rangle$. To facilitate semantic alignment between the condition image and the text prompt, we further employ GPT-4o [1] to identify and associate these extracted entities with semantically-related elements in the original text, modifying $\langle d1 \rangle$ to produce $\langle d2 \rangle$. Finally, we revise the original prompt $\mathcal{P}$ using the extracted semantic information, producing an enhanced appearance prompt $\mathcal{P}^{\text{app}}$. To help the multimodal LLM correctly follow instructions and mitigate erroneous semantic transfer, our

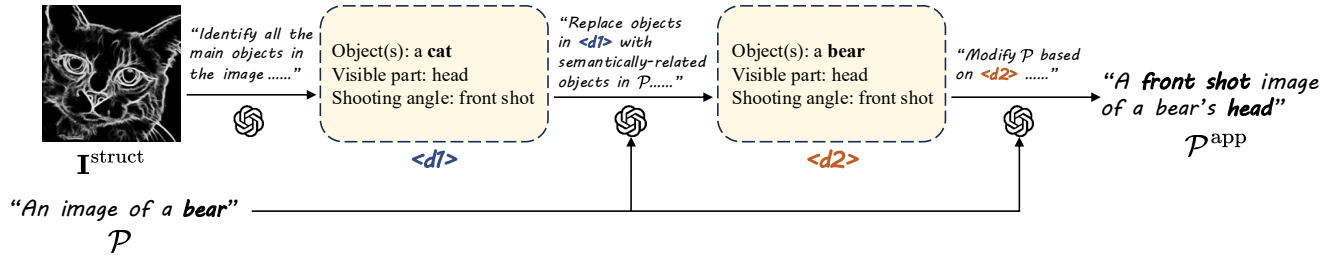


Figure 12. **Illustration of the Appearance-Rich Prompting (ARP) module**. Given the original text prompt $\mathcal{P}$, our module derives an appearance-rich prompt $\mathcal{P}^{\text{app}}$ by integrating semantic information from the condition image $\mathbf{I}^{\text{struct}}$.

pipeline stores intermediate information in structured dictionaries, enabling more controlled and interpretable prompt editing. More examples of the Appearance-Rich Prompting (ARP) module are provided in Fig. 14. For the full prompt used with GPT-4o [1] for Appearance-Rich Prompting, see the accompanying .txt file in the supplementary material.

E. Experiment Setup Details

E.1. Implementation Details

We implement our method with Diffusers [81] on SDXL 1.0 [61] and adopt the same injection layers following previous work [47]. We sample $\mathbf{I}$ with 50 steps of DDIM sampling and set $\eta = 1$ [72]. For structure-rich injection, we set $\tau = 400$ and $C = 600$. For restart refinement, we set $\sigma_{t_{\text{min}}} = 1.0$, $\sigma_{t_{\text{max}}} = 2.0$, $N = 3$, $S = 5$, where S is the total number of timesteps in the restart backward process. For self-recurrence, we set $t'_{\text{min}} = 500$, $t'_{\text{max}} = 900$, $N' = 2$, where t'_{max} is the self-recurrence starting point, t'_{min} is the self-recurrence end point, and N' is the number of self-recurrence [47]. We run all experiments on NVIDIA Tesla V100 GPUs.

For any input condition image $\mathbf{I}^{\text{struct}}$, we preprocess it with a dilation and unsharp masking operation. Specifically, we binarize the image, perform a distance transform operation to detect the minimum line width w. If $w_{\text{min}} \leq w \leq w_{\text{max}}$, we dilate $\mathbf{I}^{\text{struct}}$ with kernel size k^e. On the other hand, if the inverted image meets the standard, we erode $\mathbf{I}^{\text{struct}}$. We set $w_{\text{min}} = 25$, $w_{\text{max}} = 50$ and $k^e = 10$. Then we perform unsharp masking $(1+\gamma) \cdot \mathbf{I}^{\text{dilate}} - \gamma \cdot B$ to modify the dilated (eroded) image, where $\mathbf{I}^{\text{dilate}}$ denotes the dilated (eroded) input condition image, $\gamma = 50$, and B is the Gaussian blur operation with blur radius $r = 3$. We empirically find the two operations beneficial for highlighting object boundary and improving structure preservation.

E.2. Dataset Details

We construct our dataset based on the conditional generation datasets from Ctrl-X [47] and FreeControl [52]. Specifically, for conditions canny edge, depth map, normal map, HED edge, and scribble drawing, we select condition-prompt pairs from both datasets and merge them. We collect a total of 15 condition images per condition and form 22 condition-prompt pairs for canny edge and 21 pairs for each of the remaining four conditions.

For human pose and segmentation map, since both original datasets contain limited examples, we supplement them by collecting additional human pose images from the web and segmentation masks from the ADE20K [110] dataset. We obtain 15 images for each of these two conditions and pair them with text prompts using a combination of templates and hand annotation, resulting in 21 image-prompt pairs for human pose and 23 for segmentation mask.

F. Additional Experimental Results

F.1. Inference Efficiency

Our framework inherits the computational efficiency of injection-based pipelines. Moreover, since $g(t) = C$ in our implementation, our pipeline is able to cache and reuse $\mathbf{f}^{\text{struct}}_{l,g(t)}$, in contrast to previous synchronous pipelines that perform inference at every timestep. Tab. 3 shows the average inference time of different settings in our experiments, with the refiner of SDXL [61] enabled. As shown in the table, structure-rich injection saves inference time by up to 9% with no noticeable degradation in generation quality. Our framework still achieves superior inference efficiency even with the restart refinement schedule, demonstrating simultaneous improvements in both generation quality and inference speed. Appearance-rich prompting module improves the robustness of the framework at the expense of an 8% inference time overhead. Overall, this training-free framework provides users with the flexibility to adapt to task-specific priorities and negligible overhead in most cases.

F.2. Additional Qualitative Results

We provide additional qualitative comparisons with baselines in Fig. 16 and additional qualitative results for a broader range of condition types in Fig. 17. Our method demonstrates strong generation performance across both common and challenging conditions. It also handles diverse and complex text prompts effectively. As a training-free approach, it generalizes effortlessly to various in-the-wild conditions without any additional training cost, producing high-

Table 2. **Additional quantitative comparison of controllable T2I.** Our method consistently surpasses all training-free baselines in structure preservation, image-text alignment, and visual diversity. The best results are in **bold**, and the second best are underlined.

Method	Self-sim ↓	CLIP ↑	LPIPS ↑	Dream-Sim ↓	Image-Reward ↑	HPSv2 ↑
ControlNet [102]	0.067	0.309	0.701	0.509	0.298	0.285
T2I-Adapter [53]	0.116	0.287	0.728	0.636	-0.050	0.261
SDEdit [51]	0.154	0.259	0.315	0.734	-1.374	0.189
P2P [28]	0.197	0.251	0.266	0.724	-1.786	0.168
PnP [80]	0.157	0.256	0.151	0.724	-1.789	0.168
InfEdit [97]	0.135	0.296	0.357	0.636	-0.202	0.244
FreeControl [52]	0.116	0.320	**0.667**	0.626	0.554	0.285
Ctrl-X [47]	0.104	0.315	0.650	0.579	0.291	0.283
Ours	**0.096**	**0.322**	0.662	**0.558**	**0.897**	**0.313**

Table 3. Inference time of different module combinations.

Modules	Inference Time (s)
Synchronous Injection	53.70
SRI	48.74
SRI+RR	52.65
SRI+RR+ARP	57.32

quality outputs. This level of zero-shot generalization is often unattainable for training-based methods.

F.3. Additional Quantitative Results

Since T2I-Adapter-SDXL [53] supports only four (canny, depth, normal, and pose) out of the seven condition types in our full dataset, we further conduct a quantitative comparison limited to these four types. As shown in Tab. 2, our method outperforms all baselines across almost every metric. Notably, these metrics jointly assess both structure preservation (e.g., DINO self-similarity [79], DreamSim [22]) and generation quality (e.g., ImageReward [95], HPSv2 [89]), highlighting the effectiveness of our approach.

F.4. Additional Ablation Study

We present additional ablation studies on key components of our proposed method to validate our design choices. The results are shown in Fig. 13, Fig. 14, and Fig. 15.

Structure-Rich Injection. As a complementary study to the SRI ablation presented in Sec. 5.3, we further investigate the choice of constants in the case of constant injection. Specifically, we evaluate the effects of the injection schedule $g(t) = C$ across various C values. As shown in Fig. 13, lower C values result in severe conditional leakage due to a pronounced domain gap (*e.g.* $C = 0$). In contrast, higher values of C (*e.g.* $C = 800$) produce more natural appearances with higher fidelity but compromise structural control. Empirically, $C = 600$ achieves the best balance between appearance fidelity and structure control, significantly outperforming the synchronous injection baseline by enhancing structural alignment, suppressing condition leakage and reducing visual artifacts simultaneously.

Appearance-Rich Prompting. Fig. 14 demonstrates the effectiveness of appearance-rich prompting in enhancing semantic alignment between the structural condition and the appearance image. This strategy helps recover missing semantic elements (*e.g.*, "building" in row 1 and "hand" in row 3), significantly reducing visual artifacts and improving the overall quality of the generated images.

Restart Refinement. Fig. 15 illustrates the efficacy of restart refinement in mitigating visual artifacts (*e.g.*, the duplicated eye on the rabbit's body and the incorrect eyes in the husky's background). Additionally, it alleviates condition leakage under abstract conditions (*e.g.*, pose), further improving generation fidelity.

G. Limitations

The key limitation of our method is that the appearance-rich prompting module requires access to a multimodal language model. While the captioning task demands neither cutting-edge models nor significant inference time, we recognize that it may raise concerns regarding privacy and safety, and hope our findings and analysis can shed light on controllable visual content creation.

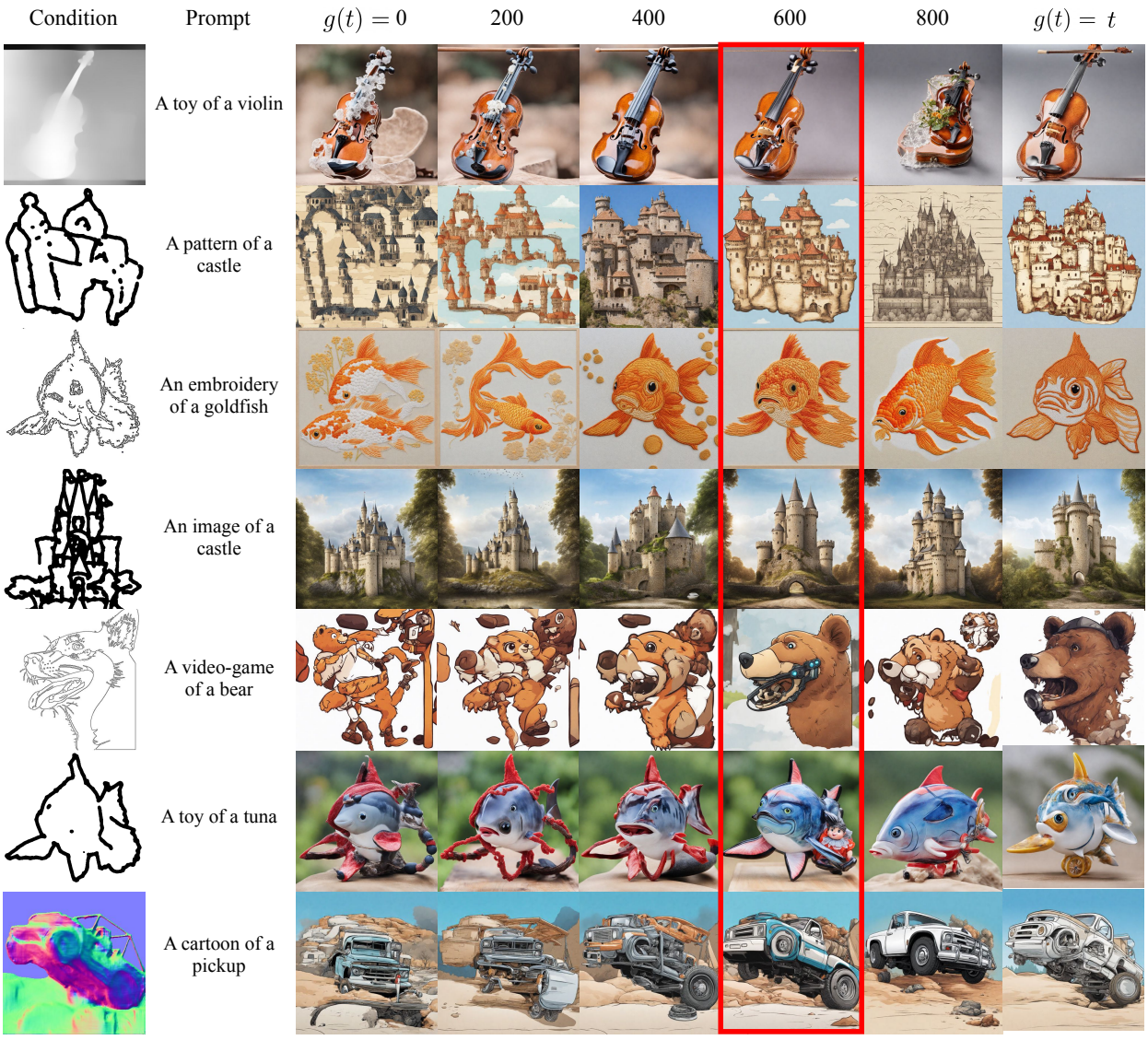


Figure 13. **Additional ablation of Structure-Rich Injection (SRI)**. For asynchronous injection $g(t) = C$, lower C suffers from conditional leakage, while higher values improve appearance fidelity at the cost of structural control. The optimal trade-off is achieved at $C = 600$, outperforming the synchronous schedule ($g(t) = t$).

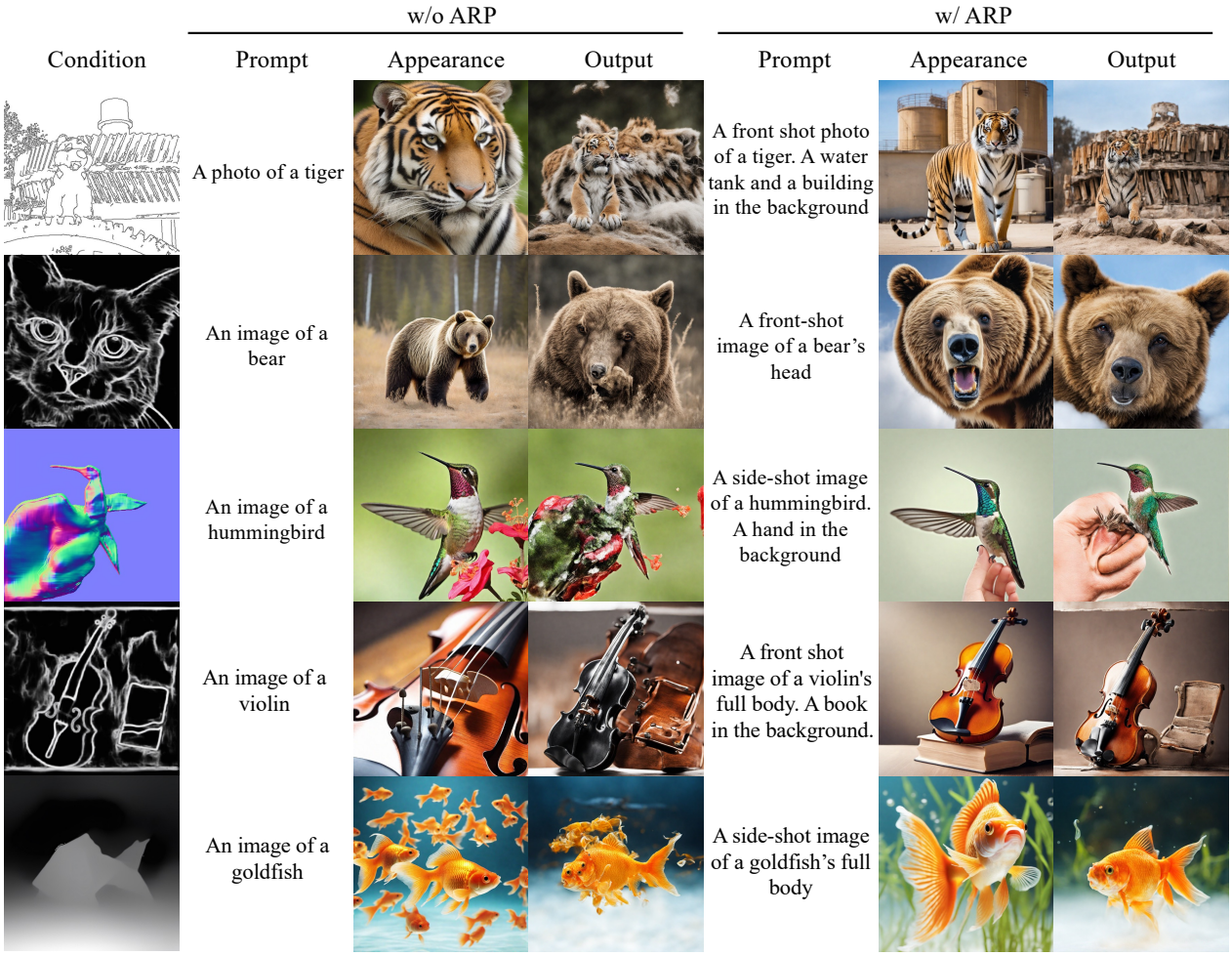


Figure 14. **Additional ablation of Appearance-Rich Prompting (ARP)**. This module improves semantic alignment with the condition image by adapting prompts to better capture key visual attributes, thereby mitigating incorrect appearance transfers and reducing artifacts.

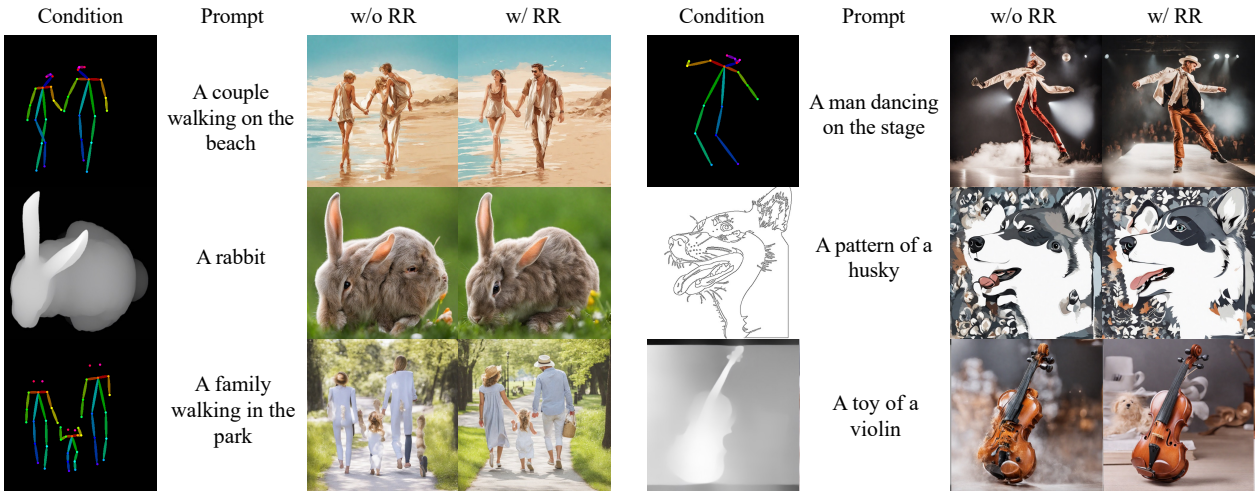


Figure 15. **Additional ablation of Restart Refinement (RR)**. This strategy significantly mitigates condition leakage and appearance artifacts, improving generation quality while maintaining structural alignment.

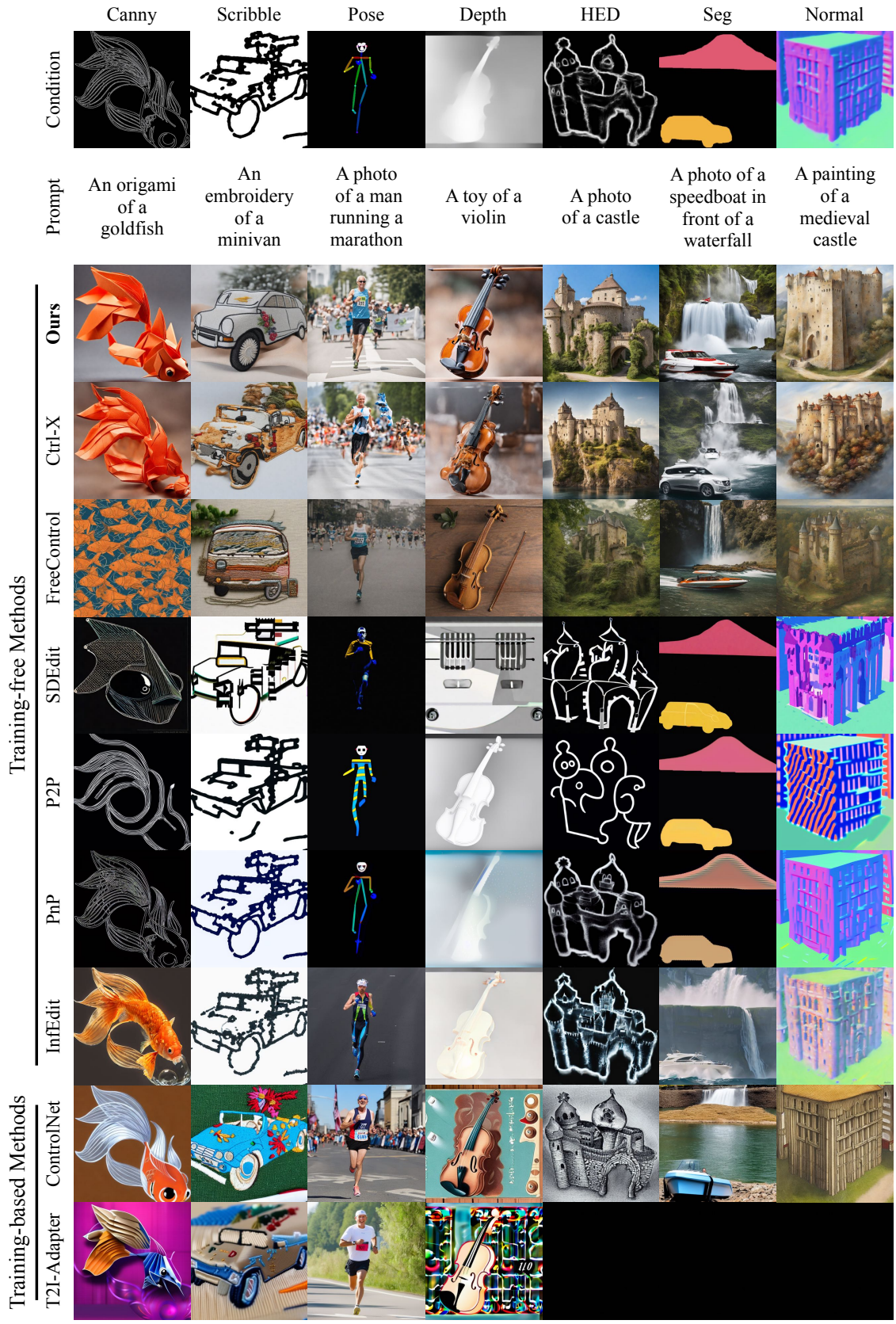


Figure 16. **Qualitative comparison with existing methods**.

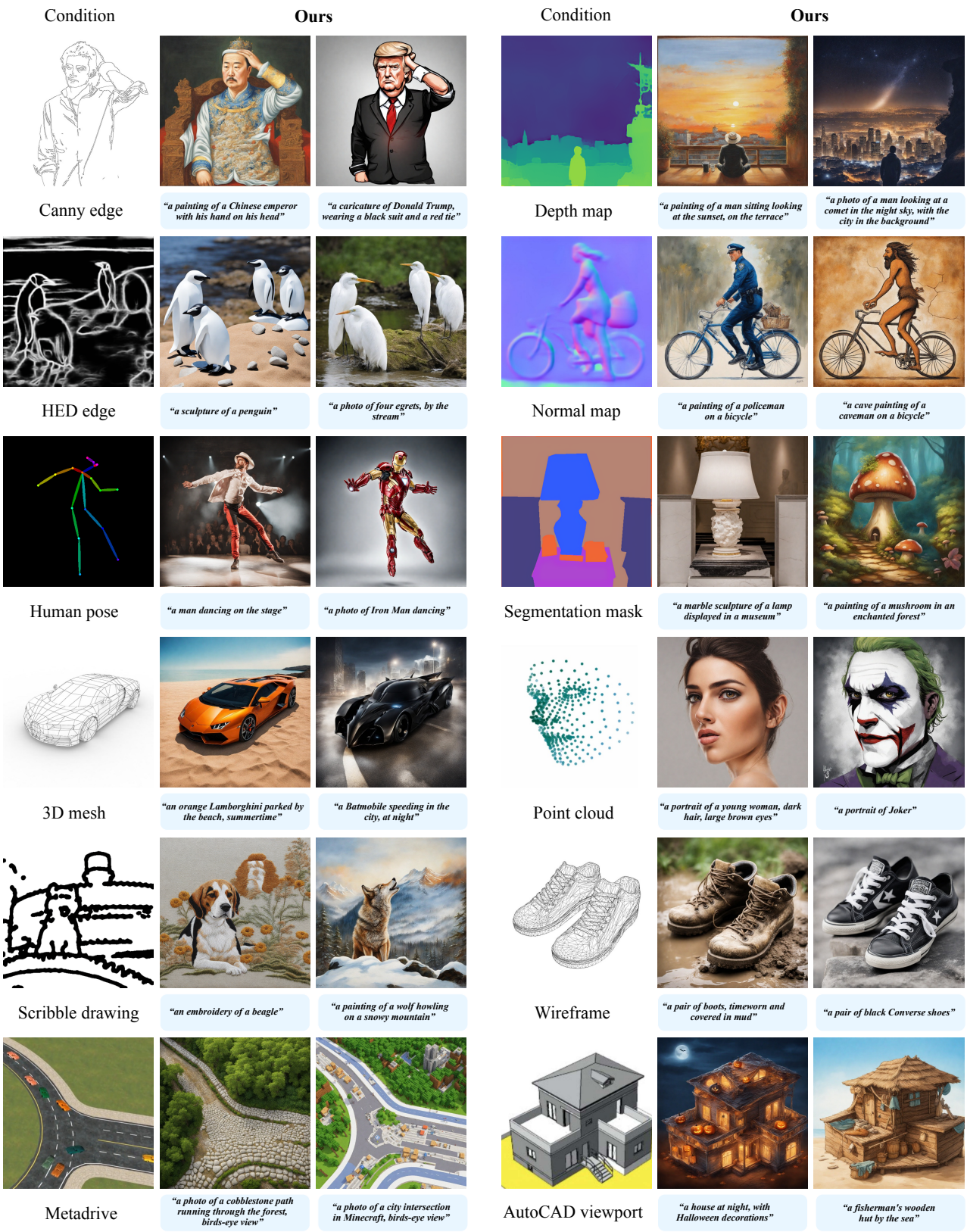


Figure 17. **Qualitative results for more control conditions.**