ID-Blau: Image Deblurring by Implicit Diffusion-based reBLurring AUgmentation

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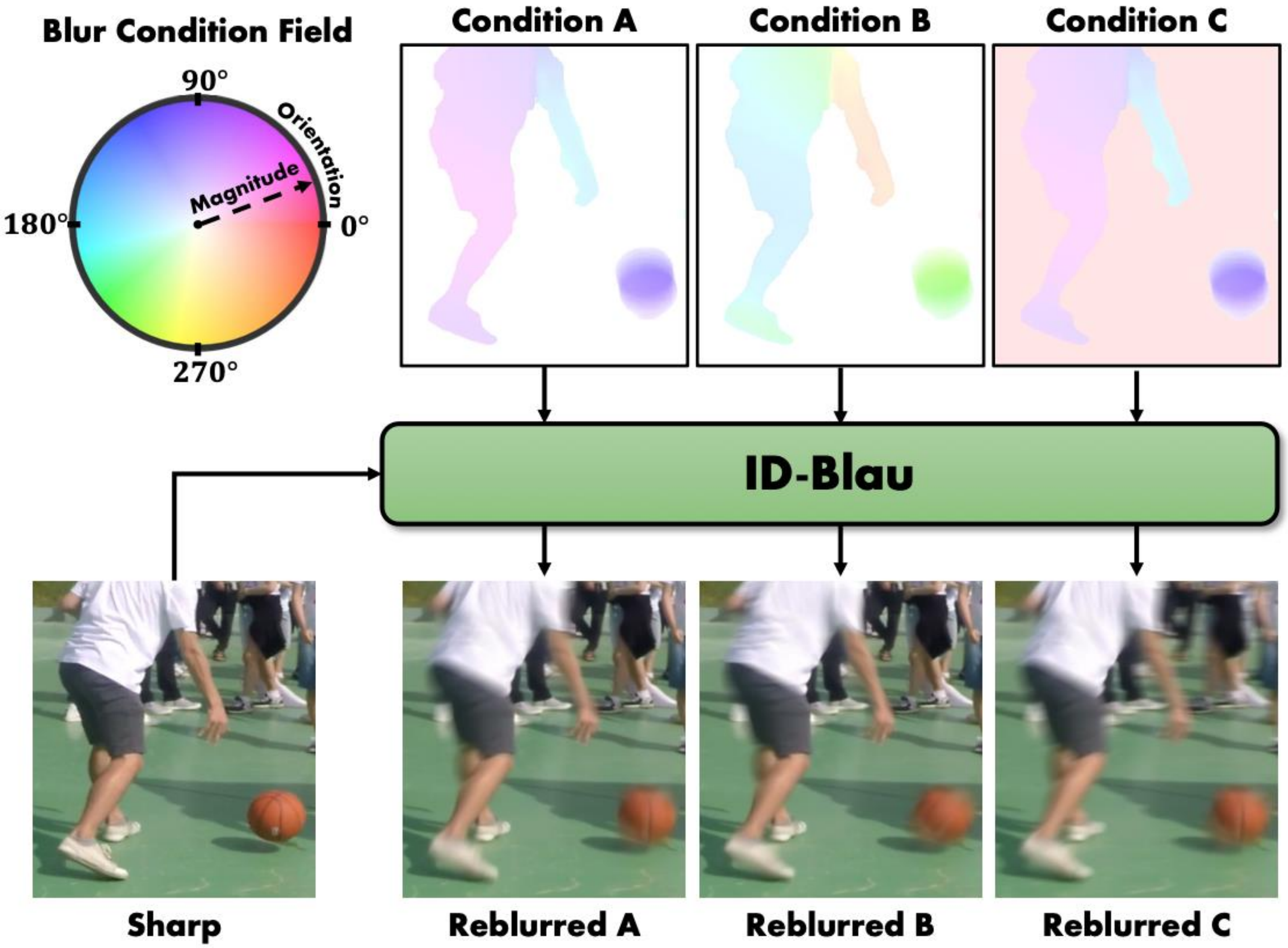
Outline

- Introduction
- Method
- Experiment
- Conclusion

Introduction

- ID-Blau, a **controllable augmentation** strategy for enhancing image deblurring
- **continuous blur condition field** to represent blur orientations and magnitudes
- Integrates **pixel-wise blur condition maps** into a **diffusion model** to generate reblurred images.



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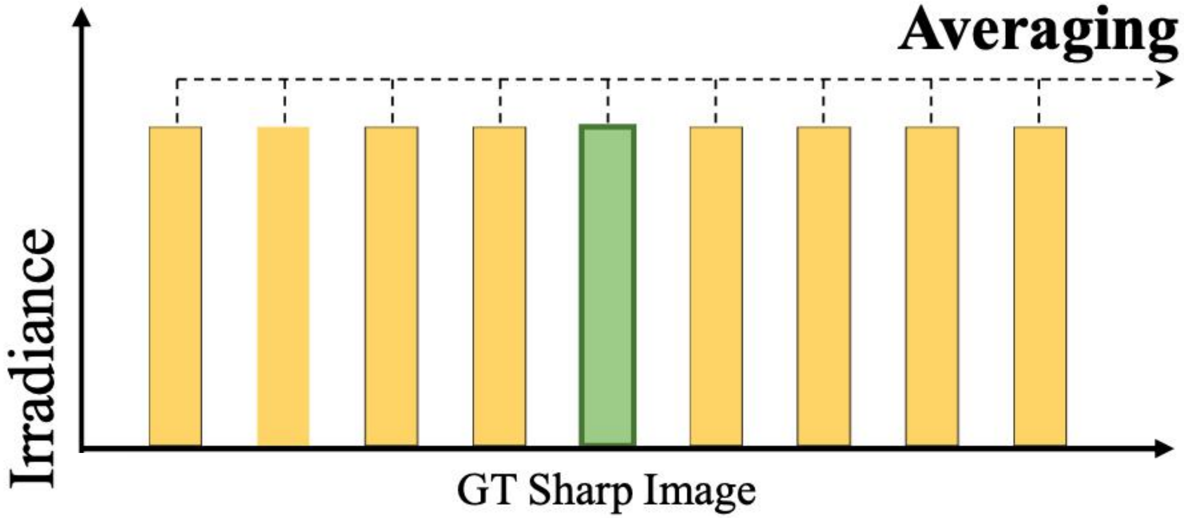
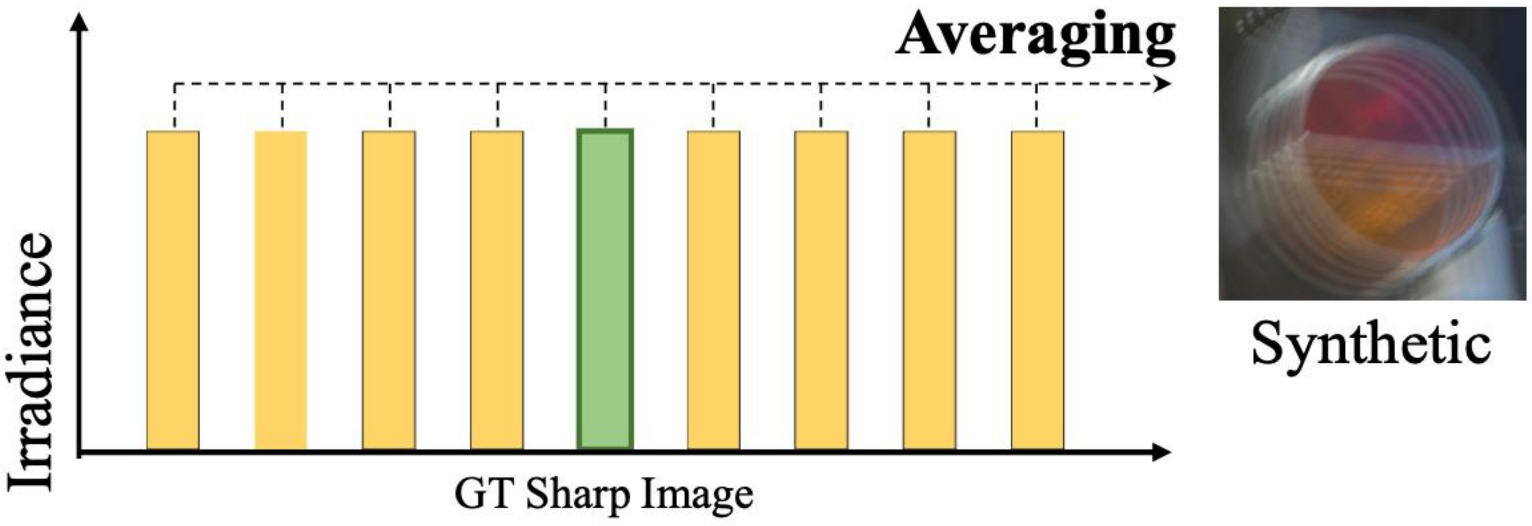
GoPro Dataset



Synthetic

$$B = g\left(\frac{1}{T}\int_{t=1}^{T} V(t)dt\right) \simeq g\left(\frac{1}{N}\sum_{n=1}^{N} V[n]\right), \qquad (1)$$

Blur Condition



$$\mathcal{F} = \sum_{n=1}^{N-1} \frac{f_\theta(V[n], V[n+1]) - f_\theta(V[n+1], V[n])}{2}$$

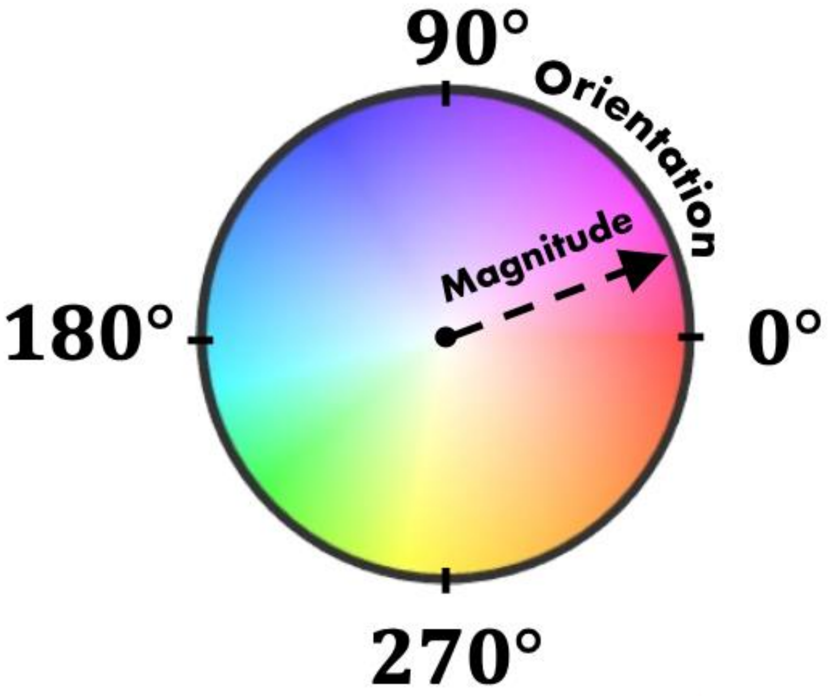
$$\mathcal{F} = [u; v] \in \mathbb{R}^{H \times W \times 2}$$

Blur Condition Field

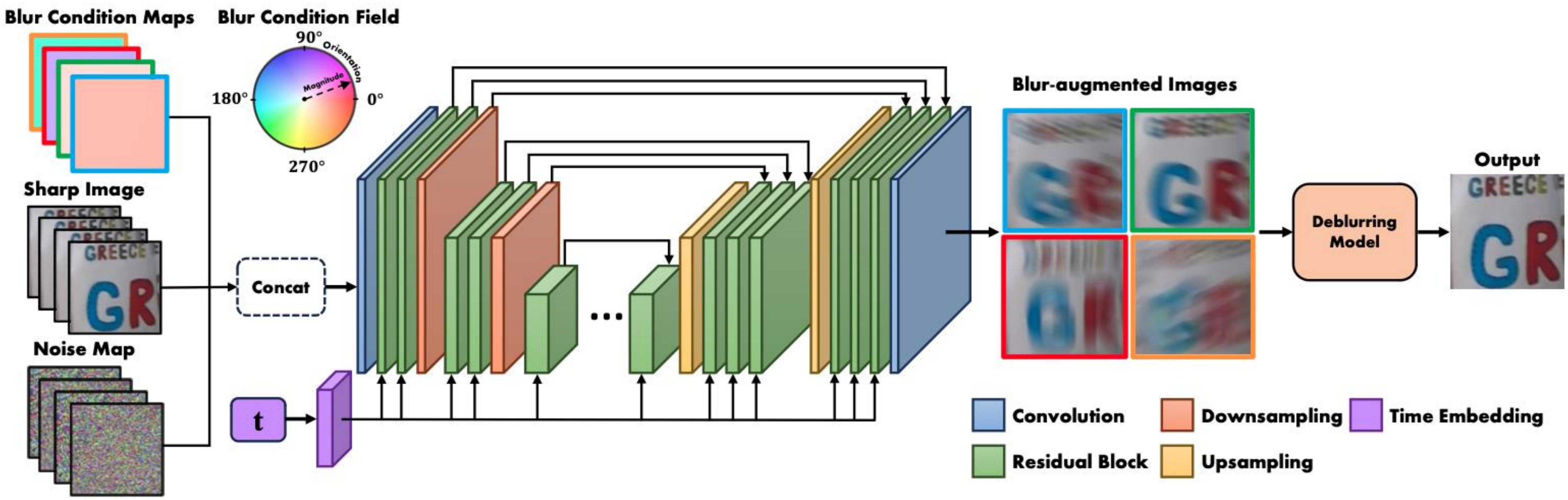
- Normalize

$$C = [x; y; z] \in \mathbb{R}^{H\times W\times 3}$$

$$\begin{cases} x_{i,j} = \dfrac{u_{i,j}}{\sqrt{u_{i,j}^2 + v_{i,j}^2}} \\ y_{i,j} = \dfrac{v_{i,j}}{\sqrt{u_{i,j}^2 + v_{i,j}^2}} \\ z_{i,j} = \dfrac{\sqrt{u_{i,j}^2 + v_{i,j}^2}}{M} \end{cases}$$



Framework



$$\{B_n, S_n, C_n\}_{n=1}^{K}$$

$$\mathcal{L} = \| \epsilon - \epsilon_\theta(\sqrt{\overline{\alpha}_t}B_0 + \sqrt{(1-\overline{\alpha}_t)}\epsilon, S, C, t) \|_1$$

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Illustration

S | ID-Blau(S, C) | ID-Blau(S, C^1) | ID-Blau(S, C^2) | ID-Blau(S, C^3) | ID-Blau(S, C^4)

Evaluation results

Model		GoPro		HIDE		RealBlur-J		RealBlur-R		Average Gain	
		PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
MIMO-UNet+	Baseline	32.44	0.957	30.00	0.930	31.92	0.919	39.10	0.969		
	+ID-Blau	**32.93 (+0.49)**	**0.961**	**30.68 (+0.68)**	**0.938**	**31.96 (+0.04)**	**0.921**	**39.38 (+0.28)**	**0.971**	**+0.37**	**+0.004**
Restormer	Baseline	32.92	0.961	31.22	0.942	32.88	0.933	40.15	**0.974**		
	+ID-Blau	**33.51 (+0.59)**	**0.965**	**31.66 (+0.44)**	**0.947**	**33.11 (+0.23)**	**0.937**	**40.31 (+0.16)**	**0.974**	**+0.36**	**+0.003**
Stripformer	Baseline	33.08	0.962	31.03	0.940	32.48	0.929	39.84	0.974		
	+ID-Blau	**33.66 (+0.58)**	**0.966**	**31.50 (+0.47)**	**0.944**	**33.77 (+1.29)**	**0.940**	**41.06 (+1.22)**	**0.977**	**+0.89**	**+0.006**
FFTformer	Baseline	34.21	0.969	31.62	0.946	32.62	0.933	40.11	0.973		
	+ID-Blau	**34.36 (+0.15)**	**0.970**	**31.94 (+0.32)**	**0.949**	**32.88 (+0.26)**	**0.934**	**40.45 (+0.34)**	**0.975**	**+0.27**	**+0.002**
Average Gain		**+0.45**	**+0.003**	**+0.48**	**+0.005**	**+0.46**	**+0.005**	**+0.50**	**+0.002**	-	-

Qualitative results

Figure 5. Qualitative results on the GoPro testing set (left) and the HIDE dataset (right).

Qualitative results

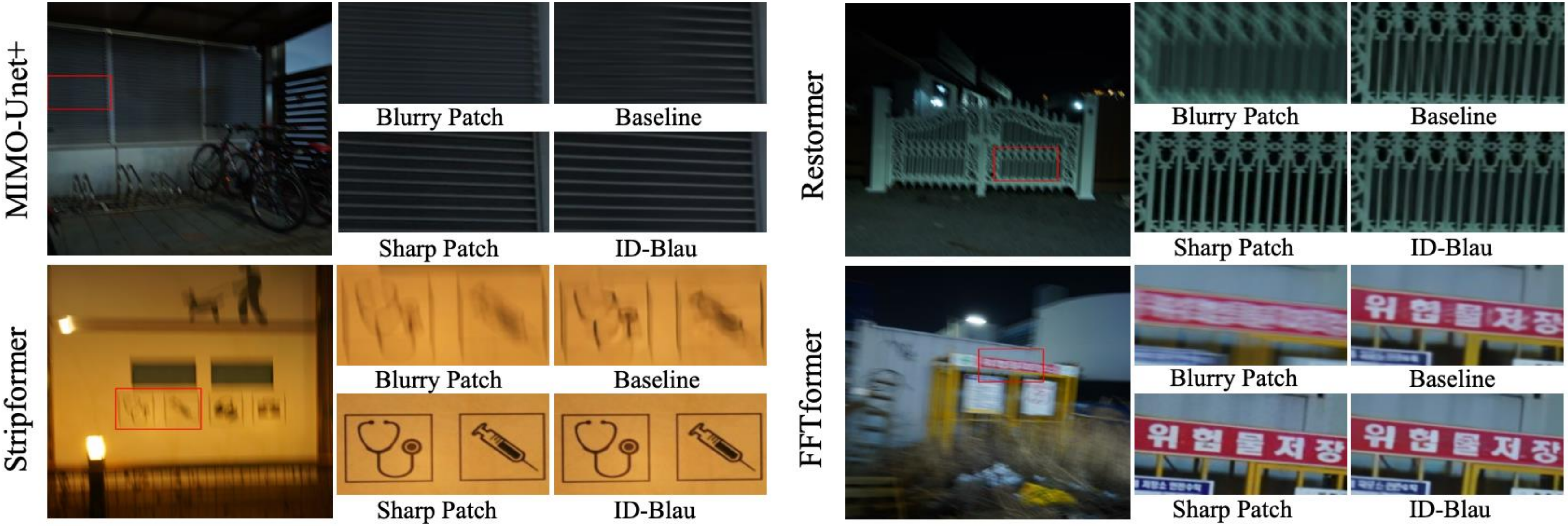
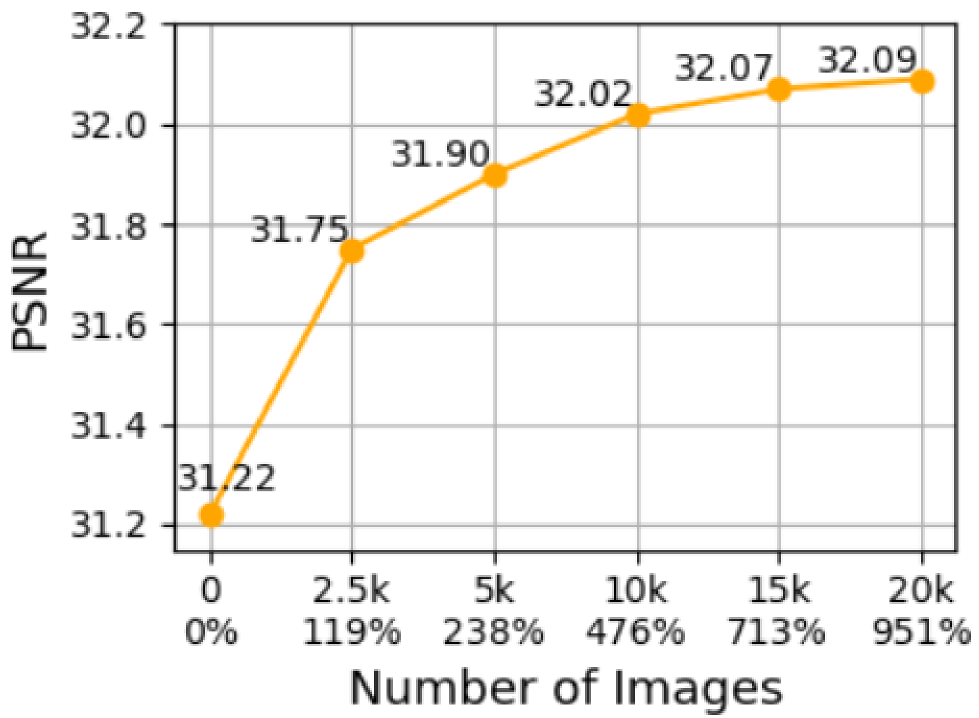
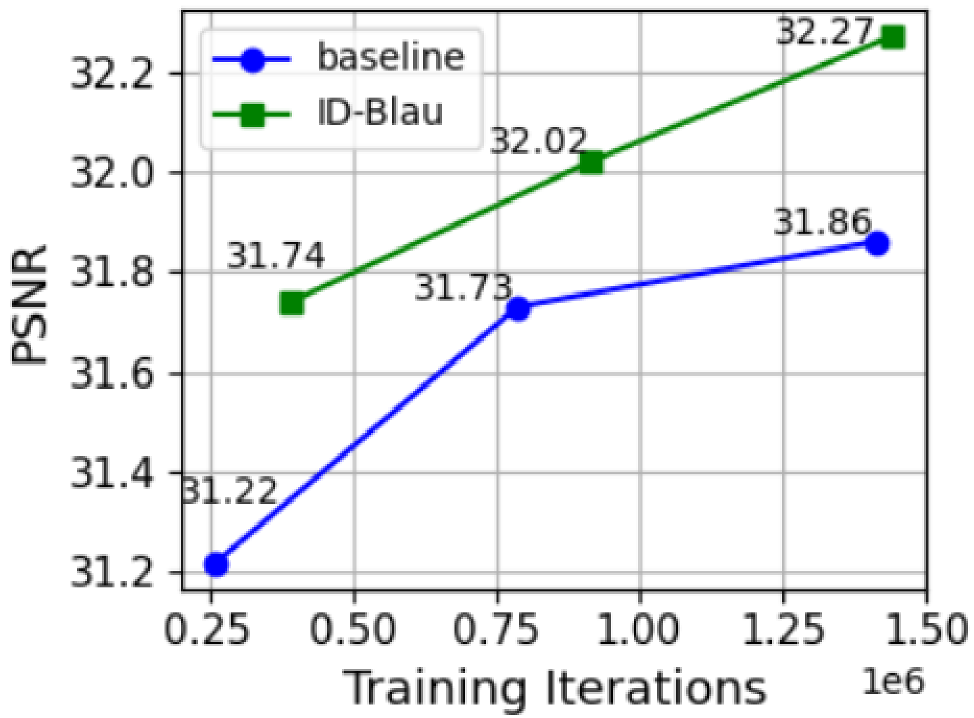


Figure 6. Qualitative results on the RealBlur-J testing set.

Ablation study





Ablation study

GoPro

ID-Blau

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Conclusion

- Proposed a diffusion-based reblurring model that can take a **sharp image** and a **controllable pixel-wise blur condtion map** to **synthesize a blurred image**.

- Parameterized the blur patterns of a blurred image with their **orientations** and **magnitudes**.

- Experimental results have shown that ID-Blau can significantly improve the performance of state-of-the-art deblurring models.