ComputerVisionLab
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https://cv.snu.ac.kr

ICLR
International Conference On Learning Representations

Clean Images are Hard to Reblur:
Exploiting the Ill-Posed Inverse Task for Dynamic Scene Deblurring

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Clean Images are Hard to Reblur

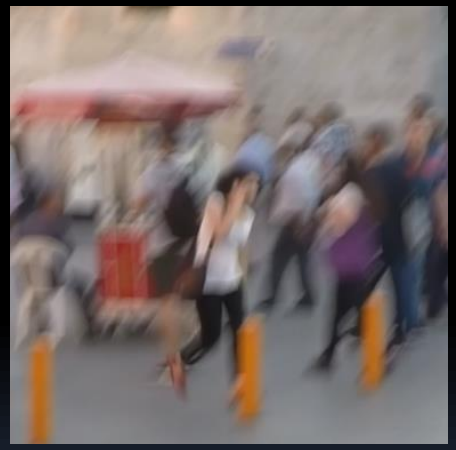
- Can we estimate the **true motion blur** from a sharp image?

Sharp

Blurring

Training with many images…

Backprop



Blur

Trained & tested on GOPRO dataset

Clean Images are Hard to Reblur

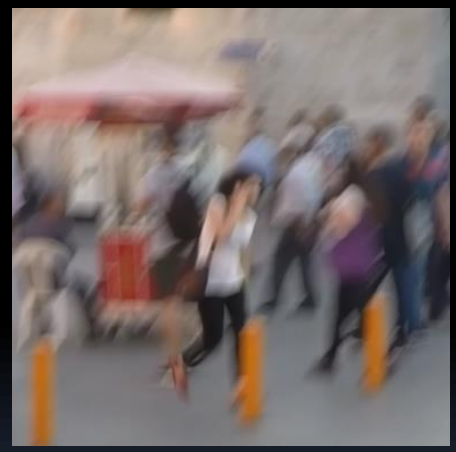
- Can we estimate the **true motion blur** from a sharp image?
- Not easily. It is an ill-posed problem.
- We are not trying to make an arbitrary blur.

Sharp

Blurring

Blurring Fails

Backprop



Blur

Trained & tested on GOPRO dataset

Clean Images are Hard to Reblur

- What about reblurring (inverse of deblurring)?

Blur

Deblurring

Deblurred

Sharp

Trained & tested on GOPRO dataset

Clean Images are Hard to Reblur

- In contrast, reblurring (inverse of deblurring) is easy!

Blur

Deblurring

Deblurred

Reblurring

Reblurred

Sharp

Blurring

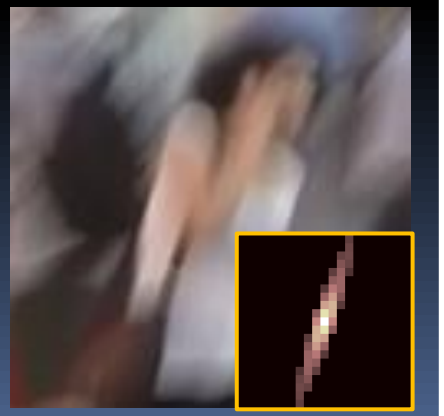
Blurred

Trained & tested on GOPRO dataset

Why Are They Different?

- Because the kernel shape remains in the deblurred images.

Sharp



Blur

SRN

SE-Sharing

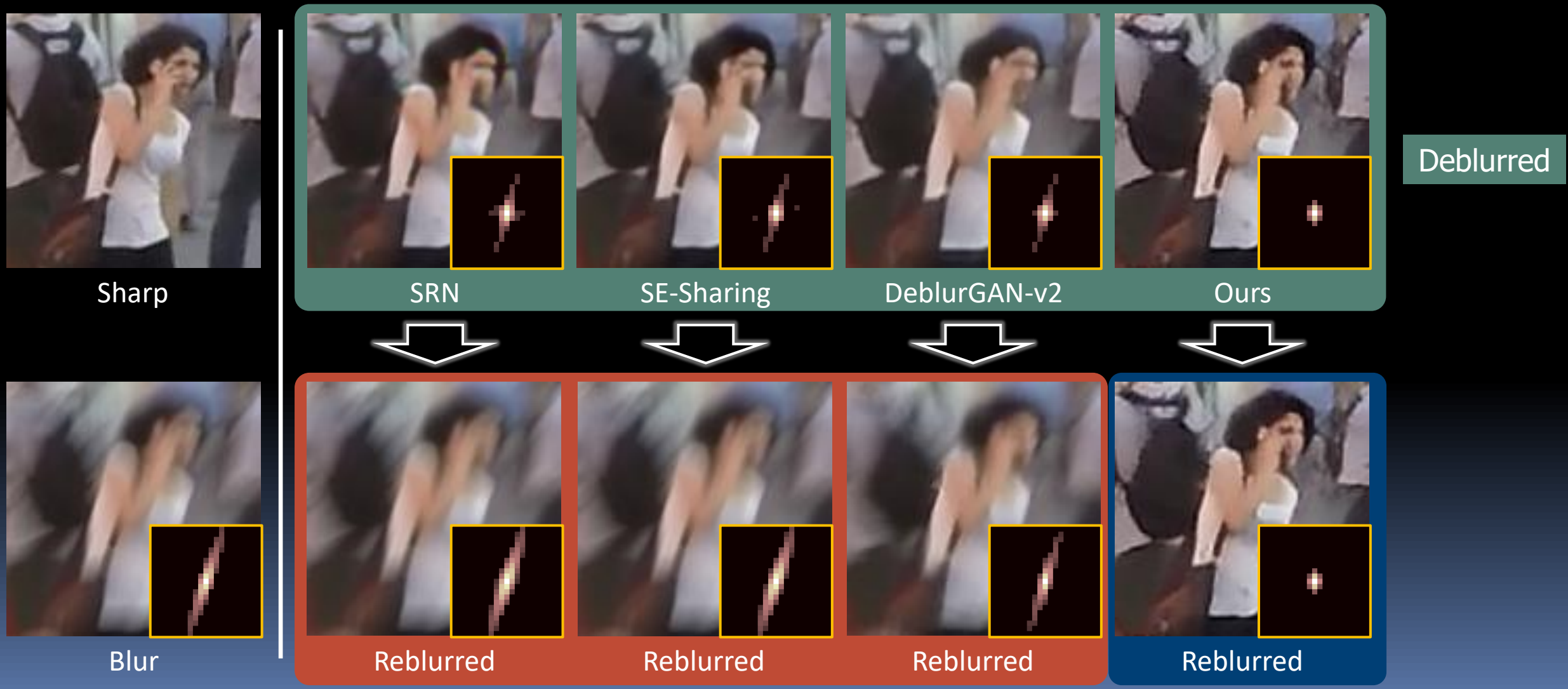
DeblurGAN-v2

Ours

Deblurred

Why Are They Different?

- Because the kernel shape remains in the deblurred images.



How Can We Deblur Better?

- By making reblurring difficult!

Blur

Deblurring

Deblurred

Reblurring

Reblurred

Sharp

Blurring

Blurred

How Can We Deblur Better?

- By making reblurring difficult!

Blur

Deblurring

Deblurred

Reblurring

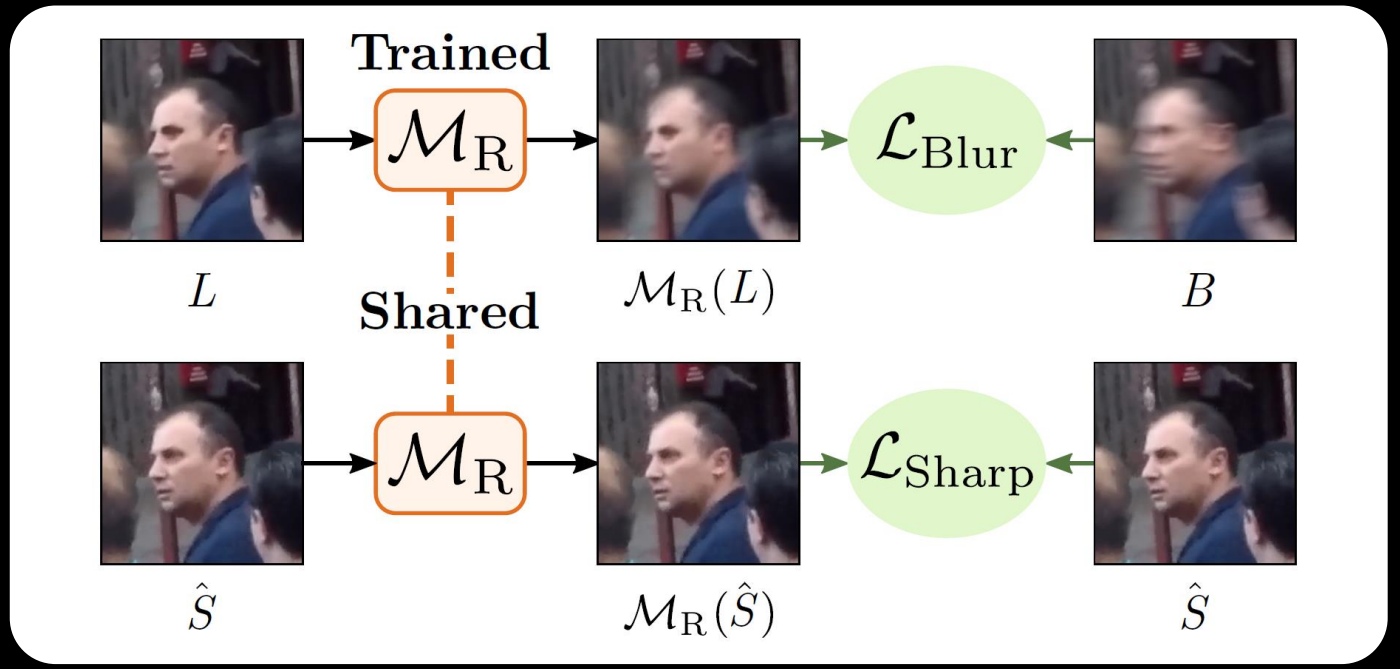
Reblurred

Blurred

Train with **reblurring loss** by joint optimization!

Reblurring Module

- Reblurring Module $\mathcal{M}_{\mathrm{R}}$
  - Estimate original blur
  - Keep sharp image sharp



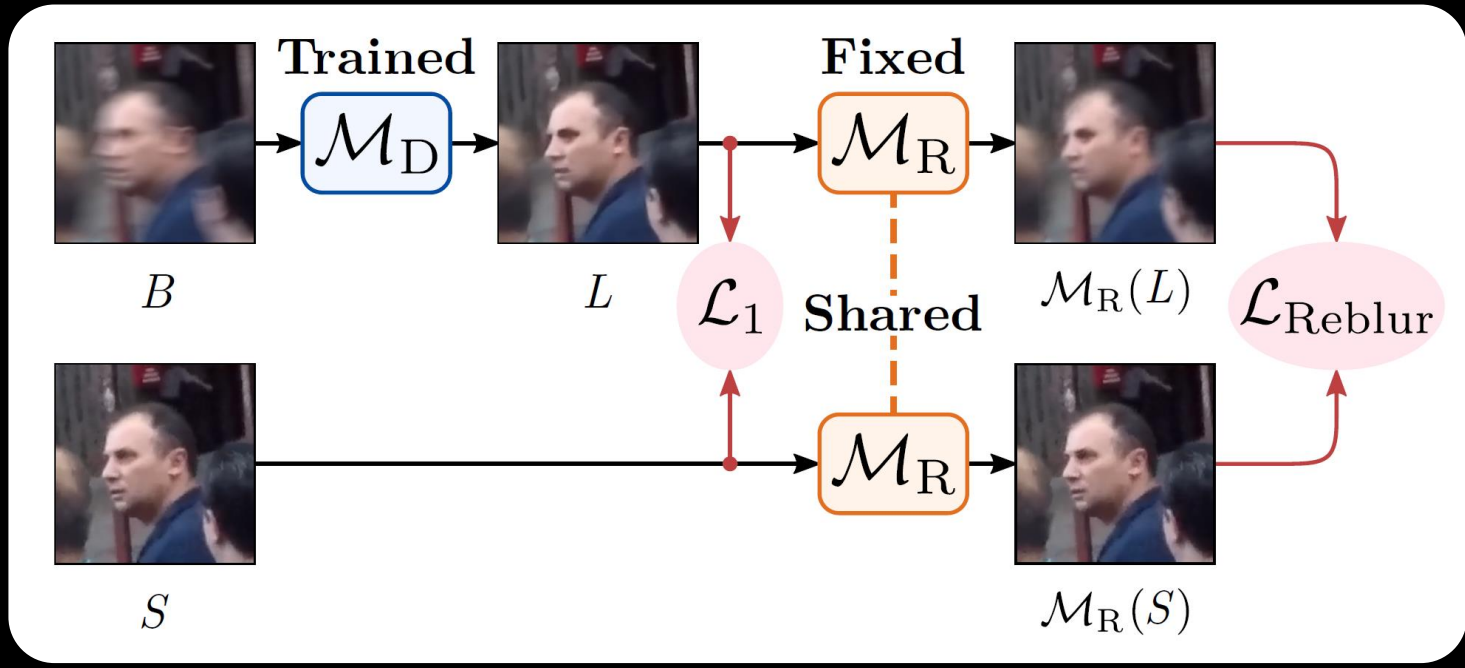
- Training
  - **Blur reconstruction**
  - Pseudo-sharp image
  - **Sharpness preservation**

$$\mathcal{L}_{\mathrm{Blur}} = \|\mathcal{M}_{\mathrm{R}}(L) - B\|$$
$$\hat{S} = \mathcal{M}_{\mathrm{D}}(S)$$
$$\mathcal{L}_{\mathrm{Sharp}} = \|\mathcal{M}_{\mathrm{R}}(\hat{S}) - \hat{S}\|$$

$$\mathcal{L}_{\mathrm{R}} = \mathcal{L}_{\mathrm{Blur}} + \mathcal{L}_{\mathrm{Sharp}}$$

Deblurring Module

- Deblurring Module $\mathcal{M}_{\mathrm{D}}$
  - Make blurry image sharp
  - Tries to resist reblurring



- Training
  - Deblurred image
  - Standard L1 loss
  - Amplified blur comparison

$$L = \mathcal{M}_{\mathrm{D}}(B)$$

$$\mathcal{L}_1 = \|\mathcal{M}_{\mathrm{D}}(B) - S\|$$

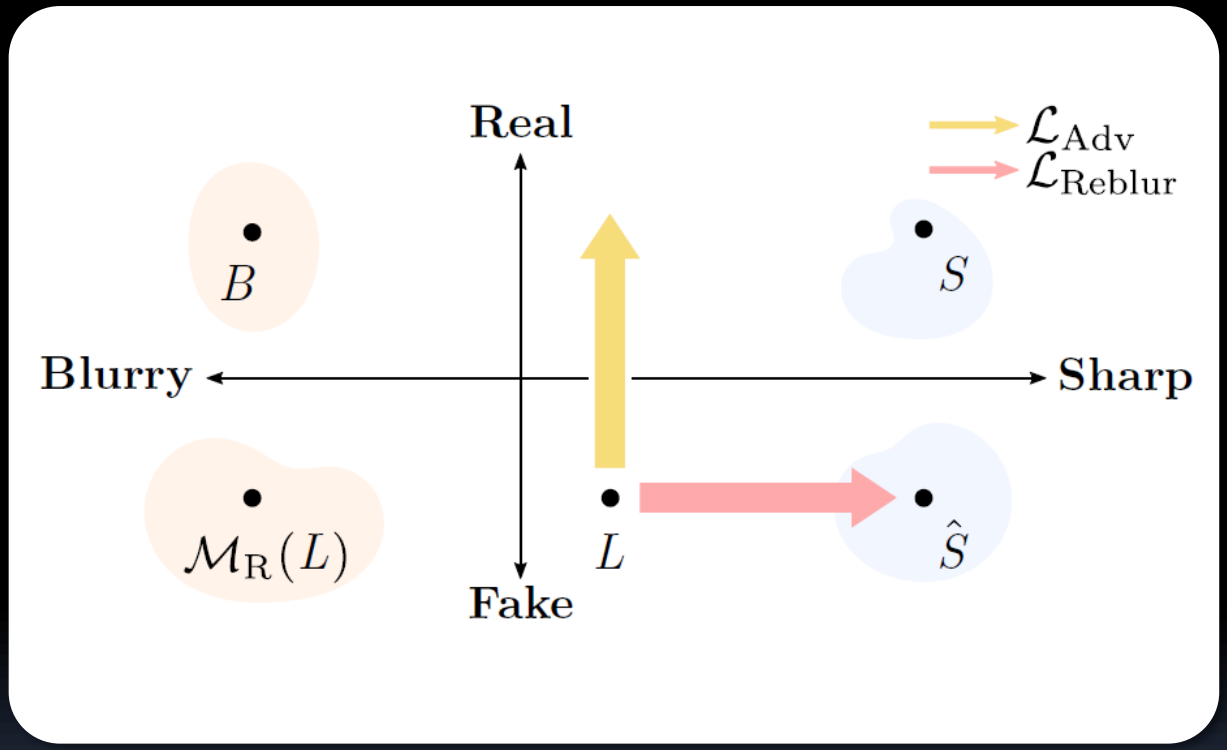
$$\mathcal{L}_{\mathrm{Reblur}} = \|\mathcal{M}_{\mathrm{R}}(L) - \mathcal{M}_{\mathrm{R}}(S)\|$$

$$\mathcal{L}_{\mathrm{D}} = \mathcal{L}_1 + \mathcal{L}_{\mathrm{Reblur}}$$

Conceptual Comparison of Loss Terms

- Adversarial loss: $\mathcal{L}_{\mathrm{Adv}}$
  - Tries to make image **realistic**
  - May not penalize real blurry image

- Reblurring loss: $\mathcal{L}_{\mathrm{Reblur}}$
  - Tries to make image **sharp**
  - Regardless of realism

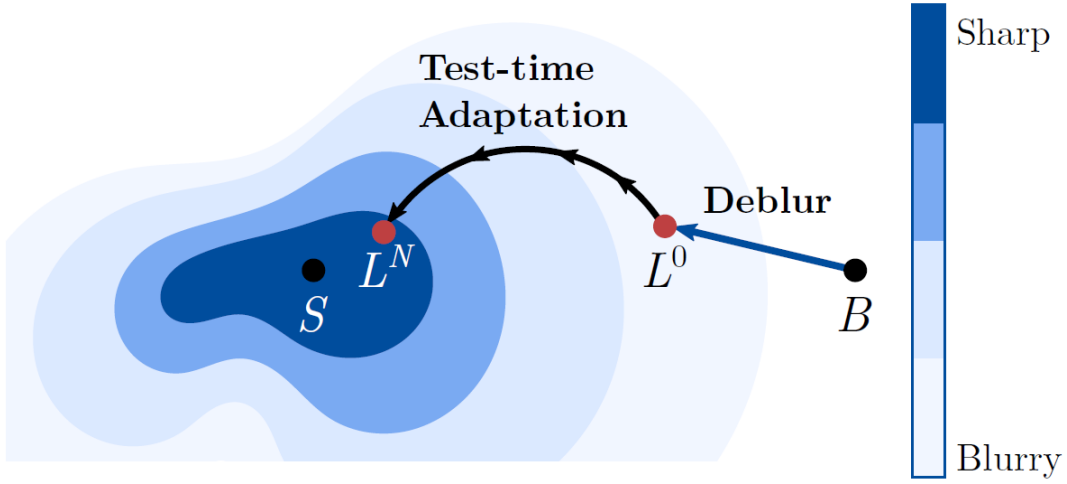


Domain of Images

Self-Supervised Reblurring Loss

- No-reference sharpness measure
  - $\mathcal{L}^{\text{self}}_{\text{Reblur}} = \|\mathcal{M}_{\text{R}}(L) - L_*\|$
  - Can serve as a **self-supervised prior**
- Test-time adaptation
  - Recursively minimize $\mathcal{L}^{\text{self}}_{\text{Reblur}}$

$L^0 = \mathcal{M}_{\text{D}}(B).$
for $i = 0 \ldots N-1$ **do**
  $L^i_* = \mathcal{M}_{\text{D}}(B).$
  $\mathcal{L}^{\text{self}}_{\text{reblur}} = \|\mathcal{M}_{\text{R}}(\mathcal{M}_{\text{D}}(B)) - L^i_*\|.$
  Update θ_{D} by $\nabla_{\theta_{\text{D}}}\mathcal{L}^{\text{self}}_{\text{Reblur}}$ and μ.
$L^N = \mathcal{M}_{\text{D}}(B).$



Qualitative Comparison

- Visual ablation on GOPRO dataset
  - Comparison of training loss

Qualitative Comparison

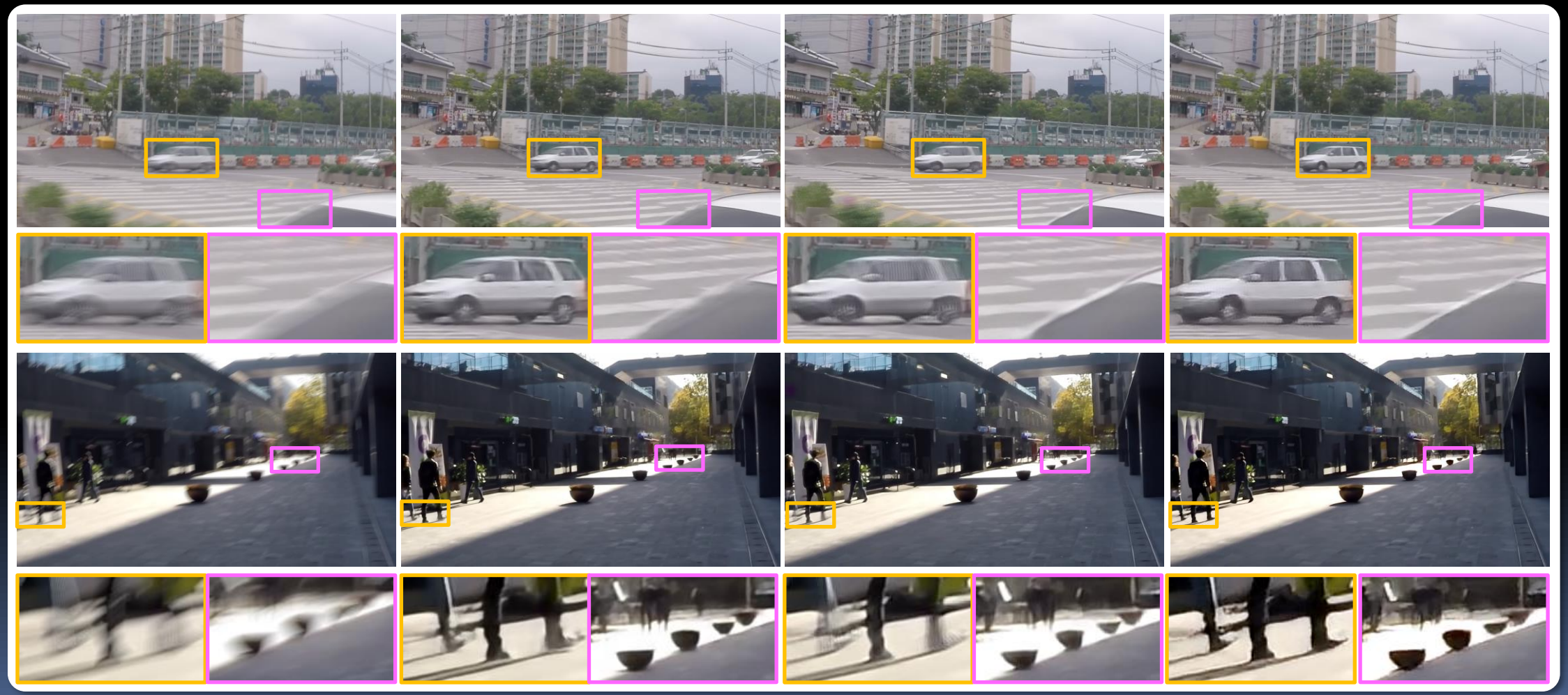
- Visual ablation on GOPRO dataset
  - Comparison of training loss

Qualitative Comparison

- Visual ablation on REDS dataset
  - Effect of test-time adaptation

Qualitative Comparison

- Comparison with the State-of-The-Art



Blur | SE-Sharing (CVPR 2019) | DeblurGAN-v2 (CVPR 2019) | Ours + TTA step 5

Quantitative Comparison

- GOPRO dataset results

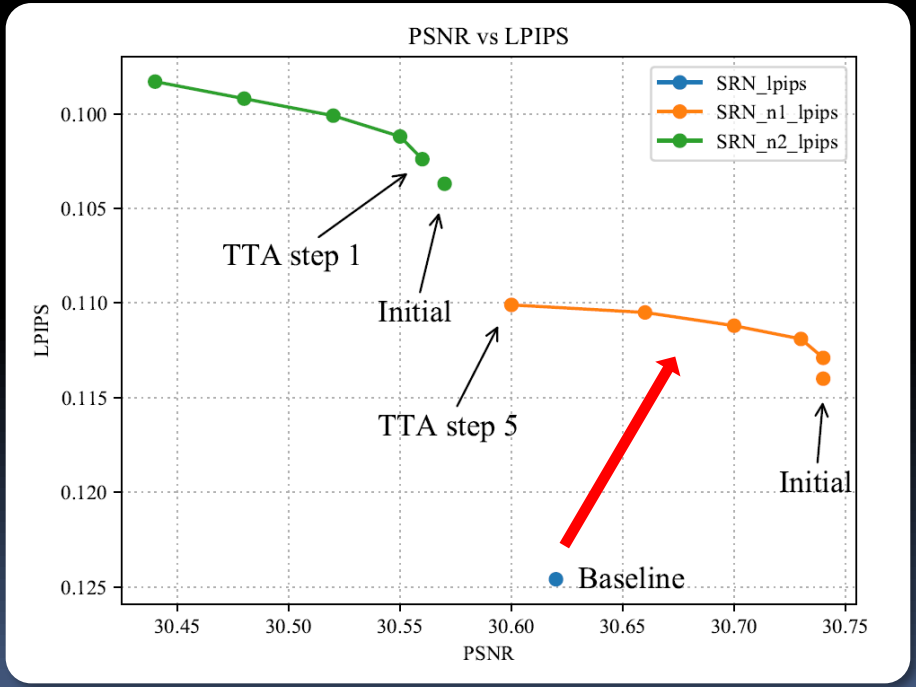
Method	LPIPS$_{\downarrow}$	NIQE$_{\downarrow}$	PSNR$^{\uparrow}$	SSIM$^{\uparrow}$
U-Net ($\mathcal{L}_1$ only)	0.1635	5.996	29.66	0.8874
$+\mathcal{L}_{\text{Reblur, n1}}$	0.1365	5.629	29.58	0.8869
$+\mathcal{L}_{\text{Reblur, n2}}$	**0.1238**	**5.124**	29.44	0.8824
SRN ($\mathcal{L}_1$ only)	0.1246	5.252	30.62	0.9078
$+\mathcal{L}_{\text{Reblur, n1}}$	0.1140	5.136	**30.74**	**0.9104**
$+\mathcal{L}_{\text{Reblur, n2}}$	**0.1037**	**4.887**	30.57	0.9074
DHN ($\mathcal{L}_1$ only)	0.1179	5.490	**31.53**	0.9207
$+\mathcal{L}_{\text{Reblur, n1}}$	0.0975	5.472	**31.53**	**0.9217**
$+\mathcal{L}_{\text{Reblur, n2}}$	**0.0837**	**5.076**	31.34	0.9177

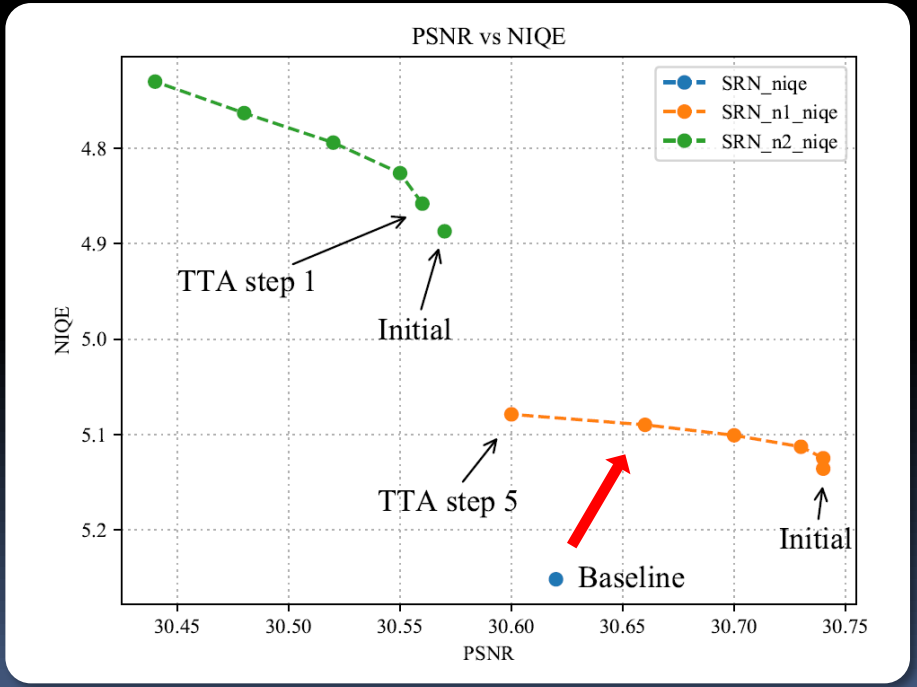
- REDS dataset results

Method	LPIPS$_{\downarrow}$	NIQE$_{\downarrow}$	PSNR$^{\uparrow}$	SSIM$^{\uparrow}$
U-Net ($\mathcal{L}_1$ only)	0.1486	3.649	30.80	0.8772
$+\mathcal{L}_{\text{Reblur, n1}}$	0.1435	3.487	30.76	**0.8776**
$+\mathcal{L}_{\text{Reblur, n2}}$	**0.1252**	**2.918**	30.46	0.8717
SRN ($\mathcal{L}_1$ only)	0.1148	3.392	31.89	0.8999
$+\mathcal{L}_{\text{Reblur, n1}}$	0.1071	3.305	**32.01**	**0.9044**
$+\mathcal{L}_{\text{Reblur, n2}}$	**0.0947**	**2.875**	31.82	0.9026
DHN ($\mathcal{L}_1$ only)	0.0942	3.288	32.65	0.9152
$+\mathcal{L}_{\text{Reblur, n1}}$	0.0931	3.248	32.57	0.9143
$+\mathcal{L}_{\text{Reblur, n2}}$	**0.0805**	**2.830**	32.44	0.9122

Perception-Distortion Trade-Off

- Reblurring loss improves perception-distortion trade-off
  - $\mathcal{L}_{\text{Reblur}}$ improves both the PSNR and perceptual metrics (LPIPS, NIQE)
  - $\mathcal{L}^{\text{self}}_{\text{Reblur}}$ further emphasizes the perceptual quality by adaptation





Summary

- **A new observation:** Clean Images are Hard to Reblur
- **Novel reblurring losses** for deblurring task
- **Test-time adaptation** from self-supervision
- **Improved visual sharpness** compared to other methods

Thank you

https://seungjunnah.github.io