

# ScaleDiff:

## Higher-Resolution Image Synthesis via Efficient and Model-Agnostic Diffusion

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Challenge

## Text-to-Image diffusion model at higher resolution



SDXL (1024x1024)



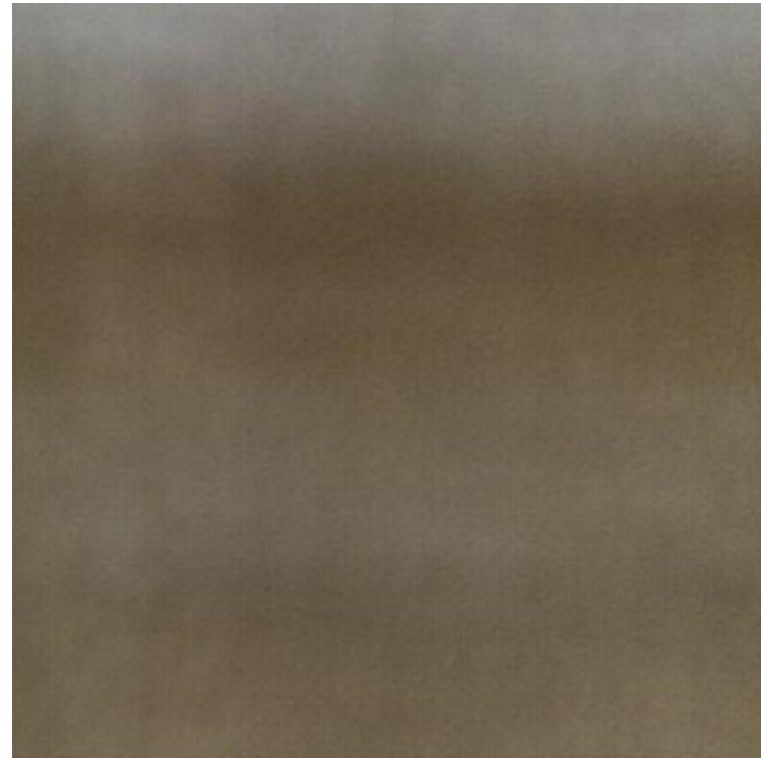
FLUX (1024x1024)

## Text-to-Image diffusion model at higher resolution

- U-Net: Exhibit **repetitive artifacts** and loss of global structure yet retain the capacity to generate local details.
- DiT: Demonstrate complete failure in generating **both global structure and local detail** at higher resolutions.



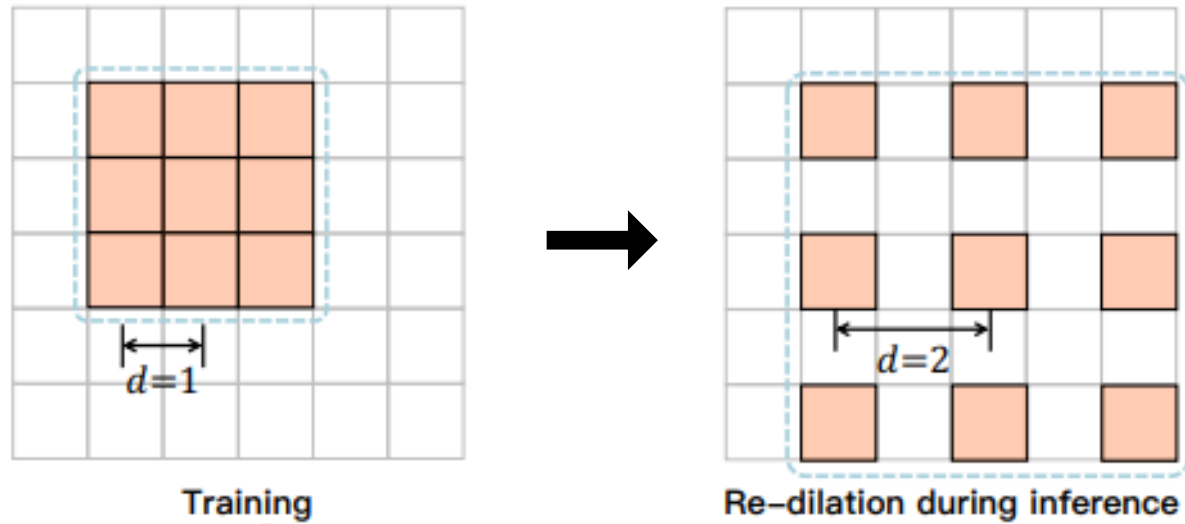
SDXL (4096x4096)



FLUX (4096x4096)

## Dilated convolution-based methods

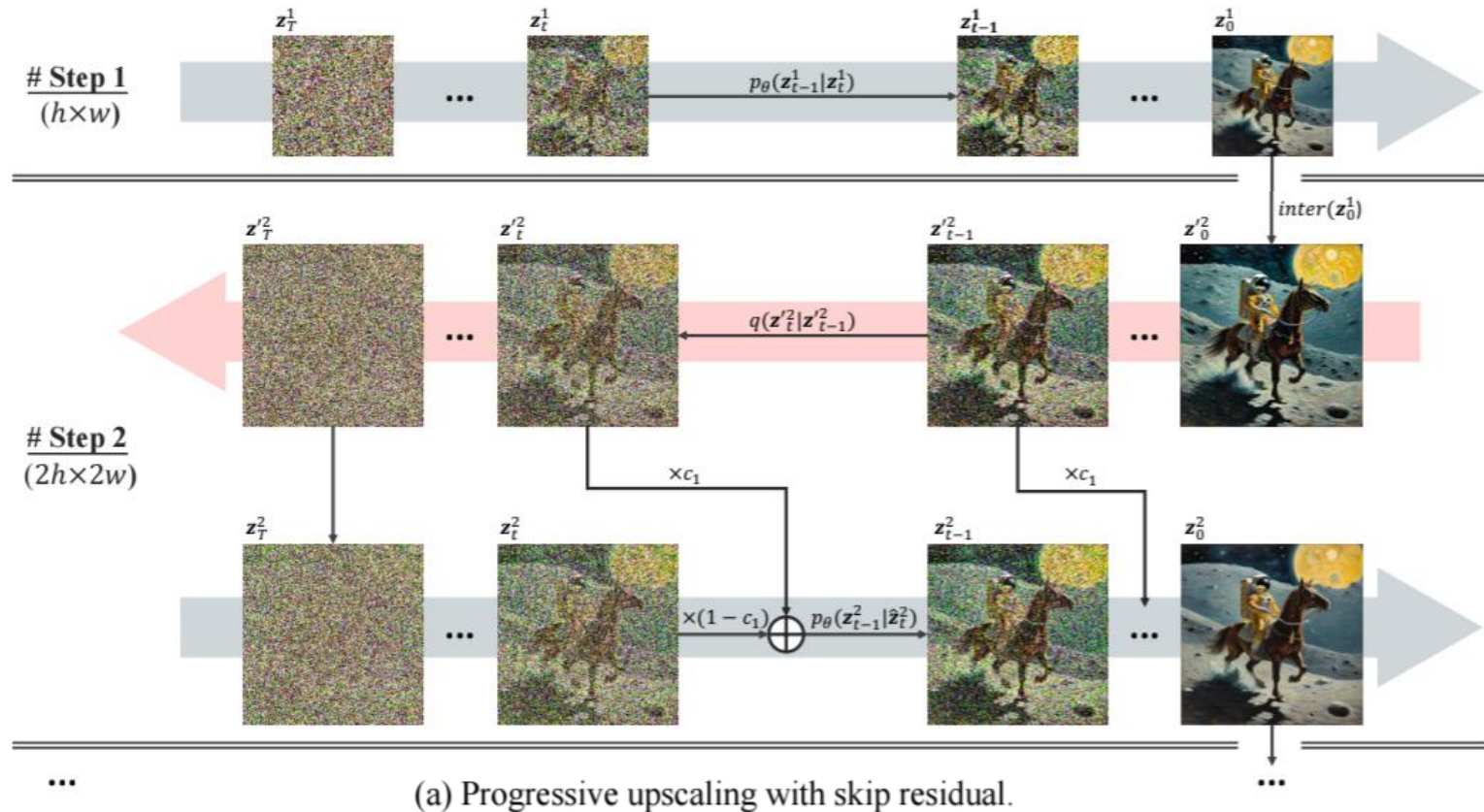
- Limited Receptive field of convolutional layer causes repetitive artifacts.
- Use dilated convolution to expand receptive field.
- **Only compatible with U-Net architectures.**





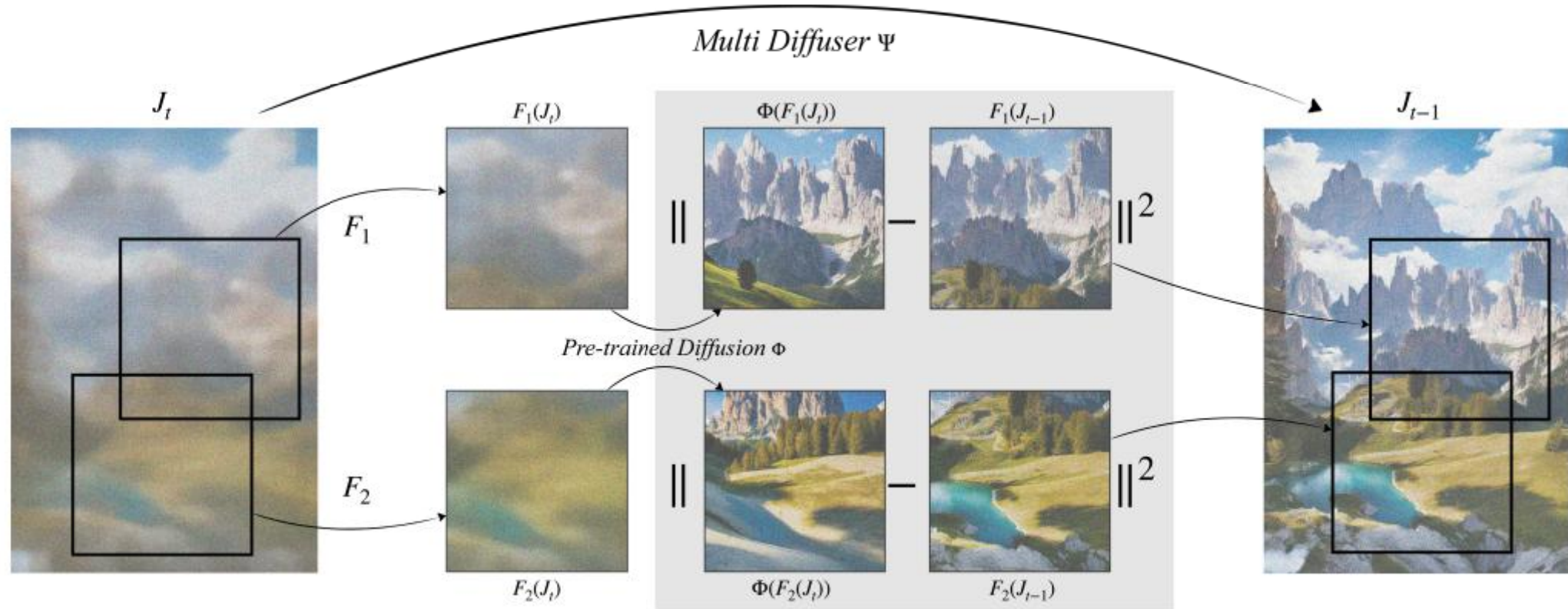
## SDEdit-based methods

- Upsample low resolution image  $\rightarrow$  diffuse  $\rightarrow$  denoise
- **Relies on local detail generation capability**, which pretrained DiT lacks at high resolution.



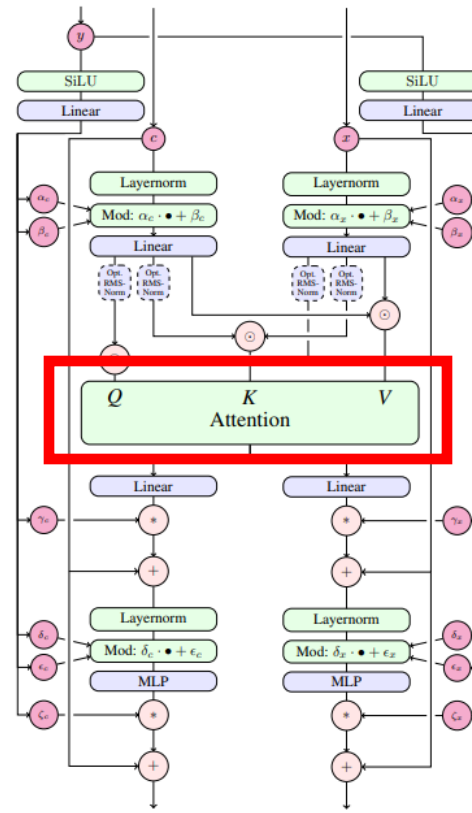
## Patch-based methods

- Divide high resolution canvas into overlapping low-resolution patches.
- Independently denoise each patch and combine their outputs.
- **Massive computational redundancy** due to necessary overlap to ensure smooth transition across patch boundary.



# Neighborhood Patch Attention (NPA)

- Only self-attention (with positional encoding) is directly affected by resolution increase
- Non-self-attention layers (MLP, CNN, Cross-Attn) perform operations on individual tokens or local regions.

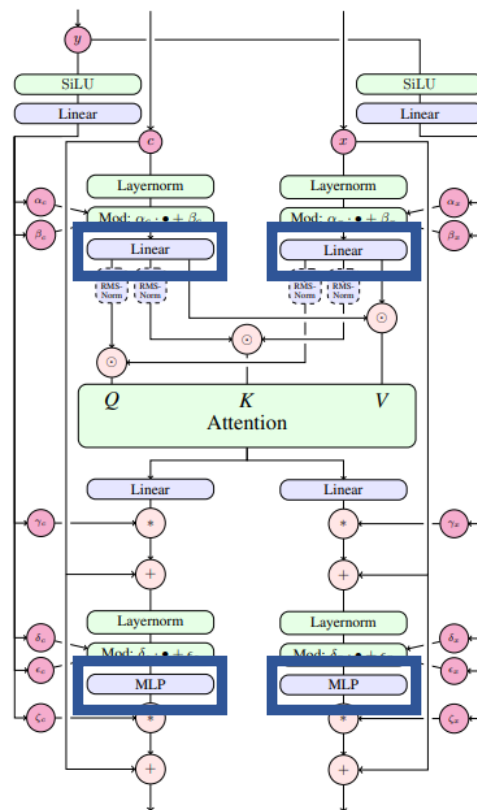


(b) One MM-DiT block

Patch based processing only in self-attention

# Neighborhood Patch Attention (NPA)

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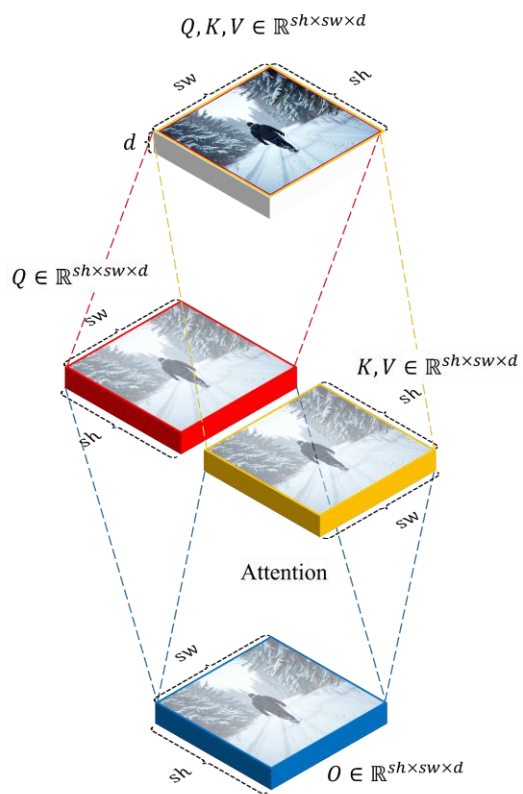
Process full high-resolution tensor in a single pass.

(b) One MM-DiT block

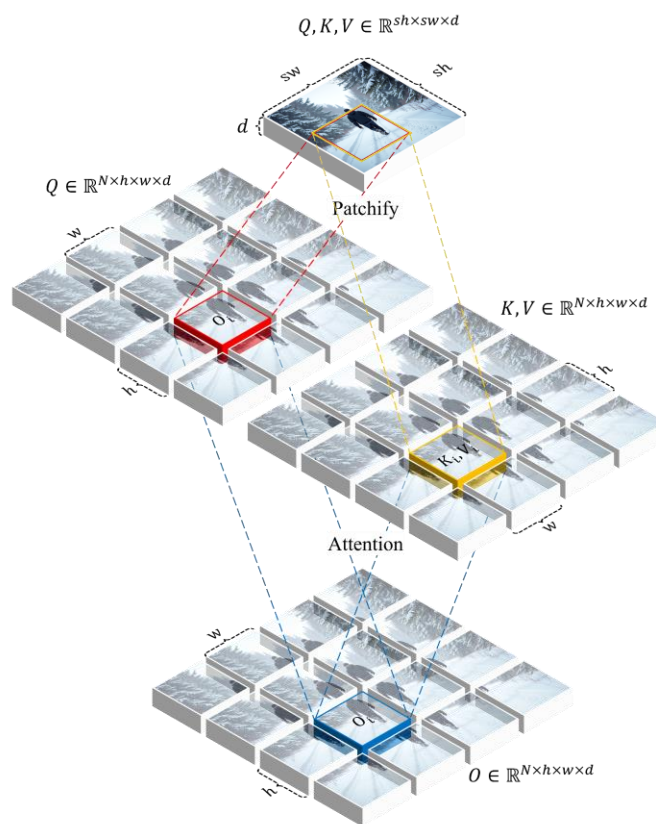


# Neighborhood Patch Attention (NPA)

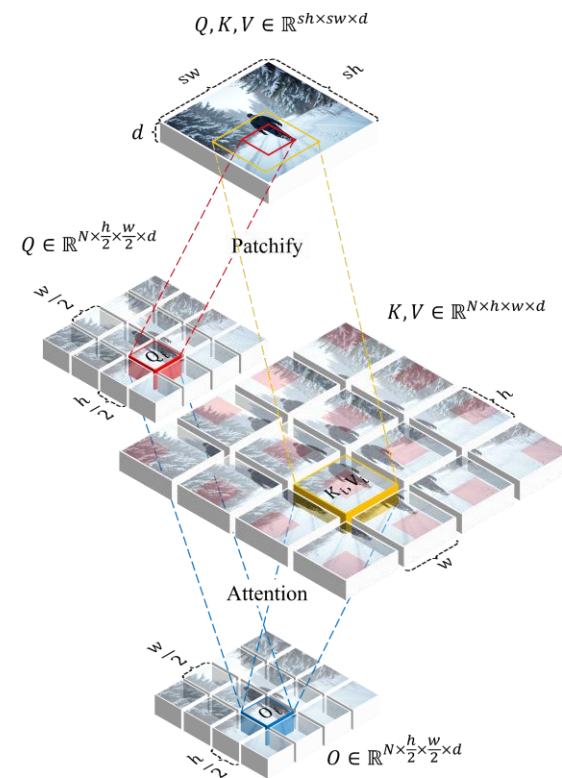
- **Non-overlapping** query patches  $\rightarrow$  eliminate redundant computation.
- Extract **overlapping** key-value patch from query's **spatial neighborhood**.
- Overlap between these patches allows every query patch to attend to a wider context, ensuring smooth transitions.



Base



Multidiffusion



NPA (Ours)

## Neighborhood Patch Attention (NPA)

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- Extract **overlapping** key-value patch from query's **spatial neighborhood**.
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Method	Linear	Conv	Cross-Attn	Self-Attn
Base	$s^2 h w d^2$	$s^2 h w k^2 d^2$	$s^2 h w l d$	$s^4 h^2 w^2 d$
MultiDiffusion	$(2s - 1)^2 h w d^2$	$(2s - 1)^2 h w k^2 d^2$	$(2s - 1)^2 h w l d$	$(2s - 1)^2 h^2 w^2 d$
NPA(Ours)	$s^2 h w d^2$	$s^2 h w k^2 d^2$	$s^2 h w l d$	$s^2 h^2 w^2 d$

## ScaleDiff Upscaling Pipeline

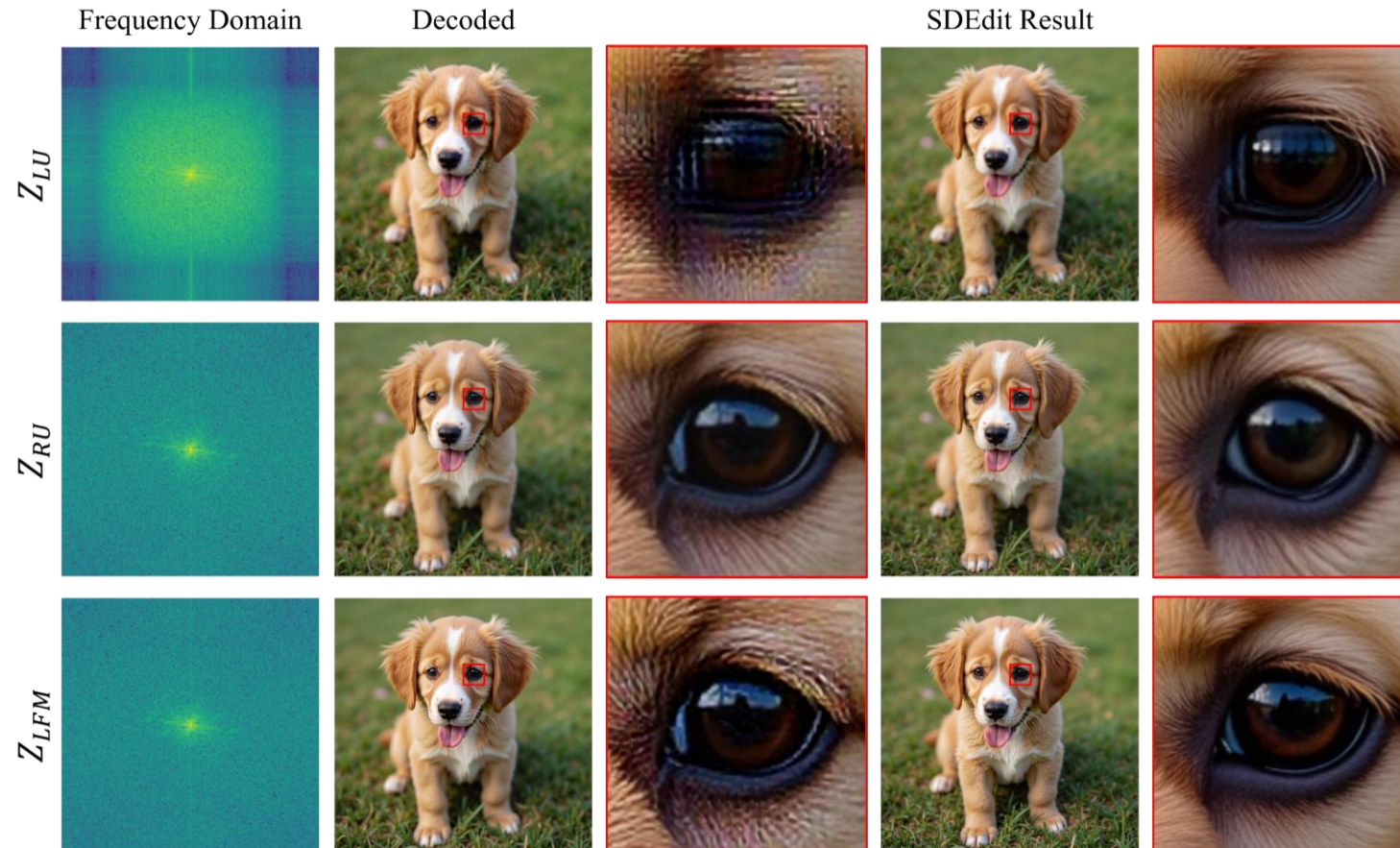
- Integrate NPA into **SDEdit** pipeline.
- Starting from low resolution image, Upample  $\rightarrow$  Diffuse  $\rightarrow$  Denoise.





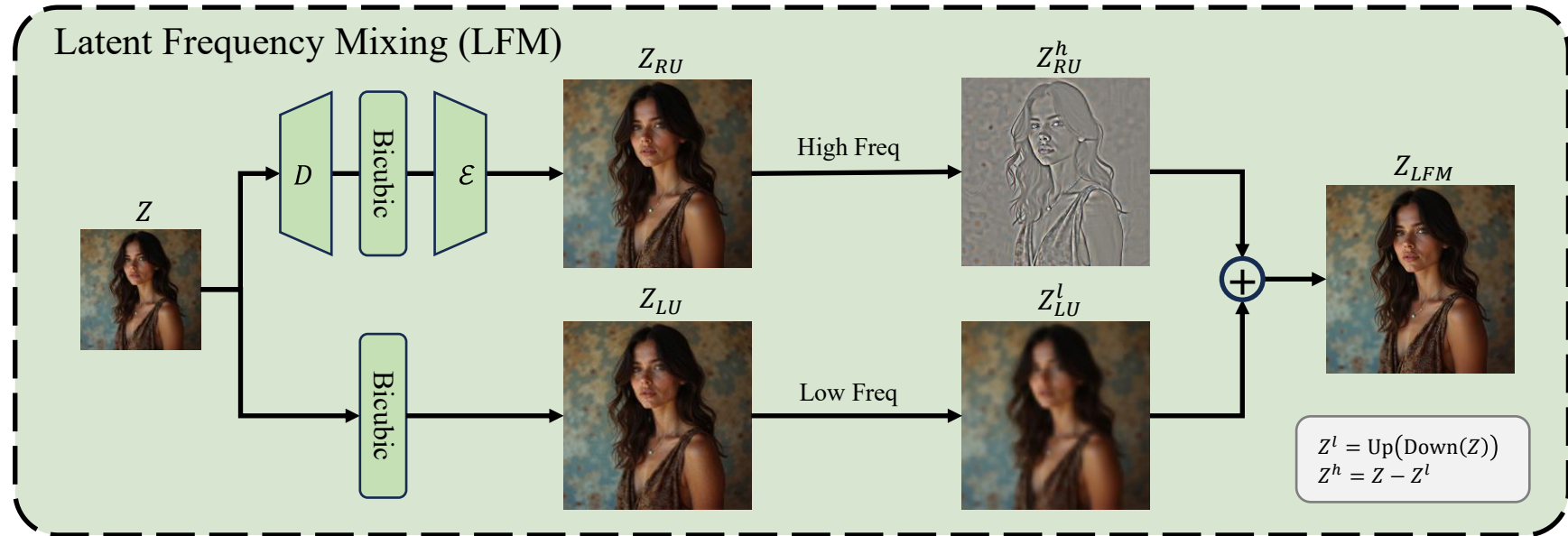
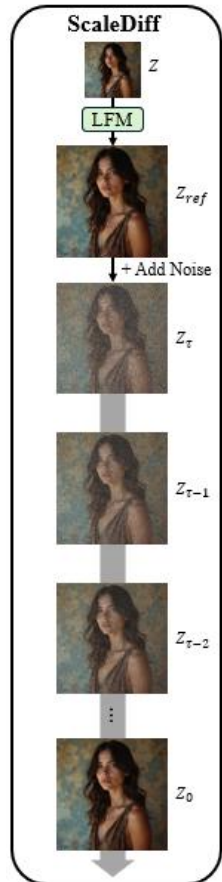
# Latent Frequency Mixing (LFM)

- Upsample in Latent-Space ( $Z_{LU}$ ) : Lack of high frequencies → **decoding artifacts**. No oversmoothing bias.
- Upsample in RGB-Space ( $Z_{RU}$ ) : Biases the model toward **oversmoothed** results. No decoding artifacts



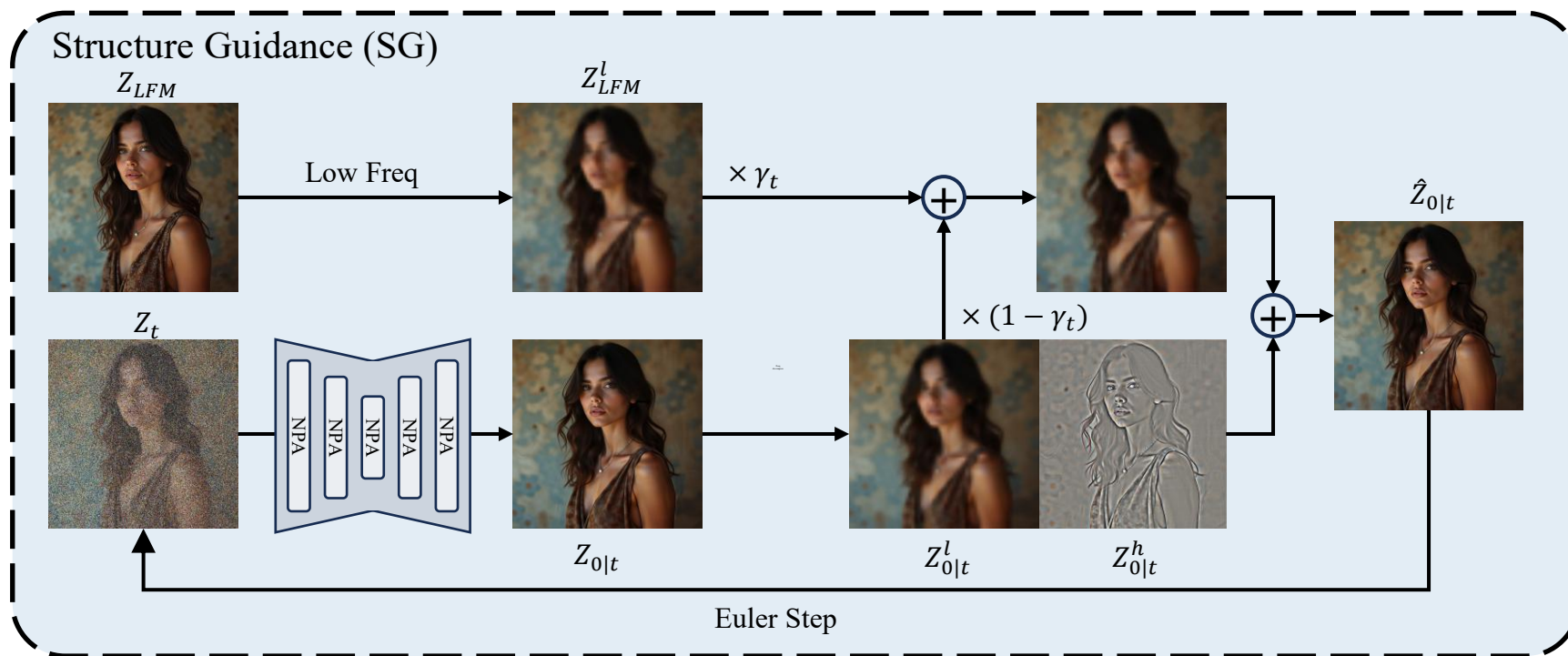
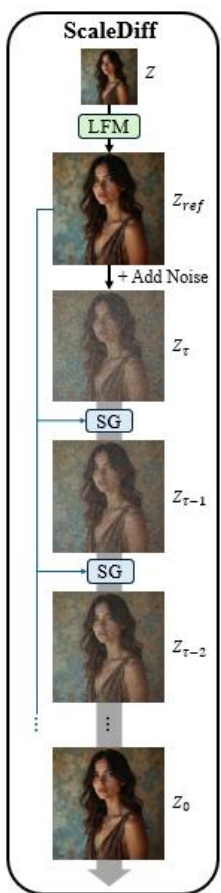
# Latent Frequency Mixing (LFM)

- $Z_{ref} = Z_{LU}^l + Z_{RU}^h$
- **Low-frequency** components are obtained from  $Z_{LU}$  to alleviate oversmoothing bias.
- While **high-frequency** components are utilized from  $Z_{RU}$  to avoid decoding artifacts..



# Structure Guidance (SG)

- $\hat{Z}_{0|t} = Z_{0|t}^h + (1 - \gamma_t)Z_{0|t}^l + \gamma_t Z_{ref}^l$
- Guide **low-frequency components** to the reference to enforce global structural consistency.



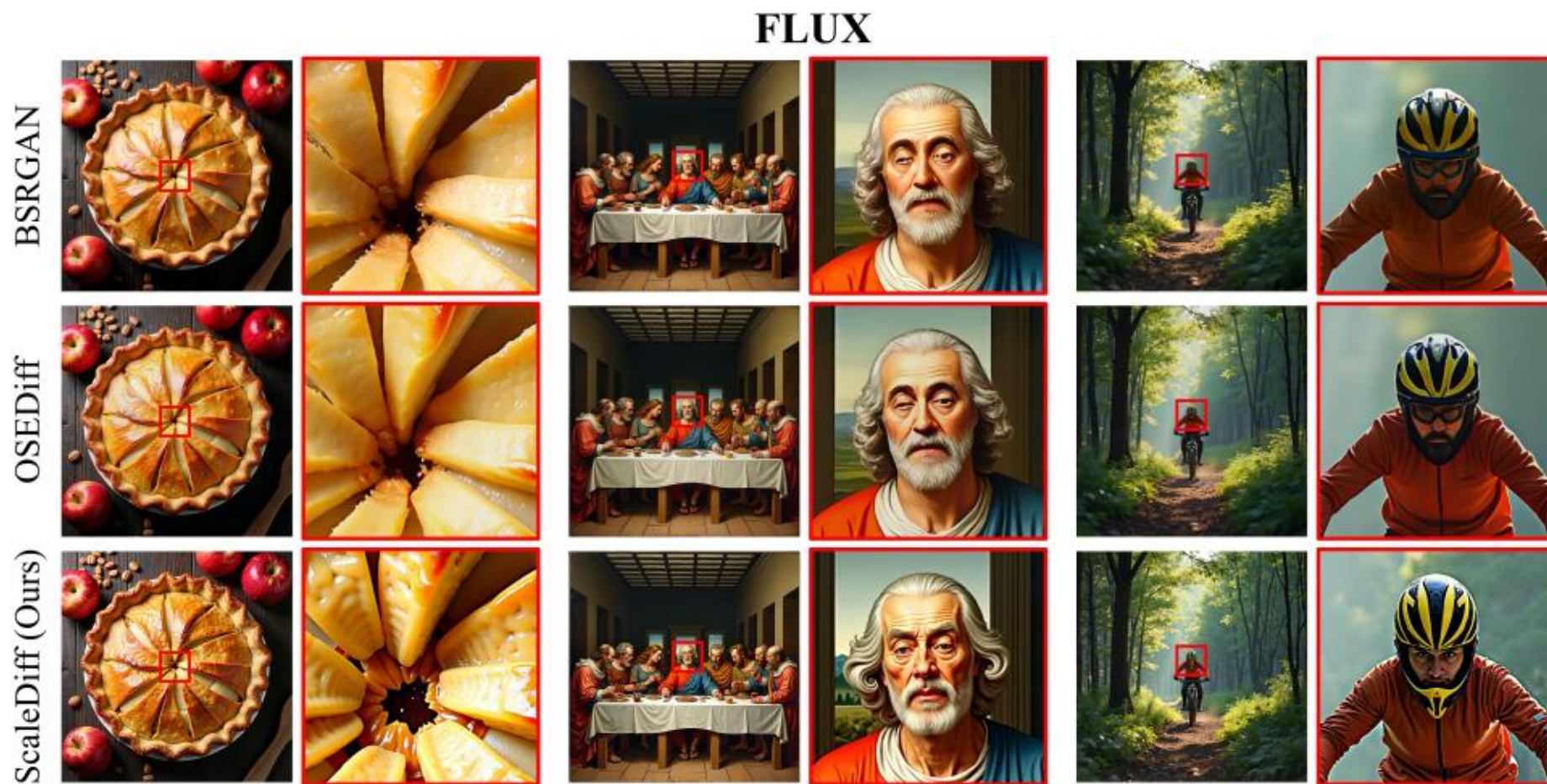


# Qualitative Comparison

		SDXL					
	OSDiff						
	DemoFusion						
	Diffusehigh						
	FreeScale						
	ScaleDiff (Ours)						



## Qualitative Comparison



## Quantitative Comparison

Model	Resolution	Method	FID ↓	KID ↓	IS ↑	FID <sub>p</sub> ↓	KID <sub>p</sub> ↓	IS <sub>p</sub> ↑	CLIP ↑	Time ↓
SDXL	2048 <sup>2</sup>	SDXL Direct	88.56	0.0124	13.25	58.73	0.0137	20.79	31.57	47
		SDXL + BSRGAN	64.60	0.0041	18.40	41.40	0.0092	23.19	33.03	<b>13</b>
		SDXL + OSEDiff	64.79	0.0046	18.89	41.76	0.0094	23.58	<u>32.79</u>	<u>29</u>
		UltraPixel	64.61	0.0056	18.58	42.44	0.0093	25.15	32.61	71
		ScaleCrafter	68.68	0.0033	16.56	43.46	0.0064	23.52	32.07	64
		HiDiffusion	69.52	0.0040	18.22	42.92	0.0067	24.01	31.50	33
		DiffuseHigh	<u>63.27</u>	0.0033	19.10	38.15	0.0062	24.95	32.77	45
		FreeScale	63.50	<b>0.0031</b>	19.06	38.27	<u>0.0062</u>	24.25	32.62	69
		AccDiffusion v2	64.86	0.0039	18.37	38.24	0.0068	25.66	32.62	199
		Demofusion	63.36	0.0032	<u>19.15</u>	<b>35.98</b>	<b>0.0050</b>	<b>26.42</b>	32.72	125
		ScaleDiff (Ours)	<b>62.98</b>	<u>0.0032</u>	<b>19.54</b>	<u>38.03</u>	0.0067	<u>25.70</u>	<b>33.11</b>	31
	4096 <sup>2</sup>	SDXL Direct	182.05	0.0717	7.99	80.80	0.0250	17.68	27.82	328
		SDXL + BSRGAN	64.88	0.0044	18.16	48.97	0.0160	17.04	<u>33.02</u>	<b>14</b>
		SDXL + OSEDiff	65.35	0.0045	18.69	45.67	0.0118	17.61	32.88	122
		UltraPixel	65.39	0.0055	19.08	47.09	0.0112	<b>20.64</b>	32.33	386
		ScaleCrafter	86.66	0.0110	15.14	79.39	0.0217	14.47	30.25	932
		HiDiffusion	105.37	0.0216	13.87	112.30	0.0494	12.22	27.21	124
		DiffuseHigh	<u>63.91</u>	<u>0.0034</u>	18.99	42.30	0.0079	19.54	32.68	325
		FreeScale	64.33	0.0036	<u>19.18</u>	<u>39.56</u>	<b>0.0079</b>	18.91	32.56	517
		AccDiffusion v2	64.64	0.0037	18.56	40.92	0.0083	18.42	32.34	1599
		Demofusion	65.06	0.0041	19.13	41.29	<u>0.0079</u>	19.59	32.61	1005
		ScaleDiff (Ours)	<b>61.87</b>	<b>0.0025</b>	<b>19.56</b>	<b>38.89</b>	0.0080	<u>20.41</u>	<b>33.04</b>	<u>113</u>



# ScaleDiff:

## Higher-Resolution Image Synthesis via Efficient and Model-Agnostic Diffusion

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Code Available

