FlowIE: Efficient Image Enhancement via Rectified Flow

CVPR 2024 Oral

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FlowIE: Background

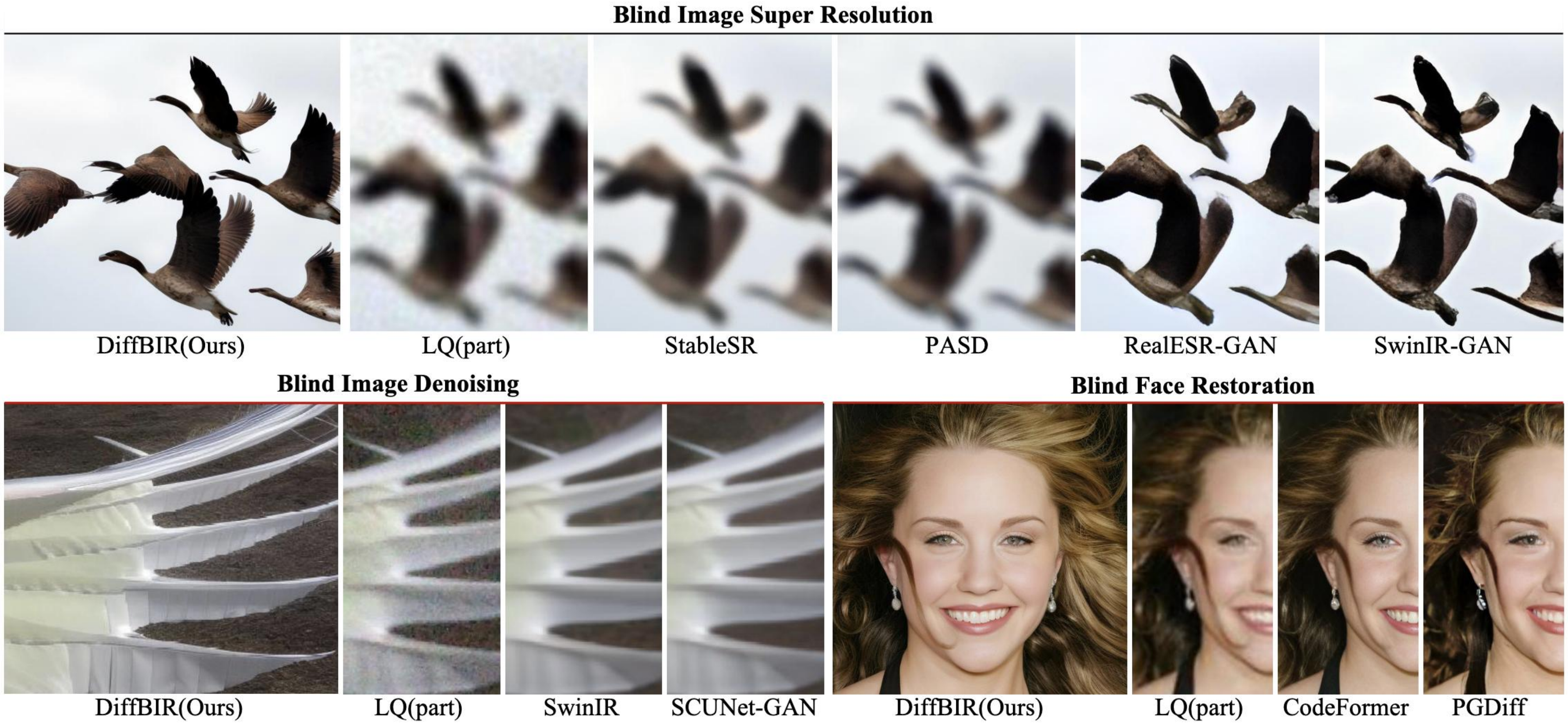
北京大學 PEKING UNIVERSITY

- Deep learning has shown strong power in image enhancement

	Model	Task	Limitation
Conventional Methods	BSRGAN	Blind image super-resolution	Generalization
	GFPGAN	Blind face restoration	Generalization
	RestoreFormer	Blind face restoration	Generalization
	CodeFormer	Blind face restoration	Generalization
Diffusion-based methods	SRDiff	Blind image super-resolution	Generalization
	DiffBIR	Blind face restoration Blind image denoising Blind image super-resolution	Inference speed

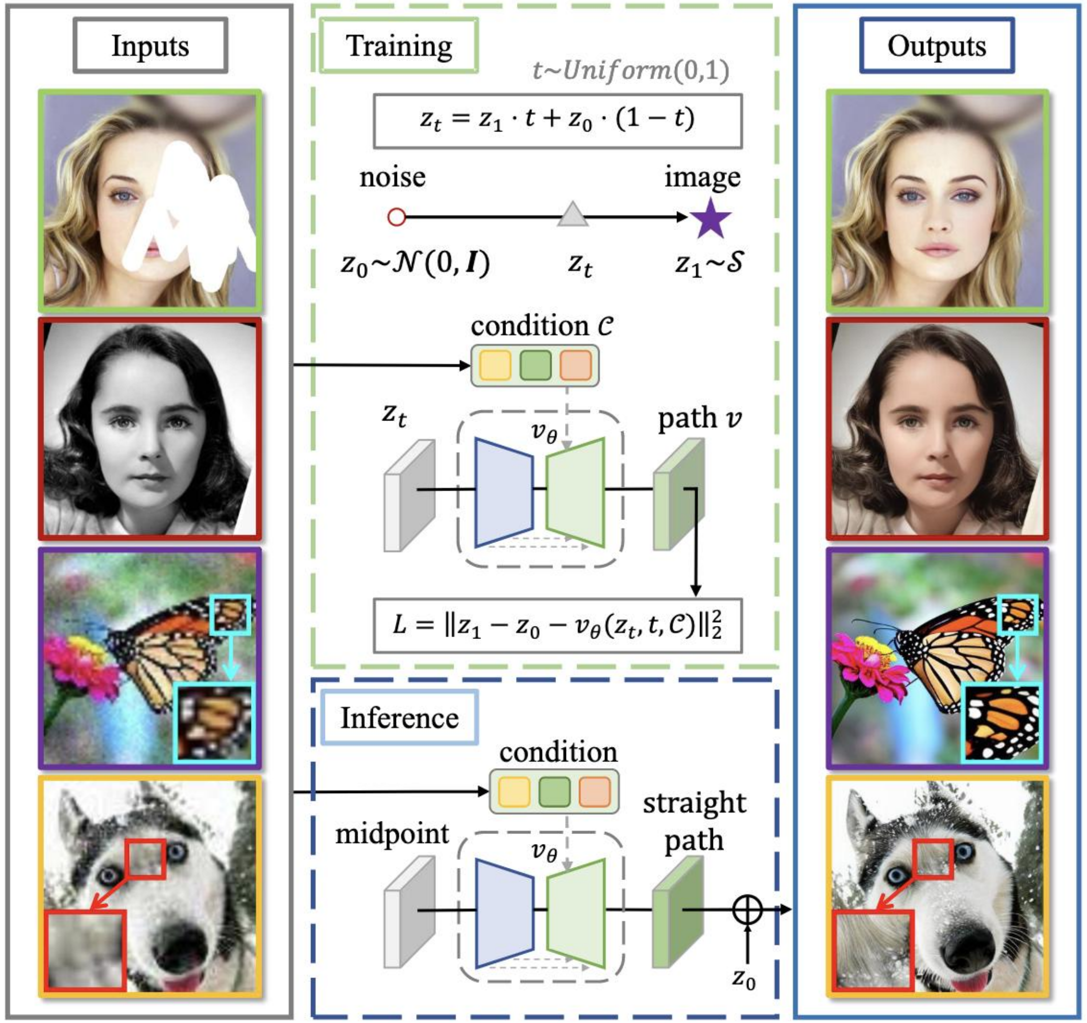
DiffBIR: Towards Blind Image Restoration with Generative Diffusion Prior

Xinqi Lin, Jingwen He, Ziyan Chen, Zhaoyang Lyu, Bo Dai, Fanghua Yu, Wanli Ouyang, Yu Qiao, Chao Dong



FlowIE: Overview

- **Task:**
  - Generalization capability
  - Less inference time cost
- **Overview:**
  - Apply conditioned Rectified Flow to diffusion models
  - Use mean value sampling
- **Performance:** surpass DiffBIR in inference speed and image details



Background: Diffusion Model

- Learn a noise predictor to gradually denoise a Gaussian distribution into a given distribution

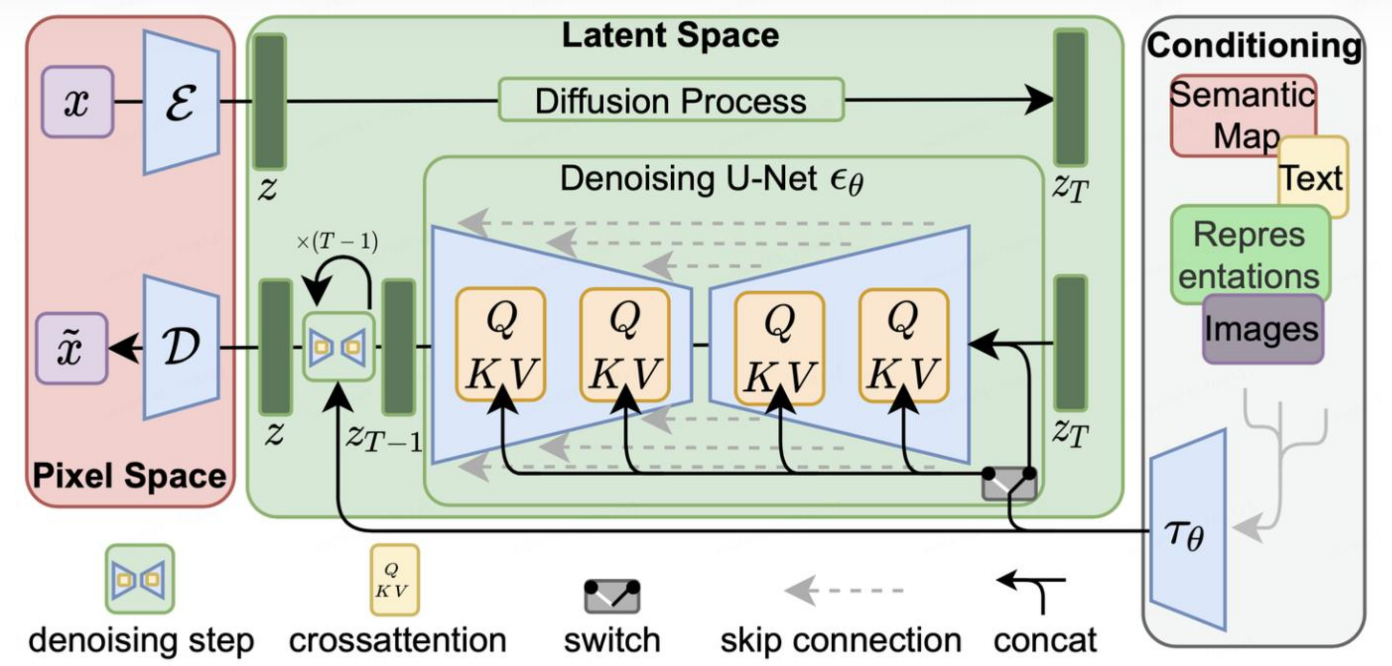
- **Forward:** $x_t = \sqrt{\overline{\alpha_t}} x_0 + \sqrt{1 - \overline{\alpha_t}} \cdot \epsilon$
- **Reverse:** $x_{t-1} = \frac{1}{\sqrt{\alpha}} \left(x_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}}} \cdot \epsilon(x_t, t) \right) + \sigma_t z$

Diffusion models:
Gradually add Gaussian noise and then reverse

Denoising Diffusion Probabilistic Models, NIPS 2020

Background: Diffusion Model

- **Latent diffusion model:**
  - Pixel space → latent space
  - Multimodal condition guidance



High-resolution Image Synthesis with Latent Diffusion Models, CVPR 2022

Background: Rectified Flow

- **Problem:** long-time inference

DDPM

$$
\begin{aligned}
L_{\mathrm{VLB}} &= \mathbb{E}_{q(\mathbf{x}_{0:T})}\Big[\log \frac{q(\mathbf{x}_{1:T}|\mathbf{x}_0)}{p_\theta(\mathbf{x}_{0:T})}\Big] \\
&= \mathbb{E}_q\Big[\log \frac{\prod_{t=1}^T q(\mathbf{x}_t|\mathbf{x}_{t-1})}{p_\theta(\mathbf{x}_T)\prod_{t=1}^T p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t)}\Big] \\
&= \mathbb{E}_q\Big[-\log p_\theta(\mathbf{x}_T) + \sum_{t=1}^T \log \frac{q(\mathbf{x}_t|\mathbf{x}_{t-1})}{p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t)}\Big] \\
&= \mathbb{E}_q\Big[-\log p_\theta(\mathbf{x}_T) + \sum_{t=2}^T \log \frac{q(\mathbf{x}_t|\mathbf{x}_{t-1})}{p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t)} + \log \frac{q(\mathbf{x}_1|\mathbf{x}_0)}{p_\theta(\mathbf{x}_0|\mathbf{x}_1)}\Big] \\
&= \mathbb{E}_q\Big[-\log p_\theta(\mathbf{x}_T) + \sum_{t=2}^T \log \Big(\frac{q(\mathbf{x}_{t-1}|\mathbf{x}_t,\mathbf{x}_0)}{p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t)} \cdot \frac{q(\mathbf{x}_t|\mathbf{x}_0)}{q(\mathbf{x}_{t-1}|\mathbf{x}_0)}\Big) + \log \frac{q(\mathbf{x}_1|\mathbf{x}_0)}{p_\theta(\mathbf{x}_0|\mathbf{x}_1)}\Big] \\
&= \mathbb{E}_q\Big[-\log p_\theta(\mathbf{x}_T) + \sum_{t=2}^T \log \frac{q(\mathbf{x}_{t-1}|\mathbf{x}_t,\mathbf{x}_0)}{p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t)} + \sum_{t=2}^T \log \frac{q(\mathbf{x}_t|\mathbf{x}_0)}{q(\mathbf{x}_{t-1}|\mathbf{x}_0)} + \log \frac{q(\mathbf{x}_1|\mathbf{x}_0)}{p_\theta(\mathbf{x}_0|\mathbf{x}_1)}\Big] \\
&= \mathbb{E}_q\Big[-\log p_\theta(\mathbf{x}_T) + \sum_{t=2}^T \log \frac{q(\mathbf{x}_{t-1}|\mathbf{x}_t,\mathbf{x}_0)}{p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t)} + \log \frac{q(\mathbf{x}_T|\mathbf{x}_0)}{q(\mathbf{x}_1|\mathbf{x}_0)} + \log \frac{q(\mathbf{x}_1|\mathbf{x}_0)}{p_\theta(\mathbf{x}_0|\mathbf{x}_1)}\Big] \\
&= \mathbb{E}_q\Big[\log \frac{q(\mathbf{x}_T|\mathbf{x}_0)}{p_\theta(\mathbf{x}_T)} + \sum_{t=2}^T \log \frac{q(\mathbf{x}_{t-1}|\mathbf{x}_t,\mathbf{x}_0)}{p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t)} - \log p_\theta(\mathbf{x}_0|\mathbf{x}_1)\Big] \\
&= \mathbb{E}_q[\underbrace{D_{\mathrm{KL}}(q(\mathbf{x}_T|\mathbf{x}_0)\parallel p_\theta(\mathbf{x}_T))}_{L_T} + \sum_{t=2}^T \underbrace{D_{\mathrm{KL}}(q(\mathbf{x}_{t-1}|\mathbf{x}_t,\mathbf{x}_0)\parallel p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t))}_{L_{t-1}} \underbrace{- \log p_\theta(\mathbf{x}_0|\mathbf{x}_1)}_{L_0}]
\end{aligned}
$$

- **Solution:** one-step inference

Rectified Flow

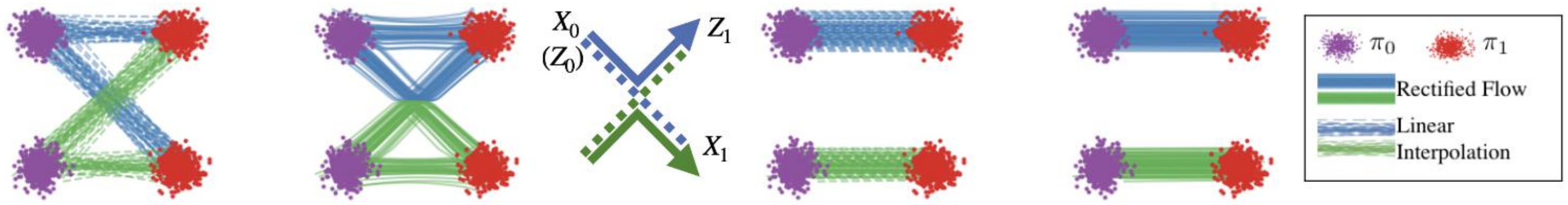
$$
L = \int_0^1 \mathbb{E}_{X_0\sim\text{noise},\, X_1\sim\text{data}} [\|\, (X_1 - X_0) - v(X_t, t)\, \|^2]\, \mathrm{d}t,
$$

$$
\text{with } X_t = t\, X_1 + (1-t) X_0
$$

Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow, ICLR 2023

Background: Rectified Flow

- **Question:** find a transport map $T: R^d \to R^d$ from $X_0 \sim \pi_0$ to $X_1 \sim \pi_1$
- Build as a continuous normalized flow problem
  - $dX_t = v(X_t,\ t)dt$
- **Main idea:** Build straight flow from π_0 to π_1
  - $dX_t = (X_1 - X_0)dt \Leftrightarrow X_t = tX_1 + (1-t)X_0,\ t \in [0,1]$



(a) Linear interpolation $X_t = tX_1 + (1-t)X_0$

(b) Rectified flow Z_t induced by (X_0, X_1)

(c) Linear interpolation $Z_t = tZ_1 + (1-t)Z_0$

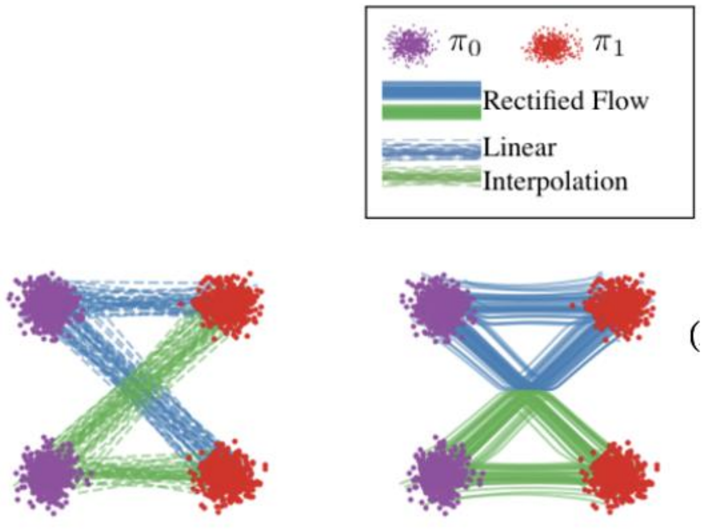
(d) Rectified flow Z_t' induced by (Z_0, Z_1)

Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow, ICLR 2023

Background: Rectified Flow

- **1-Rectified:** $\min_{v} \int_0^1 E[\|(X_1 - X_0) - v(X_t, t)\|^2]\, dt, \quad with\; X_t = tX_1 + (1-t)X_0$
  - Randomly sampled pair $\langle X_0, X_1 \rangle$
  - Flows are not straight
  - $dX_t = v(X_t,\ t)dt$ promises the uniqueness

$$
\begin{aligned}
\mathcal{L} &= \int_0^1 \mathbb{E}_{x_0,x_1}\left[\|x_1 - x_0 - v_\theta(x_t,t)\|^2\right] dt \\
&= \int_0^1 \mathbb{E}_{x_0,x_1}\left[\|x_1 - x_0\|^2 + \|v_\theta(x_t,t)\|^2 - 2(x_1 - x_0)^T v_\theta(x_t,t)\right] dt \\
&= \int_0^1 \left\{\mathbb{E}_{x_0,x_1}\left[\|v_\theta(x_t,t)\|^2\right] - 2\mathbb{E}_{x_0,x_1}\left[(x_1 - x_0)^T v_\theta(x_t,t)\right]\right\} dt + C \\
&= \int_0^1 \left\{\mathbb{E}_{x_t}\left[\|v_\theta(x_t,t)\|^2\right] - 2\mathbb{E}_{x_t}\left[\mathbb{E}_{x_0,x_1}\left[x_1 - x_0 \mid x_t\right]\right]^T \mathbb{E}_{x_t}\left[v_\theta(x_t,t)\right]\right\} dt + C \\
&= \int_0^1 \mathbb{E}_{x_t}\left[\|\mathbb{E}_{x_0,x_1}\left[x_1 - x_0 \mid x_t\right] - v_\theta(x_t,t)\|^2\right] dt + C'
\end{aligned}
$$



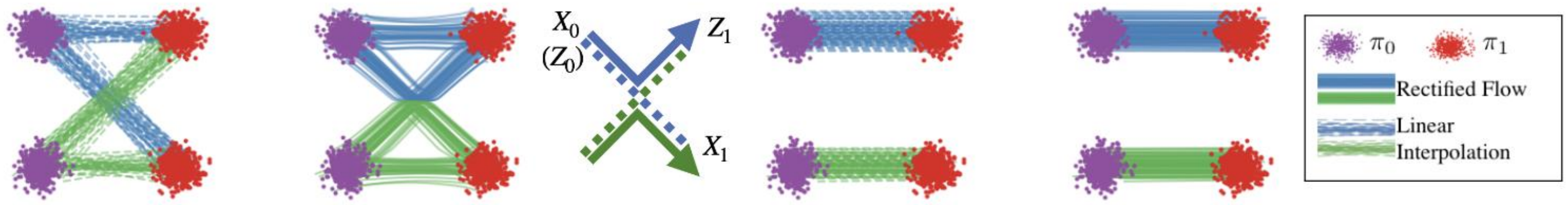
(a) Linear interpolation $X_t = tX_1 + (1-t)X_0$

(b) Rectified flow Z_t induced by (X_0, X_1)

Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow, ICLR 2023

Background: Rectified Flow

- **2-Rectified:** $\min_{v} \int_0^1 E[\|(Z_1 - Z_0) - v(Z_t, t)\|^2]\, dt, \quad with\ Z_t = tZ_1 + (1-t)Z_0$
  - Paired data $\langle Z_0, Z_1 \rangle$ from rectified flow, i.e. $T(Z_0) = Z_1$
  - Most of the flows are straightened



(a) Linear interpolation $X_t = tX_1 + (1-t)X_0$

(b) Rectified flow Z_t induced by (X_0, X_1)

(c) Linear interpolation $Z_t = tZ_1 + (1-t)Z_0$

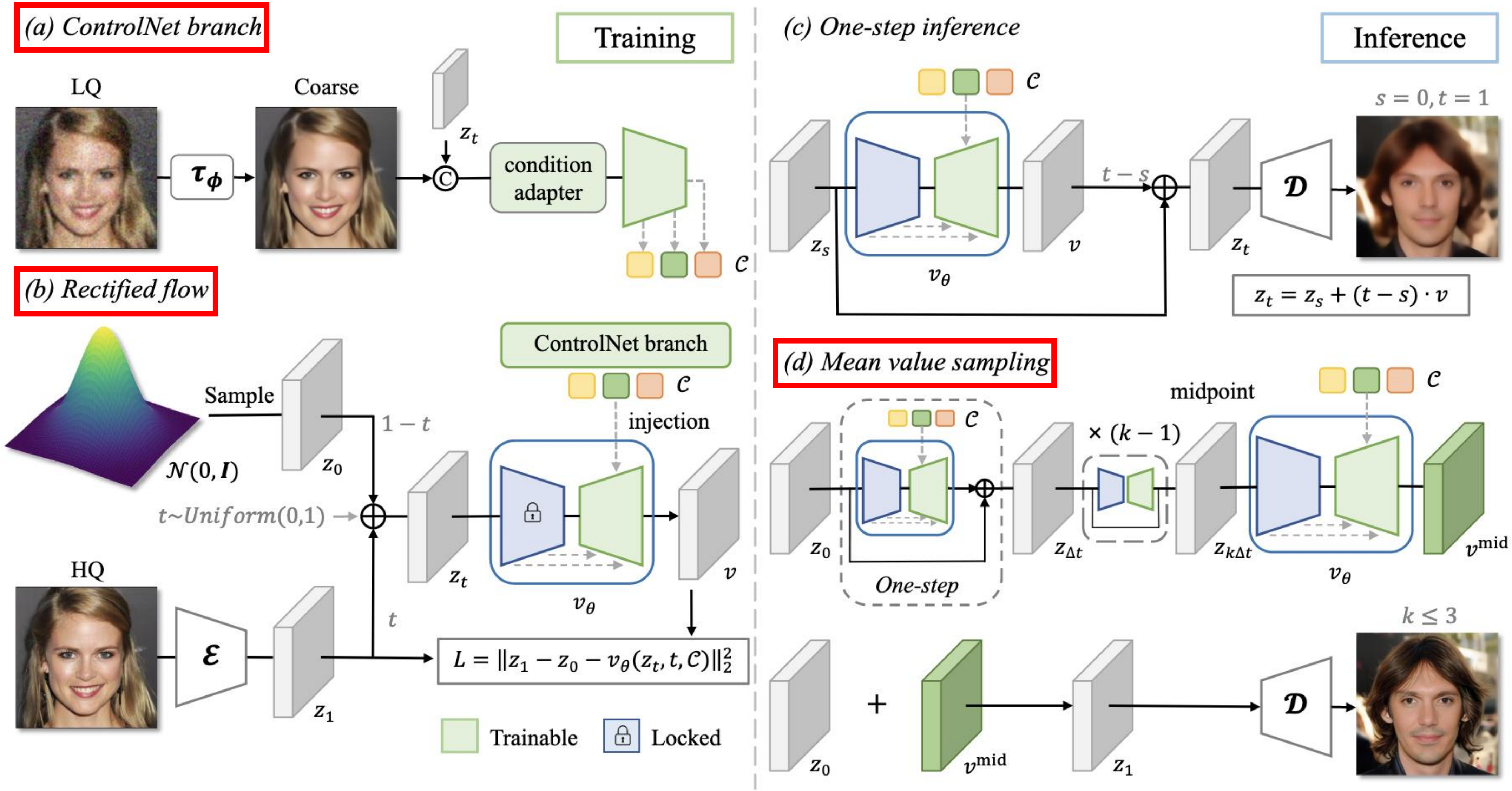
(d) Rectified flow Z'_t induced by (Z_0, Z_1)

Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow, ICLR 2023

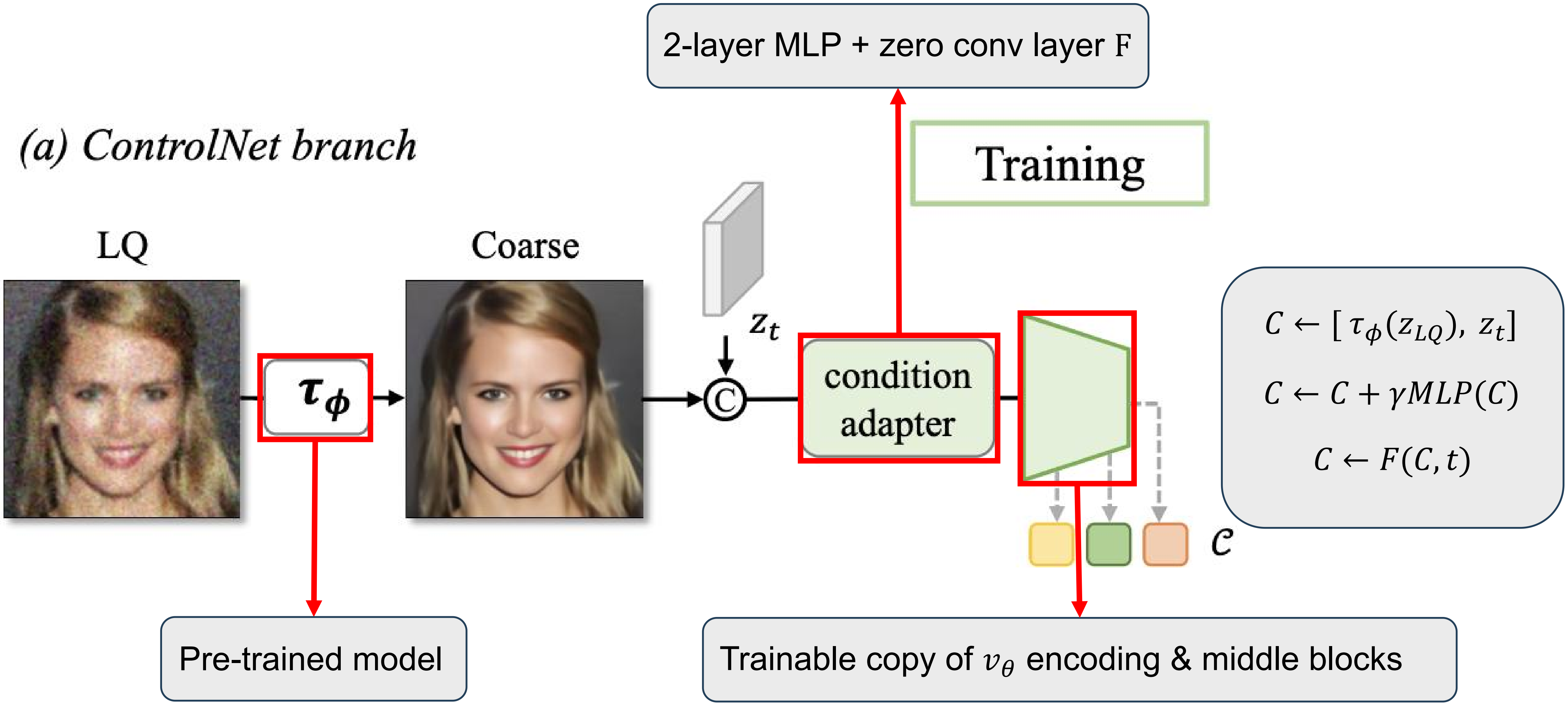
FlowIE: Methods

- **Flow-based image enhancement:**
  - Apply conditioned Rectified Flow to diffusion models
  - U-Net ϵ_θ → velocity predictor v_θ
  - LQ input z_{LQ} → condition guidance C
- **Improve quality via mean value sampling:** more precise v_{pred} from z_0 to z_1

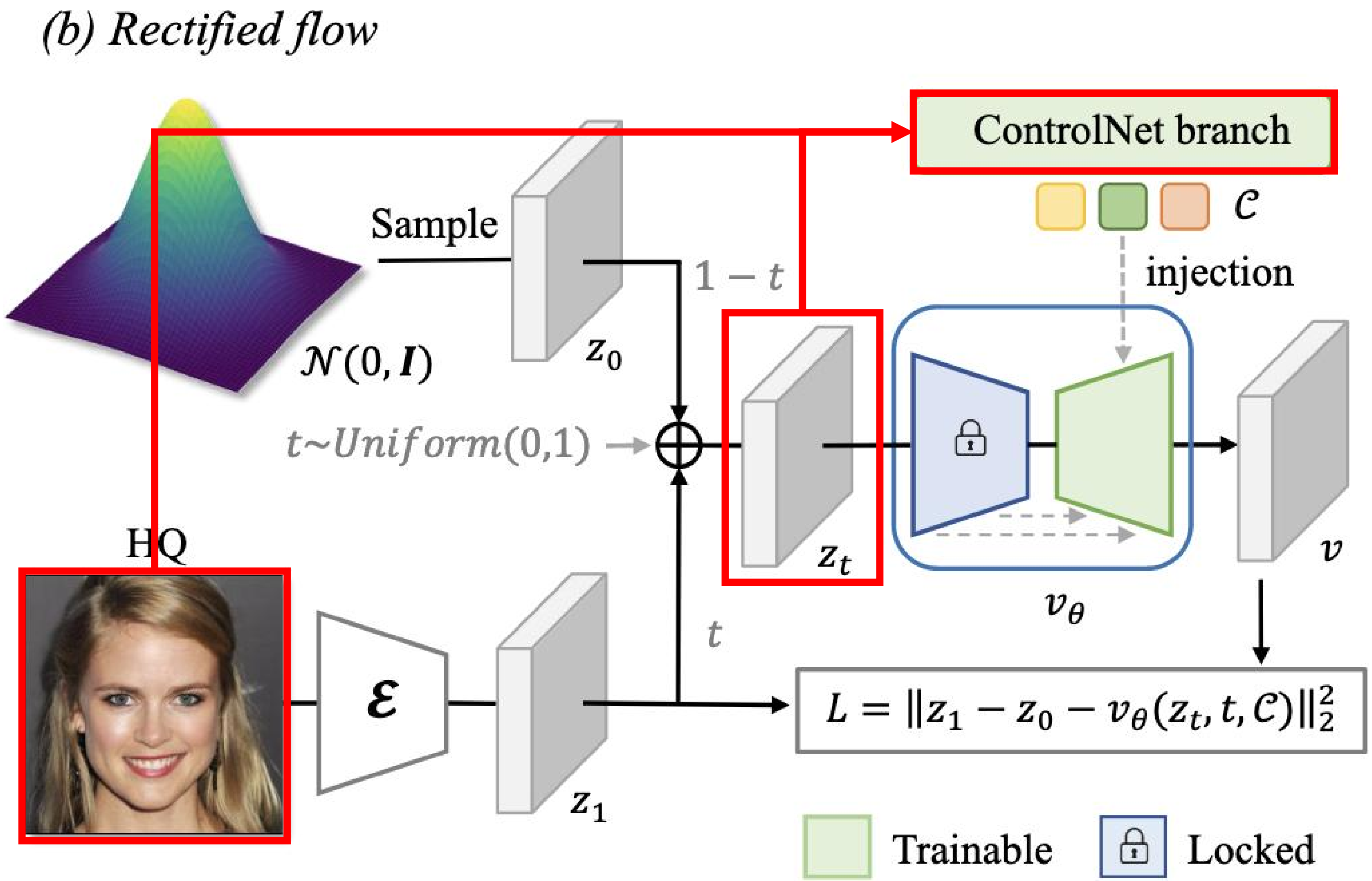
FlowIE: Pipeline



FlowIE: Pipeline



FlowIE: Pipeline



$$Z_{LQ} = D_h(Z_{HQ})$$

$$z_t = t \cdot z_1 + (1-t) \cdot z_0$$

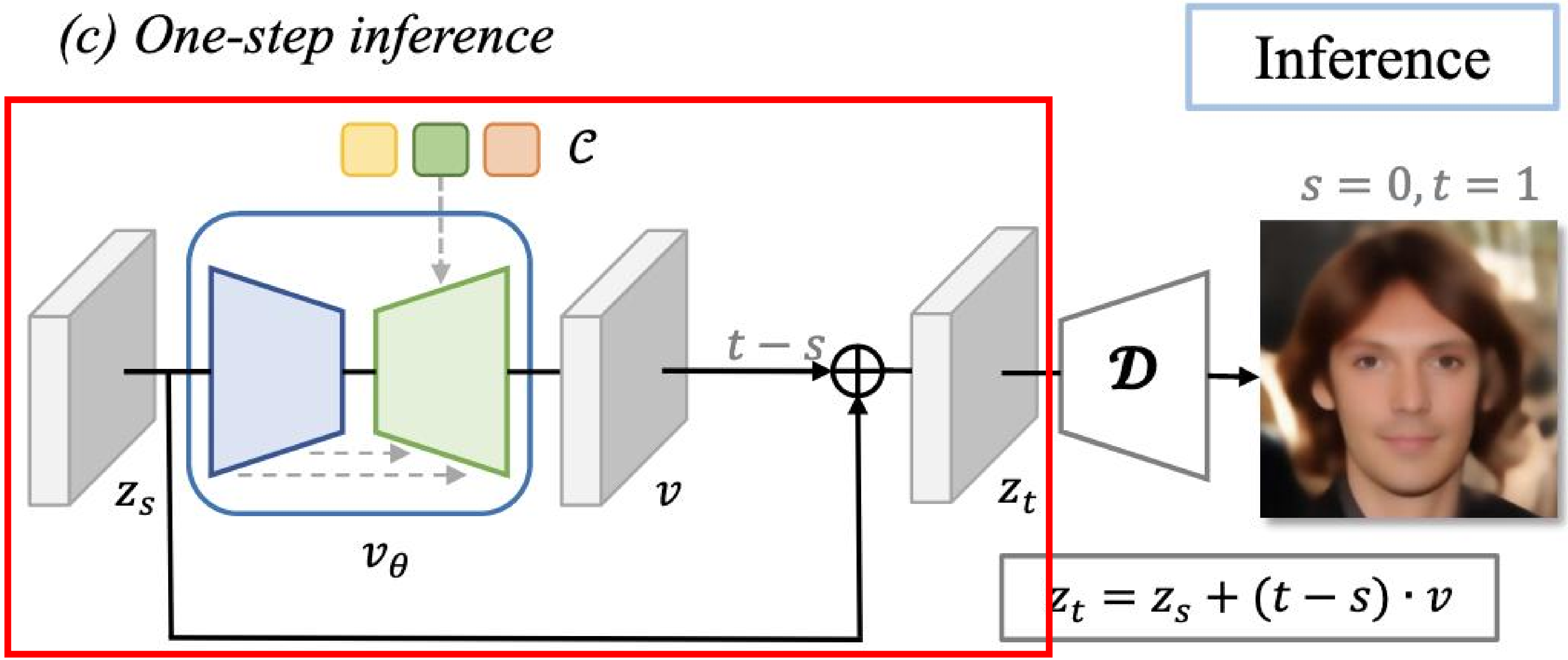
$$C \leftarrow [\,\tau_\phi(z_{LQ}),\ z_t]$$

$$C \leftarrow C + \gamma MLP(C)$$

$$C \leftarrow F(C, t)$$

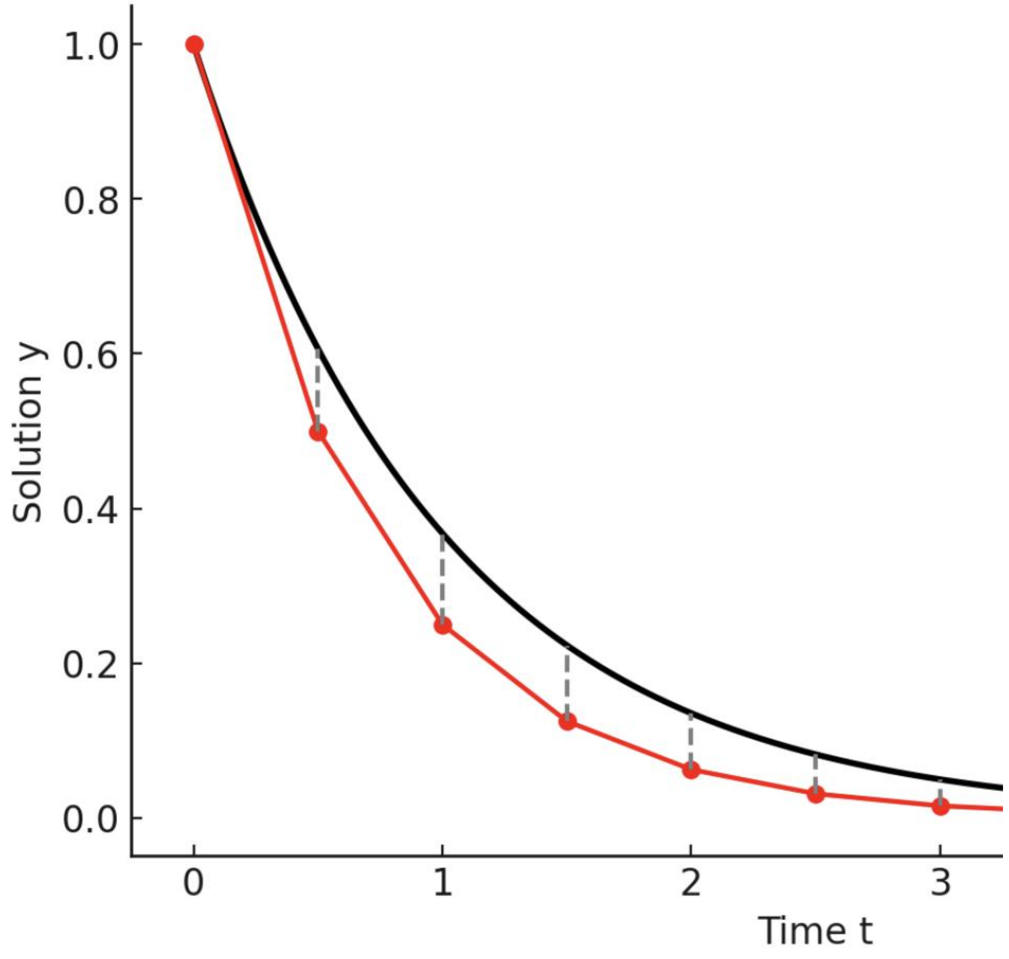
FlowIE: Pipeline

Forward Euler Method
$z_{t+\Delta t} = z_t + \Delta t \cdot v_\theta(z_t, t, C)$



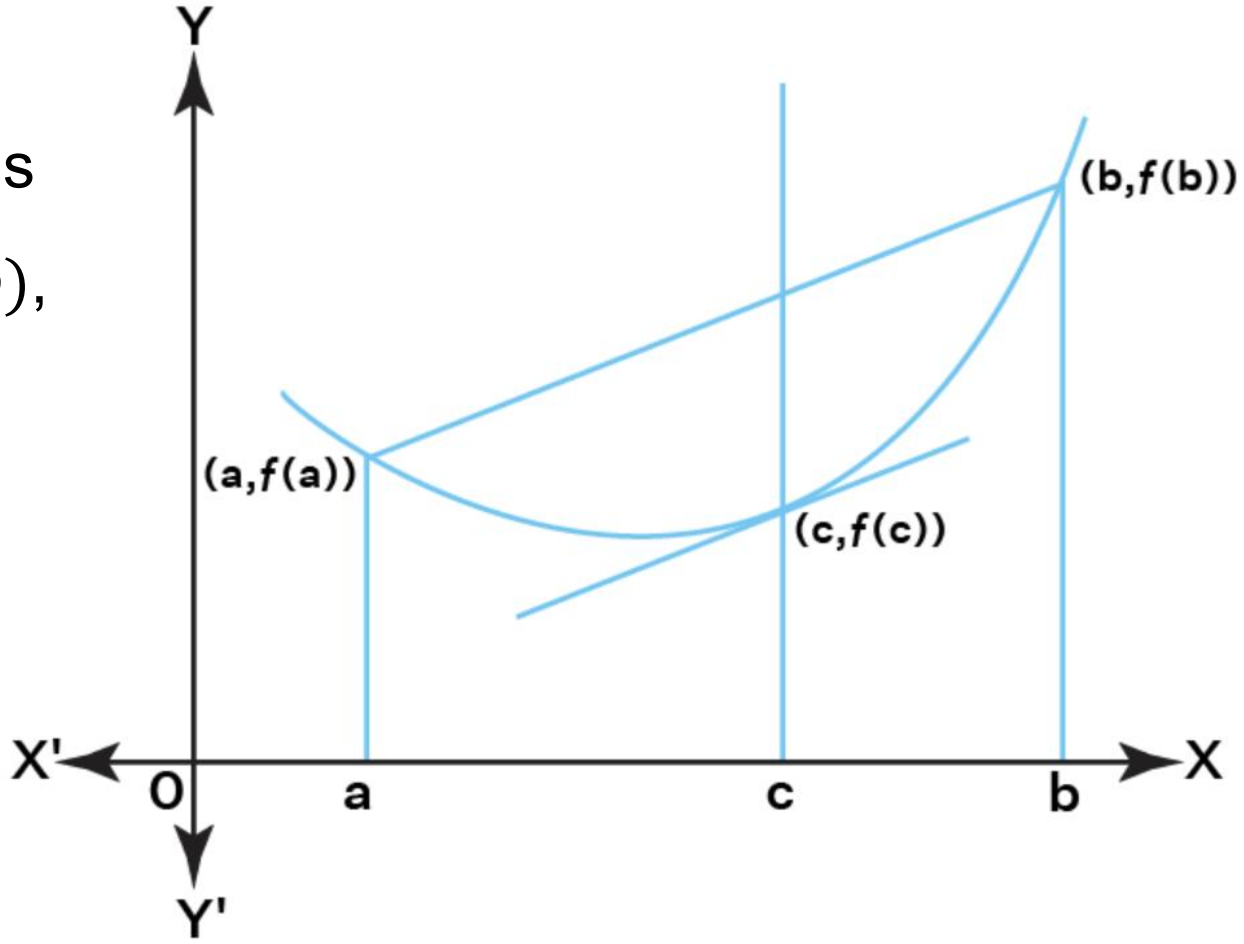
FlowIE: Pipeline

- **Forward Euler Method:**
  - $z_{t+\Delta t} = z_t + \Delta t \cdot v_\theta(z_t, t, C)$
  - may cause error accumulation
- Reduce error accumulation while obtaining correct results
- Lagrange’s Mean Value Theorem



FlowIE: Pipeline

- Lagrange's Mean Value Theorem: for function $f\colon [a,b] \to R$ continuous on $[a,b]$ and differentiable on (a,b), exists $c \in [a,b]$, such that $f'(c) = \frac{f(b)-f(a)}{b-a}$



FlowIE: Pipeline

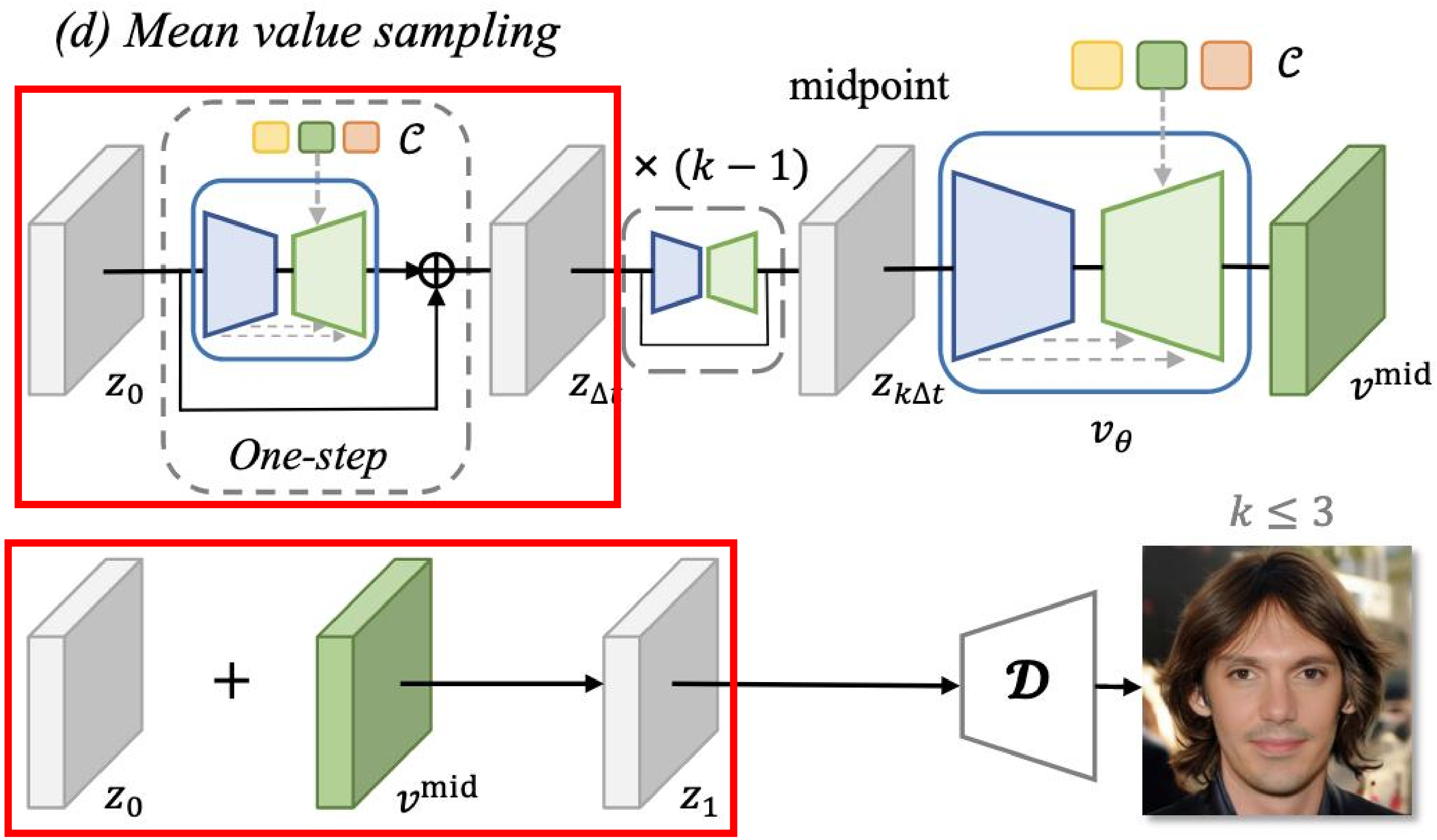
$$z_{(r+1)\Delta t} = z_{r\Delta t} + \Delta t \cdot v_\theta(z_{r\Delta t}, r\Delta t, C)$$
$$\Delta t = 1/N$$

$$C \leftarrow [\,\tau_\phi(z_{LQ}),\ z_t]$$

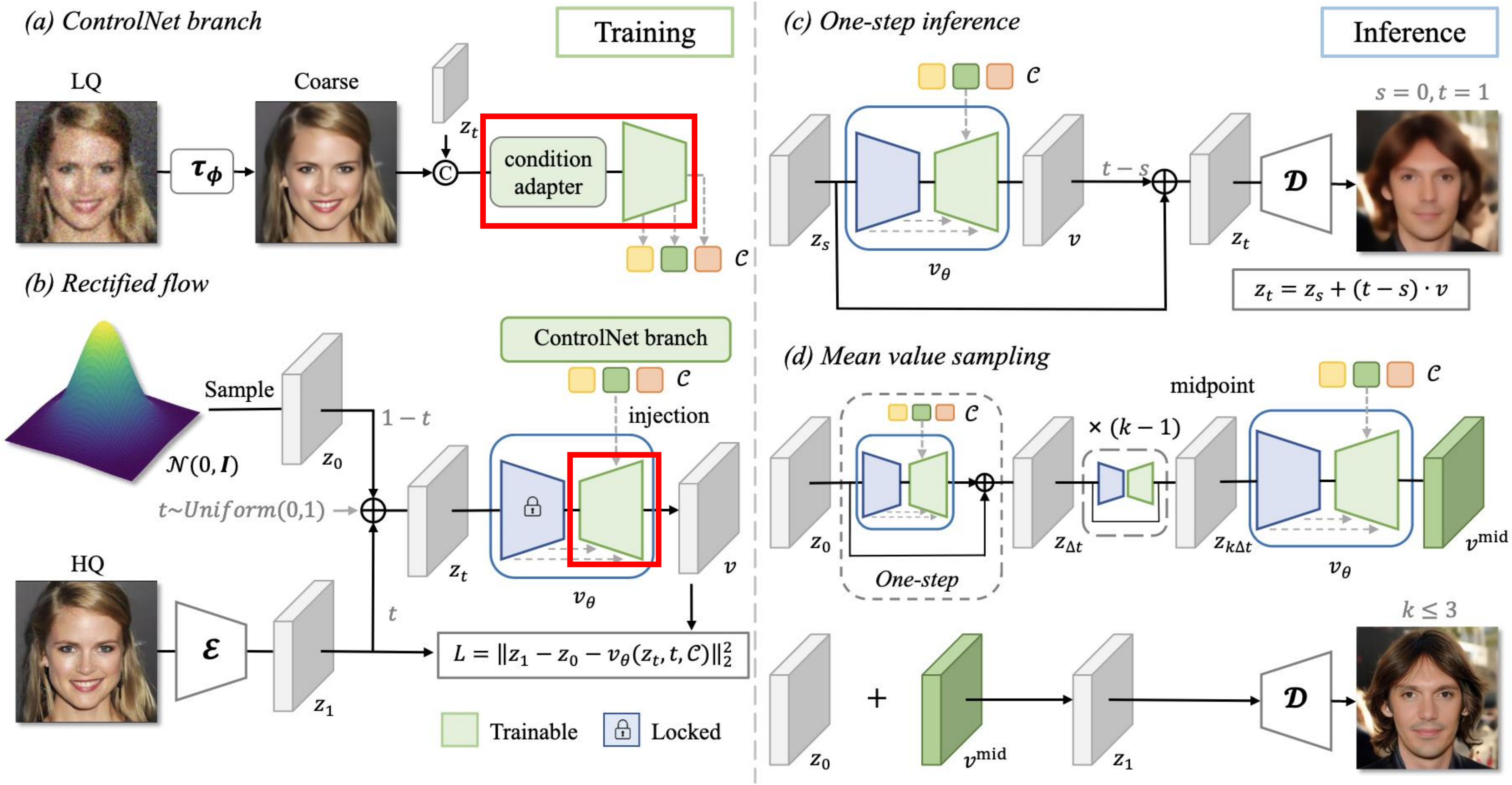
$$C \leftarrow C + \gamma MLP(C)$$

$$C \leftarrow F(C, t)$$

$$z_1 = z_0 + v_\theta(z_{k\Delta t}, k\Delta t, C)$$



FlowIE: Pipeline



FlowIE: Experiments

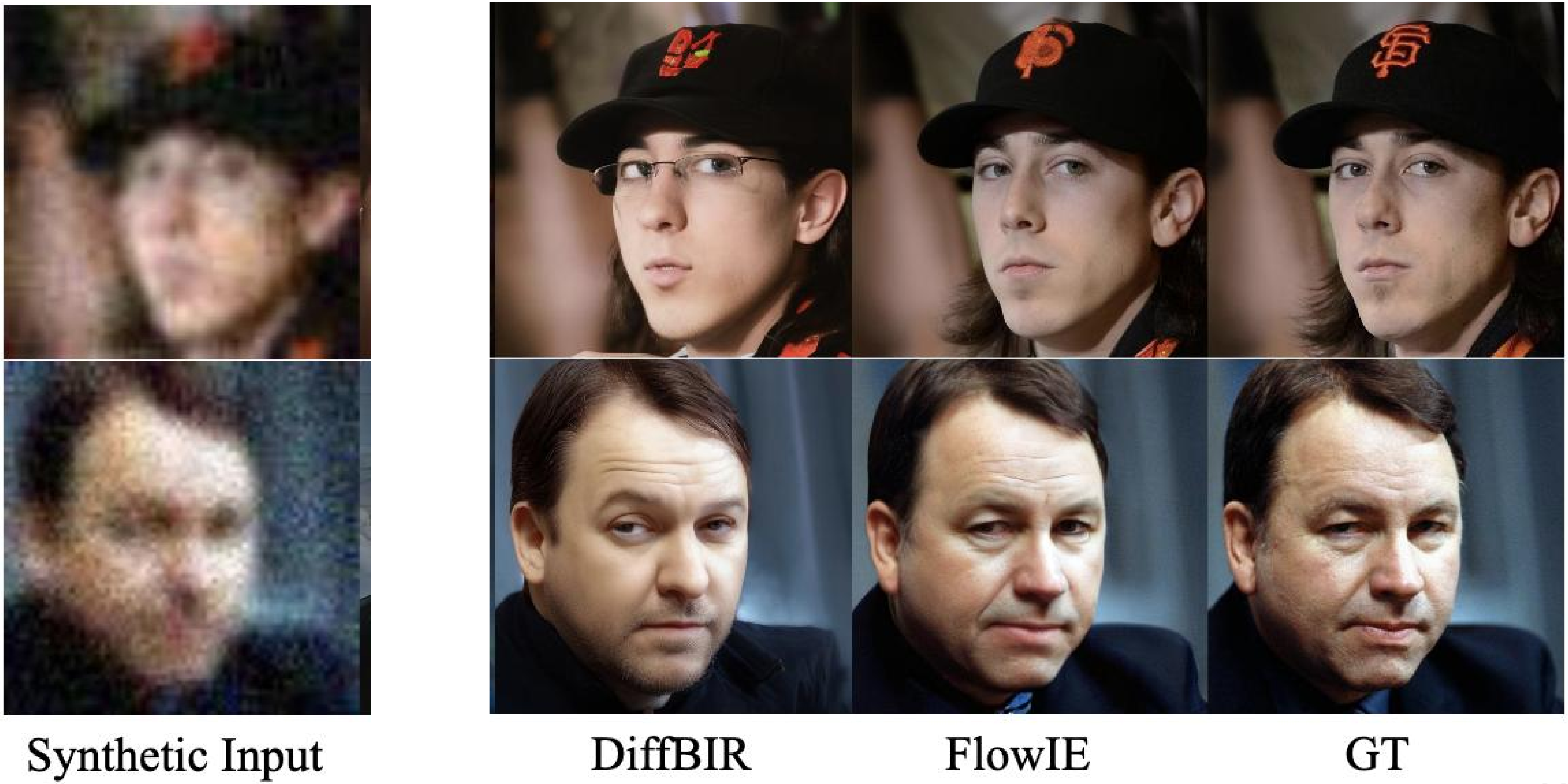
- **Face-related task (blind face restoration, face color enhancement, face inpainting):**
  - Train datasets: FFHQ
  - Test datasets:
    - CelebA-Test (synthetic),
    - LFW-Test & CelebChild-Test & WIDER-Test (real-world)
- **Blind image super-resolution:**
  - Train datasets: ImageNet
  - Test datasets: RealSRSet & collect-100 (newly constructed)
- Use image restoration baseline SwinIR as τ_ϕ

FlowIE: Experiments

- **Blind face restoration:**
  - Tune τ_ϕ on corresponding dataset
  - Lower FID
  - Higher PSNR, higher efficiency (compared with DiffBIR)

Method	Wild Datasets LFW	Wild Datasets WIDER	Wild Datasets CelebChild	Synthetic Dataset CelebA					FPS↑
	FID↓	FID↓	FID↓	PSNR↑	SSIM↑	LPIPS↓	FID↓	IDS ↑	
GPEN [50]	51.95	46.41	76.62	21.3941	0.5745	0.4685	23.88	0.49	7.278
GCFSR [16]	52.18	40.89	76.32	21.8789	0.6070	0.4579	35.52	0.45	9.243
GFPGAN [42]	52.11	41.70	80.69	21.6953	0.6060	0.4304	21.69	0.49	8.152
VQFR [15]	49.92	37.89	74.75	21.3012	0.6125	0.4127	20.47	0.48	3.837
RestoreFormer [47]	48.41	49.82	71.09	21.0029	0.5289	0.4791	43.76	0.55	4.964
DMDNet [23]	43.38	40.53	79.37	21.6620	0.5997	0.4825	64.21	0.66	3.454
CodeFormer [58]	52.34	38.79	79.58	22.1513	0.5949	0.4057	22.23	0.48	5.188
DiffBIR [25]	39.61	33.51	77.74	21.7512	0.5968	0.4575	20.19	0.52	0.285
FlowIE (Ours)	38.66	32.41	74.25	21.9211	0.6005	0.4367	19.81	0.69	2.846

FlowIE: Experiments



FlowIE: Experiments

Real Input

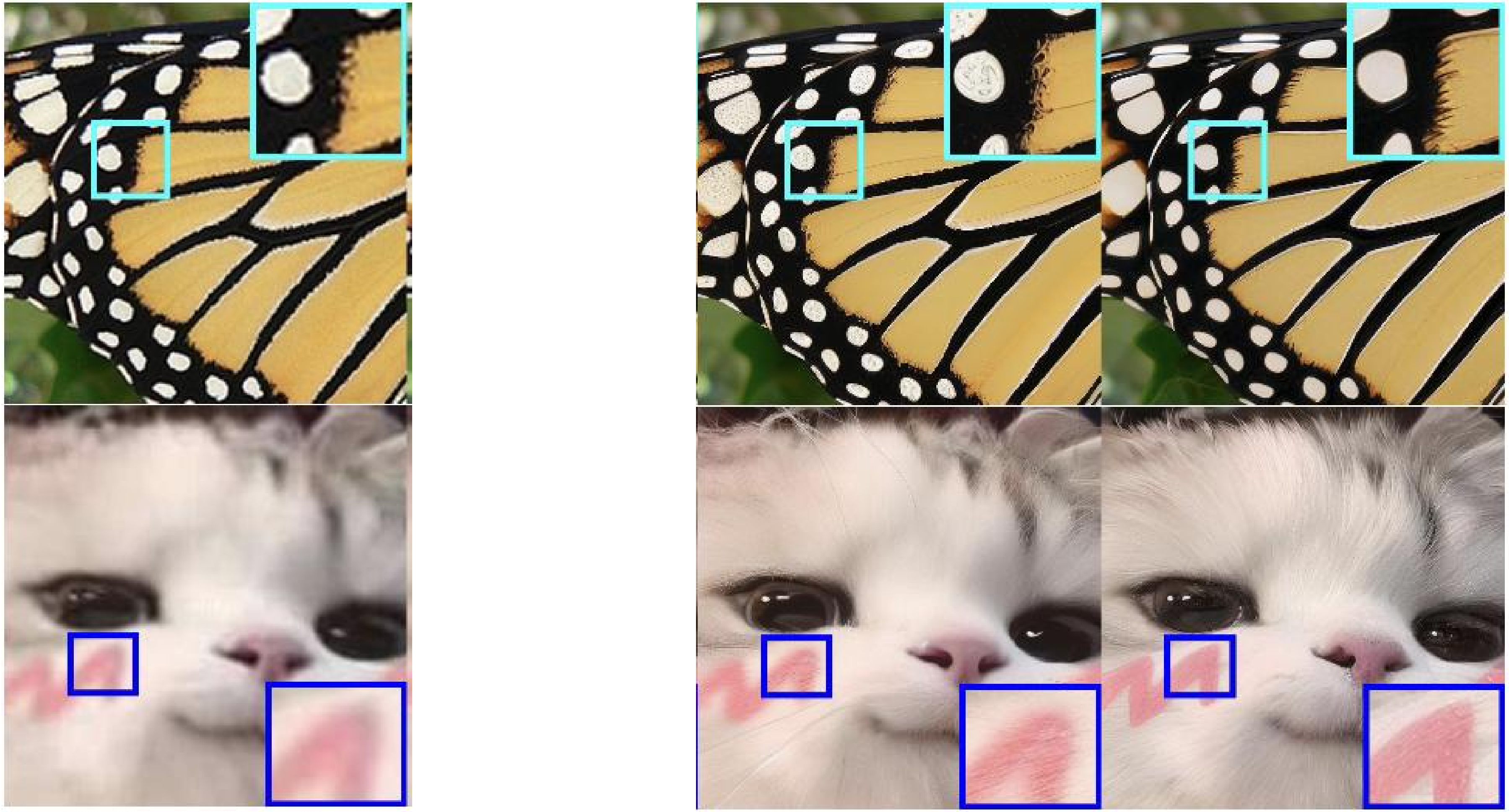
DiffBIR FlowIE

FlowIE: Experiments

- **Blind image super-resolution:**
  - Tune τ_ϕ on corresponding dataset
  - Higher MANIQA, higher efficiency (compared with DiffBIR)

Type	Method	MANIQA↑		FPS↑
		RealSRSet	Collect-100	
GAN	Real-ESRGAN+ [43]	0.5373	0.5901	1.875
	BSRGAN [57]	0.5638	0.5889	1.725
	SwinIR-GAN [24]	0.5296	0.5721	5.978
	FeMaSR [2]	0.5250	0.5718	3.167
Diffusion	DDNM [44]	0.4539	0.4813	0.071
	GDP [10]	0.4583	0.5237	0.016
	DiffBIR [25]	0.5906	0.6022	0.286
Flow	FlowIE (Ours)	**0.5953**	**0.6087**	2.853

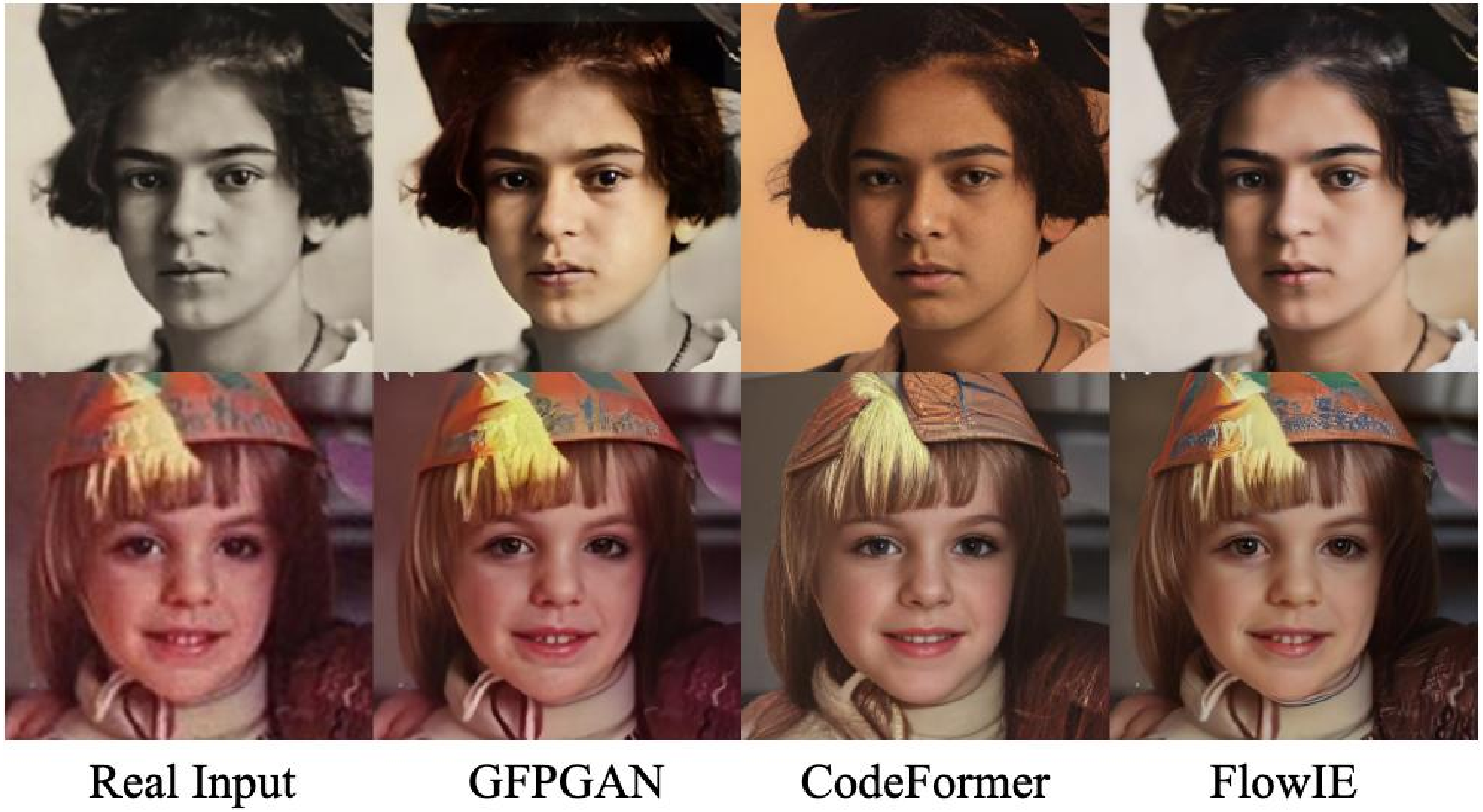
FlowIE: Experiments



LQ DiffBIR FlowIE

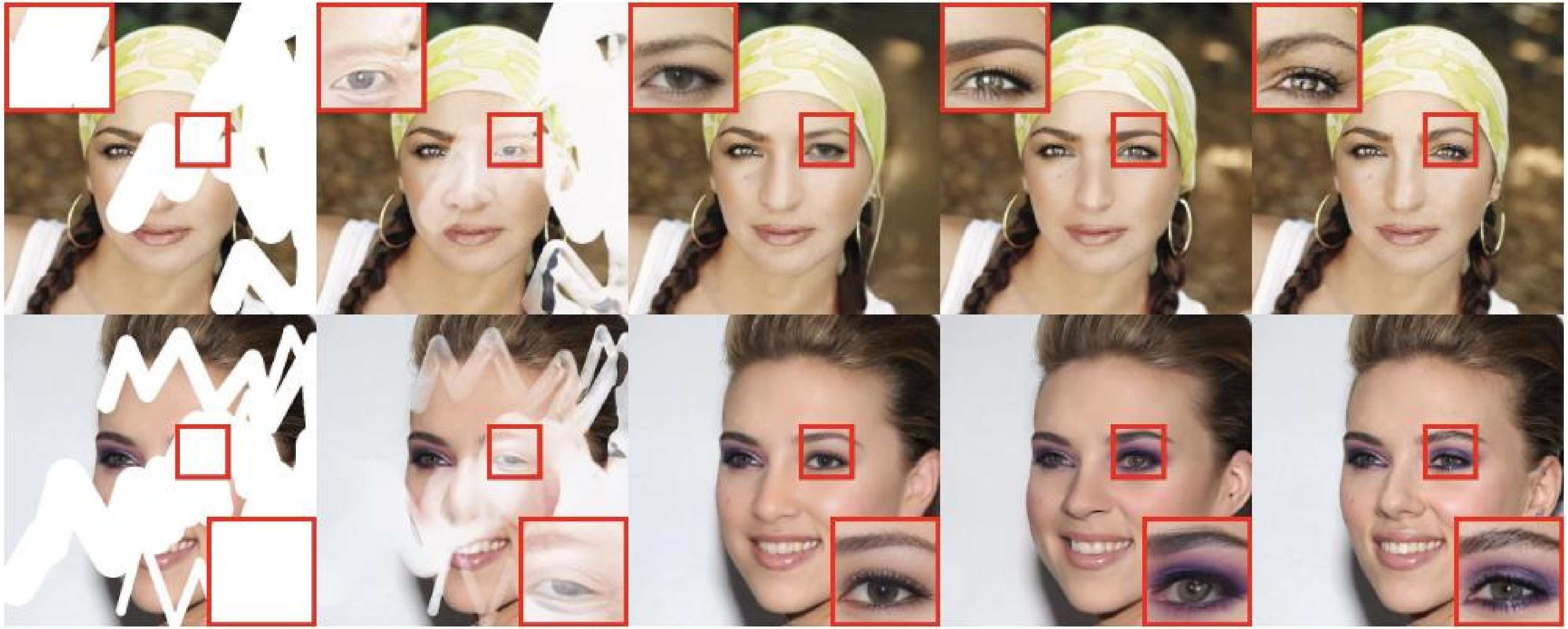
FlowIE: Experiments

- **Face color enhancement**
  - Fine-tune rectified flow



FlowIE: Experiments

- **Face inpainting**
  - Fine-tune rectified flow



Masked Input GPEN CodeFormer FlowIE GT

FlowIE: Ablation Study

- **w/o flow:** direct distillation rather than using Rectified Flow
  - Set the student identical to v_θ during training
  - Fix $t = 0$ during training

Method	FID↓		MANIQA↑	
	CelebA	LFW	RealSRSet	Collect-100
w/o flow	49.74	53.71	0.5311	0.5723
w/o mid sample	25.19	48.95	0.5489	0.5805
w/o init	27.76	52.63	0.5301	0.5698
FlowIE (Ours)	**19.81**	**38.66**	**0.5953**	**0.6087**

FlowIE: Ablation Study

- **w/o mid sample:** always use Forward Euler Method instead of mean value sampling
  - Euler method: struggling to produce HQ images in very few steps (e.g. 5)
  - Mean value sampling: a more efficient process (< 5 steps)

Method	FID↓		MANIQA↑	
	CelebA	LFW	RealSRSet	Collect-100
w/o flow	49.74	53.71	0.5311	0.5723
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FlowIE: Ablation Study

- **w/o init:** train model without initial stage model τ_ϕ

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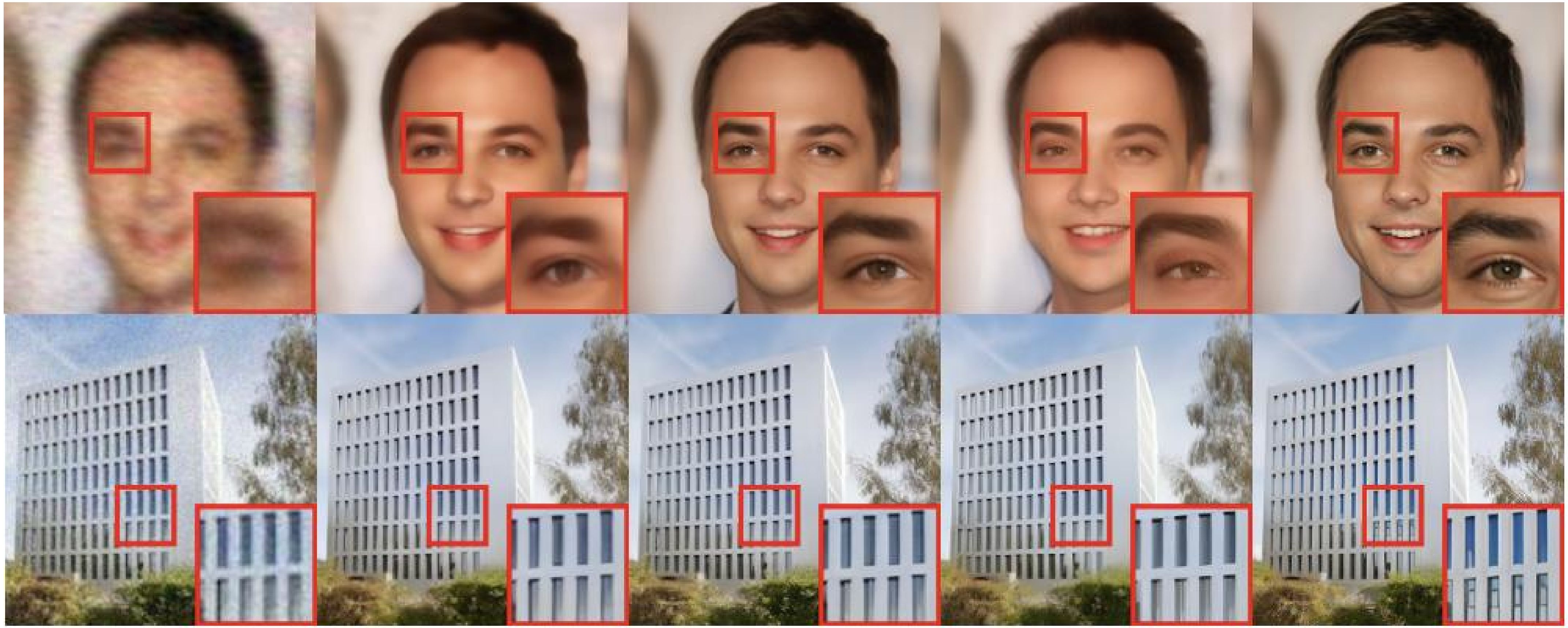
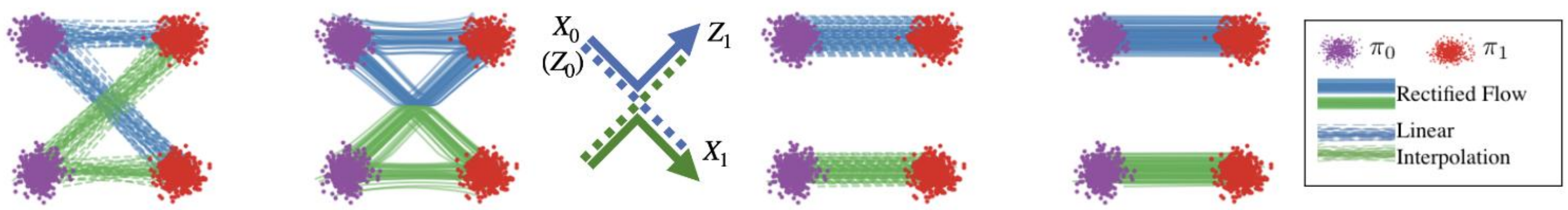
FlowIE: Ablation Study



LQ w/o flow w/o mid sample w/o init FlowIE

FlowIE: Discussion

- Problems of mean value sampling
  - Necessity: 2-Rectified can straighten flows
  - Rationality:
    - FlowIE uses 1-Rectified
    - Some points of flows produced by 1-Rectified may not be differentiable



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(d) Rectified flow Z'_t induced by (Z_0, Z_1)

Thanks for listening!

Presenter: Junxin Lin
2025.03.16