



PixelMan@AAAI2025
liyaojiang1998.github.io

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PixelMan: Consistent Object Editing with Diffusion Models via Pixel Manipulation and Generation

Liyao Jiang^{1,2}, Negar Hassanpour², Mohammad Salameh², Mohammadreza Samadi², Jiao He³, Fengyu Sun³, Di Niu¹
¹Dept. ECE, University of Alberta ²Huawei Technologies Canada ³Huawei Kirin Solution

Background

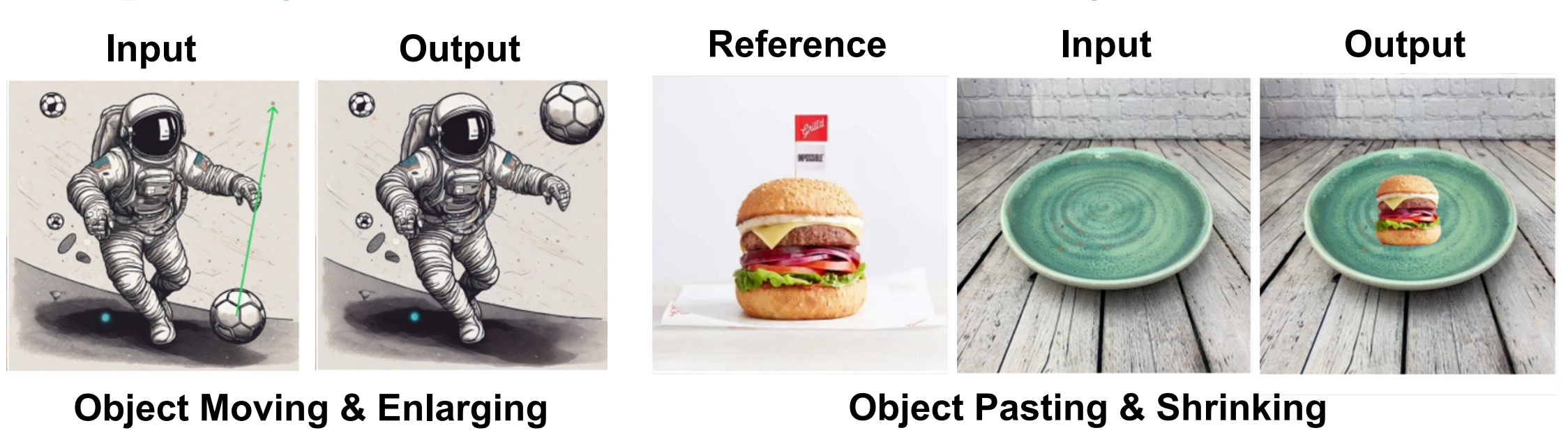
Promising results in **text-guided rigid image editing** (i.e., editing color, texture, attributes, and style)

Our focus: consistent object editing

- Preserve consistency for object and background
- Only edit **non-rigid object attributes** (e.g., position, size, composition)
- **Applications:** object repositioning (moving), resizing, pasting

A challenging task involving multiple sub-tasks

1. Faithful reproduction at the target location
2. Maintain background scene details
3. Seamless harmonization of new object and its surrounding
4. **Inpainting** the vacated area with cohesive background



Methodology

1. Three-branched inversion-free sampling

- Pixel manipulation: **preserve consistency**
- Inversion-free: **improve efficiency**

Three-branches:

- a) **Pixel-manipulated branch:** copy to target location in pixel space
- b) **Target branch:** anchor target latents to pixel-manipulated latents at each step
- c) **Source branch:** preserve clean K, V as context to enhance harmonization (e.g., lighting, shadow, edge blending)

2. Editing guidance techniques

$$z_0^{\text{out}} = z_0^{\text{man}} + (z_0^{\text{tgt}} - z_0^{\text{man}}) \times (1 - m_{\text{new}})$$

Output = Anchor + Delta Edit Direction x Mask

Generation: find delta edits for **harmonization and inpainting** on top of the anchor

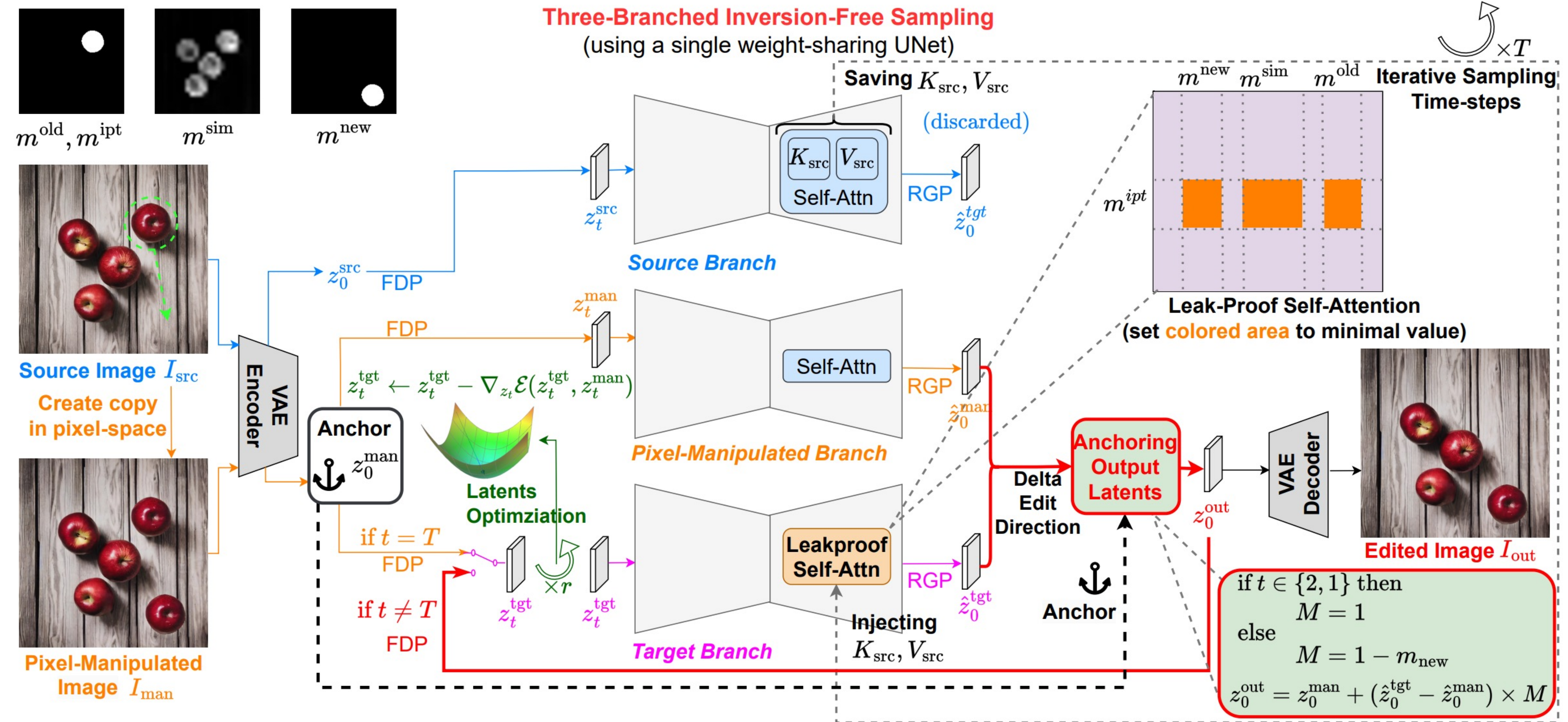
- a) Use energy functions with **latents optimization** (updates z instead of ϵ), reducing NFE
- b) **Injection of source K, V** into the target branch
- c) Apply **leak-proof self-attention** in target branch

3. Leak-proof self-attention

To achieve **complete and cohesive inpainting**

- Root cause of inpainting failure
 - **Information leakage** from similar objects through self-attention
- **Leak-proof self-attention:** prevent attention to source, target, and similar objects
 - Set the corresponding QK^T elements to minimal values

Three-Branched Inversion-Free Sampling (using a single weight-sharing UNet)



Challenges

1. **Low efficiency**
 - Rely on inversion, requiring many (e.g., at least 50) steps
 - Compromising quality when steps are reduced
2. **Low object and background consistency**
 - Altered object identity, inconsistent background
3. **Incomplete & incoherent inpainting**
 - Fail to inpaint vacated area with cohesive background

Results

PixelMan improves editing quality

- **Object is consistent** to the source (attributes and identity)
- **Background is preserved** after editing (texture and color)
- Original object is **inpainted with cohesively background**

While having better efficiency

- PixelMan@16 steps outperforms other methods@50steps
 - Reduce latency: 24s -> 9s; Reduce #NFEs: 176 -> 64
- Consistently outperform other methods when using the same #Steps (at 8,16,50 steps)

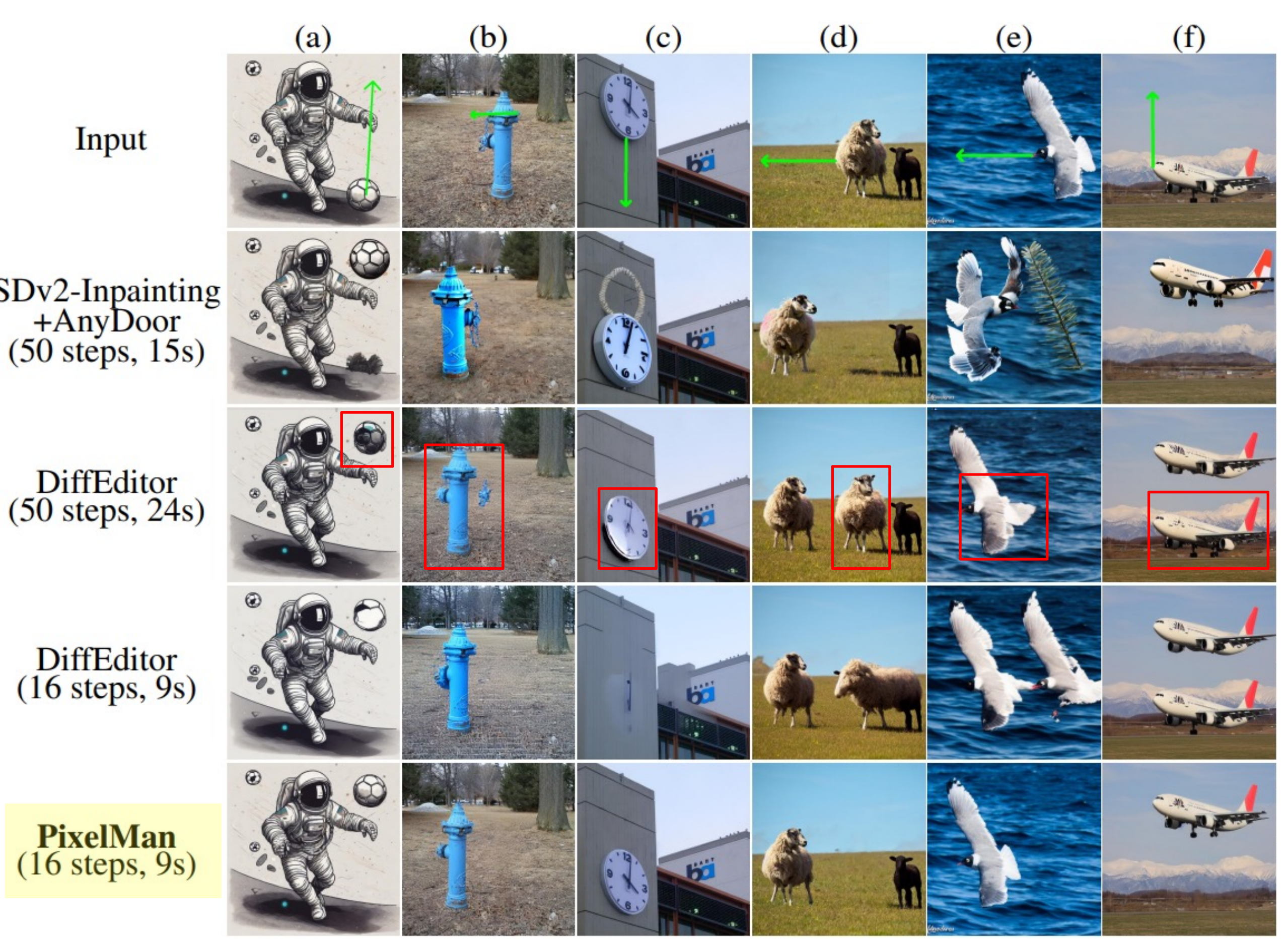
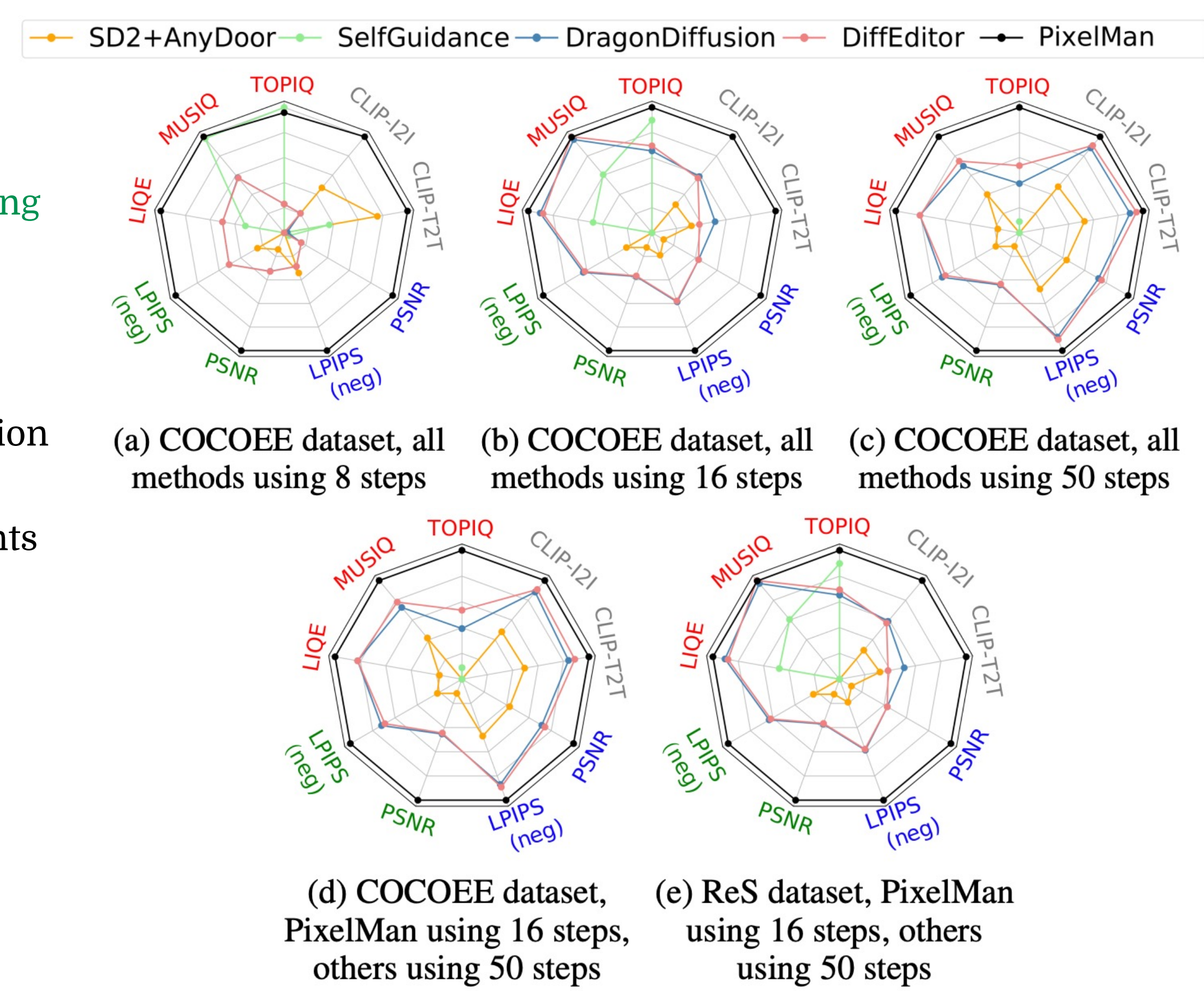


Figure: Visual comparison examples (on COCOEE dataset).



Quantitative Evaluation Aspects:
IQA, Object Consistency, Background Consistency, Semantic Consistency

Conclusion

- PixelMan is an **inversion-free** and **training-free** method
 - Achieve high-quality consistent object editing
 - Improve **editing quality** and enables **faster editing**
 - Surpass methods requiring 50 steps with only 16 steps
- Superior performance in object, background, and semantic consistency metrics on COCOEE and ReS datasets
- Achieve higher or comparable overall image quality while reducing latency