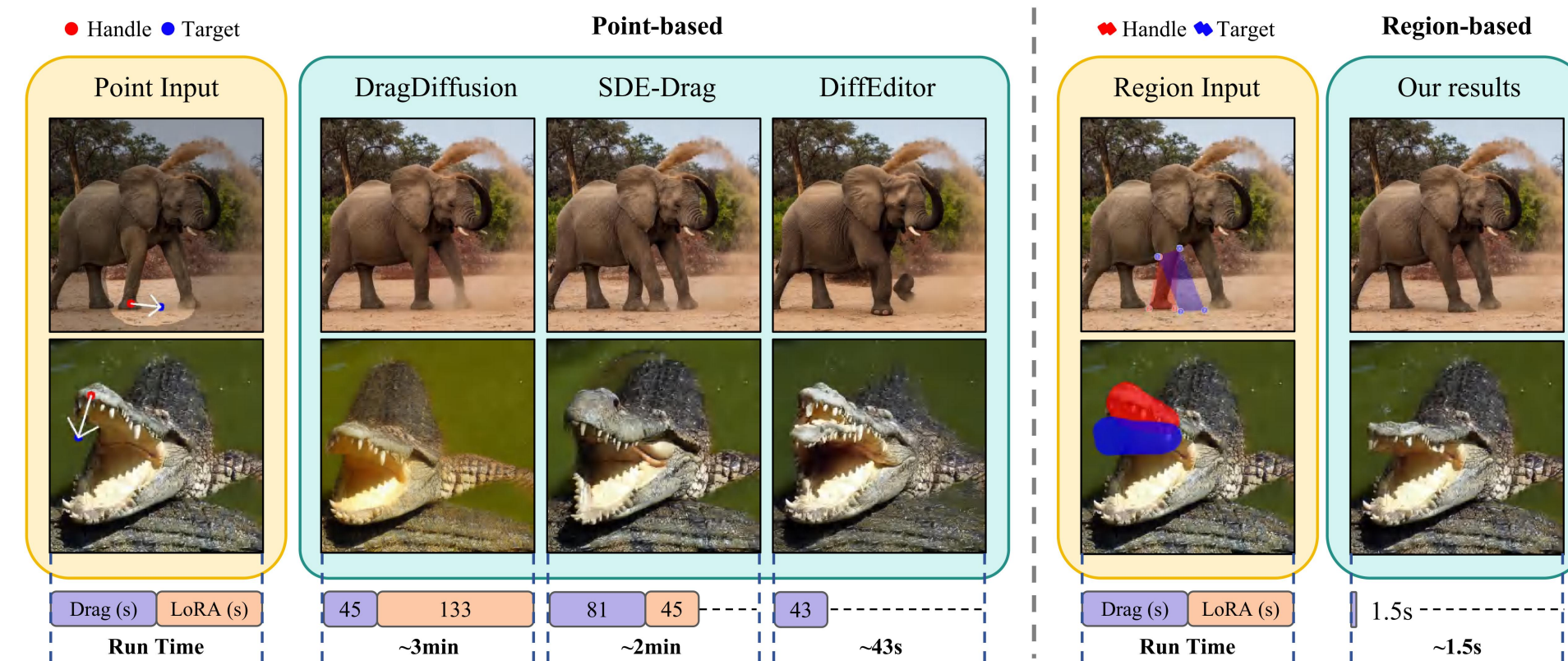




Background & Contribution

Goal: Fast and precise image editing with region-based user inputs.



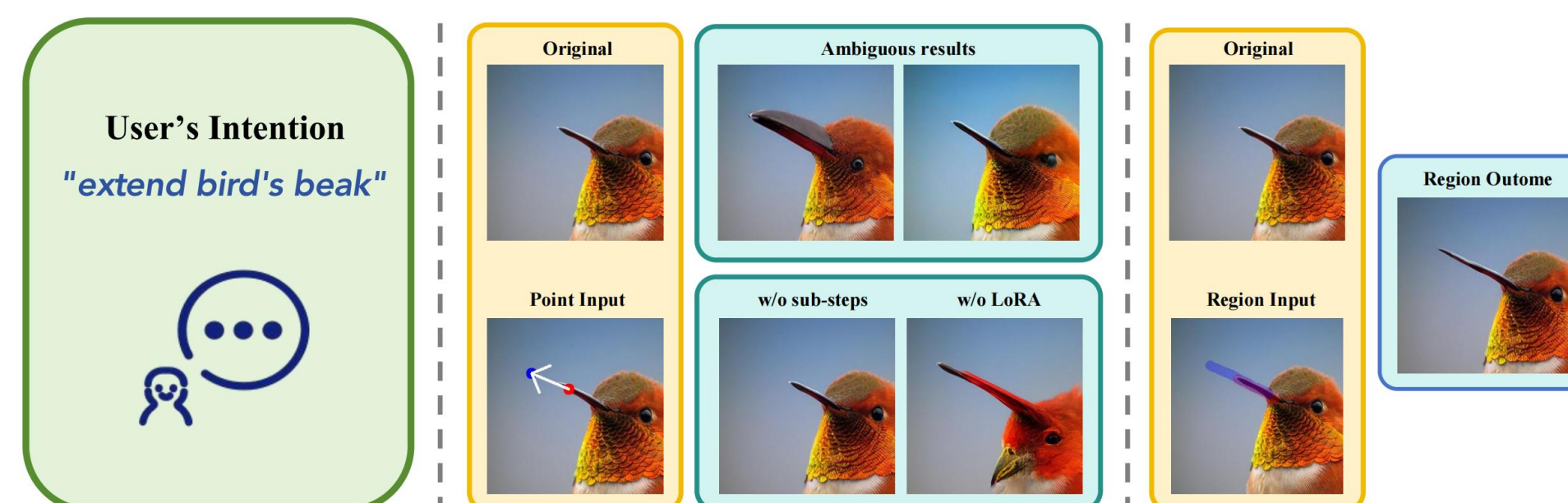
Key Contributions

- (1) Region-based image editing method for better user intention alignment.
- (2) Gradient-free, single-iteration editing pipeline for fast inference.
- (3) Extended datasets with region-based instructions for benchmarking.

Motivation

Why Move Beyond Point-Based Image Editing?

- (1) Sparse point inputs often lead to ambiguous interpretations of user intentions.
 - Models must infer global image changes from limited point movements.
- (2) Point-based methods are slow due to iterative editing and expensive LoRA training.
 - Each region corresponds to a large number of points after dense mapping.
- (3) Region pairs provide richer context and denser mapping compared to sparse point pairs.



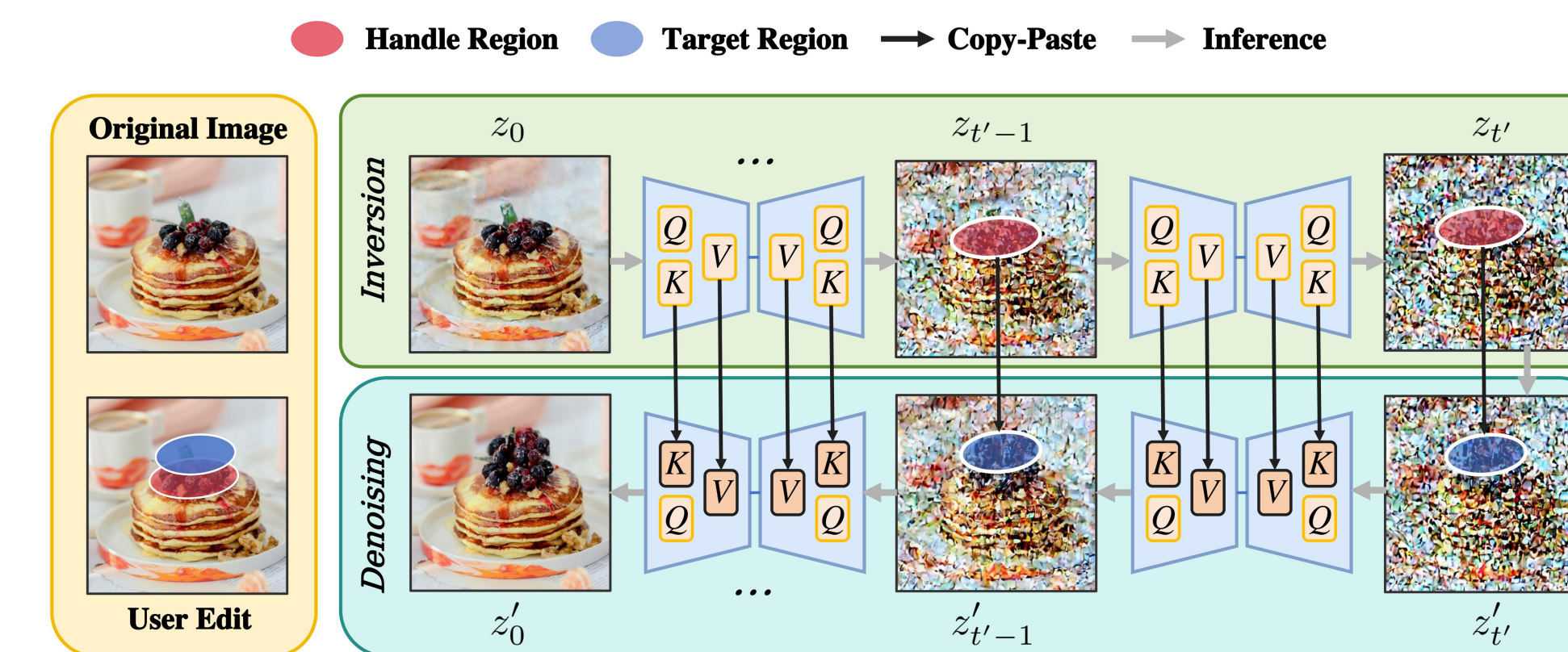
Related papers

- [1] Nie, S., Guo, H.A., Lu, C., Zhou, Y., Zheng, C., Li, C.: The blessing of randomness: Sde beats ode in general diffusion-based image editing. arXiv preprint arXiv:2311.01410 (2023)
- [2] Shi, Y., Xue, C., Pan, J., Zhang, W., Tan, V.Y., Bai, S.: Dragdiffusion: Harnessing diffusion models for interactive point-based image editing. arXiv preprint arXiv:2306.14435 (2023)
- [3] Pan, X., Tewari, A., Leimkühler, T., Liu, L., Meka, A., Theobalt, C.: Drag your gan: Interactive point-based manipulation on the generative image manifold. In: ACM SIGGRAPH (2023)

Method

Editing Pipeline

- (1) **Region-based Input:** User selects **handle** and **target** regions for editing.
- (2) **Multi-step Copy-Paste:** Repetitively copy latent representations from **handle** to **target** regions during a single inversion-denoising cycle.
- (3) **Attention Swapping:** Maintain image consistency using mutual self-attention control.



Dense mapping between user-defined regions

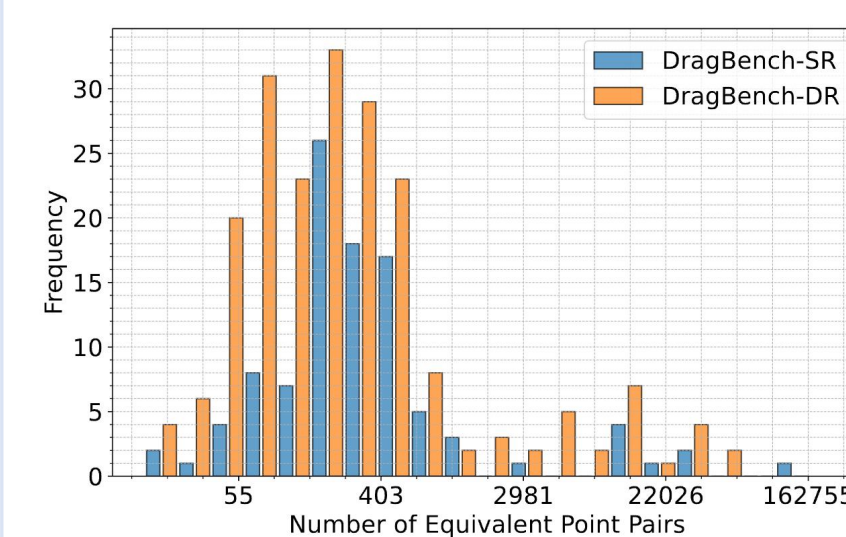
- (1) **Flexible Input Methods:** Support both polygon vertices and brush strokes for region selection.
- (2) **Mapping Technique:**
 - For polygons: Apply affine or perspective transformations.
 - For brush strokes: Apply horizontal and vertical scaling to map points between **handle** and **target** regions.

Datasets

New benchmarks for region-based editing evaluation

DragBench-S [1] and DragBench-D [2] are existing benchmarks for evaluating point-drag methods. We modify these benchmarks to use regions instead of points to reflect user intentions, creating DragBench-SR and DragBench-DR (where R stands for 'Region').

Frequency distribution of equivalent point pair counts



Quantitative Results

Mean Distance (×100) & LPIPS (×100)

Method	DragBench-S(R)		DragBench-D(R)	
	Time (↓)	MD (↓) LPIPS (↓)	MD (↓)	LPIPS (↓)
SDE-Drag	126.1	7.5 12.4	8.1	14.9
DragDiffusion	177.7	7.0 18.0	6.7	11.5
DiffEditor	43.1	23.6 17.6	22.1	10.9
Ours	1.5	6.4 9.9	6.6	9.2

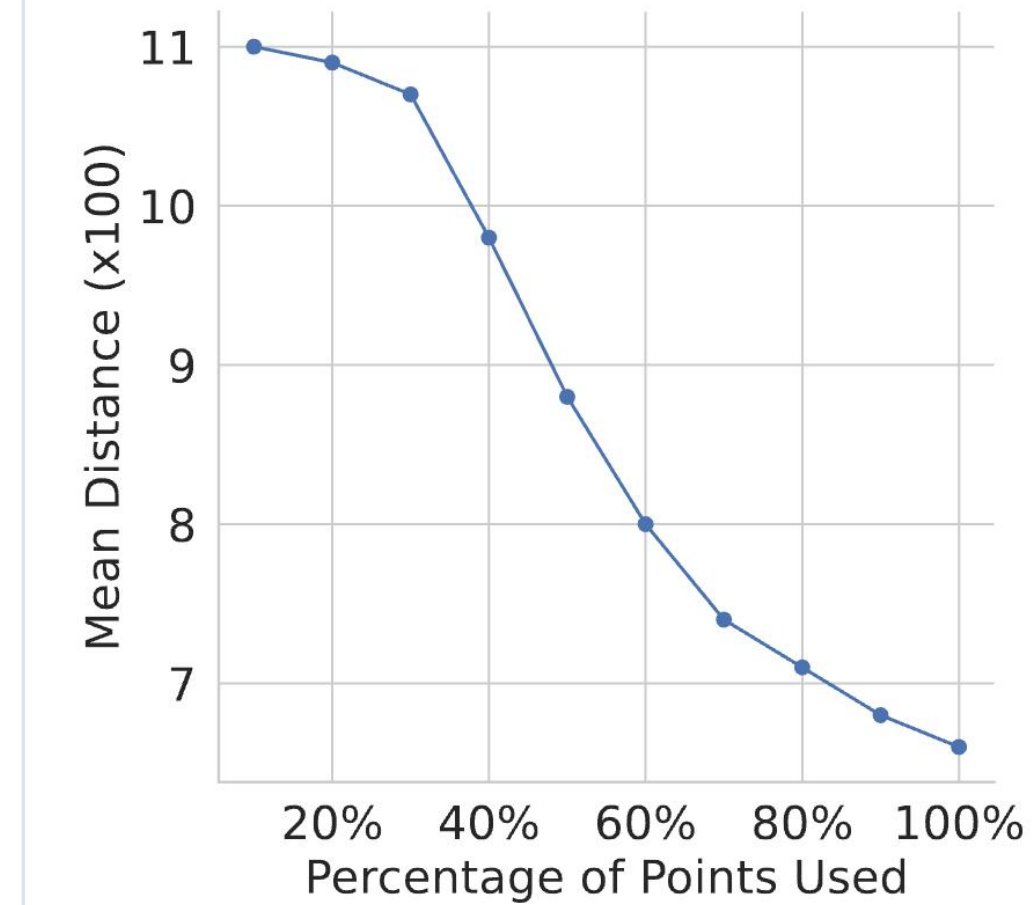
Running Time Comparison (512 × 512 Resolution)



Analysis

Effectiveness of region inputs

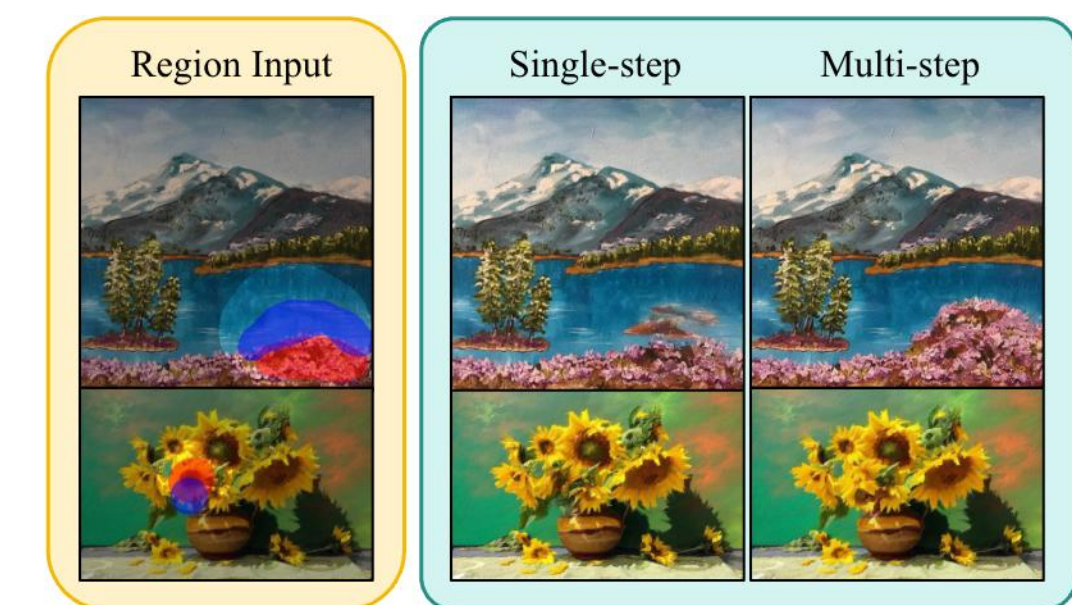
- Randomly sample different percentages of transformed points from each annotated region and conduct inference.



- Region-based inputs lead to superior results by providing stronger constraints than sparse points.

Effectiveness of multi-step copy-paste

- Copy-paste the image's latent representation across either multiple denoising timesteps or a single step.



- Initial single-step edits may be lost in subsequent denoising, leading to unpredictable results.
- Multi-step copy-paste provides guidance at smaller timesteps, preserving image fidelity.

Qualitative Results

RegionDrag achieves targeted modifications while maintaining image coherence.

