RAGD: Regional-Aware Diffusion Model for Text-to-Image Generation

Supplementary Material

1. More Model Details

In Figure 1, we present example images of $m^i = \{m^i_{offset}, m^i_{scale}\}$, $n^i = \{n^i_{offset}, n^i_{scale}\}$ in regional hard binding and $o^i = \{h^i_{split}, w^i_{split}\}$ in regional soft refinement. As shown, m^i and n^i are primarily responsible for precise positional control of objects, ensuring that the generated content adheres to the specified spatial layout. In contrast, o^i focuses on expanding the global area of objects, thereby enhancing interaction and fusion with adjacent regions. This collaborative design significantly improves the attribute fidelity of the generated images while promoting harmonious coordination across different regions, resulting in more cohesive and visually consistent outputs.

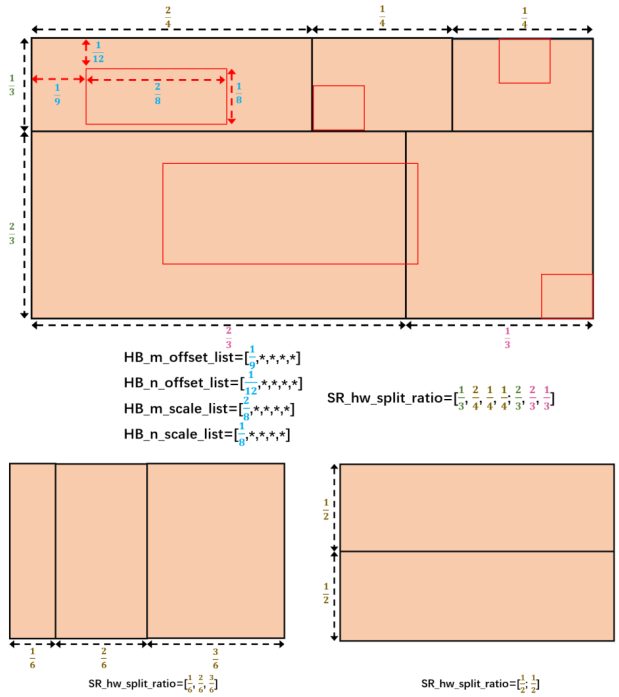

Figure 1. Several schematic diagrams of regional division.

2. Usage of MLLM.

In order to facilitate quantitative testing and user use, we use MLLM to automatically segment spatial regions and generate bounding boxes and sub-prompts from a long prompt, as shown in Figure 2. It is worth noting that our method does not inherently rely on MLLM, as this process can also be performed manually.

3. More Analysis

3.1. Effectiveness of Parameter r.

We introduced a parameter r to control the frequency of hard binding applications. As shown in Figure 3, excessive hard binding limits the opportunity for subsequent soft refinement, weakening its impact. This may diminish interactions between adjacent objects, potentially causing noticeable boundaries to reappear. By adjusting r, we aim to balance precise object placement with smooth integration, optimizing both the structure and cohesion of the generated image.

3.2. Effectiveness of Coefficient δ.

We introduced the coefficient δ to modulate the intensity of regional soft refinement. As illustrated in Figure 3, excessively low or high δ values may result in noticeable partitioning or slight misalignment between text and image. Setting δ to an optimal level enhances the fusion of image regions, yielding a more natural overall output.

3.3. Quantitative Experiment of Repainting.

In contrast to conventional inpainting approaches, the proposed repainting scheme in this paper eliminates the dependency on original image inputs, enabling iterative local adjustments through the reuse of parameter configurations from prior generation processes. To further validate the feasibility of our methodology, we conducted quantitative comparative experiments with advanced inpainting model BrushNet [2] and RAGD. We randomly selected 100 distinct text prompts from the Geneval and T2I-CompBench benchmark to generate initial images. The resulting outputs served as image inputs for BrushNet, while retaining corresponding generation parameters as input conditions for RAGD. As demonstrated in Table 1, without requiring secondary training or external inpainting models, RAGD exhibits significant advantages across all evaluation metrics.

Metrics	Image Quality		Masked Region Preservation		Text Align
Models	$IR_{\times 10} \uparrow$	$AS \uparrow$	$PSNR \uparrow$	$LPIPS_{\times 10^3} \downarrow$	$CLIPSim \uparrow$
BrushNet	5.1006	5.8474	22.4292	8.7020	21.6796
RAG	**6.3304**	**6.1093**	**26.5401**	**7.7600**	**24.3563**

Table 1. Comparison with state-of-the-art inpainting solutions.

3.4. Stability of RAGD

We validated stability by applying different random seeds under identical parameter settings. As shown in Fig-

ure 4, varying seeds generated results with diverse characteristics, highlighting the model's creative potential. However, in scenarios with a higher number of regions, occasional suboptimal outcomes were observed, such as incorrect object counts or pronounced boundaries between regions. These cases can be regarded as acceptable variations, given that similar issues are inherent in most existing T2I models during image generation.

3.5. More Qualitative Results

As shown in Figure 5, we present additional qualitative results comparing RAGD, Flux [1] and RPG [3] that further highlighting RAGD's superior performance in attribute depiction and spatial control. Through the generation of multi-region complex scenes, RAGD demonstrates its ability to accurately capture the details described in the input text while maintaining overall coherence and naturalness in the generated content.

Figure 6 showcases the potential applications of RAGD in image repainting tasks, such as removing unsatisfactory areas from previously generated results or adding new objects. These examples underscore RAGD's flexibility and controllability in image repainting, particularly its capability to execute complex modifications without requiring model fine-tuning.

Figure 2. Usage of MLLM.

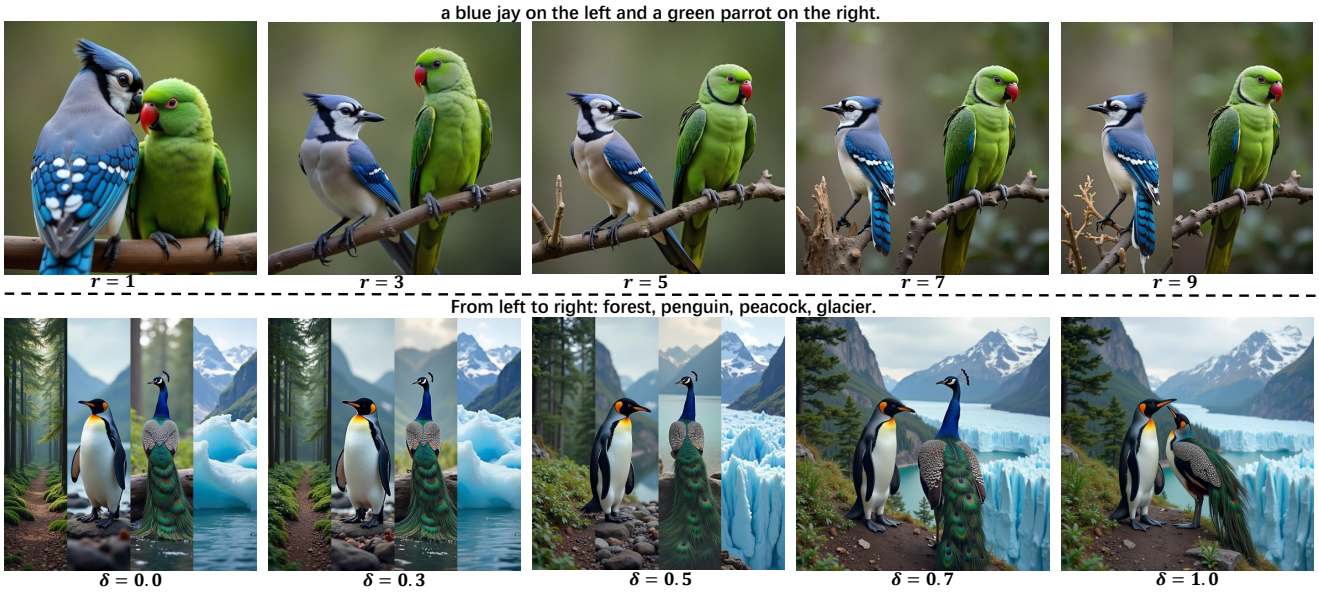

Figure 3. Qualitative analysis of hard binding steps r and soft refinement strength δ. A few steps of binding is sufficient for regional completeness, and appropriate soft refinement intensity leads to improved regional coherence.

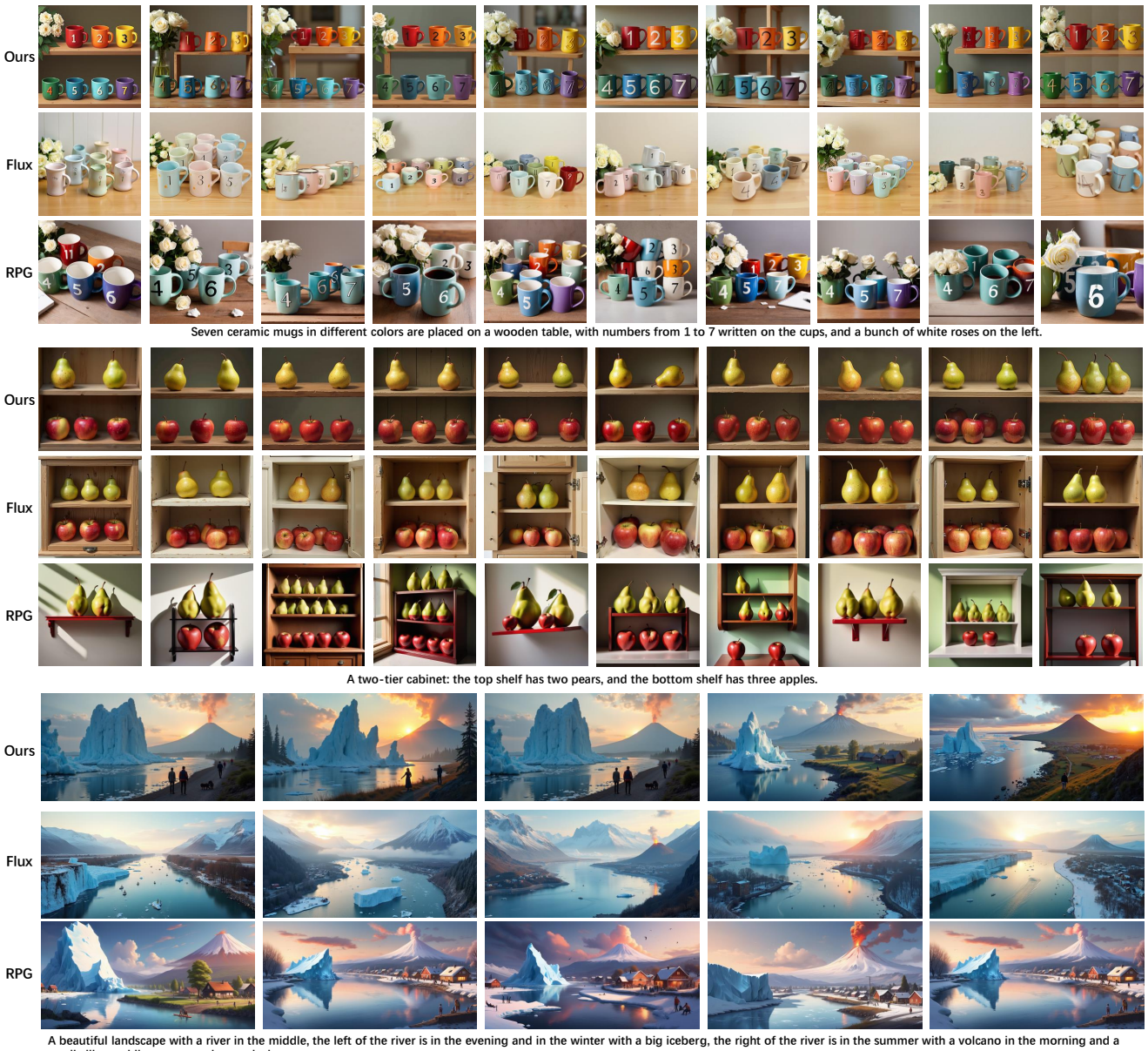

Figure 4. RAGD generation results using different seeds show more stable generation results than other methods.

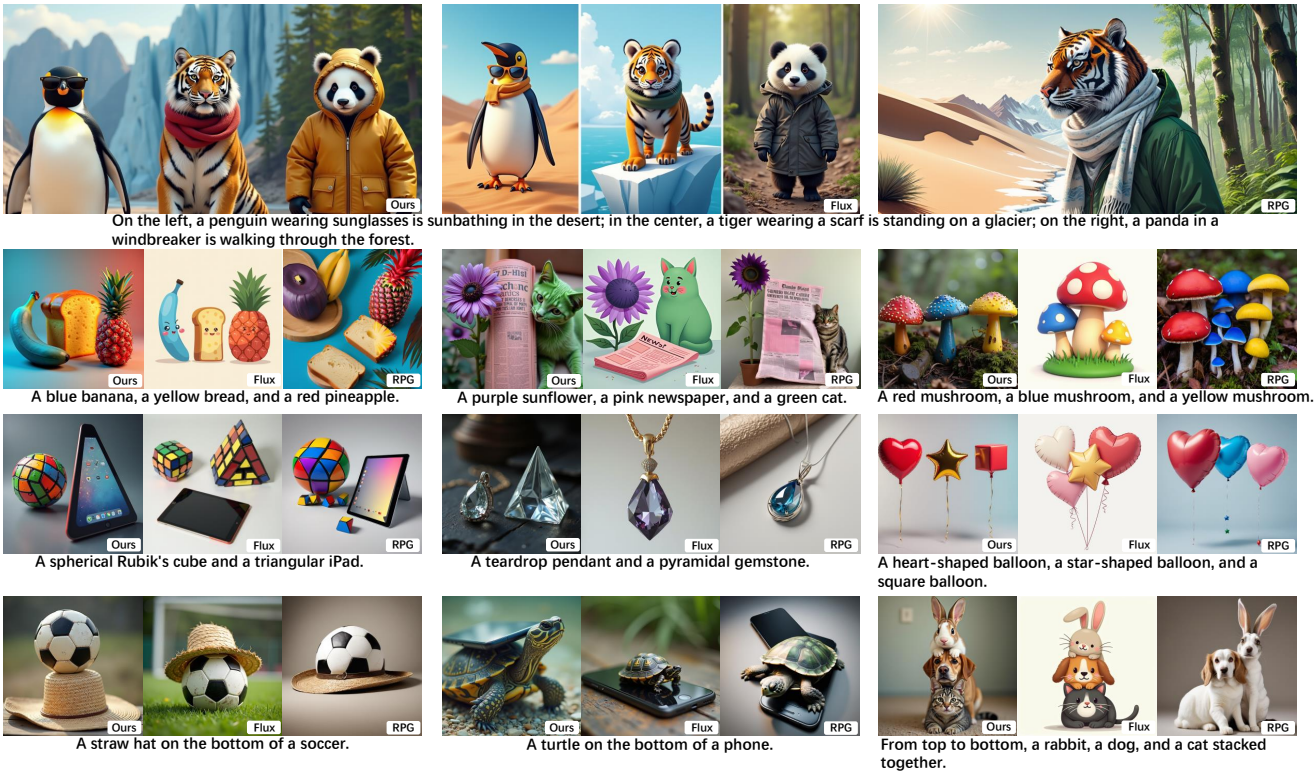

Figure 5. More qualitative results of RAGD.

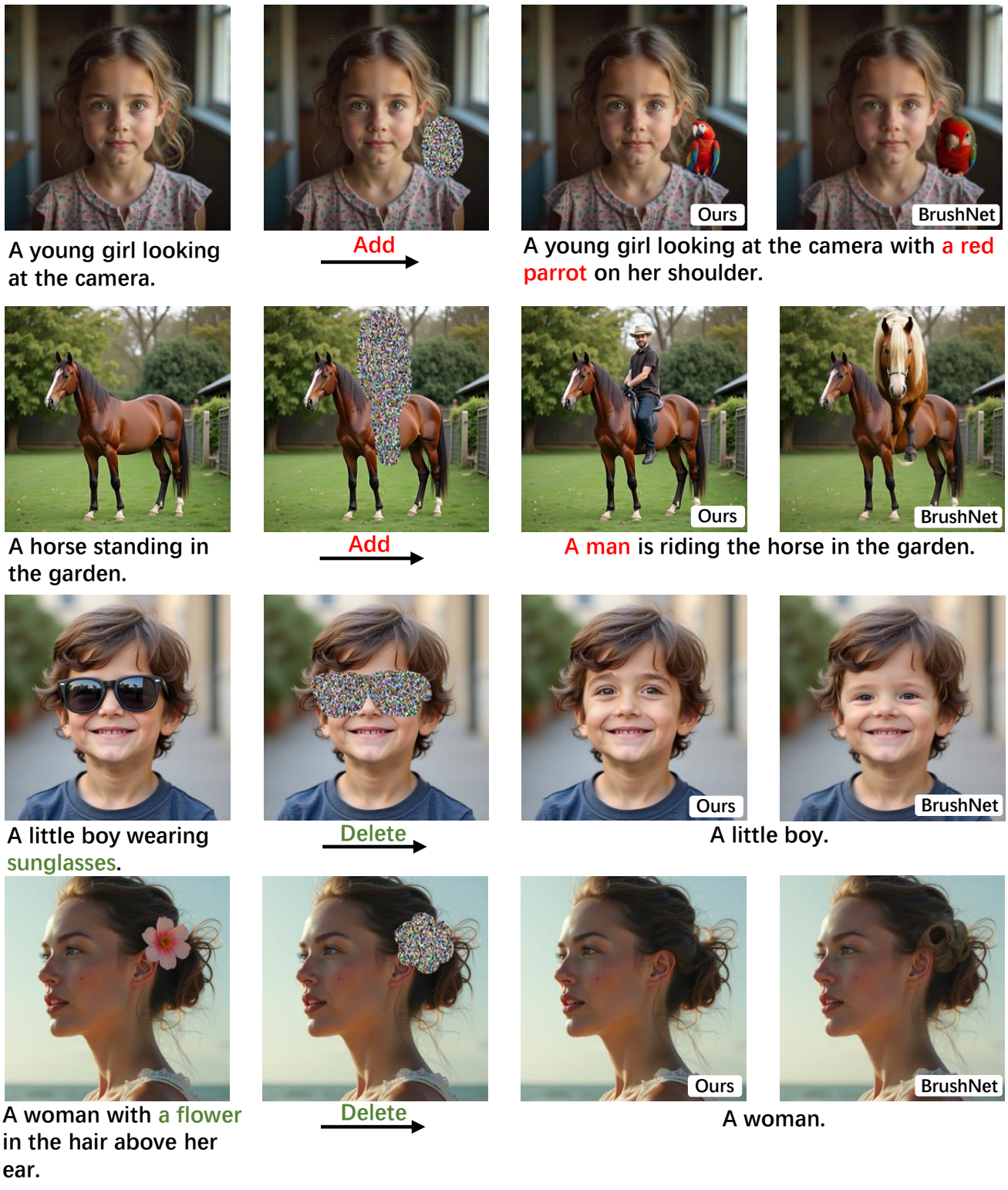

Figure 6. The diverse applications of image repainting demonstrate the flexibility of this method.

References

[1] BlackForest. Black forest labs; frontier ai lab, 2024. 2

[2] Xuan Ju, Xian Liu, Xintao Wang, Yuxuan Bian, Ying Shan, and Qiang Xu. Brushnet: A plug-and-play image inpainting model with decomposed dual-branch diffusion. *arXiv preprint arXiv:2403.06976*, 2024. 1

[3] Ling Yang, Zhaochen Yu, Chenlin Meng, Minkai Xu, Stefano Ermon, and CUI Bin. Mastering text-to-image diffusion: Recaptioning, planning, and generating with multimodal llms. In *Forty-first International Conference on Machine Learning*, 2024. 2