

华中科技大学
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FSI-Edit: Frequency and Stochasticity Injection for Flexible Diffusion-Based Image Editing

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2025-12-4

CONTENTS

- 1 Background
- 2 Methods
- 3 Experiments
- 4 Conclusion

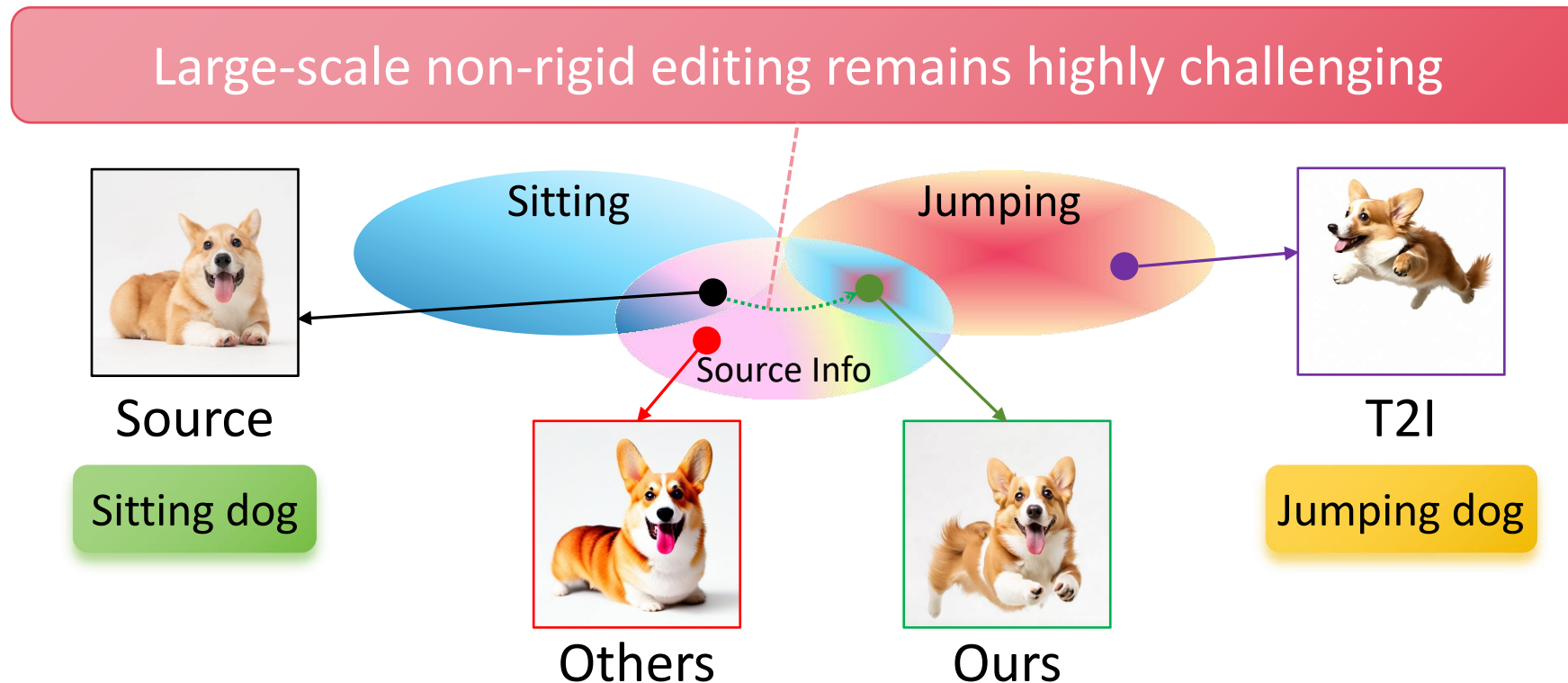
1.1 Image Editing

□ Image editing

modify *source image* according to *target textual prompt* while preserving the unedited regions

➤ Non-rigid editing

substantial modifications including *object addition, removal*, or *significant pose alteration*

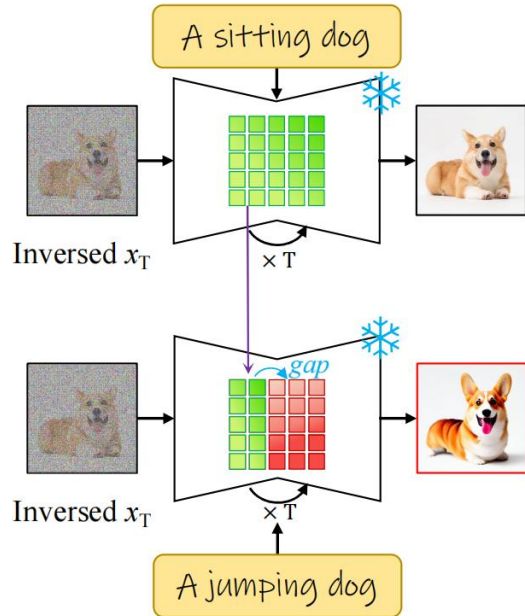


CONTENTS

- 1 Background
- 2 Methods**
- 3 Experiments
- 4 Conclusion

2.1 Limitation in previous methods

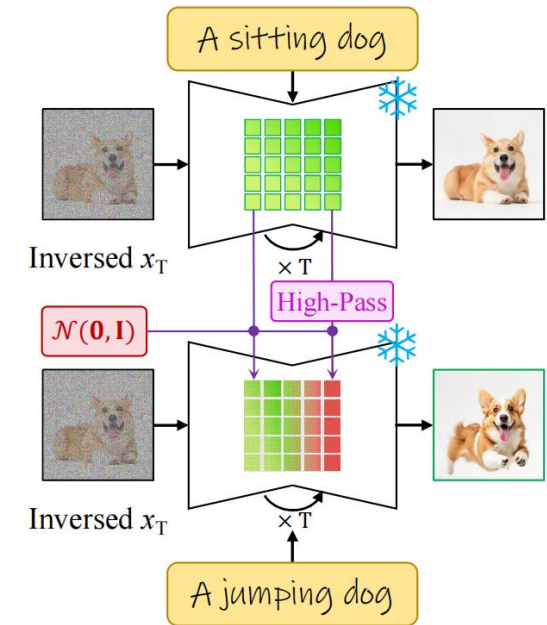
□ Editing Paradigm Comparison



✗ **Semantic gap:** directly inject attention features from the reconstruction branch to target branch

✗ **Constrained generative capacity:** excessive reliance on the source limits the model's ability to fully unleash its generative potential on non-rigid editing

- ✓ **Frequency residual fusion:** selectively inject high-frequency component from source, avoiding interference from structural information
- ✓ **Stochastic noise injection: controlled perturbation** enriches the latent space and empowers the model to perform substantial structural changes



2.2 Framework

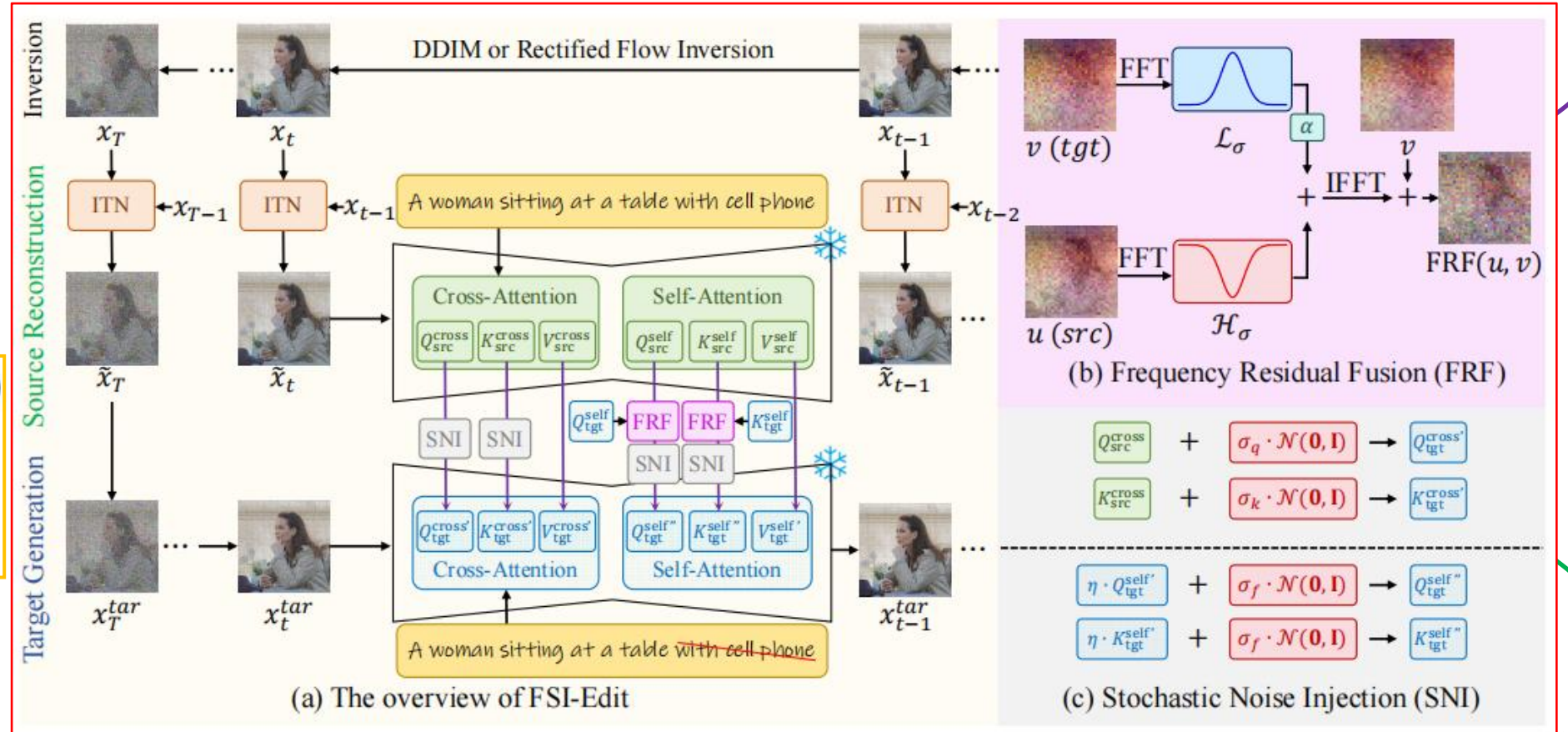
FSI-Edit

✓ **FRF**: Residual injection of *source high-frequency* details into the target

$$\mathcal{F}_{\text{fuse}} = \mathcal{H}_{\sigma} \cdot \text{FFT}(u) + \alpha \cdot \mathcal{L}_{\sigma} \cdot \text{FFT}(v)$$

✓ **ITN**: Fusing *low-frequency* guidance from *early timestep* to enhance reconstruction

$$\begin{aligned} \tilde{x}_t = & \text{IFFT}(\mathcal{H}_{\sigma} \cdot \text{FFT}(x_t) \\ & + \mathcal{L}_{\sigma} \cdot \text{FFT}(x_{t-1})) \\ & + \sigma_x \cdot \mathcal{N}(\mathbf{0}, \mathbf{I}) \end{aligned}$$



✓ **SNI**: Injecting *bounded noise* to unleash the generative cap-acity of the base model

$$K_{\text{tgt}}^{\text{cross}'} = K_{\text{src}}^{\text{cross}} + \sigma_k \cdot \mathcal{N}(\mathbf{0}, \mathbf{I})$$

$$Q_{\text{tgt}}^{\text{cross}'} = Q_{\text{src}}^{\text{cross}} + \sigma_q \cdot \mathcal{N}(\mathbf{0}, \mathbf{I})$$

CONTENTS

- 1 Background
- 2 Methods
- 3 Experiments**
- 4 Conclusion

3.1 Datasets

□ Dataset

1. PIE-Bench^[1]
2. 700 image-prompt pairs across 10 diverse editing categories



□ Metrics

➤ Structural Similarity

Structure Distance

➤ Content Preservation

PSNR, LPIPS, MSE, SSIM

➤ Text-Image Consistency

CLIP similarity

- **original_prompt:**

a slanted mountain bicycle on the road in front of a building

- **editing_prompt:**

*a slanted [**rusty**] mountain bicycle on the road in front of a building*

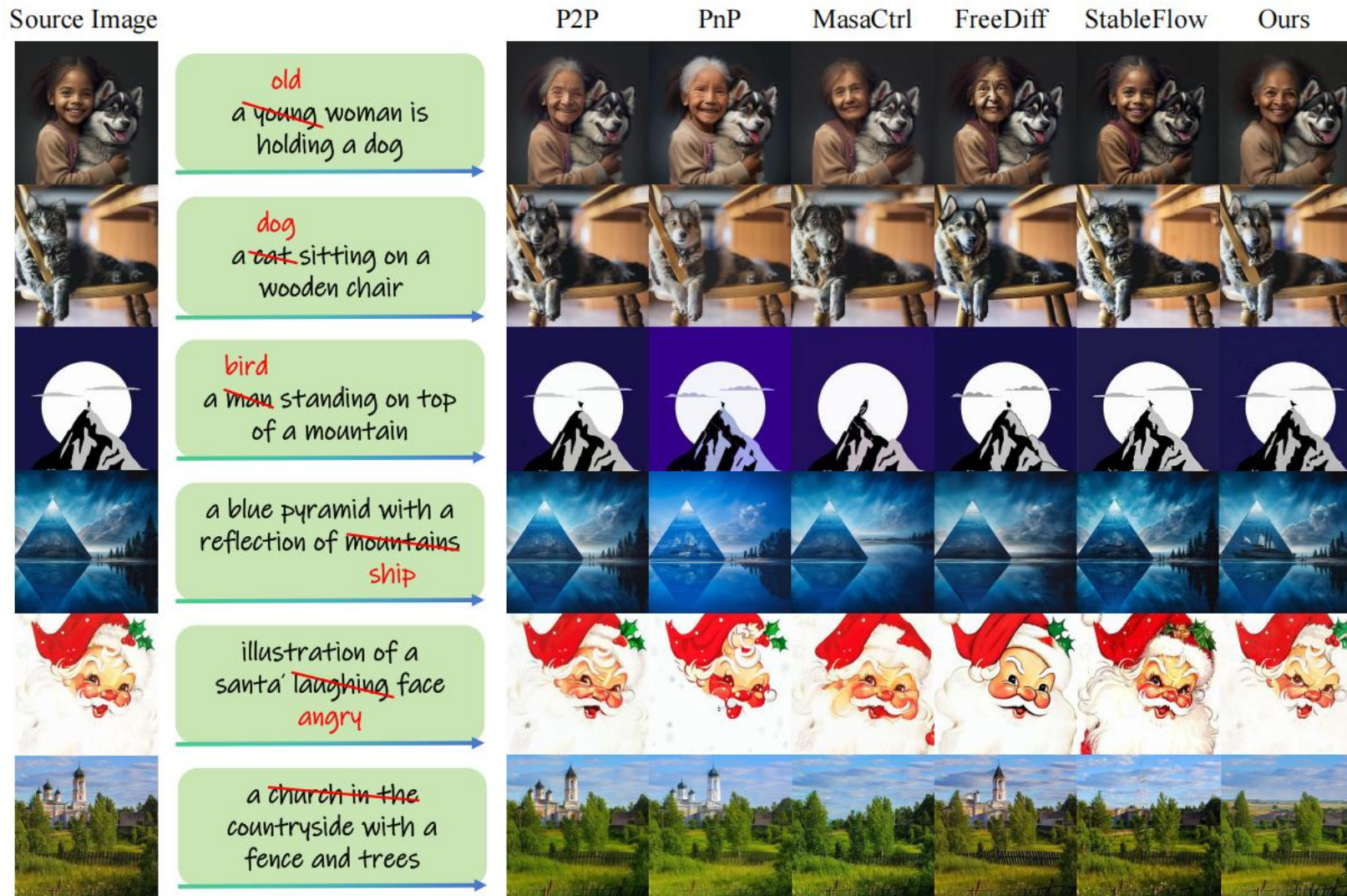
3.2 Comparison with SOTA

Method	Model	Structure	Background Preservation				CLIP Similarity	
		$Distance_{\times 10^3} \downarrow$	$PSNR \uparrow$	$LPIPS_{\times 10^3} \downarrow$	$MSE_{\times 10^4} \downarrow$	$SSIM_{\times 10^2} \uparrow$	$Whole \uparrow$	$Edited \uparrow$
P2P [8]	UNet	11.65	27.22	54.55	32.86	84.76	25.02	22.10
PnP [9]		24.29	22.46	106.06	80.45	79.68	<u>25.41</u>	<u>22.62</u>
MasaCtrl [19]		24.70	22.64	87.94	81.09	81.33	24.38	21.35
FlexiEdit [16]		22.13	<u>25.74</u>	<u>80.45</u>	58.45	<u>82.62</u>	25.15	22.87
FreeDiff [34]		18.70	24.73	89.76	55.32	81.68	25.03	22.12
Ours-LDM		<u>15.84</u>	24.69	88.42	<u>52.21</u>	81.93	25.46	22.30
RF-Inv [39]	Transformer	48.76	19.51	195.85	155.74	68.95	25.11	<u>22.50</u>
StableFlow [40]		<u>19.24</u>	23.04	76.94	84.85	87.22	24.30	21.28
RF-Edit [31]		24.45	24.41	113.44	56.46	83.84	25.03	22.28
DCEdit [33]		22.36	<u>25.41</u>	94.17	<u>48.09</u>	85.60	<u>25.47</u>	22.71
Ours-DiT*		13.71	26.61	<u>85.44</u>	36.50	<u>86.25</u>	25.69	<u>22.50</u>

*: Ours runs on an RTX 4090 GPU (24 GB memory) and completes within 20 seconds.

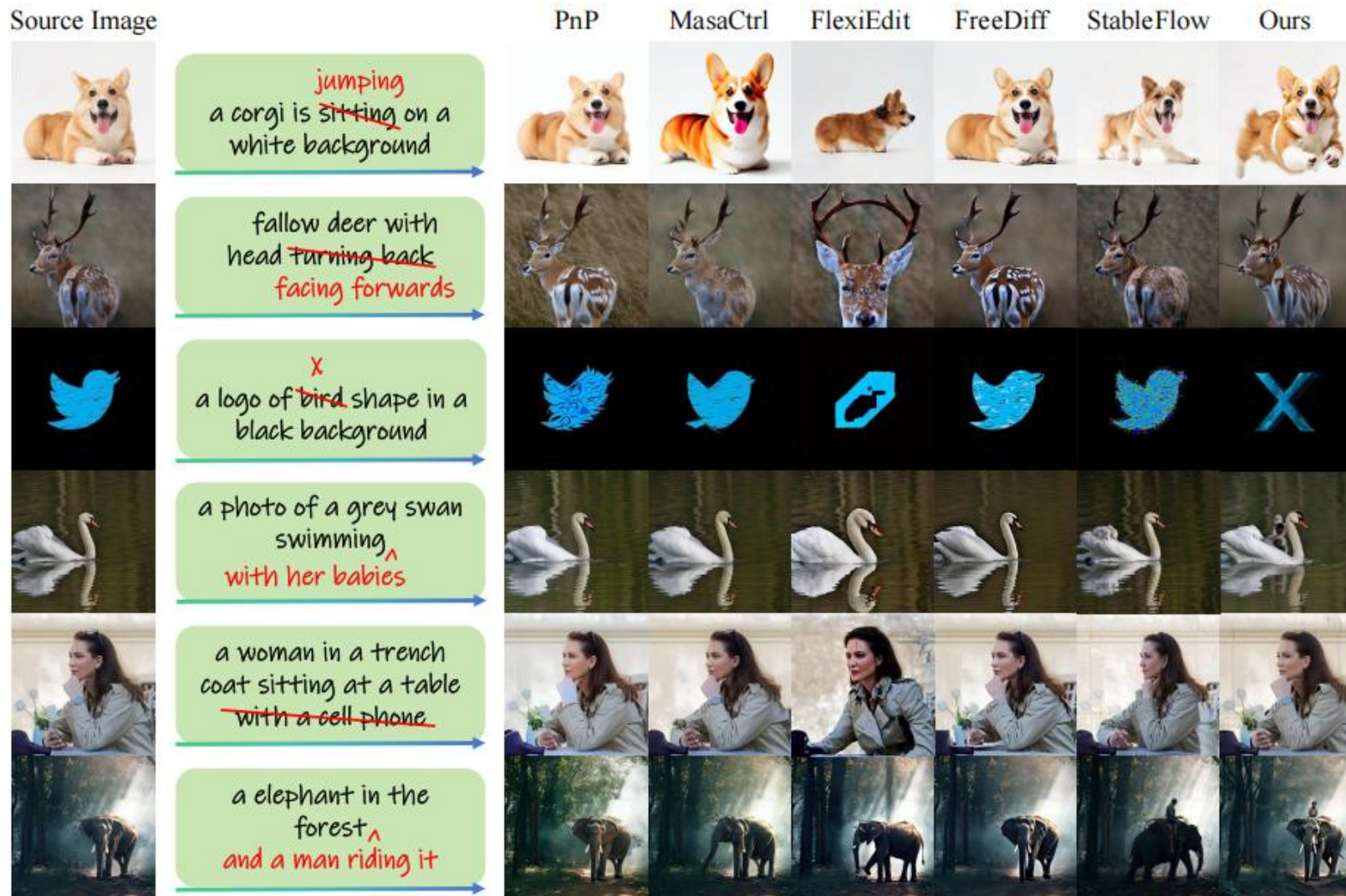
★ The results show that our method better balances background fidelity in unedited areas and semantic consistency in edited regions.

3.3 Visualization



✦ Our edited images visually align better with the given editing instructions, producing more satisfactory visual results.

3.3 Visualization



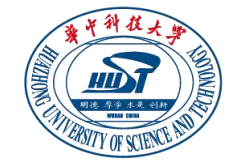
✦ Our method achieves superior visual quality in non-rigid editing tasks.

CONTENTS

- 1 Background
- 2 Methods
- 3 Experiments
- 4 Conclusion**

4 Conclusion

- We identify and address two core limitations of most current image editing methods for non-rigid edits, e.g., semantic inconsistency between reconstruction and generation features, and insufficient generative flexibility due to strong image priors.
- We propose FSI-Edit, featuring a new frequency residual fusion module that selectively transfers high-frequency details for more accurate feature alignment, and a stochastic noise injection strategy that expands the generation space to enable more precise and flexible structural transformations.
- We conduct extensive experiments on PIE-Bench benchmark, and the comparison results demonstrate that FSI-Edit significantly outperforms existing methods on both rigid and non-rigid editing tasks, confirming its effectiveness and generalizability across diverse editing scenarios.



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Thank you

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